清华大学

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THESIS PROPOSAL

Powers of Recall in Autonomous, Vision-Based Navigation of MAVs

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Declaration of Authorship

I, Friedrich C. V. MANGELSDORF, declare that this proposal for the thesis titled, "Powers of Recall in Autonomous, Vision-Based Navigation of MAVs" and the work presented in it are my own. I confirm that:

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- Where any part of this proposal has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this proposal is entirely my own work.
- I have acknowledged all main sources of help.
- Where the proposal is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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Contents

Declaration of Authorship **iii**

1 Introduction **1**

2 Literature Review **3**
- 2.1 Introduction to Unmanned Aerial Vehicles 3
  - 2.1.1 Basics and Classification 3
  - 2.1.2 Commercial Applications 5
  - 2.1.3 Autonomous Functions 10
- 2.2 Autonomous Navigation of MAVs 14
  - 2.2.1 Subdivision of Navigation 15
  - 2.2.2 Reliability and Qualities 16
  - 2.2.3 State of Research 17

3 The Research Project **21**
- 3.1 Research Objective and Anticipated Contribution 21
- 3.2 Methodology and Elaboration 22
  - 3.2.1 Setup of the UAS 22
  - 3.2.2 Design of the Navigation Control System 23
  - 3.2.3 Test Setup 25
- 3.3 Schedule of the Master Thesis 25
  - 3.3.1 Equipment 25
  - 3.3.2 Research Plan 26
  - 3.3.3 Thesis Writing and Proposed Date of Defense 26

A Levels of Automation by Sheridan and Verplank **27**

B Autonomous Control Levels by Clough **29**

C Milestones in UAV Delivery **31**

Bibliography **33**

List of Figures

2.1 Underlying Concept of the OODA Loop by Boyd 13
2.2 Hierarchical Control Architecture of Autonomous Control for UAV by Chen, Wang and Li 14
2.3 The Sub-tasks of Navigation 15

A.1 Levels of automation in man-computer decision making for a single elemental decisive step 28

List of Tables

2.1 Selected UAV Classes of the Classification System by Watts, Ambrosia and Hinkley 6

B.1 Chart of Autonomous Control Levels by Clough 30

C.1 Timeline - Milestones of developments of UAV based B2C delivery . . 32

Chapter 1

Introduction

In "four, five years", the technology would be mature to use drones in parcel delivery, Jeff Bezos forecasted optimistically back in 2013, while he was announcing Amazon Prime Air, bringing the idea of drone delivery to the public for the first time. [1] Across the globe many big corporations and also smaller start-ups have joined the idea with own research initiatives. Nevertheless, apart from a few smaller test projects in sparsely populated areas, drones have not yet really been able to assert themselves in this field, contrary to the back-then predictions of Bezos. Decisive reasons for this are of a technical nature. In particular, autonomous navigation methods are not yet robust enough for reliable deployment in densely populated urban areas. [2]

In science as well as in this thesis proposal, the colloquial term "drone" is referred to as an unmanned aerial vehicle (UAV). Originating from the military, adopted by hobbyists, UAVs are gaining more and more acceptance in commercial applications today. Main areas of application are infrastructure, transport, insurance, media and entertainment, telecommunication, agriculture, security and mining. [3] Predominantly micro aerial vehicles (MAVs) are employed, a sub-class of UAVs around which the research of this master thesis revolves. MAVs navigate through the air, unaffected by obstacles on the ground and largely independent of the infrastructure. Difficult to access areas can be reached without great effort or even danger for the pilot. From a bird's eye view, onboard sensors can easily record extensive data with high precision. These capabilities pay off all the more, the more functions MAVs perform independently, without the control of human pilots. This is especially true for delivery applications, where, due to limited payloads, a MAV transports significantly fewer parcels than a conventional delivery truck.

A basic function of every flight mission is navigation, i.e., reaching a target position thereby avoiding obstacles and coordinating with other agents. In undisturbed airspace in rural areas, an automated approach of GNSS-based waypoint navigation may be sufficient. In contrast, urban areas exhibit a variety of unstructured and dynamic obstacles as well as a high density of other agents. To cope with the resulting uncertainty in these environments, a high level of autonomy is required which autonomous navigation methods have not achieved yet. Recent research on autonomous navigation is mainly based on deep learning in order to deeply perceive and reason the immediate environment. State-of-the-art navigation methods achieve a high spatial understanding of the environment by feeding convolutional neural networks (CNN) with vision or depth data. This research aims to develop a simple navigation method that extend this spatial perception onto temporal extension by serially connecting a CNN with a long-short-term-memory (LSTM) network. Based on the assumption that powers of recall are crucial for humans when navigating, I am convinced that future autonomous navigation systems will encompass this ability. The navigation method will be tested in simulation and real world in a simplified test scenario, which, however, requires the MAV to remember the expansion and relative motion of obstacles while considering its own elapsed acceleration.

This thesis proposal is structured as follows. In chapter 2 relevant literature is reviewed. First, section 2.1 provides a generic introduction to the aircraft class of UAVs and related concepts. Sub-classifications of the aircraft class are presented to identify the UAV class of MAVs. Commercial applications of UAVs with agriculture and urban delivery as examples are reviewed to show the enormous potential of UAV technologies as well as currently open technologic issues that hinder the breakthrough of UAV technologies. The concept of autonomy in the context of UAV technology is presented in general. Second, section 2.2 specifically deals with autonomous navigation of MAVs. Navigation is sub-divided into sub-tasks in order to show the whole scope that would have to be covered by a mature, autonomous navigation system. Reliability and qualities of autonomous navigation are introduced to offer comparison criteria for the design and the comparison of autonomous navigation methods. Existing navigation methods, classical and current research, is referred to in order to identify advantages as well as technical issues that have not been solved yet. In chapter 3, the intended research of this master thesis is presented. The potential contribution of powers of recall to the robustness of autonomous navigation for MAVs is discussed. The methodology, i.e., the general design of the unmanned aerial system, the navigation system and the test scenario, is presented. This proposal ends with a schedule of research and thesis writing.

Chapter 2

Literature Review

This chapter provides a comprehensive background for the research of this master thesis. Section 2.1 introduces the aircraft class of UAVs. Section 2.2 reviews the research on autonomous navigation for MAVs.

2.1 Introduction to Unmanned Aerial Vehicles

This section, first, introduces the aircraft class of UAVs by presenting a definition, related concepts and further sub-classification of the UAV aircraft class. Secondly, commercial applications that integrate UAVs are discussed in order to show the actual benefits as well as the future potential of UAV technologies. Thirdly, the concept of autonomy in the context of UAVs is examined. Therewith, this section provides a comprehensive background for the topic of section 2.2, i.e., the autonomous navigation of MAVs.

2.1.1 Basics and Classification

The International Civil Aviation Organization (ICAO) [4] defines unmanned aerial vehicles (UAVs) as aircrafts without a human pilot onboard, which are either remote-controlled by a human operator or "preprogrammed and fully autonomous". It should be noted that in science, autonomy is viewed more differentiated. In this sense recent developments of UAVs may incorporate individual, autonomous functions, however, fully autonomous UAVs have not been realized yet (see subsection 2.1.3). An UAV is a component of an unmanned aerial system (UAS), which in addition consist of a ground control stations (GCS), communication link and payload. Fahlstrom and Gleason [5] introduce UASs as follows.

The GCS is the "operational control center" and accommodates human operators, computers, control and display consoles as well as a ground data terminal. At the GCS, the human operators plan and monitor missions of the UAV. Via the control consoles, they issue operational commands (e.g., switching the UAV on/off, setting the flight control mode to remote-controlled or preprogrammed, uploading preprogrammed flight missions) and, if necessary, manually remote-control the UAV and the payload. The ground data terminal forwards these operational and control commands to the UAV and receives video and telemetry data as well as command responses and status information from the UAV. The computer units process these data and show the results to the human operators via the display consoles. For small UAS, the GCS may require only a single human operator and be portable consisting only of a laptop, a wireless LAN router and a radio control (RC) controller, whereas for advanced systems, the GCS may require a fixed building for an entire team of operators and a satellite system.

The communication link establishes a reliable connection between the GCS and the UAV. It consists of the air data terminal mounted onboard the UAV, the ground data terminal located at the GCS and optionally satellite relays for communication over long distances. The air and ground data terminal may incorporate an RC receiver/controller and wireless LAN and satellite antennas.

The payload is mounted onboard the UAV. However, it is considered as an independent component of the UAS since payloads are interchangeable systems that are directly related to the individual mission of the UAV. For example, the payload for agricultural crop monitoring may be a thermal sensor, while for UAV-based delivery it may be a parcel loading-and-unloading system (see subsection 2.1.2). A video camera, in case of a surveillance mission, is payload, while for some autonomous UAVs, the camera may be a sensor which is part of the navigation control system.

Basic components of UAVs are the airframe, the electric power system, the flight control system and the air data terminal. For UAVs with autonomous functions, the necessary computation power is realized with additional onboard computers. The airframe, which can be of different type (see the following paragraph), constitutes the mechanical structure, on which the other components are mounted, and incorporates airframe type specific elements, such as control surfaces, propulsion units and rotors. The flight control system consists of the flight controller, actuators and sensors, and either supports human operators, executes preprogrammed missions or is a subsystem of an autonomous control structure. The flight controller is a circuit board with processors and is the central unit of the UAV in terms of state estimation and control as well as data and power distribution. Driven by the battery, it monitors the battery status and distributes power to the other electronic elements onboard. Through the air data terminal, the flight controller relays data, commands and status information between the sensors, the payload and the GCS. Moreover, it communicates with the GCS for control mode switch and status information of the UAV. In the remote-controlled flight mode, the flight controller translates human flight commands, such as ac-/decelerate, turning left/right and maintaining pose, into individual commands and sends them to the individual actuators which finally realize the motion of the UAV. Thereby, the flight controller assists the human in close-loop control by stabilizing the UAV based on input from the sensors. In the autopilot flight mode, the flight controller tracks trajectories and waypoints, which are either defined in a preprogrammed mission or generated from a superior autonomous control unit. Advanced control algorithms (i.e., PID, neural network, fuzzy logic, sliding mode and $H\infty$ control) are applied for a smooth flight in face of the strong non-linearity in the dynamics of UAVs. [6] Used sensors differ depending on the specific design of the flight control system. However, typical sensors are inertial measurement units (IMU), satellite-based navigation sensors, video cameras, light detection and ranging (LIDAR) sensors, barometers, compasses, sonar sensors.

Various classification systems for UAVs exist. The following introduces the classification by the means of the airframe type and flight key characteristics.

Classification by airframe type Kong and Mettler [7] conclude that the airframe type determines the suitability of an UAV for certain applications and environments. Austin [8] lists three main categories of airframe types (i.e., horizontal take-off and landing (HTOL), vertical take-off and landing (VTOL) and hybrid) and describes them as follows.

The HTOL airframe type is foremost represented by airplanes. Basic, airplanes are composed of two fixed wings and a propulsion unit. During forward motion, the wings generate lift, which compensates for gravitational force, by downward accelerating the air that flows in horizontally from the front. The wings also have stabilizing effects on the aircraft and hold control surfaces that enable navigation. This airframe type is highly aerodynamically efficient and therefore, exceptionally suitable for missions including high speed as well as long flight range and time. On the downside, because the lift generation depends on forward motion, UAVs of this aircraft type first, are unable to maintain their position in the air and second, require infrastructure for launching and landing, either a runway or a launch and recovery system. [9] Thus, HTOLs cannot be deployed on missions which include hovering (e.g., stop-and-go in densely populated areas) or lack launching and landing infrastructure (e.g., urban delivery).

The VTOL airframe type is foremost represented by copters which are composed of a single or multiple rotors. A copter generates lift by rotating its rotor(s) and accelerating air downwards. Since the air is drawn in from above the rotor(s), a copter is able to hover as well as launch and land vertically. Besides vertical force, a running rotor induces also torque on the aircraft. In case of a helicopter (single rotor copter), an additional, small tail rotor cancels the torque of the main rotor and stabilizes the yaw motion of the aircraft, whereas in case of a multicopter, the torques induced by the individual rotors cancel themselves since the individual rotors are arranged in opposite directions of rotation. Depending on the particular aircraft design, the flight is controlled by adjusting either rotational speed or tilt of the constituent rotors. This generates differential thrusts and torques accelerating the aircraft in the desired direction. At the prize of lower flight speed, range and time, UAVs of this aircraft type are suitable for missions which require hovering as well as launching and landing on small areas without previously installed infrastructure.

The hybrid airframe type combines the benefits of the HTOL and VTOL aircraft type which is usually realized with an aircraft of two fixed wings with a 90 degree tiltable propulsion unit, e.g., rotors mounted on the fixed wings, an array of jets mounted on the wings and the fuselage. UAVs of this aircraft type are able to hover as well as to take off and land vertically while they still provide the speed that is necessary for long range and high altitude flights.

Classification by flight key characteristics Various official authorities have published different classification systems that often classify UAVs by their flight key characteristics. Most of these classification systems were formulated in the military context, such as the UAS groups of the United States Department of Defense [10] which are based on maximum gross takeoff weight, normal operating altitude and airspeed. There also exist classification systems for UAVs in the civil realm, such as the seven classes of the China Civil Aviation Administration [11] which are based on empty weight, take-off weight and usage. Besides Watts, Ambrosia and Hinkley [12] classify UAVs for scientific usage. Table 2.1 shows a selection of the UAV classes they mentioned, i.e., micro air vehicles (MAV), low altitude, short endurance (LASE), low altitude, long endurance (LALE), medium altitude, long endurance (MALE) and high altitude, long endurance (HALE).

2.1.2 Commercial Applications

The emergence of air warfare in the early 20th century is also the begin of UAV technology. Over the last 100 years, it has been mainly the military research that has driven the development of UAVs. [13] The significant increase in performance and reduction of the acquisition costs of electronic components around the turn of the

TABLE 2.1: Selected UAV Classes of the Classification System by Watts, Ambrosia and Hinkley. *Source: assembled from [12].*

Class	Altitude	Endurance	Range	Takeoff/Landing
MAV	< 330 m	< 30 min	< 1 km	Any small area
LASE	< 450 m	< 2 h	< 10 km	Human hand, catapult system or runway
LALE	< 5,000 m	< 20 h	< 100 km	Runway
MALE	< 9,000 m	< 40 h	< 1,000 km	Runway
HALE	< 25,000 m	< 30 h	< 10,000 km	Runway

millennium, made UAVs attractive for the civilian sector as well. [14] [6] First, private persons explored UAVs as a hobby. A global market for consumer UAVs, with the quadcopter MAV class at the forefront, has established itself with projected revenues of 17 US dollars from 2016 to 2020. [15] Many companies emerged that manufacture UAVs. Most notable is the China-based UAV manufacturer DJI, which in 2014 accounted for around 70 percent of global consumer UAV sales. [16] UAV technology has became a hot topic in industrial and public research resulting in numerous innovative UAV designs, new concepts and advanced control algorithms. [17] Around the year of 2015, this opened the door for UAVs to commercial applications in industry and civil applications in projects of public interest. Right now, the commercial and the civil applications of UAVs are evolving rapidly into a prognosticated commercial/civil UAV market size of 13 billion U.S. dollars in revenue from 2016 to 2020. [15] Present commercial areas of application for UAVs are infrastructure, transport, insurance, media and entertainment, telecommunication, agriculture, security and mining. [3] Present civil areas are, among others, environmental protection [18], pollution monitoring [19], search and rescue [20] as well as healthcare [21]. UAVs are especially useful on missions characterized as either dangerous or inefficient, i.e., "human pilot operations would be at a disadvantage or at high risk" [12]. In connection with currently evolving technologies such as big data, cloud computing and machine learning, the ability of UAV technologies to precisely gather data at low costs is a key to significantly increase efficiency and productivity. [14]

This subsection presents two examples of commercial application areas of UAV technologies, i.e., agriculture and urban delivery. While a large number of UAV-based solutions are already being offered in the agricultural sector, UAV-based/integrated delivery remains a future technology, especially in urban areas. In the application of delivery, the benefits of UAV technologies come into full effect if they operate autonomously. In contrast to extensive farmland, urban areas represent a major technical obstacle, also for state-of-the-art UAV technologies. Companies and research institutions worldwide are conducting research in this field. An important critical point is the low robustness of autonomous navigation in uncontrolled environments. The research within this master thesis should make a contribution here as presented in chapter 3.

Agriculture The United Nations [22] estimate that the world population will increase sharply from 7.8 billion people in 2019 to 10.9 billion in the year of 2100. At the same time, extreme weather conditions are becoming much more frequent due to climate change. [23] Both pose great challenges for agriculture. Ahirwar, Swarnkar, Bhukya and Namwade [24] point out that UAV technologies can be a solution to meet increasing agricultural consumption in the face of deteriorating weather conditions and provide an overview of UAV applications in agriculture as follows.

For some years now, farmers have been integrating UAVs into their work to overcome the "largest obstacle" in agriculture, i.e., the inefficiency caused by the expanse of farmlands. UAVs can navigate freely across the wide fields, with different types of sensors (e.g. spectral, thermal, visual) as payloads. From a bird's eye view, the sensors are able to collect extensive data covering the entire farmland. The data can be used to apply in powerful analytical methods. These methods offer great economic potential for farmers, i.e., productivity increase, cost reduction. In addition, they offer solutions to ecological (e.g., fewer chemicals contaminating groundwater through precise calculation) and social (e.g., higher protection against crop failures through preventive measures) aspects. Various start-ups have developed UAV technologies that together cover almost the whole crop lifecycle: soil analysis for the development of planting patterns as well as irrigation and nitrogen management systems [25], seed planting with precise, individual nutrient supply [26], crop spraying with the precise, necessary amount of chemicals [27] and crop monitoring for health and economic assessments, the determination of the harvest date as well as the documentation for potential insurance cases [28]. JD.com, which is the second biggest Chinese online retailer and a pioneer in UAV and smart technology, launched the initiative, "JD Smart Agriculture Development Community" [29] aiming at increased efficiency of the agriculture industry and improved quality and safety of foods in China. Thereby, the UAV technologies developed by the researchers of JD-X, the logistics innovation lab belonging to the firm, are deployed to "monitor and analyze water, soil, pesticides, fertilizer, weather, diseases and pests".

The largely undisturbed airspace over the wide areas of arable land is structured and essentially predictable. Thus, state-of-the-art, autonomous systems are already robust enough for use in agricultural environments. Mazur [30] declares that the quality of the collected data is the essential criterion for the actual breakthrough of UAV technologies in agriculture which therefore depends on the development of more sophisticated sensors. A higher agree of autonomy, however, would also drive deployment by allowing more and more tasks to be transferred from human workers to UAVs and other robots.

Urban Delivery Retail, i.e., the selling of consumer goods and services, has been changing. Instead of visiting physical retail stores, consumers are shopping more and more online. An eMarketer [31] statistics projects the e-commerce share of total global retail sales to grow from 10.4% in 2017 to 22% in 2023. Increasing e-commerce entails a transition in road transportation from people driving their cars to physical retail stores to single parcels being transported to customers' addresses or returned to retailers by delivery vehicles. [32] As a result, especially last mile delivery (i.e., the last step of the supply chain from the final warehouse to the customer) is gaining even more importance - economically for the suppliers, ecologically in face of the climate change and air pollution. With the widespread use of new, more environmentally friendly delivery technologies, the shift from private transport to product delivery is an opportunity to enormously reduce global greenhouse gas emissions and local particulate pollution. So that this opportunity can be seized, new technologies must also be economical in comparison with existing delivery systems. At present, last mile delivery is inefficient, costly, and detrimental to the environment - especially in urban areas that are prone to traffic jams. Delivery systems based on or integrating UAVs that have autonomous functions could revolutionize the delivery on the last mile. Instead of or in addition to truck drivers transporting the parcels on urban roads that are congested by people and vehicles, autonomous, electronically driven UAVs could make use of the wide and undisturbed airspace above the cities.

The concept of commercial UAV delivery was first brought to the public by Jeff Bezos, the founder of Amazon, who announced the initiative "Amazon Prime Air" [33] in December 2013 and forecasted that UAV delivery could become common within 5 years. [34] Across the globe, Major retailers and postal services are conducting tests. Until now, major companies launched test programs around the world to prove that delivery by UAVs can be safe, efficient and environmentally friendly. In some rural areas, UAV delivery already deployed and reduce extensive delivery times due to bad accessibility and poor infrastructure. [35] See Appendix C for milestones in UAV delivery. However, until today widespread urban delivery by UAVs has not yet been realized due to "regulatory thickets, technical complexity and the public's skittishness" [36]. The following identifies the potential, economic and environmental benefits of the use of UAVs for last mile delivery in urban areas and analyzes the reasons why UAVs are not yet part of the urban landscape.

Suppliers can profit from the use of UAVs in urban delivery by reducing costs and offering more profitable delivery services. According to a statistics by Capgemini [37], last mile delivery accounts for 41% of the costs of the supply chain, followed by sorting (20%), parceling (16%), warehousing (13%) and remaining costs (11%). It is not only the most expensive part of the shipping process but also consumes the most time. [38] Multiple stops combined with low drop sizes cause high inefficiency which is referred to as last mile problem. [38] In rural areas long distances between delivery points, in urban areas congestion in between are the main issue. [38] Deutsche Bank estimated that a delivery system integrating UAVs and robots could reduce last mile costs by 80% and delivery time to 30 min. [39] In an A.T. Kearney [40] report, the costs, that emerge on the last mile of e-commerce routes through high-density urban areas, are estimated to consist of labor (72%), maintenance and other (14%), vehicle cost (7%) and fuel (7%). All of the above partial costs could be reduced due to the integration of UAVs into delivery. First, autonomy can essentially reduce labor cost. The higher the level of autonomy, the more functions and tasks can be transferred from humans to the UAVs. While traditional last mile delivery requires one driver per vehicle, in future, a small team of humans may supervise a whole fleet of largely autonomously operating UAVs. Second, the overall acquisition and maintenance costs of a UAV based delivery system can be expected to be reduced. One traditional delivery vehicle, indeed, would have to be replaced by many UAVs to remain the same capacity. However, UAVs and their individual components are way cheaper than traditional delivery vehicles and related spare parts. Third, UAV delivery systems can save delivery time and reduce energy consumption since they can fly on linear distances through airspace thereby omitting detours and congestion on the road. Chiang, Li, Shang and Urban [41] conclude that the joint operation of UAVs and traditional delivery vehicles can save "fixed costs by reducing the total delivery time and the number of vehicles required" as well as "variable costs, which is primarily the expenditure on fuel". A delivery truck follows its route for a whole day reaching many destinations to unload the parcels, whereas the route of UAVs, due to a lower capacity, would only cover one or several addresses. However, Lee [42]'s results show that a whole fleet of UAVs embedded in a modular supply structure provides a high flexibility that allows much space for the optimization of the delivery process. A delivery system of autonomously operating UAVs may have the capabilities to satisfy specific, individual customer requests. For their profit, suppliers could efficiently offer right away/same day deliveries to individually set, specific locations, e.g., balcony, backyard, garage. Real time, precise parcel tracking together with dynamic adjustments of delivery time and location could be possible.

Besides profiting suppliers, the use of UAVs in urban delivery can be beneficial to both globally the climate and locally the air quality. Lower fuel consumption reduces not only the costs for the suppliers but also the amount of exhaust gases. Conventional delivery trucks with combustion engines emit exhaust gases that drive the greenhouse effect and cause fine dust pollution, whereas UAVs are usually electrically powered by batteries. Thus, if the batteries are recharged with power from renewable energy resources, the operation of UAVs is even emission-free. Exhaust gases contain carbon monoxide (CO), carbon dioxide (CO_2), nitric oxide (NO), nitrogen dioxide (NO_2), etc.[43] CO_2 mainly damages the climate by driving the greenhouse effect. Currently, road transportation accounts for a large proportion of anthropogenic greenhouse gas (GHG) emissions (e.g., 24% of the United States [44] and 20.5% of the EU-28+ISL [45] total GHG emissions in 2017). Stolarof et al. [46] propose that "drone-based delivery could reduce greenhouse gas emissions and energy use". Goodchild and Toy [47] conclude that a delivery system integrating UAVs into the traditional delivery process would emit the least carbon dioxide (CO_2). Nitric oxide (NO) and nitrogen dioxide (NO_2) are part of the fine dust pollution which also contains stirred up conventional dust as well as particles from abrasion of tires and brake linings. Outdoor air pollution seriously threatens the health of people worldwide. The World Health Organization (WHO) [48] points out that in 2016, 91% of the world's population were affected by air pollution above WHO air quality guidelines. In urban areas, road transport is a major source of air pollution with commercial vehicles often with diesel engines contributing over-proportionally much. [49] An examples is the NO_2 emissions in German cities that exceed the limit adopted by the European Union [50]. Transferring urban delivery from vehicles with combustion engines to emissions-free, electrically driven UAVs could, thus, be an effective measure against fine dust pollution in cities.

While in rural areas, UAV delivery is already deployed in sporadic pioneer projects, the use of autonomous UAVs in urban areas is "unlikely in the near-to midterm". [49] UAVs have not yet established themselves in the supply industry due to strict regulations, technical problems and skeptical public attitudes. [36] Hereby, the development of advanced technical solutions that increase the safety is the major key to convince administrations to loosen regulations and the public to accept the technology. [51] The following lists several of many concerns dealing with accidental damage and injuries, privacy, security, vandalism and stealth of the parcel as well as disturbance. First, the probability and impact of accidents involving UAVs is difficult to assess. There is little experience of UAVs participating in urban traffic. A lot of accidents and injuries by UAVs have been reported. [52] However, in 2015 Susini [53] pointed out that not any fatal commercial UAV crash had been taken place. Mejias, Fitzgerald, Eng and Liu [51] identify advanced technologies for sense-and-avoid and force landings to be critical for the integration of UAVs in the civil environment. In an emergency case (e.g., power loss, engine failure), force landing technologies should be able to safely land the UAV preventing damage and injury. Currently, autonomous flight of UAVs is not robust enough for the safe operation in uncontrolled urban environments. [2] Second, UAVs can be easily misused to violate other people's privacy. UAVs with autonomous functions are often equipped with visual and range sensors (i.e., cameras, LiDAR). Researchers even work on UAVs that can look through walls. [54] During flight, these sensors reach heights and areas that have not yet been monitored. Already a single UAV can collect data that violate privacy, for example by looking through windows on higher floors. An entire fleet of delivery UAVs, on the other hand, could produce so much data that their misuse could have enormous consequences for entire sections of the population. State regulation and control could ensure the security of people's privacy. Third, UAVs can easily threat critical infrastructure. The fences of restricted areas of critical infrastructure (e.g., nuclear power plants, military bases) are not an obstacle for UAVs. Autonomously flying UAVs could unauthorizedly enter these areas either accidentally due to navigation failures or in the intention of hackers that have taken control of the UAV. This means heavy punishments (e.g., fines, imprisonment) for the suppliers or threats to public security. Fourth, delivered products could be damaged or stolen. During transport the parcel must be protected against rain and outer forces. The load and unload mechanism must be gentle so the product keeps undamaged. Criminals could easily down delivery UAVs in an act of vandalism or in order to steal the parcel. To equip UAVs with video surveillance technology could reduce criminal actions. But at the same time would intensify the privacy concern. Fifth, UAVs emit a buzzing noise during flight. An extensive application of UAV delivery would lead to a new, dominant source of noise pollution in traffic. This could affect the quality of life in urban areas. New, bladeless UAV designs that fly in silence may be a solution in future. [55] Above concerns reflect in strict regulations of local administrations and skeptical public attitudes hindering autonomous UAVs in cities. For example, the United States Federal Aviation Administration (FAA) forbids the flight of UAVs over people, out-of-sight and to be autonomous. [56] An eMarketer statistics [57] shows the share of internet users in the United States in 2016 that would not trust UAV delivery because of concerns related to damage (72%), theft (72%), safety (68%), privacy concerns (72%). Advanced technical developments that increase the safety of autonomous UAV operation could face a majority of the sorrows. Autonomous navigation methods are not yet robust enough which threats the safety of citizens. The objective of this work is to develop an autonomous navigation method that has the power of recall and due to that ability is more robust.

2.1.3 Autonomous Functions

This subsection recaps the general concept of autonomy in relation to human operation and automation and successively presents autonomy in the context of UAV.

Human Operation, Automation and Autonomy Human operation, automation and autonomy are concepts related to technologies by which tasks are executed. Various, currently existing definitions and understandings of autonomous systems cause conceptual confusion. [58] Caterpillar Inc. [59], the world's largest manufacturer for heavy machinery [60], proposes a simple, terminological distinction by the degree of human control during the completion of the task, whereas Chen, Wang and Li [61] foremost differentiate automation and autonomy by means of the ability of self-governance in substantial uncertainty. The following paragraph refers to both resources in order to provide a overview of the three concepts and provides an exemplary task of *domestic floor cleaning* for a better illustration.

A task is executed by human operation, if during its completion a human controls the machine at any time. *A person living in the house monitors the floor from time to time. If the person feels that the floor is dirty he or she decides to start cleaning. The person actively moves a conventional vacuum cleaner over the floor. At all times the person is in* *control of the vacuum cleaner. By the time the person adjudges that the floor is clean, he or she decides to stop cleaning.*

Automation replaces human action by a machine integrating control systems for a previously defined task in an assessable environment. The machine has only limited, functional control, whereas the human operator remains the overall control of the machine. *The person utilizes a robotic vacuum cleaner that cleans the floor in a self-drive mode. During the cleaning process, the robot is not actively guided by the person. Still, the person is responsible for the monitoring of the floor and for the decision to start and stop the cleaning process.* In the majority of cases, automation considerably outperforms human operation with respect to precision, speed, costs, etc. Machines can work non-stop, faster and more precise than the replaced humans that in addition cause labor costs. Due to their rational, numerical nature, machines can apply complex, mathematical optimization that is beyond the linear thinking of humans. On the other hand, an automated system is doomed to fail if it exceeds its design purpose since it was engineered to consider only a limited amount of parameters, variations and disturbances. In contrast to humans an automated system by itself is not able to properly cope with substantial uncertainty in the form of situational changes and unexpected events. *On the one hand, the robotic vacuum cleaner cleans the whole floor in less time than the person using a vacuum cleaner who also leaves out small areas of the floor. On the other hand, the robot is stopped by an unexpected blockage or is unexpectedly knocked over by a pet. In order to continue the work, the person has to clear the blockage or set the robot upright again. A coin that unexpectedly lies on the floor is sucked up by the robot, whereas the person would rather put it into his wallet. In case of the situational change that the person spontaneously decides to watch a movie while the robot is in cleaning process, the robot by itself does not realize and continues the noisy cleaning. In order to not be disturbed by the cleaning noise, the person has to actively turn off the robot.*

Autonomy is the conceptual extension of automation to substantial uncertainty. An autonomous system is not only able to perform previously defined tasks in assessable environments but also able to re-define tasks to react to situational changes and operate successfully in uncontrolled environments without the interaction of a human operator which however, may has the option to intervene into the system at a supervisor level. An autonomous system combines the benefits of automation and human operation by extending conventional control systems with intelligent components. Especially , methods of machine learning deepen the perception and reasoning of autonomous systems and integrate capabilities that have been associated with the intelligence and flexibility of human behavior. Machines learn to anticipate upcoming events, to react to unexpected events, to re-define tasks to react to situational change, to be able to perform new tasks, to operate in unknown and uncontrolled environments, to estimate uncertainty, to learn from failures, etc. *The robotic vacuum cleaner non-stop monitors the floor and is able to detect if the floor is dirty. The robot by itself decides to start cleaning and, when sensing that the floor has become clean enough, decides to stop cleaning. Defined tasks for blockage clearing and upright setting are integrated. The robot does not have the ability to pick up and preserve the coin so it re-defines the task to clean the floor by avoiding the close area around the coin. In order to spare the person watching a movie from cleaning noise, the robot creates a cleaning schedule based on the regular daily routine of the person. Through the feedback from the person whether he or she is satisfied with the level of cleanliness, the robot tunes itself to the person's sense of cleanliness and adjusts the cleaning plan and the individual cleaning programs.* Human operation, automation and autonomy are fluent concepts that are rather merging than mutually exclusive. Whether a technology with a high degree of automation, i.e., the system automatically performs the majority of its tasks, is an autonomous system, depends on the contextual view, e.g., the tasks and processes that are taken into consideration. Thus, Williams [58] prefers "system with autonomous functions" over the term "autonomous system" that often causes ambiguity. *The autonomous robotic vacuum cleaner from above has the abilities to autonomously perform the cleaning process over an extended period of time. It is able to throw a full vacuum cleaner bag into the garbage can and put in a new, empty vacuum cleaner bag. However, this period of autonomous work is bounded since the robot cannot order by itself and has to rely on the person to supply vacuum cleaner bags. If one considers not only the cleaning process but also the sourcing process, the robot is not an autonomous system since it relies on human operation. But with respect to the cleaning process the system indeed integrates autonomous functions.*

Various scales exist that categorize generic as well as specific, technical systems into levels of autonomy. [58] The first scale was presented in 1978 by Sheridan and Verplank [62] (see figure A.1) in the context of their research on underwater teleoperators. The scale, formulated for generic "computers", constructs ten levels of automation (including autonomy) for an "elemental decisive step". A single dimension entails two successive metrics to measure autonomy, i.e., levels 2 to 4 and 5 to 10 mostly consider decision making and execution, respectively. Human operation (level 1) and full autonomy of the computer (level 10) bound the dimension. Considering that both underwater teleoperators and UAVs are technical systems in which humans are physically separated from unmanned operators or vehicles, but still issue commands to some extent, this relatively simple scale also provides an initial understanding of human interaction with autonomous UAVs. More recent scales accomplish an increased comparability between autonomous control systems by taking multiple metrics parallelly into account. Such a multi-dimensional scale is introduced in the following paragraph that deals with autonomy in the explicit context of UAVs.

An autonomous system successfully integrates a variety of controllers that solve specific problems. The design of these controllers as well as their synthesis require competences from various technical fields, i.e., control theory, system identification and estimation, communication theory, computer science (in particular artificial intelligence) and operations research. Furthermore, expertise from non-technical fields must be involved, i.e., ethics, philosophy and law, in order to address issues that arise with machines that make decisions on their own.

Autonomous Control for UAVs Autonomous navigation is an important key to establish UAV solutions in various commercial application areas, as previously stated in subsection 2.1.1 using urban delivery as an example. In order to provide a background for section 2.2, which deals with autonomous navigation of MAVs, this paragraph introduces first, the autonomous control levels for UAVs by Clough [63], and, second, the hierarchical control architecture of autonomous control for UAV by Chen, Wang and Li [61].

During his work at the US Air Force Research Laboratory, Clough [63] proposed a sophisticated, multi-dimensional scale of autonomous control levels for UAVs in a military context (see table B.1). Eleven levels of autonomy, from remote-controlled (level 0) to preprogrammed (level 1-2) to fault/event reaction (level 3-4) to multi-vehicle interaction (level 5-6) to battlespace abilities (level 7-9) to full autonomy (level 10), are constructed with respect to four, parallel metrics, i.e., observe, orient, decide and act. These metrics are oriented towards the OODA (observe, orient, decide and act) loop which was originally developed by Boyd to analyze the decision making process of military enemies but has been also adopted in the context of

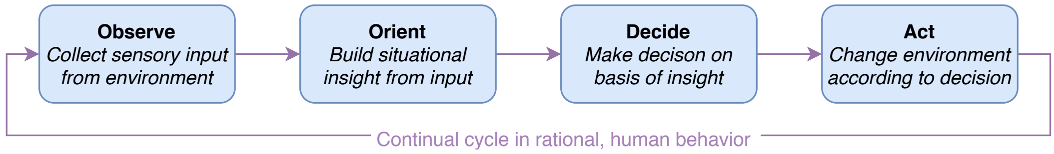

FIGURE 2.1: Underlying Concept of the OODA Loop by Boyd. *Source: figure 1 from [64] (edited), created with draw.io*

business management. [64] Figure 2.1 shows the underlying concept of the loop. A cycle through four, serial processes (i.e., observe, orient, decide and act) represents rational behavior of humans, as individuals or integrated into organizations. For simplicity, feedback mechanisms (e.g., the decision to further observe) and implicit control mechanisms (control that continually run in background) are not graphed.

The hierarchical, autonomous control architecture for UAVs by Chen, Wang and Li [61] (see figure 2.2) disaggregates the complex, autonomous control system of a generic UAV into three control levels (i.e., organization, coordination and execution level) as well as a supervisor level for human intervention and an overlapping module for system monitoring. By means of the IPDI (increasing precision with decreasing intelligence) concept, authority and tasks are distributed downwards. In general, downstream from higher to lower levels, commands are distributed and system parameters are modified, whereas command responses and preprocessed data are passed upstream from lower to higher level. According to the outer/inner loop principle, higher control levels require longer intervals of planning and execution than lower control levels.

The most intelligent, least precise organization level implements artificially intelligent methods that assess the situation and manage the mission, on the basis of the multi-sensor data from the coordination level, and eventually, make decisions which are sent downstream to the coordination level.

The medium intelligent, medium precise coordination level runs conventional and artificially intelligent methods that, in accordance with the decisions from the organization level, navigate and generate trajectories on the basis of multi-sensor data which is merged from preprocessed information sent by the execution level. Operational parameters are determined and, together with control and identification algorithms, are efficiently distributed to the subsystems of the execution level.

The least intelligent, most precise execution level directly interfaces with the sensors and actuators of the UAV. While receiving sensor data corresponding to the state of the UAV and the environment, this level runs conventional control algorithms (e.g., attitude, trajectory, velocity and propulsion control) with operational parameters as determined by the coordination level and sends low level control commands directly to the actuators of the UAV. Moreover, this level runs identification algorithms that process the sensor data in order to determine parameters, to perform state estimation and to detect faults. The gained information is sent upstream to the coordination level.

The supervisor level enables humans at the GCS to interact with the autonomous UAV. However interaction is limited to the organization level, from where human commands are passed downstream.

The system monitoring module monitors the status and health information of all subsystems of the control system. In the occurrence of a fault, this module first, detects and localizes the fault and second, modifies operational parameters in order

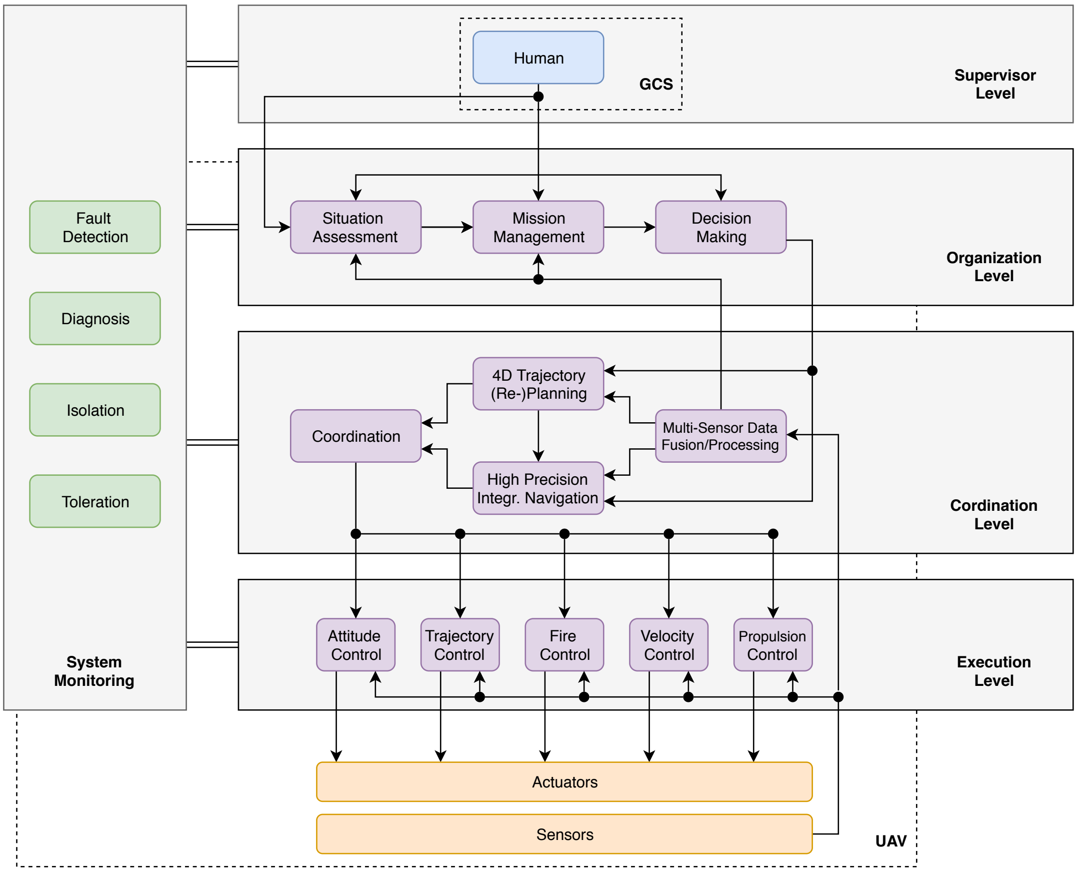

FIGURE 2.2: Hierarchical Control Architecture of Autonomous Control for UAV by Chen, Wang and Li *Source: figure 2, 3 and 4 from [61] (edited), created with draw.io*

to eliminate, reduce or tolerate the fault.

2.2 Autonomous Navigation of MAVs

Autonomous navigation of MAVs is a current theme in recent research. State-of-the-art methods are sophisticated, yet they fail in uncontrolled environments. The current trend is to integrate deep learning into autonomous navigation methods in order to give the MAVs perception and reasoning capacities. Both abilities are fundamental for boosting the robustness of navigation methods which is necessary to cope with the uncertainty that occurs in uncontrolled environments. MAVs fly at low attitudes in proximity to obstacles and other agents. Moreover, they are restricted to lightweight sensors, computers and other devices which strongly constrains applied navigation methods, that must reliably run in real time, in computational complexity. Especially the sub-task of obstacle avoidance has remained highly challenging. [65]

This section, first, examines the task of navigation in detail and identifies all sub-tasks. Second, reliability and navigation qualities by which methods can be compared are discussed. Third, the state of research on autonomous navigation for MAVs is reviewed.

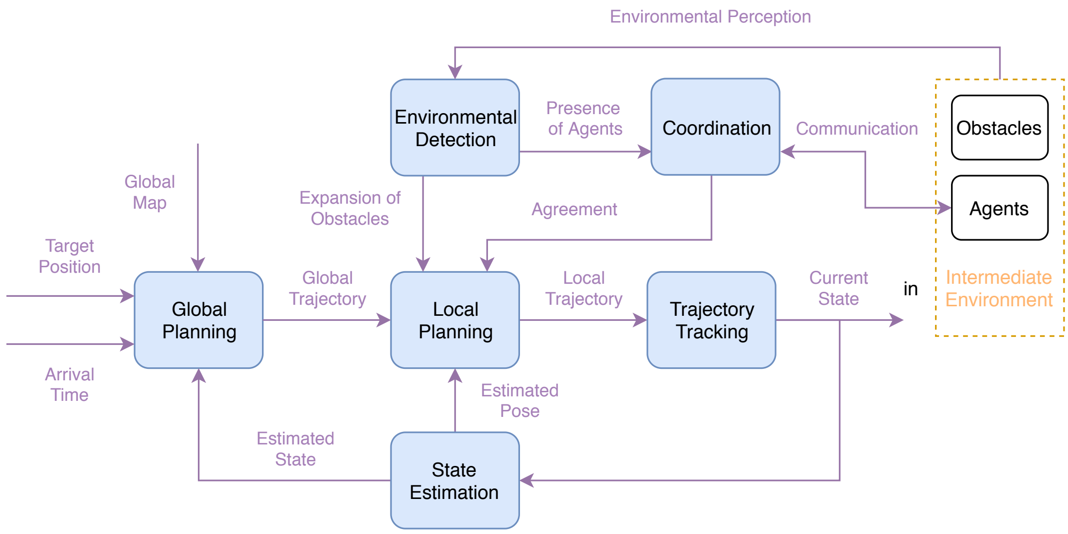

FIGURE 2.3: The Sub-tasks of Navigation. *Source: own figure, created with draw.io*

2.2.1 Subdivision of Navigation

The online dictionary Lexico.com [66] defines navigation as "the process or activity of accurately ascertaining one's position and planning and following a route". The navigation task of a generic system may be divided into six continues and simultaneous sub-tasks (see figure 2.3). A sophisticated method for autonomous navigation should cover all of the sub-tasks.

The overriding goal of a navigation method is that the system to be navigated arrives at the target position at the desired time as demanded by a higher-level unit (human operator or autonomous control structure). Usually a map is used for this purpose. First, the target position is identified in the coordinate frame of the map. The current state (position, orientation and derivatives) of the system is estimated in the frame of the map. A global trajectory in the frame of the map is generated that continuously connects the current state at the current time with the target position at the desired arrival time. (Trajectories are 4D arrays consisting of consecutive 3D positions, each with a corresponding point in time and are often calculated with optimization methods, for example, to minimize the distance travelled or the time required.) Depending on the level of detail of the map, static obstacles may already be bypassed by the trajectory. Based on the estimation of the current pose, the global trajectory in the coordinate frame of the map is converted to the local trajectory in the frame of the system. The current, immediate environment is scanned to detect the expansion of obstacles and the presence of other agents in the frame of the system. If necessary, communication with other agents is established to coordinate further motion. In case of conflicts, the local trajectory is adjusted to avoid the obstacles or to follow the agreement with the other agents but to still follow the rough course of the global trajectory. Finally the collision-free trajectory is tracked by accordingly move the system.

All the above actions are performed more or less simultaneously and constantly. At all time the current state of the system is estimated. If at any time this estimation essentially differs from the global trajectory or changes occur in the map, the global trajectory may be re-planned. Since the system is continuously changing its state, the global trajectory is constantly converted to the local trajectory in the frame of the system. The system must perceive the environment and may adjust the local trajectory at all times in order to be able to cope with unpredictable, dynamically moving obstacles and agents. Simultaneously, the system must continuously follow the trajectory.

Considering the complexity, it is admirable how humans can accomplish the navigation task without much effort. The street scenes of their residential areas may be the map stored in their mind. They may estimate their current state based on their vision of the immediate environment and transfer the global trajectory to the frame of their own body. While continuously walking along the local trajectory, at ease, they properly react to red traffic light, puddles, other pedestrians, etc. From experience, they may choose alternative routes accordingly to the current situation and know how to adjust their walking speed to arrive at the desired time.

2.2.2 Reliability and Qualities

Lazzaroni, Cristaldi, Peretto, Rinaldi and Catelani [67] define reliability of a system as the "probability [...] of performing its required function in the established time interval, under established conditions". In the context of autonomous navigation of MAVs, the required function is to safely fly to the target position. Thereby, the time interval is established by the desired arrival time. Depending on the intended application, the time interval may be short requiring the MAV to navigate at high speeds. For this, not only the flight control system of the MAV but also the navigation method must be highly agile. The intended application environment through which to be navigated and the design of the MAV determine the conditions. Depending on the application environment, the navigation method must integrate certain sub-functions to ensure safety. The design of the MAV constrains the capacities of electric and computation power available for the navigation method.

This subsection discusses the impact of functional scope, efficiency and agility of autonomous navigation methods for MAVs on their reliability, i.e., the probability that the navigation method performs the required function (safely navigate to the target position in time) in a certain environment, with certain resources, in a certain application. Functional scope, efficiency and agility can be considered as qualities which are applicable in the development of autonomous navigation methods for MAVs and the comparison of their performance.

Functional scope The application environment poses which sub-functions of navigation (see figure 2.3) are required to be integrated into the navigation method. In controlled and undisturbed environments, such as the airspace of rural areas, navigation methods may be considered reliable without the ability to perceive and reason the immediate environment since the environment is highly predictable. In contrast, uncontrolled environments which may be unstructured and dynamically variable and in which multiple agents may simultaneously act, exhibit substantial uncertainty. An example is the traffic environment in urban areas, in which a large number of different road users participating. Those uncontrolled environments demand the robust performance of all sub-tasks of navigation. The lack of structure, dynamic changes and multiple simultaneously acting agents may be too complex to be fully captured on global maps. For example, maps may show the position of a tree or an other agent but not the tree's branches or the agent's next movement. Thus, the MAV must be able to detect the expansion of the tree and the presence of the agent, in order to locally re-plan or coordinate a collision-free trajectory. Environments with highly dynamical obstacles may require a high agility for the navigation method for fast reactions.

Efficiency In the design of MAVs, hardware components are severely limited in size and weight which in turn strongly constrains power capacities and computational power. Bigger batteries and processors would sensitively affect the size and weight of the MAV and thus, may decrease the maneuverability and agility of the MAV. [68] Therefore, navigation methods are required to be energetic and computational efficient. Methods are only reliable, if they are processible in real time by the constrained hardware. The navigation system may be a significant electricity consumer of the MAV. The less energy the navigation system requires, the more energy is available for longer flights and payload. Autonomous navigation methods may essential differ in energy consumption by the type and number of sensors they are based on as well as their computational complexity which determines the processor performance required to run them in real time. [6]

Agility The online dictionary Lexico.com [69] defines agility as the capability, first, "to move quickly and easily" and, second, "to think and understand quickly". In the context of aviation, agility is closely linked to maneuverability. Both are "flight qualities" [70] that find application in aircraft design. Lawrence, Corning and Wharburton [71] define maneuverability as the "ability to change the aircraft flight path by application of forces from the main rotor, tall rotor or other control devices" and agility as "how quickly the aircraft flight path can be changed". Whalley [70] measures maneuverability/agility of an aircraft by "the maximum achievable time-rate-of-change of the velocity[/acceleration] vector". Accordingly, maneuverability and agility encompass the execution control and dynamics of an aircraft and reflect the first part of the definition of Lexico.com.

MAVs are generally very agile due to their small size. However, their agility is very sensitive to their weight and is therefore in a strong conflict with higher endurance and payloads. [68] Agility often suffers in favor of safety which is the top priority of autonomous navigation. In contrast to professional human pilots, autonomous navigation control methods have not yet been able to push the dynamics of MAVs safely to the limit. [72] Especially with navigation methods based on global state estimation, high speeds easily leads to failure. [2] For a better comparability of autonomous navigation methods, it may be advisable to extend the above definitions of maneuverability and agility to the second part of the definition of Lexico.com. Agility in the context of autonomous navigating MAVs should not only include the execution control level (see figure 2.2) and the dynamics of the airframe but also the autonomous navigation control. In this case, all steps of the OODA loop (see figure 2.1), i.e., to observe, orient, decide and act, would be covered by the extended concept of agility.

2.2.3 State of Research

The development of comprehensive, autonomous navigation methods for MAVs is complex because the method must integrate several functions that perform simultaneously running sub-tasks (see figure 2.3). Loquercio and Scaramuzza [2] categorize the numerous existing autonomous navigation methods for MAVs into classical methods that follow the scheme of mapping-localization-planning-tracking, and modern methods which, with the use deep learning, train the MAV to learn end-to-end navigation policies. In turn, they subdivide deep learning methods into methods based on imitation learning and reinforcement learning. Following the classification of Loquercio and Scaramuzza, this section presents the state of research on autonomous navigation methods of MAVs and discusses advantages and disadvantages.

Classical methods Traditionally, navigation methods follow the scheme of intermeshed steps, i.e., mapping-localization-planning-tracking.

A common and simple type of system architecture for the navigation of MAVs through undisturbed outdoor environments estimates the state of the MAV based on data from an onboard GNSS sensor and localizes the MAV in a given map. Based on the current position of the MAV, the target position and the information of the map, a trajectory is generated and tracked. This type has two main disadvantages. First, in environments where the GNSS signal may be weak, as for example in urban areas, GNSS based navigation methods are not reliable. Second, functions to cope with obstacles and other agents in the immediate environment are absent.

More sophisticated system architectures integrate simultaneously localize and mapping (SLAM) algorithms, which do not require GNSS signals but visual or range sensors. SLAM algorithms generate and update a map of an unknown environment which captures present obstacles and simultaneously localize the system in the map. [73] Path planning algorithms (e.g., [74], [75]) identify collision-free trajectories in 3D depth maps build by the SLAM algorithm. Sophisticated navigation methods for MAVs exist that estimate the MAV state based on data from an inertial measurement unit (IMU) together with the output of vision-based SLAM algorithms (e.g., [76], [77], [78], [79]).

The main disadvantage of SLAM methods is that generating the map of the environment coerces global consistency. This increases computational complexity and causes extreme effort to capture the dynamics of environments. Thus, classical methods reach their limits in environments which are not pre-dominantly static, i.e., fast changes may occur. Moreover, they are prone to fail at high speeds due to visual aliasing. In contrast to end-to-end policies, classical methods are a compound of clearly separated sub-systems. As a result, possible positive feedback effects between perception, reasoning and control are prevented in the first place and one-way, complex algorithms must be deployed to connect the sub-systems by generating control commands based on 3D maps.

Methods based on deep reinforcement learning Recent Research has publicized various navigation methods involving deep reinforcement learning (RL) algorithms. Automatically generated control policies input raw sensor data and output complex flight control commands. RL Navigation methods are vision- or range-based, i.e., they input images of a video camera or depth maps (at each pixel the distance to an object) of a LiDAR. The foremost benefit of deep RL methods is that policies are not affected by the control shift problem that occurs with IL methods, because the policies are learned with "trial-and-error" [80] from direct environmental interaction without the need for expert intervention.

However, this way of learning requires an enormously high degree of sample complexity to achieve generalizing policies. [81] For MAVs, limited flight endurance makes the learning process inefficient. [80] Moreover, any collision is highly uncontrolled and thus very likely critical for the health of the system and the safety of the environment. [80] Thus, to acquire the required sample complexity is extremely costly and dangerous. Researchers tried to circumvent this by transferring part or all of the learning process to simulation while still testing the learned policies in the real world.

Sadeghi and Levine [80] propose a vision-based policy for collision avoidance in real world indoor flight which is exclusively trained with simulated training data. From raw monocular RGB images, a deep convolutional neural network directly outputs velocity motor commands. A variety of highly randomized environments, textures and lighting, produces control policies that generalize to the real world. In real world test flights, they prove collision-free navigation through indoor environments. But the MAV flies with extremely low agility.

State-of-the-art simulation environments are capable of comprehensively modelling the dynamics of a quadcopter MAV. [82] Nevertheless, open problems have not been solved yet. First, complex aerodynamic effects such as rotor drag, which become important with the flight close to structures, is not yet be modelled. [83] Second, learned policies are affected by a domain shift between simulation environments and the real world. Even in the presence of photorealistic simulators (e.g., AirSim [84], CARLA [85]), the quality of rendered images is not yet sufficient. Zhu, Mottaghi, Kolve, Lim, Gupta, Fei-Fei and Farhadi [81] address the domain shift by fine-tuning their vision-based deep RL policy learned in simulation with training data from the real world.

Methods based on deep imitation learning Over the last years, more and more research has been done on methods of autonomous navigation that involve deep imitation learning in order to learn control policies from raw sensor data, usually camera images or depth maps. Compared to reinforcement learning, imitation learning is easier to implement and characterized by a low sample complexity. This means that smaller amounts of training data are necessary to generalize learned control policies to test scenarios. However, the collection of training data as well as the evaluation of learned control policies may be inefficient and dangerous, especially in uncontrolled environments. Therefore, some researchers have chosen alternative ways to collect training data. Loquercio, Maqueda, del-Blanco and Scaramuzza [86] trained a deep neural network with real world data that has been safely gathered by cars and bicycles driving through urban areas. They achieved a generalized control policy that also could safely navigate the MAV at high altitude in urban areas and also through indoor environments. Similarly, Giusti, Guzzi, Cirsan, He, Rodríguez, Fontana, Faessler, Forster, Schmidhuber, Di Caro, Scaramuzza and Gambardella [87] as well as Smolyanskiy, Kamenev, Smith and Birchfield [88] used image data collected by human hikers. The derived control policies could safely navigate MAVs through forest trails. Alternatively, the learning process can be shifted to simulation, i.e., train the network on simulated data (see next paragraph).

Many navigation methods are restricted to planar motion not exploiting the agile dynamics of MAVs. Ross, Melik-Barkhudarov, Shankar, Wendel, Dey, Bagnell and Hebert [65] developed a navigation system that inputs images from a monocular camera and reactively controls the MAV in planar motion in order to avoid trees. The policy, in the form of visual feature extraction plus a neural network is trained to mimic yaw control of human pilot experts. They could demonstrate collision-free flight with velocities up to 1.5 $\frac{m}{s}$ in a controlled indoor environment as well as in outdoor forest environments. Giusti et al. [87] used a deep convolutional neural network to map images to the direction of forest trails relative to the MAV. They could achieve a classification accuracy that is comparable to human decision. However, the flight control of the MAV was restricted to planar motion (i.e., yaw and speed control) The convolutional neural network of Loquercio et al. [86] outputs a steering angle and a collision probability. The policy can follow roadways and simultaneously avoid obstacles but is also limited to planar control, i.e., forward velocity and yaw control.

Chapter 3

The Research Project

For my master thesis within the "Double/Joint Degree Master Program in Mechanical Engineering/Physikalische Ingenieurwissenschaft of Tsinghua University and the Technical University of Berlin", I decided to research on the topic "Powers of Recall in Autonomous, Vision-Based Navigation of MAVs". This chapter, first, clarifies the objective of the research of this master thesis and discusses the potential contribution to the field of autonomous navigation of UAVs. Secondly, the intended methodology and elaboration of the general design of the unmanned aerial system, the navigation system and the test scenario, is presented. Thirdly, the scope of this master thesis is reflected in a schedule of research and thesis writing.

3.1 Research Objective and Anticipated Contribution

Although many sophisticated methods for the autonomous navigation of MAVs already exist, open-world environments of high uncertainty have not yet been conquered by autonomous MAVs (see section 2.2). Current research is making effort to face the uncertainty of these environments by using deep learning techniques that empower MAVs with necessary perception and reasoning abilities. State-of-the-art, vision-based navigation methods integrate policies in the form of feedforward, deep convolutional neural networks that map the current state in form of the current picture to action. Convolutional neural networks already achieve a high, spatial perception and reasoning of the immediate environment, however, this alone may not be enough for the long-term objective to robustly apply autonomous MAVs in open-world environments.

Kaufmann, Loquercio, Ranftl, Dosovitskiy, Koltun and Scaramuzza[72] developed a vision-based method that navigates a MAV through a drone racing track with possibly dynamically moving race gates. Thereby, they achieved a high reliability and agility at high speeds. But the method, exemplarily of other methods, has a decisive deficiency that stands out due the inherent problem of high-level goal formulation in deep learning. At any time, the next gate must be in the frame of view (FOV) of the onboard camera. If not, the navigation method has no target position. This is also the case, even if the MAV has seen the next gate in the past. For example, a section of the racetrack that consist of two successive gates, in between a steep curve could not successfully be navigated through by the method, even if both gates have already appeared on images. Before the MAV navigate through the first gate, both gates are in the FOV of the camera. After it has flown through the first gate, because the curve is too steep, the second gate is out the FOV and the navigation method has no goal to be achieved.

The lack of high-level goal planning is an inherent problem of deep learning policies. In the navigation method of this research, I want to meet the lack of high-level goal planning by introducing powers of recall to navigation. To my knowledge, Kelchtermans and Tuytelaars [89] are the only ones who used a recurrent neural network for memory abilities in autonomous, vision-based UAV navigation. **Shakeri2019** However, they only tested their method in simulation and did not comprehensively evaluate their results. If the method, after passing the first gate, could remember that it has seen the second gate before, the method could plan to navigate through the second gate based on elapsed images.

Deep learning enables machines to learn human-like abilities of perception and reasoning. Thus, it seems promising to orient methods also on human behavior. Powers of recall in human navigation has an important function. For example, after entering a room, humans can still locate themselves relatively to the door which is not in their FOV anymore. In addition, humans cannot estimate the velocity and direction of motion of themselves, obstacles or other agents based on a short blink with their eyes but they need to observe over at least a short period of time. Not only localization but also situational reasoning is strengthened by memory, e.g., a car driver observes a child that runs from the sidewalk through the parking cars onto the road and has enough reaction time or even anticipation to brake. Without any power of recall, the driver may start braking in anticipation when the child is still on the sidewalk, but may stop braking after the child disappears behind a parking car.

In my method, I plan to use deep convolutional neural networks serially connected to a long-short-term-memory (LSTM) neural network. While the CNN has the ability to perceive and reason spatial structures of the environment, the LSTM is able to establish connections through time. In other words, the CNN is responsible to predict waypoints or generate trajectories based on single images, whereas the LSTM empower the method to recall and remember by evaluating the temporal structure between the predictions of the CNN. Besides the above steep curve scenario, this memory would show great benefit in situations when the quadcopter lost track of the goals and he can recall elapsed images. In case of the application in urban areas, for example, quadcopters could remember obstacles that were visible but have become occluded and thus, could better anticipate. Or after an evasive maneuver, the quadcopter could return to the actual path much faster because he memorizes its maneuver. In that sense, the memory of the quadcopter is another form of localization in the environment, which is not global but namely local. In addition, memory could enable better optimization, e.g., the imitation learning of optimal trajectories which are not only spatial but also temporal objects. However, this research, in a simplified scenario, should only prove if powers of recall are applicable and generally useful for the autonomous navigation of MAVs.

3.2 Methodology and Elaboration

3.2.1 Setup of the UAS

The GCS is represented by a laptop, a wireless LAN router as ground data terminal and an RC controller for emergency cases. At the GCS, the human operator switches on/off and arms the MAV as well as sets the flight control mode to preprogrammed (normal operation) or to remote-controlled (emergency case). In the preprogrammed mode, the human operator only supervises the autonomously navigating MAV and the navigation control system autonomously controls the MAV as described in the next subsection. In the remote-controlled mode, the human operator manually sends navigation commands (e.g., turn left, assume the pose) via the RC controller to the RC receiver of the air data terminal onboard the MAV. The flight controller tracks those navigation commands while also stabilizing the MAV by sending out corresponding low-level control commands to the individual actuators of the flight control system of the MAV.

3.2.2 Design of the Navigation Control System

The navigation control system of this thesis builds on the navigation methods of Kaufmann et al. [72]. Similarly, the system is subdivided into the perception/reasoning, the path-planning and the low-level control system. While the path-planning and the low-level control system remain broadly the same, the perception/reasoning system is structurally oriented towards the design of Kelchtermans and Tuytelaars [89], i.e., the serial connection of a CNN and a LSTM network that can perceive and reason in both the spatial and temporal dimension. However, instead of using the CNN to extract generic features from images like Kelchtermans and Tuytelaars, the CNN maps images to a higher level representation in the form of waypoints and desired velociy similarly to original approach by Kaufmann et al. [72]. With this, I aim to significantly reduce computational costs in comparison to Kelchtermans and Tuytelaars while remaining the agility qualities of the method of Kaufmann et al. [72].

The perception/reasoning system is a serial connection of a deep convolutional neural network and a LSTM network. The CNN policy inputs the current image from the forward-facing onboard camera of the MAV and outputs for each of the next two gates a waypoint in the images coordinates as well as a corresponding normalized speed.

$$\left\{\vec{x}_i \in [-1,1]^2 \in \mathbb{R}^2,\ v_i \in [0,1] \in \mathbb{R}\right\},\ i = 1,2 \tag{3.1}$$

If the image does not depict gate i, the corresponding normalized speed is zero, i.e., if there is no gate, both velocities are zero; if there is one gate, the first velocity is a non-zero value and the second velocity is zero; if there are two gates, both velocities are non-zero values.

$$v_i \in \begin{cases} \{0\}, & \text{if picture does not depict gate } i \\ ]0,1], & \text{else} \end{cases},\ i = 1,2 \tag{3.2}$$

Indices $i = 1/2$ refer to the closer/farther one of two closest gate, which is detected by the expansion (e.g., area or diameter) of the gates on the image. In case there are more than two gates in the picture, the gates besides the closest two are neglected. Assuming that in a common racetrack the next gate is also the closest gate, indices $i = 1/2$ correctly reflect the sequence of the race gates in the racetrack.

The LSTM policy inputs the output of the CNN network as well as acceleration data from onboard sensors. In case that the current image depicts one or two race gates (i.e., $v_1 \in]0,1]$), the LSTM directly outputs $\vec{x} = \vec{x}_1,\ v = v_1$ to the path-planning system. In case that the current image depicts no race gate (i.e., $v_1 = 0$), the LSTM outputs a bridging waypoint $\vec{x} = \vec{x}_b$ with a corresponding bridging velocity $v = v_b$.

$$\left\{ \vec{x} = \begin{cases} \vec{x}_1 & \text{if } v_1 \in]0,1] \\ \vec{x}_b & \text{else} \end{cases},\ v = \begin{cases} v_1 & \text{if } v_1 \in]0,1] \\ v_b & \text{else} \end{cases} \right\} \tag{3.3}$$

Assuming the next gate had been depicted before the MAV has navigated through the last race gate, the relative position of the next gate to the unaccelerated MAV can be estimated by the course of the elapsed waypoints of the farther gate (i.e., $\vec{x}_2$) before the gate had left the FOV (i.e., before $v_2 = 0$). However, the MAV has been accelerated in the meantime. Therefore, the LSTM also inputs the acceleration data in order to estimate the additional, relative displacement of the race gate due to acceleration of the MAV since the gate has left the FOV. This bridging navigation is required to be too accurate because the goal is that the race gate, that has disappeared in the meantime, re-appears in the FOV of the camera. Then again, the LSTM only passes the predictions from the CNN as described.

The path-planning system inputs the waypoint $\vec{x}$ in image coordinates and the normalized velocity v. First, the actual speed is computed with the maximum velocity $v_{\max}$ which is set by the human operator to determine the maximum and therewith also average speed of the MAV.

$$v_{\text{out}} = v_{\max} \cdot v \tag{3.4}$$

Secondly, the prediction horizon is determined proportionally to the velocity v_{out}, however, in the range $[d_{\min}, d_{\max}]$. The proportionality factor m_d as well as the range parameters $d_{\min}$ and $d_{\max}$ are set by the human operator to influence the aggressiveness of the flight of the MAV. A smaller prediction horizon at lower speed allows agile flight required in sharp curves, whereas a bigger prediction horizon at higher speed smoothens the flight which is beneficial on straight racetrack sections.

$$d = \min\{\max\{d_{\min}, m_d \cdot v_{\text{out}}\}, d_{\max}\} \tag{3.5}$$

Thirdly, the waypoint $\vec{x}$ in image coordinates is transformed to the waypoint $\vec{p} = (p_1, p_2, p_3)^T \in \mathbb{R}^3$ in the coordinate frame of the MAV. The x-component is set equal to the prediction horizon (i.e., $p_1 = d$). With a back-projecting transformation T of a library (e.g., OpenCV [90]) the y- and z-components are computed.

$$\vec{p} = (p_1, p_2, p_3)^T \in \mathbb{R}^3 \text{ with} \qquad \begin{aligned} p_1 &= d \\ (p_2, p_3) &= T\{\vec{x}\} \end{aligned} \tag{3.6}$$

Fourthly, a computationally efficient, minimum-jerk trajectory segment t_s, as proposed by Mueller, Hehn D'Andrea [91], is computed. In the coordinate frame of the MAV, the trajectory segment connects the current state, (i.e., the position $(0,0,0)^T \in \mathbb{R}^3$ as well as velocities and accelerations from onboard sensors), with the waypoint $\vec{p}$ in the time span defined by the velocity v_{out}. Thereby, the velocity and acceleration at the waypoint remain unconstrained since a trajectory segment is computed for each incoming prediction of the perception/reasoning system and thus, only the first part of the trajectory segment is tracked.

The low-level control system (e.g., as proposed by Faessler, Fontana, Forster and Scaramuzza [92]) tracks the trajectory segments t_s by outputting low-level commands that are sent to the actuators of the MAV.

The perception/reasoning system is trained with imitation learning (IL) as follows. During the training, the position of the race gates $\vec{p}_{\text{r},n}$, and the estimates of the pose of the MAV must be known in the global reference frame. First, a global, minimum-snap trajectory t_g as proposed by Mellinger and Kumar [93] traversing through all race gates is calculated. The trajectory can be constrained in maximum velocity, body rates and thrust. To collect the training features, the MAV captures images throughout the racetrack. For each image, the corresponding label is derived in the following process. According to the position and orientation of the MAV, all race gates ahead the MAV are projected onto the image plane. If then no race gate is in the FOV of the camera, the ground truth label of the image, as above, is set to be $\vec{x}_i = (0,0)^T,\ v_i = 0,\ i = 1,2$. If there is one gate in the FOV of the camera, first, the closest point on the global trajectory $\vec{p}_c$ to the position of the MAV $\vec{p}_M$ is determined. Second, a testing prediction horizon is determined that adapts to gate proximity in the racing track, i.e., $d_{\text{train}} = \max\{d_{\min}, \min\{s_{\text{last}}, s_{\text{next}}\}\}$ with the distances to the lastly passed s_{last} and the next to be passed gate s_{next}. The point on the forthcoming global trajectory that has the distance of the prediction horizon to the MAV is determined, i.e., $\vec{p}_g$ with distance$\{\vec{p}_c, \vec{p}_g\} = d_{\text{train}}$. Then, according to the position and orientation of the MAV, the point $\vec{p}_g$ is projected onto a point of the image plane $\vec{x}_g$. Besides, the velocity at the point $\vec{p}_c$ is normalized with the maximum speed on the global trajectory, i.e., $v_g = v(\vec{p}_c)/\max\{v(t_g)\}$. The point on the image plane and the normalized velocity are the label for the first waypoint while the second waypoint remains as in the no gate case, i.e., $\vec{x}_1 = \vec{x}_g,\ \vec{x}_2 = (0,0)^T,\ v_1 = v_g,\ v_2 = 0$. In case of two or more gates in the FOV, the first waypoint is labeled as in the one gate case. The second waypoint is labeled with the position of the second closest gate in the coordinate frame of the MAV.

3.2.3 Test Setup

For the final test, a simple setup of two racing gates connected with a sharp curve is used. To show that powers of recall can increase robustness of navigation, after passing the first gate, there must be a time span, where the images from the onboard camera show no gate at all. Different time spans without current orientation that the navigation system has to bridge with powers of recall could be examined. The MAV could be pushed to different speeds to compare the agility with the original method of Kaufmann et al. [72]

3.3 Schedule of the Master Thesis

This section outlines the scope of the master thesis by presenting the necessary equipment, the research plan and the schedule of writing.

3.3.1 Equipment

- Quadcopter MAV with
  - onboard camera
  - Companion computer
  - WLAN antenna
- WLAN router
- Laptop

3.3.2 Research Plan

The research plan is divided into four main tasks, i.e., the framework for the test scenario in simulation as well as in real world, the design of the navigation method and the test execution.

Framework for experiments in simulation

- In the simulation environment, implement randomized test scenario (i.e., steep curve between two successive gates of a drone racetrack).
- Generate the minimum-snap expert trajectory through the scenario.
- Use available flight control implementation that can track the trajectory.
- Implement the onboard camera to generate images in simulation.

Framework for experiments in real world

- Find an appropriate environment and build two race gates.
- Deploy a system that precisely localizes the MAV and the gates.
- Configure MAV hardware (i.e., companion computer, camera, etc.).
- Generate the minimum-snap expert trajectory through the scenario.
- Use available flight control to track the trajectory.
- Collect data with carrying the MAV through the racetrack section.

Design of the navigation method

- Establish interface to sensors in simulation/real world.
- Configure architecture of the CNN and LSTM.
- Automate data collection and training of the network.

Test execution

- Plan the parameters of the test.
- Define evaluation criteria.
- Organize required equipment.
- Conduct the test.

3.3.3 Thesis Writing and Proposed Date of Defense

I am going to return to Germany on December 16, 2019. With the begin of the New Year I will continue my research at the Technical University of Berlin. I intend to complete the research plan within three months and subsequently start writing the master thesis based on that research. At my present discretion, I will finalize the thesis until the end of May 2020. According to the regulations of Tsinghua University, one year after this thesis proposal in January 2021, I am going to complete the master thesis by undergoing the final defense either in personal appearance or via video conference.

Appendix A

Levels of Automation by Sheridan and Verplank

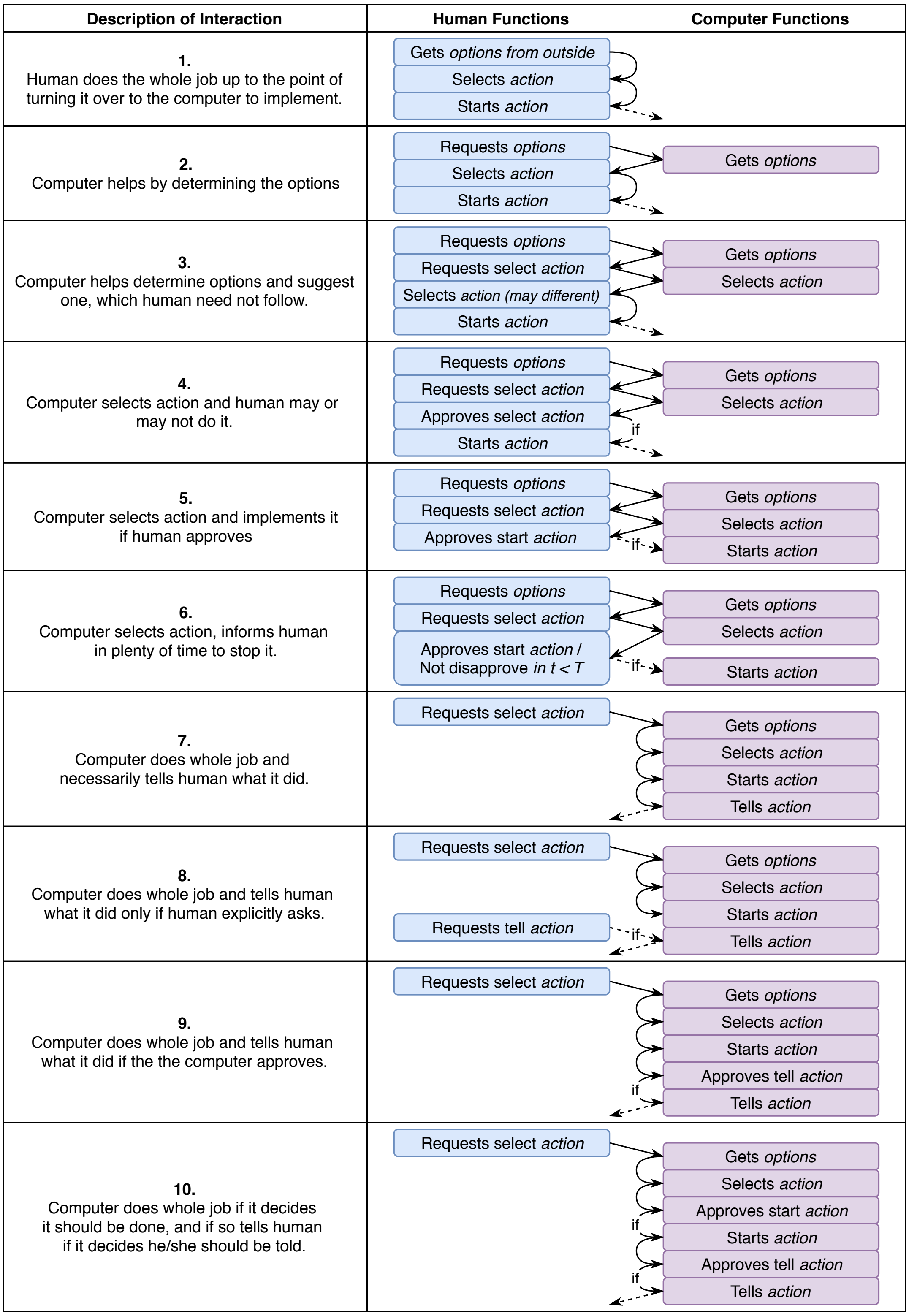

FIGURE A.1: Levels of automation in man-computer decision making for a single elemental decisive step. *Source: table 8.2 from [62] (edited), created with draw.io*

Appendix B

Autonomous Control Levels by Clough

TABLE B.1: Chart of Autonomous Control Levels by Clough. *Source: table 4 from [63], edited.*

Lvl	Label	Observe	Orient	Decide	Act
0	Remotely piloted vehicle	Flight control (attitude, rates), sensing, nose camera	Telemetered data, remote pilot commands	N/A	Control by remote pilot
1	Execute preplanned mission	Preloaded mission data, flight control and navigation sensing	Pre/post flight BIT, report status	Preprogrammed mission and abort plans	Wide airspace separation requirements (miles)
2	Changeable missions	Health/status sensors	RT health diagnosis (do I have problems?), offboard replan (as required)	Execute preprogrammed or uploaded plans in response to mission and health conditions	Self accomplishment of tactical plan as externally assigned
3	Robust response to real time faults/events	Health/status history & models	Tactical plan assigned, RT health diag (what is the extent of the problems?), ability to compensate for most control failures and flight conditions (i.e. adaptive inner-loop control)	Evaluate status vs required mission capabilities, abort/RTB if insufficient	Self accomplishment of tactical plan as externally assigned
4	Fault/event adaptive vehicle	Deliberate awareness - allies communicate data	Tactical plan assigned, assigned rules of engagement, RT health diagnosis, ability to compensate for most control failures and flight conditions - inner loop changes reflected in outer loop performance	Onboard trajectory replanning - event driven, self resource management, deconfliction	Self accomplishment of tactical plan as externally assigned, medium vehicle airspace separation (100's of yds)
5	Real time multi-vehicle coordination	Sensed awareness - local sensors to detect others, fused with off-board data	Tactical group plan assigned, RT Health Diagnosis; Ability to compensate for most failures and flight conditions; ability to predict onset of failures (e.g. prognostic health mgmt), group diagnosis and resource management	On-board trajectory replanning - optimizes for current and predictive conditions, collision avoidance	Group accomplishment of tactical plan as externally assigned, air collision avoidance, possible close air space separation (1-100 yds) for AAR, formation in non-threat conditions
6	Real time multi-vehicle cooperation	Ranged awareness - on-board sensing for long range, supplemented by off-board data	Tactical group goals assigned, enemy location sensed/estimated	Coordinated trajectory planning and execution to meet goals - group optimization	Group accomplishment of tactical goal with minimal supervisory assistance, possible close air space separation (1-100 yds)
7	Battlespace knowledge	Short track awareness - history and predictive battlespace data in limited range, timeframe, and numbers, limited inference supplemented by off-board data	Tactical group goals assigned, enemy trajectory estimated	Individual task planning/execution to meet goals	Group accomplishment of tactical goal with minimal supervisory assistance
8	Battlespace cognizance	Proximity inference - intent of self and others (allies and foes), reduced dependence upon off-board data	Strategic group goals assigned, enemy tactics inferred, ATR	Coordinated tactical group planning, individual task planning/execution, choose targets of opportunity	Group accomplishment of strategic goal with minimal supervisory assistance (example: go SCUD hunting)
9	Battlespace swarm cognizance	Battlespace inference - intent of self and others (allies and foes), complex/intense environment - on-board tracking	Strategic group goals assigned, enemy strategy inferred	Distributed tactical group planning, individual determination of tactical goal, individual task planning/execution, choose tactical targets	Group accomplishment of strategic goal with no supervisory assistance
10	Fully autonomous	Cognizant of all within battlespace	Coordinates as necessary	Capable of total independence	Requires little guidance to do job

Appendix C

Milestones in UAV Delivery

TABLE C.1: Timeline - Milestones of developments of UAV based B2C delivery

Year	Month	Country	Company	Details	Source
2013	Dec	USA	Amazon	Announcement of development *Amazon Prime Air*[33]	[34]
		USA	UPS	research of an own UAV delivery service is announced	[94]
		Germany	DHL	test delivery flight is conducted	[95]
2014	Aug	Australia	Google X	development of *Project Wing* is revealed	[96]
	Sep	Germany	DHL	launch of *Parcelcopter* test program	[97]
	Oct	USA	FedEx	research of UAV integration into existing delivery system is announced	[98]
	Dec	France	La Poste	launch of test program	[99]
2015	Feb	China	Alibaba, YTO Express	launch of tea delivery program	[100]
	Mar	China	SF Express	launch of test UAV delivery service	[101]
		UK	FPS	First commercial UAV delivery in the UK	[102]
	May	Korea	CJ Group	development on UAV delivery system is revealed	[103]
	Jul	USA	Flirtey	First commercial UAV delivery in the US	[104]
2016	Jul	USA	7-Eleven, Flirtey	first "store-to-door" UAV deliveries to private customers in the US with an autonomously flying drone relying on precision GPS	[105]
	Dec	UK	Amazon	first UAV delivery in the United Kingdom	[106]
2017	Aug	Iceland	Aha, Flytrex, DJI	launched a project to fly drones preprogrammed missions to deliver consumer goods to customers' houses in Rejkjavik	[107]

Bibliography

[1] I. A. Hamilton, “Amazon drone deliveries are coming, but jeff bezos still missed his own deadline for airborne logistics,” *Business Insider*, Jun. 6, 2019. [Online]. Available: `https://www.businessinsider.com/jeff-bezos-predicted-amazon-would-be-making-drone-deliveries-by-2018-2018-12` (visited on 12/07/2019).

[2] A. Loquercio and D. Scaramuzza, “Learning to control drones in natural environments: A survey,” in *e ICRA Workshop on Perception, Inference, and Learning for Joint Semantic, Geometric, and Physical Understanding*, 2018. [Online]. Available: `http://rpg.ifi.uzh.ch/docs/WICRA18_Loquercio.pdf` (visited on 10/24/2019).

[3] M. Mazur, A. Wiśniewski, J. McMillan, V. Huff, R. Abadie, J. Smith, S. Stroh, P. Romanowski, A. Krasoń, F. Orliński, A. Babicz, P. Lulkowska, E. Boguszewska, B. Czerkies, A. Głąb, R. Hołoga, J. Jagiełło, W. Jankowska-Tofani, A. Kramza, S. Kuprijaniuk, R. Piwowarski, J. Sygutowski, G. Urban, M. Walczak, M. Wolski, and E. Zdrojowy, *Clarity from above, PwC global report on the commercial applications of drone technology*. PwC Poland, May 2016. [Online]. Available: `https://www.pwc.pl/pl/pdf/clarity-from-above-pwc.pdf` (visited on 10/12/2019).

[4] *Global Air Traffic Management Operational Concept (Doc 9854)*. International Civil Aviation Organization (ICAO), 2005. [Online]. Available: `https://www.icao.int/Meetings/anconf12/Document%20Archive/9854_cons_en%5B1%5D.pdf` (visited on 10/25/2019).

[5] T. G. Fahlstrom, *Introduction to UAV Systems 4e*. John Wiley & Sons, Sep. 7, 2012, 308 pp., ISBN: 1119978661. [Online]. Available: `https://www.ebook.de/de/product/19222078/fahlstrom_thomas_gleason_introduction_to_uav_systems_4e.html`.

[6] H. Chao, Y. Cao, and Y. Chen, “Autopilots for small unmanned aerial vehicles: A survey,” *International Journal of Control, Automation and Systems*, vol. 8, no. 1, pp. 36–44, 2010. DOI: `10.1007/s12555-010-0105-z`. [Online]. Available: `https://link.springer.com/content/pdf/10.1007/s12555-010-0105-z.pdf` (visited on 10/27/2019).

[7] Z. Kong and B. Mettler, “Evaluation of guidance performance in urban terrains for different UAV types and performance criteria using spatial CTG maps,” *Journal of Intelligent & Robotic Systems*, vol. 61, no. 1-4, pp. 135–156, 2010. DOI: `10.1007/s10846-010-9485-9`.

[8] R. Austin, *Unmanned Aircraft Systems: UAVS Design, Development and Deployment (Aerospace Series Book 55)*. Wiley, 2011, ISBN: 9780470058190. [Online]. Available: `https://www.amazon.com/Unmanned-Aircraft-Systems-Development-Deployment-ebook/dp/B005UQLG0C?SubscriptionId=AKIAIOBINVZYXZQZ2U3A&tag=chimbori05-20&linkCode=xm2&camp=2025&creative=165953&creativeASIN=B005UQLG0C`.

[9] T. J. Gleason and P. G. Fahlstrom, “Recovery of uavs,” *Encyclopedia of Aerospace Engineering*, pp. 1–7, 2010.

[10] *Unmanned Aircraft System Airspace Integration Plan, Version 2.0*, United States Department of Defense, Mar. 2011. [Online]. Available: https://web.archive.org/web/20160121155841/http://www.acq.osd.mil/sts/docs/DoD_UAS_Airspace_Integ_Plan_v2_(signed).pdf.

[11] J. Wei, E. Tazewell Ellet, L. Ellman, P. R. Rizzi, and L. E. T. E. Zhou, “China launches first operational rules for civil unmanned aircraft,” *Hogan Lovells*, Jan. 2016. [Online]. Available: https://www.hlmediacomms.com/2016/01/21/china-launches-first-operational-rules-for-civil-unmanned-aircraft/.

[12] A. C. Watts, V. G. Ambrosia, and E. A. Hinkley, “Unmanned aircraft systems in remote sensing and scientific research: Classification and considerations of use,” *Remote Sensing*, vol. 4, no. 6, pp. 1671–1692, 2012. DOI: 10.3390/rs4061671.

[13] J. Sifton, “A brief history of drones, With the invention of drones, we crossed into a new frontier: Killing that’s risk-free, remote, and detached from human cues.,” *The Nation*, Feb. 7, 2012. [Online]. Available: https://www.thenation.com/article/brief-history-drones/ (visited on 11/22/2019).

[14] O. R. Garcia and A. Santoso, “Comparative evaluation of drone delivery systemsin last-mile delivery,” Master’s thesis, MASSACHUSETTS INSTITUTE OF TECHNOLOGY, Jun. 2019. [Online]. Available: https://dspace.mit.edu/bitstream/handle/1721.1/121319/Garcia_Santoso_2019.pdf?sequence=1&isAllowed=y#cite.IWM.

[15] Goldman Sachs Research, *Drones - reporting for work*. [Online]. Available: https://www.goldmansachs.com/insights/technology-driving-innovation/drones/ (visited on 11/23/2019).

[16] D. Weinswig, M. Driscoll, J. Harmon, A. Hedrick, A. Ho, J. Mercer, C. Poon, S. Reilly, L. Rosengard, and J. Wang, *Send in the Drones! An In-Depth View on the Growing Market for Drones*. Fung Business Intelligence Centre, The Fung Group, Apr. 21, 2015, p. 6. [Online]. Available: https://www.fbicgroup.com/sites/default/files/FBIC%20Global%20Retail%20Tech%20Report%20Drones%20Apr.%2021_%202015.pdf (visited on 10/12/2019).

[17] J. Desjardins, “The emergence of commercial drones,” *Visual Capitalist*, Dec. 4, 2016. [Online]. Available: https://www.visualcapitalist.com/emergence-commercial-drones/ (visited on 11/23/2019).

[18] L. Lei and H. Yan, “Forests breathe life into province, keep desert at bay,” *China Daily*, Sep. 4, 2019. [Online]. Available: https://www.chinadaily.com.cn/a/201909/04/WS5d6f1680a310cf3e3556999d.html (visited on 11/23/2019).

[19] L. Xiang, “Nonprofit leads crackdown on air pollution,” *China Daily*, Jul. 12, 2019. [Online]. Available: https://www.chinadaily.com.cn/a/201907/12/WS5d27dc46a3105895c2e7d0f6.html (visited on 11/23/2019).

[20] S. McCarthy, “Chinese police use drone to rescue man lost in xinjiang desert, Flying machine used to track down man who went missing for over an hour after going sightseeing in taklimakan desert without food or water,” *South China Morning Post*, Oct. 11, 2018. [Online]. Available: https://www.scmp.com/news/china/society/article/2168091/chinese-police-use-drone-rescue-man-lost-xinjiang-desert (visited on 11/23/2019).

[21] "Zhejiang hospital tests 5g uav ambulance in emergency rescue," *People's Daily Online*, Apr. 10, 2019. [Online]. Available: http://en.people.cn/n3/2019/0410/c90000-9565324.html (visited on 11/23/2019).

[22] "World population prospects 2019," United Nations, Department of Economic and Social Affairs, Population Division, Tech. Rep., 2019. [Online]. Available: https://population.un.org/wpp/ (visited on 10/28/2019).

[23] National Academies of Sciences, Engineering and Medicine, *Attribution of Extreme Weather Events in the Context of Climate Change*. Washington DC: The National Academies Press, 2016. DOI: 10.17226/21852. [Online]. Available: https://books.google.com/books?hl=en&lr=&id=WWEpDQAAQBAJ&oi=fnd&pg=PR1&dq=climate+change+extreme+weather+&ots=DeJAR0sdmb&sig=r0XKAsVPKo1qpetuUR5vM5ICrBM#v=onepage&q=climate%20change%20extreme%20weather&f=false (visited on 10/28/2019).

[24] S. Ahirwar, R. Swarnkar, S. Bhukya, and G. Namwade, "Application of drone in agriculture," *International Journal of Current Microbiology and Applied Sciences*, vol. 8, no. 01, pp. 2500–2505, 2019. DOI: 10.20546/ijcmas.2019.801.264.

[25] Deveron UAS, *Imagery & targeted soil sampling*. [Online]. Available: https://deveronuas.com/about-us/advisory-board/.

[26] DroneSeed, *Services*. [Online]. Available: https://www.droneseed.co/services.

[27] HSE UAV, *Hse agriculture uav crop duster sprayers*. [Online]. Available: http://www.uavcropdustersprayers.com/.

[28] PrecisionHawk, *Drone data collection and analytics for agriculture*. [Online]. Available: https://www.precisionhawk.com/agriculture.

[29] JD.com Corporate Blog, *Jd cultivates new smart agriculture push in china*, Apr. 2018. [Online]. Available: https://jdcorporateblog.com/jd-cultivates-new-smart-agriculture-push-in-china/.

[30] M. Mazur, "Six ways drones are revolutionizing agriculture," PricewaterhouseCoopers, Tech. Rep., 2016. [Online]. Available: https://www.technologyreview.com/s/601935/six-ways-drones-are-revolutionizing-agriculture/.

[31] A. Lipsman. (Jun. 27, 2019). Report global ecommerce 2019, eMarketer, [Online]. Available: https://www.emarketer.com/content/global-ecommerce-2019 (visited on 10/31/2019).

[32] D. Weideli, "Environmental analysis of us online shopping," Master Thesis Executive Summary, Master's thesis, Ecole Polytechnique Fédérale de Lausanne (EPFL) and Massachusetts Institute of Technology (MIT) Center for Transportation & Logistics, 2013. [Online]. Available: https://ctl.mit.edu/sites/ctl.mit.edu/files/library/public/Dimitri-Weideli-Environmental-Analysis-of-US-Online-Shopping_0.pdf (visited on 10/31/2019).

[33] Amazon, *Amazon prime air*. [Online]. Available: https://www.amazon.com/b?node=8037720011.

[34] F. Manjoo, "Think amazon's drone delivery idea is a gimmick? think again," *The New York Times*, Aug. 2016. [Online]. Available: https://www.nytimes.com/2016/08/11/technology/think-amazons-drone-delivery-idea-is-a-gimmick-think-again.html.

[35] McKinsey&Company, *Parcel delivery - the future of last mile*, Sep. 2016. [Online]. Available: https://www.mckinsey.com/~/media/mckinsey/industries/travel%20transport%20and%20logistics/our%20insights/how%20customer%20demands%20are%20reshaping%20last%20mile%20delivery/parcel_delivery_the_future_of_last_mile.ashx.

[36] E. Rosen, "Skies aren't clogged with drones yet, but don't rule them out," *The New York Times*, Mar. 19, 2019. [Online]. Available: https://www.nytimes.com/2019/03/19/technology/drone-deliveries-faa-pilot-programs.html (visited on 11/02/2019).

[37] K. Jacobs, S. Warner, M. Rietra, L. Mazza, J. Buvat, A. Khadikar, S. Cherian, and Y. Khemka, *The last-mile delivery challenge, Giving retail and consumer product customers a superior delivery experience without impacting profitability*. Capgemini Research Institute, Capgemini, Jan. 10, 2019, p. 20. [Online]. Available: https://www.capgemini.com/wp-content/uploads/2019/01/Report-Digital-%E2%80%93-Last-Mile-Delivery-Challenge1.pdf (visited on 10/12/2019).

[38] S. Dolan, "The challenges of last mile logistics & delivery technology solutions," *Business Insider*, May 11, 2018. [Online]. Available: https://www.businessinsider.com/last-mile-delivery-shipping-explained (visited on 11/06/2019).

[39] E. Kim, "The most staggering part about amazon's upcoming drone delivery service," *Business Insider*, Jun. 16, 2016. [Online]. Available: https://www.businessinsider.com/cost-savings-from-amazon-drone-deliveries-2016-6 (visited on 11/06/2019).

[40] S. Monahan, J. Ward, M. Zimmerman, B. Sonthalia, and K. Acar, *CSCMP'S Annual State of Logistics Report, Steep Grade Ahead*. A.T. Kearney and Council of Supply Chain Management Professionals (CSCMP), 2018. [Online]. Available: https://info.atkearney.com/30/2134/uploads/steep-grade-ahead-2018-state-of-logistics-report.pdf (visited on 10/30/2019).

[41] W.-C. Chiang, Y. Li, J. Shang, and T. L. Urban, "Impact of drone delivery on sustainability and cost: Realizing the UAV potential through vehicle routing optimization," *Applied Energy*, vol. 242, pp. 1164–1175, 2019. DOI: 10.1016/j.apenergy.2019.03.117.

[42] J. Lee, "Optimization of a modular drone delivery system," in *2017 Annual IEEE International Systems Conference (SysCon)*, IEEE, 2017. DOI: 10.1109/syscon.2017.7934790.

[43] G. Hetzke, "Feinstaub, nox, co2 – was ist eigentlich was?" *Deutschlandfunk*, Jul. 19, 2017. [Online]. Available: https://www.deutschlandfunk.de/luftverschmutzung-feinstaub-nox-co2-was-ist-eigentlich-was.1773.de.html?dram:article_id=391466 (visited on 11/02/2019).

[44] *Fast Facts - U.S. Transportation Sector Greenhouse Gas Emissions 1990-2017*. United States Environmental Protection Agency (EPA), Office of Transportation and Air Quality, 2019. [Online]. Available: https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100WUHR.pdf (visited on 10/31/2019).

[45] "Annual european union greenhouse gas inventory 1990–2017 and inventory report 2019," European Environment Agency (EEA), May 27, 2019. [Online]. Available: https://www.eea.europa.eu//publications/european-union-greenhouse-gas-inventory-2019 (visited on 10/31/2019).

[46] J. K. Stolaroff, C. Samaras, E. R. O'Neill, A. Lubers, A. S. Mitchell, and D. Ceperley, "Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery," *Nature Communications*, vol. 9, no. 1, 2018. DOI: 10.1038/s41467-017-02411-5.

[47] A. Goodchild and J. Toy, "Delivery by drone: An evaluation of unmanned aerial vehicle technology in reducing CO 2 emissions in the delivery service industry," *Transportation Research Part D: Transport and Environment*, vol. 61, pp. 58–67, 2018. DOI: 10.1016/j.trd.2017.02.017.

[48] "Air pollution," World Health Organization (WHO), May 2, 2018. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (visited on 11/02/2019).

[49] S. Bouton, E. Hannon, L. Haydamous, B. Heid, S. Knupfer, T. Naucler, F. Neuhaus, J. Tijs Nijssen, and S. Ramanathan, *An integrated perspective on the future of mobility, part 2, Transforming urban delivery*. McKinsey Center for Business and Environment, McKinsey&Company, Sep. 2017, p. 14. [Online]. Available: https://www.mckinsey.com/~/media/mckinsey/business%20functions/sustainability/our%20insights/urban%20commercial%20transport%20and%20the%20future%20of%20mobility/an-integrated-perspective-on-the-future-of-mobility.ashx (visited on 10/12/2019).

[50] B. Wehrmann, *Air pollution remains too high in nearly 60 german cities – environment agency*, Jun. 2019. [Online]. Available: https://www.cleanenergywire.org/news/air-pollution-remains-too-high-nearly-60-german-cities-environment-agency.

[51] P. E. Luis Mejias Daniel Fitzgerald and X. Liu, *Aerial Vehicles*, T. M. Lam, Ed. IntechOpen, Jan. 1, 2009, ch. Forced Landing Technologies for Unmanned Aerial Vehicles: Towards Safer Operations, 780 pp., ISBN: 9537619419. [Online]. Available: https://www.ebook.de/de/product/36334387/aerial_vehicles.html (visited on 11/03/2019).

[52] C. Forrest, "17 drone disasters that show why the faa hates drones," *Innovation*, 2018. [Online]. Available: https://www.techrepublic.com/article/12-drone-disasters-that-show-why-the-faa-hates-drones/ (visited on 11/01/2019).

[53] A. Susini, "A technocritical review of drones crash risk probabilistic consequences and its societal acceptance," *RIMMA Risk Information Management, Risk Models, and Applications*, vol. 7, pp. 27–38, 2015. [Online]. Available: https://www.researchgate.net/profile/Alberto_Susini/publication/291697791_A_Technocritical_Review_of_Drones_Crash_Risk_Probabilistic_Consequences_and_its_Societal_Acceptance/links/56a5365a08ae232fb207a641.pdf (visited on 11/01/2019).

[54] J. Biggs, "Researchers train drones to use wi-fi to look through walls," *TechCrunch*, 2017. [Online]. Available: https://techcrunch.com/2017/06/19/researchers-train-drones-to-use-wi-fi-to-look-through-walls/ (visited on 11/01/2019).

[55] B. Holt, "The herrera bladeless drone drops the blades for a safer and quieter design," *The Manual*, 2017. [Online]. Available: https://www.themanual.com/outdoors/herrera-bladeless-drone-concept/ (visited on 11/01/2019).

[56] The Daily Caller, "Drone deliveries in us stalled by more regulations," *Small Business Trends*, Nov. 2017. [Online]. Available: https://smallbiztrends.com/2016/12/faa-drone-regulations.html.

[57] "How do consumers feel about drones delivering their packages?" *Retail & Ecommerce*, 2016. [Online]. Available: https://www.emarketer.com/Article/How-Do-Consumers-Feel-About-Drones-Delivering-Their-Packages/1014138 (visited on 11/01/2019).

[58] A. Williams, "Defining autonomy in systems: Challenges and solutions," *Issues for Defence Policymakers*, p. 27, 2015. [Online]. Available: https://www.act.nato.int/images/stories/media/capdev/capdev_02.pdf (visited on 10/24/2019).

[59] "Automation & autonomy: What's the difference?," Caterpillar, Ed., [Online]. Available: https://www.catallday.com/articles/challenges/technology/automation-autonomy-whats-difference/ (visited on 10/15/2019).

[60] J. L. Yang, *Fortune 500 2009: Top 100 American Companies – Caterpillar – CAT*. Cable News Network, Inc., May 4, 2009. [Online]. Available: https://money.cnn.com/magazines/fortune/fortune500/2009/snapshots/81.html (visited on 10/16/2019).

[61] H. Chen, X. min Wang, and Y. Li, "A survey of autonomous control for UAV," in *2009 International Conference on Artificial Intelligence and Computational Intelligence*, IEEE, 2009. DOI: 10.1109/aici.2009.147.

[62] T. B. Sheridan and W. L. Verplank, "Human and computer control of undersea teleoperators," Man-Machine Systems of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge Massachusetts, Tech. Rep., 1978, pp. 8–17. [Online]. Available: https://apps.dtic.mil/dtic/tr/fulltext/u2/a057655.pdf (visited on 10/17/2019).

[63] B. T. Clough, "Metrics, schmetrics! how the heck do you determine a uav's autonomy anyway," Air Force Research Laboratory, Wright-Patterson Air Force Base, Ohio, Tech. Rep., 2002. [Online]. Available: https://apps.dtic.mil/dtic/tr/fulltext/u2/a515926.pdf (visited on 10/17/2019).

[64] W. S. Angerman, "Coming full circle with boyd's ooda loop ideas, An analysis of innovation diffusion and evolution," Master's thesis, Air Force Institute of Technology, Wright-Patterson AFB OH School of Engineering and Management, 2004. [Online]. Available: https://apps.dtic.mil/dtic/tr/fulltext/u2/a425228.pdf (visited on 10/19/2019).

[65] S. Ross, N. Melik-Barkhudarov, K. S. Shankar, A. Wendel, D. Dey, J. A. Bagnell, and M. Hebert, "Learning monocular reactive UAV control in cluttered natural environments," in *2013 IEEE International Conference on Robotics and Automation*, IEEE, 2013. DOI: 10.1109/icra.2013.6630809.

[66] Oxford University Press (OUP), "Navigation," *Lexico.com*, 2019. [Online]. Available: https://www.lexico.com/en/definition/navigation (visited on 11/08/2019).

[67] M. Lazzaroni, L. Cristaldi, L. Peretto, P. Rinaldi, and M. Catelani, *Reliability Engineering*. Springer Berlin Heidelberg, 2011. DOI: 10.1007/978-3-642-20983-3.

[68] J. Verbeke and J. D. Schutter, "Experimental maneuverability and agility quantification for rotary unmanned aerial vehicle," *International Journal of Micro Air Vehicles*, vol. 10, no. 1, pp. 3–11, 2017. DOI: 10.1177/1756829317736204.

[69] Oxford University Press (OUP), "Agility," *Lexico.com*, 2019. [Online]. Available: https://www.lexico.com/en/definition/agility (visited on 11/08/2019).

[70] M. S. Whalley, "Development and evaluation of an inverse solution technique for studying helicopter maneuverability and agility," United States Army Aviation Systems Command (USAAVS-COM), National Aeronautics and Space Administration (NASA), Tech. Rep. NASA TM 102889, USAAVS-COM TR 90-A-008, Jul. 1991. [Online]. Available: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19910022831.pdf (visited on 11/07/2019).

[71] T. H. Lawrence, S. Corning, and F. Wharburton, "Helicopter maneuverability and agility design sensitivity and air combat maneuver data correlation study," United States Army Aviation Systems Command (USAAVSCOM), Tech. Rep. USAAVSCOM TR 91-D-3, Oct. 1991. [Online]. Available: https://apps.dtic.mil/dtic/tr/fulltext/u2/b160550.pdf (visited on 11/07/2019).

[72] E. Kaufmann, A. Loquercio, R. Ranftl, A. Dosovitskiy, V. Koltun, and D. Scaramuzza, "Deep drone racing: Learning agile flight in dynamic environments," *Conference on Robotic Learning (CoRL), 2018*, Jun. 22, 2018. arXiv: http://arxiv.org/abs/1806.08548v3 [cs.RO].

[73] R. Mur-Artal, J. M. M. Montiel, and J. D. Tardos, "ORB-SLAM: A versatile and accurate monocular SLAM system," *IEEE Transactions on Robotics*, vol. 31, no. 5, pp. 1147–1163, 2015. DOI: 10.1109/tro.2015.2463671.

[74] A. Bircher, M. Kamel, K. Alexis, H. Oleynikova, and R. Siegwart, "Receding horizon path planning for 3d exploration and surface inspection," *Autonomous Robots*, vol. 42, no. 2, pp. 291–306, 2016. DOI: 10.1007/s10514-016-9610-0.

[75] T. Cieslewski, E. Kaufmann, and D. Scaramuzza, "Rapid exploration with multi-rotors: A frontier selection method for high speed flight," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, IEEE, 2017. DOI: 10.1109/iros.2017.8206030.

[76] Y. Lin, F. Gao, T. Qin, W. Gao, T. Liu, W. Wu, Z. Yang, and S. Shen, "Autonomous aerial navigation using monocular visual-inertial fusion," *Journal of Field Robotics*, vol. 35, no. 1, pp. 23–51, 2017. DOI: 10.1002/rob.21732.

[77] D. Scaramuzza, M. C. Achtelik, L. Doitsidis, F. Friedrich, E. Kosmatopoulos, A. Martinelli, M. W. Achtelik, M. Chli, S. Chatzichristofis, L. Kneip, D. Gurdan, L. Heng, G. H. Lee, S. Lynen, M. Pollefeys, A. Renzaglia, R. Siegwart, J. C. Stumpf, P. Tanskanen, C. Troiani, S. Weiss, and L. Meier, "Vision-controlled micro flying robots: From system design to autonomous navigation and mapping in GPS-denied environments," *IEEE Robotics & Automation Magazine*, vol. 21, no. 3, pp. 26–40, 2014. DOI: 10.1109/mra.2014.2322295.

[78] I. Sa, M. Kamel, M. Burri, M. Bloesch, R. Khanna, M. Popovic, J. Nieto, and R. Siegwart, "Build your own visual-inertial drone: A cost-effective and open-source autonomous drone," *IEEE Robotics & Automation Magazine*, vol. 25, no. 1, pp. 89–103, 2018. DOI: 10.1109/mra.2017.2771326.

[79] G. Loianno, C. Brunner, G. McGrath, and V. Kumar, “Estimation, control, and planning for aggressive flight with a small quadrotor with a single camera and IMU,” *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 404–411, 2017. DOI: 10.1109/lra.2016.2633290.

[80] F. Sadeghi and S. Levine, “Cad2rl: Real single-image flight without a single real image,” Nov. 13, 2016. arXiv: http://arxiv.org/abs/1611.04201v4 [cs.LG]. [Online]. Available: https://arxiv.org/pdf/1611.04201.pdf (visited on 11/24/2019).

[81] Y. Zhu, R. Mottaghi, E. Kolve, J. J. Lim, A. Gupta, L. Fei-Fei, and A. Farhadi, “Target-driven visual navigation in indoor scenes using deep reinforcement learning,” in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, IEEE, 2017. DOI: 10.1109/icra.2017.7989381.

[82] J. Meyer, A. Sendobry, S. Kohlbrecher, U. Klingauf, and O. von Stryk, “Comprehensive simulation of quadrotor UAVs using ROS and gazebo,” in *Simulation, Modeling, and Programming for Autonomous Robots*, Springer Berlin Heidelberg, 2012, pp. 400–411. DOI: 10.1007/978-3-642-34327-8_36.

[83] M. Faessler, A. Franchi, and D. Scaramuzza, “Differential flatness of quadrotor dynamics subject to rotor drag for accurate tracking of high-speed trajectories,” *IEEE Robotics and Automation Letters*, vol. 3, no. 2, pp. 620–626, 2018. DOI: 10.1109/lra.2017.2776353.

[84] S. Shah, D. Dey, C. Lovett, and A. Kapoor, “AirSim: High-fidelity visual and physical simulation for autonomous vehicles,” in *Field and Service Robotics*, Springer International Publishing, 2017, pp. 621–635. DOI: 10.1007/978-3-319-67361-5_40.

[85] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, “Carla: An open urban driving simulator,” Nov. 10, 2017. arXiv: http://arxiv.org/abs/1711.03938v1 [cs.LG].

[86] A. Loquercio, A. I. Maqueda, C. R. del Blanco, and D. Scaramuzza, “DroNet: Learning to fly by driving,” *IEEE Robotics and Automation Letters*, vol. 3, no. 2, pp. 1088–1095, 2018. DOI: 10.1109/lra.2018.2795643.

[87] A. Giusti, J. Guzzi, D. C. Ciresan, F.-L. He, J. P. Rodriguez, F. Fontana, M. Faessler, C. Forster, J. Schmidhuber, G. D. Caro, D. Scaramuzza, and L. M. Gambardella, “A machine learning approach to visual perception of forest trails for mobile robots,” *IEEE Robotics and Automation Letters*, vol. 1, no. 2, pp. 661–667, 2016. DOI: 10.1109/lra.2015.2509024.

[88] N. Smolyanskiy, A. Kamenev, J. Smith, and S. Birchfield, “Toward low-flying autonomous MAV trail navigation using deep neural networks for environmental awareness,” in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, IEEE, 2017. DOI: 10.1109/iros.2017.8206285.

[89] K. Kelchtermans and T. Tuytelaars, “How hard is it to cross the room? – training (recurrent) neural networks to steer a uav,” Feb. 24, 2017. arXiv: http://arxiv.org/abs/1702.07600v1 [cs.CV].

[90] O. Team, “Camera calibration and 3d reconstruction,” *OpenCV Documentation*, Dec. 4, 2019. [Online]. Available: https://docs.opencv.org/2.4/modules/calib3d/doc/camera_calibration_and_3d_reconstruction.html (visited on 12/04/2019).

[91] M. W. Mueller, M. Hehn, and R. D'Andrea, "A computationally efficient algorithm for state-to-state quadrocopter trajectory generation and feasibility verification," in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, IEEE, 2013. DOI: 10.1109/iros.2013.6696852.

[92] M. Faessler, F. Fontana, C. Forster, and D. Scaramuzza, "Automatic re-initialization and failure recovery for aggressive flight with a monocular vision-based quadrotor," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, IEEE, 2015. DOI: 10.1109/icra.2015.7139420.

[93] D. Mellinger and V. Kumar, "Minimum snap trajectory generation and control for quadrotors," in *2011 IEEE International Conference on Robotics and Automation*, IEEE, 2011. DOI: 10.1109/icra.2011.5980409.

[94] S. Hessinger, "Ups considers delivery drones too," *Small Business Trends*, Dec. 2013. [Online]. Available: https://smallbiztrends.com/2013/12/ups-delivery-drones.html.

[95] D. Elliot, "Dhl testing delivery drones," *CBS News*, 2013.

[96] A. C. Madrigal, "Inside google's secret drone-delivery program," *The Atlantic*, Aug. 2014.

[97] M.-A. Russon, "Dhl to launch parcelcopter medicine drone delivery service to remote german island," *IBTimes*, Sep. 2014. [Online]. Available: https://www.ibtimes.co.uk/dhl-launch-parcelcopter-medicine-drone-delivery-service-remote-german-island-1467141.

[98] F. Bermingham, "Fedex researching drone delivery but not for widespread use," *IBTimes*, Oct. 2014. [Online]. Available: https://www.ibtimes.co.uk/fedex-researching-drone-delivery-not-widespread-use-1471063.

[99] H. Samuel, "France's la poste develops drone to deliver parcels," *The Telegraph*, Dec. 2014. [Online]. Available: https://www.telegraph.co.uk/news/worldnews/europe/france/11313044/Frances-La-Poste-develops-drone-to-deliver-parcels.html.

[100] J. Barrie, "Drones are delivering ginger tea in china," *Business Insider*, Feb. 2015. [Online]. Available: https://www.businessinsider.com/alibabas-tea-delivery-drones-in-china-2015-2?IR=T.

[101] XAircraft, *Sf-express logistics uav by xaircraft*, Mar. 2015. [Online]. Available: https://www.youtube.com/watch?v=NOJd7x2fqBE&index=17&list=PLL3t5xY2V44xOxvTIxS4AHuUhFE_bMwhz.

[102] FPS, *Fps takes flight with first commercial uk drone delivery*, Mar. 2015. [Online]. Available: https://fpsdistribution.com/fps-take-flight-with-1st-commercial-uk-drone-delivery/.

[103] "Cj group unveils cargo-carrying drones," *Post & Parcel*, May 2015. [Online]. Available: https://postandparcel.info/65116/news/cj-group-unveils-cargo-carrying-drones/.

[104] Flirtey, *Flirtey making history with the first us drone delivery*, Jul. 2015. [Online]. Available: https://www.youtube.com/watch?v=xEm7bI_meQY.

[105] "Flirtey and 7eleven hail home drone delivery," *Post & Parcel*, Jul. 2016. [Online]. Available: https://postandparcel.info/74430/news/faa-approved-home-drone-delivery/.

[106] Amazon, *Amazon prime air's first customer delivery*, Dec. 2016. [Online]. Available: https://www.youtube.com/watch?v=vNySOrI2Ny8.

[107] P. E. Ross, "Iceland's consumers try drone delivery: The startup aha takes on amazon with basic drones bearing burgers - [news]," *IEEE Spectrum*, vol. 55, no. 10, pp. 12–13, 2018. DOI: 10.1109/mspec.2018.8482412.