Development of a heterogeneous robotic system for automated inventory stocktaking of industrial warehouse

Doctoral Thesis
by

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Doctoral Program in Engineering Systems

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I hereby declare that the work presented in this thesis was carried out by myself at Skolkovo Institute of Science and Technology, Moscow, except where due acknowledgement is made, and has not been submitted for any other degree.

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Abstract

Micro unmanned aerial vehicles (UAVs) have been gaining popularity and being used in numerous domains for the last ten years. The tendency of using drone technologies in the industry completely changes the business model and redraws enterprise landscapes. The growing e-commerce market has led to an increase in warehouse space and stricter tracking requirements at all stages. Due to these requirements and the latest technological achievements in UAV indoor navigation, drones have become widely used in warehousing operations, i.e., for automated warehouse stocktaking. This fact is confirmed by the increased number of scientific papers and patents over the past five years. UAV-based system for this application can help warehouse employees eliminate tedious and dangerous procedures.

However, there are several fundamental aspects, which limit the widespread implementation of drones for warehouse stocktaking. They are the quality of the computer vision system, the error rate, and ability to navigate in indoor environment.

Nowadays, there is no universal autonomous solution that would fully meet the industry needs and could be implemented in most warehouses. There are several solutions for conducting an inventory of manned drones, but this approach does not allow taking an inventory at any time and insuring against human error. Some solutions in the field of autonomous drones are capable of solving SLAM tasks in the warehouse space, with the huge volume of on-board sensors does not allow the size of the drone to be suitable for flights in most warehouses and limit its flight time. Other solutions do not have a computer vision system that could provide a reliable reading of markers for conducting stocktaking.

An all-new heterogeneous robotic system for automated stocktaking of industrial warehouses was created in the thesis to cope with these tasks. A new architecture of interaction between two robots unmanned ground vehicle (UGV) and UAV was developed to solve the problem of localization and navigation inside the warehouse, as well as active perception method for effective and robust barcode detecting and reading.

One of the strengths of the thesis is a comprehensive analysis of the problem of

inventory taking in warehouses. This analysis includes relevant scientific literature review on the inventory process, industrial research of more than 30 companies, conducting patent research and scientific articles in the field of robotization of the inventory process. Based on the comprehensive analysis of the stocktaking problem, we were able to determine the key factors for solving it, which formed the basis for the development of a new concept of a heterogeneous robotic system.

The first significant contribution of the thesis is a novel high-precision localization system for the autonomous heterogeneous robotic system and a method of getting global position in *xyz* coordinates with 2 cm precision in a large indoor environment. UAV localization is based on the developed adaptive active infrared (IR) marker system to achieve reliable flight on different altitudes and light conditions. Using high-precision localization data, we also create a three dimensional (3D) map of goods in a warehouse that can be used in the following flights for more accurate localization amplification. We achieve this by using the UGV as an intermediate station that provides precise global coordinates in two dimensional (2D) space and gives the information about its vertical coordinate to the UAV.

The second significant contribution of the thesis is a novel approach for real-time barcode detection and scanning using convolutional neural network (CNN). The proposed approach improves the UAV localization using scanned barcodes as landmarks in a real warehouse with low-light conditions. Instead of using the standard overlapping snake-based grid (OSBG) trajectory, we implement a novel approach for flight-path optimization based on barcode locations. This approach significantly reduces the time of warehouse stocktaking and decreases the number of mistakes in barcode scanning.

In order to achieve efficient and reliable operation of the system for a long time, we have developed a new method for the soft landing of the UAV on a ground robot based on impedance control, applied for the heterogeneous robotic system for continuous automated warehouse stocktaking. We describe the operating and mathematical principles of the impedance control for the landing system of the UAV and present the results of the real-world experiments.

In addition to the presented system, at the request of the industry, we created an interface to supervise an autonomous robot remotely from a secluded workstation in a warehouse. The proposed interface allows regular warehouse workers without experience in robotics to teleoperate the drone for a more detailed inspection. One of the promising application of developed interface is the automatic detection of damaged pallets by machine learning, we assumed that the warehouse workers could mark damaged pallets in the presented interface and thereby create a marked dataset for us while supervising the system.

These achievements allow us to state that we have created the all-new autonomous universal robotic system for inventorying industrial warehouses.

Publications

Main author

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Co-author

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Grants and awards

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Dedicated to my family.

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Chapter 1

Introduction

The main focus of this thesis is the development of a tool for automated stocktaking of industrial warehouses. As a result of our work, we will offer our vision for solving this problem. It is a heterogeneous robotic system. We will also give a complete analysis of this system in terms of its applicability to solving the stocktaking problem. Also in this thesis will be presented technical know-how for creating a heterogeneous system and the results of the presented system performance in a laboratory and warehouse environments, to assess its effectiveness. This chapter will cover such important parts as the motivation for this thesis as well as the problem that the thesis is intended to solve.

1.1 Motivation

Vertical take-off and landing (VTOL) unmanned aerial vehicles (UAVs) have been gaining popularity and being used in numerous domains for the last ten years. The tendency of using drone technologies in the industry completely changes the business model and redraws enterprise landscapes. The growing e-commerce market has led to an increase in warehouse space, but also to stricter tracking requirements at all stages Thanapal et al. [2017], Wawrla et al. [2019]. Due to these requirements and the latest technological achievements in UAV indoor navigation, drones have become widely used in warehousing operations i.e., for automated warehouse stocktaking Maurer et al. [2018]. UAV-based system for this application can help warehouse employees eliminate tedious and dangerous operations. However, one of the fundamental aspects of the introduction of drones for warehouse stocktaking is the quality of the computer vision system and the error rate. UAVs should work autonomously, provide appropriate accuracy, while the equipment installed on the UAV has to have as little weight as possible and have low power consumption for increasing operation time.

1.2 Stocktaking problem

Upon receipt of the goods or raw materials for production can often cause errors in the documents. This is especially evident with large quantities of deliveries, as a result of which there is a discrepancy between the actual balance in the warehouse and what is recorded in the acceptance papers. In order to equalize these numbers and understand the state of affairs on the availability of products, a stocktaking is carried out. This is the process of counting each item yourself to get the most accurate results. At large enterprises, such a procedure has a plan for the frequency of inspection, and therefore it is carried out regularly.

According to Traxler [2003] at each warehouse, the question of the conformity of the quantity of goods and consignments of goods is relevant, as well as reporting documentation in the form of receipts, statements and electronic databases. Ideally, these data should match exactly, but in practice this does not always happen. One of the factors that significantly complicate the accounting procedure is the difficulty of tracking the decrease in the amount of organic goods due to natural physical and chemical processes: shrinkage, deterioration and other aspects that can generally be called natural loss. Sometimes undisclosed facts of theft of property are also possible (of course, in case of theft, no one will document the fact of theft). In addition, the staff who work in the warehouse, when receiving and shipping goods, may periodically make mistakes that lead to mis-grading, shortages or surpluses.

The probability of such errors can be reduced by several times if we apply the address storage method (Bagoye [2013]). Sometimes there are situations when an arithmetic or other technical error is made in the process of processing primary documents. To eliminate all accounting inaccuracies, an stocktaking of the stored property is carried out. This event is carried out to eliminate discrepancies between the data recorded and the actual amount of valuables, as well as to identify the facts of theft and damage to property.

Each planned stocktaking should be preceded by an order, decree or any other regulatory document on the stocktaking, which approves the timing of this event, the objects being inventoried and the composition of the stocktaking commission. Usually, the commission includes: the head of the warehouse complex or his deputy, as well as the warehouse manager, chief accountant or his deputy, a public representative, a representative of the security service, storekeepers on duty and other officials involved in this procedure. Independent experts and representatives of audit services may also be involved in this process. If one of the members of the approved commission is absent at the beginning of the stocktaking, then it is considered invalid.

Before carrying out a stocktaking, all divisions of the company that are responsible for the location of goods in the warehouse need to carry out all operations to reconcile balances (returns to customers and suppliers, write-off of defects, exchanges and not delivered to the warehouse). If, for some reason, the goods remained in the warehouse, then they are folded separately, marked and not included in the stocktaking.

Defective and non-marketable goods must be in a separate place in the warehouse and in separate virtual warehouses of the information system, it is inventoried on a separate sheet. Before the start of this event, new receipts must be transferred to the status of goods for sale and be transferred in the information system to storage locations.

There is also a virtual warehouse to denote a product that “disappears” between inventories. For example, it is located in an unspecified location or "mis-sorted" with other products. Before the stocktaking, this product is also moved to the storage location for getting into the stocktaking database.

The number of inventories is regulated by the order on the accounting policy of the enterprise, but it must comply with the article of the law, according to which the stocktaking must be carried out at least once a year before drawing up the annual report.

But in practice, most warehouses that carry out temporary storage of goods carry out a full stocktaking at least once a month, or even recount certain types of goods (usually valuable goods) when each new shift of storekeepers goes to work (carry out a partial unscheduled stocktaking). This is done in order to avoid material liability in the event of loss or damage to valuable goods.

1.2.1 Stocktaking process

By the beginning of the stocktaking, all primary reporting documentation must be submitted to the accounting department and conducted through the database of the accounting program. Accordingly, all balances must be counted, and known inconsistencies must be justified and documented. When recalculating, the stored property should not be received and shipped, and it is also prohibited to move goods between warehouses. Moving goods and materials within the cells in the warehouse is also prohibited.

During the inventory process, objects can be recalculated both manually and using the database terminals, whose work is based on the principle of barcode scanning. Also, when the assortment list of the warehouse complex is small, you can do with manual counting. If, for example, it is necessary to recount the goods at a large grocery warehouse, then using the database terminal will help increase the recounting speed due to the significant automation of the goods identification. Therefore, it is always necessary to compare the label and the name that appears on the terminal display (Traxler [2003]). If the database terminals were not used during the stocktaking, then the actual quantity is recorded in collation statements, and then manually entered into the accounting program. In such actions, you must be very careful and avoid typing errors, as this will lead to distortion of the stocktaking results.

If the discrepancies between the accounting and actual data for some positions are large, then they must be recalculated. It is best if another person is appointed to recount. If there are many cases of discrepancy, then on the initiative of the management, it is possible to check the results of the stocktaking. For this, by order of the head, a new commission is created.

After the final recount and revealing discrepancies between the accounting and actual quantities of goods, the result of the stocktaking is displayed in items and also it is displayed in monetary terms. This is either a shortage or a savings. And this and that in large quantities is the subject of proceedings for the security service.

Timely stocktaking of the warehouse, carried out by professionals in accordance with modern standards, using modern technical solutions, allows you to quickly calculate bottlenecks in supply chains and links that are important for the sustainable development of business processes, identify violations and stop them in time (Kirui [2013]). Also, a promptly carried out stocktaking of warehouses helps to identify the factors most strongly influencing the formation of shortages, which include unfavorable storage conditions (including non-compliance with the temperature regime), systemic failures in accounting policies, and finally, facts of theft, concealment and postings on the part of unreliable company employees.

1.2.2 Types of warehouse inventories

According to Kirui [2013] there are the following types of stocktaking of goods in the warehouse:

- Partial stocktaking - in the course of it, the presence of only a certain part of tangible assets is checked;
- Full stocktaking - absolutely all goods in the warehouse are checked.

A full stocktaking must be carried out (Bagoye [2013]) in the following cases:

- reorganizing or liquidating a warehouse;
- the preparation of the accounting report, generated every year;
- moving a warehouse to another location;
- any emergency situation;

- an employee who is financially responsible is replaced, as well as when more than half of the warehouse employees leave the team;

- in case of damage, theft or abuse of assets in warehouse.

1.2.3 The stocktaking stages

Such large-scale events as warehouse stocktaking should be carried out regularly. This procedure allows you to regulate the process of selling and producing goods - when the manager knows the exact amount of the remainder, then you can make the right decisions about ordering or shipping goods (Faber [2015]).

Nevertheless, this work requires the attraction of the maximum amount of resources. And at the same time it is associated with significant costs. For example, during a warehouse stocktaking, you cannot ship orders to customers, and the number of employees involved (which requires additional payment) is usually quite large (Billingsley and Connolly [2008]).

As practice shows, not every company can afford to conduct a warehouse stocktaking once a month, as the professionals recommend. Nevertheless, at least once a year, this event is inevitable - it must be carried out before preparing the annual accounting report (Kirui [2013]).

The first stage is the preparation of an order for a stocktaking. It should indicate the scope of the audit, its timing, materially responsible persons, as well as the composition of the commission responsible for the event. The second stage is the stocktaking of the warehouse. It can take a different amount of time. Checking out a small, well-equipped warehouse with clear zoning and barcodes on all items will take less time. And if the products are arranged chaotically, and accounting will be carried out "manually", without using barcode readers, then this time will take significantly more. The third stage is comparing the actual results of the stocktaking with the database. If storage violations, shortages or surpluses are identified, then an investigation and measures to solve the problem follow. This is a simplified description of how to do stocktaking in a warehouse. In fact, the procedure requires a responsible approach - at least for the preparation of the premises itself, goods and their location for verification. The speed of the stocktaking directly depends on the professionalism of the employees and applied automation tools.

The main problem in carrying out such a stocktaking is stopping the warehouse for a fairly long period of time. Usually they try not to stretch it additionally and limit the process to 1 day or 1 night. But this is not always the case. In any case, the stocktaking of the warehouse should not be allowed to be interrupted - this is fraught with reasons for falsifying the result and general inaccurate data (Custodio and Machado [2020]).

1.2.4 The stocktaking procedure methods

At the moment, warehouses are dominated by three main methods of inventory taking.

Method 1 - the complete removal of pallets by workers. The pallet is first removed from the rack, scanned and then placed back. This method is the safest and is prescribed in most international companies in accordance with the company regulations. Using this method, the scan time for one pallet is the longest compared to the other two methods. In this case, the storekeeper, the driver of the reach truck, the reach truck itself, and also, in most cases, the WMS operator for issuing and processing tasks are involved in it.

Method 2 - high-altitude pallet scanning. When stocktaking is carried out using this method, the same technique is used and the same people are involved. The only difference is that the storekeeper is lifted to the pallet with the help of a reach truck. This method is faster than the first method, but much less secure. Nevertheless, it is used much more often in Russia, including in the Moscow region.

Method 3 - use of manned aerial vehicles. At the moment, this method is used much less often than the first two. Warehouse companies most often use this method by subscription, with an independent company arriving with a team of pilots and a UAV.

Table 1.1: Comparison of the warehouse stocktaking methods with prices in Russia

	method 1	**method 2**	**method 3**
average scanning time of one pallet, seconds	180	30	15
penetration into the Moscow region warehouses	21%	76%	3%
number of employees involved	3	3	1
involved technique	reach truck	reach truck	Piloted UAV
payroll labor for 1 hour, rubles	1200	1200	
equipment rent per hour, rubles	600	600	
consolidated price per one pallet, rubles	90	15	30

In Table 1.1 is presented comparison of these three methods. Cost estimates have been calculated taking into account prices and wages for Moscow and Moscow region (Average personnel costs are about 1,200 rubles per hour (for three people, taking into account the average salary of 60,000 rubles, including all deductions and taxes), excluding the cost of attracting equipment)[1].

Nevertheless, sometimes companies using the third method think about purchasing drones and maintaining their own team of pilots or purchasing fully autonomous systems. The figure 1-1 shows the dependence of the price of scanning one pallet in three cases.

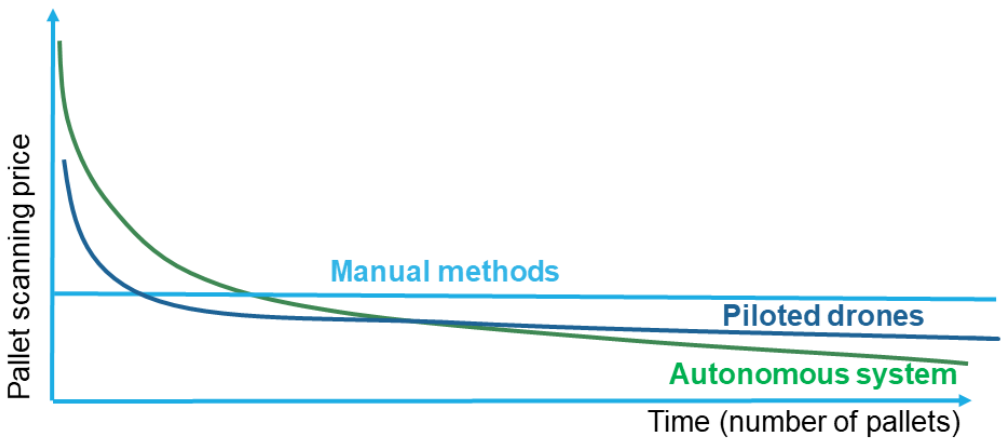


Figure 1-1: Dependence of the price of scanning one pallet on time (the total number of scanned pallets) with different methods implementation.

- When the first or second method is used to carry out an inventory, the price of one pallet remains constant and does not change over the years (it can grow

[1] http://www.logistika-prim.ru/sites/default/files/16-17_puchenkov.pdf.

with rising wages and inflation in the country).

- When hiring own team of pilots and purchasing manned drones, an initial investment is required, but gradually the cost of scanning one pallet decreases over time and taking inventories (since the initial investment is divided by the total number of pallets scanned). Nevertheless, there remain constant costs of maintaining the pilot team. As a result, the price of scanning one pallet asymptotically approaches the cost of maintaining a team of pilots per pallet.
- When buying a fully autonomous system, the price of the initial investment is higher, but there is no fixed cost of maintaining employees. All that remains is the cost of maintaining an autonomous system, which is similar to the cost of maintaining a manned drone or reach truck. In this regard, the price of scanning one pallet over time becomes several times lower compared to other methods.

It is also important to note that a fully autonomous system is able to provide a lower cost price even when using a service business model, since there are no costs for maintaining a pilot team.

1.2.5 The stocktaking limitations

The main limitations of the inventory are the presence of a large number of errors as a result of manual inventory using methods "Method 1 - the complete removal of pallets by workers" or "Method 2 - high-altitude pallet scanning". During the inventory using "Method 1", an error most often occurs as a result of pallet position changes during the inspection. For example, a pallet is removed for inspection from 5-th tier of the rack. And after inspection, it is placed on a lower vacant tier. Errors of this kind also occur in the process of collecting orders, when, after removing a part of the goods, the pallet can be returned to a symmetrical place on the other side of the row. In "Method 2" of warehouse stocktaking, workers unintentionally scan barcodes of adjacent pallet locations. All these errors directly affect the company profit, the duration of the inventory, forcing the warehouse to stop operating activities for several days.

1.3 Problem statement

A typical warehouse is a huge building with a big number of shelves over 10 meters in height. In such warehouses, every pallet and pallet-place has a unique one dimensional (1D) barcode, rarely a radio radio frequency identification (RFID) marker or a quick response (QR) marker. Barcodes and especially 1D-barcodes are the most common type of identifiers which are being used in 87% of warehouses Thanapal et al. [2017], that is why my method is focused on barcode scanning. Most of the inventory processes are done manually. Warehouse workers put down every pallet manually, then scan it and put it back on the rack. It is a very routine and time-consuming procedure. Full inventory checking deducts more than three days of the regular warehouse operation Sett et al. [2012].

A UAV would be a great solution for this task, but the main problem of all UAVs for indoor flight is a lack of precise localization and navigation system for reliable barcode scanning, thus current commercial systems Pons and Leppan [2020], Hardis Group LLC [2020] use piloted UAVs in order to scan the tags. For this purpose, we develop a heterogeneous robotic system of two collaborative robots: unmanned ground vehicle (UGV) and UAV. This system is capable of autonomous navigation and precise localization in the indoor environment. We solve the problem of the robust system operation by dividing localization into two parts for each subsystem, i.e., UAV and UGV. For localization and navigation of UGV, we use a combination of well-known methods (Gálvez-López et al. [2016], Grisetti et al. [2010]) with optimizations for my system, which is explained in more detail in Section 5.1. Implementation of such methods allows UGV to know its global coordinates. For the drone localization, we have developed a system of estimation of pose relative to the UGV. This approach enables to calculate relative coordinates of UAV to UGV and then to calculate the global coordinates of UAV. In addition, my method does not imply the use of any additional infrastructure for navigation, as opposed to motion capture systems, since all necessary equipment is installed on the UAV and UGV.

Scanning information from barcodes using a camera is a complex and ineffective method. Existing camera-based methods for barcode scanning Maurer et al. [2018]

are not suitable for usage in real warehouse conditions because of lack of lighting, image artefacts of rolling shutter cameras, and small size of barcodes. In order to get reliable information from the barcode during the flight, the UAV should be equipped with a global shutter camera and an on-board computer with enough computational performance for processing images. The real size of a pallet on a rack is usually about 1 meter wide and 0.9 meter high. According to IC Barcode Tool Recommendations by Imagine Source company ImagingSource LLC [2020] the on-board global shutter camera should have 55.8 Mpx image resolution and 53° field of view (FoV) to scan barcodes from a distance of 1 meter. For stable scanning we should have at least 2 pixels for 1 bar of a barcode with standard width 10 thousandth of an inch (mil) ImagingSource LLC [2020]. This requirement is impossible due to the unavailability of such camera in mass production. In order to solve this problem we developed my own approach based on a cheap rolling shutter camera for barcode detection and a laser scanner for reading.

1.4 Thesis structure and information work flow

In this section is the representation of thesis structure and description of information work flow.

Chapter 1 - Introduction. In the first chapter we introduce motivation for this research, formulate problem statement and observe stocktaking problem.

Chapter 2 - Background. In this chapter we provide analysis of the drone market and logistics, understand industry needs and stocktaking problem. This chapter includes industry survey of companies from Moscow Region, result of the survey formulated in the form of system requirements, and use cases of survived companies. We also perform patent analysis of stocktaking automation tools using own Cipher classifier and investigate technology leaders among companies and countries. In the end of this chapter we discuss the most relevant researches for building an automated stocktaking tool. In addition we will link the analysis of patents and research to the key factors of this thesis.

Chapter 3 - Thesis Objectives. Based on the analysis of the industry, scientific works and patents, we will confirm the key parameters of the reference model, build the final impact model. Then we will make our proposal of the heterogeneous robotic system. Then we will formulate the main research question, gap, and specific goals of this thesis.

Chapter 4 - Development of the heterogeneous robotic system. In this chapter we will describe an experimental prototype of a developed system consisting of the UAV and the UGV with a list of the necessary equipment. We will also demonstrate a prototype VR interface for super vision of our system.

Chapter 5 - Development of the indoor localization, navigation system. In the following chapter we introduce localization and navigation system of the UGV, mathematical principles of the IR-based localization system of the UAV and impedance-based control, which is important for the soft UAV landing during continuous operations.

Chapter 6 - Active perception in warehouse. In this chapter we present a UAV-based system for real-time barcode detection and scanning using scanned barcodes as landmarks in a real warehouse with low-light conditions CNN for the localization improvements, flight-path optimization, and warehouse stocktaking time reduction.

Chapter 7 - System evaluation. In this chapter we provide the results of the experiments and performance of the system in different environments i.e. laboratory condition and the real warehouse environment. We also demonstrate localization accuracy, scanning rate and flight-time comparison between several method and confirm effectiveness of presented system in comparison with current manual stocktaking by user study.

Chapter 8 - Conclusion. In the last chapter, we discuss our results obtained in this thesis, formulate thesis contribution and discuss future work, possible application of this thesis and limitations.

"if I have seen further it is by standing on the shoulders of Giants."

Isaac Newton, 1675

Chapter 2

Background

2.1 Drone market and logistics transformation

The information technology (IT) revolution, which began in the 1980s, has completely changed the modern economy, giving industry companies the ability to rebuild their operations. Today we are witnessing revolutionary changes that are similar in scale: the technology of using UAVs has radically changed business models and created new working conditions in various industries, starting with agriculture and ending with the film industry. In the very near future, customers of enterprises from various sectors of the economy will see the first effect of the use of UAVs in various fields - from delivery to interaction with insurers.

Of great interest are not only the devices themselves (drones), but also their wider use in business, for example, to obtain unprecedented amounts of data. Solutions using unmanned devices are most relevant for those industries where both mobility and high quality information are needed. In particular, companies that manage assets located in vast territories have long been faced with problems and tasks that can be solved using unmanned technology.devices. The integration of such devices into the daily operational process will help to create great advantages in the implementation of large capital construction projects, in infrastructure management and in agriculture. Insurance and mining companies will be able to find opportunities to improve the efficiency of their processes as they move to a new level in terms of data quality and availability. And of course, the transport industry will be able to completely change its concept of delivery on the last kilometer of the route (“last mile”).

Given the wide scope of the possible use of unmanned aerial vehicles, we wanted to understand what the international market for solutions using unmanned aerial vehicles will be in the future. At the same time, not only drones are considered as tools, but also all related solutions and programs that will be used in the industries covered by this study. According to our estimates, the cost of an affordable market for implementing solutions using unmanned devices exceeds \$ 127 billion.

This is the cost of ongoing business services and labor, which will be replaced in the very near future by solutions using unmanned devices. But when discussing the continuous emergence of new ways to use unmanned aerial vehicles, it is important to consider regulatory and technological issues. Departments controlling the country’s airspace must solve a difficult task: how to ensure the safety of citizens and privacy, while not restraining innovative development and growth.

In many countries, standards are being introduced that require pilots to pass a practical and theoretical exam for flights in specific areas and beyond direct line of sight, undergo a medical examination and obtain permission. The application of these standards is accompanied by technological improvements in collision avoidance and air traffic control systems. The absence of such technological solutions can prevent the expansion of the scope of unmanned devices in a particular region.

For the first time for commercial purposes, unmanned aerial vehicles were used in Japan in the early 1980s, when unmanned helicopters perfectly complemented conventional helicopters when processing rice fields with pesticides. At that time, remote-controlled aircraft technology was expensive and time-consuming.

Progress went by leaps and bounds: new technologies were developed, the regulatory framework developed, funds were allocated. Thanks to this, a large number of new applications for unmanned devices have appeared, in particular in agriculture, the infrastructure industry, security, transport, the media and the entertainment industry, the telecommunications sector, the mining industry and insurance .

The use of unmanned device technologies in existing business processes allows companies from various sectors of the economy to create new operational and business models. Each industry has diverse needs, and, as a result, industries need different solutions based on the use of unmanned devices, and the different functionality of such devices. For some sectors of the economy, flight speed and payload are important, while others choose solutions that provide high quality real-time data at an effective cost level. Given the wide scope of the possible use of unmanned aerial vehicles, we wanted to understand what the international market for solutions using unmanned aerial vehicles will be in the future. Since there are few sources of data on the current value of this market, we decided to show the potential of accessible markets.

To evaluate these markets, we determined the cost of current business services and labor, which will be replaced in the very near future by solutions using unmanned devices. According to PwC Mazur et al. [2016], the total cost of an affordable market for implementing solutions using unmanned devices exceeds $ 127 billion. Most of all the prospects for applying these solutions are in the infrastructure sector and, as well as logistics, where the total value of the accessible market is more than $ 45 billion.

Digital solutions have already gone beyond information and communications technology. They help to create new business models, types of operations, marketplaces and services that can become new sources of income in the field of logistics and warehouse storage. Digital solutions are implemented in all areas of the transport and logistics industry. The economic benefits of digitalization are real. Significant funds are being invested in the development of new digital technologies and companies, and financial markets encourage pioneer innovators with an unprecedentedly high value for their business. Changes in the processes in connection with the introduction of new software. In the near future will be relevant in view of the development of basic technologies such as artificial intelligence (AI), the Internet of things, big data analysis, blockchain. These changes will primarily concern the following areas:

- Robotization of business processes (RBP),
- Robotization of storage systems (including drones),

- Storage systems using virtual reality (VR) and augmented reality (AR),
- Optimization of delivery at the "last mile".

These trends were reflected in the forecasts and estimates the prospects of the industry in the near future, given that the leaders of the transport and logistics companies. Systems using AI in the field of logistics are divided into four basic types:

- Auxiliary Intelligence - AI-based systems that help users make decisions or perform actions. Systems with hard logic are not able to learn in the process of interaction;
- Augmented Intelligence - AI-based systems that complement human decisions and can learn in the process;
- Automation - Automation of standard and non-standard tasks. This is not about new ways of working, but about automating the implementation of existing tasks;
- Autonomous intelligence - AI-based systems that can adapt to different conditions and operate autonomously without human intervention.

PwC also cites CEOs plans Mazur et al. [2019] for transforming of warehouse using robots: 31% of managers of technology companies plan to allocate considerable resources to robotics in the next three years. Over the past two years, the view on the introduction of robots has changed and now it is formulated as - Robots support people, not replace them.

All this leads to confirmation of the relevance of the studied problem and the importance of developing this system.

2.2 The first version of the research reference model

At the first stage of investigating the problem of stocktaking, after the first meeting with a company engaged in warehouse operations, we formed a primary list of key factors for our system:

- the percentage of errors during stocktaking,
- the speed of stocktaking (by it we initially understood the mean time of scanning one pallet),
- the price of stocktaking.

We believed that the main problem is the large number of mistakes that employees make during stocktaking, as well as the salary fund, which affects the final price of stocktaking. We also believed that the current speed of the stocktaking (time to scan one pallet) is also important as it affects the duration and price of the stocktaking. The number of errors during stocktaking directly affects the company's profit, as they lead to losses and shortages of goods. Errors also affect the quality of stocktaking, which in turn does not allow the warehouse to collect orders on time, thereby reducing the overall efficiency of the warehouse and adversely affecting the company's profit. All of the above formed the first version of my reference model Fig. 2-1.

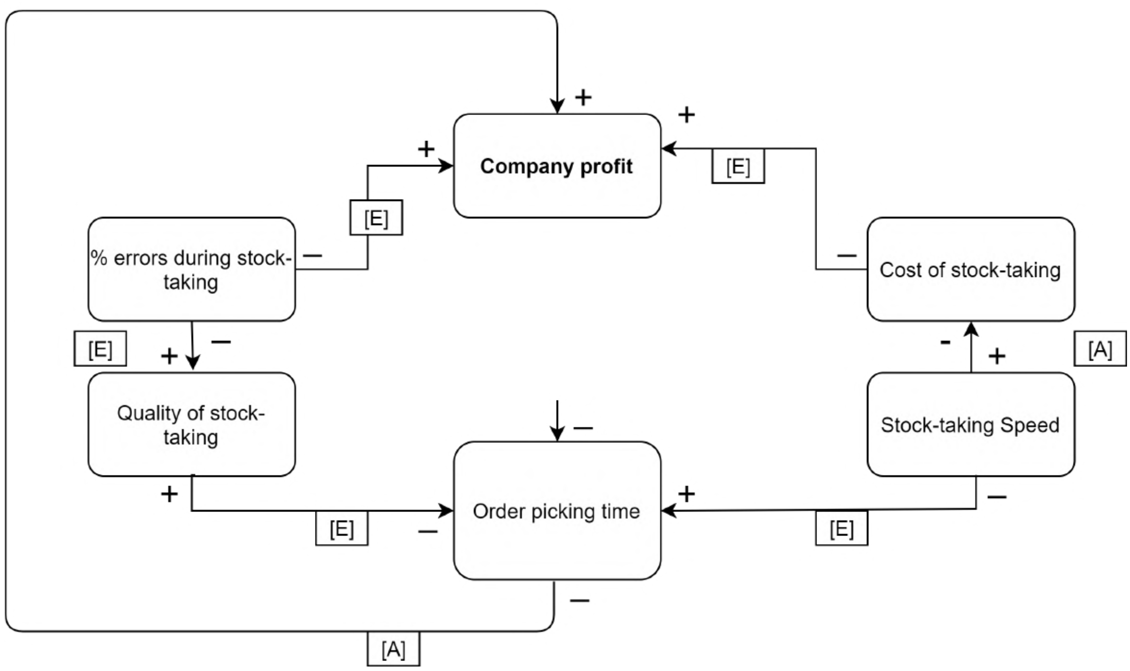


Figure 2-1: The first version of the reference model

After the first analysis of the problem and analysis of possible solutions we understood that the drone-based system could be appropriate solution, I formed the first version of my research question:

How drone-based solution will improve quality of the stocktaking and speed up it?

The drone-based solution was supposed to reduce the percentage of errors during stocktaking, increase the average scanning speed of one pallet. At the same time, we assumed that the solution being developed should also cost as little as possible, so as not to evade the price of stocktaking. This allowed me to form the first version of the impact model of this research (Fig 2-2. In order to test this model, we decided to make the first prototype of the system. It was a semi-autonomous drone that was manually piloted but also had a collision avoidance system. Also, a simple barcode scanning system was installed on it based on the global shutter camera and the Intel Nuc on-board computer. Then there were already presented solutions with similar characteristics on the market, nevertheless, we had to study whether such a system could solve the problem of stocktaking in the warehouse Pons and Leppan [2020], IFM-Tech [2019].

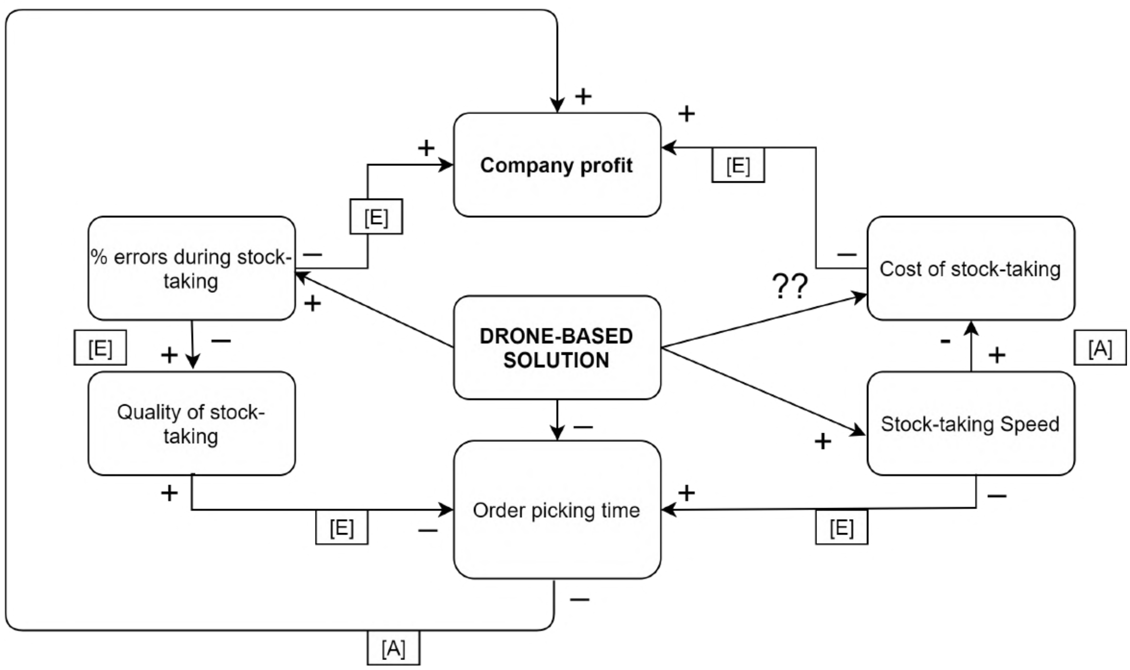


Figure 2-2: The first version of the impact model

We began to actively communicate with warehouse complexes, proposing and discussing our solution. Many companies were interested in it, but already during the first tests, we realized that to operate such a system in a warehouse, an experienced drone pilot is required and an ordinary warehouse worker without experience cannot cope with this task. Then we decided to analyze in detail other commercial solutions on the market.

2.3 Analysis of commercial solutions

DroneScan by Pons and Leppan [2020] was one of the first manned stocktaking drone solutions on the market appeared in 2015. It included a commercially available DJI Matrice 100 drone[1] with DJI Guidance[2] collision avoidance system and a laser scanner based scanning system. Nevertheless, according to open sources, the company did not have sales in the global market, and all of them were tested at a local warehouse. The drone scan solution was built based on the same drone as in our project, but the scanning system was different since we used a camera and computer vision algorithms. Nevertheless, the need to use a pilot is also a complicating factor for implementations, because the drone scan company was selling a semi-autonomous drone and not a stocktaking service.

Next on the market was a solution from IFM-Tech [2019] company appeared in 2016. They positioned their product as a fully autonomous drone that uses computer vision algorithms as well as machine learning algorithms for autonomous flight and barcode reading in a warehouse. To perform these operations in real time, the company used one of the most powerful single-board computers, Nvidea Tegra[3], as an on-board computer. In this configuration, the UAV flight time could not exceed 5-7 minutes. Also, the algorithms for localization and navigation of UAVs in warehouse conditions should work without failure, because the slightest mistake can lead to the fall of the drone, which happened during their presentation. It is important to note that the failure of localization and navigation algorithms for

[1] https://www.dji.com/matrice100
[2] https://www.dji.com/guidance
[3] https://developer.nvidia.com/tegra-development

UAVs is more critical than for ground robots. Since the failure of these algorithms in a ground robot will lead to its stop, in the case of a UAV, the drone will be destroyed. Due to the complex technical implementation and low reliability, such a system could not solve the needs of warehouse owners.

Following the previous projects, two more autonomous drone concepts from GEODIS in conjunction with DeltaDrone Caetano et al. [2017] and the EyeSee project by Hardis Group LLC [2020] Group were presented. These two projects were very similar to each other, they did not represent real projects, but showed only concepts and animated videos. Later, both companies also presented prototypes of semi-autonomous systems. Fully autonomous systems based only on UAVs could not solve the problems of the industry, since they could not guarantee their reliability due to the high complexity of localization and navigation algorithms in flight, as shown for the previous solution from the IFM-Tech [2019] company. Also, the flight time of such UAVs could not exceed 15-20 minutes.

As a result of the analysis of competitors existing at that time, we realized that the industry needs a reliable solution, which at the same time does not require professional drone control skills. It was at that moment that we got the idea of creating a heterogeneous system of two robots and a reliable localization system described in Chapter 5. Such a system had a number of main advantages:

- High reliability due to simplification and partitioning of localization and navigation algorithms;
- Long operating time due to the possibility of recharging the UAV from a ground robot;
- Autonomy, which does not require a professional pilot in the warehouse.

To evaluate our concept, we decided to better study the market and conduct research with companies in the Moscow and regional market that own warehouses. Also, after we developed a heterogeneous system and presented it on the Falling Wall Venture I. A. Kalinov and Tsetserukou, similar concepts of hybrid robotic systems for warehouse stocktaking by Woon and Ulun [2020], InventAIRy LLC [2019] and also Caetano et al. [2017] (this company changed their direction of development to design heterogeneous system) were presented, which emphasized the correct choice of the development strategy.

2.4 Analysis of the logistics industry

In order to comprehensively study the stocktaking problem, we examined and observed it from two sides, we studied the scientific literature, and also conducted this research with companies that are engaged in warehouse activities.

2.4.1 Importance of the stocktaking problem

In the course of his research, Savin [2017] noted that although the implementation of warehouse management system (WMS) is a complex process and errors usually appear after it, the introduction of WMS can simplify and improve the stocktaking process. The study also cited the fact that software vendors claim that the new solution will reduce stocktaking cost and duration, labor costs and increase storage capacity, customer service, and inventory accuracy, but the reality may be different.

According to the author, through the introduction of WMS, it is possible to increase accuracy, reduce labor costs and increase the ability to serve customers by reducing time, but this is only one side of the coin. There is little likelihood of inventory reduction and storage capacity increase. There are other factors that vary with WMS, but in most cases the value is very similar to be acceptable. It depends on how careless your processes were before the WMS. Thus, the implementation of WMS systems will not be able to completely solve the problem of human errors during the inventory, but will only slightly simplify the process.

Mohan [2012] notes in his research the problem of the importance of stocktaking, confirms the fact that this problem cannot be solved by means of the WMS implementation, and that a separate automation tool is needed to solve it. Also, this study discusses how to conduct an inventory, describes the business processes of conducting it, and discusses the technology of barcodes and RFID with their application to simplify the stocktaking process.

Wawrla et al. [2019] noted the high potential of UAV application in the logistics industry, on the basis of MarketsAndMarkets [2019] they predict the growth of the logistics UAV market by $ 29 billion by 2027 with an annual growth rate of almost 20 %. One of the most promising tasks of application in warehouse operations Amazon [2016] is the automatic inventory Xu et al. [2018].

In the field of inventory management, drones can be used for the following tasks: inventory audit, inventory management, cycle counting, item search, buffer stock maintenance and inventory. The stocktaking is a physical check of the quantity of goods stored in warehouses. Partial stocktaking is usually calculated daily or weekly by a small trained team of inventory control staff. Among other things, stocktaking is slow, time-consuming, dangerous (risky operations due to work at high altitudes), expensive and highly susceptible to the human factor errors Wawrla et al. [2019]. Drones can add value to optimize this process Briod and Thevoz [2019]. The main goals of using drones for inventory management are to increase inventory accuracy, reduce labor costs and minimize hazardous tasks for the workforce.

Also Wawrla et al. [2019] made small overview of already introduced projects, those that we have already analyzed in Section 2.3, as well as two new ones that have only recently introduced their concepts in drones for automating inventory and which have started development after beginning of this thesis Aeriu LLC [2019], Granato [2019].

2.4.2 Industry survey of Moscow Region Companies

During first and second year of the thesis development we have done a huge industrial survey and involved more than 20 companies in Moscow region. There were huge companies with their own logistic services and third partly logistic providers and the map of some companies respondents is presented in Fig. 2-3. we mainly talked with warehouse managers who held positions from an innovation manager to a warehouse director.

At the first stage, we made a list of questions, which included information about the warehouse, its size and other statistics. We also asked to identify there main problems of the warehouse, which, depending on the respondents, could be solved using automation or the robots implementation.

Figure 2-3: Map of surveyed companies in the Moscow region.

A total of 46 people from 24 companies participated in the survey. 87 % of respondents (40 people) noted the problem of inventorying among the three most important warehouse problems that they would like to solve with the help of automation by robots.

We have developed a lot of concepts to find optimal one using requirements from industry. But these concepts did not give a complete answer to solve the inventory problem. Then we asked the respondents in free form to describe the requirements for a robotic product that would help them. And this approach had had a positive effect. All of companies said something very similar to each other:

- Work without people,
- Work as 1 man during 8-hour shift,
- Work without additional active infrastructure,
- Be launch by average warehouse worker,

- Work with barcodes as they are the most common type of identification,
- Work with humans in one environment,
- Have ability to be controlled or supervised by human,
- Scan the rack at 12 meter.

These answers allowed me to formulate a list of system requirements.

2.4.3 Outcomes of the industry survey

Based on this analysis, we have received not only a list of approximate technological requirements for the developed system, but also changes in some key parameters in the reference model of our research. The **percentage of errors during stocktaking** was indeed one of the key parameters for all companies that affected the quality of stocktaking.

Prior to industry survey, we assumed that **scanning time per pallet** is the most important key factor. But our research has shown that this is not entirely true. As a result of the survey, it was revealed that the total duration of the stocktaking is critical for the warehouse that consists of: **scanning time per pallet** multiplied by the number of pallets, **setup time before each start**, and other delays (battery replacement, battery charging). In other words, you also need to consider the time it takes to set up and start the system before each stocktaking. Warehouses often carry out selective stocktaking not on a schedule, but at convenient times or at the request of the client. Thus, companies such as UVL LLC [2019] Robotics, offering an stocktaking service with semi-autonomous drones and a team of professional pilots, cannot solve this problem, since any stocktaking must be planned in advance, and the time before its launch can be up to several weeks. In addition, the presence of unauthorized people (drone pilot team) in the warehouse during stocktaking is a complicating factor for any warehouse.

In addition, the warehouse representatives paid special attention to a new factor for us: **quantity of infrastructure changes**. As most of the warehouse space is designed in the most optimal way for the daily operations. Therefore, some changes to implement autonomous systems could not be made in the warehouse, for example:

- Installation of additional power supply for each rack, for example, for active sensors, which are required for reliable localization or navigation of some autonomous systems or for charging UAVs on the upper tiers of the racks;
- Increasing the width of the passage between the racks, for greater reliability of UAV flights between them.

The following types of infrastructure changes could be considered acceptable and not costly in the warehouse:

- Installation of reflective passive beacons on the legs of the shelving in the warehouse;
- Installation of an additional charging station in the room with forklifts and other equipment;
- Bonding of additional passive AR-tags on the floor and racks to improve the reliability of the UAV localization.

Another important parameter for them was the ability to monitor the system to control and more thoroughly analyze some areas of the warehouse with expensive products, as well as record the entire inventory process for analysis in case of errors. Such a system should be interactive and provide a simple remote adjustment in case of additional inspection. One of the ways to implement such a system is the VR interface.

The warehouses also counted on a long system working time (at least 8 hours) to increase the average stocktaking speed. In addition, the system should be safe and easy to use for ordinary warehouse workers, without special knowledge. In other words, as a result of the survey, a list of informal requirements for the system from the industry was formed.

Based on the results of this analysis, a list of requirements for the development of the system was formed in the following subsection, and the key factors for the impact model of this study were clarified in Chapter 3.

2.4.4 Identified system requirements

On the basis of industry request we formed final concept of the heterogeneous robot that consists of mobile platform and UAV and formulated System requirements:

- Fully automated solution,
- Safety for people,
- Indoor navigation and localization,
- All equipment is installed on the robot,
- No additional infrastructure,
- Working height is up to 12 meters,
- Barcode detection and recognition,
- Faster than people,
- Working time is equal to 8 hours,
- Have VR interface for supervision and task planning,
- Easy to use as home vacuum cleaner.

After compiling a list of requirements for the system, we began searching for relevant patents and scientific articles, on the basis of which it would be possible to make the first concepts of proposed system, to define our research contribution and novelty.

2.4.5 Industry use cases

During market research and a review of the stocktaking problem, the most popular examples and consequences of this problem were found. The first kind of problems is inherent in companies that are picking orders at the warehouse, most often these are providers of outsourcing logistics services and the warehouse area of such a company starts at 10,000 square meters. In such companies, it is necessary to fully load the car within 15-45 minutes, depending on the regulations and the order collection system (Picker to Part, Part to Picker, Sorting System, Pick to Box Dallari et al. [2009]). If in the process of collecting orders the allotted time is exceeded, then this entails a number of consequences:

- The planned schedule for shipment of orders from the warehouse is violated
- The gate for shipment cannot be cleared for the next truck
- The schedule for truck transport companies is completely lost

Thus, the delay of one order has a wave-like effect both in the work of the warehouse and in the work of transport companies. All participants in the process begin to incur losses. According to surveys of companies conducted during market research, it's possible to compensate for 10-15 minute delays when finding goods quickly during the day, as this is incorporated into warehouse risk management systems. But several times a month there are cases when the search for the necessary product takes 1 to 8 hours, which certainly entails the problems and costs described above. Losses in the efficiency of the warehouse operation due to such an accident can reach 30% over several days, plus to these losses are compensations to transport companies. The following kind of problems was identified among companies that are engaged in the production of non-food products and equipment. As a rule, for such companies, the territory of the enterprise is divided into three main zones:

- Warehouse of raw materials for production;
- Production Line;
- Finished products warehouse.

The finished products warehouse in such companies is much less prone to problems of the first kind, since there is strict control over the production schedule, and it is production failures that entail the main costs. Failures in production often arise precisely due to untimely and inaccurate stocktaking conducted at the warehouse. While studying the market of Moscow and the Moscow region, we found a vivid example of such a problem in a Samsung production warehouse. Their production chain was aimed at assembling TVs and washing machines of various models. Weekly, they had a situation when components from another TV model came to the assembly line, or could not find the necessary components at the assembly stage in the warehouse. The company estimated its losses from $ 10,000 per minute of assembly line downtime.

The third kind of problems was identified among companies that are engaged in food production and picking soon spoiled products. Their warehouse is usually divided into several zones related to the storage conditions of finished products and raw materials. Due to inaccurate stocktaking, such companies either violated the shelf life of finished products or raw materials, so they did not fall into production or order picking until they expired. The second aspect of this problem was the violation of storage conditions for raw materials and products in different parts of the warehouse, which also led to direct product losses. The costs in this situation were the price of raw materials, as well as fines for untimely finished products.

2.5 Patent analysis of stocktaking automation tools

Since this thesis project should have significant influence and application in industry, it is essential to provide patent analysis and understand world trends, market leaders, as well as leading technological countries. Proposed technology is very complex, thus we decided to build a custom classifier for patented technology search via the Cipher analytics tool Cipher [2020] and teach it for the best result.

2.5.1 Building of Cipher classifier

The defined training set in the Cipher contains a combination of the following technologies: stocktaking using UAVs, stocktaking automation, methods of positioning, navigation, landing and controlling of quadcopters; visual and image processing by drones; obstacle avoidance systems during the flight; tracking methods via camera, RFID, barcode, QR code.

Since the main product in our system is the mobile robot and the UAV, we began creating the training set by searching for patents via various synonyms like UAV, drone, multirotor, quadrotor, aerial vehicle. However, the use of a multitude of synonyms introduced a certain "noise" in the suggested patents at the initial stage, since the terms of UAV and drone are used for a wide class of vehicles. Another "noise" was caused by the presence of a lot of patents related to the delivery applications of quadcopters from such companies like Walmart, Amazon, etc. However, there is not our area of interest and we had to exclude all associated patents. The main difficulty during the preparation of the training set was that many of the considered patents had not yet been published and it is difficult to get a full understanding of technology only by the abstract. In addition, around half of patents were Chinese or Korean and in this case, we could reckon only on the provided figures and abstract in Cipher.

In order to improve a search of necessary technologies it was created the following request in Cipher: (navigation OR recognition OR marker OR barcode OR RFID OR positioning OR visual OR "computer vision" OR image OR inventory OR warehouse OR using OR stocktaking) AND (quadcopter OR quadrotor OR drone OR UAV OR multirotor)

2.5.2 Technology leaders among companies

One of the main parts of the patent analysis is defining the corporate landscape, i.e., the study of the organizations involved in the formation of the intellectual property (IP) pool. In general, two types of organizations can be identified.

1. Scientific institutions and researchers.

A lot of universities have entire laboratories engaged in the development of cutting edge technologies and their applications in the industry. Scientists and engineers work on their projects looking at the potential areas where the developed technology could be potentially commercialized. To protect the inventions universities work on preferential transfer of IP in the exclusive licensing to authors and co-authors. Besides, research institutes can be considered as holders of IP in case they are not interested in license sales. Institutes can share their rights with sponsors or research investors or with external researchers to avoid jurisdictional issues (such as copyright infringement upon publication).

2. Private companies.

Private companies are the most active players in the developing projects which potentially can have commercial success. Many large enterprises have their own departments managing assets based on one or another IP. For the strategic development of the organization, management conducts systematic protection of IP. Companies often work in collaboration with institutes in the same type of developing problem. Thus, they finance laboratories or teams of researchers. Thereby, they can get not only the technology but also diversified the IP rights.

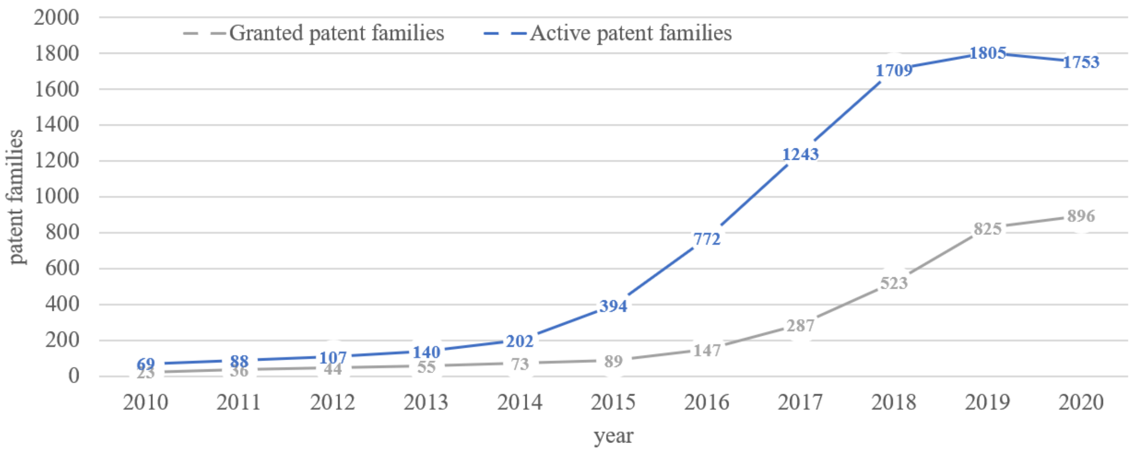


Figure 2-4: Number of patent families by year.

The market for our technology scope is growing fast. As we can see in Fig. 2-4, there is a growing demand for such a type of technology. In addition, it is a relatively new market niche since the first patents appeared only in the year 2003.

According to the result of patent analysis we could name companies-worldwide known leaders: Private owner, DJI, Amazon Technologies Inc, Korea Aerospace Research Institute, Parrot SA, Qualcomm Inc, LG Electronics Inc, Korean Air Lines Ltd, University Beihang, International Business Machines Corp, Intel Corporation, JD.com Inc, Honeywell International Inc, Nanjing University of Aeronautics and Astronautics, Walmart Stores Inc (Fig. 2-5).

For better understanding we provided following statistics:

- Count of patent families that are granted and pending in each year. Patent

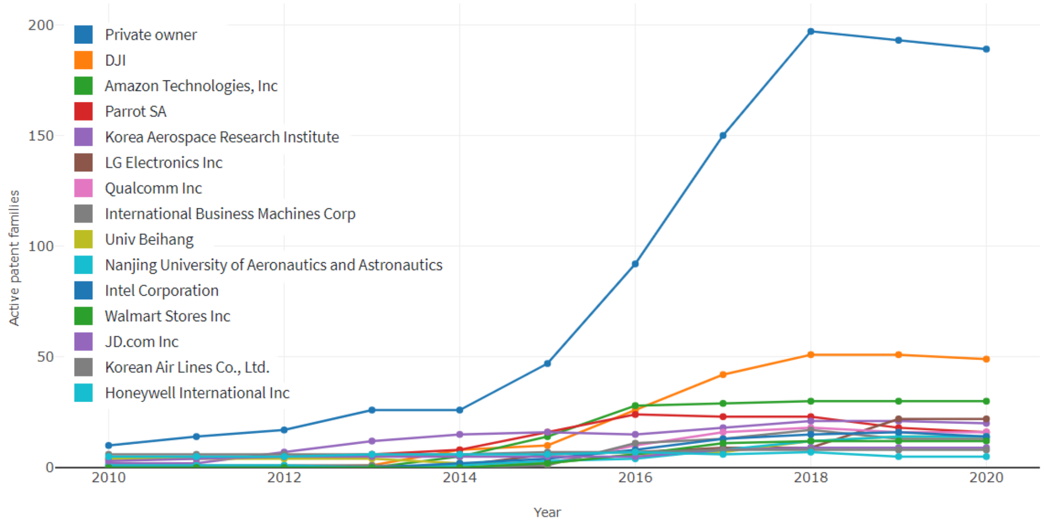


Figure 2-5: Count of patent families that are granted and pending in each year.

families are only counted for the years they are active (Table 2.1),

- Currently pending and actively prosecuted patent families by organisation (Fig. 2-6),
- The number of patent families published each year by publication year and organisation (Fig. 2-7).

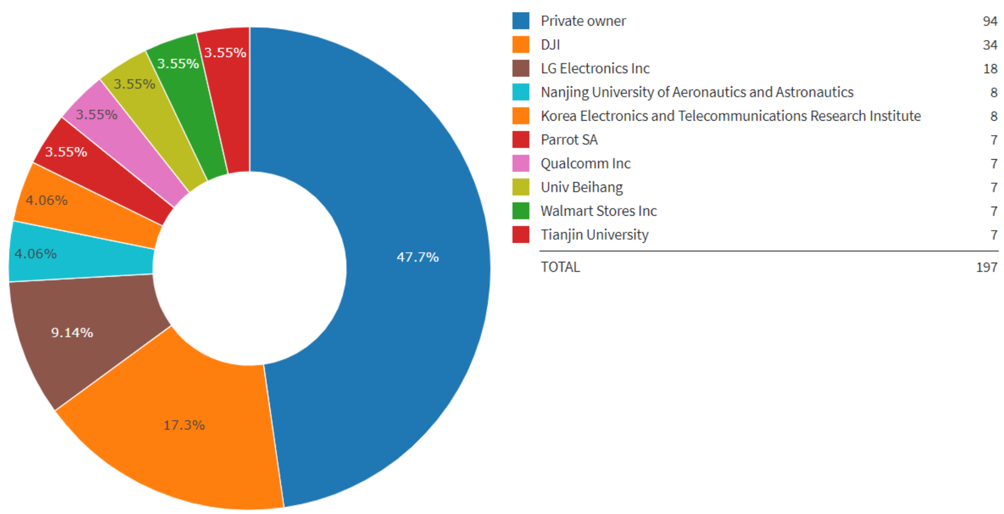


Figure 2-6: Currently pending and actively prosecuted patent families by organisation.

Table 2.1: Count of patent families that are granted and pending in each year.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Private owner	10	14	17	26	26	47	92	150	197	193	189
DJI	0	0	0	1	8	10	26	42	51	51	49
Amazon Technologies, Inc	0	0	0	0	5	14	28	29	30	30	30
Korea Aerospace Research Institute	2	2	7	12	15	16	15	18	21	21	20
Parrot SA	4	5	5	6	8	16	24	23	23	18	16
Qualcomm Inc	0	0	0	0	0	2	10	16	18	16	16
LG Electronics Inc	0	0	0	0	1	6	7	9	9	22	22
Korean Air Lines Co., Ltd.	6	6	6	6	6	7	7	8	8	8	8
Univ Beihang	4	4	4	4	2	2	6	7	12	14	14
International Business Machines Corp	1	1	1	1	0	1	11	13	17	13	13
Intel Corporation	0	0	0	0	2	4	8	13	15	16	14
JD.com Inc	3	4	5	5	5	5	5	8	9	9	9
Honeywell International Inc	5	5	5	6	6	6	7	6	7	5	5
Nanjing University of Aeronautics and Astronautics	1	1	1	0	1	3	4	8	12	14	14
Walmart Stores Inc	0	0	0	0	0	2	6	11	12	12	12
TOTAL	36	42	51	67	85	141	256	361	441	442	431

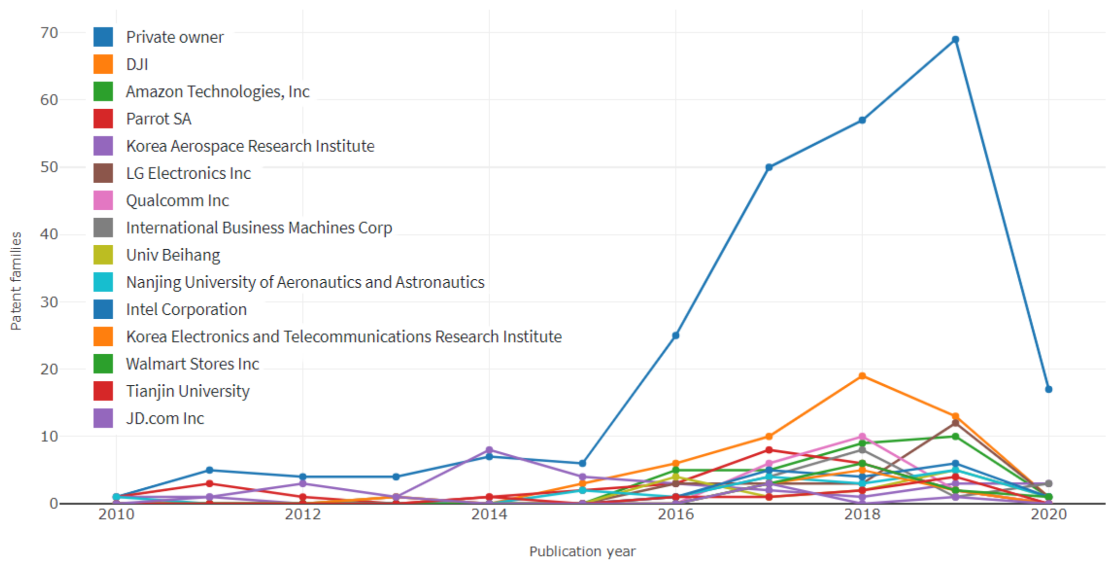


Figure 2-7: The number of patent families published each year by publication year and organisation.

It is important to note that among the 15 leading companies there are three such companies as Amazon Technologies Inc, JD.com Inc, Walmart Stores Inc. These companies are the absolute leaders in the retail industry. The number of patents in the selected field indicates that these companies invested huge internal resources

Table 2.2: The number of patent families published each year by publication year and organisation.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	TOTAL
Private owner	1	5	4	4	7	6	25	50	57	69	17	245
DJI	0	0	0	0	0	3	6	10	19	13	1	52
Amazon Technologies, Inc	0	0	0	0	0	0	5	5	9	10	1	30
Parrot SA	1	3	1	0	1	2	3	8	6	2	0	27
Korea Aerospace Research Institute	1	1	0	1	8	4	3	2	1	3	3	27
LG Electronics Inc	0	0	0	0	0	0	3	3	3	12	1	22
Qualcomm Inc	0	0	0	0	0	0	0	6	10	2	0	18
International Business Machines Corp	0	0	0	0	0	0	1	4	8	1	3	17
Nanjing University of Aeronautics and Astronautics	1	0	0	0	0	2	1	4	3	5	1	17
Intel Corporation	0	0	0	0	0	0	1	5	4	6	1	17
Univ Beihang	0	0	0	1	0	0	4	1	2	5	1	14
Walmart Stores Inc	0	0	0	0	0	0	0	3	6	2	1	12
Korea Electronics and Telecommunications Research Institute	0	0	0	1	0	0	0	3	5	2	0	11
Tianjin University	0	0	0	0	1	0	1	1	2	4	0	9
JD.com Inc	0	1	3	1	0	0	0	3	0	1	0	9
TOTAL	4	10	8	8	17	17	53	108	135	137	30	527

in the development of technologies for the automated stocktaking process, which allowed them to carry out per-minute planning of warehouse operations. And as a consequence of this fact, Amazon, JD and Walmart were able to provide the best service and become absolute leaders in the industry.

2.5.3 Geographical analysis of patent families

The territory analysis, where patents with the same technology field were granted, is a very important part for monitoring potential competitors in different countries and developing further marketing strategies. A number of granted patents for all companies in our technology field is quite big, but we have found three absolute leaders those about 75% of all granted patent: Republic of Korea (333), USA (320), China (296), these countries marked red in Fig. 2-8.

The shares of other countries are presented in Fig.2-9.

The overall leader between countries in a patent application in investigated scientific area is China (Fig. 2-10).

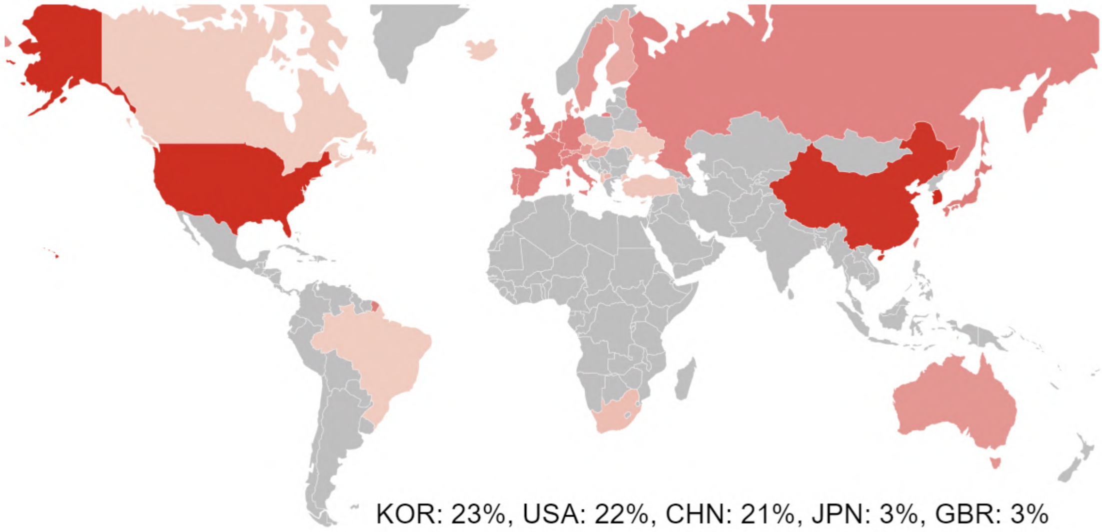


Figure 2-8: The number of granted patents in world map.

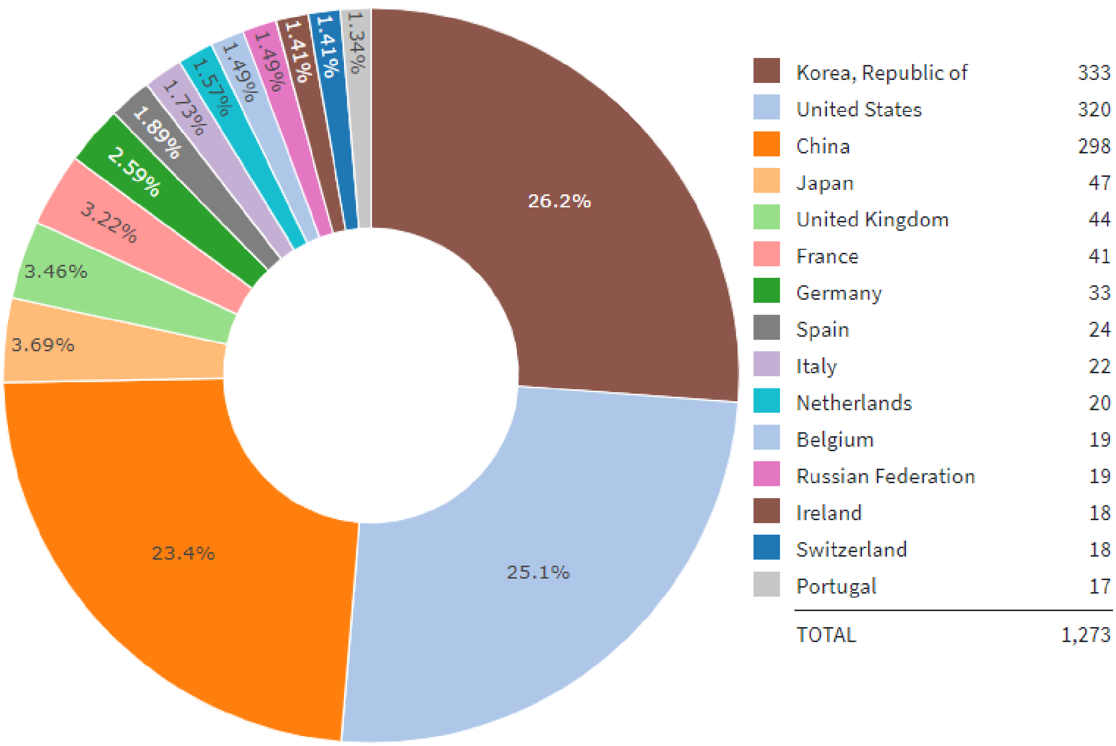


Figure 2-9: Currently active individual patent grants per country.

Also we have done analysis taking into account the country and company

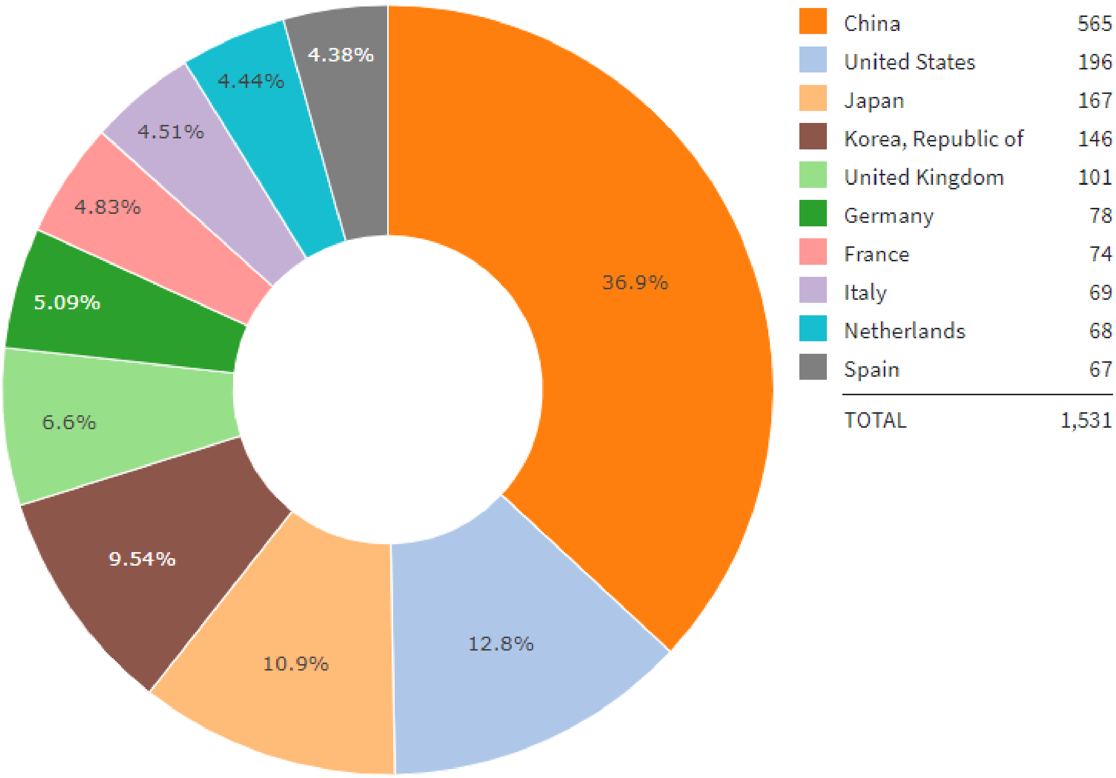


Figure 2-10: Currently active individual patent applications per country.

	United States	Korea, Republic of	China	United Kingdom	France	Germany	Italy	Japan	Spain	Netherlands	Belgium	Ireland	Switzerland	Australia	Russian Federation	TOTAL
Private owner	14	49	21	8	1	1	0	1	5	0	0	0	0	1	5	106
DJI	17	0	13	5	5	5	3	10	0	5	3	4	3	0	0	73
Amazon Technologies, Inc	34	0	0	1	1	1	1	2	1	1	1	1	1	0	0	45
Parrot SA	8	0	2	6	11	6	3	1	1	2	1	1	2	0	0	44
Qualcomm Inc	11	0	0	3	3	3	2	0	2	2	3	3	3	0	0	35
DCNS Group	2	2	0	2	3	2	2	1	2	2	0	0	0	2	1	21
Korea Aerospace Research Institute	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	20
LG Electronics Inc	2	1	0	2	2	2	2	0	2	1	2	2	2	0	0	20
Eagleview Technologies Inc	8	0	0	1	1	1	1	0	1	1	1	0	0	1	0	16
Panasonic Corporation	2	0	0	1	1	1	1	2	1	1	1	1	1	0	0	13
Saab AB	2	0	0	2	2	2	2	0	2	0	0	0	0	0	0	12
Kim Si-Eun	1	1	1	1	1	1	0	1	0	0	1	1	1	1	0	11
Kim Keun-Young	1	1	1	1	1	1	0	1	0	0	1	1	1	1	0	11
Siemens AG	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	9
Tecteco Security Systems, S.L.	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	9
TOTAL	102	74	38	35	34	28	19	19	19	17	16	16	16	6	6	445

Figure 2-11: Currently active and granted individual patents per country by organisation.

2.5.4 Most relevant patents of automated stocktaking tools

After a thorough analysis of the patent area of all technologies connected with this topic we found the most relevant patents to proposed system.

Patent Olivo and Buzaki [2016] concludes various methods for carrying out an inventory using a UAV with a barcode scanner. These inventory processes require constant operator control. A employee walks with a drone and a computer in a warehouse and launches the drone only when he comes to the necessary place in the warehouse. The UAV exchanges information with the computer and with the WMS. However this patent includes only principles of solving stocktaking problem but does not include any technical realization.

The method for navigating the drone inside the warehouse using RFID tags is patented Jones et al. [2017]. This patent describes only the method of navigation inside warehouses without a specific application. The patent owner is the US company Azure Sky Group LLC that provides an integrated solution for civilian unmanned aerial vehicles. Currently, this company has only one active patent family granted in the USA.

Patent Parpia and Singh [2016] decrides one of the possible application of the UAV for warehouse stocktaking using RFID tag scanning. This technology was granted in 2016 in the United States. However, it expired due to failure to pay the maintenance fee this year.

System for security monitoring in closed spaces using a drone is described in patent DeCenzo et al. [2017]. The main technical solution is avoidance of duplication of all necessary sensors on the walls and shelving and replacing them with a single copy of each installed on the drone in warehouse. The system does not provide solution for warehouse stocktaking, it only uses similar sensors for indoors navigation.

Patent Mehranfar [2016] presents a system for monitoring objects in an enclosed space, such as a construction site, a campus or a shopping center with many small shops. Only a monitoring system with the help of drones and a radio frequency identification network is presented here as an economically advantageous method of preventing emergencies, which differs from current project's role.

This patent family Lakshminarasimha et al. [2019] relates generally to inventory management, and more particularly to system and method for airborne shelf inspection and inventor management. When a UAV has to be navigated based on navigation information embedded in visual markers on different items in the inventory, and if one or more of the visual markers are not completely visible due to occlusion, then the UAV automatically recovers data that is missing due to the occlusion, and accordingly navigates the UAV. However they still use visual preinstalled visual markers.

Following patent Ramirez et al. [2016] describes the drone system for spotting, tagging, localizing, registering and inventorying objects located inside large outdoor areas via Ultra High Frequency (UHF) RFID, but system could not read barcodes, what is essential for the most warehouses.

This invention of Kiewicz et al. [2017] includes a system for tracking goods in the distribution centre by a UAV via RFID tags but could not use any other identifier.

Patent by Hyo and Won [2015] describes the ground mobile robot for controlling the path of a UAV via processing the image information received from the flying drone, that could be applied in proposed system.

Invention of GmbH [2020] presents the use of a UAV, in particular a quadrocopter or multicopter, for maintenance work on warehouses with shelves, storage and retrieval machines and conveyor technology within the warehouse when installed or in operation but without mobile platform.

The invention of Yuqing et al. [2017] belongs to air vehicle technique field, in particular to a kind of UAV system suitable for container warehouse logistics. Including drone body, vacuum cap type grasping mechanism, visual identifying system and control system. Also authors presented utility model as a separate patent Yuqing et al. [2019].

The present utility model Niu et al. [2019] discloses the UAV system in a kind of unmanned plane landing storehouse and application the unmanned plane landing storehouse, wherein unmanned plane landing storehouse includes: warehouse braced frame, is formed with accommodating space in warehouse braced frame.

The invention of Liu et al. [2018] discloses a kind of warehouse patrol UAV system and its inspection methods, it is related to storehouse management field, including infrared obstacle avoidance module, shooting module, charging module, camera cradle head, altimeter, stabilizer, server, fly control module and processor, the inspection method carries out successively around line walking shelf by unmanned plane.

The Amazon company disclosed inventory systems and methods can be used to retrieve and transport items from one location in an inventory system to another Purwin and Stubbs [2018]. Specifically, an unmanned aerial vehicle (UAV) including passive buoyancy element, a thrust unit, and a retention feature, can be controlled by a management component to retrieve one or more items, transport the item or items, and deposit the item or items. Also Amazon disclosed unmanned aerial vehicle (UAV) includes a buoyant airbag, a drive unit, a retention feature, and an onboard control module that can be configured to cause the drive unit to displace the UAV, cause the retention feature to retain one or more items for transport, and receive instructions to transfer items from one location to another Purwin and Stubbs [2018].

Univ Zhejiang Technology presented the unmanned plane three-dimensional paths planning method made an inventory based on RFID inventory Yan et al. [2019].

The present invention Cai et al. [2019] relates to air vehicle technique fields, in particular a kind of UAV Intelligent hangar inventory and optimization method based on RFID, including UAV Intelligent hangar inventory method and UAV Intelligent hangar inventory optimization method

Summing up the analysis of the patents presented above, it becomes clear that the main goal of almost all of the submitted patents is to positively influence two main factors, to reduce **percentage of errors during stocktaking**, and to reduce the time for conducting an inventory, in another words to increase **mean stocktaking speed**. It is also worth noting that most of the presented solutions are built-in and do not imply significant infrastructure changes to the warehouse. This fact also highlights the importance of another key factor for this research implementation - **quantity of infrastructure changes** in the warehouse. We highlight all key factors and sum up the reason for each of them in Section 3.1

2.6 Relevant researches for building an automated stocktaking tool

2.6.1 Manned aerial vehicles for stocktaking

Over the past few years, a lot of systems related to drone-assisted inventory management in warehouses were presented. Fernández-Caramés et al. [2019] presented design of an the UAV and blockchain-based system for Industry 4.0 inventory with ability to use smart contract to automate certain processes without human intervention. Their work focuses on industrial inspection with RFID tags but the flight of the UAV is not autonomous and requires a pilot unlike our system. Also, it is important to note that presented system doesn't cover barcode reading and use RFID tags, that is not suitable for the most warehouses. In addition, a UAV with a pilot does not satisfy one of the key factors **setup time before each start**.

Macoir et al. [2019] presented the high accuracy and low cost of ultra-wideband (UWB) devices for indoor positioning and tracking drones in warehouses for autonomous stocktaking. They also developed a multi-technology UWB medium access control (MAC) protocol for localization but their solution still requires communication infrastructure and power supply in a warehouse. In addition, the experimental flight data were not presented in the real warehouse for validation of the system. Thus, this work couldn't satisfy following key factor **quantity of infrastructural changes**.

2.6.2 UAV path planning for stocktaking

Choi et al. [2019] introduced framework for multi-UAV trajectory optimization to scan the entire inventory space and a multi-layer CNN architecture to track inventory. Nevertheless, the paper presents only possible approaches for solving the problem of trajectory optimization, the results of numerical modeling of trajectories, and the results of post-processing of collected photographs with the help of various CNN without any experiments with real flights. Thus, in this work, theoretical methods were presented for optimizing the flight path of several UAVs when detecting scanned objects in the image. Nevertheless, the problem of reliable reading of tags (barcodes) was not covered in this work, which does not allow influencing the key factor **% of errors during stocktaking**. Also the authors of the work did not mention whether the UAV is manned or unmanned, which makes it impossible to assess the impact on factors such **quantity of infrastructural changes** and **setup time before each start**.

Barlow et al. [2019] also tried to solve problem of multi-the UAV trajectory optimization for operations in the confined environment for the UAV-based inventory tracking problem. However, the work did not go further than numerical modeling of trajectories and the results of experiments with real flights are absent. This approach is interesting and applicable both to a group of UAVs and to a group of heterogeneous systems; nevertheless, the solution to the problem of conducting an inventory was not described in the work.

2.6.3 UAVs with on-board SLAM

Reliable positioning of the UAV indoors is a necessary requirement. For accomplishing this task it is a common approach to use different tags, e.g. AprilTag Olson [2011]. Kayhani et al. [2019] presented the improvements of the state estimation process for the indoor localization framework of the UAVs using AprilTag markers. Also, they represented the implementation of an Extended Kalman Filter (EKF) to improve the estimation process by accounting for uncertainty and to fuse data from two sources - multiple tags and the on-board inertial measurement unit (IMU).

Beul et al. [2018] presented the UAV that is capable of fast autonomous indoor and outdoor flight without the aid of external infrastructure. They use omnidirectional laser scanner for localization and RFID system for stocktaking. However, this system is not suitable for barcode inventory process, although barcodes are the most common type of tags in warehouses. Thus barcode scanning process and factor **% of errors during stocktaking** cannot be estimated. In addition, the system consists of one UAV with a flight time of no more than 20 minutes. This directly affects the factor **setup time before each start**, since it is necessary to constantly replace the batteries, and when the battery is replaced, the sensors may be misaligned. One of the advantages of the system is minimal **quantity of infrastructural changes** only charging station and AR-tags throughout the warehouse.

Kwon et al. [2019] proposed an autonomous UAV with a low-cost sensing system and multi-sensor fusion framework to be used effectively for narrow and dark warehouse environments. To address the problems of UAV localization methods, authors suggested robust data fusion methods: outlier rejection using component based Mahalanobis norm test, incorporation of visual SLAM by introducing pseudo-covariance, and recognition of floor lanes for absolute lateral position and yaw measurements. These allow them to perform safe and fully autonomous flights for the cyclic inventory inspections at our materials warehouse. This work is similar to the previous one in terms of its contribution and influence on key parameters **setup time before each start**, **quantity of infrastructural changes**. The presented system requires only charging station and -tags throughout the warehouse. The scanning process was also not consecrated in the work, therefore the impact on **% of errors during stocktaking** couldn't be estimated.

Kouris and Bouganis [2018] presented a two-stream CNN to predict the distance-to-collision between the robot and its environment in multiple directions. In our approach we use CNN to detect barcodes for active perception.

Chen et al. [2019] presented the online active pose-graph simultaneous localization and mapping (SLAM) method for robot operation in a 3D unknown environment by adding loop-closure trajectories to reduce pose uncertainty, but high computational load makes it unsuitable for warehouse environment.

Asenov et al. [2019] presented localization via minimization of the discrepancy between observed measurements and gas concentrations predicted by the simulator. In our approach we use similar method for localization improvement by detecting barcodes with CNN.

Polvara et al. [2017] presented a SLAM algorithm with prediction based on reinforcement learning for the UAV landing in unexplored environment on the stable target.

2.6.4 Heterogeneous robotic systems and method for relative localization

The next pool of scientific works is already devoted to the direct implementation of this scientific research, namely to the topics of reliable indoor localization, the scanning system, and the use of heterogeneous systems for various tasks, for example, landing a UAV on a moving mobile platform.

One of the latest trends in robotics is the indoor localization of mobile robots. At the same time, the most important systems of local positioning of robots are not just in space, but also relative to each other. This is true for systems with robots of one type (drone swarms etc.), as well as for systems with robots of multiple types. The most common way of dealing with this problem, is to install a camera on the UAV for tracking various tags from light-emitting diode (LED)s to AR-tags on the ground robot and evaluating the relative position.

Sharp et al. [2001] was one of the first research in area of autonomus landing of UAVs on the target. Authors presented the design and implementation of a real-time computer vision system for a rotorcraft unmanned aerial vehicle to land onto a known landing target. This research became fundamental in the field of automatic UAV landing at a given mark. Later, the work began to become more complicated and, at first, manually moved carts began to be used as a target for landing. Then carts were replaced by mobile robots, and new computer vision methods were invented to assess the position.

Bi and Duan [2013] presented an implementation of a hybrid system consisting of a low-cost quadrotor and a small pushcart. The quadrotor is controlled with classical PID controller for autonomous visual tracking and landing on the moving carrier.

Serra et al. [2016] addressed the landing problem of a vertical take-off and landing vehicle, exemplified by a quadrotor, on a moving platform using image-based visual servo control. The main part of this work was devoted to finding the optimal UAV landing trajectory.

Wenzel et al. [2011] presented miniature UAV and a small carrier vehicle, in which the UAV is capable of autonomously starting from the moving ground vehicle, tracking it at a constant distance and landing on a platform on the carrier in motion. Their visual tracking approach differed from other methods by using low-cost, lightweight commodity consumer hardware.

Lee et al. [2012] described a image-based visual servoing (IBVS) method for position estimation of moving robot for the UAV landing on it. The main limitation of that research is a small tracking area with a limit of 1 meter of height.

Falanga et al. [2017] presented a system of two robots for UAV landing on moving mobile robot with a printed marker. The ground robot had no navigation and localization functions, and only on-board detection algorithm of UAV did not allow to work in low light conditions.

Rodriguez-Ramos et al. [2017] described a system based on visual tagging similar to the previous research, with forecasting the mobile robot position. However, their work has the same disadvantages.

Araar et al. [2017] designed a landing pad equipped with a large number of AR-tags for a UAV. The UAV used visual pose estimation of the landing pad with two filters i.e., EKF and Extended H∞ (EH∞). The main disadvantage of this system is the maximum height of the working area equal to 2 meters.

Khithov et al. [2017] explained the use of IR beacons for tracking precise fixed-wing drone landing. Herissé et al. [2012] developed method of nonlinear control to estimate the position of a moving mobile robot by optical flow in order to land accurately.

Faessler et al. [2014] firstly presented one infrared (IR) pattern for the tracking a UAV from a mobile robot. Nevertheless, the accuracy of the proposed method was equal to 20 centimeters at a height of 5 meters, thus the system is not applicable in the warehouse with such accuracy, because even with a linear increase in error, the error of 0.4 meters at a height of 10 meters is critical in narrow aisles of a warehouse.

Harik et al. [2017] were the first to propose a system consisting of an the UAV and a ground robot to carry out an inventory in warehouses. The structure of the a fuzzy logic controller (FLC) autonomous tracking controller was presented, and the results of the flight tests in laboratory, where AR-markers were selected for localization. The positioning error reached one meter. In the conditions of narrow high storage capacity this error is unacceptable and makes it impossible for implementation of such a system in a real warehouse. In addition, the authors noted that their methods cannot be applied in a warehouse without additional localization systems for UAVs and a mobile robot, which makes it impossible to assess the impact on the parameters **quantity of infrastructural changes** and **setup time before each start**. The process of scanning barcodes was not consecrated in the work at all, and without this, factor **% of errors during stocktaking** assessment is not applicable.

2.6.5 Object recognition for stocktaking

Hansen et al. presented an approach for real-time barcode detection and classification using deep learning, but their system works with high-quality images which are difficult to obtain during the flight, and this method requires high computing power for high performance which makes it impossible to use on the drone for inventory purposes.

Xu et al. [2018] introduced algorithms for the automatic extraction of barcodes from video data. For a known barcode region, a Harris corner detector and Hough transform-based algorithm were applied to estimate the bars' orientation angle quickly. No flight experiments were presented in the article, and all results were obtained during post-processing.

Cho et al. [2018] proposed a system that uses three steps, region candidate detection, feature extraction, and SVM classification, for barcode detection and recognition in factory warehouses. Authors applied a feature algorithm to four types of 2D-barcodes and measured the performance by comparing the precision and learning recall by feature. This work, unlike the previous two, is more focused on the scanning process, but only 2D barcodes, which limits its use.

2.6.6 RFID/UWB-based indoor localization methods

In addition to an overview of the most relevant methods for solving the problem of localizing UAVs in indoor environment, it is important to note the presence of other methods, which are based on technologies such as RFID, UWB, etc. Despite the fact that now it is not enough to completely solve the problems of localization, in the future a combination with them can lead to a good result.

Forster et al. [2013] presented one of the first papers on the use of RFID tags for the localization of a robot with a reliable result. They proposed a novel RFID-based hybrid metric-topological SLAM algorithm which enables autonomous navigation in GPS-denied environments. The algorithm required only odometry and RFID measurements to localize the RFID tags with a relative accuracy of approximately 0.3 meters, but such accuracy is not enough to achieve reliable autonomous flight of a UAV. In addition, it is required to install an expensive RFID scanner on the UAV and a large number of RFID tags throughout the warehouse.

Won et al. [2018] presented a study to overcome the limitations of current approaches by proposing a localization method based on UAV-RFID integrated platform. With data from the platform, they also applied a machine learning algorithm to localize tags. Their approach estimated the location of the tag with 94% accuracy. Nevertheless, this approach allows only to determine the approximate position of the scanned RFID tags in space, but does not make it possible to use it for reliable UAV flight.

Zhang et al. [2019] proposed an indoor localization system for UAVs, which provides precise 6- orientation and location estimation with several RFID readers in testing zone and tags attached to the UAV. Authors also implemented a Bayesian filter to estimate the location of tags with phase difference, and then to estimate pose with an SVD-based algorithm. To evaluate the performance of presented system, researchers conducted experiments in an indoor environment and could achieve reliable flight in small testing zone. However, this method requires a large volume of expensive RFID scanners and antennas around the UAV. Also, the work did not investigate the issue of accumulation of localization error over time when moving in large spaces, such as a warehouse.

Lazzari et al. [2017], presented the numerical investigation of the UWB localization technique suitable for the tracking and control of a UAV in a specific outdoor scenario is presented. A set of UWB nodes are located on a moving/still ground station and interrogate an UWB node placed on the UAV that is flying in front of the ground station. Experimental results shown that a decimeter order localization accuracy can be obtained for a 3D localization process, which is not enough for a reliable UAV flight in the warehouse.

Tiemann et al. [2018] presented the method to augment and fuse state of the art UWB localization with monocular simultaneous localization and mapping to enable autonomous flight in indoor environment. For the validation of the proposed approach, two experiments were performed: the first one provided an extensive experimental analysis of the accuracy of different localization methods for drones, whereas the second experiment showed that precise waypoint flight in areas not covered by wireless localization was feasible, what prevents the implementation of UWB-based methods for localizing UAVs in industrial applications.

Queralta et al. [2020] presented one of the latest works with novel dataset for UWB-based localization of aerial robots. They focused on the localization accuracy for ad-hoc deployments with fast self-calibration of anchor positions. The dataset included data from an autonomous flight with an UAV. The ground truth recorded using an Optitrack motion capture system. The presented approach in the future could be useful when installing a sufficient number of UWB sensors on the UAV and UGV to solve the problem of UAV localization relative to the UGV. Nevertheless, at this stage it is required to place a huge number of sensors throughout the warehouse.

Zhou et al. [2017] presented a design of the UAV patrol system based on Bluetooth location. The system has subscriber terminal and UAV terminal. They used Bluetooth location to improve the positional accuracy in some areas that GPS signal is unstable. In this system, Bluetooth was not a source of information for a reliable flight, but was used only to confirm the approximate location of the UAV.

Dressel and Kochenderfer [2018] presented a pseudo-bearing measurement method for improved localization of radio sources with multirotor UAVs. They equiped a multirotor UAV with a directional antenna and an omnidirectional antenna. The omnidirectional antenna served to normalize measurements made by the directional antenna, yielding "pseudo-bearing" measurements. The method presented in this work helps only to better determine the position of the radio wave source after a long flight, but at the same time it cannot be used for localization and navigation in a warehouse, where a reliable and stable flight is required.

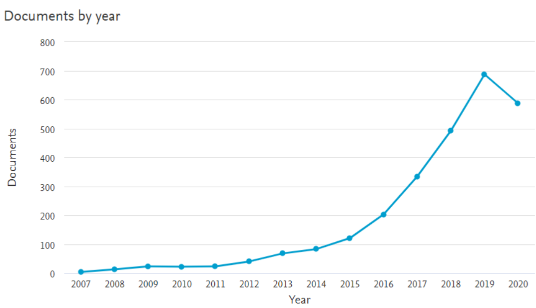
The methods described above cannot be applied to UAV flights in the warehouse, due to the current accuracy limitations, as well as the they could not satisfy following key factor **quantity of infrastructural changes**. However, in the future, it makes sense to use data from UWB and RFID if they have already been installed in the warehouse.

2.6.7 Literature review outcomes

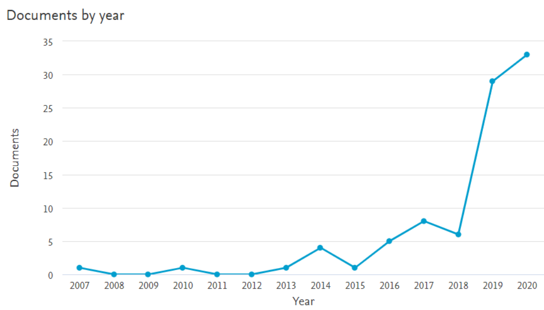
Thus, the scientific works discussed above show that there is no robotic solution for inventory taking in warehouses that can positively affect the necessary key factors (**quantity of infrastructural changes**, **setup time before each start**, **% of errors during stocktaking**) identified in the course of this thesis. Nevertheless, individual scientific works touch on the subject of stocktaking using UAV-based systems, and the use of heterogeneous systems for solving problems of assessing the position in an environment.

To build a fully autonomous system for inventorying warehouses, it is necessary to create a stable combination of technologies such as precise indoor localization and navigation (in this case, the task can be solved by the on-board SLAM system of the UAV, or it can be divided into two subtasks for each of the UAV and UGV systems, with the solution of their localization relative to each other), as well as a system for reliable recognition of inventory objects and barcode detection.

We would like to note that the structure of this thesis implies a review of relevant works before each part of the presented system in: subsection 5.6.2, subsection 4.4.2, subsection 6.1.2. This is done for better understating of the material by the reader and for the clarity of presentation and comparison of each subsystem.



(a) Key words: "UAV" and "inventory".



(b) Key words: "UAV", "inventory", and "warehouse".

Figure 2-12: The total number of scientific papers in the selected topic during searching by keywords in the Scopus database.

2.6.8 Relevant research statistics

Also, along with studying statistics on patents, we decided to study the dynamics of the appearance of new scientific works in this topic. The Scopus knowledge base toolkit was selected for the analysis. We chose Scopus for several reasons, on the one hand, this database includes most of the high-quality scientific publications, publications in which go through peer-review procedures, in contrast to the Google Scholar database. Despite the fact that Google Scholar is much more extensive, it also includes simple Internet publications without peer-review procedure. On the other hand, Scopus is much broader than the Web of Science base, as well as the knowledge base of individual communities (IEEE, ACM, MDPI). Unfortunately, in the Scopus database, the creation of a smart classifier is not available, unlike the Cipher tool, which we used for patent analysis (Section 2.5). In this regard, the search was carried out using keywords.

At the first stage, we used "UAV" and "inventory" as keywords. At the same time, it was noticed that, in contrast to the industry, in scientific works the term "inventory" or "inventory taking" or "inventory automation" is much more often used than "stocktaking".

There has been a tremendous (almost exponential) increase in the number of jobs since 2007 (Fig. 2-12.a). At the same time, a detailed examination showed these works showed that they often relate to the topic of an inventory of forests,

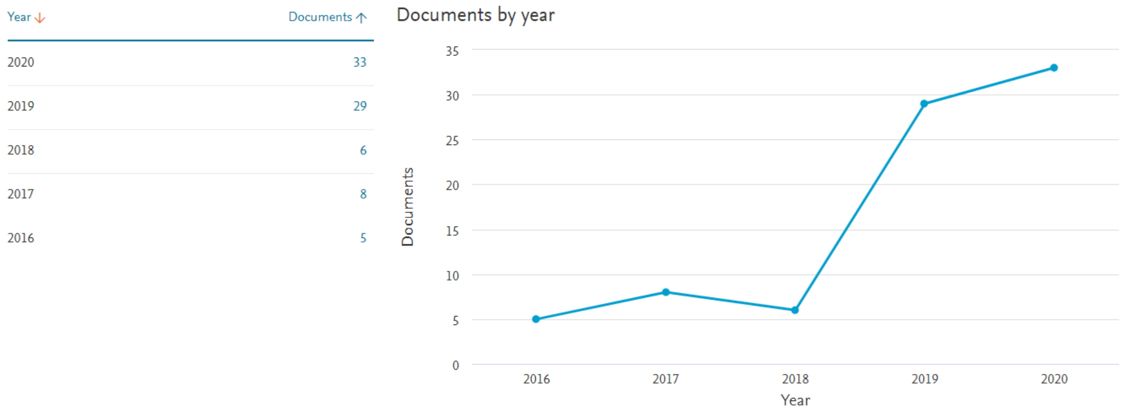


Figure 2-13: The total number of scientific papers in the selected topic during searching by keywords "UAV", "inventory", and "warehouse" in the Scopus database since 2016.

agricultural land, and various structures. Then we decided to narrow down the search and added a third keyword "warehouse". The search data has changed a lot, and there has been an explosive growth in work since 2015 (Fig. 2-12.b). The first work on this topic appeared in 2007 Ong et al. [2007]. In it, for the first time, the possibility of using a UAV to automate inventory was discussed. At the same time, the total number of works from 2007 to 2020 was 89, while the most of 81 works were published from 2016 to 2020 (Fig. 2-13). These statistics show the increased relevance of the selected topic.

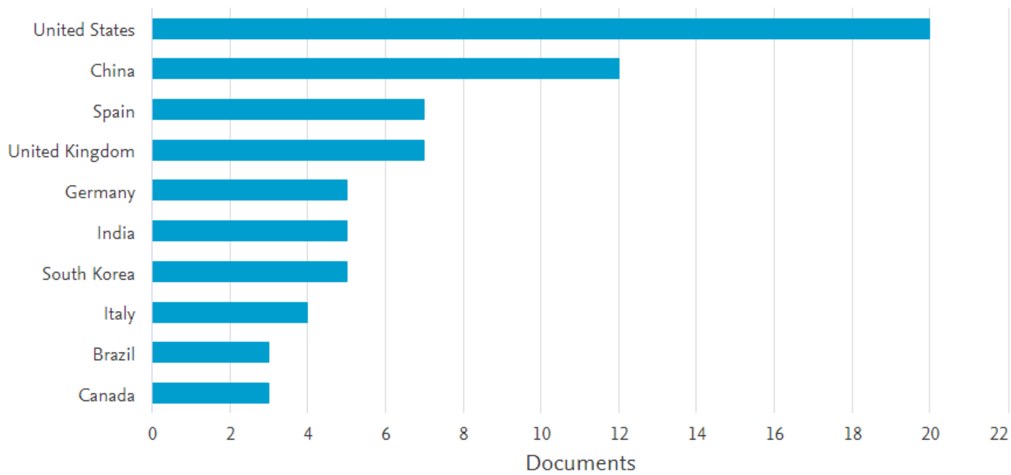


Figure 2-14: Leaders of publications of scientific papers in the selected topic by country.

We also analyzed the leaders of publications by country and by university (company). Among the countries, the first two places were taken by China and the United States, and the third place was shared by Spain and Britain (Fig. 2-14). The Universidade da Coruña became the leader, and the top 10 included such well-known institutions as Georgia Institute of Technology, Universität Bonn, Massachusetts Institute of Technology, ETH Zürich, as well as Samsung Electronics Co. Ltd (Fig. 2-15).

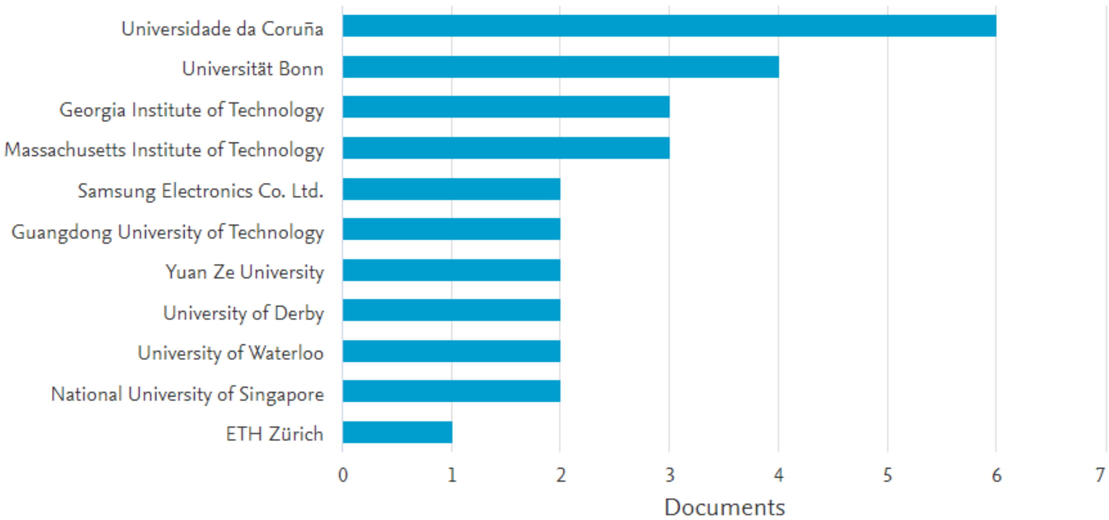


Figure 2-15: Leaders of publications of scientific papers in the selected topic by university (company).

Chapter 3

Thesis Objectives

In this chapter we define the goals and derive the specific questions to be addressed in our research.

3.1 Key factors and final reference model

Based on the analysis of companies, patents, as well as testing various ideas with industrial partners, a list of key factors for this study was compiled. It is necessary to clarify each of these factors separately for a better understanding.

The main success factor that requires an automated stocktaking device is the **company's profit**. Since the stocktaking carried out on time allows you to avoid fines, downtime in the warehouse, the product expiration date, and also helps to increase the efficiency of the warehouse (subsection 2.4.5). In addition, we also concluded in subsection 2.5.2 that the technology leaders in number of patents and patent applications in the field of automated stocktaking tools (Amazon Technologies Inc, JD.com Inc, Walmart Stores Inc.) are the leaders in the world in the field of retail.

Unfortunately, this factor is quite difficult to measure, since various factors often affect the total profit: seasonality, company growth, or, for example, the coronavirus pandemic. Therefore, despite the fact that often a company's profit is associated with specific numbers for our research, the company's profit factor will be a key success factor, but not measurable.

During industry research (subsection 2.4.3), we found such a factor as the **setup time before each start**. This factor is easy enough to measure for the system being developed, and the less preparation time before each launch, the better (subsection 2.4.3). Nevertheless, this factor is not key for our study, since it is already taken into account in a more complex factor - the average speed of the stocktaking.

The **mean stocktaking speed** is a key and measurable factor for our research. This factor consists of several components, such as the average time of stocktaking of one pallet, the time to recharge the system, the **setup time before each start** of the system. The higher **mean stocktaking speed**, the faster the entire stocktaking is carried out. And accordingly, the downtime of the warehouse and the **cost of stocktaking** due to downtime are reduced. In addition, the overall efficiency of the warehouse increases, and due to this, the average time of order shipment subsection 2.4.5 is reduced. Due to this reduced the time it takes from receipt of order to its final delivery to the client (**customer delivery time**).

The next key factor is the **quantity of infrastructural changes** required to implement an automated tool for stocktaking management system that we decribed in subsection 2.4.3. This factor is measured by the means that need to be spent on the implementation of the proposed system. For example, for a system developed within the framework of this thesis, it is necessary to equip the warehouse with a charging station and passive reflective beacons at the base of the racks. The cost of these changes does not even exceed 5% of the cost of the system.

And the last key factor, but not least, is the **% of errors during stocktaking**. It directly affects the quality of stocktaking and the company's profit (subsection 2.4.3, subsection 2.5.4). It can be measured experimentally, during the next partial or complete stocktaking.

Everything described above led us to the logical conclusion that it is necessary to develop a fully autonomous system that will require minimal changes in the warehouse infrastructure. At the same time, he will be able to work for 8 hours as a warehouse worker, but at the same time perform a larger volume of tasks and make many times less mistakes. In other words, you need an autonomous robot and a computer vision system on it. Also we put all of these factors to reference model for my research (Fig. 3-1).

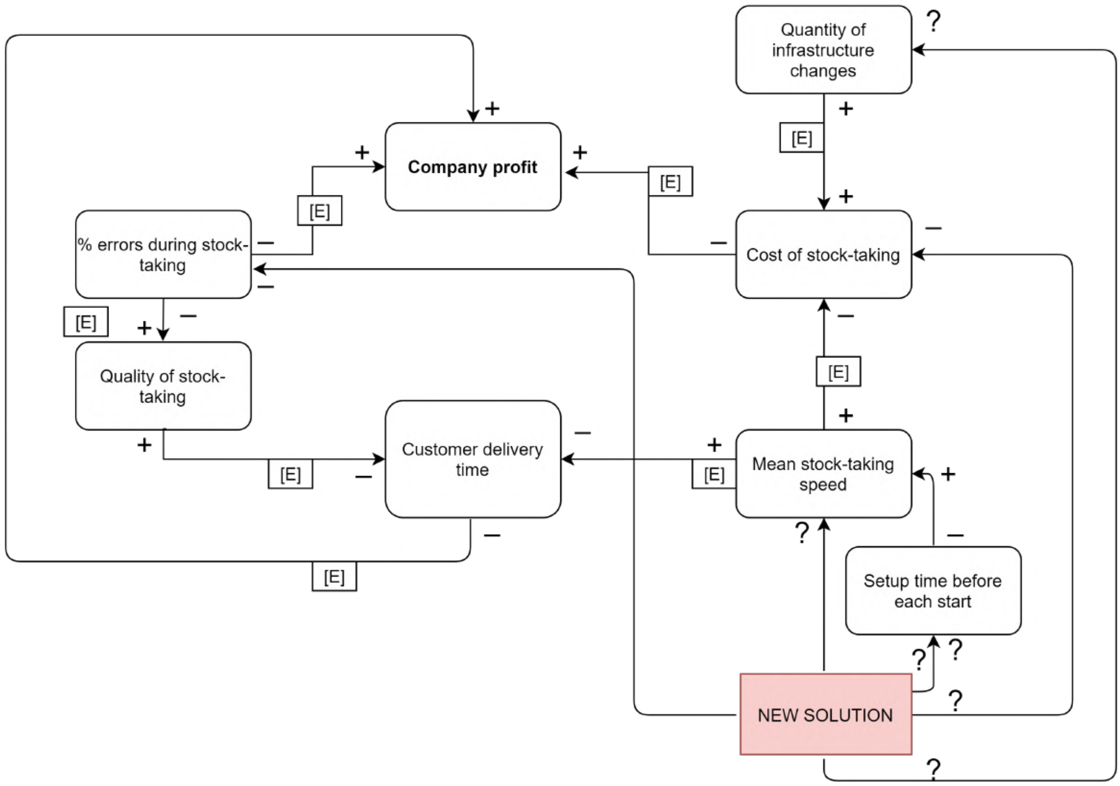


Figure 3-1: Final reference model

3.2 Proposed heterogeneous robotic system

In order to exclude human from stocktaking completely we propose an autonomous heterogeneous robotic system of two robots: the UGV and the UAV. This combination gives an opportunity to keep an always-up-to-date inventory record of the contents within the warehouse.

This system will be capable of autonomous navigation and precise localization in indoor environment. The problem of robust system operation will be solved by dividing localization into two parts for each subsystem, i.e. the UAV and the UGV. The UGV performs global localization and navigation in a warehouse, whilst the UAV always flies above the platform, detects and scans barcodes on the racks and pallets. For drone localization we propose to develop a method of pose estimation relative to the UGV. This approach enables to calculate coordinates of the UAV relative to the UGV and then to calculate the global coordinates of the UAV. Also, proposed method does not imply the utilization of any additional active infrastructure for navigation and localization, as opposed to motion capture systems, since all necessary equipment is installed on the UAV and the UGV.

The proposed system should influence the above key factors in the following way:

- the % of errors during stocktaking should decrease, it will lead to increase of the quality of stocktaking;
- quantity of infrastructure changes will be minimal (only passive reflective beacons and charging station), because the most warehouse couldn't change their infrastructure for each new solution;
- setup time of the system before each start will be about 5 minutes, because all third party logistics providers should be able start partial stocktaking immediately after a customer phone call. Therefore, they need a robot that will be in warehouse and ready to start work at any moment, and not pilots who will come with their UAVs;
- mean stocktaking speed should increase due to process automatising, that should decrease the duration of whole stocktaking.

Everything formulated above lead us to the impact model of our research (Fig. 3-2).

3.3 Research questions and gap

Since the result of this thesis will be a new heterogeneous system of two robots from a technical point of view, we can formulate the **Research question** and **Research Gap** based on the following facts.

An analysis of the industry (section 2.4) and a study of the problem of inventory taking in warehouses (section 1.2) showed that the current methods are ineffective and require significant improvements. Also, during the survey of companies, the

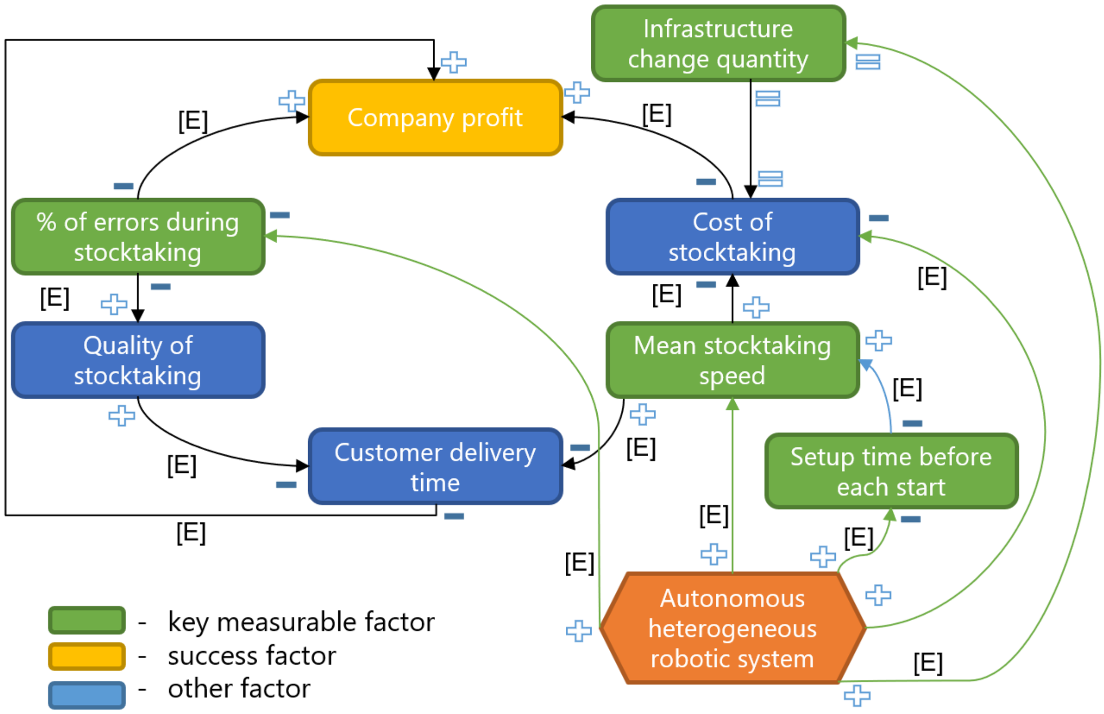


Figure 3-2: Final impact model

urgency of the problem was confirmed, since it is included in the top 3 most frequently cited problems in the warehouse industry. The analysis of use cases showed that companies lose significant funds due to minor mistakes (subsection 2.4.5). All this led us to an analysis of current commercial solutions (section 2.3), patents (section 2.5) and scientific works (section 2.6) devoted to the development of automated tools for conducting accurate stocktaking. Analysis of current commercial solutions showed that there is no absolute leader, and some of the already applicable tools are fragmented and cannot completely solve this problem due to the limited work scenarios. Also, no decision could affect the identified key factors for solving the stocktaking problem. The analysis of patents in the selected topic, based on the constructed classifier in Cipher, also confirmed the absence of solutions that fully satisfy the solution of the stocktaking problem based on the identified key factors. When searching for relevant studies in this area, several works were found that also tried to solve the problems of inventory taking in warehouses using automated systems, while attempts did not go further than theoretical research when trying to influence one of the key factors, while forgetting about others factors. In other words, we can formulate the research gap as follows:

Research Gap: the absence of any device or system to automate and improve the quality of manual warehouse stocktaking, which is very susceptible to errors due to human factor.

The main novelty in the proposed work is the development of a heterogeneous robotic system. The proposed system should take into account all the key factors (described section 3.1) when solving the problem of stocktaking in the warehouse, as well as theoretically and technically realizable under current conditions. The main research issue will be just to study the impact of the proposed system on the stocktaking process and the effectiveness of this system. In addition, the system being developed should take into account not one of the key factors, but influence everything at once. Therefore, the main research question can be formulated as follows:

Main Research question: How the creation of autonomous heterogeneous robotic system will improve quality of stocktaking and decrease its duration?

In addition, this thesis should also provide a comparison of the proposed heterogeneous robotic system for conducting automated stocktaking with individual scientific papers, patents and commercial solutions. Since the vast majority of these works are based on , it is worth making a comparison of the proposed heterogeneous system with a system based on a single drone into a separate research additional question.

Additional Research question: What are advantages of using a heterogeneous system compared with a single drone?

3.4 Thesis goal and objectives

The main goal of this work is to develop an autonomous solution for stocktaking, and the solution being developed should qualitatively improve the stocktaking process. The qualitative improvement of the stocktaking process is understood as the impact on two key factors as follows: an increase in the average speed of stocktaking, and a decrease in the percentage of errors during it.

A hybrid robotic system consisting of a UAV and a UGV was chosen as the main hardware solution, this is a novel concept that meets the technical requirements of the industry. In addition to developing the hardware part of this system, it is necessary to develop a software part that would allow solving the stocktaking problem. In other words, the following goals for our research can be formulated in terms of technical development:

- Develop a heterogeneous robotic system for autonomous stocktaking of industrial warehouses, that will be able to operate during 8 hours;
- To develop a localization and navigation system capable of providing accurate and robust self-positioning of the system inside the warehouse, taking into account the specific infrastructure of the environment (large volume of metal structures, long narrow spaces with a height of up to 12 meters);
- Ensure long operating time of the system in terms of repeatability of experiments. Since we mean that the UAV will take off and land on the mobile robot a large number of times, it is necessary that the landing be smooth and does not lead to the uncalibration of the UAV sensors.
- Develop a robust and accurate system for scanning product identifiers in the warehouse (barcodes), which would qualitatively improve the stocktaking scanning process and reduce the number of errors. In addition, this scanning system should provide a working speed higher than currently used stocktaking methods;
- Provide binding of global coordinates to scanned identifiers in the warehouse, for subsequent analytics and analysis of stocktaking results;

- Develop an interface for a system supervision in a warehouse with the ability to remotely control and send commands, which could also record and store data about stocktaking;

- Evaluate system performance in laboratory condition and conduct stocktaking experiments in real environment of warehouse.

Succinctly, three main scientific objectives of the thesis can be formulated as follows:

1. Design the concept of novel heterogeneous robotic system for automated inventory stocktaking.

2. Develop a control system for heterogeneous robotic system, which does not require significant infrastructure changes and could provide:

    - Autonomous and Precise ($\pm$ 2 cm accuracy) localization and navigation for UAV and UGV.

    - Continuous operation with quick start.

3. Create a novel method of effective and robust scanning for the autonomous heterogeneous robotic system, that could work:

    - Faster than people (mean stocktaking speed).

    - More precisely than people (% of errors during stocktaking).

"If you optimize everything, you will always be unhappy."

Donald Knuth

Chapter 4

Development of the autonomous heterogeneous robotic system

The thesis is focused on the development of a heterogeneous robotic system consisting of a mobile platform and UAV, so it is important to give an understanding of how the experimental prototype of the system is built and what it consists of. Nevertheless, the development of the mechanical and electrical parts of the robot is not the subject of this thesis, therefore, their brief description will be given.

4.1 Mechanical and electrical design of the UGV

The main tasks of the mobile platform are transportation of the drone in the warehouse, localization and navigation in 2D space, charging the UAV for ability to work 8 hours without downtimes, as well as part of the computational operation for localizing the drone also occur on the on-board computer of the mobile platform.

The design of the first version was developed jointly with students of the Intelligent Space Robotics Laboratory (ISR Lab) of Skoltech Vladimir Karandaev and Alexander Petrovsky, in accordance with the requirements for thesis project. The render of the first version of the UGV is presented in Fig. 4-1.

At the first stage of research, we tried to bring together all the necessary characteristics of a mobile platform and draw up a technical task for its development. From the point of view of the overall dimension, the platform should be able to

Figure 4-1: The render of the first version of the UGV.

move around the warehouse and rotate in the space between the racks 1.5 m wide. Therefore, the maximum length of the platform was set at 1.295 m, and rotation can be carried out using two central wheels around its axis. In addition, an UAV should be able to land on the platform, with the width of the gap between the legs 0.4 m, so we chose the UGV width of 0.749 m with a margin. This size provides not only a margin for the UAV landing, but also makes it easy to transport the platform through the doorway. There were no special requirements for the height of the platform, so the only requirement was clearance. The maximum height of obstacles on the floor for "A" class warehouses has a height of not more than 20 mm, so the platform clearance was chosen equal to 30 mm with a margin. The total height of the UGV is equal to 0.243 m. Most of the components for assembly, such as aluminum profiles, are publicly available on the market. Components modeled specifically for this platform were manufactured using the following technologies:

- Steel body fastenings are made using laser cutting,
- Acrylic body is also made by laser cutter,
- Complex fastenings, which do not have large loads, are made using additive technologies (3D-printer).

- Some parts are made using a computer numerical control (CNC) machine, for example, charging pads for the UAV.

The electrical diagram of the UGV is presented ib Fig. 4-2.

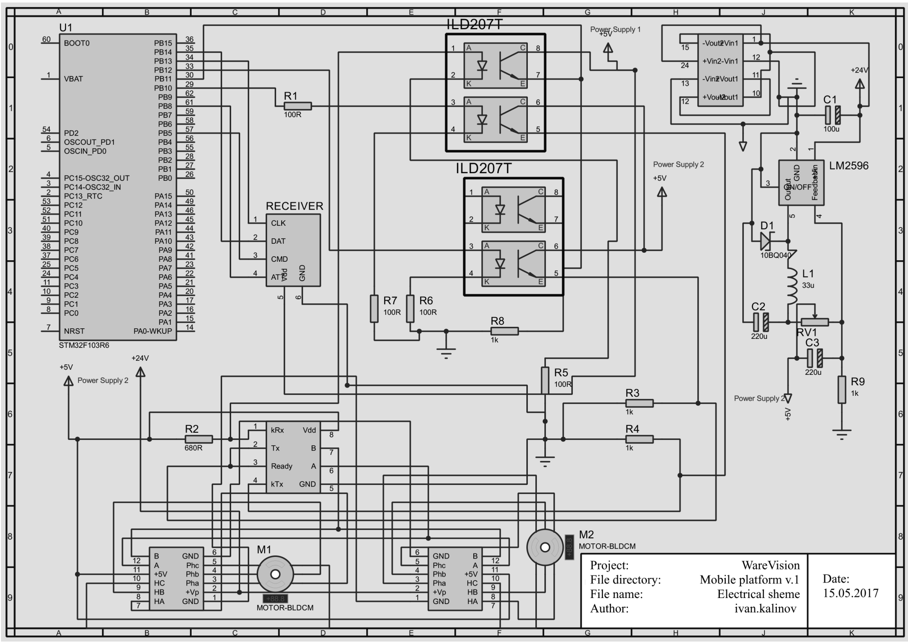


Figure 4-2: Electrical scheme of the UGV

The render of base frame of the UGV (Fig. 4-3), the list of key components with their placement inside the UGV (Fig. 4-4) and with corresponding numbers are presented here:

1. Maxon motors with integrated encoders and wheels that are controlled by Brushless Motor Controllers BLSD-20;

2. Passive wheels for stability;

3. Emergency stop buttons on each side of the platform for safety;

4. Battery with a capacity of 105 600 mAh to provide 8 hours of continuous operation of the heterogeneous system;

5. Two LIDARs Hokuyo UST-10lx for localization;

6. Two Intel RealSence D435 RGB-D cameras for collision avoidance;

7. STM32F4 microcontroller for low level control;

8. On-board computer NUC with Core-i7 7567U;

9. Imaging Source camera DFK33UX250 for the UAV tracking.

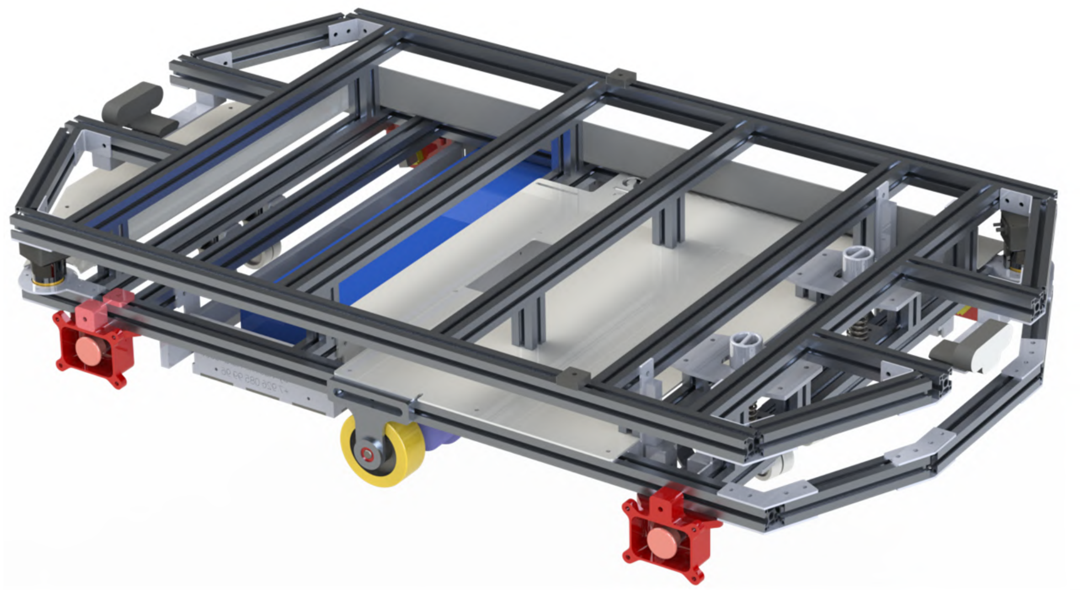


Figure 4-3: The render of base frame of the UGV.

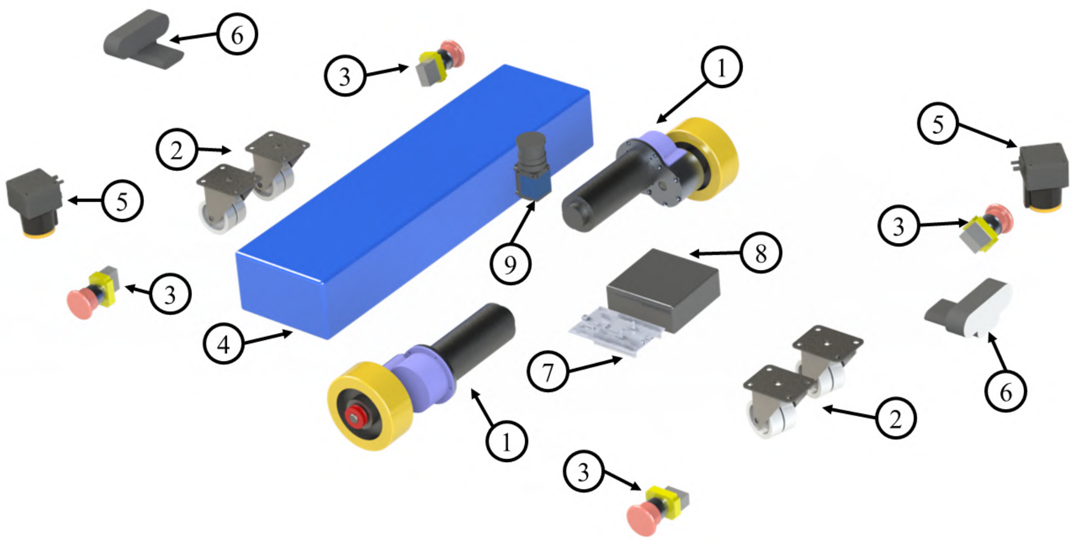


Figure 4-4: The key components with their placement inside the UGV.

4.2 Unmanned aerial vehicle for stocktaking

The UAV is the main part of the developed system, because it performs barcode scanning during stocktaking process. One of the main tasks was to make it as small and light as possible. For this, it was decided to develop a new localization algorithm that would not require expensive and heavy lidars. More information about the UAV localization system is described in the chapter 5.

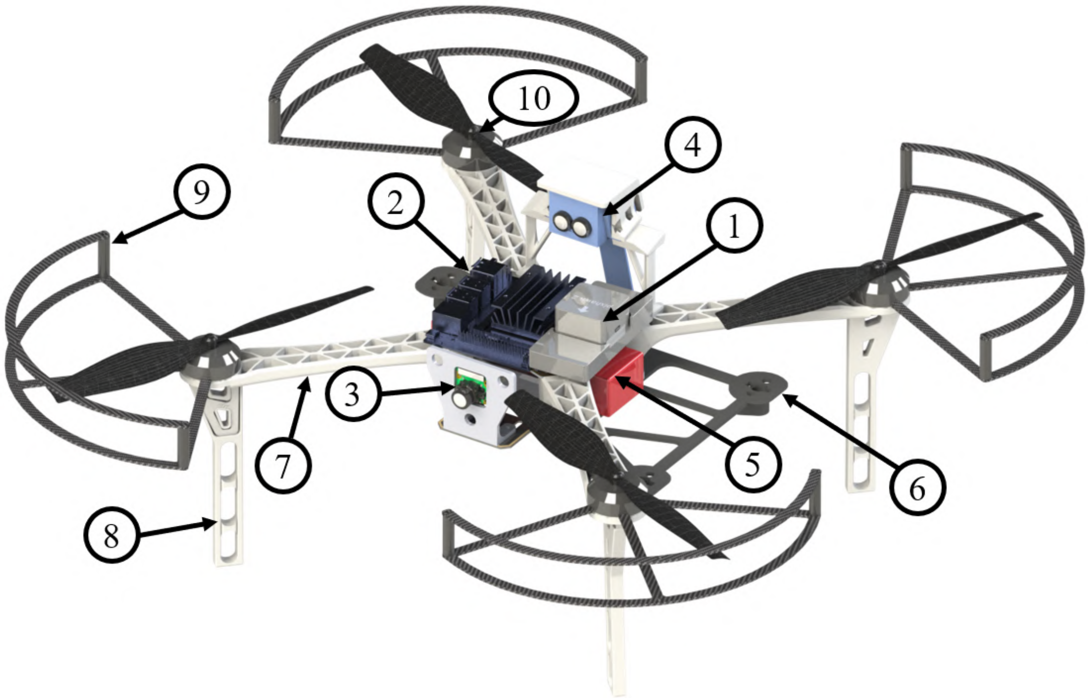


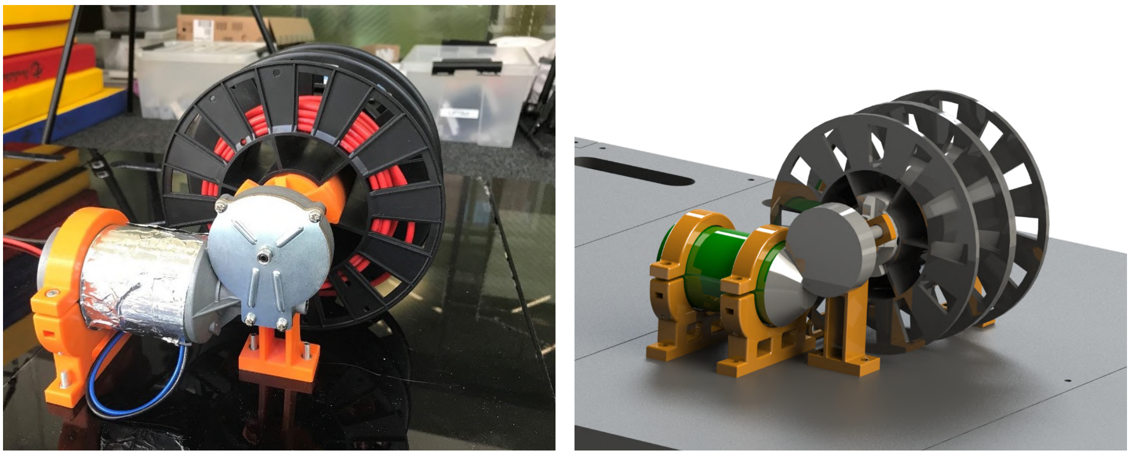
Figure 4-5: CAD renders of the developed UAV with the key components. (1)-flight controller HEX Pixhawk 2.1 CUBE; (2)-NVIDIA Jetson Nano; (3)-PiNoIR Camera V2; (4)-Zebra DS3608ER laser scanner; (5)-LiPo Battery; (6)-IR-patterns; (7)-DJI F450 frame; (8)-legs for landing; (9)-propeller guards; (10) - brushless E310 motor with propeller.

The UAV was built on the basis of the F450 frame and E310 propeller-motor group by the DJI company (Fig. 4-5. The carbon propeller guards were also modeled, and then manufactured on a CNC machine. The final size of the UAV does not exceed 0.65 meters in length and width, taking into account the protection of the propellers. The UAV controlled by flight controller HEX Pixhawk 2.1 CUBE Meier et al. [2011]. As the on-board computer we used NVIDIA Jetson Nano (2019). The UAV is equipped with the 4S LiPo Battery 14.8V 5000 mAh battery, which supports quick charge option, this battery can provide up to 25 minutes of flight for the UAV. The small PiNoIR Camera V2 is installed on the UAV for barcodes detection and the Zebra DS3608ER laser scanner is installed to read them. Also pattern of IR-markers is also placed on the drone to detect drone's position from the mobile platform, the detailed description of the localization system is provided in the section 5.3.

4.3 System for the UAV charging

For the possibility of continuous operation of the heterogeneous system for 8 hours, we have implemented contact charging of the UAV on a mobile platform. It is important to note that in such a modification, in order to ensure continuous operation, it is necessary to have two UAVs in the system so that the second one works during the charging of the first UAV, therefore the dimensions of the UAV and the mobile platform are selected in such a way that two UAVs are freely placed on the UGV. In the current implementation of the prototype of the UAV system, there is only one, but this is enough to carry out the necessary experiments.

At the first stages of the development of a heterogeneous system, various UAV charging technologies were worked out. It was originally planned that the UAV would receive electrical power using a wired (Fig. 4-7) or telescopic mechanism, which was patented by us in I. A. Kalinov et al. [2019]. But the results of the



(a) Real Prototype. (b) CAD render.

Figure 4-6: Prototype of a wired charging mechanism for a UAV.

(a) Skycharge LLC [2018]. (b) Wibotic LLC [2020].

Figure 4-7: Commercial solutions for UAV charging.

experiments showed that such a mechanism strongly affects the dynamics of the UAV and degrades the accuracy of localization. Therefore, we decided to consider other possible technical implementations of solving this problem.

Skycharge LLC [2018] and Wibotic LLC [2020] offer contact and wireless charging solutions for UAVs and mobile robots. For example, Solution 1 is a four-part charging pad. Such a system assumes the possibility of inaccurate UAV landing up to 30-40 centimeters and an angle error up to 40 degrees. This solution is convenient for many UAVss that are designed for outdoor flights.

We decided to improve this approach based on the capabilities of our system. Since the UAV landing with an accuracy of 2 centimeters has already been decided by us. We decided to install on the mobile platforms landing pads with a diameter of 10 centimeters, which are supplied with electrical power (Fig. 4-1). Cone-shaped contacts are installed on the legs of the UAV. During landing, due to their geometric shape of the pads and the legs of the UAV, the legs of the UAV slide exactly into the center of each of the platforms. After landing, the UAV starts charging.

4.4 VR interface for system supervision

WareVR is a novel human-robot interface based on a VR application for interaction with the heterogeneous robotic system for automated inventory management. We have created an interface to supervise an autonomous robot remotely from a secluded workstation in a warehouse. Description of proposed interface is presented in this section.

4.4.1 Motivation for VR system development

Nowadays we are witnessing revolutionary changes in UAV technology resulting in redesigning the business models and creating a new operating environment in a variety of industries, from entertainment and meditation La Delfa et al. [2019] to assistance in 3D drone teleoperation Thomason et al. [2019]. At an early date, customers from a wide range of industries will see the first impact of UAVs in a variety of areas, from delivery services to power line inspection Zhou et al. [2018]. UAV-based solutions are most relevant for industries that require both mobility and high-quality information. The integration of such devices into the daily operating process will help to create significant advantages in the implementation of large capital construction projects, infrastructure management, agriculture, and 3D surface deformation Braley et al. [2018].

We have developed a heterogeneous robotic system that can localize and navigate in the indoor warehouse environment autonomously. The system copes with its task and makes an inventory with photos, uploading all the information into a database, and building a product location map I. Kalinov et al. [2019]. In some cases, the data from the autonomous inventory (recognition result, coordinates, photo) is insufficient, and a more detailed inspection of a particular pallet is needed. This type of inspection is not available offline, but sometimes it is required promptly and remotely. Therefore, it is essential to have an intuitive human-computer interface to interact with the autonomous system with clear feedback, so that even warehouse workers inexperienced in robot control can easily handle it. Such an interface should include two operation modes for the system: automatic and manual. The use of VR

Figure 4-8: VR interface.

can provide a comfortable perception of the environment around the robot, as well as increase the level of involvement and realism during teleoperation in comparison with the regular screen interface.

The WareVR developed by us allows regular warehouse workers without experience in robotics to control the heterogeneous robotic system in the VR application, which provides visualization of the heterogeneous robotic system in the digital twin of the warehouse. Also, our application can stream video from the UAV camera in the real environment into the virtual environment (VE) and provide velocity control of the system by tracking the position of the user's hand with the HTC VIVE controller.

4.4.2 Literature review of VR systems for teleportation and guidance

In the evolution of the human-computer interaction (HCI) discipline, recently, special attention is paid to human-drone interaction (HDI). Drones are becoming more and more diffused, being used with different purposes in various control modes, e.g., automatic, manual, mixed-initiative, when the user can execute some operations while the autonomous system works. Silvia Mirri et al. [2019] presented a thorough overview of the latest papers in HDI. One of the main problems with almost all such interfaces is the necessary experience in drone control for their use in challenging tasks, e.g., indoor operation Erat et al. [2018], risky operation Aleotti et al. [2017], inspection Irizarry et al. [2012], etc. One of the most common approaches to remote control of drones is the use of computer vision methods. In several works Naseer et al. [2013], MohaimenianPour and Vaughan [2018], the operator implemented UAV control using an on-board camera (RGB camera, Kinect sensor) that recognizes face and hand gestures. However, this approach cannot be applied in the tasks of remote control of UAVs. One of the most prospective approaches for remote robot control nowadays is teleoperation via physical sensor-based (e.g., motion capture or electromyography) interface Miehlbradt et al. [2018], Wu et al. [2019]. Thus, Rognon et al. [2018] developed FlyJacket, a soft exoskeleton for UAV control by body motion. The exoskeleton contains a motion-tracking device to detect body movements and VR goggles to provide visual feedback. However, such interfaces can be bulky and complicated for deploying and using quickly and require preliminary training of the operator. Besides, the exoskeleton as a concept for robot control significantly limits the motion of the operator. VR user interfaces provide the operator with more immersive interaction with robots. Thomason et al. [2019] developed a VR interface for safe drone navigation in a complex environment. The teleoperation system provides the user with environment-adaptive viewpoints in real-time to maximize visibility. In Vempati et al. [2019], it was proposed a VR interface to control of an autonomous spray painting UAV. It allows the user to move around the target surface in a VE, and paint at desired locations using a virtual spray gun. Paterson et al. [2019] presented an open-source platform for 3D aerial path planning in VR. The introduced VR interface has benefits in both usability and safety over manual interfaces and can significantly reduce path planning time compared to a 2D touchscreen interface. The most of VR teleoperation systems propose direct robot manipulation via VR controllers or wearable interfaces. However, in our case, it is needed a semi-autonomous interface that allows choosing the operation mode of the autonomous robotic system and, if necessary, providing manual operation mode.

These needs can be met with intuitive graphical user interface (GUI) in VR.

4.4.3 VR system overview

Fig. 4-9 shows the overall architecture of the developed system, which includes the key equipment of the heterogeneous robot, ROS framework, Unity, and the operator workplace. We used the HTC VIVE headset for representing a VE of Unity application, and the HTC VIVE controller for tracking user's hand position to control the system. The desktop computer with installed ROS and Unity is located in the operator workspace, the mobile platform is controlled by an on-board computer based on the Intel NUC with Core i7 processor, the on-board computer of the UAV is Nvidia Jetson Nano, which directly interacts with the Pixhawk flight controller. All three computers operate in multi-master mode in ROS to ensure reliable information transfer within the one local Wi-Fi network in the warehouse. The connection between ROS and Unity application is based on the ROS-Unity Communication Package (ROS#).

We have developed the VR interface based on the Unity game engine, which allows monitoring the robot inventory process and controlling it directly in real-

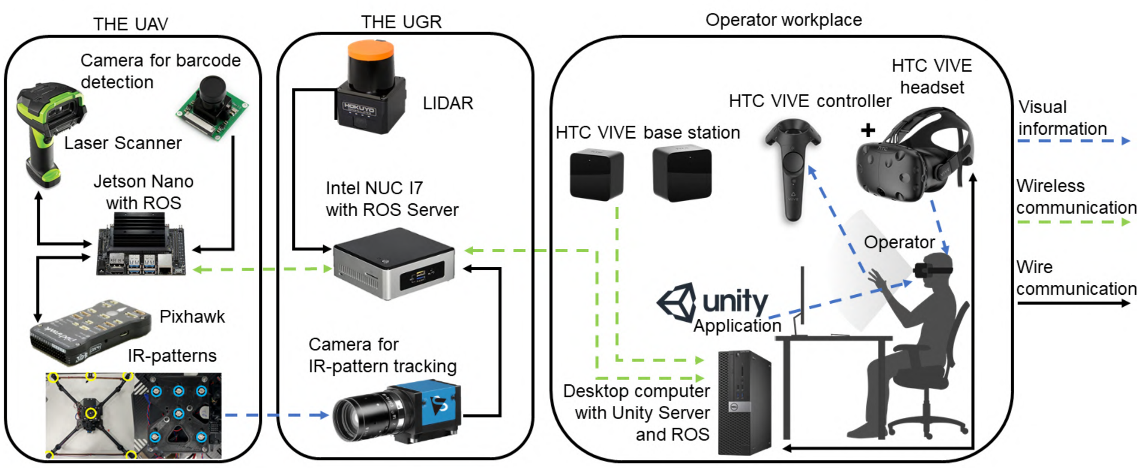


Figure 4-9: The overall architecture of developed system, showing the key equipment of the heterogeneous robot, server information flow using the ROS, and operator layers as block diagrams.

time. The VR setup includes HTC VIVE Pro base stations, head-mounted display (HMD), and the HTC VIVE controller attached to the HMD for tracking the user's hand motion in VR. The 3D GUI developed by us includes a panel for control of a full inventory process, as well as a manual operation of the UAV, one screen for providing visual feedback from the drone camera and the other for representing a digital twin of the warehouse (Fig. 4-8). Control board consists of there panels: panel for choosing the operational mode, panel for the input of pallet place number, and panel for the manual UAV control. These panels are fixed at the desk by default, but the operator can turn on the release mode and places them in the desired position or hold in the hands.

4.4.4 Operational modes of the robot

The control panel includes four operational modes of the stocktaking for the operator:

- Full stocktaking. During this mode, the system works fully automated and conducts stocktaking of the whole warehouse. In this mode operator just supervises the system and checks the conditions of the pallets (damaged, opened, etc.) visually using a video stream from the UAV camera. In any time operator could pause the stocktaking, then zoom in the image from the UAV and then give a command to continue stocktaking in automatic mode.
- Partial stocktaking. During this mode, the system works fully automated and conducts stocktaking of a selected part of the warehouse. The operator supervises the system, checking pallet as in "Full stocktaking mode".
- Tag search. During this mode, the system works fully automated and searches a defined tag, using the previous stocktaking information as the initial parameters. If the pallet was not found in its past location, the system automatically gradually increases the search area within the same alley. If, upon completion of the search, no pallet was also found in this alley, the system offers to select another alley for searching or switch to "Visual inspection mode".

- Visual inspection. During this mode, the system is controlled manually by the operator. The first step for the operator is to enter the target location for the inspection. The system autonomously arrives at the desired row, and quadcopter takes off at the desired height. Then the operator can guide the drone manually closer to the rack with different angles and adjust the view.

UAV teleoperation

A drone control panel allows the user to operate the UAV in the manual mode. It comprises four buttons for the translational positioning of a drone along X (left, right) and Z (up, down) axes. Besides, there is an opportunity to zoom in and out the distance between the quadcopter and the rack with a slider (movement along the Y-axis). All buttons are selected with HTC VIVE controller. For velocity control of the UAV without buttons, we track the position and orientation of the HTC VIVE controller by HTC VIVE base stations. To control 4 DoF of the UAV, we use four parameters of the HTC VIVE controller state (x_c, y_c, z_c, yaw) to calculate four control inputs (V_x, V_y, V_z, α). The controlled UAV responds to changes in the position and orientation of the controller in the following way. For example, if the HTC VIVE controller is moved in the horizontal direction (forward, backward, left, or right), the drone is commanded to change its velocity in the horizontal plane, proportionally to the controller displacement. Controlling the angle and movement along the Z-axis works the same way.

Visual Feedback

The right screen on the GUI in the VR application is used for providing visual feedback during the work of the robotic system from the inspection place. A video from the UAV camera is streaming in real-time to the predefined IP address in the local network during the inventory process. Unity application displays this video-stream from the URL source to the interface screen.

4.4.5 A digital twin of the warehouse

The left screen on the GUI is used for visualization of the target warehouse in the VR environment. Initially, the warehouse digital twin is generated based on the input parameters received from the warehouse owners. This list includes a 2D map of the warehouse walls, the ceiling height, the initial positions of the racks, the number of racks, the distance between racks, the number of tiers and sections in each rack, and the size of the rack cells (pallet places). Then we place the heterogeneous robot in our model of digital twin. Filling of shelves with pallets and boxes occurs during the stocktaking based on the created card of verified barcodes.

When the UAV detects a barcode on the real goods during the stocktaking, a virtual pallet is filled with a box in the digital warehouse only after barcode verification. In addition, at the time of verification, the UAV takes a photo of the pallet and link it in the database with the scanned barcode. Thus, we reconstruct a simplified model of the inspected warehouse (Fig. 4-10).

4.4.6 User study

We conducted a preliminary experiment of the drone control using the VR and desktop applications before tests with a real system to assess the convenience of control modes and identify possible emergency situations with the real system.

The purpose of the user study was to evaluate the effectiveness of the proposed approach of the UAV control through developed VR interface in comparison with one the most popular method of the UAV control using First Person View (FPV) glasses and remote controller Grijalva and Aguilar [2019]. Since usually only the picture from the drone camera is transmitted in FPV glasses, it is impossible to use the advantages of the VR interface, e.g., 360-degree view of the scene by head rotation, in this mode. Therefore we decided to stream the image from the drone camera from the digital twin to the desktop display. Thereby in our approach, we would like to make a comparison between desktop and VR-based applications to prove the effectiveness of using the VR mode.

Figure 4-10: Visualisation of the UAV flight above the UGV near one rack in the warehouse digital twin.

Experimental Description

For the user study, the following scenario was developed. The system was launched in the "visual inspection" mode. The participant had to find 5 pallets and fly up to them, thereby making an inventory. All pallets that the user had to scan during the experiment, we highlighted in red, after scanning, the highlight color changed to green (Fig. 4-10). To simulate a flight in FPV mode, we broadcast the video stream from the drone camera from the VR application to the desktop display (Fig. 4-11 (a)). Flight control was carried out using two thumbsticks on the Logitech gamepad F710 (the left thumbstick for the velocity control along z-axis and yaw rotation, the right one for movement in the horizontal direction: forward, backward, left, or right). This setup was chosen to simulate the most common drone control using RC controller. In this mode, no other camera views were available, only video from the drone camera, as in normal control through FPV glasses. In the VR scenario of the developed interface, control was carried out using HTC VIVE controller. The trigger was used to move the UAV to the holding position mode. The subjects controlled the quadcopter from the third-person view and could rotate the head to look around the space. Besides, the additional feedback from the drone camera was available for the user (Fig. 4-11 (b)). Before the experiment, each subject had short training to get acquainted with the control procedure. After completing the tasks using both modes, we asked participants to respond to a 9-question survey using bipolar Likert-type seven-point scales. The survey results are presented in Fig. 4-12.

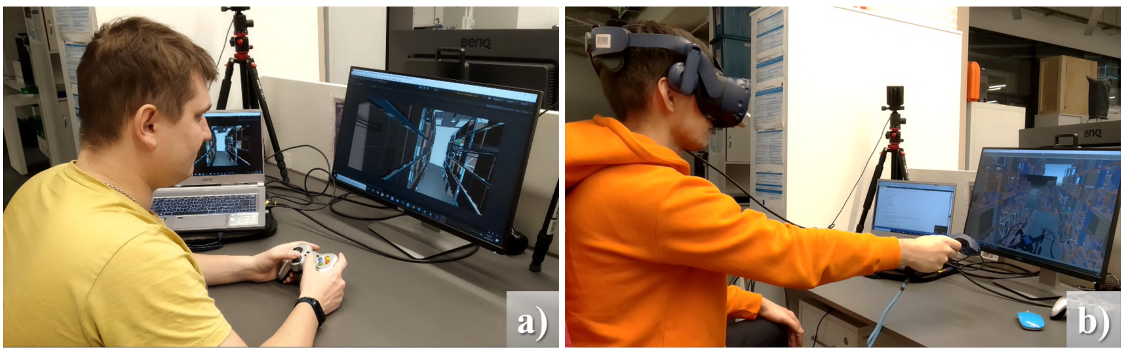


Figure 4-11: Overview of the experiment process: a) Desktop mode, b) VR mode.

Participants

In total, 10 subjects took part in the experiments (3 women and 7 men). Participants were students with a background in mechanical engineering, computer science, and robotics. The average participant age was 25 (standard deviation (SD) = 2.9), with a range of 21–31. Our population sample contained both novice users and experienced users at piloting drones. In total, 3 participants had never interacted with drones before, 4 participants piloted drones several times, and 3 reported regular experience with aerial robots. As for VR experience, 6 participants used VR only a few times, and 4 people answered that they used VR devices regularly.

Results and discussion

Overall, the subjects assessed the ease of the robot control process (Q1, Q2, Q3). The participants noted that the control mechanism (Q1) was more natural and easier (Q2) in the case of using a VR mode (Q1: $\mu = 5.9$, $SD = 1.14$ for VR and $\mu = 5.1$, $SD = 1.64$ for the RC control mode; Q2: $\mu = 6.3$, $SD = 0.64$ and $\mu = 5.4$, $SD = 1.63$ for VR and RC control respectively). According to ANOVA results, the type of control interface affects the involvement (Q7) of the task ($F(1, 18) = 6.34, p = 0.02 < 0.05$) and ability to concentrate (Q3) on a task ($F(1, 18) = 13.05, p = 2 \cdot 10^{-3} < 0.05$). The subjects noted the convenience of the

Questions	Mean	SD
Q1. How natural was the mechanism which controlled the robot movement during the task?	5.1	1.64
	5.9	1.14
Q2. How easy was it to use the control interface?	5.4	1.63
	6.3	0.64
Q3. How well could you concentrate on the assigned task rather than on mechanism used to perform this task?	4.6	1.43
	6.5	0.67
Q4. How much the interface was good for achieving the stocktaking?	5.4	1.02
	6.3	0.9
Q5. How much did you feel fatigued after the experiment?	2.0	1.41
	1.8	0.98
Q6. Were you stressed while completing the task?	1.8	0.98
	2.1	0.94
Q7. How much were you involved in the task?	5.7	1.1
	6.7	0.46
Q8. Is the position of the third-person view for the drone control convenient?	6.1	1.45
Q9. Do you consider visual feedback from the drone camera useful?	3.2	2.27

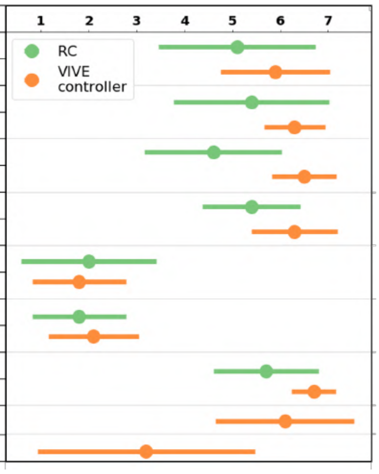


Figure 4-12: Evaluation of the participant's experience for both control methods in the form of a 7-point Likert scale (1 = completely disagree, 7 = completely agree). Means and SD are presented.

third-person view during the robot control (Q8). Fig. 4-13 shows the results for task completion time and evaluation of control modes in the form of radar chart across all participants. The difference in completion times is insignificant: $F(1, 18) = 1.14$; $p = 0.3$ (ANOVA test). Thus task execution time was comparable by control modes (the average completion time is 137.5 s with $SD = 35.95$ for the desktop mode and 127 s with $SD = 39.98$ for the VR mode). The radar chart shows the user evaluation of two control modes in terms of Performance (Q3, Q4), Ease of control (Q1, Q2), Stress (Q6), Fatigue (Q5), and Involvement (Q7). According to results of the user study, VR-based interface increases involvement and performance, whereas the stress level during task completion and fatigue of participants were almost the same for both control modes. At the same time, participants noted that it is easier to control the system through the VR application.

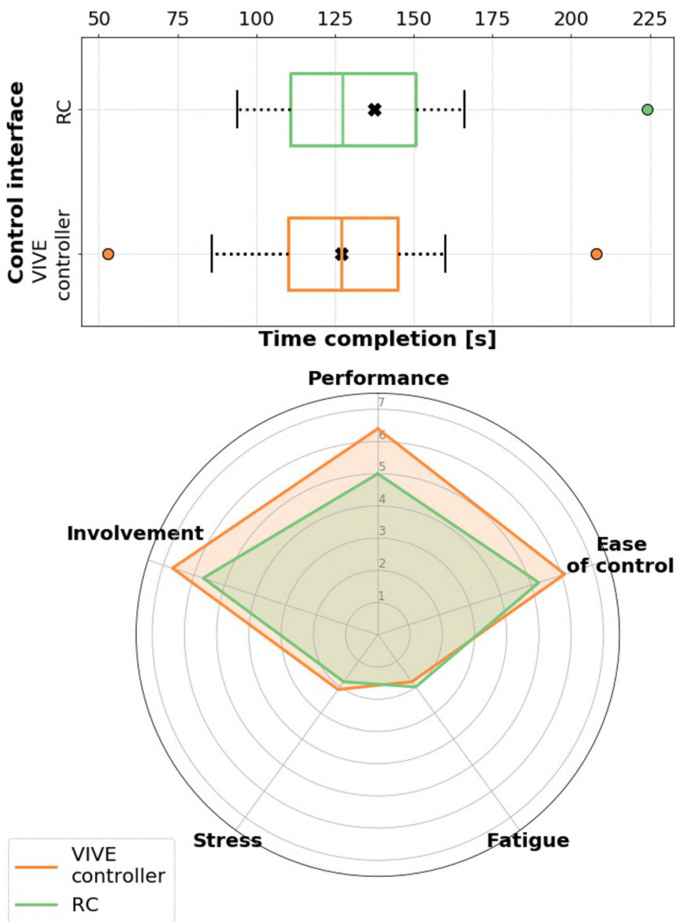


Figure 4-13: Experimental results averaged across all participants. Top: completion time; crosses mark mean values. Bottom: radar chart.

In addition, we analyzed the results of the participants based on their previous experience with VR and the piloting of drones. We compared the time completion for VR and desktop modes between groups of persons with different levels of technology experience. According to our findings, more experience in VR did not affect task performance ($\mu = 139.5$, $SD = 44.35$ and $\mu = 118.66$, $SD = 34.35$ for advanced and ordinal users accordingly). Similarly, all subjects had comparable average time for RC control task. However, persons with zero experience in drone piloting assessed the VR interface more ease of control compared to RC control (Q1, Q2).

4.4.7 Outcomes and following implementation

We have proposed a novel interactive interface based on VR application for natural and intuitive human interaction with the autonomous robotic system for stocktaking. It allows the operator to conduct different levels of stocktaking, remotely monitor the inventory process, and teleoperate the drone for the more detailed inspection.

WareVR suggests a new way of communication between the robotic warehouse system and operator that can potentially improve and facilitate the inventory process.

In the further development if proposed interface we plan to:

- Implement hand gesture recognition to control the drone instead of HTC VIVE controller.

- Incorporate smart glove with a tactile feedback system for the operator. It will facilitate the UAV control by introducing an understanding of the surrounding environment, working area, and obstacles.

- Add the functionality of the gesture control system, to be able to control not only a single drone, but a whole swarm of drones (see Fig.4-14). Conducting experiments on gesture recognition with machine learning machine learning (ML).

- Currently, only individual tests of real flights in the warehouse have been conducted, and tests for remote control with the developed interface in the laboratory. The next stage will be testing the whole integrated system in the warehouse and conducting experiments with workers in the warehouse industry.

Figure 4-14: The heterogeneous robotic system with swarm of drones in the digital twin environment.

Chapter 5

Development of the indoor localization, navigation and control system

5.1 Localization of the mobile platform in 2D environment

The main objective of the UGV is to to accurately calculate the position of each pallet in order to determine the coordinates relative to the surrounding objects in a warehouse. The ground robot uses SLAM algorithms with graph-based approaches Grisetti et al. [2010] for finding its location in space and building a map. For mapping robot uses two dimensional LIDAR and receives scans, which are then compared with local submaps. Thus, the mobile platform complements the submaps with new obstacles. Further, the robot finds the final terrain map using nonlinear optimization methods by combining the submaps into one graph, which helps the UGV to find its position in space.

Also, we use Object SLAM Gálvez-López et al. [2016] in addition to the described localization method. This complementation helps the UGV to recognize randomly placed objects in a warehouse. This information helps the robot to understand that those objects are not a part of a standard warehouse environment and determine its location more accurately. Using a combination of described methods, the UGV localization becomes much more robust, which allows it to operate in a warehouse without external stationary beacons (Fig. 5-1). This is a high-quality map of the warehouse, since it shows the same number of corners as the warehouse environment. Moreover, it can be seen that the map is fully enclosed. Such qualitative metrics are used in Filatov et al. [2017] to compare SLAM algorithms. It is also important to note that the presented map matches the geometry and dimensions of the warehouse map where this experiment was carried out. It is important to note that the final map is of sufficient quality, nevertheless, at the beginning of its construction process, the quality was worse and there were unclosed areas.

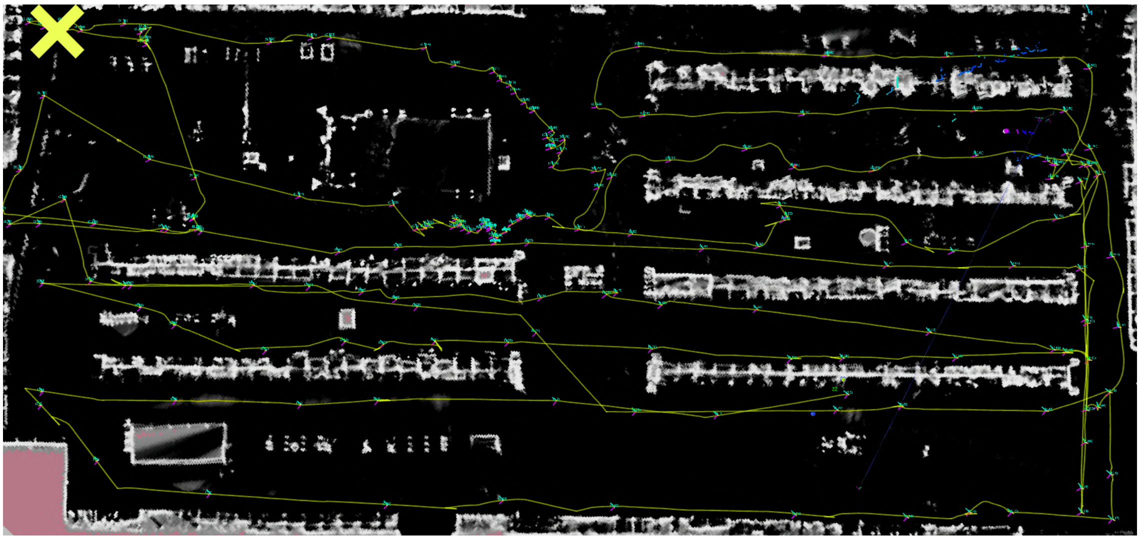


Figure 5-1: Localization of the ground robot in warehouse. The yellow cross indicates the starting point, which coincides with the end point. Colored lines represent the robot's path, white lines indicate obstacles and racks.

In order to navigate on the final map the robot finds the path and follows it, locating and avoiding the obstacles. The path finding uses the modern grid map tracing methods. For obstacle avoidance the robot looks for a local path with minimal cost using differential orthogonal exponential controller (DOEC) method. The maximum speeds, values of the path and distances to the obstacles influence the path cost. In order to determine static and dynamic obstacles the ground robot uses an red, green, blue, depth (RGB-D) camera and a laser rangefinder. It utilizes Alpha Filter for LIDAR data processing. For the 3D camera the UGV uses Voxel

Filter and Statistical Filter. Combining processed data from these two sensors the mobile platform acquires a 3D point-cloud. After that robot projects it to the plane, which yields a map with all surrounding obstacles. The UGV uses this data to detect people and safety interact with them.

For better understanding we make a brief description of localization and navigation principles of the ground robot. The software architecture is represented in the block-diagram (Fig. 5-2). All on-board calculations are performed by Intel NUC with Core-i7 7567U. The robot uses the following key hardware components for localization, navigation and collision avoidance:

- Two LIDARs Hokuyo UST-10lx for localization;
- Two Intel RealSence D435 RGB-D cameras for localization and collision avoidance;
- Built-in encoders which receive information about wheels odometry;
- Integrated IMU for robot odometry.

At the first stage, we filter data from sensors, producing a separate filtered point cloud for each of them. Then, we combine data from the sensors into a single point cloud, which is used as an input for localization and obstacle avoidance modules. Then, data from the LIDARs get filtered by intensity for detecting and verifying stationary retro-reflective beacons in a warehouse.

In the "SLAM" block the robot creates and updates the map. As the initial data, graph-based SLAM Hess et al. [2016] uses the map of stationary beacons. It helps the robot to understand that the other objects are dynamical. Scans from RGB-D camera (point clouds projected on 2D surface) supplement the global map

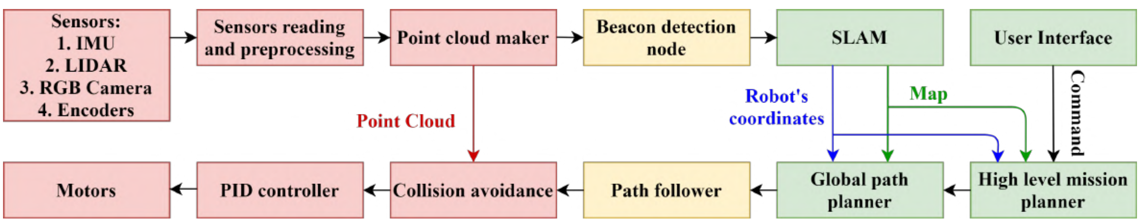


Figure 5-2: Software architecture of the ground robot

with new obstacles. Wheels odometry, fast correlative scan matching help the robot to localize itself on the global map.

The “High level mission planer” is responsible for detection of racks and their contours. Also, it understands which areas of the warehouse are already covered and sends these data to the "Global Planner" module. This module calculates the most optimal path to the end point, depending on the type of inventory. For local path planning the robot utilizes A*-based path planning Kong et al. [2015] which selects the trajectory according to the principle of finding the shortest path in the graph. The "Path follower" module tracks the completion of the path adjusting the desired speed at the same time. The “Collision Avoidance” module monitors static and dynamic obstacles based on a single, filtered point cloud, sets the current speeds and accelerations, which are then transmitted to the "proportional–integral–derivative (PID) controller" module and then directly to the "Motors" module.

5.2 Stocktaking procedure strategy

To conduct an inventory of the system presented in the thesis, we initially request data from the warehouse company. We request a 2D warehouse map, as well as the typical size of the racks (width, length and height of pallet places, number of tiers) and the total number of pallet places. Since the typical pallet size is fairly well standardized, in most of the pallet storage warehouses the rack size is typical. By requesting these parameters from the warehouse company and using them in setting the flight route using the OSBG method. At the input of the algorithm, we send the starting point (it directly depends on the selected part of warehouse for stocktaking), the maximum flight height (depends on the number of tiers), and the horizontal movement step (it is selected based on the selected percentage of overlap OSBG).

- The robot starts stocktaking at the beginning of an alley;
- the UAV flies up to the highest desired point scanning the first row of boxes;
- the UGV performs horizontal movement step, the UAV follows it;

- the UAV descends until it reaches an altitude of 0.3 meters above the UGV, scanning the barcodes of the second row of boxes;
- the UGV performs horizontal movement step, the UAV follows it.

This set of actions is repeated until the robotic system reaches the opposite edge of the rack. During partially inventory of one side of the rack after completing this set of actions, the inventory ends. When should be performed of all the selected alley, the system, after scanning one side, unfolds inside the alley and repeats the same list of actions. Consequently, the system understands that to complete the inventory of one alley, it needs to scan both sides of each alley. Thus, to carry out a complete inventory, the system needs to scan all the alleys from both sides. The last racks in the warehouse are indicated at the initial stage as exceptions, depending on the configuration of the warehouse map, since often the alley near them needs to be scanned from one side only. It should be noted that with implementation of the active perception method (chapter 6, the set of actions changes according to the Algorithms 2.

5.3 IR-based localization of the UAV

Visual detection of AR markers is a common approach for VTOL in mobile robots domain. However, researches show, that cameras are usually installed on UAVs while the markers are attached on the ground robot. On high altitudes ($\sim 10m$) small UAV's camera pitch or roll errors result in high localization error in (x, y) plane.

$$\delta x \simeq \delta\alpha \cdot h. \tag{5.1}$$

We use the opposite approach: we install a camera on the UGV and place two concentric patterns of active IR markers on the UAV (Fig. 5-3). In this setup the UAV always has to fly in a small cylindrical working area above the ground robot. In order to measure the altitude of the UAV we fuse data from UGV camera and ultrasonic sensors, which yields the UAV precise xy coordinate on any altitude. On the UGV we use an Imaging Source camera DFK33UX250 2448x2048 with a

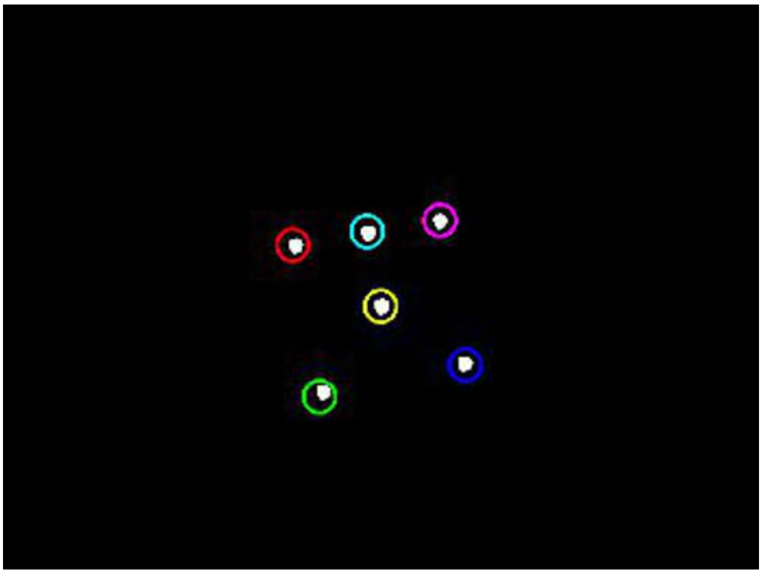


Figure 5-3: Sample of processed camera frame. Different colors represent different markers from the pattern.

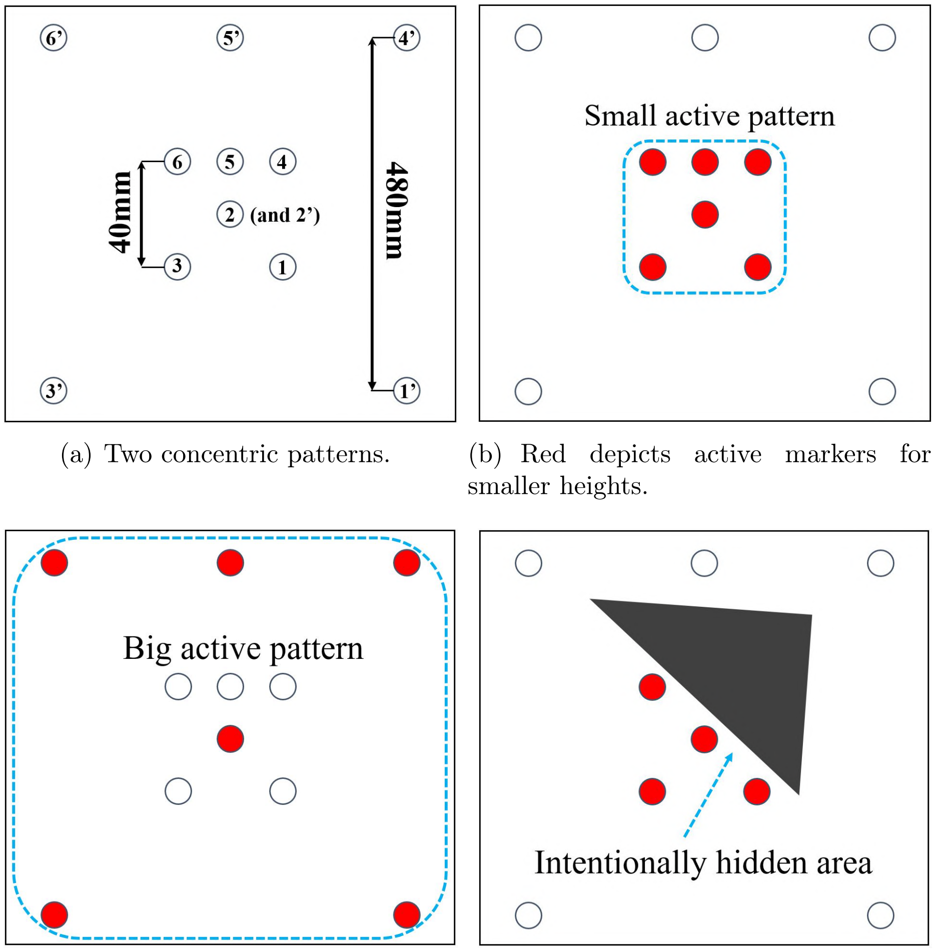
Computar lens T2314FICS (approximately 137.9° FoV). In addition, we install an IR-passing filter on the camera obtain only IR-markers in the image. To remove the other light with similar wavelength we perform simple brightness thresholding, adjust diaphragm and exposure. After that we find parameters of non-zero regions (x, y, S_i), where S_i stands for area of the region. Both thresholding and calculation of contours moments were done using OpenCV library.

$$S_i = m_{i00}, x_i = \frac{m_{i10}}{m_{i00}}, y_i = \frac{m_{i01}}{m_{i00}}, \tag{5.2}$$

$$m_{ipq} = \iint_{x,y \in Si} x^p y^p F(x, y) dx dy, \tag{5.3}$$

where $F(x, y) \in 0, 1$ is the thresholded image.

With IR-passing filter, proper exposure and diaphragm settings only non-zero regions of the image refer to markers in warehouse conditions. For recognition of the pattern, we assign each region to its point on the pattern. It is very important to detect the pattern even when some markers of the pattern are not visible, e.g., when the UGV detects only 4 out of 6 points in the image. When mobile robot detects all the points of the pattern, we can solve the task not relying on previously



(a) Two concentric patterns.

(b) Red depicts active markers for smaller heights.

(c) Red circles present active markers for bigger heights.

(d) Example of a partially covered pattern that would still be correctly processed.

Figure 5-4: IR-patterns used in UAV setup.

processed images. If the UGV misses even 1 point, the mapping between pattern points and contours of the image might be non-unique. In this case, orientation and/or coordinates could not be extracted, therefore we need to take into account previously processed image frames. For detection of the central point marked as (2) (see Fig.5-4a) we calculate average angular coordinates $x_a v^a, y_a v^a$ of all six contours (superscript a denotes projective coordinates). Closest to $x_a v^a, y_a v^a$ point will always be the point (2). Point (5) will always be the closest to the central one. Other points can be found from their relative distances and orientation to (2) and (5). If the pattern is partially covered, we minimize translational loss function for minimizing the rotation of consistent frames. Due to a small number of possible positions it is equal to $A_n^k \leq 6! = 720$, translation loss function minimum can be found reliably without specific optimization methods. Such an approach enhances the redundancy of the system and extends the field of view for detection.

$$\min_{M \in A_n^k} \sum_{\vec{x} \in M, \vec{x}_{prev} \in M_{prev}} ||\vec{x}^a - \vec{x}^a_{prev}||, \tag{5.4}$$

$$\vec{x^a} \equiv (x^a, y^a). \tag{5.5}$$

Now we have angular coordinates x_2^a, y_2^a of the drone and its orientation α. After the localization task, we have to find the height of the UAV. From (x_2^a, y_2^a) we can extract real (x, y) coordinates using scale factor.

$$S = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{|\vec{x}^a_{ij}|}{|\vec{x}^{original}_{ij}|}, \tag{5.6}$$

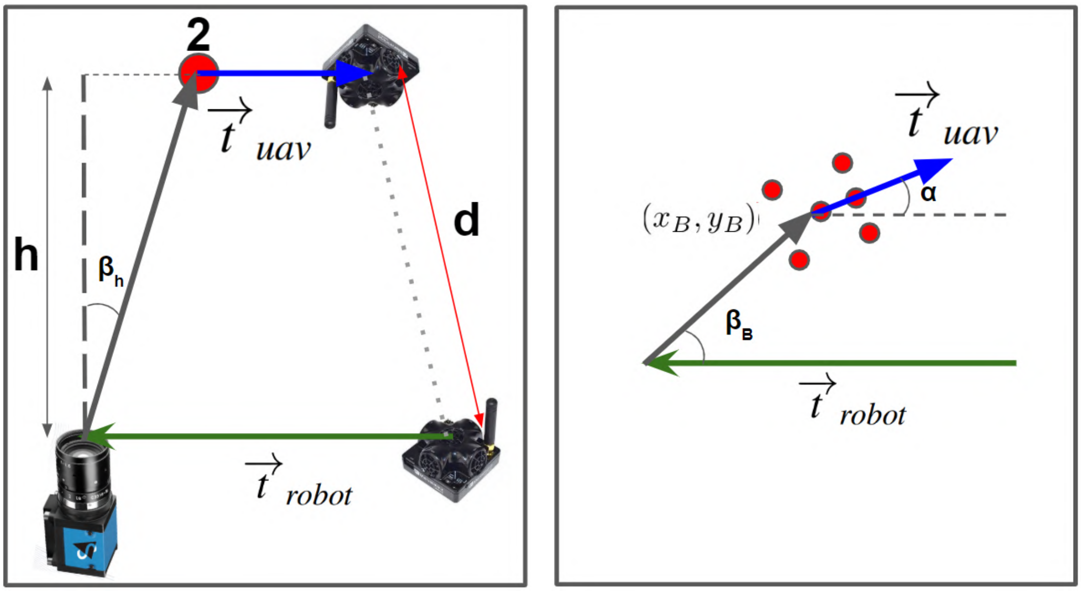
where n is the number of markers in the pattern, $\vec{x}_{ij} = \vec{x}_i - \vec{x}_j$.

As for the image, we calculate the scale factor according to the priori known distance between the IR markers. Then, height can be found as $z = 1/s$. This source of height can be used only at low altitudes. The error for visual estimation of height could not be lower than error caused by a finite number of pixels N in $FoV \simeq \omega$. At the high altitudes it can be estimated as:

$$h = \frac{X}{\tan(\alpha)}; \delta h = X |\frac{d(\frac{1}{\tan(\alpha)})}{d\alpha}| \delta\alpha. \tag{5.7}$$

$$h \simeq \frac{X}{\alpha^2}\delta\alpha = \frac{h^2}{X}\delta\alpha = \frac{h^2\omega}{X \cdot N}. \tag{5.8}$$

On 10 m altitude standard $\sim 2000px$ camera gives height error ~ 0.3 m because of pixel limitation for bigger $(X = 0.4m)$ pattern. Such an error is unacceptable to solve the problem of UAV localization in the narrow space between the racks in the warehouse. Often during the operation of the UAV in the warehouse echo distorts the data from ultrasonic sensors, which makes it impossible to use them as the main localization system of the UAV. However, two beacons can be used to



(a) Side view. (b) Top-bottom view.

Figure 5-5: Height correction for ultrasonic measurements using Marvelmind sensors, corrected height is equal to $\vec{d} = \vec{z} + \vec{t}_{robot} + \vec{t}_{uav}$.

measure the distance between them. This method is more accurate than using a single ultrasonic distance sensor to measure height. Ultrasonic positioning system manufacturers Marvelmind declare the accuracy of distance measurements between two beacons up to 2 cm mar [2019]. Nevertheless, the two beacons in our hardware setup are not always directly above each other. In order to obtain accurate data, it is necessary to correct the altitude in the coordinate system of the UGV (Fig. 5-5):

$$\vec{d}(z) = \vec{t}_{robot} + z \begin{pmatrix} \tan(x_2) \\ \tan(y_2) \\ 0 \end{pmatrix} + R\vec{t}_{uav}, \tag{5.9}$$

$$R = \begin{pmatrix} \cos(\alpha) & -\sin\alpha & 0 \\ \sin\alpha & \cos(\alpha) & 0 \\ 0 & 0 & 1 \end{pmatrix}, \tag{5.10}$$

$$\alpha = \arctan\left(\frac{y_5 - y_2}{x_5 - x_2}\right). \tag{5.11}$$

Then, we solve minimization task with Broyden–Fletcher–Goldfarb–Shanno (BFGS) method implemented in SciPy framework:

$$\underset{h>0}{min}(||\overrightarrow{d}(h)|| - d_{measured})^2. \tag{5.12}$$

Thereafter we finally calculate required x, y, z coordinates:

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = z \begin{pmatrix} \tan(x_2) \\ \tan(y_2) \\ 1 \end{pmatrix}. \tag{5.13}$$

5.4 System setup for LPE

In order to solve the problem of warehouse inventory, i.e. to read barcodes during flight with a high recognition rate, the UAV must be able to fly stably in narrow aisles between racks. In our system the UAV localization is performed by means of remote visual assessment of the IR pattern position in space, so it is important not only to determine its position, but also to transfer these coordinates and coordinates of the next point of the route to the UAV. The scheme of Local Position Estimation (LPE) of the UAV from the UGV is shown in Fig. 5-6.

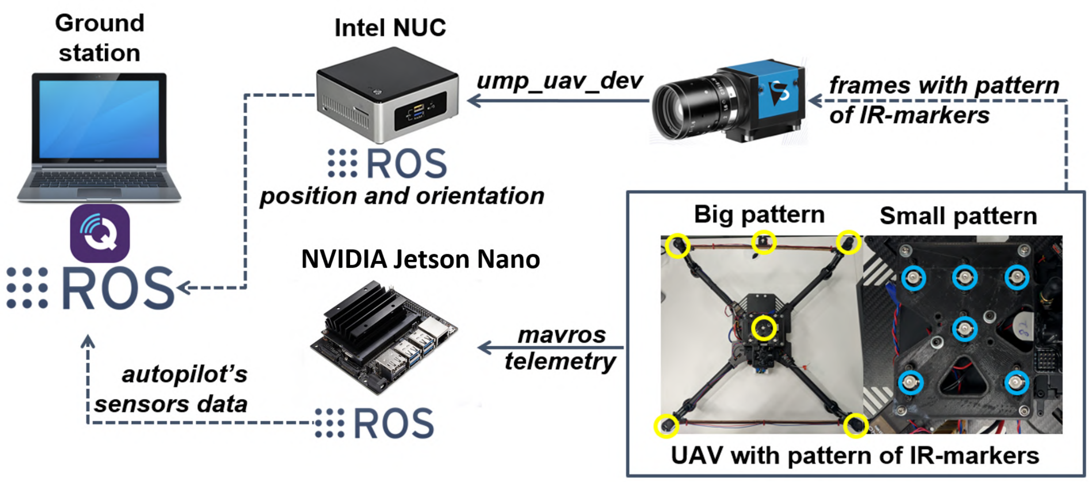


Figure 5-6: LPE using visual information.

The core of our control system is the ROS, which is installed on the UAV's and UGV's on-board computers. For communication between the UAV and the UGV, ROS was set up in a multi-master mode. The Pixhawk autopilot communicates with the UAV's on-board computer by means of MAVROS package, which sends the sensors data of internal equipment of the Pixhawk autopilot to ROS. The UAV position in space is set in the coordinate system according to PX4-firmware standards in NED frame, and ROS uses East-North-Up (ENU) frame positioning system when detecting the IR pattern position in a warehouse relative to the camera. Therefore, for the reliable flight of the UAV it is necessary to make the appropriate transformation of coordinates before sending LPE-data to the UAV control system (5.14).

$$\begin{cases} x_{NED} = x_{ENU} \\ y_{NED} = -y_{ENU} \\ z_{NED} = h - z_{ENU} \end{cases} \tag{5.14}$$

The communication system between the UAV and the UGV and key equipment are shown in Fig.5-7. The Intel NUC on-board computer is installed on the UGV and ASUS RT-AC68U router is connected to it to create a local Wi-Fi network. The UGV is also equipped with a camera for tracking patterns, a Marvelmind router and a beacon. The UAV is equipped with two IR patterns, which we use for localization system of the UAV, the small one for takeoff and landing, the large one to track the drone at high altitudes. Also a Marvelmind beacon to calculate the distance to the platform, a camera for video streaming in the local Wi-Fi network and barcode detecting, and a laser scanner for barcode recognition are installed on the UAV. Each computer connected to the local Wi-Fi network is able to view the video stream from the UAV's camera, as well as to monitor the status of the UAV with the help of QgroundControl software.

In chapter 7. the accuracy of the developed localization system was verified using the "Vicon Vantage 5" motion capture (mo-cap) system, which simultaneously recorded the local UAV position relative to it in the laboratory, while the UAV was equipped with small passive infrared markers and monitored by multiple tracking cameras.

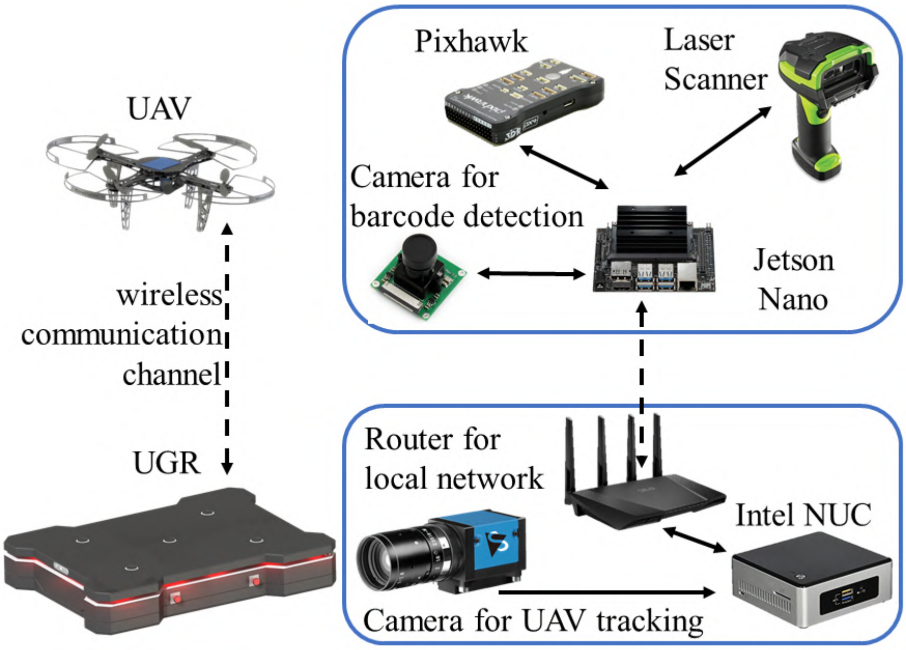


Figure 5-7: Communication system setup.

5.5 Robust Extended Kalman Filter

For drone localization we used I. Kalinov et al. [2019] IR markers and ultrasonic rangefinders. However, this preliminary localization method with Kalman Filter was not enough for flying on altitudes of more than 10 meters outliers appeared during flight tests in real warehouse. First of all we implement Robust Extended Kalman Filter (REKF) Majumder and Sadhu [2016] to get rid of outliers, the comparison of flight results with these two methods is presented in this section section 7.2 after filter description.

EKF algorithm could be represented in the following algorithmic view.

Algorithm 1 Extended Kalman Filter($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t$)

1: $\overline{\mu}_t = g(u_t, \mu_{t-1})$
2: $\overline{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + R_t$
3: $K_t = \overline{\Sigma}_t H_t^T (H_t \overline{\Sigma}_t H_t^T + Q_t)^{-1}$
4: $\mu_t = \overline{\mu}_t + K_t(z_t - h(\overline{\mu}_t))$
5: $\Sigma_t = (I - K_t H_t)\overline{\Sigma}_t$
6: **return** μ_t, Σ_t

Where:

- μ_{t-1} is the previous state vector;

- $\overline{\mu}_t$ is the prediction state vector;
- g is the transition function;
- G_t is the Jacobian of transition function g;
- h is the function that converts state vector to measurement;
- H_t is the Jacobian of $\mathbf{h}$ function
- K_t is the Kalman gain;
- Σ_{t-1} is the previous covariance matrix;
- Σ_t is the covariance matrix;
- $\overline{\Sigma}_t$ is the prediction covariance matrix;
- u_t is the motion vector;
- z_t is the measurement;
- Q_t is the current measurement error matrix;
- R_t is the current motion error matrix;

In our case the state vector μ is equal to:

$$\mu = \begin{pmatrix} x \\ y \\ z \\ \alpha \\ v_x \\ v_y \\ v_z \\ v_\alpha \end{pmatrix}. \tag{5.15}$$

The measurement z is the vector, that is equal to:

$$z = \begin{pmatrix} X \\ Y \\ \alpha \\ Markerlength \end{pmatrix}, \tag{5.16}$$

where X is the x coordinate in camera frame in pixels, Y is the y coordinate in camera frame in pixels, α is the angle in camera frame in radians, *Marker length* is the length of marker in camera frame in pixels.

$$g = \begin{cases} x_t = x_{t-1} + v_{xk-1}dt, \\ y_t = y_{t-1} + v_{yk-1}dt, \\ z_t = x_{zt-1} + v_{zk-1}dt, \\ \alpha_t = \alpha_{t-1} + v_{\alpha k-1}dt, \\ v_{xt} = v_{xt-1}, \\ v_{yt} = v_{yt-1}, \\ v_{zt} = v_{zt-1}, \\ v_{\alpha t} = v_{\alpha t-1} \end{cases} \tag{5.17}$$

$$h = \begin{cases} X = \frac{-f_y y}{z} \\ Y = \frac{f_x x}{z} \\ Markerlength = \frac{dml * f_x}{z} \\ \alpha = \alpha \end{cases} \tag{5.18}$$

Where *dml* is the default marker length (the known marker length in pixels on the known height), f_y is the number of pixels, that camera could see per one radian along y axis, f_x is the number of pixels, that camera could see per one radian along x axis.

Q_t matrix is constant diagonal matrix, that is equal to:

$$Q_t = \begin{pmatrix} X_e \ 0 \ 0 \ 0 \\ 0 \ Y_e \ 0 \ 0 \\ 0 \ 0 \ \alpha_e \ 0 \\ 0 \ 0 \ 0 \ L_e \end{pmatrix}, \tag{5.19}$$

where X_e is the error of measurement of camera by X-axis in pixels, similarly Y_e is along Y-axis, α_e is the error of measurement of camera by angle in radiance, L_e is the mean error of measurement of marker length in camera frame in pixels.

R_t is the current motion error matrix, that is equal to:

$$R_t = \begin{pmatrix} \frac{dt^2}{2} \ 0 \ 0 \ 0 \ dt^3 \ 0 \ 0 \ 0 \\ 0 \ \frac{dt^2}{2} \ 0 \ 0 \ 0 \ dt^3 \ 0 \ 0 \\ 0 \ 0 \ \frac{dt^2}{2} \ 0 \ 0 \ 0 \ dt^3 \ 0 \\ 0 \ 0 \ 0 \ \frac{dt^2}{2} \ 0 \ 0 \ 0 \ dt^3 \\ dt^3 \ 0 \ 0 \ 0 \ \frac{dt^2}{2} \ 0 \ 0 \ 0 \\ 0 \ dt^3 \ 0 \ 0 \ 0 \ \frac{dt^2}{2} \ 0 \ 0 \\ 0 \ 0 \ dt^3 \ 0 \ 0 \ 0 \ \frac{dt^2}{2} \ 0 \\ 0 \ 0 \ 0 \ dt^3 \ 0 \ 0 \ 0 \ \frac{dt^2}{2} \end{pmatrix} A, \tag{5.20}$$

where dt is the time delta between iteration and A is the double acceleration vector. The next is outliers detection algorithm. Condition of outlier detection is that Square of Mahalanobis distance of innovation more than critical value of χ^2 distribution. The calculations for evaluation of this condition could be performed in three steps:

$$\textbf{Innovation} : \nu_t = z_t - h(\overline{\mu}_t) \tag{5.21}$$

$$\textbf{Innovation covariance}: P_{\nu t} = H_t \Sigma_t H_t^T + Q_t \tag{5.22}$$

$$\textbf{Square of Mahalanobis distance of innovation}: M^2 = \nu_t^T P_{\nu_t}^{-1} \nu_t \tag{5.23}$$

If M^2 more than χ^2 we should optimize function below by the parameter k in the following way: $f(k) = \nu_t^T (\overline{P_{\nu_t}})^{-1} \nu_t - \chi^2_{max,\alpha}$ where $\overline{P_{\nu_t}} = H_t G_t \Sigma_t G_t H_t^T + H_t R_t H_t^T + kQ_t$. After all steps we should recalculate Kalman Gain with measurement error matrix multiplied by k and then repeat last steps with recalculated Kalman Gain.

5.6 Landing system with impedance-based control

In this section, we present a new method for soft landing of the UAV on a ground robot based on impedance control, applied for a heterogeneous robotic system for continuous automated warehouse stocktaking. We describe the operating and mathematical principles of the impedance control for the landing system of the UAV and present the results of the real-world experiments. We evaluate the softness of landing using force sensors attached to each of four legs of the drone by measuring the impact force during the contact. Experimental results revealed that proposed landing impedance control decreased the impact force by 60%. The main purpose of this approach is its application in the heterogeneous robotic system for continuous operations during automated warehouse stocktaking.

5.6.1 Importance of the soft UAV landing for continuous operations

For continuous inventory stocktaking in warehouses, it is also essential to be able to accurately and softly land and take off multiple times in a row. For accurate localization and navigation of the UAV proper sensor calibration is crucial. However, during a hard landing, such calibration can be lost. All the work that investigated the landing of the drone on a mobile platform focused on accurate landing, target detection, landing under various conditions of the system dynamics. In all works, the experiments were carried out either once or each time anew, in other words, the repeatability of the experiments was not investigated. Thus, soft landing is a critical condition for being able to repeat the experiment. For our system, this parameter is fundamental, as for the other industrial systems based on UAVs. Various methods could be applied for soft landing. For instance, physical softening of the landing surface or/and dampers on the legs. Also, the control method to soften the landing could be implemented. One of the possible approaches for the soft UAV landing is impedance control, which we applied in our work.

5.6.2 Literature review of relevant approaches

For continuous inventory stocktaking in warehouses, it is also essential to be able to accurately and softly land and take off multiple times in a row. For accurate localization and navigation of the UAV proper sensor calibration is crucial. However, during a hard landing, such calibration can be lost. All the work that investigated the landing of the drone on a mobile platform focused on accurate landing, target detection, landing under various conditions of the system dynamics. In all works, the experiments were carried out either once or each time anew, in other words, the repeatability of the experiments was not investigated. Thus, soft landing is a critical condition for being able to repeat the experiment. For our system, this parameter is fundamental, as for the other industrial systems based on UAVs. Various methods could be applied for soft landing. For instance, physical softening of the landing surface or/and dampers on the legs. Also, the control method to soften the landing could be implemented. One of the possible approaches for the soft UAV landing is impedance control, which we applied in our work.

The impedance control was firstly introduced by Hogan Hogan [1984]. Impedance control is frequently used for human-robot interaction Tsetserukou et al. [2006], and has found an extended application in haptics Adams and Hannaford [1999], teleoperation Love and Book [2004], and rehabilitation Hussain et al. [2013]. In terms of the application of impedance control for a UAV several significant papers Fumagalli and Carloni [2013], Mersha et al. [2014], Ruggiero et al. [2014], Tomić and Haddadin [2014], Tsykunov et al. [2018] have been presented. In paper Mersha et al. [2014] authors presented the control architecture that is capable of varying the impedance of the controlled aerial robot and regulating time-varying interaction forces when contact is detected, the described controller provides a great degree of flexibility to increase performance. They used it only in terms of interacting with quadrotor during flight. Paper Tomić and Haddadin [2014] describes the unified framework for external wrench estimation, interaction control and collision detection for flying robots based on impedance control. Authors designed admittance and impedance control, which shape the robot's disturbance response to external forces. The paper Fumagalli and Carloni [2013] describes the modified impedance control strategy for a generic robotic system that can interact with an unknown environment and a human. The controller makes use of a virtual mass, coupled with the robotic system which allows for stable interaction. Ruggiero et al. [2014] developed a controller ensuring a closed-loop impedance behavior for both the translational and rotational parts of a VTOL UAV. The collision identification technique had been suitably modified and adapted as an estimator of external generalized forces (forces plus torques) acting on the aerial vehicle. The authors of Tsykunov et al. [2018] implemented human-swarm interaction based on impedance-controlled interlinks. Operator guides the swarm of drones by hand movement and feels dynamic state of swarm through tactile patterns at fingertips. All these researches were devoted to the implementation of impedance control for the UAV control during flight and interaction with a human or environment.

The main contribution for this chapter: a new approach for the soft landing of the UAV based on impedance model with evaluation of the softness of landing using four force sensors attached to each of four legs by measuring the force during the first contact.

5.6.3 Mathematical approach for impedance based landing system

Our approach for landing the UAV on the UGV is based on the implementation of impedance model where the inputs are position and velocity of the UAV and the UGV, and the output is a virtual force that influences the UAV. In our system the dynamic of the UGV is represented by a system of equations:

$$\begin{cases} \dot{p}_x = v_t \cos\theta \\ \dot{p}_y = v_t \sin\theta \\ \dot{p}_z = 0 \\ \dot{\theta} = a_1 \\ \dot{v}_t = a_2 \end{cases} \tag{5.24}$$

In 5.24, p_x, p_y,p_z are the three dimensional (3D) coordinates of the ground robot position in the world frame, θ is the angle between the x-axis of the robot body frame and the world x-axis, v_t is the tangential velocity of the vehicle, and a_1 and a_2 represent the control input to the system. The dynamic model of the UAV that we use on the altitudes higher than 1 meter is fully described in Dong et al. [2013] and is represented by:

$$ma_m = \begin{bmatrix} 0 \\ 0 \\ mg \end{bmatrix} + R_B^N \begin{bmatrix} 0 \\ 0 \\ -\chi \end{bmatrix} + F_D, \tag{5.25}$$

where m is the mass of the UAV, a_m is the total acceleration of the UAV, g is the nominal acceleration, χ is the total thrust generated by the UAV rotors, and F_D is the air drag force, and R_B^N is the rotation matrix from the North-East-Down (NED) reference frame to the body frame:

$$R_B^N = \begin{bmatrix} c_\theta c_\psi & s_\phi s_\theta c_\psi - c_\phi s_\psi & c_\phi s_\theta c_\psi + s_\phi s_\psi \\ c_\theta s_\psi & s_\phi s_\theta s_\psi + c_\phi c_\psi & c_\phi s_\theta s_\psi - s_\phi c_\psi \\ s_\theta & s_\phi c_\theta & c_\phi c_\theta \end{bmatrix}. \tag{5.26}$$

The force equations can be simplified in the following way:

$$m \begin{bmatrix} \ddot{x}_m \\ \ddot{y}_m \\ \ddot{z}_m \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ mg \end{bmatrix} - \begin{bmatrix} c_\phi s_\theta c_{\psi z} + s_\phi s_\psi \\ c_\phi s_\theta s_\psi - s_\phi c_\psi \\ c_\phi c_\theta \end{bmatrix} \chi - \begin{bmatrix} k_d \dot{x}_m |\dot{x}_m| \\ k_d \dot{y}_m |\dot{y}_m| \\ k_d \dot{z}_m |\dot{z}_m| \end{bmatrix}. \tag{5.27}$$

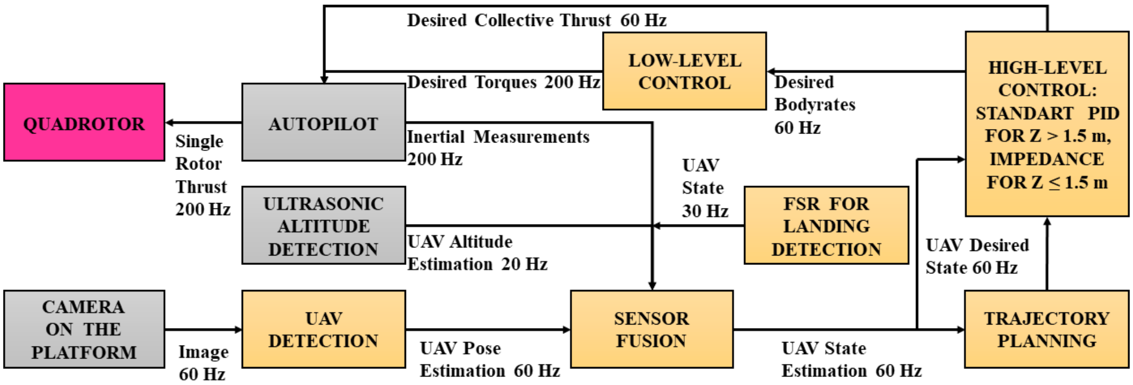


Figure 5-8: The schematic of the framework of our system.

During the landing from altitudes less than 1.5 meter we add a virtual force that does not allow the quadrotor to land quickly and be damaged in the moment of landing. Fig. 5-8 presents our framework where orange blocks represent software modules; grey blocks represent hardware components; the quadrotor is represented by a rose block. Communication between modules is done in Robot Operating System (ROS). Implementation of the virtual force changes the dynamic model of the UAV to:

$$m \begin{bmatrix} \ddot{x}_m \\ \ddot{y}_m \\ \ddot{z}_m \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ mg \end{bmatrix} - \begin{bmatrix} c_\phi s_\theta c_\psi + s_\phi s_\psi \\ c_\phi s_\theta s_\psi - s_\phi c_\psi \\ c_\phi c_\theta \end{bmatrix} \chi + F_D - F_{imp}, \tag{5.28}$$

where F_{imp} is the virtual impedance force applied to the UAV. In order to calculate the correction for the UAV goal position, we need to solve a second order differential equation for each coordinate.

$$\begin{bmatrix} M_d^x \ddot{x}_{imp} \\ M_d^y \ddot{y}_{imp} \\ M_d^z \ddot{z}_{imp} \end{bmatrix} + \begin{bmatrix} D_d^x \dot{x}_{imp} \\ D_d^y \dot{y}_{imp} \\ D_d^z \dot{z}_{imp} \end{bmatrix} + \begin{bmatrix} K_d^x x_{imp} \\ K_d^y y_{imp} \\ K_d^z z_{imp} \end{bmatrix} = \begin{bmatrix} F_{imp}^x(t) \\ F_{imp}^y(t) \\ F_{imp}^z(t) \end{bmatrix}, \tag{5.29}$$

where $\Delta x_{imp} = x_{imp}^c - x_{imp}^d$ is the difference between current and desired position, M_d is the desired mass of the virtual UAV body, D_d is the desired damping coefficient, and K_{dis} is the desired stiffness. In our experiments we use this model only in application to the Z-axis in term of our ground robot being static (Fig. 6).

In accordance with this fact we could write the impedance equation in discrete time-space after integration for Z-axis:

$$\begin{bmatrix} \Delta z_{k+1} \\ \Delta \dot{z}_{k+1} \end{bmatrix} = A_d \begin{bmatrix} \Delta z_k \\ \Delta \dot{z}_k \end{bmatrix} + B_d F_{imp}^k, \tag{5.30}$$

where $A_d = e^{AT}$,$B_d = (e^{AT} - I)A^{-1}B$, T is the sampling time, we is the identity matrix, and e^{AT} is the state transition matrix. In our system A and B are equal to:

$$A = \begin{bmatrix} 0 & 1 \\ -\frac{K_d^z}{M_d^z} & -\frac{D_d^z}{M_d^z} \end{bmatrix}, \tag{5.31}$$

$$B = \begin{bmatrix} 0 \\ -1/M_d^z \end{bmatrix}. \tag{5.32}$$

According to Cayley-Hamilton theorem, we can find A_d and B_d how it was done in Ruggiero et al. [2014], where λ is the eigenvalue variable of the matrix A. For the case of overdamped second order system we have the following solution:

$$A_d = e^{\lambda T} \begin{bmatrix} 1 - \lambda T & T \\ -\frac{K_d^z}{M_d^z} T & 1 - \lambda T + \frac{D_d^z}{M_d^z} T \end{bmatrix}, \tag{5.33}$$

$$B_d = \frac{1}{K_d^z} \begin{bmatrix} e^{\lambda T}(1 - \lambda T) - 1 \\ -\frac{K_d^z}{M_d^z} T e^{\lambda T} \end{bmatrix}. \tag{5.34}$$

Then we use A_d and B_d to calculate the impedance correction term x_{imp}^c for the current position of the UAV. In order to control the UAV during landing by $F_{imp}^z(t)$, the force must be formalized using the UAV state parameters e.g., speed, acceleration. As landing softness depends on the UAV speed we propose to calculate the impedance force as the function of the UAV velocity along z-axis:

$$F_{imp}^z(t) = -k_v^z \dot{z}(t), \tag{5.35}$$

where k_v^z is the scaling coefficient. In terms of landing of the UAV on the moving mobile platform the impedance force along x and y axes could be a function of the platform velocities $\dot{p}_x$ and $\dot{p}_y$:

$$F^x_{imp}(t) = -k^x_v \dot{p}_x(t), \tag{5.36}$$

$$F^y_{imp}(t) = -k^y_v \dot{p}_y(t). \tag{5.37}$$

5.6.4 Experimental evaluation of the impedance model

It is well known that the behavior of an impedance model described with the second-order ordinary differential equation of the type 5.29, in general, is divided into several modes, based on the choice of M^z_d, D^z_d, K^z_d coefficients: undamped, underdamped, critically damped, overdamped.

The main goal of the proposed impedance control-based model is to make landing trajectory of the drone smooth and decrease the UAV velocity. Because of this fact, the critically damped and overdamped model is more preferable. In our case, the coefficients were selected as follows: $M^z_d = 1.0$, $D^z_d = 37.8$, $K^z_d = 2.0$, in order to provide the overdamped response which would decelerate the UAV slowly enough

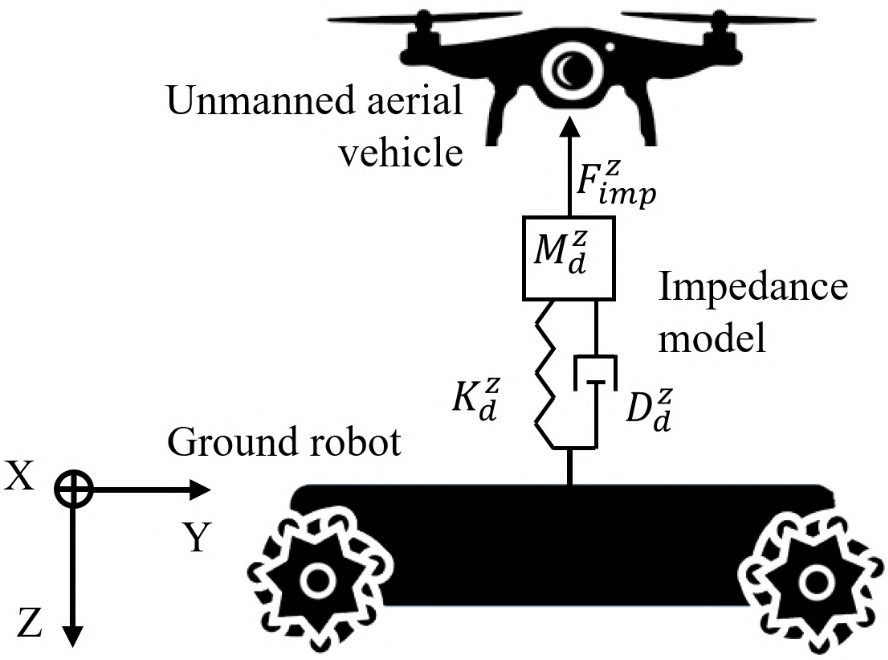
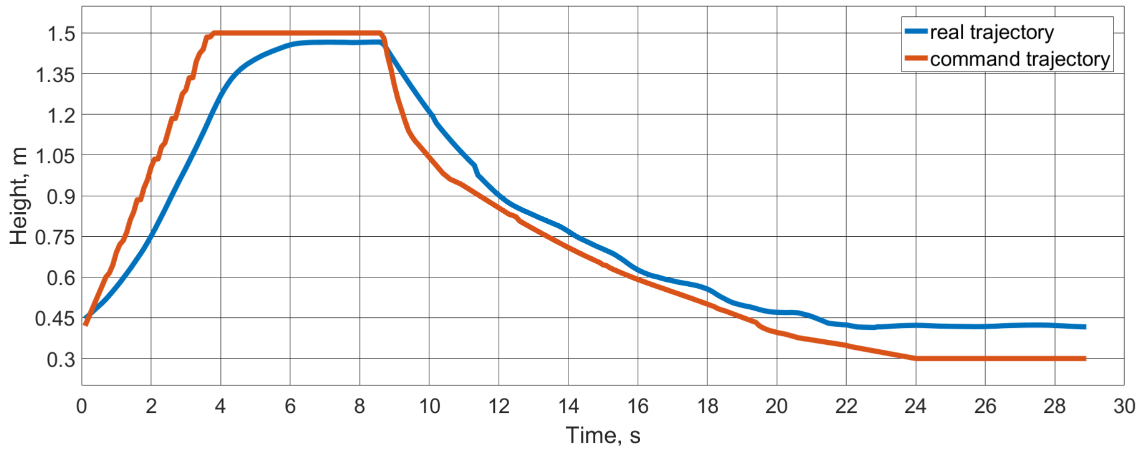


Figure 5-9: Impedance model during the UAV landing.

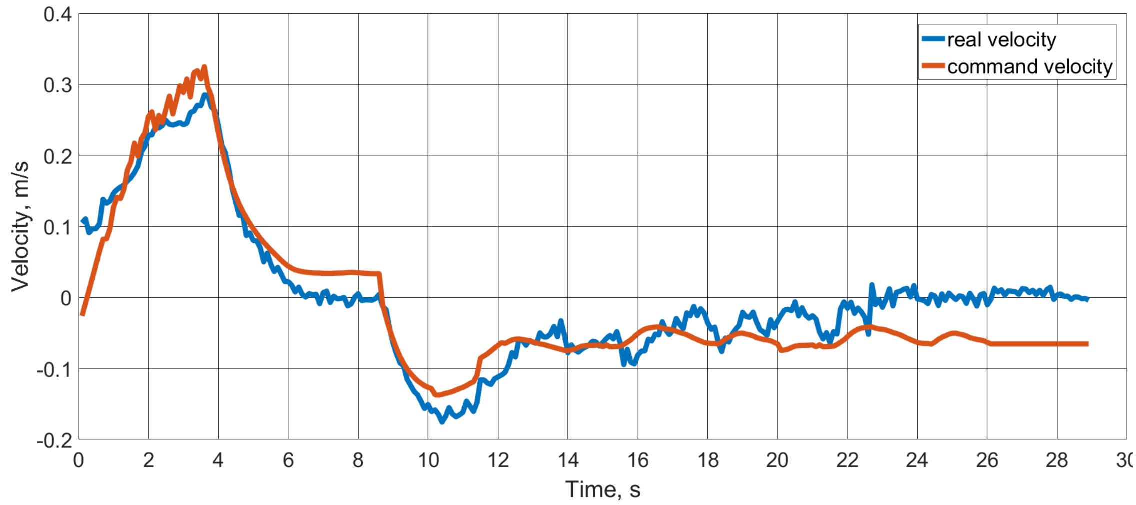
in order to touch the ground robot with the velocity close to zero.

For better understanding, we flipped the Z axis on Fig. 5-10 and 5-11, despite the fact that in subsection 5.6.3 it is pointing down, as shown in Fig. 5-9. In Fig. 5-10a we present the landing trajectory with impedance control method. The drone adapts its velocity during landing starting at second 9 (see Fig. 5-10b). The UAV starts its descending with a maximum velocity, $V_z = 0.18$ $[m/s]$ and then decelerates gradually until reaching a small constant speed, $V_z = 0.05$ $[m/s]$ at second 20, at which it afterwards reaches the UGV, the height of the UGV is 40 cm.

During the first experiments, we noted that the UAV almost reached the UGV



(a) Trajectory of the UAV along Z axis.



(b) Velocity of the UAV along Z axis.

Figure 5-10: Impedance control method during the UAV landing.

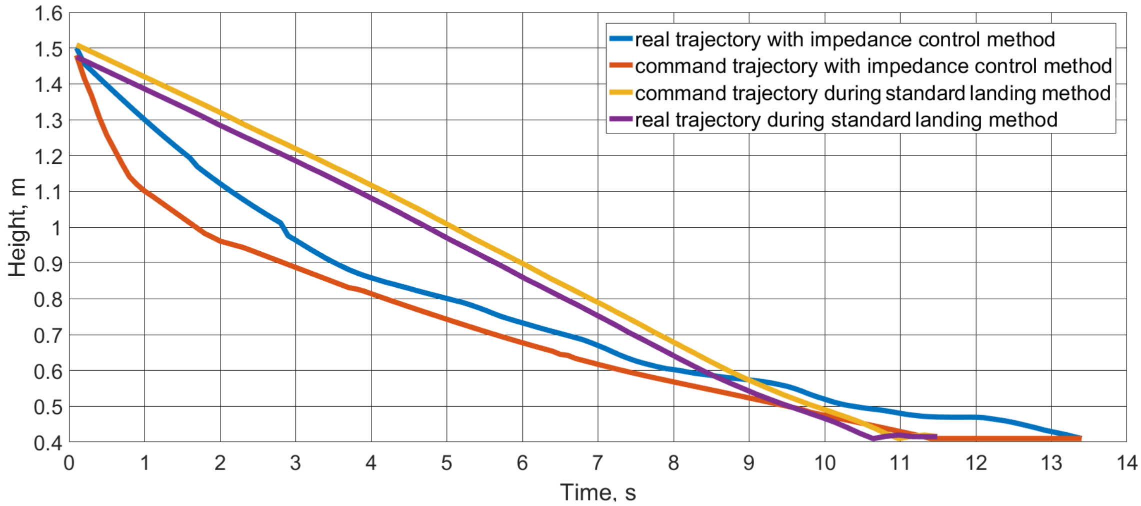


Figure 5-11: Trajectories along Z axis during the UAV landing.

already at 22th second of flight. Despite this fact, the final landing is not carried out for about 7 seconds. Because of this, the UAV begins to drift from side to side due to aerodynamic effects. In addition, such a drift is extremely undesirable for the operation of the UAV localization system, since the field of view of the camera at such low altitudes is extremely small and at any moment the position of the UAV may be lost. The main task of the presented robotic heterogeneous system is to carry out inventory autonomously at warehouses; it is essential for us to land not only softly but also accurately. The force sensors on each leg of the UAV were used for landing detection. Therefore, we tested the following landing algorithm: at the height of 1.5 m the impedance landing model turns on and works until one of the force sensors detects the first contact with the UGV, after that the rotors turn off and the UAV lands, we called this method “Landing detection”. Proposed approach allows us to reduce the UAV speed in comparison with the standard landing method and also reduce the duration of landing in comparison with the first impedance approach, that we called “No landing detection”. Fig. 5-11 represents real and command trajectories during standard landing method of the Pixhawk flight controller and during proposed impedance based control method. Using this approach we reduced the landing time from 20,4 seconds to 13,3 seconds in comparison with 11,4 seconds in the standard method.

The force sensors attached to each leg were also used to evaluate the softness of landing by measuring the mean force during the first contact as the most reliable parameter of softness. We use force sensitive resistors (FSR)-402. The data is collected using Arduino Uno 30 times per second. For each method, we produce up to 15 attempts of landing to compare them according to 8 parameters: maximal and mean velocities V_{max}, $\overline{V}$, maximal and mean accelerations a_{max}, $\overline{a}$, maximal and mean forces during the first contact F_{max}, $\overline{F}$, maximal and mean duration of landing t_{max}, $\overline{t}$, respectively. The results of the comparison are presented in Table 5.1.

Fig. 5-12 shows the box-plot for forces at the moment of the first contact of the UAV with the UGV for all methods.

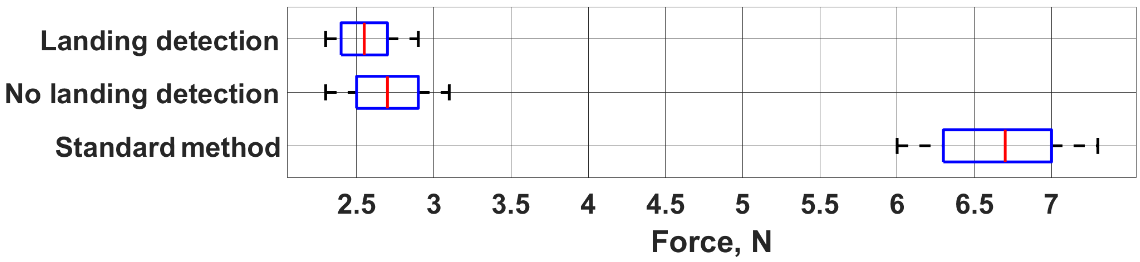


Figure 5-12: Box-plot of forces at the first moment upon landing of the UAV

To evaluate the result and find the most optimal method we introduce the coefficient of optimal landing (the lower value of the coefficient means more optimal

Table 5.1: Comparison of landing methods

	Standard method	Impedance-based methods No landing detection	 Landing detection
$\overline{a}, m/s^2$	4,93	4,49	**4,45**
$\overline{V}, m/s$	0,14	**0,06**	0,11
$\overline{t}, s$	**11,1**	19,8	**13,1**
$\overline{F}, N$	6,7	**2,55**	**2,7**
$a_{max}, m/s^2$	5,41	5,33	**5,29**
$V_{max}, m/s$	**0,23**	0,24	0,24
t_{max}, s	**11,8**	21,1	**14,2**
F_{max}, N	7,3	**3,1**	**2,9**

landing):

$$C_{landing} \sim \overline{F}\overline{t} \tag{5.38}$$

This coefficient could be modified by using a weight component for force and landing duration. In our case, we estimate the weight component equals to 1. In accordance with this fact, the most optimal was the impedance-based method with landing detection.

5.6.5 Impedance landing outcomes

We have developed the operating and mathematical principles of the impedance control for the landing system of the UAV and presented the results of the real-world experiments. We evaluated the softness of landing using the FSR attached to each leg using measurements of the force during the first contact. Our experiments showed that the developed method of adaptive landing allows to reduce the force during the first contact more than two times. Based on this evidence we conclude that the proposed impedance control for a UAV landing will considerably decrease the risk of damaging a drone and on-board equipment. This approach has been developed to support continuous operation of the heterogeneous robotic system during automated warehouse stocktaking. Further work will be devoted to conducting the experiments of the landing of the UAV on the moving UGV with adaptive impedance control.

Chapter 6

Active perception in warehouse

This chapter presents a UAV-based system for real-time barcode detection and scanning using CNN. The proposed approach improves the localization of UAV using scanned barcodes as landmarks in a real warehouse with low-light conditions. Instead of using the standard OSBG trajectory, we implement a novel approach for flight-path optimization based on barcode locations. This approach reduces the time of warehouse stocktaking and decreases the number of mistakes in barcode scanning.

6.1 Barcode recognition system for UAV

6.1.1 Problem statement of robust barcode reading

Scanning information from barcodes using a camera is a complicated and ineffective method. Existing camera-based methods for barcode scanning Maurer et al. [2018] are not suitable for usage in real warehouse conditions because of lack of lighting, image artifacts of rolling shutter cameras, and small size of barcodes. In order to get reliable information from the barcode during the flight, the UAV should have a global shutter camera and an on-board computer with enough computational performance for processing images. The real size of a pallet on a rack is usually about 1 meter wide and 0.9 meter high (Fig. 6-1). According to IC Barcode Tool Recommendations by Imagine Source company ImagingSource LLC [2020], the on-board global shutter camera should have 55.8 Mpx image resolution and 53° FoV to scan barcodes from a distance of 1 meter. For stable scanning, we should have at least 2 pixels for 1 bar of a barcode with a standard width of 10 mil ImagingSource LLC [2020]. This requirement is impossible due to the unavailability of such a camera in mass production. To solve this problem, we developed an approach based on a cheap rolling shutter camera for barcode detection and a laser scanner for reading. A detailed description is presented in section 6.2.

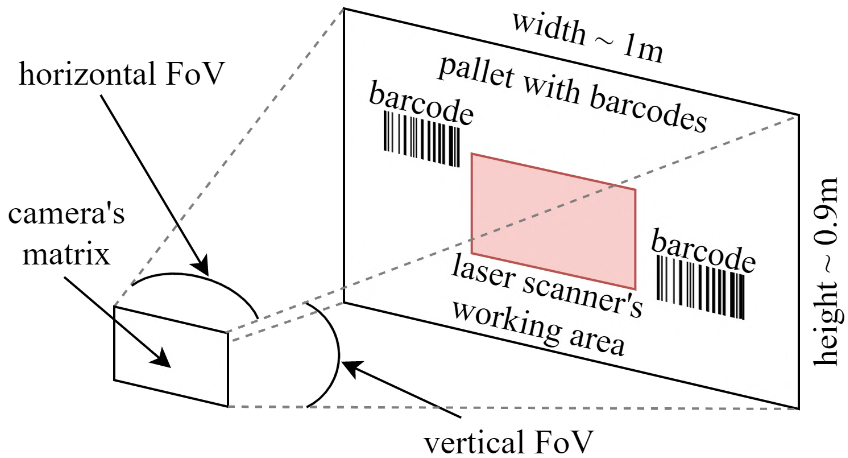


Figure 6-1: Schematic representation of a real scene from the UAV point of view, including a camera frame and working area of the laser scanner.

From equation 6.1 we can calculate width of the frame. In our case, horizontal FoV is $\phi_{width} = 62.2°$, thus, from a distance $L = 1\ m$, we could receive a $width = 1.2\ m$. Similarly, from equation 6.2 with $\phi_{height} = 48.8°$, the height of the captured area, that is equal to $height = 0.9\ m$, could be calculated.

$$width = 2 \times L \times \tan(\frac{\phi_{width}}{2}). \tag{6.1}$$

$$height = 2 \times L \times \tan(\frac{\phi_{height}}{2}). \tag{6.2}$$

The average size of the barcode is 0.09 meters. With an optimal resolution of 1280×720 the final width of a barcode in a picture is 90 pixels. With decreasing the image size, a barcode becomes invisible against the background. Noises that occur in low light conditions also affect the visibility of barcodes in the final frame.

6.1.2 Literature review of existing methods

Over the past few years, many systems related to drone-assisted inventory management in warehouses were presented. The most relevant of them introduced frameworks for a multi-UAV solution or a UAV + ground robot solution. However, they describe either half-autonomous systems with piloted UAVs or autonomous systems with high positioning error (up to one meter) or unsuitable system configurations, which are not applicable for stable flight in narrow passages between racks in warehouses Barlow et al. [2019], Choi et al. [2019], Harik et al. [2017]. Fernández-Caramés et al. [2019] presented a design of the UAV and blockchain-based system for Industry 4.0 inventory. Their work focuses on an industrial inspection with RFID tags, but the UAV flight is not autonomous and requires a pilot, unlike our system.

Beul et al. [2018] presented a UAV capable of fast autonomous indoor flight and scanning RFID tags in a warehouse. Kwon et al. [2019] proposed an autonomous UAV with a low-cost sensing system to be used effectively for narrow and dark warehouse environments, but the approach for barcode scanning was not mentioned.

Cho et al. [2018] introduced a 2D barcode detection system based on neural networks. The work states the precision and recall are about 95% during post-processing. The system's configuration was not mentioned in the article, as well as the results of flight experiments. Besides, the system requires more than 12,000 images for training and testing, while we achieved similar results with only 537 images in training data set, and our system works in real-time.

Hansen et al. presented an approach for real-time barcode detection and classification using deep learning, but their system works with high-quality images which are difficult to obtain during the flight, and this method requires high computing power for high performance which makes it impossible to use on the drone for inventory purposes.

Xu et al. [2018] introduced algorithms for the automatic extraction of barcodes from video data. For a known barcode region, a Harris corner detector and Hough transform-based algorithm were applied to estimate the bars' orientation angle quickly. No flight experiments were presented in the article, and all results were obtained during post-processing.

Initially, the problem of barcode localization in the image was solved by complicated transformations of the image matrices, distance search, and pattern matching Ohbuchi et al. [2004]. With the release of the OpenCV library Bradski and Kaehler [2008], the solution to this problem was simplified: the researchers began to add image offset, blur filters, and perform the other transformations to solve the problem of barcode detection Xu and McCloskey [2011]. Creusot and Munawar [2015] used the optimal detected parameters in the Maximally stable extremal regions (MSER) Donoser and Bischof [2006] algorithm to highlight the dark areas of the barcode in the image. Combining the obtained areas, he received a reliable barcode mask. This method requires a minimum amount of noise in the image and the big size of the barcodes, which is impossible in real warehouse conditions. Zhou and Guo [2016] introduced an angle-robust method for multiple 1D barcode detection based on a line extracting algorithm. The algorithm is resistant to image rotation. However, it shows low accuracy in photos with a small barcode size.

Katona et al. [2019] presented a robust solution based on OpenCV methods composition that allows detecting barcodes with high precision. The main feature of the method is the usage of a template match algorithm Jurie and Dhome [2001]. After implementing the presented approach, we discovered that it is not suitable for our solution. In the images from a distance of 1 meter, even with big barcodes, it gave poor results. Also, their approach requires a large number of specific patterns for every new environment.

Works described above Bradski and Kaehler [2008], Creusot and Munawar [2015], Donoser and Bischof [2006], Katona et al. [2019], Ohbuchi et al. [2004], Xu and McCloskey [2011], Zhou and Guo [2016] did not use machine learning models for barcode detection. Redmon and Farhadi [2018] presented one of the most popular CNN for object detection. Despite the high accuracy of this method it requires the high consumption of computing resources. In addition CNNs for semantic segmentation are more sensitive to noise, which may be the barcode, and also gives more accurate coordinates, which is important for position adjustment.

Also, let us consider existing path optimization methods for UAVs, since our robot has to build an optimal trajectory to cover all the barcodes. Cheng et al.

[2018] presented the UAV trajectory optimization method for data offloading in the edge area of multiple adjacent cells. In the proposed scheme, three adjacent cells were considered, and the trajectory was optimized to maximize the sum rate of edge users by avoiding the interference between base stations and UAV. Presented results showed increased effectiveness of their scheme in comparison to the other methods. However, their results are obtained only in simulation and not applicable to indoor flight in narrow spaces.

Oleynikova et al. [2016] proposed a continuous time trajectory optimization method for real-time collision avoidance of UAVs. Their methods recomputes trajectories as the robot gains information about its environment. Although this approach is able to work indoor in real-time it uses visual-inertial stereo sensor for obstacle recognition. Also, all computing is done entirely on-board on an 2.1 GHz Intel i7 CPU which has high power consumption.

Andrew Klesh et al. [2008] presented a new information-based formulation for optimal exploration of a given environment by UAVs. The presented approach solves Traveling Salesman Problem for exploration of three objects of interest only in a simulation.

Chen et al. [2016] introduced an additional control force into the artificial potential field planning method for the UAV path planning problem. The proposed approach decreases flight-time in comparison with the previous method. However, introduced path following process based on the six degrees of freedom simulation model without real-environment tests.

6.1.3 Contributions of the chapter

To exclude humans from stocktaking completely, we have developed an autonomous heterogeneous robotic system of two robots: the UGV and the UAV. This combination allows keeping an always-up-to-date inventory record of the contents within the warehouse (Fig. 8-1).

This system is capable of autonomous navigation and precise localization in an indoor environment. We solve the problem of robust system operation by dividing localization into two parts for each subsystem, i.e., the UAV and the UGV. The

UGV performs global localization and navigation in a warehouse, while the UAV always flies above the platform, detects and scans barcodes on the racks and pallets.

For drone localization, we have developed a method of pose estimation relative to the UGV. This approach enables us to calculate coordinates of the UAV relative to the UGV and then to calculate the global coordinates of the UAV. Also, our method does not imply the utilization of any additional infrastructure for navigation, as opposed to mo-cap systems, since all necessary equipment is installed on the UAV and the UGV. This setup is described in detail in our previous work I. Kalinov et al. [2019].

Our main contributions for this chapter are:

- UAV-based, robust, and lightweight system for real-time barcode detection and scanning;
- Active perception by the UAV based on detected barcodes, which improves its localization in comparison with the previous method I. Kalinov et al. [2019]. By active perception we imply real-time position adjustment of the UAV using standard objects of warehouse environment (1D barcodes);
- Proposed approach with CNN for barcode detection reduces fly-by time optimizing the UAV's trajectory in comparison with the standard OSBG fly-by method;
- The robot is able to get global coordinates of each detected and scanned barcode for warehouse planogram and further analytics.

6.2 Barcode-based UAV trajectory optimization

6.2.1 Barcode detection and scanning system

In stocktaking, the most critical parameters are the duration of the inventory process, the number of tags correctly identified, and the coordinates of scanned tags in the warehouse. Barcodes are the most common type of tags for labeling in warehouses Thanapal et al. [2017]. In subsection 6.1.1, we stated that it is impossible to use a global shutter camera in our conditions. Even if we had a global shutter monochrome camera with resolution 55.8 Mpx, the video received with such a camera with 8-10 Frames per second (FPS) could not be transmitted over a local wireless network for processing due to minimal size of frame equal to 6.65 MB. It would have to be processed directly on-board the UAV. Such an approach directly affects its flight-time by increasing the weight of on-board computer and drone's energy consumption. All these factors increase the duration of stocktaking. Besides, for increasing the percentage of correctly scanned barcodes, it is necessary to fly several times in front of each pallet to increase the overlapping area of the image frames.

Therefore, we propose a novel approach. The core idea is to install a small Pi NoIR Camera V2 for barcodes detection and determine their position relative to UAV using CNN, then read them with the Zebra DS3608ER barcode laser scanner. Such a combination is necessary for precise barcode detection since the laser scanner has 12° FoV, and the scanning band has a width of around 0,21 m from a distance of 1 m, which is not enough to cover the whole pallet. Combining the camera with the scanner, the UAV can detect barcodes and read them.

Taking into account the previous works Creusot and Munawar [2015], Donoser and Bischof [2006], Jurie and Dhome [2001], Katona et al. [2019], Xu and McCloskey [2011], Zhou and Guo [2016] and the small size of barcodes in the frame, it makes sense to use a CNN based algorithm to detect all barcodes in the image and solve the segmentation problem for barcode areas detection. Since we have only one class for recognition, we have chosen the most efficient binary segmentation method based on U-net Ronneberger et al. [2015] architecture. The architecture of the implemented CNN, similar to U-net, is presented in Fig. 6-2.

For the training we defined EarlyStopper service to control training process of our network. As a metric, we chose the Jaccard index (or Intersection over Union (IoU)). Formulaic view of this metric is presented in equation 6.3. And training IoU graph from our training process is presented in Fig. 6-3.

$$IoU(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{6.3}$$

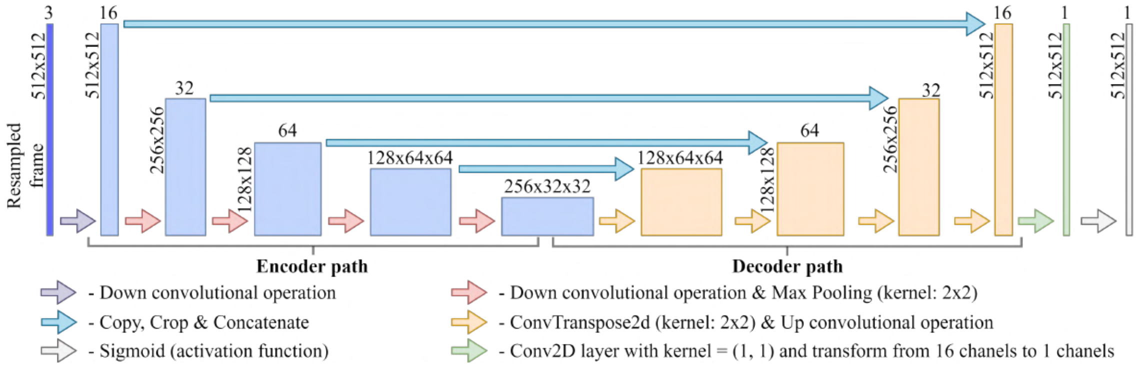


Figure 6-2: U-net based architecture of our system

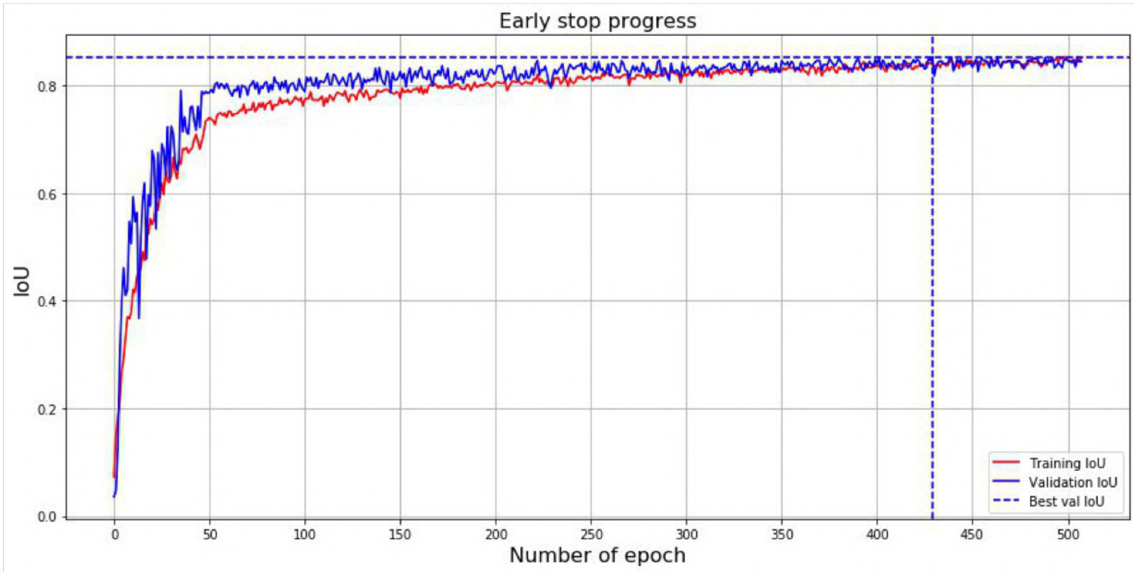


Figure 6-3: Graph of training with metric

The main module in our network is "Down convolutional operation" ((Fig. 6-4)) which includes a sequence of the following layers: convolution, activation (ReLU), and batch normalization. "Up convolutional operation" uses the same layers but instead of increasing the number of channels "Up convolutional operation" decreases it. For feature restoration, we also use "Copy, Crop, and Concatenate" operations. The final layer of the network is "Sigmoid" which allows us to detect a barcode class probability for each pixel in the image.

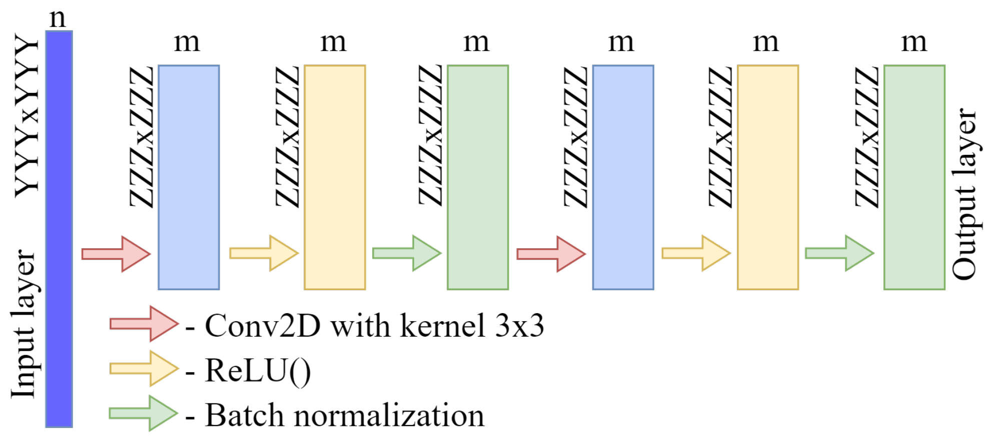
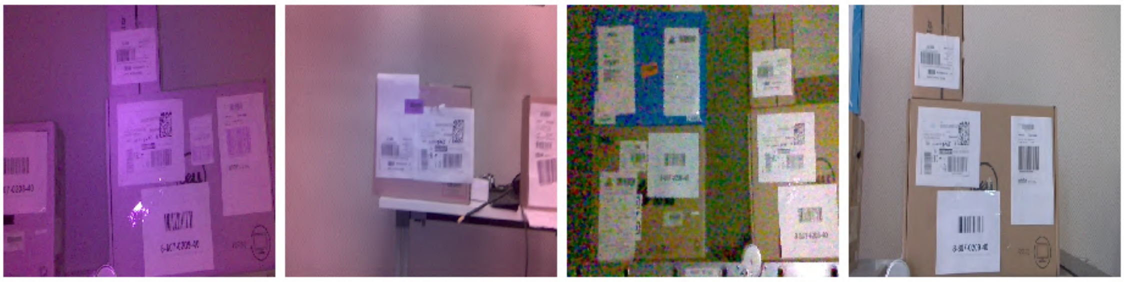
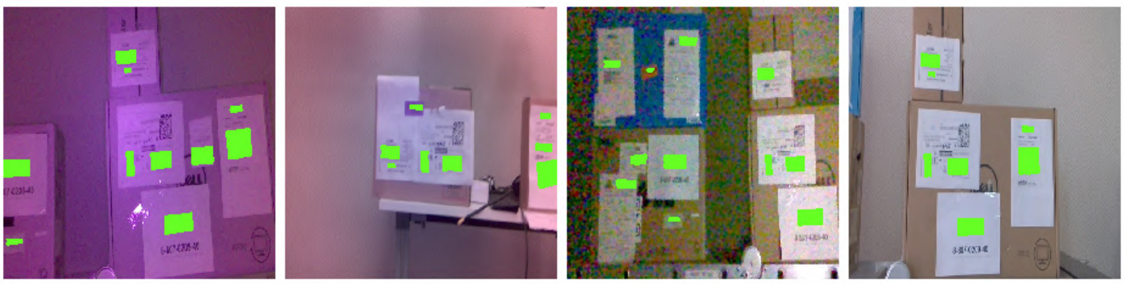


Figure 6-4: Down convolutional operations



(a) Source images.



(b) Detected barcodes.

Figure 6-5: Segmentation results on validation data.

We have trained our CNN with a relatively small dataset consisting of 537 images. The validation dataset consists of 67 images; the test dataset has 66 images. Mean barcode instance in each image is 7. These datasets include image frames from Raspberry Pi Camera v1.0 and v2.0 (with rate 50/50). The frames were taken with different lighting conditions: street, room, and IR (in darkness). The collected and marked dataset that is used in our approach is open and available via link[1].

For the training, we used original 3-channel images (RGB). During the training, we randomly applied one of the following augmentation tricks (flip, rotation, contrast, and brightness change; cropping, gamma changing, and channel shuffling) to each image of the trained dataset in every epoch. The possibilities of each trick are equal, and the total number of epochs is 500. The source image with segmentation results of our CNN is presented in Fig. 6-5. Then we processed the CNN output with standard OpenCV morphological transformations to erase noise and applied contours detection to get the coordinates of areas with barcodes.

6.2.2 Experimental comparison of computer vision methods

We mentioned several methods for detecting barcodes in the introduction section. Before implementing the Unet-like CNN in our system, we conducted an experiment and compared all these methods in Table 6.1. For comparison, we chose two classes of metrics. The first class is the standard metrics for the object detection - IoU, Precision, and Recall. It is worth noting that this class of metrics involves pixel-by-pixel comparison and gives not entirely accurate data on the number of barcodes. Therefore, the second class of metrics, we decided to show quantitatively: correctly recognized barcodes (True positive - TP) with intersection more or equal to 50% of source barcode, mistakenly detected (False Positive - FP) with intersection less than 50%, and undetected (False Negative - FN), which we calculated as the difference between the total number of barcodes and TP. It is important to note that our system checks any detected region for the presence of a barcode with the laser scanner during the flight. FP errors are not so fundamental and will only increase the flyby time, in contrast to FN errors, which lead to skipping the inventory object. Also, as another comparison criterion, we added FPS to work on Nvidia Jetson Nano (2019). The total number of barcodes in the test data set is 446.

We received all parameters for our approach (Table 6.1) with a threshold of 0.909 (Fig. 6-6). This threshold value is optimal since its reduction does not change the number of FN cases but significantly impairs the other parameters.

[1]https://box.skoltech.ru/index.php/s/jnoqSwZpes4CnuO

Table 6.1: Comparison of computer vision methods

	Objects			Pixels metrics, %			FPS
	TP	**FP**	**FN**	**IoU**	**Precision**	**Recall**	
OpenCV based Xu et al. [2018]	30	439	416	9,1	41,4	10,5	29
Multiple barcodes Zhou and Guo [2016]	61	217	385	20,3	52,63	26,73	26
Template matching Katona et al. [2019]	87	125	359	57,2	63,2	43,51	20
Yolo v.3 Redmon and Farhadi [2018]	438	45	8	81,7	89,13	88,7	3
Our approach	**445**	**17**	**1**	**90,7**	**91,56**	**96,96**	13

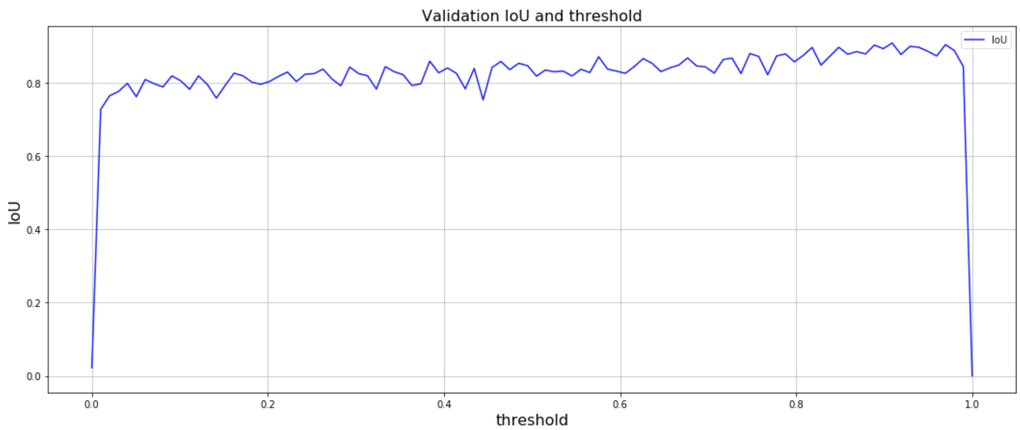


Figure 6-6: Graph of training with IuO metric

The comparison shows that standard methods have insufficient results for barcodes recognition. Yolo v.3 CNN has comparable results to our approach (Fig. 6-7; however, it has much lower FPS.

(a) Good light condition. (b) Low light condition with IR-camera.

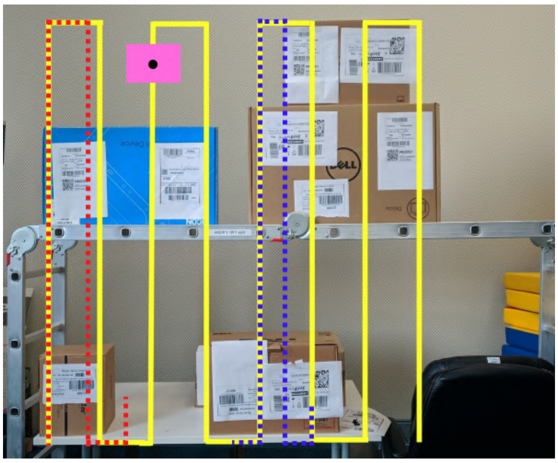
Figure 6-7: Example of object detection using Yolo v.3 in test data set.

6.2.3 Active perception method

For drone localization, we use IR markers I. Kalinov et al. [2019]. However, this IR-based localization was not enough for flying on altitudes of more than 8 meters since it yields a 10 - 15 cm error in altitude. For localization improvement, we decided to use the surrounding objects of a warehouse, for example, barcodes.

This section describes in detail how UAV's active perception works. We simultaneously plan the drone exploration path, detect barcodes, make a barcode map, and estimate the UAV position on this map using verified barcodes as an additional source of information. Initially, we generate a list of waypoints with an interval of 0.5 meters, taking into account the maximal and minimal height of the rack. The drone starts following the generated fly-path along these waypoints. When the CNN detects a new region in the UAV camera image as a barcode (Fig. 6-5b), our algorithm adds this region to the factor graph, marks it as a new waypoint and optimizes the path by solving traveling salesman problem. On the next step, the drone flies to the barcode and verifies it with the laser scanner:

- If the barcode gets verified - the algorithm adds it to the barcode database. Then, the UAV updates its position relative to the barcode map. At the



(a) Standard OSBG trajectory.

(b) Optimized trajectory.

Figure 6-8: Trajectories of the UAV. For OSBG trajectories, three examples are presented: yellow line - 0% overlapping; red dotted line - 25%; blue dotted line - 50%. The pink rectangle indicates the working area of the laser scanner, the black dot in the middle is the position of the UAV.

last step, the robotic system performs simultaneous optimization of the previous UAV trajectory and the barcode positions using methods of graph-based SLAM Dellaert [2012].

- If the laser scanner cannot verify the barcode - our algorithm deletes this waypoint from the graph, rebuilds the path, and gives the drone the next waypoint.

As the final result, the drone continues to follow the planned path, as shown in Fig. 6-8b.

It is important to note that all detected regions from CNN go to the factor graph. The drone updates and specifies its localization relative to each detected barcode region in every UAV camera image even before the laser scanner's verification. The pseudo-code of our algorithm is presented in three blocks below (Algorithms 2-4).

Algorithm 2 Scanning process

```
WayPoints = {x_1, x_2, x_3, ..., x_n}
BarcodeDataBase = ∅
FactorGraph = ∅
while WayPoints do
    NextPoint = WayPoints.pop()
    FlightPath = OptimizePath(NextPoint, FactorGraph)
    while FlightPath do
        GoToPoint(FlightPath.pop())
        Barcode = GetBarcodeInfo(FactorGraph)
        if Barcode.IsDetected = True then
            BarcodeDataBase.append(Barcode)
        else
            FactorGraph.remove(Barcode)
        end if
        FlightPath = OptimizePath(NextPoint, FactorGraph)
    end while
end while
```

We called the described approach of improving the UAV localization "active perception". During this process, we get the verified location of the pallet in a warehouse with an accuracy of $10 - 15$ cm, which is undoubtedly essential for warehouse stocktaking. The result of this work is an accurate map of the detected and scanned barcodes and their position in a warehouse (Fig. 7-8).

Algorithm 3 OptimizePath($FinalPoint$, $FactorGraph$)

Input: $FinalPoint$, $FactorGraph$
Output: $Path$

```
Barcodes = GetBarcodeFromCNN()
FactorGraph.addBarcodesMeasurements(Barcodes)
FactorGraph.addIMUMeasurement(IMU)
FactorGraph.optimize()
UAVPosition = FactorGraph.GetUAVPosition()
BarcodePositions = FactorGraph.GetPosition(Barcodes)
Path = SolveTravellingSalesmanProblem(FinalPoint, UAVPosition,
    BarcodePositions)
return Path
```

Algorithm 4 GetBarcodeInfo($UAVPosition$)

Input: $UAVPosition$
Output: $Barcode$

```
Barcode = BarcodeStucture()
Barcode.ID = LaserScannerData()
if Barcode.ID is None then
    Barcode.IsDetected = False
else
    Barcode.IsDetected = True
end if
Barcode.Position = FactorGraph.getPosition(Barcode)
return Barcode
```

"Everything is possible. The impossible just takes longer."

Dan Brown

Chapter 7

System evaluation

7.1 Experiments with IR-based localization of the UAV

To evaluate our system, we have conducted several experiments. The first experiment was devoted to testing the localization system error and verifying the correction procedure by data fusing from ultrasonic sensors and camera, described in section 5.4. In this setup, the UAV was controlled manually while our system and the "Vicon" mo-cap system track the UAV position (Fig. 7-4). Our system collected two types of logs: raw logs of visual estimation from two patterns which are denoted "raw" in Fig. 7-2 and log from visual recognition system with data fusion from ultrasonic sensors denoted "visual". According to obtained results, the correction procedure based on data fusion allowed reducing the Root mean square error (RMSE) twice from the initial 2.5 cm to 1.25 cm (Fig. 7-2).

The aim of the second experiment was to evaluate the error with respect to the distance between the UGV camera and UAV through position estimation on different heights in automatic mode. The UAV used the UGV for localization, and "Vicon" data were utilized as a ground truth. In this mode, the UAV started flying from an altitude of 1 meter and then goes up to 3 meters with 0.5 meter step. On each step, the UAV hovered for 1 minute. In the second experiment, we collected the dataset which consisted of 8523 images. Fig. 7-3 shows the box-plots for both position and orientation. All calculations were carried out on an Intel NUC computer with Core i7-7567U (3.50 GHz) processor. It is installed on the UGV, but could also be installed on the UAV. During experiments, the processor load was not more than 24%. In such conditions, our system is able to process the visual data with up to 60 FPS, but during experiments, it was limited to 30 FPS.

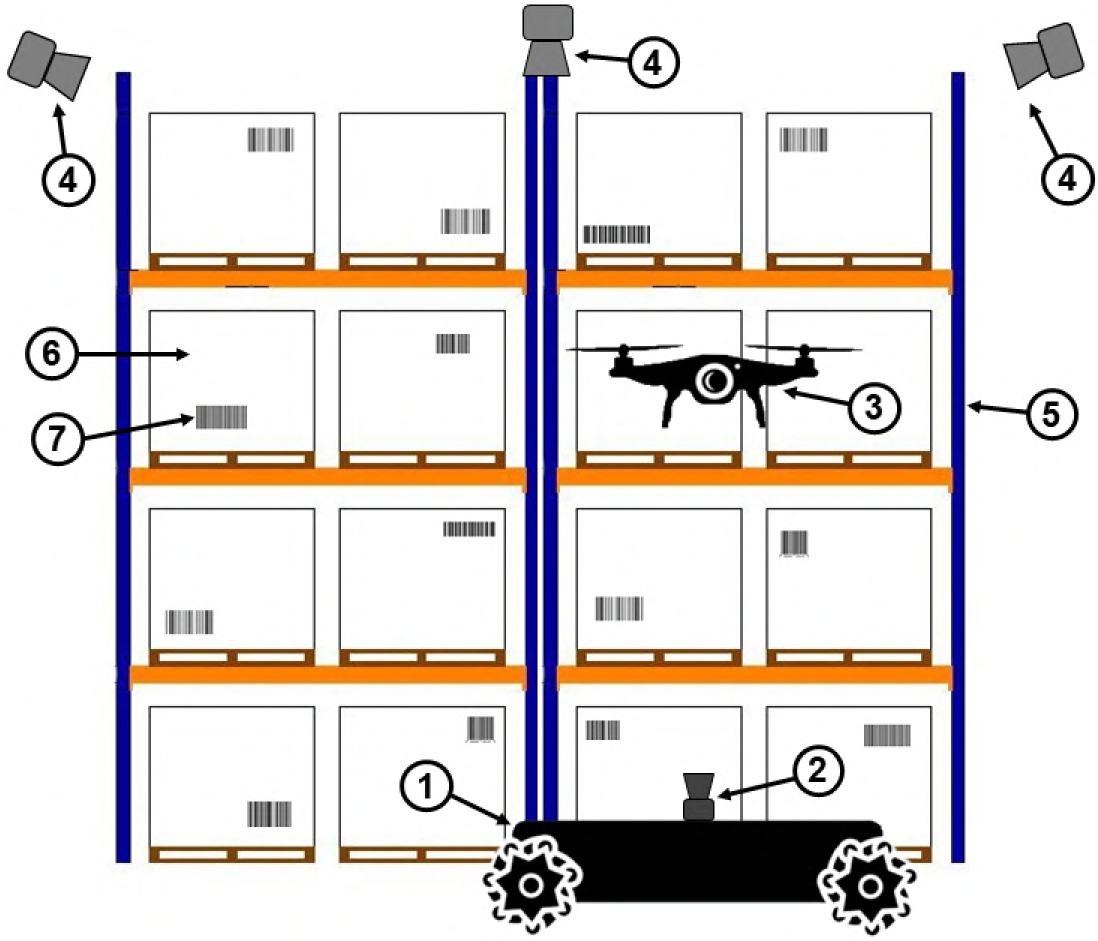


Figure 7-1: Experimental stand description for testing the localization accuracy in laboratory conditions. The maximum possible UAV flight height is 3 meters. Under the conditions of such an experimental stand, the UAV uses data from a heterogeneous robotic system for self-localization and navigation, and the Vicon mo-cap system located on the ceiling is used to measure ground truth and then calculate the accuracy. 1 - UGV, 2 - camera for UAV tracking, 3 - UAV with barcode detection and scanning system, 4 - mo-cap cameras, 5 - rack with boxes, 6 - boxes with barcodes, 7 - barcodes. The rack with boxes is used for experiment described in section 7.3 and is not used in section 7.1.

7.1.1 Performance in the laboratory conditions

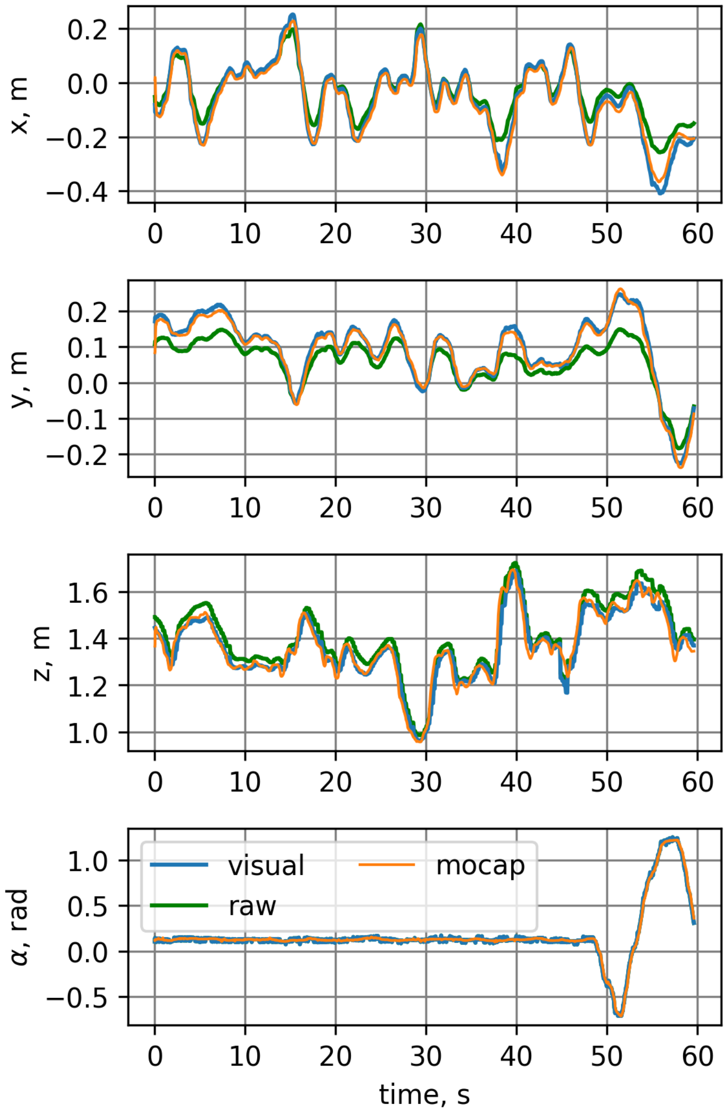


Figure 7-2: Test of visual localization in compare with the "Vicon" mo-cap. RMSE 1.25 cm.

The developed localization system has shown good accuracy under various experimental conditions, including landing of UAV on a moving mobile ground robot. Our testing room equipped with a motion capture system does not allow testing at altitudes above 3 meters. The main purpose of the developed system is the UAV localization relatively to the UGV using IR marker pattern recognition. The aim of the developed heterogeneous robot is an automation of warehouse inventory management, therefore, it is very important to have a robust and accurate localization system in terms of narrow spaces with a ceiling height of up to 15 meters with a low level of illumination. According to our calculations, systematic error based on the camera resolution ~ 2000 pixels and FoV of approximately 138° should not exceed 10 cm at 15 meters altitude, this calculation was confirmed by our experiments in the warehouse is section 7.2. Experimental results and calculations of current section show that the presented system is fully suitable for accomplishment of such tasks. The processing time of a single frame from the camera on the on-board Intel Nuc did not exceed 5 ms, which allowed us to talk about a high update rate, sufficient for reliable localization of UAVs. In comparison with the state-of-the-art methods, that could operate in warehouse Faessler et al. [2014], we have better accuracy on the altitude of 3 meter (1.25 cm vs. 10 cm).

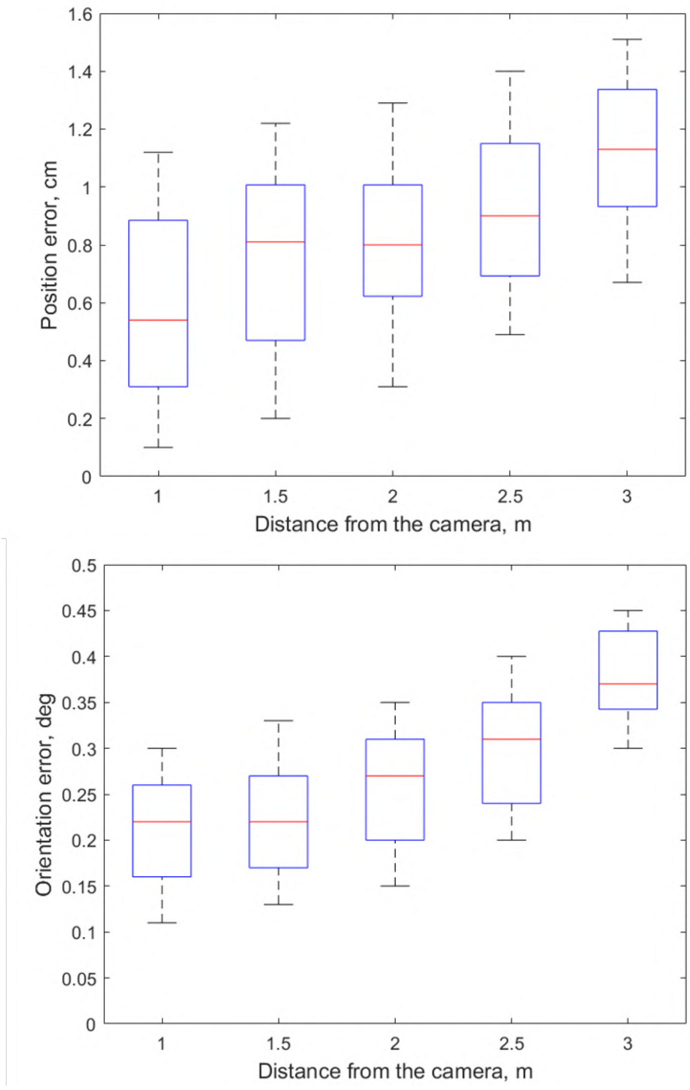


Figure 7-3: Box-plot of the pose estimation errors with respect to the distance between the UAV and the camera on the UGV

7.2 Outliers rejection by REKF in warehouse experiment

The first experiment was devoted to the testing of localization system error in warehouse conditions. In this setup, the UAV performed autonomous flight by our localization system with REKF in a warehouse. Since we couldn't use the mo-cap system as the ground truth data in the warehouse, we installed several Marvelmind beacons on the racks in warehouse and tracked the UAV flight with them.

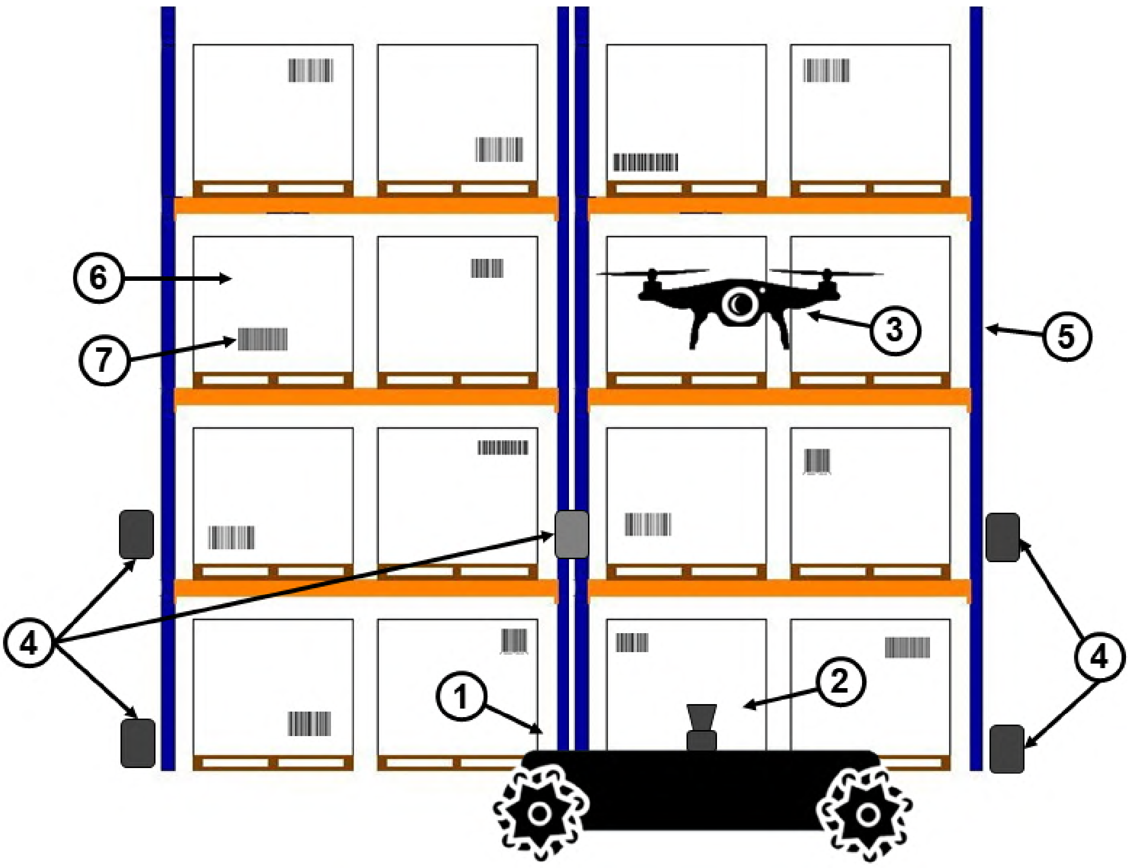


Figure 7-4: Experimental stand description for testing the localization accuracy in warehouse environment. The maximum possible UAV flight height is 12 meters. Under the conditions of such an experimental stand, the UAV uses data from a heterogeneous robotic system for self-localization and navigation, and the Marvelmind beacons located at the bottom of the racks are used to measure ground truth and then calculate the accuracy. 1 - UGV, 2 - camera for UAV tracking, 3 - UAV with barcode detection and scanning system, 4 - Marvelmind beacons, 5 - rack with pallets, 6 - pallets, 7 - barcodes.

Thus, we collected three types of data, Marvelmind data as a ground truth which is denoted "Ground truth", data from preliminary localization system without REKF which is denoted "Preliminary localization", and data from the UAV flight performed by our localization system with REKF denoted "With REKF" in Fig.7-5 and Fig.7-6. According to obtained results, the developed system allowed to get rid of all outliers on the 10 meters altitudes in comparison with preliminary localization (Fig. 7-5).

The aim of the second experiment was to evaluate the error with respect to the distance between the UGV camera and the UAV through position estimation on different heights in automatic mode. The UAV used REKF developed localization system for autonomous flight, and Marvelmind data were utilized as ground truth. In this mode, the UAV started flying from an altitude of 1 meter and then went up to 10 meters with 1 meter step. On each step, the UAV hovered for 1 minute. In the second experiment, we collected the dataset which consisted of 18973 images from the UGV camera with recognized pattern. Fig. 7-7 shows the box-plots for both position and orientation. All calculations were carried out on Intel NUC computer with Core i7-7567U (3.50 GHz) processor. It is installed on the UGV, but could also be installed on the UAV. During experiments, the processor load was not more than 24%. In such conditions, our system is able to process the visual data with up to 60 FPS, but during experiments, it was limited to 30 FPS.

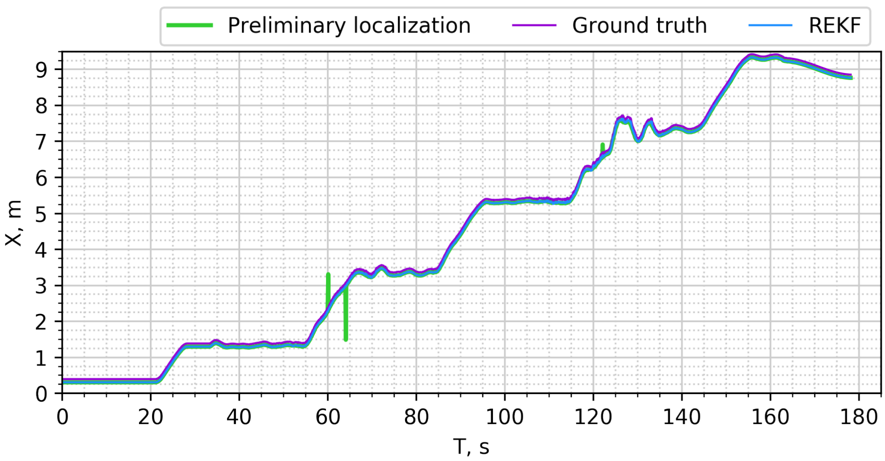
7.3 Performance of the active perception

7.3.1 Flight-path correction and trajectory optimization

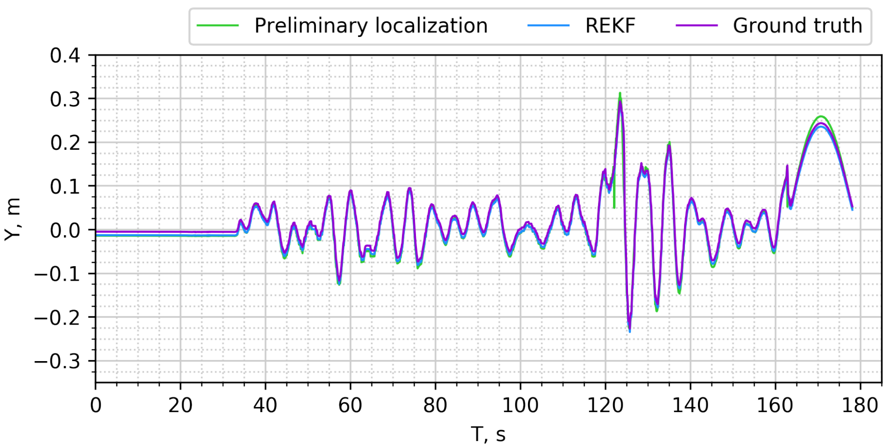
Since the robotic system (UGV + UAV) is designed to automate the stocktaking procedure in warehouses, we need to detect and scan as many barcodes as possible. The goal of this experiment is to check the performance of the algorithm responsible for the UAV flight-path correction. We compare the results of barcode detection and scanning using two different strategies for the UAV:

1. Flight with standard OSBG trajectory (Fig. 6-8a);

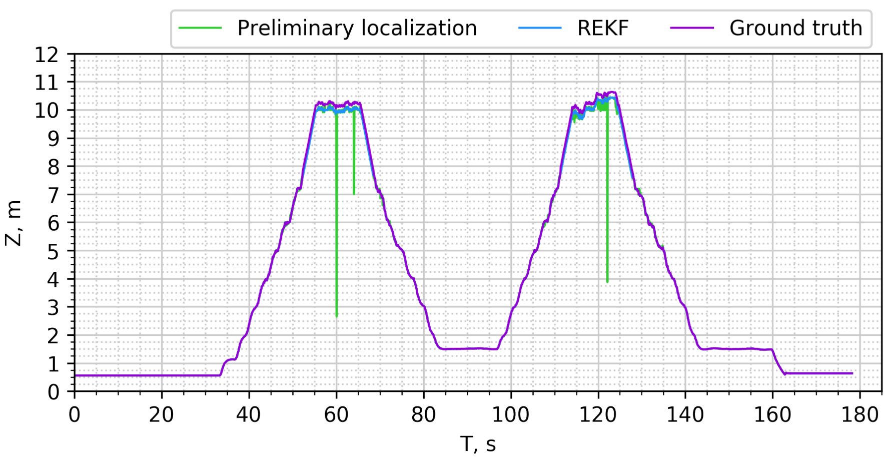
2. Flight with adjusted trajectory using the active perception module (Fig. 6-8b).



(a) X-coordinate.



(b) Y-coordinate.



(c) Z-coordinate.

Figure 7-5: The x, y, z -coordinates during the real experiment in the warehouse.

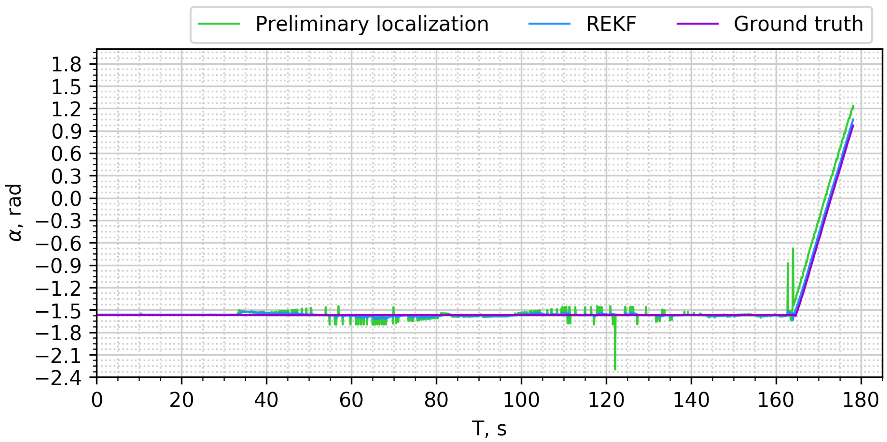
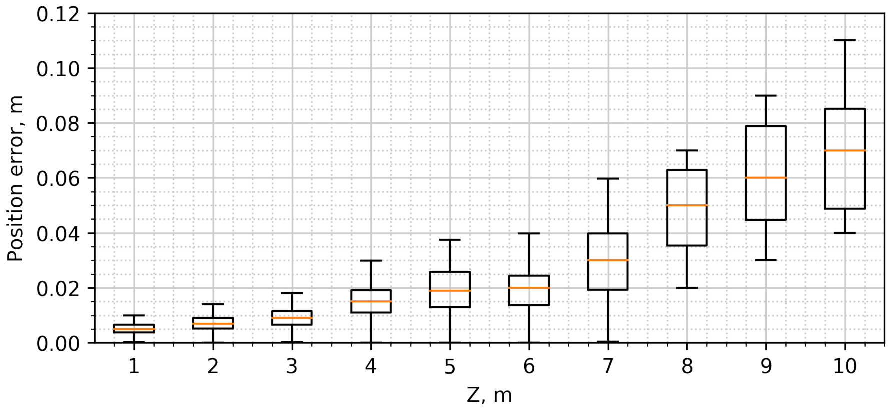
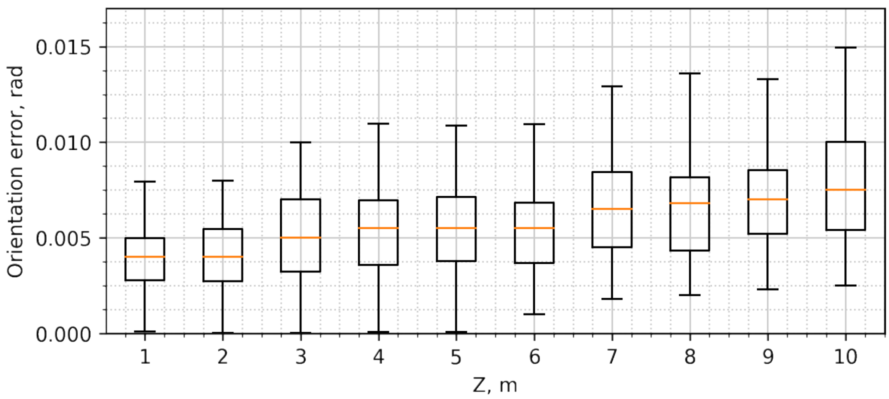


Figure 7-6: Angle of orientation during the real experiment in the warehouse.



(a) Position error.



(b) Orientation error.

Figure 7-7: Box-plot of the pose estimation errors with respect to the height of the UAV under the UGV.

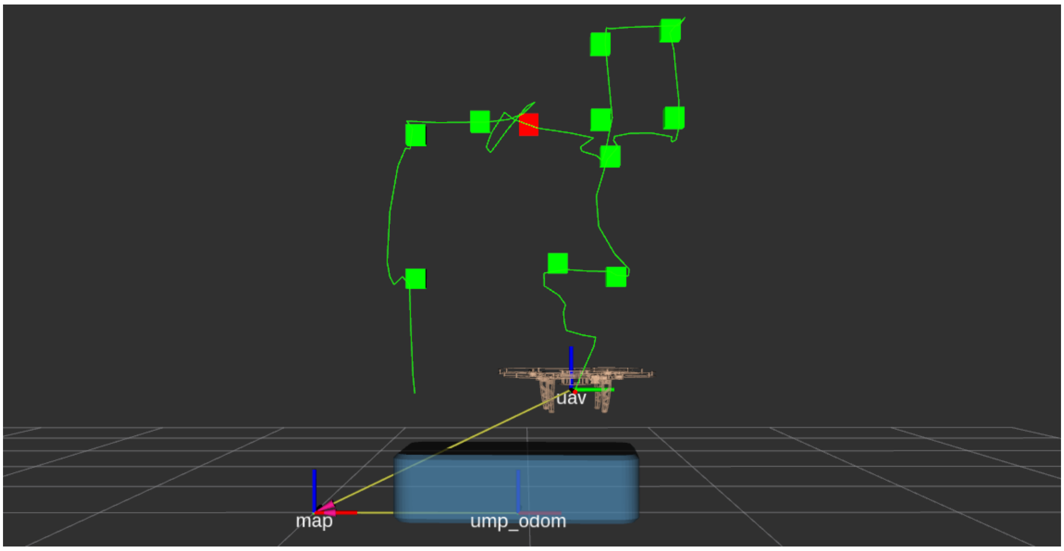


Figure 7-8: The accurate map of barcodes. The green boxes represent verified barcodes. The red box represents false-positive barcode detected by the CNN.

For both setups, we used the UGV and the UAV for the barcodes detection in laboratory conditions. Barcodes have adhered to each box in random order as they do in the real warehouse. In the first setup, CNN is not enabled, and it goes as following:

- The robot starts stocktaking at the beginning of an alley;
- the UAV flies up to the highest desired point (2.3 meters above the UGV) scanning the first row of boxes;
- the UGV moves to the second row, the UAV follows it;
- the UAV descends until it reaches an altitude of 0.3 meters above the UGV, scanning the barcodes of the second row of boxes.

For the second setup, we use the active perception module described in 6.2.3 to recognize the area in front of the UAV. The UAV starts take-off along the first row of boxes (Fig. 7-4) to the highest point where a barcode is detected, adjusting its trajectory if needed. Then the UAV follows the platform repeating the same procedure. The result of trajectory adjustment using the active perception module is presented in Fig. 6-8b.

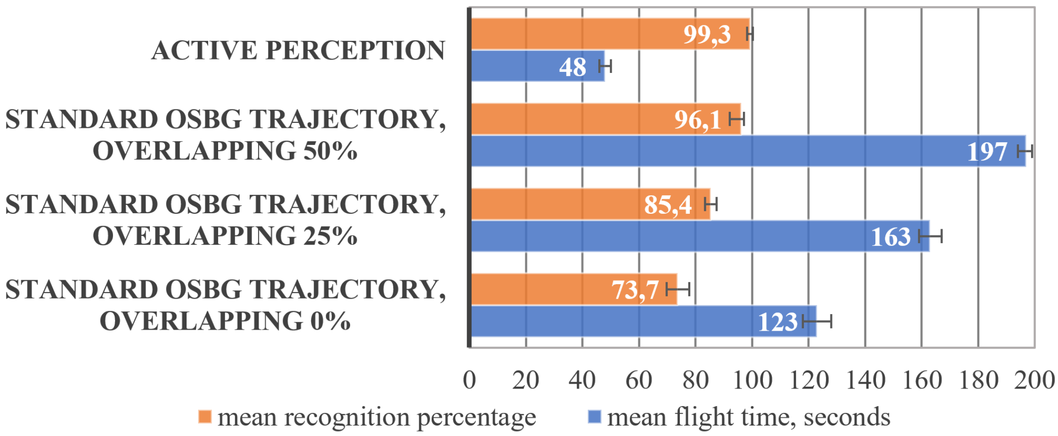


Figure 7-9: Comparison of the methods

Since stocktaking is the main task of the developed system, we need to count as many barcodes as possible. To get the maximum percentage of detected and scanned barcodes, we need to cover the entire front of the stand during the flight with steps no more than 0.21 meters. This constraint comes from the scanner's FoV, which is described in section 6.2. Also, we evaluated the percentage of scanned barcodes based on the percentage of scanning area overlapping for the first setup (Fig. 6-8). The experiment was conducted twenty times for each of three different percentages of overlapping and proposed active perception approach. Fig. 7-9 shows a comparison between them.

We used one order of boxes arrangement, as well as barcodes in both setups. The predefined flight speed was 0.5 m/s, and the laser scanner rate was 30 FPS in all setups. Fig. 7-9, that represents the result of this experiment, mean flight time drastically decreased with a flight-path correction method, while the recognition percentage is comparable with standard OSBG flight trajectory with 50% overlapping.

Taking acquired results into consideration, we can conclude that the active perception method for barcodes detection and scanning has much better performance than the standard OSBG method with a simple flight trajectory of the UAV.

7.3.2 Localization improvements with active perception

As a part of the experiment, we used the second setup from the accuracy section to estimate the active perception localization accuracy, i.e., how supplemented localization data from the UAV camera influences the drone's flight-path. The positions of all barcodes on the experimental bench were measured using the Vicon mo-cap system. The resolution of the camera on the UGV was reduced linearly by a factor of 4, so the dots per inch (DPI) were reduced by a factor of 16. We did it due to the limitations of our experimental setup: the maximum height of the mo-cap system was 3 meters. The actual flights were carried out at the altitudes of 12 meters, so the resolution was reduced to recreate the real warehouse conditions.

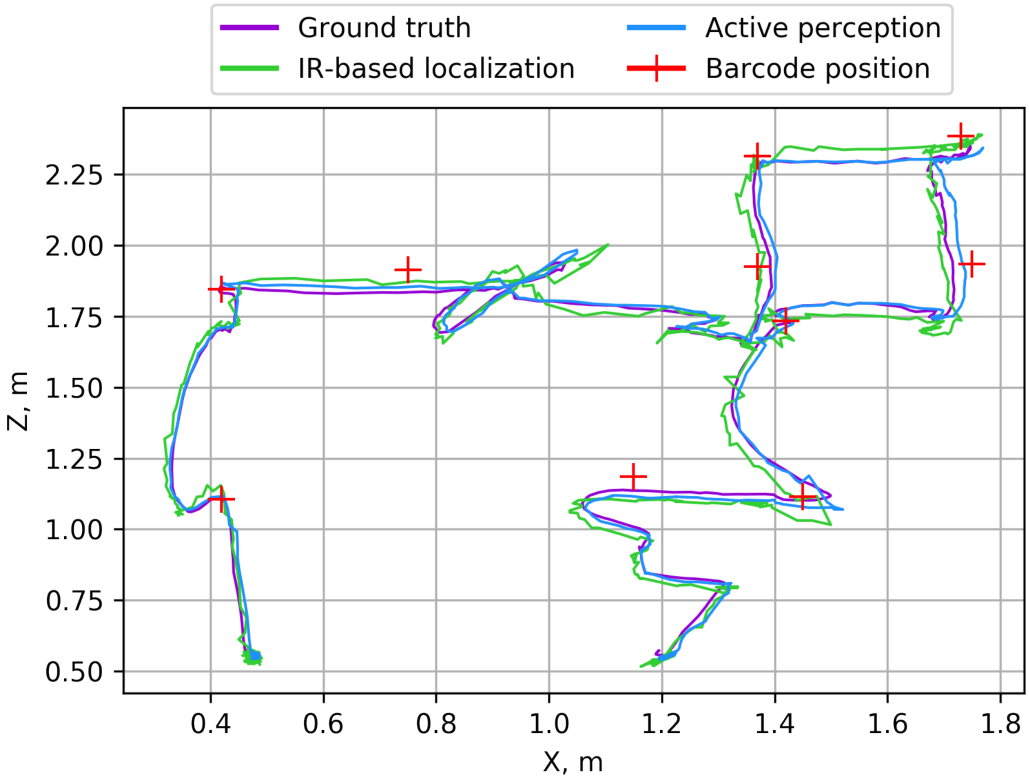


Figure 7-10: Visual comparison of three trajectories with the real positions of barcodes. Root mean square error (RMSE) for IR-based localization is 2.5 cm and RMSE for active perception localization is 1.8 cm.

The flight-path of the UAV was detected by mo-cap as ground truth, IR-based localization from the UGV, and active perception localization. Fig. 7-10 shows a graph of the comparison of three trajectories with the real positions of barcodes.

The green line indicates the drone's flight-path with the IR-based localization for barcodes detection. The violet line indicates ground truth obtained by the Vicon mo-cap system. The blue line represents the flight-path with the use of barcode coordinates for active perception localization, and red crosses indicate barcode positions.

Fig. 7-10 depicts that active perception localization is more accurate relative to the ground truth data and shows much better accuracy on high altitudes than the IR-based localization system.

7.3.3 Achieved results by active perception implementation

In this subsection, we evaluate a CNN barcode detection-based system for UAV trajectory optimization implemented in a heterogeneous robot for autonomous warehouse stocktaking. Active perception allowed us to detect and scan barcodes with higher precision compared with the standard OSBG flight trajectory, even with 50% overlap. Also the UAV's flight becomes more stable and 1.38 times more accurate than the previously developed localization method. In addition, the proposed approach decreases the duration of an inventory process without any loss in barcode recognition percentage.

7.4 Warehouse stocktaking experiments

To assess the overall performance of the system, we carried out a series of tests at several warehouses of companies that participated in our survey at the first stages of the study. In this section, we will describe the design of the experiment and present its results. A partial inventory of the warehouse was chosen as the main scenario for the experiment. In Fig. 7-11, this area is marked, this is one row of racks with a length of 80 meters, the height of the racks reached 10 meters, and the number of tiers was 5. The total number of pallet spaces in the selected part of the warehouse reached 320. The width of one span reached 4 meters. On the first, third, and fifth tiers the number of pallet places was 4, on the second and fourth tiers, the number of pallet places was 2. The result of recognizing such a scene by our method is shown in Fig. 7-12.

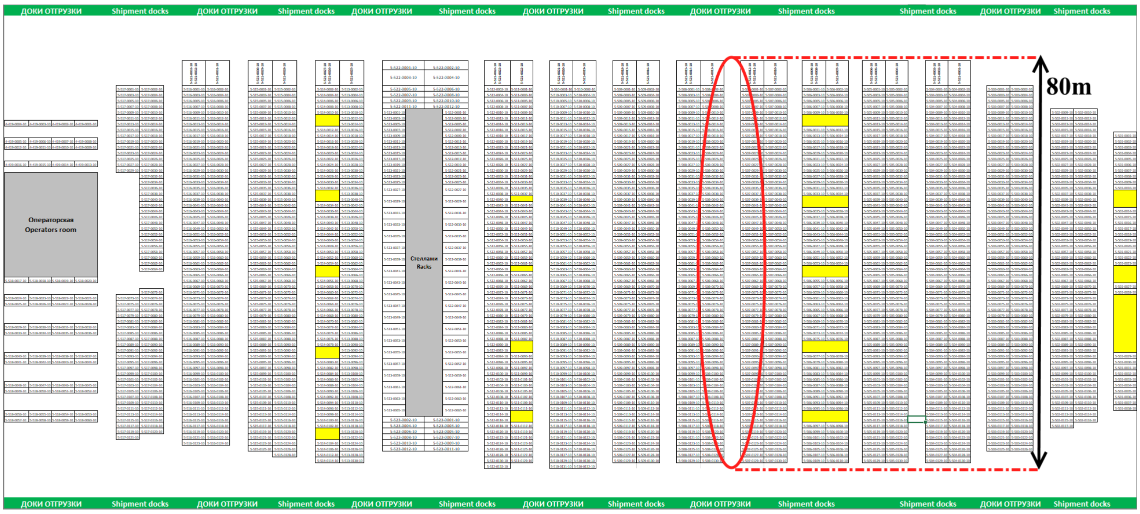


Figure 7-11: Map of the warehouse part with identified area for stocktaking experiment with the proposed heterogeneous robotic system. The area is marked by the red ellipse.

In this part of the warehouse, an inventory was recently taken, which did not reveal any errors. The stocktaking in this warehouse is carried out in manual mode described in the subsection 1.2.4 (method 1). The pallet is first removed from the rack, scanned on the floor, and then put back. It took 16 hours 10 minutes to take inventory of the selected area using this method, the average speed per pallet was 3.12 minutes, and the number of empty pallet places out of 320 was 9. It should

Figure 7-12: Stocktaking process with the proposed heterogeneous robotic system. At the right side is working system. At the left side is recognized image frame from the UAV camera.

be noted that only three people and one reach truck took part in the stocktaking of the selected area, at the same time ten teams were taking inventory of other alleys in parallel.

The system proposed in this work coped with the task of conducting an inventory in the selected area with the following output data (Table 7.1).

Table 7.1: Stocktaking output data after implementation of the proposed heterogeneous robotic system

parameter	**value**
total stocktaking time	55 minutes 48 seconds
total number of pallet places	320 items
average time per pallet place	10.46 seconds
number of correctly detected empty pallet places	9 items
number of detected areas with possible barcodes	739 items
number of recognized barcodes	715 items
number of recognized barcodes of pallet places	319 items
number of recognized barcodes of pallets	311 items
number of other recognized barcodes	85 items

There are several important points to note. First, empty pallet spaces were detected not using a separate computer vision system, but through subsequent comparison of the coordinates of the read pallet barcodes and pallet locations (if the pallet barcode was not detected above the pallet barcode read in the 1 by 1.2 meter area, then the place is empty). In addition to the barcodes used in the warehouse, the pallets also sometimes were equipped with barcodes left by the manufacturer, which led to an increase in the number of waypoints.

As a result, with an average time for detection, approach and recognition of one barcode of 4.53 seconds, the average time for scanning one pallet location was 10.46 seconds. Also, the proposed method was unable to read the barcode of one pallet location due to jamming of barcode, but it was restored according to the UAV coordinates and barcodes read before and after.

Nevertheless, as a result, it was possible not only to increase the stocktaking speed 16 times, but also to find 3 pallets that were not in their places, since as a result of removal during manual inventory they were placed in adjacent empty spaces.

Everything described above shows the effectiveness of the proposed system and makes it possible to implement this project commercially.

Chapter 8

Conclusion

In this last chapter, we discuss the results, the limitations of our work, and provide an outlook on future work.

8.1 Summary

This thesis was devoted to the development of the heterogeneous robotic system consisting of the UGV and UAV. The main part of the thesis is focused on the development of the localization system for the heterogeneous robot aimed at automated stocktaking of industrial warehouses.

In the first part of the thesis, we have investigated the problem of warehouse stocktaking through the industry survey with more than twenty companies with warehouses in Moscow Region. At the next stage, we performed a patent analysis to confirm importance of the problem and find some commercial solutions. Then we have developed approaches that improved the quality of stocktaking and decreased its duration using the autonomous heterogeneous robotic system with robust scanning system (chapter 6).

In chapter 5, we described the control system of the heterogeneous robot. Firstly a novel high-precision localization system of two collaborative autonomous vehicles for the stocktaking of warehouses is described. Our system has several significant advantages in comparison with previously developed systems. First of all, we used data fusion from two IR active patterns and ultrasonic sensors for more accurate the

UAV position estimation. Also, we place the camera for UAV tracking on the ground robot, which allowed us to get rid of inaccuracies associated with the UAV shaking. Our UAV is able to calculate its global coordinates using its coordinates relative to the ground robot and the global coordinates of the ground robot. We conducted several experiments with a system of two collaborative autonomous vehicles in the indoor environment of a warehouse. During the tests, the proposed localization system demonstrated good accuracy in comparison with the ground truth system. The average value of RMSE was equal to 2.93 cm during the tests on all heights. Nevertheless, the RMSE depends on the UAV's altitude and reaches its highest value (7.06 cm) on 10 meters above the UGV. Secondly, we developed impedance control for the soft UAV landing system, landing system is essential for continuous operations and the repeatability index of the heterogeneous robot depended on it directly. We developed the operating and mathematical principles of the impedance control for the landing system and presented the results of the real-world experiments. Our experiments showed that the developed method of adaptive landing allows to reduce the force during the first contact more than two times.

In chapter 6, we have presented a CNN barcode detection-based system for UAV trajectory optimization implemented in a heterogeneous robot for autonomous warehouse stocktaking. The proposed solution has three significant advantages. Firstly, the flight-path correction using a developed approach with CNN allowed us to detect and scan barcodes with higher precision compared with the standard OSBG flight trajectory, even with an overlap of 50% . Secondly, the active perception localization system makes the UAV's flight more stable and 1.38 times more accurate than the previously developed localization method. Thirdly, the proposed approach decreases the duration of an inventory process without any loss in barcode recognition percentage, which is crucial for a real warehouse stocktaking. Moreover, the proposed approach used standard objects of a warehouse environment (1D barcodes) for UAV localization improvement. The advantages mentioned above allow our robot to get global coordinates of each scanned barcode for warehouse planograms and further analytics.

In chapter 4, the prototype development is described. Also, we proposed the subsystem for the heterogeneous robot that was essential for whole system development according to the requirements from industry. This subsystem is the novel interactive interface based on VR application for natural and intuitive human interaction with the autonomous robotic system for stocktaking. Developed interface provided remotely monitoring of the inventory process, and teleoperation of the drone for the more detailed inspection during stocktaking. Our VR application for this purpose can potentially improve the stocktaking process.

Finally in chapter 7, we confirmed the research results with the series of experiments in laboratory conditions and in a real warehouse environment. Some videos from experiments with the system are available on the following links: YouTube channel[1] of the PhD supervisor and the media file[2] of the published paper Ivan Kalinov et al. [2020].

8.2 Thesis contribution

In order to exclude human from stocktaking completely we have developed an autonomous heterogeneous robotic system of two robots: the UGV and the UAV. This combination gives an opportunity to keep an always-up-to-date inventory record of the contents within the warehouse.

This system is capable of autonomous navigation and precise localization in indoor environment. We solved the problem of robust system operation by dividing localization into two parts for each subsystem, i.e. the UAV and the UGV. The UGV performs global localization and navigation in a warehouse, whilst the UAV always flies above the platform, detects and scans barcodes on the racks and pallets. For drone localization we have developed a method of pose estimation relative to the UGV. This approach enables to calculate coordinates of the UAV relative to the UGV and then to calculate the global coordinates of the UAV. Also, my method does not imply the utilization of any additional active infrastructure for navigation and localization, as opposed to motion capture systems, since all necessary equipment

[1] `https://www.youtube.com/watch?v=Ssuh-zq8k1o&t=49s&ab_channel=DzmitryTsetserukou`

[2] `https://ieeexplore.ieee.org/document/9145639/media#media`

is installed on the UAV and the UGV. This setup is described in detail in my first paper I. Kalinov et al. [2019].

Our main contributions for this work are:

- Autonomous heterogeneous robotic system;
- New localization method for UAV indoor flights;
- UAV-based, robust, and lightweight system for real-time barcode detection and scanning;
- Active perception by the UAV based on detected barcodes, which improves its localization in comparison with the previous method I. Kalinov et al. [2019]. By active perception we imply real-time position adjustment of the UAV using standard objects of warehouse environment (1D barcodes);
- Proposed approach with convolutional neural network (CNN) for barcode detection reduces fly-by time optimizing the UAV's trajectory in comparison with the standard fly-by method;
- The robot is able to get global coordinates of each detected and scanned barcode for warehouse planogram and further analytics.

All contributions described above have a direct influence on the key factors in the presented impact model (Fig. 3-2). The developed heterogeneous system made it possible to influence four key factors in following way. The presented system for implementation requires minimal changes in the warehouse infrastructure. These changes require the installation of passive reflective beacons at the legs of the shelves in the warehouse. Thus, the implementation of this system is possible at any warehouse after a minimal change in infrastructure.

After the first setup, the system could be easily started within 1 minute by the user without any experience in the field of robotics, just as he starts his vacuum cleaner at home. Thereby, the presented system has incomparable advantages compared to manned drones, when a team of pilots with UAVs needs to be ordered in advance, and it is impossible to conduct a partial stocktaking during any window is warehouse schedule. Also, the developed system does not require complicated maintenance and recalibration after each launch, unlike UAVs with installed LIDARs and RGB-D cameras.

The time before each start directly affects the mean stocktaking speed. Also, in this thesis, an active perception approach for UAV based on CNN was presented, which allows us to significantly reduce the flight time of all pallet places in the warehouse, and thereby increase the mean stocktaking speed. In addition, this approach minimizes the number of errors during the inventory, which is also a key factor for the developed system.

It is also necessary to mention that the tests and experiments with the developed system took place in real warehouses of three companies: Samsung, Leroy Merlin and L'Oreal (Fig. 8-1). The results of experiments were evaluated by experts from the warehouse industry.

Figure 8-1: Heterogeneous robotic system in the industrial warehouse.

The described characteristics of the developed system and their influence on the key factors in the impact model allow us to conclude that the goals set for this thesis are fully completed. The research gap of the absence of any device or system to automate and improve the quality of manual warehouse stocktaking, which is very susceptible to errors due to human factor is overcame. Besides we have found answer on the two research questions:

- How the creation of autonomous heterogeneous robotic system will improve quality of stocktaking and decrease its duration?
- What are advantages of using a heterogeneous system compared with a single drone?

8.3 Applications

The range of applications developed in this thesis of technology is quite wide. The developed subsystems and the system as a whole have vast application horizons. For example, a system of two robots, a rover and a helicopter, based on the same concept, is used in the Mars 2020 project (Balaram et al. [2018], Grip et al. [2019], Koning et al. [2019]). In the current pandemic conditions, the topic of processing and disinfection of large premises (warehouses, factories) has become relevant as never before. It is for such a task that a heterogeneous system of two robots can be applied. In addition, the developed concept can be applied to solve the problems of monitoring agricultural land, where a detailed inspection is important not only from above when flying around a UAV, but also point monitoring from the ground. Orchards of fruit trees are one particular example. When the UAV flies from above, it is not possible to study each plant in detail, it is only possible to estimate the overall scale and calculate the NDVI index. The use of a heterogeneous system will make it possible to carry out an accurate and more accurate analysis at the beginning of the crown of plants, to detect various diseases at early stages, while carrying out general monitoring from above.

8.4 Limitations

The main limitations of the current work are the use of visual methods for assessing the position of the UAV from a ground robot. To increase the versatility of the proposed heterogeneous system, it is necessary to equip the UAV with an additional simple visual localization and navigation system. This will increase both the autonomy of the UAV itself and the heterogeneous system as a whole. Then the operation of the heterogeneous system will not be limited by line-of-sight conditions, which will expand the number of scenarios for the possible application of the developed concept. When the environment changes, objects other than barcodes can be selected as standard infrastructure. This is available by simply retraining the used CNN or replacing the CNN with another one that is more suitable for a new range of tasks.

Figure 8-2: The third version of the platform with a swarm of drones.

8.5 Future work

In the future, we plan to conduct more experiments in different warehouses, implement the swarm technology and launch up to eight UAVs from our platform. It is also planned to develop several scenarios of a safe UAV landing for emergencies.

In addition, this thesis will be the scientific basis for the development of the WareVision startup (WareVision LLC [2019]). The main priorities are testing and resolving bugs in current systems, ensuring reliable operation. We hope to grow into a successful company, as well as to prove that science should be the basis of robotic startups.

The final product should be a mobile platform with a swarm of drones, which can take inventories several times faster due to smart recharge cycles on the mobile platform. The render of the third version of the platform with a swarm of drones presented in Fig. 8-2

Glossary

1D one dimensional. 26, 124, 126, 151, 153

2D two dimensional. 4, 60, 75, 84, 88, 97, 98, 123

3D three dimensional. 4, 62, 76, 82, 84, 86, 96, 97, 113

AI artificial intelligence. 31, 32

AR augmented reality. 32, 41, 57–59, 99

BFGS Broyden–Fletcher–Goldfarb–Shanno. 103

CAD computer-aided design. 13, 79, 80

CNC computer numerical control. 77, 79

CNN convolutional neural network. 4, 14, 28, 55, 57, 121, 124, 126, 127, 129–133, 143, 146, 151, 153, 154, 156

DOEC differential orthogonal exponential controller. 96

DPI dots per inch. 145

EKF Extended Kalman Filter. 56, 59, 106

ENU East-North-Up. 105

FLC fuzzy logic controller. 59

FoV field of view. 27, 100, 121, 122, 127, 138, 144

FPS Frames per second. 127, 130, 131, 136, 140, 144

FPV First Person View. 88, 90

FSR force sensitive resistors. 119, 120

GUI graphical user interface. 85–88

HCI human-computer interaction. 83

HDI human-drone interaction. 83, 84

HMD head-mounted display. 86

IBVS image-based visual servoing. 59

IMU inertial measurement unit. 56, 97

IoU Intersection over Union. 127, 130

IP intellectual property. 45, 46

IR infrared. 4, 13, 14, 28, 59, 79, 80, 100–102, 104–106, 129, 131, 132, 137, 145, 146, 150

ISR Lab Intelligent Space Robotics Laboratory. 8, 75

IT information technology. 29

LED light-emitting diode. 58

LIDAR light detection and ranging device. 77, 95–97, 154

LPE Local Position Estimation. 104, 105

MAC medium access control. 55

mil thousandth of an inch. 27, 122

ML machine learning. 93

mo-cap motion capture. 14, 105, 126, 135–137, 139, 145, 146

MSER Maximally stable extremal regions. 124

NED North-East-Down. 105, 113

OSBG overlapping snake-based grid. 4, 14, 98, 121, 126, 132, 140, 144, 146, 151

PID proportional–integral–derivative. 58, 98

QR quick response. 26, 44

RBP Robotization of business processes. 31

REKF Robust Extended Kalman Filter. 106, 139, 140

RFID radio frequency identification. 26, 37, 44, 52–56, 61, 63, 123

RGB red, green, blue. 84, 130

RGB-D red, green, blue, depth. 77, 96, 97, 154

RMSE Root mean square error. 14, 135, 137, 145, 151

ROS Robot Operating System. 13, 85, 104, 105, 114

SD standard deviation. 13, 91–93

Skoltech Skolkovo Institute of Science and Technology. 8, 75

SLAM simultaneous localization and mapping. 57, 61, 63, 95–97, 133

UAV unmanned aerial vehicle. 3, 4, 13, 14, 17, 18, 26–28, 35–38, 41, 42, 44, 45, 52–59, 61–63, 69, 70, 73–90, 93, 98, 99, 101, 102, 104, 105, 110–123, 125–127, 132, 133, 135–140, 142–146, 150–157

UAVs unmanned aerial vehicles. 3, 17, 18, 26, 29, 35, 36, 41, 44, 55, 56, 58, 60–62, 70, 80–82, 84, 99, 111, 123–125, 138, 153, 154, 157

UGV unmanned ground vehicle. 3, 4, 12–14, 26, 28, 62, 63, 69, 70, 73–78, 80, 89, 95–101, 103–105, 112, 113, 117–120, 125, 126, 135–140, 142, 143, 145, 150–153

UHF Ultra High Frequency. 53

UWB ultra-wideband. 55, 61–63

VE virtual environment. 83–85

VR virtual reality. 13, 28, 32, 41, 42, 82–88, 90–93, 152

VTOL Vertical take-off and landing. 17, 99, 112

WMS warehouse management system. 37, 52

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