A methodology to monitor multiple Asphalt Paving and Compaction Machineries using UAV and implementing it in a road construction project

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Preface

In the first module of the BSc Civil Engineering degree, the class had a one-day excursion at a Hot Mix Asphalt (HMA) production plant and a visit to a road construction site. I was fascinated about how a road is constructed and wanted to learn more about it. This subject was not extensively covered in the curriculum, therefore I chose to investigate it in my thesis to broaden my knowledge in the materials and construction techniques generally used in the Civil Engineering sector. Additionally, I have always been passionate about flying drones, so investigating the use of UAVs for the surveillance of asphalt paving and compaction operations really enticed me.

Working on this report was a long and challenging journey, as it also required to learn Python programming language, which I had little knowledge about before. However, I am really happy for this experience as it required to push myself to learn new skills which I'm most certain will be very useful in the future. I want to thank first and foremost my internal supervisor Shen Qinshuo for his outstanding support and assistance from the beginning to the end. His academic expertise and knowledge in the road construction sector, helped me become a better researcher and taught me how to perform an organised and thorough research. His optimistic outlook was especially helpful as it gave me confidence when I felt doubtful. I would like to thank my internal supervisor Fariddadin Vahdatikhaki for supporting me with his extensive understanding of asphalt paving operations and monitoring, as well as for his encouragement and assistance in making sure my thesis had all the necessary elements. I want to thank Seirgei Miller for first introducing me to the subject of this thesis, for sharing his extensive expertise of asphalt paving operations with me, and for putting me in touch with the right people.

I also want to thank my external supervisors, Cor Uiterwijk and Reinier Blokhuis for their constant support and availability throughout the execution of the thesis. Their professional expertise has helped me greatly in improving and progressing my research.

I wish to thank drone experts from Boskalis, Michiel Klomp and Corné Klaver, for welcoming me in their office in Lelystad, showing me their drone and explaining me its functionalities and real applications, which helped me in the case study. By going to a real road construction site, I had the opportunity to witness first-hand the step-by-step process to construct a road. I would like to thank Boskalis site surveyor, Geert de Winter, for his guidance and assistance during the experiment at the site, as well for taking the time to collect data, used to analyse the method proposed in this thesis. I want to thank Michiel Klomp once more for his presence on the experiment day, for flying the drone and ensuring the safety of everyone on the job site. As well for gathering aerial videos that were essential to the success of my thesis, and for demonstrating to me how a drone professional should operate and behave while on the job.

My BSc in Civil Engineering at the University of Twente comes to a conclusion with the completion of this thesis, and I would like to thank my family and all of my friends for their encouragement and support throughout the execution of this thesis and throughout my degree!

Gianluca Belardo, 29/08/2022

Abstract

Roads are an essential part of the urban infrastructure. Their quality and durability directly influence the safety and economy of a country and the life of its’ population. During road construction there are a lot of aspects that influence the quality of an asphalt layer, temperature being one of the most prominent ones. If the asphalt layer becomes too cold, its consistency becomes too thick to compact, on the contrary if the layer is too hot, the asphalt will only get displaced instead of being compacted. The way the machineries are operated is one of the most important aspects to manage these fluctuations in temperatures and thus the quality of the final layer. The operators of these machineries often follow their own personal intuitions and knowledge they have gained in previous works. At times, not following a clear process for the paving operations can lead to a suboptimal quality of the asphalt layer. In 2016, Christiaan G. Arbeider, developed a plan that allows for a more consistent and uniform paving process. In his research he determined that it is as important to monitor the operations in real time. The technology that was used in his research, still used nowadays to monitor road construction operations, is based on GPS (Global Positioning system). This technology is not very efficient and presents a number of drawbacks, with the main one being the degree in inaccuracy. The research presented in this thesis, provides an alternative method which makes use of UAVs. The method was initially investigated by Shihao Sun in 2019, at the time a student at the University of Twente, who showed promising results. Its research, however, lacked the application of the method at a real construction site, and it didn’t have concrete results in the degree of accuracy that this method can provide. The research in this paper attempts to establish a clear framework for the implementation of this method, based on a real-life case study at a construction site. The research will also demonstrate how accurate this method is, and whether it is more suitable in terms of accuracy and precision than the more traditional method which makes use of GPS rovers.

Abstract (Dutch version)

Wegen zijn een essentieel onderdeel van de stedelijke infrastructuur. Hun kwaliteit en duurzaamheid hebben een directe invloed op de veiligheid en economie van de bevolking van een land. Bij de aanleg van wegen zijn er veel aspecten die de kwaliteit van een asfaltlaag beïnvloeden, waarvan de temperatuur een van de meest prominente is. Als de asfaltlaag te koud wordt, wordt de consistentie te dik om te verdichten, daarentegen als de laag te heet is, zal het asfalt alleen maar verschuiven in plaats van verdichten. De manier waarop de machines worden bediend, is een van de belangrijkste aspecten om deze temperatuurschommelingen en daarmee de kwaliteit van de laag te beheersen. De operators van deze machines volgen vaak hun eigen persoonlijke intuïties en kennis die ze in eerdere werken hebben opgedaan. Soms kan het ontbreken van een duidelijke structuur in het verhardingsproces leiden tot een slechtere kwaliteit asfaltlaag. In 2016 ontwikkelde Christiaan G. Arbeider een plan dat zorgt voor een consistenter en uniformer bestratingsproces. In zijn onderzoek stelde hij vast dat het net zo belangrijk is om de operaties in realtime te volgen. De technologie die in zijn onderzoek werd gebruikt en tegenwoordig nog steeds wordt gebruikt om deze operaties te volgen, is GPS. De laatste is een inefficiënte techniek met een aantal nadelen, waarvan de belangrijkste de mate van onnauwkeurigheid is. Het onderzoek dat in dit proefschrift wordt gepresenteerd, biedt een alternatieve methode die gebruik maakt van UAV's. De methode is in 2019 voor het eerst onderzocht door Shihao Sun, destijds student aan de Universiteit Twente, die veelbelovende resultaten liet zien. Zijn onderzoek miste echter de toepassing van de methode op een echte bouwplaats en had geen concrete resultaten in de mate van nauwkeurigheid die deze methode biedt. Het onderzoek in dit artikel probeert een duidelijke structuur vast te stellen voor de implementatie van deze methode, met een real-life case study op een bouwplaats. Het onderzoek zal ook bepalen hoe nauwkeurig deze methode is, en of deze nauwkeuriger is dan de meer traditionele methode die gebruik maakt van GPS-rovers.

Table of Contents

Glossary of terms

GNSS – Global Navigation Satellite System (Global system)

GPS – Global Positioning System (USA system). The rovers deployed in the Netherlands today utilise a number of different satellite systems that are part of the GNSS. However, for easier terminology throughout the report GPS will be used to refer to GNSS.

UAV – Unmanned Aerial Vehicle. Drones and UAV are used interchangeably in this paper.

AEC – Architecture, Engineering and Construction

HMA – Hot Mix Asphalt

DTW – Dynamic Time Warping

Python – High level programming language

OpenCV – Computer vision library accessible in Python

ArUco – Open-source library for camera pose estimation using squared markers

Feature markers – Markers on the side of the road that each have their GPS location registered

Target markers – Markers representing the machinery that is being tracked

PQI – Process Quality Improvement

BLE – Bluetooth Low Energy

EASE – European Aviation Safety Agency

RTK – Real Time Kinematic

LIDAR – Laser Imaging Detection and Ranging

U-blox – Wireless modules

Introduction

According to the United Nations, the world's population will reach 9.7 billion people in 2050, and by 2030, 61 percent of people will live in urban areas (UN, 2019). Urbanization has been shown to directly correlate with an increase in transportation (Aljoufie, Zuidgeest, Brussel, & van Maarseveen, 2011). This will have a stronger impact on the infrastructure, particularly the roadways, which emphasises the significance of having stable and long-lasting asphalt layers. The quality and durability of the asphalt pavement are tremendously influenced by the construction process. Naturally, there are several challenges to building high-quality roads, with temperature and time standing out as the two main ones.

The first stage in making roads starts at an asphalt production plant, where asphalt gets produced and heated up to 150-190°C, also known as Hot Mix Asphalt (HMA) (Vidal, Moliner, Martínez, & Rubio, 2013). The asphalt mixture gets transported to a construction site where the paver lays down and spreads the asphalt to the desired thickness, and finally the rollers compact the asphalt to a certain density (Vasenev, Dorèe, & Hartmann, 2012). As soon as the asphalt is produced, the temperature gradually drops; as a result, the asphalt becomes more rigid and more challenging to compact to the desired density. On the other hand, if the mixture temperature is too high, the consistency becomes softer and the rollers will just displace the asphalt instead of compacting it, resulting in permanent deformation of the layer (Bahia, Fahim, & Nam, 2006).

Over the years, it has been discovered that operational control techniques used on the construction site, which control how the different strategies were conducted on-site to perform construction activities and corresponding construction equipment , have a significant impact on the overall quality and lifetime of the roads (Makarov, 2017). These machines need to be closely monitored because if interventions are not taken right away, permanent deformations and non-optimal density may result. Over the past years, various operational control techniques have enabled the monitoring of key construction characteristics, including the movement of the machineries and the temperature of the asphalt over time, using Global Positioning System (GPS) and thermal sensors (Oloufa, 2002). Various systems utilise GPS, and the technique used by ASPARi is known as PQi, which stands for Process Quality improvement. The latter cycle's aim is to precisely measure the relevant process parameters and record the team's behaviour while paving asphalt (ter Huerne, Oosterveld, Moenielal, & Dekkers, 2012). The accuracy of the GPS system used by ASPARi to monitor the machinery is about 10 cm. However, the accuracy that this technology offers is occasionally inconsistent due to signal interference from outside objects. If the method is used in the proximity of common objects, such as buildings, trees, and plants, the quality of signal may be so affected that accuracy in monitoring the machinery is heavily degraded if not completely lost at all. In addition, the setup for this technique can be very challenging, time-consuming and costly to deploy which makes it an ineffective method (Sholes, 2020).

A novel technology, unmanned aerial vehicles (UAVs), which has improved in intelligence and adaptability over the past ten years, may be able to address the aforementioned problems. Numerous case studies in the AEC sector have investigated UAVs, and the majority of them have shown very encouraging findings, especially in terms of their capacity for 3D mapping and surveying, as shown in a research by (Hallerman, Morgenthal, & Rodehorst, 2015) for the inspection of concrete dams. Similarly as investigated by (Li & Liu, 2018) drones showed outstanding performance for land surveying and emphasized their ease of use compared to the application of GPS. Drones are so versatile and adaptive to the environment that can be used for dangerous jobs that would otherwise be done by humans; for instance in a research conducted by (Mullenders, 2019), drones demonstrated to be very effective in the inspections of offshore platforms in the oil and gas industry.

When it comes to the domain of road construction, Sun suggested with his research a drone-based technique as an alternative to the widely used GPS (Sun, 2019). In simple terms, the technique involved using posters with identifiable codes printed on them, which can be detected and tracked using a computer vision algorithm. Although Sun’s research has showed some positive results in machine tracking, it lacked the use of the method in a real-life context and was only applied to the monitoring of one machinery. Additionally, there is no comparison with a more traditional monitoring method such as the GPS system used in the PQi cycle.

On these premises, this research aims to provide a clearer understanding and planning of this method at a real construction site, as well as discussion regarding the various potential obstacles. In essence, the method in question makes use of identifiable markers, visually similar to ‘QR codes’, that are placed on the machinery and systematically on the road construction site. Through the video data retrieved from the drone and the use of an algorithm, multiple machineries can be detected and monitored.

A case study at a Boskalis road construction site is used to assess the proposed algorithm and the overall methodology. To follow the processes in the research, including data collection, data processing, and data analysis, a system framework and conceptual model are first obtained from the literature review. In the case study the accuracy that this system provides for tracking multiple machines will be investigated and evaluated, as well as presenting a comparison with a conventional GPS tracking device.

Research gaps

To the best of the author’s knowledge, there are not many additional research on the subject since Sun's report was published, so there are still a number of aspects that have not been addressed or further examined. First of all, Sun's research lacks the application of this method at a real construction site because it was conducted in a simulated environment. Consequently, there are several issues in and of itself that need to be addressed, such as how the method may be set up at a site properly, without interfering with the construction activities. An actual comparison between this method and a more traditional way for tracking the machineries, as well as details about the accuracy this method offers for the detection of multiple machineries, are lacking in the literature.

Research objective

The aim of this project is to achieve a clearer understanding of the application of UAV as a monitoring method for the paving and compaction operations. This research will aim to extend Sun’s research by focusing on the real-life application of the method. A clear plan for its application at an asphalt paving site is currently lacking in literature, and this research will aim to fill that void. This research will make use of the knowledge gained at a real construction site and from the previous studies in this field, and discuss what are the drawbacks or aspects that need to be changed in order to avoid implementation issues, expedite the system’s setup and promote visibility. An additional aim is to develop a system that can accurately track multiple objects with two most identifiable moving patterns on road construction sites, along with discussing the possibility of using the proposed method as an alternative to the more conventional method used on sites.

On these premises, the objective of this research is:

To develop and validate a UAV-based machinery monitoring system with up-to-date visual-based techniques to measure and improve the asphalt construction operations.

Research questions

How and to which extent can UAVs and visual-based techniques be used to detect real-time locations of machinery considering accuracy, scalability, robustness, and efficiency?

1. What are the mechanisms of UAV in object detection and how do all the elements of the system work together?

When working with the proposed method there are various elements, each with different coordinate systems. By researching each element thoroughly, the system can more successfully function in its entirety.

2. What is the most appropriate algorithm for multi object detection considering speed, accuracy, scalability, robustness and efficiency?

In addressing the question, the algorithm will be developed with the attempt of providing fast feedback, accurate measurements and support multi-object detection. The algorithm should also be scalable, meaning that it can be extended to different numbers of machines on-site, no matter how many objects want to be detected, the performance on accuracy will not be yielded. The system should also be robust, meaning that it can be functional under any given circumstance or scenario without compromising the performance.

3. What are the parameters involved in the system, what is the output data and what are the corresponding formats?

The method involves various parameters with different outputs and coordinate systems. Each parameter will be researched thoroughly, in order to successfully coordinate all of them and reach a final singular format that can be analysable efficiently.

4. What is the measuring strategy including the method setup and flying strategy?

By using the case study, valuable insights will be gained about the setup of the components of the method and the way they influence each other with the flying strategy. A clearer implementation of the method will be attained after analysing the data from the case study.

Research structure

To give readers a better grasp of the methods and theories employed in the research, the thesis will first go through the literature review. In the latter, the usage of UAVs in the construction sector will first be examined, followed by a focus on the application of this novel technology in the road construction sector. The method as originally presented in Sun's research will next be examined together with additional explanations for how the strategy is put into practise on a building site. The method will next be presented in more detail, including everything from system setup to algorithm logic and operation. The exact steps that should be followed at a site and during post-data processing of the data for the approach are then shown in a flowchart. The case study and all the procedures used to collect the data will next be presented. The collected data will then be investigated in the research paper's subsequent section, which will analyse this data and present the case study's findings. The study concludes with a discussion section that contains a critical evaluation of the system application and recommendations for future research. The algorithm can be found in the Appendices, which will be referred to throughout the thesis.

Literature review

As stated in the paper's introduction, the first stage in the research is establishing a distinct conceptual model, which begins by examining the literature currently available. To do this, it is necessary to first consider why a monitoring system is required and why the construction sector would benefit from one. The report will next go into detail on process monitoring and the associated methods, with a focus in the road construction industry. Then it will examine the numerous UAV types employed in the construction sector and each one's unique advantages. The benefits of further integrating UAVs in this sector are then discussed, along with the utilization of UAVs specifically in the road construction industry.

Construction monitoring

The primary objective of monitoring building projects is to find any undesired deviations from the agreed plan (Gredka, Zioberski, & Dziadosz, 2014). Construction monitoring offers a clearer picture of a project's development and enables to solve issues both before and while they are occurring (Nazari, n.d.). It is an accurate and beneficial technique to verify the quality, accuracy, and progress of a construction project. Thus, the ability to continuously check the progress of the scope of the construction activities is a crucial concern.

Monitoring can have different scopes according to the project that is being monitored. For example, structural health monitoring is meant to ensure the structural reliability in the operation and maintenance phase, while construction process monitoring such as PQi are meant to work for the construction quality assurance and control by monitoring key process characteristics (Song, Wang, & Wang, 2017). The research presented in this paper is focused on the latter type of monitoring, thus the next sub-chapter explores some of the many construction process monitoring applications in the construction industry.

Construction process monitoring and corresponding techniques

Precise, timely, and intuitive information is essential for project managers to successfully control progress at a construction site (Deng, Hong, Luo, & Deng, 2020). A research by Deng et al. provides a system for automated tile progress monitoring that blends building information modelling (BIM) and computer vision. This technique can measure a construction site's progress information automatically, as well as providing graphical real-time progress information. The results of the experiments showed that the method was capable of performing accurate “real-time automatic quantity calculations”. Another research by Lehtonen developed a system to monitor the logistics at construction firms (Lehtonen, 2001). The latter presents results of improvement in the applied process monitoring measures.

These studies lead one to assume that process monitoring might likewise be beneficial for the road construction sector. In the field of road building, process monitoring entails monitoring the crucial elements of asphalt installation and compaction. This entails monitoring the equipment used on site, namely the rollers and pavers used to spread and compact the asphalt. As mentioned in the introduction, the temperature of the asphalt largely influences the final quality of the product, and monitoring these machineries is essential for managing this variable.

Road construction process monitoring

ASPARi being at the forefront in the research of asphalt quality and lifespan, has developed the PQi circle which aims to measure the equipment movement and temperature of the layer of asphalt. To do this the ASPARi research team uses various technologies to inspect the characteristics of asphalt. To measure the temperature and pressure of an asphalt layer, RFID sensors are used, which can also measure the weather conditions and other long-term parameters (Miller, Bijleveld, Erkens, & Anupam, 2015). In regards to monitoring equipment movement, ASPARi uses a number of GPS rovers which estimate the GPS location of the pavers and rollers with a 10 cm accuracy (ter Huerne, Oosterveld, Moenielal, & Dekkers, 2012). Nevertheless, this technique is not optimal due to signal interference caused by external objects and the required large initial investment cost. Another research showed that by using a thermal based technique the movement of the rollers can be tracked (Lu, Dai, & Zaniewski, 2021). In the latter the roller movement was found by using the optical flow technique and the roller's heading direction. Through laboratory and field testing it was found that this technique can achieve a similar accuracy to GPS in position estimation, while also being a cheaper option. Ublox and BLE are additional machine movement tracking technologies that are less expensive than GPS but offer substantially lower precision (Jamshidi, 2021). On the other hand, very accurate position estimation can be achieved with technologies like Lidar and RTK but at a higher cost of investment.

An alternative technology that has made its way in the construction industry in the past years are UAV. UAVs are a relatively cheaper option than GPS, Lidar and RTK, have high video resolution, are able to manoeuvre around obstacles and can cover large areas. Theoretically they may be a solution to the problems mentioned previously from the other technologies. The following section of the literature review will examine the many benefits and drawbacks that drones offer to the construction industry.

Applying drones in the road construction process monitoring

In the introduction of this paper only a few examples of UAV application have been mentioned. However, drones have been used in the construction industry for many more environments such as for the inspection of roads, bridges, wind turbines, power transmission lines, building exteriors, and roofs (Cornwell & Knapp, 2017). They have also been used for tasks such as surveying, mapping, construction monitoring, wetland/environmental, drainage and erosion, traffic monitoring and emergency services. Nowadays, there are four types of drones, namely: Multi rotor drones, Fixed wing drones, Single rotor drones and Fixed wing hybrid drones (Tkáč & Mésároš, 2019).

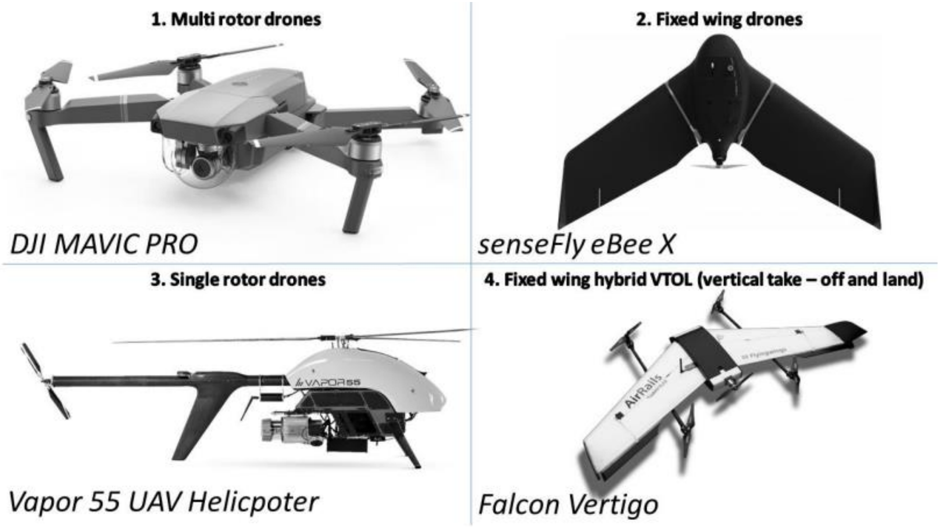

Figure 1: Types of drones, source: (Tkáč & Mésároš, 2019)

Each drone is more capable than others in specific activities. For example, Fixed wing drones are more suitable compared to multi rotor drones in topographic mapping, as they need less energy to function and can cover vaster areas in a shorter time span. However, for more detailed activities such as the mapping of a building, multi rotor drones are a way better choice because they are a lot more manoeuvrable, because of their four motors, and can hover steadily in the air. For most building surveys, it is necessary to visualise and inspect the roof of a building. Usually this task would be done by workers with the use of ladders or other structures, which results it in being dangerous, time consuming and costly.

A surveyor may find it challenging to find an appropriate place to laser scan high-up parts of a building, which results in the point cloud being returned with important data missing (Ayemba, 2022). With laser scanning from drones and aerial photogrammetry techniques, a 3D model can be created in the form of point clouds which includes all the parts that would otherwise be missed with the use of only terrestrial laser scans. The same concept can be applied to other less reachable constructions by humans such as bridges and skyscrapers.

Another efficient use of drones in the construction industry is in finding possible cold and warm spots (e.g., near electric circuits) of a building. This can provide engineers with crucial information they need to find and fix construction flaws (Ayemba, 2022).

Moreover, drone operators have the option of sharing the images with on-site employees, co-workers, and even remote subcontractors (Bourque, 2017). Overall, drones are a highly effective technology which present many benefits for the construction industry, namely their high manoeuvrability, vast area coverage, high accuracy in data collection, ability to present information in real time, medium/high speed, ability to hover in one place in the air, ability to have payloads, reduced danger for workers and lower investment cost.

According to the researcher, there have not been many studies conducted on drone use in the road construction sector, particularly in the process monitoring. A multi-rotor drone is most likely the best drone for process monitoring in road building sites based on the characteristics highlighted in this chapter. This can be inferred from the way construction equipment moves on road construction sites, which is overall very slow and involves repeated back-and-forth motions by the roller. Additionally, because of situations on site such as the re-supply of asphalt in the paver, the UAV should be able to hover steadily in the air and the four motors of the multi rotor drone excellently provide that. The next subchapter goes through some applications of these specific drones in the road construction industry.

UAV usage in the road construction industry

One of the few researches on this topic has developed a system to automatically detect a road construction site using deep learning methods and aerial photographs captured by a drone (Lee, Song, Jun, & Han, 2021). Site managers typically inspect the footage while watching the videos on the screen of the controller. The researchers pointed out that it is difficult to compile progress records or conduct an analysis of the state of the development just by watching a video.

Another study indicated that drones were incredibly accurate when utilised to assess road structure deformations (Varbla, Ellmann, & Puust, 2021). The UAV was flown at elevations of 40, 50, and 60 m, and it was discovered to be much quicker and simpler to use on site, and with less risk to the surveyors compared to the conventional method.

Another study investigates the potential for employing UAVs to monitor deformation at Korean expressway construction sites (Lee, Song, Kim, & Won, 2020). Researchers concluded that UAV photogrammetry is useful for managing construction projects and monitoring deformation, and they highlighted that drone use on construction sites is expected to increase in the years to come.

These examples of drone use at road construction sites, together with the impressive capabilities of UAVs like excellent stability, simple manoeuvrability, and high video quality, give the impression that drones could be very useful for inspecting the machineries used during asphalt paving. The method used in this project and the many components that must be managed are covered in detail in the next section.

Method

Overall concept

The overall concept consists of a tracking method, which was initially researched by Sun (2019), and is based on the use of markers, respectively, feature and target markers. At a construction site the feature markers are distributed at a specific distance between each other on both sides of the road, and their GPS location is registered with land survey equipment. The target markers are allocated on top of the paving equipment, respectively the pavers and the rollers. While these machineries are operated by the construction workers, a drone is flown by a drone pilot at a certain altitude, who will try to keep within the same frame the pavers and rollers, and capture as many feature markers as possible. The image below is a schematic representation of the method.

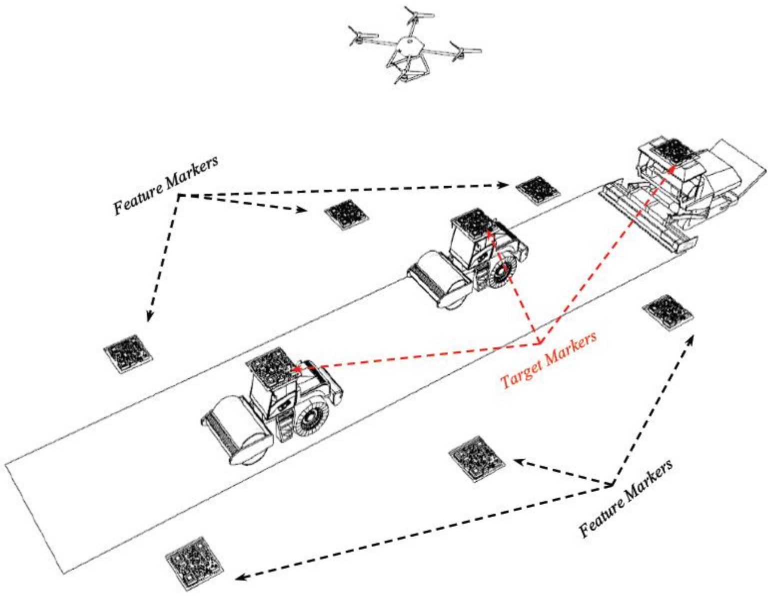

Figure 2: Schematic representation of the method, source: (Sun, 2019)

The output that derive from this method are the video data from the drone and the GPS locations of the feature markers. Through an algorithm developed in Python and by using OpenCV, the GPS location of the target markers can be found. Within OpenCV the ArUco library is present, which comprises of tools to detect and track ArUco markers (OpenCV documentation, n.d.). These markers are binary square fiducial markers, and their detection has been defined as 'robust, fast and simple', mainly because of how distinctly visible they are.

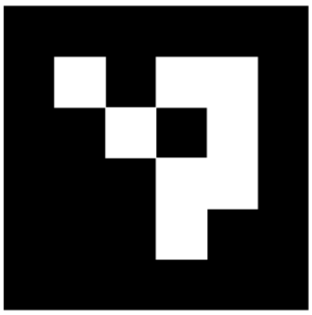

Figure 3: Example of an ArUco marker

Although Sun's research did show promising results in the accuracy that this method provides, his research is not enough to be applied to a construction site. The following sections of the report cover all the necessary components to apply the method on site and promote visibility for the detection of markers.

Flowchart

The method is momentarily not a real-time procedure as that would require for the drone to have a computer connected to it and be able to send a signal to a separate device. It is instead a two-phase procedure composed of the tasks required to be completed on site and in post processing, namely data collection and data analysis.

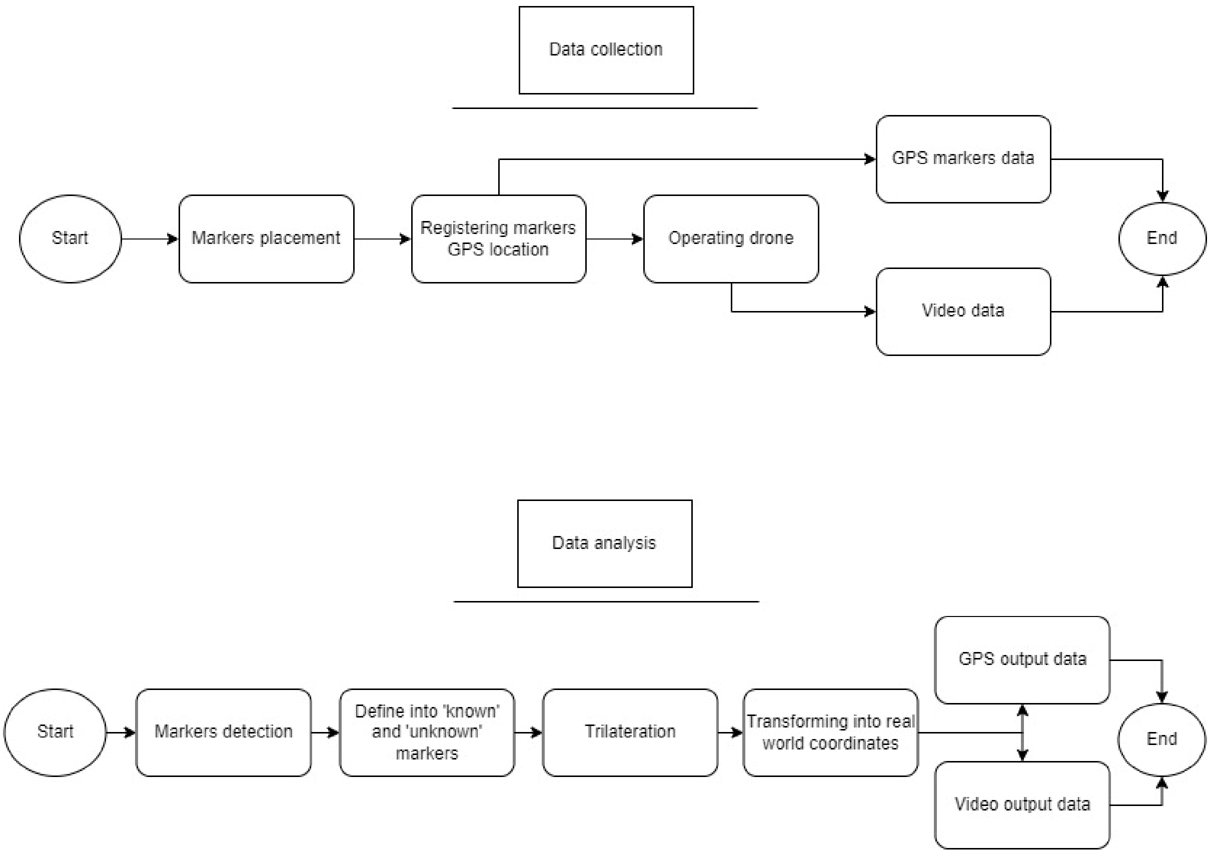

Figure 4: Method's flowchart

Reasoning behind method's choice

As mentioned earlier for the moment this method can only be executed in a 2-phase procedure. But given how quickly technology is developing year after year, it is anticipated that this method will be incorporated into a single, continuous process.

The first step in the data collection phase begins with marker placement as that is the one that requires the most amount of time and can be complicated depending on the machineries involved and the surrounding environment. The markers should be placed at a fixed distance between each other, this should be measured with a construction measuring tape. Immediately after or even simultaneously along with the marker's placement, the GPS location of the centre of each marker can be registered with a GPS surveying device. The latter data points will be used in the data analysis phase for the pose estimation of the machineries. Once the registration is completed, the drone can be activated and flown into the air, while always considering safety measures for the personnel on site. The drone should be flown along the road at a consistent pace while attempting to catch all machinery in one frame. When the drone's battery is close to running out, the drone operator should bring the UAV back to its take-off point and swap out the battery for a fully charged one. Once the data has been retrieved it should be stored in a secure manner and be prepared for the data analysis.

The literature has shown that this marker-based strategy is the most reliable and visually quicker detection method. Additionally, there is little initial expenditure needed because just posters must be printed and a company drone can be employed.

Data collection

The core objective when at the site, is to create an environment that allows the drone to detect as many markers as possible, as visually clear as possible. There are a series of factors that influence the detectability of markers, which are: the marker size, markers registration, flight height, flight orientation, weather conditions and the characteristics of the soil around the road that is being paved.

Marker size

Two factors that must be regulated simultaneously are the size of the markings and the height at which the drone is flying. The UAV would need to fly at a lower height if the marker size is too small for it to be fully visible. When doing this kind of investigation at a construction site, worker safety comes first. Generally according to EU law, drones are not allowed to fly above civilians because doing so could be dangerous in the event of a technical failure or an unanticipated external event (Specific Category - Civil Drones, 2021). However civil drone operations under the 'specific' category, where the operator of the drone ensures safety of the workers on site by getting an operating authorization from the National Aviation Authority prior to beginning the operation. The drone operator must complete a risk assessment in order to receive the operational authorization, which will identify the conditions needed for the civil drone's safe operation. For more information into this topic, the latter reference can be checked.

A drone cannot be flown below a height of 35 metres, as drone expert Michiel Klomp pointed out. Given this, the markers ought to be printed on papers that are at least size A1. For improved detection an A0 paper would be even better, though installing that many on site would be more challenging as they occupy more space and are more costly to print.

Flight orientation

If necessary, the drone's flight orientation can be adjusted while it is being controlled. However, an orientation parallel to the road would be ideal to collect more markers and attempt to follow multiple machines in the same frame.

Weather conditions

For this method to work, the weather conditions shouldn't exceed the litimations set by the EASA. The main factors that should be paid attention to are: high/low temperatures, precipitation and wind.

High/low temperatures do not affect in any way the markers, and the drone is also able to fly, however the flying time substantially decreases if temperatures are too extreme (Kucharczyk, et al., 2021). Commercial drones can usually tolerate temperatures from 0 to 40 degrees Celsius, however that highly depends on the characteristics of the drone itself. In the case study which will be presented in the next section of the thesis, the drone used is the DJI Matrice 300, which can operate in temperatures ranging from -20 to 40 degrees Celsius (Matrice 300 RTK - Specs, n.d.).

Precipitation makes it difficult for most drones to fly because water can easily disrupt the internal mechanisms of the drone. An exception is again the drone that is used in the case study as it has achieved an IP45 rating in a laboratory environment, which makes it very water and dust resistant (Knisely, 2020). Although it is challenging to accurately link these laboratory testing to specific environments, the M300 RTK's IP45 rating indicates that essential, brief missions won't be impeded by light and moderate rain. For more information in the specific weather conditions this drone can endure the latter reference can be checked.

If the *wind speed* is too high, a drone may be less stable and produce shaky video data. The majority of drones today feature level 5 wind resistance, allowing them to fly up to winds of 8.5 to 10.7 metres per second (Posea, 2022). The DJI Matrice, in contrast to a conventional commercial drone, can withstand wind speeds of up to 15 m/s, which makes it a better choice if wind speeds are too strong (Knisely, 2020). Nonetheless, it should be noted that in case of strong winds, markers may fly away if they are not firmly fixed on the ground.

Soil characteristics

For the markers to get detected correctly they should be placed on a flat surface. This can be problematic at road construction sites as, often the terrain can be uneven and consequently it can be difficult to place the markers.

Data management

Once the markers are placed as flat as possible on the sides of the road, the centre of each marker should be registered with land survey equipment. This can be done by a project surveyor or researcher. The subsequently gathered data can then be exported as an excel file and be applied in the algorithm which will be explained in the upcoming section of the report.

Just before the construction operations start, the UAV operator should begin flying the drone. According to DJI, the DJI Matrice can fly up to 50 minutes per charge (Matrice 300 RTK - Specs, n.d.). However, according to drone expert Michiel Klomp because of factors such as resistance to wind and long-term use of the drone, the battery of the DJI Matrice usually lasts up to 30 minutes per charge. Thus, depending on the chosen drone, the battery needs to be changed every specific amount of time during the monitoring of the machines. The data is saved in video format (.mp4) in time intervals.

Data analysis

In this section of the research, the techniques and theories used to track the paving equipment will be described in more detail. The method works in a straightforward manner by first performing the camera calibration, which aims to calibrate the camera's lens, and then performing the marker identification and detection. The third step is to define and separate the markers into two subcategories, “known markers” and “unknown markers”, which respectively represent the feature markers and target markers. Lastly, a technique known as trilateration is used to determine the GPS location of the "unknown markers" at intervals of one second by using the GPS locations of three "known markers."

Camera calibration

Camera calibration is a technique used to determine the drone's camera's slightest deflections so that minor adjustments can be applied (Zhang, 2000). Because the calibration parameters change when zooming in and are no longer reflective of the values discovered when the camera does not employ the zoom functionality, this technique should be used when a camera is fully zoomed out. The DJI Matrice can be equipped with a variety of payloads, but for this case study, the H20 series was chosen for its wide camera. In addition to the latter, the H20 series also has a thermal camera and a zoom camera which can all record footage at the same time.

A purpose of this project is to record videos that can record as many markers as visually clear as possible. In order to accomplish this, it was initially believed that the drone's wide camera would serve as the primary camera because it would have been able to record more markers in a single frame compared to the zoom camera. The algorithm failed to find the markers in the wide camera's footage, as will be further detailed in the case study part of this thesis. However, by using the videos taken by the zoom camera, the markers could be detected. The calibration parameters discovered from the wide camera are therefore disregarded for this research because they are not representative of the zoom functionality for the reasons previously outlined. The procedure for calibrating a camera is described in greater detail in the literature (Zhang, 2000).

ArUco marker detection

The first step in marker detection is the analysis of the video frames, which attempts in finding square shapes that could be identified as markers (OpenCV, n.d.). The markers are first segmented using an adaptive thresholding technique, and then the "thresholded" image is used to extract the square's outlines. The forms in the video frame, are disregarded if they are not comparable to a square.

A reason why Aruco markers are popular detection methods is because they have a thick outer border, as shown previously in Figure 2, which provides a clear and rapidly detectable square shape. It is necessary to examine the candidate square shapes' inner matrices in order to establish if they are in fact ArUco markers. The markers are first put through a perspective transformation, which returns them to their standard form. The image is then separated into cells after being “thresholded” to separate the white and black bits. To determine if a bit is a white or black one, the number of black or white pixels in each cell is counted. As a final step, each cell is checked to see if the marker belongs to the selected ArUco dictionary. The latter can range between 4x4 and 7x7, with the number indicating the number of bits in the inner matrix. These bits are arranged to form a particular ArUco marker with a unique identification number. For instance, the Aruco marker in Figure 2 has the identification number "0" and is a member of the 4x4 dictionary, as it has 4 cells in length and in width.

Coordinate systems

The method relies on the interaction of several coordinate systems, namely:

- Geographic coordinate system
- Camera coordinate system
- Pixel coordinate system

The *Geographic coordinate system* is a spherical coordinate system used to locate any given point's latitude and longitude on the surface of the earth (Geographic coordinate system, n.d.). The coordinates of any point described in that space are defined with regard to the origin of the coordinate system, which is known as the world origin (Computing the Pixel Coordinates of a 3D point, n.d.). Any place on earth can be found as long as there are at least three satellites that can receive a signal. Atomic clocks are used by satellites to provide exceptionally accurate time information (Applications: Timing, n.d.). These signals are decoded by GPS receivers which effectively synchronizes every receiver to the atomic clocks. As a result, the data gets registered in “Degrees, minutes and seconds” also known as DMS format. This data must first be translated to "Decimal degrees" (DD) in order to be used for computations and data analysis. The following formula is used to accomplish this:

$$DD = Degrees + (Minutes/60) + (Seconds/3600)$$

The *Camera coordinate system* is a 3d coordinate system as well, with its origin being at the centre of the camera. Cameras points onto the world coordinate system negative z-axis, such that a point from the world can be converted to camera space and then to the Pixel coordinate system (Computing the Pixel Coordinates of a 3D point, n.d.).

The *Pixel coordinate system* is used to locate points in an image, and is the coordinate system used when the algorithm counts the number of pixels in each cell of the markers.

Marker position estimation and tracking

After the ArUco markers are found, the algorithm starts to distinguish markers into "known" and "unknown" markers. A marker will be referred to as a "known" marker if its GPS coordinates are recorded in the Excel file provided by the site surveyor. On the other hand, if a marker's GPS coordinates are not registered, it will be labelled as an "unknown" marker.

Trilateration is a technique used by satellites to locate any position on earth, as long as there are at least three satellites that can receive a signal. The technique makes use of the geometry of spheres, and the same approach can be used for estimating the position of the “unknown” markers.

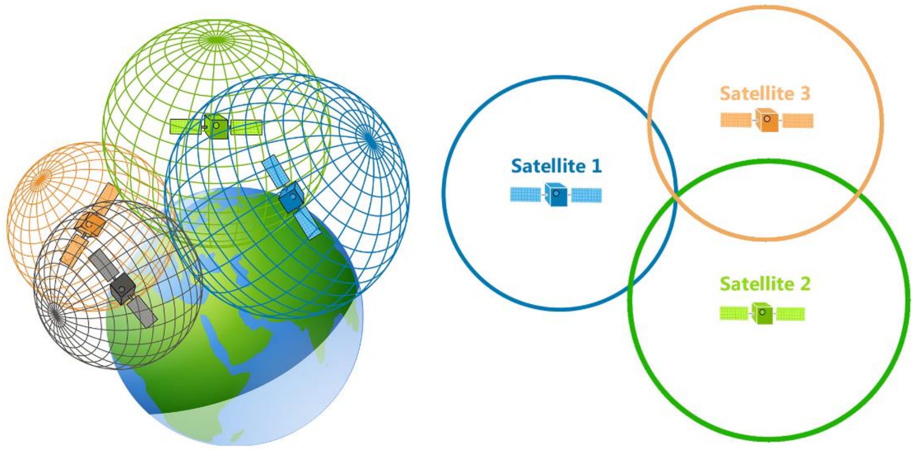

Figure 5: Trilateration visualization in satellites

Before doing the trilateration, the translation between the coordinate systems, 3D to 2D, needs to be accomplished. To do this the metres per pixel need to be found first. This requires to first find the pixel distance between two known points and then for the same points also the distance in the geographic coordinate system.

To calculate the distance between two points in a pixel coordinate system, it is quite straightforward and can be achieved with the following formula:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

The geographic coordinate system is a spherical coordinate system, and to calculate the distance between two points on a sphere, another formula needs to be used. The following is the haversine formula which takes the radius of the earth 'r', and the latitude and longitude of two points to calculate the distance (Haversine formula, n.d.).

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{lat_2 - lat_1}{2}\right) + \cos lat_1 \cdot \cos lat_2 \cdot \sin^2\left(\frac{lon_2 - lon_1}{2}\right)}\right)$$

Once the distance between two points is known in both pixel and geographic coordinate systems, the metres per pixel are found with the following formula:

$$metres\ per\ pixel = \frac{metre\ distance}{pixel\ distance}$$

Next to find the distance between three known markers, A, B and C, and the detected unknown marker is achieved by using the following formula:

$$distance_A = \left(\sqrt{(x_A - x_u)^2 + (y_A - y_u)^2}\right) \cdot metres\ per\ pixel$$

As can be seen in Appendix B, the same formula is applied to the other points B and C. 'x_A' represents the x coordinate in the pixel coordinate system of point A, and 'x_u' represents the x coordinate of the unknown marker. When an ArUco marker is detected in OpenCV, its pixel coordinates are known and that is why 'x_u' and 'y_u' of the unknown marker are also known.

Once the distances of three known points to an unknown point are found, the algorithm for the trilateration can be used. The trilateration code can be found in Appendix A, and it uses various formulas for the determination of latitude and longitude of the unknown markers. For more information into the usage of these formulas, the attached reference can be checked (Trilateration, n.d.).

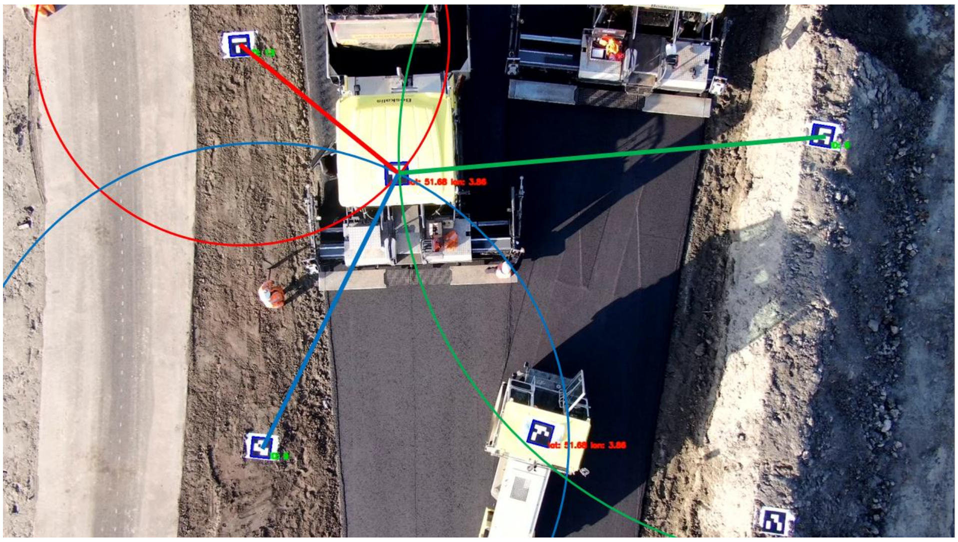

Figure 6: Visual representation of trilateration for the pose estimation of the paver

Implementation and case study

The proposed approach cannot be tested, and the research aim cannot be satisfied in the absence of data or with "poor quality" data. Therefore, the examination of the location and the preparation of the method there are crucial. The site analysis is accomplished by using AutoCAD, a computer-aided design program which allows for precise and real-world measurements (Autodesk, Inc. History, n.d.). The file was made available by a site surveyor from Boskalis, who was present during the experimentation day. The professional opinions and long experience in the field of the site surveyor and drone expert from Boskalis, gave a lot of valuable information for the execution of the experiment.

The experiment took place at a Boskalis construction site near Serooskerke, a small village in the province of Zeeland. The exact geographic coordinates of the site are:

51°40'49.0"N 3°51'39.5"E

The project consisted in the construction of a roundabout along with the paving of the four roads connected to it. The asphalt layer was placed within the magenta and red coloured lines (Figure 7).

Figure 7: AutoCAD project of the roundabout

In total 5 machines were used:

Type of machine	Name	Quantity	Used for experiment
Asphalt Paver	Vogele 1900-3	2	1
Static Roller	Hamm HW90	1	1
Tandem Roller	Hamm DV70	2	0

Table 1: Type of construction machines used on site

Figure 8 is a representation of the start and end points of the pavers and the direction they took throughout the day, each colour representing one paver.

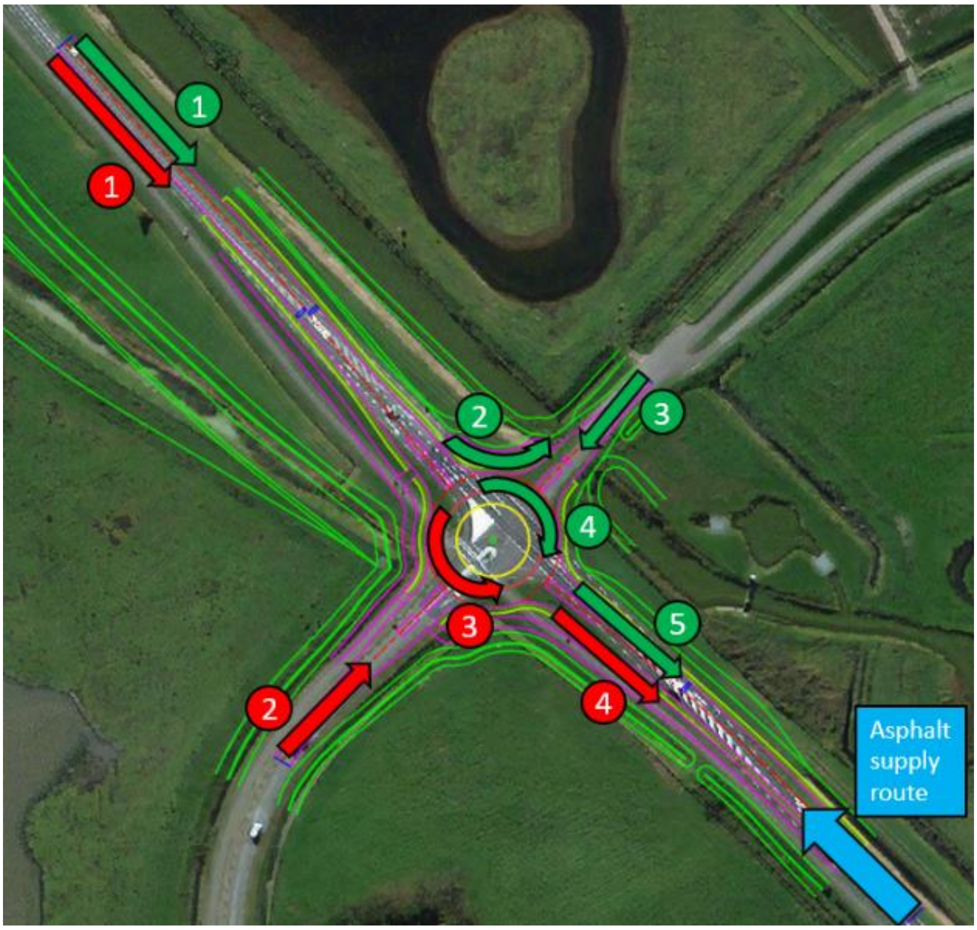

Figure 8: Schematic representation of the direction that the pavers take during the project

Target markers and GPS rovers

Attaching the target markers and GPS rovers to the machinery was the first task the researchers did when they got to the site at around 5:30 am. With tape, the target markers were attached to the machineries as close as possible to the centre of the roof. This task was challenging when doing it to the paver, as it can be difficult to climb on it. It was easier to reach the roof of the roller, however, it was quite difficult to firmly attach the markers because there was rainwater and mud left from previous works. Consequently, there wasn't enough time to add another marker to a roller as the asphalt operations were just starting. An initial goal of the research was to apply the markers on three machineries, namely one paver and two rollers. Nevertheless, two markers on one paver and one roller still satisfies an objective of the research which is to test the algorithm for the tracking of multiple machineries as they represent the two identical moving patterns of machines on-site. The paver moving at a slow and straightforward pace, while the roller moving back and forth repeatedly at a faster pace.

The researcher placed the GPS rovers at a certain distance from the markers, as otherwise the rovers would cover the markers. This is something that will be taken into account in the report's data analysis for this experiment. The data collection for the rovers began at different times, specifically the paver at 05:59:42 and the roller at 06:50:00. This time difference was due to the aforementioned difficulties and also because of the inexperience in applying this new method on a real construction site.

The data from the GPS rovers was registered at one-second intervals and was retrieved in CSV format.

Feature markers

The section indicated in red in Figure 9 was first selected for the experiment because it would have been paved first and would have provided a long enough road for the collection of numerous data points. Unfortunately, because of the previously mentioned problems found while on site, time restrictions and tall grass next to the road, it was quite challenging to place the markers in this area.

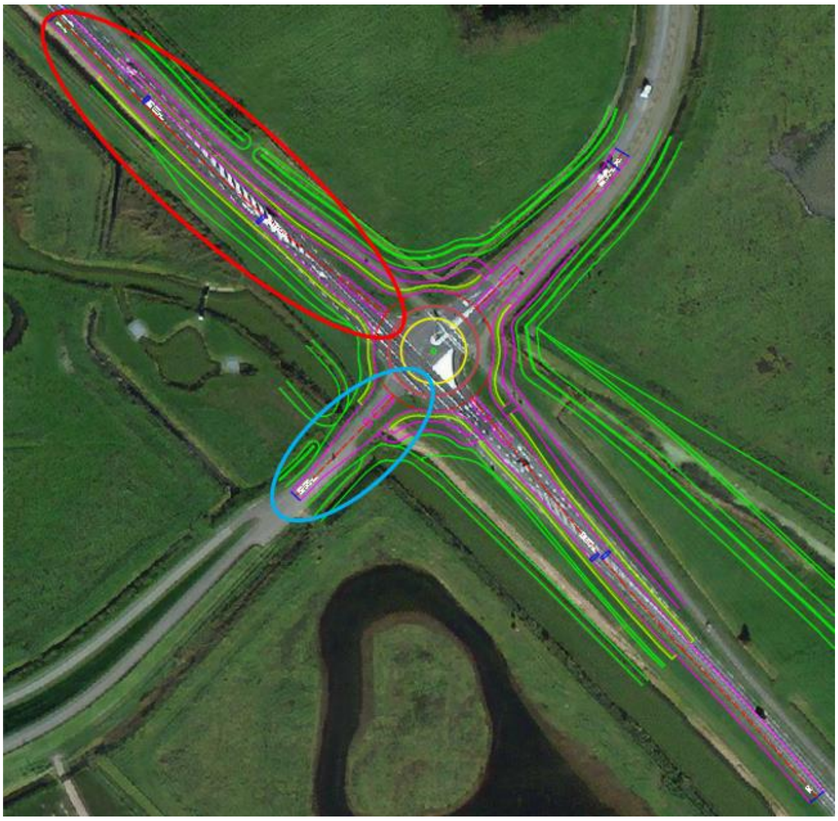

Figure 9: A visual depiction of the road selection for the experiment

The area circled in blue was then chosen, as it was going to be the next section of road to be paved. The conditions of the area next to this road were not optimal but they were better compared to the initial road section for the placement of the markers. While the asphalt operations were being conducted, the researcher placed each marker at an in between 10 metre distance, measured with a construction measuring tape provided by the project surveyor. This distance was chosen according to the video quality that the wide camera of the drone would provide. Additionally, not too many markers were available thus a 10-metre distance was decided. The way the markers were placed on site is shown in figure 10. In total 26 markers were used.

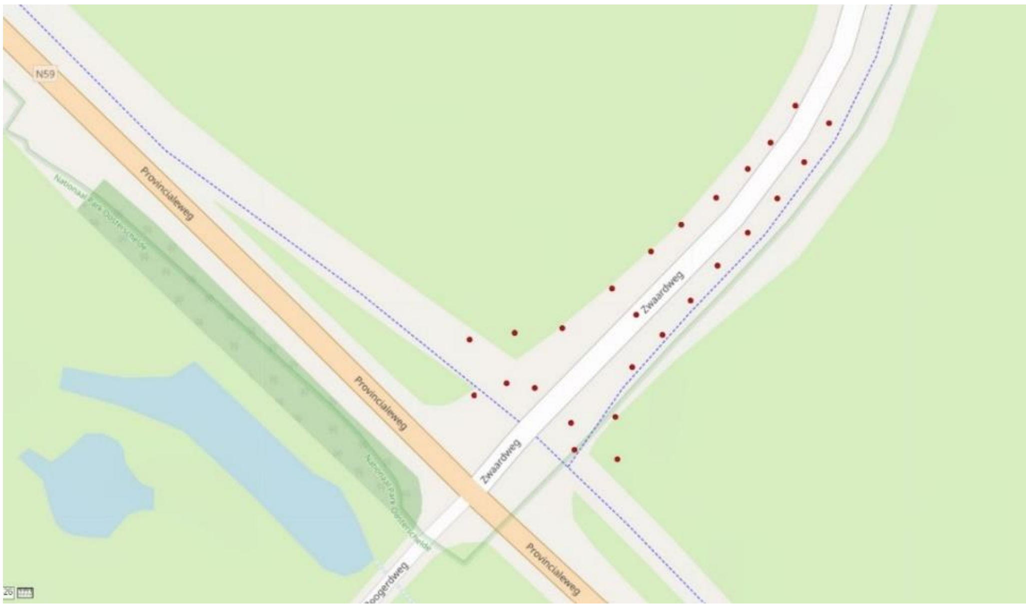

Figure 10: Markers placed on site

Following the placement of each marker, the project surveyor used a GPS surveying device to record the GPS location of the centre point of each marker. The surveyor emphasised that if a point had been marked in the middle of each marker, it would have been faster and easier to do that task. Although the surveyor made every effort to aim at the exact centre, there may be very slight deviations in the exact locations of the markers. The data was then sent to the researcher in Excel format and all the data was converted into decimal degrees (DD).

Figure 11: Image of the chosen road section for the experiment

Drone video data

The drone used for this project is the DJI Matrice 300 RTK with payload Zenmuse H20, provided by the Boskalis drone division. It is a widely used drone across many different industries because of its many functionalities, such as its wide lens and thermal camera, and its high-quality video capabilities.

The drone operator started to fly the DJI Matrice slightly after the beginning of the paving of the chosen road section. The exact time it started recording was at 08:34:55 and the time it finished to record the chosen road was at 09:08:26. That makes the total flight time of 33 minutes and 31 seconds.

The Zenmuse H20 has a wide lens camera, a thermal camera and a zoom camera, and during the experiment all of them were activated at the same time (Zenmuse H20 series: specs, n.d.). The video data was saved at around 5 minutes intervals and for each interval three mp4 files were saved, each one representing the wide lens data, thermal data and zoom data.

The experiment's initial goal was to fit as many markers into a frame as possible in order to improve detection; as a result, the wide lens was primarily employed to record data. Unfortunately, it was later discovered that the markers in the wide lens data couldn't be detected when applying the algorithm because they were too small to be seen. This is mainly due to the fact that the drone could not be flown lower than 35 metres above the ground, for the workers' safety and peace of mind.

On the other hand, the algorithm was successful in detecting the markers while using zoom video data. This is due to the exceptional video quality and the range that the zoom camera provides. However, due to the lower altitude, only a few occasions can both machines be detected simultaneously. The latter is demonstrated in the figure below. The paver moves at a constant slow pace and the roller constantly drives back and forth. As the drone operator was instructed in trying to capture both machineries in the same frame with the wide lens, there are a lot of moments in which only one machinery is detected or none at all.

Figure 12: Example of two machineries being detected by the algorithm on OpenCV

Nevertheless, a significant number of data points from the zoom data were still recorded, and these data were sufficient to analyse the data in the following section of the report.

The drone moved at a slow, steady speed, and even though it moved a little faster, all the markings were still visible enough for the algorithm to find them. This is made possible by the camera's high resolution and frame rate. The drone was flown for the first half of the recording at a height of 45 metres, but as the equipment got closer to the roundabout, it was decided to variate the altitude of the drone, from 35 metres up to 55 metres, to collect more diverse data. Additionally, the drone's orientation was adjusted about this time from “perpendicular” to the road to “parallel” to the road. This would have allowed for the detection of more markers, but the machines had already arrived at the roundabout and could only be seen briefly through the zoom lens.

Data analysis

The data analysis section of the report attempts to evaluate the data collected during the case study. The time the DJI Matrice started recording video data was from 08:34:55 till 09:08:26. During the experiment some changes were made in regard to flight height and flight orientation to give some variety to the data and later test how the algorithm would react to these changes.

For the first half of the flight time the drone had an approximate 45 m altitude, which as mentioned previously didn't provide any results with the wide lens videos. On the other hand, with the zoom videos the markers were visible enough to be detected. After half of the flight time, the machineries began to get closer to the roundabout where also the road was getting wider. At this same time the drone was being flown at a lower altitude, which theoretically would've been better for the detection of the markers with the wide lens data, however the markers still were not visible enough to be detectable. From this point on, the lower altitude of the drone and the markers being more far away between each other because of the larger width of the road, made it impossible for three markers to be in the same frame and thus for the trilateration to work. Because of these reasons the total time interval of collected data that can be analysed by the algorithm is 18 minute and 4 seconds.

To analyse the data series in this time frame, the concept of k-nearest neighbour based Dynamic Time warping is used. The k-nearest neighbour algorithm, commonly referred to as KNN, employs proximity to produce classification or predictions about the grouping of a single data point (K-Nearest Neighbours Algorithms, n.d.). It is commonly employed as a classification algorithm because it relies on the idea that comparable points can be discovered close to one another. KNN can also be applied in time series problems. A common method for data analysis of two time series which vary in time is called Dynamic Time Warping, also known as DTW. The latter aims for 'temporal alignment that minimizes Euclidean distance between aligned series' (Tavenard, n.d.) The minimum distance discovered by DTW is then stored after computing the Euclidean distance between the first point in the first series and each point in the second series. By using KNN and DTW along with dynamic programming techniques the similarity between the time series of the paver and roller can be found (Regan, 2018). This measure of similarity between the two series can be found by adding up all the minimum distances that were stored. The upcoming figures show the results of this procedure for the paver and roller, respectively.

Paver

The two trajectories have a somewhat similar shape, as shown in Figure 13, although they are fairly far apart. They differ in the precise location from which they begin and stop.

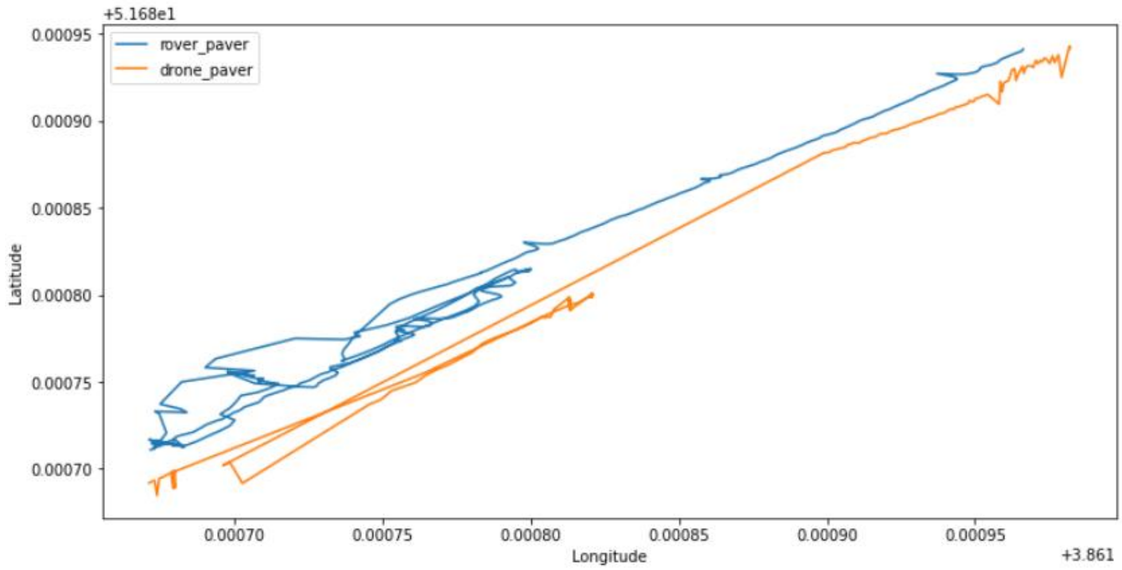

Figure 13: Two trajectories of the paver

The result from the heatmap in Figure 14 is 0.013 which means a very low similarity between the two data series. A reason for this might be due to the fact that in this research the technology of GPS rovers are considered as the ground truth. Even though GPS rovers do provide accurate measurements they still have a 20 cm sphere of plausible inaccuracies (The Real World Accuracy of Network GPS Rover Surveying Equipment, n.d.). Additionally, such a low similarity number might derive from the accuracy of the registration of the markers placed on site or also from the algorithm itself. The discussion section of this report will further examine these issues along with giving future improvements in the application of this method.

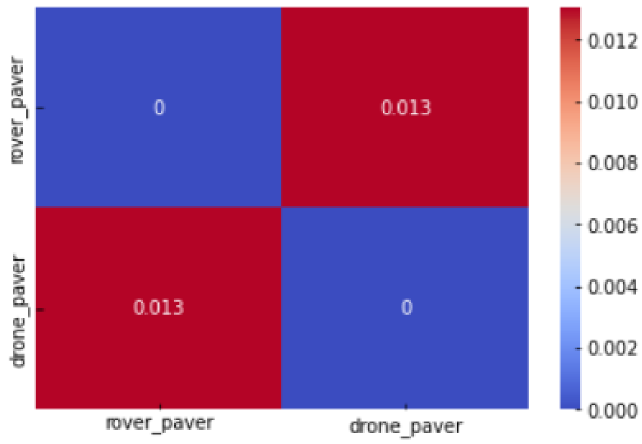

Figure 14: Paver Dynamic Time Warping Heatmap

Rover

Figure 15 shows the trajectories of the roller from the drone and GPS rover data sets. It can be clearly seen that in this graph the amount of data points of the GPS rover are a lot more compared to the paver data. This is because, in contrast to the paver, which moves forward most of the time at a slower pace, the roller rapidly moves back and forth to compact the asphalt several times.

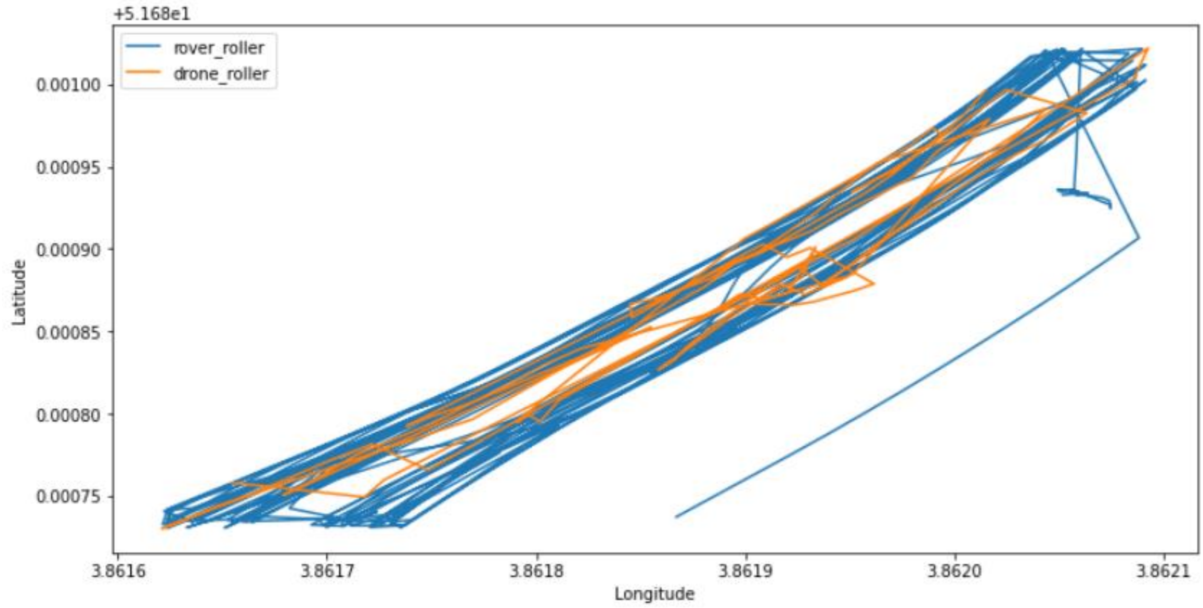

Figure 15: Two trajectories of the roller

The results shown in Figure 16 demonstrate a substantially higher similarity between the data sets which might be due to the overlapping of several data points as can be seen in Figure 15.

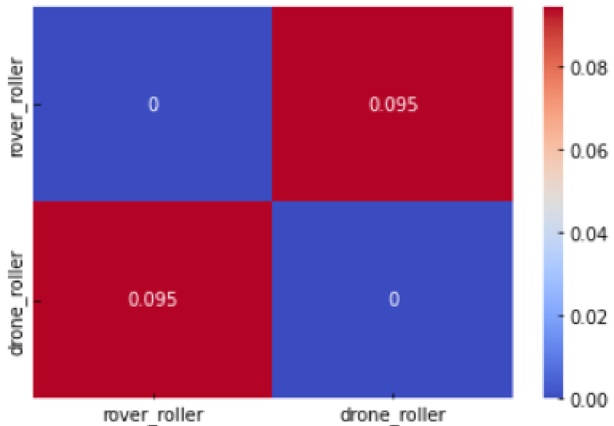

Figure 16: Roller Dynamic Time Warping Heatmap

Distance between trajectories

As a consequence of the rather low similarity measurements found with the DTW, it is worth exploring another data analysis method which attempts to find the point-to-point distance between the data collected of the two monitoring methods. The algorithm takes all the data points collected by the GPS rover and compares them to the data points received by the developed algorithm, and uses the points of the GPS rover that are closest to the trajectories from the algorithm.

The following graphs represent this distance, and it is very clear that there is a large difference in the outcomes found for the two machineries.

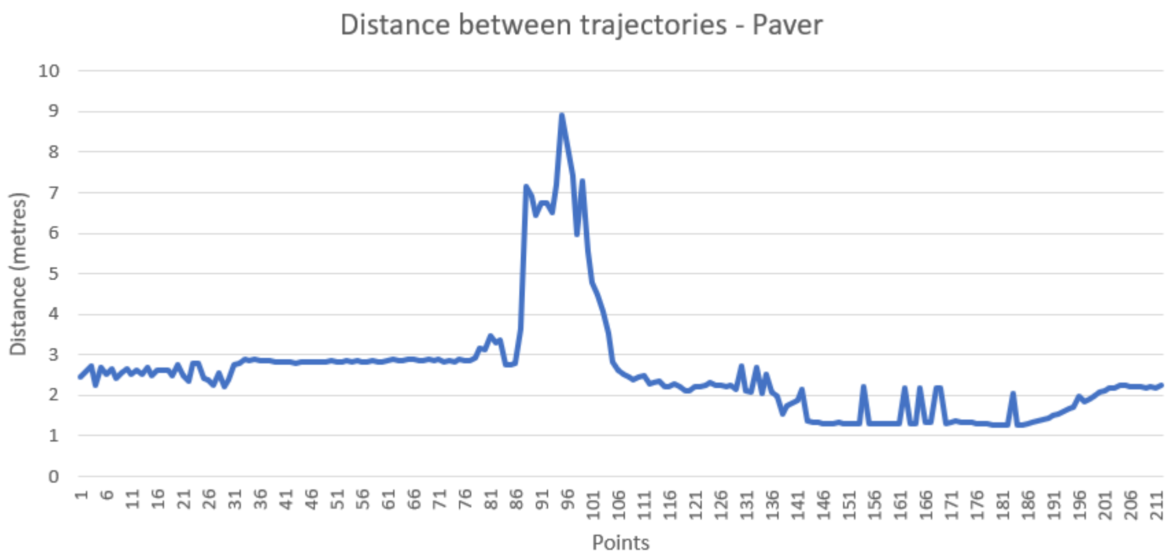

Figure 17: Distance point-to-point of the paver

The line resulted from the comparison of the datasets of the paver is quite steady apart from the jump found between point 86 and point 106. For most of the data points, the distance between trajectories fluctuates between 1 and 3 metres, which shows good similarity and coherence.

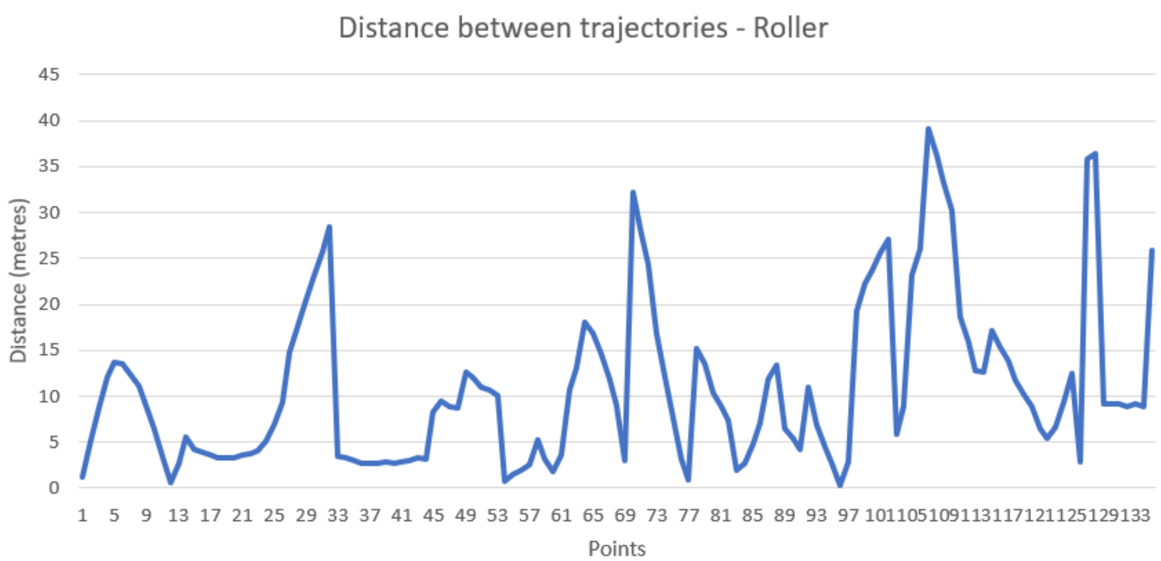

Figure 18: Distance point-to-point of the roller

The line from the graph of the roller shows a lot more variation in the found point-to-point distances. Compared to the graph of the paver, this one has some points that are very close to the x axis meaning a very small in between distance almost close to zero. However, the peaks from the line of the latter graph are much higher and occurring in increased frequency.

As shown in the table below, the paver data has much more stable and accurate values compared to the roller data.

	Mean	Standard deviation	Standard error
Paver	2.578519	1.317707	0.0905
Roller	10.78321	8.817565	0.758895

Table 2: Statistical values from the paver and roller trajectories

The mean of the data of the paver is 2.57 metres and instead of the roller it is 10.78 metres. The difference in the averages is 8.21 which is very large. The standard deviation is a measure of the amount of dispersion of a set of values; a low standard deviation implies that the data are grouped around the mean, whereas a large standard deviation reveals that the data are more scattered (Standard deviation, n.d.). The plots of the two machineries' make the numbers of the standard deviations be quite apparent. “The standard error of a statistic is the approximate standard deviation of the sampling distribution” (Kenton, 2021). The lower the value of this statistic the closer it is to the actual value of the mean, as can be seen with the paver. Contrariwise, the larger the number of the standard error the less representative the data set is to the value of the mean, as is for the roller.

The results of the data analysis clearly show that there are significant differences, but the potential causes of these discrepancies have not yet been examined. This subject will be covered in more detail in the report's following part, which will also include the report's overall challenges, strengths, and conclusions.

Discussion and future research

Although the data analysis didn't yield the best outcomes, using this strategy in a real-world setting revealed a lot of insightful information. This research played a significant role in the future development of this technique because there was no prior literature on the subject, to the best of the researcher's knowledge.

The movement of the machines on site has a significant impact in the outcomes of the data analysis. The paver moves at a slow pace in a straightforward manner apart from when the asphalt needs to be refilled. This might be for example a reason to why there is such a large peak in the distance between trajectories of the paver's graph. Overall, the statistics found from the second data analysis method are quite satisfactory, as it shows that the values are not too far off from the mean and are coherent. Contrariwise the results from the roller data in the second data analysis method are not satisfactory, as the data set shows too much variation and very low continuity. This might be due to the fact that the roller moves at a much faster rate and stops several times, and it might be that the GPS rover could not accurately monitor its movement.

Although the results from the distance between trajectories method are more positive for the paver than the roller, the results from DTW method show quite the opposite. In the latter, the methods show a higher similarity between trajectories of the roller than the paver. This might be because the roller data had much more data points over the span of the road, which means a higher probability that similarity is found if trajectories overlap. On the other hand, in figure 13 the trajectories of the paver don't overlap and there obviously is a substantial in-between distance, which causes the DTW algorithm to find less similarity.

Nonetheless, there are a number of improvements that may be made to the algorithm's operation as well as the system implementation of the approach, and this section of the report will explore these suggestions.

For the system implementation part, during the experiment at the Boskalis construction site a lot of time was lost initially as a step-by-step plan was not developed to place the markers on site. The markers placed on the construction machineries were difficult to place as a consequence of the difficulty in climbing the construction machinery and reaching the centre of the roof. Tape was used to attach the two markers however it wasn't very efficient, as on the roller there was a thin layer of rainwater which made it difficult for the tape to stick. Moreover, the surface of the roof of these machineries are not exactly flat which may cause detection problems when running the algorithm. For future research into the efficiency of this method compared to a more conventional monitoring method, it is recommended to find a faster and more efficient implementation. This could for example be with the use of a thin flat wooden plate of the size of the marker which can be attached to the roof with the use of ropes or clippers.

The same could be applied to the markers placed on the sides of the road. In this experiment, to place the markers, portions of dirt were allocated on the sides of the posters. This way the marker could still be visible. The latter are most of the times uneven because of the environment at the construction site, that includes elements such as plants, grass, piles of dirt etc. During the experiment of the case study this was the case and that caused small waves in the paper which caused reflection of the sun on the markers in the video data. When these were present the algorithm could not detect the markers. In order to prevent this, a thin wooden plate could again be used below the markers and attached to the ground with nails on the four angles of the plate, which would also prevent the marker to fly away in the case of higher wind force. As mentioned also in the case study of the report, for future implementation of this method it is recommended to mark the centre of the marker with a small red dot, for faster and easier usage of GPS surveying devices.

Marker density highly depends on the drone that is being used. However, in all cases it would be better if more markers and lesser in between distance would be used, recommending a distance of 5 to 8 metres. If the same drone that is used in the case study, the DJI Matrice with Zenmuse H20 payload, a 10-metre distance is enough because of the high resolution of the zoom camera.

It is not possible to monitor both machineries at the same time with only one drone, as the machineries move at different pace and repetitions. The paver moves slowly and straightforward and the roller moves faster continuously back and forth. If both machineries need to be monitored, at least two drones would be needed. Nonetheless if only the movement of the roller is required to be monitored that can easily be done by one drone, while at the same time being able to provide data points of the paver when both machineries are visible in the same frame.

For further research, if the same drone and camera attachment are used, it is advised for the drone to be flown higher in the air and follow the machineries using the zoom camera for the final output data. This way the operators can remain calmer and focus on their operations, and the drone can capture more markers in the same frame. The video quality of the zoom of the camera is high enough to enable clear detection. Also, the orientation of the camera of the drone should be parallel to the road being paved, as more markers can be detected. It should be attempted to calibrate the zoom camera of the drone in order to provide more accurate location measurements.

Additionally, it would be useful to experiment with different heights when using the zoom camera of the drone to find the most optimal height for the effective detection of Aruco markers. It would be recommended to experiment with heights of 45 metres above the ground to test how many markers would be in a single frame.

In regards to the functioning of the algorithm, it would be efficient to adapt the algorithm so that trilateration can use more markers for more accurate pose estimation of the moving markers.

These suggestions aim to provide more data points. In order to give a more meaningful comparison between the two monitoring systems and to produce greater accuracy measures, it is advised that future research into this method make use of the aforementioned recommendations. The GPS rovers' data was used as the basis for the data analysis. That is not quite the case, though, as the rovers' data are not highly accurate. It is suggested that future testing of this technology compare the commonalities between the data sets using a more precise GPS monitoring system.

The research presented in this paper has provided significant information for the future developments in the use of this monitoring method. It has given accuracy dimensions which before lacked in literature, along with suggestions to improve accuracy. The monitoring method presented is much cheaper than other more expensive monitoring methods, and researching it is valuable for the construction industry. The paper presented a clear plan for implementation and algorithm execution, along with the algorithm that is used to track the machineries (given in the Appendix). It has also presented information as well as clear references for the legal implications involved in the application of this method.

Conclusions

It is apparent that the research as a whole has shown itself to be very fruitful for future development and application of this method for the monitoring of the paving and compaction operations. One of the aims of this paper was to extend Sun’s research by testing the method in a real-life context and analyse the results. Along with this, thanks to the knowledge gained in the case study this research has shown the setbacks that are found when applying this method on site and provided solutions and a clearer overall plan to solve the issues found during the case study. Future recommendations have also been presented to solve these issues so that future researchers can implement them to further progress and expedite the implementation of this method.

In contrast to Sun's research, this one has developed an algorithm that can effectively track multiple moving machines and produce two outputs, one of which is a video output with accurate GPS position estimation and visual marker detection, and the other of which is an excel file with GPS data for each machine every second. As was suggested in the discussion, it is possible to make changes to the algorithm and system implementation that will minimize errors and enhance detection accuracy even further.

Appendix A

```
import math
import numpy


earthR = 6371*1000
def lat_lon_2_cart(lat, lon):
        x = earthR *(math.cos(math.radians(lat)) *
math.cos(math.radians(lon)))
        y = earthR *(math.cos(math.radians(lat)) *
math.sin(math.radians(lon)))
        z = earthR *(math.sin(math.radians(lat)))

        return x, y, z

def trilateration(A, B, C):
        LatA, LonA = A["lat"], A["long"]
        LatB, LonB = B["lat"], B["long"]
        LatC, LonC = C["lat"], C["long"]

        DistA = A["dist"]
        DistB = B["dist"]
        DistC = C["dist"]

        xA, yA, zA = lat_lon_2_cart(LatA, LonA)
        xB, yB, zB = lat_lon_2_cart(LatB, LonB)
        xC, yC, zC = lat_lon_2_cart(LatC, LonC)

        P1 = numpy.array([xA, yA, zA])
        P2 = numpy.array([xB, yB, zB])
        P3 = numpy.array([xC, yC, zC])

        ex = (P2 - P1)/(numpy.linalg.norm(P2 - P1))
        i = numpy.dot(ex, P3 - P1)
        ey = (P3 - P1 - i*ex)/(numpy.linalg.norm(P3 - P1 - i*ex))
        ez = numpy.cross(ex,ey)
        d = numpy.linalg.norm(P2 - P1)
        j = numpy.dot(ey, P3 - P1)

        x = (pow(DistA,2) - pow(DistB,2) + pow(d,2))/(2*d)
        y = ((pow(DistA,2) - pow(DistC,2) + pow(i,2) + pow(j,2))/(2*j))
- ((i/j)*x)

        z = numpy.sqrt(pow(DistA,2) - pow(x,2) - pow(y,2))

        triPt = P1 + x*ex + y*ey + z*ez

        lat = math.degrees(math.asin(triPt[2] / earthR))
        lon = math.degrees(math.atan2(triPt[1],triPt[0]))

        print(lat, lon)
        return lat, lon

if __name__ == "__main__":
        A = {"lat":37.418436, "long":-121.963477, "dist":0.265710701754}
        B = {"lat":37.417243, "long":-121.961889, "dist":0.234592423446}
```

```
        C = {"lat":37.418692, "long":-121.960194,
"dist":0.0548954278262}
        trilateration(A, B, C)
```

Appendix B

```python
import cv2
import numpy as np
import cv2.aruco as aruco

import numpy
from numpy import sqrt, dot, cross
from numpy.linalg import norm
import math

from trilateration_v1 import *

def distance_between_3d_pts(pt1, pt2):
    return np.sqrt((pt1[0] - pt2[0])**2 + (pt1[1] - pt2[1])**2 +
(pt1[2] - pt2[2])**2)

def distance_between_2d_pts(pt1, pt2):
    return np.sqrt((pt1[0] - pt2[0])**2 + (pt1[1] - pt2[1])**2)

def distance_between_long_lat(pt1, pt2):
    lat1, lon1 = pt1["lat"], pt1["long"]
    lat2, lon2 = pt2["lat"], pt2["long"]

    lon1 = math.radians(lon1)
    lon2 = math.radians(lon2)
    lat1 = math.radians(lat1)
    lat2 = math.radians(lat2)

    # Haversine formula
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = math.sin(dlat / 2)**2 + math.cos(lat1) * math.cos(lat2) *
math.sin(dlon / 2)**2

    c = 2 * math.asin(math.sqrt(a))

    # Radius of the earth in kilometers
    r = 6371

    return (c * r)*1000

def convert_str_to_deg(str_val, dict_var):
    str_val = str_val.split("°")
    degree = float(str_val[0])

    str_val = str_val[-1]

    str_val = str_val.split("\'")
    minutes = float(str_val[0])

    str_val = str_val[-1]

    str_val = str_val.split('"')
    seconds = float(str_val[0])

    dict_var["deg"] = degree + minutes/60 + seconds/3600
```

```python

    dict_var["dir"] = str_val[-1]

def load_csv(file):
    ID_dict = {}
    in_file = open(file, "r")
    all_data = in_file.readlines()
    in_file.close()

    for line in all_data:
        line = line.replace("\n", "")
        line = line.replace("Â", "")
        line = line.split(",")

        ID = line[-1]
        longitude_str = line[1]
        latitude_str = line[0]

        long_dict = {"deg": 0, "dir": ""}
        lat_dict = {"deg": 0, "dir": ""}

        convert_str_to_deg(longitude_str, long_dict)
        if latitude_str[0] == '"':
            latitude_str = latitude_str[1:]
        convert_str_to_deg(latitude_str, lat_dict)

        ID_dict[ID] = {"long": long_dict,"lat": lat_dict}

    return ID_dict

ID_dict = load_csv("220410_RoZe_markers_WGS84_DMS.csv")
print(ID_dict)
for ID in ID_dict:
    print(ID_dict[ID]["lat"])
# exit()
aruco_dict = aruco.Dictionary_get(aruco.DICT_4X4_50)
print("arucodict ", aruco_dict)

parameters =  aruco.DetectorParameters_create()
print("parameters ", parameters)

cap = cv2.VideoCapture("DJI_20191231171649_0005_Z.mp4")

_, img = cap.read()

fps = int(cap.get(cv2.CAP_PROP_FPS))
H, W, _ = img.shape
font = cv2.FONT_HERSHEY_SIMPLEX

codec = cv2.VideoWriter_fourcc('M','J','P','G')
output_video = cv2.VideoWriter(f"op.avi",
                                codec, fps,
                                (W, H))

output_dict = {}
output_list = []
```

```
frame_ctr = 0

current_time = 0

while True:
    sucess, img = cap.read()
    if not sucess:
        break
    current_time = 1/fps*frame_ctr
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    corners, ids, rejected_points = aruco.detectMarkers(gray,
aruco_dict, parameters=parameters)

    print("=============")
    idx = 0
    # known_pts = []
    # unknown_pts = []

    known_pts = {}
    unknown_pts = {}
    for aru in corners:
        # print(ids[idx])
        aru = aru.astype("int")

        id_str = str(ids[idx][0])
        if len(id_str) == 1:
            id_str = "0" + str(ids[idx][0])
        ID = "ID"+id_str + ''

        for i in range(len(aru[0])-1):

            if i == len(aru[0])-2:
                cv2.line(img, aru[0, 0], aru[0, -1], (255, 0, 0), 2)

            cv2.line(img, aru[0, i], aru[0, i+1], (255, 0, 0), 2)

        if ID in ID_dict:
            cv2.putText(img,
                        "ID: " + str(ids[idx][0]),
                        aru[0][0],
                        font,
                        0.5,
                        (0, 255, 0),
                        2,
                        cv2.LINE_AA)


        if ID in ID_dict:
            # known_pts.append(ID)
            known_pts[ID] = {"lat": ID_dict[ID]["lat"]["deg"],
                            "long": ID_dict[ID]["long"]["deg"],
                            "x":aru[0][0][0],
                            "y":aru[0][0][1]}
        else:
```

```
            # unknown_pts.append(ID)
            unknown_pts[ID] = {"lat": None,
                                "long": None,
                                "x":aru[0][0][0],
                                "y":aru[0][0][1]}
        idx += 1
    # print("Known Pts:", len(known_pts), "Uknown Pts:",
len(unknown_pts))
    if len(known_pts)<3 or len(unknown_pts) == 0:
        if frame_ctr%fps == 0:
                current_minutes = current_time//60
                current_seconds = current_time%60
                output_list.append([current_minutes, current_seconds,
"nan", "nan", "nan"])
    if len(known_pts) >= 3:
        pixel_dist = 0
        meters_per_pixel = 0
        known_IDs = list(known_pts.keys())

        for i in range(len(known_IDs)-1):
            ID1, ID2 = known_IDs[i], known_IDs[i+1]
            pt1 = (known_pts[ID1]["x"], known_pts[ID1]["y"])
            pt2 = (known_pts[ID2]["x"], known_pts[ID2]["y"])

            pixel_dist = distance_between_2d_pts(pt1, pt2)
            meter_dist = distance_between_long_lat(known_pts[ID1],
known_pts[ID2])

            meters_per_pixel += meter_dist/pixel_dist

        ID1, ID2 = known_IDs[0], known_IDs[-1]
        pt1 = (known_pts[ID1]["x"], known_pts[ID1]["y"])
        pt2 = (known_pts[ID2]["x"], known_pts[ID2]["y"])

        pixel_dist = distance_between_2d_pts(pt1, pt2)
        meter_dist = distance_between_long_lat(known_pts[ID1],
known_pts[ID2])
        meters_per_pixel += meter_dist/pixel_dist

        meters_per_pixel = meters_per_pixel/len(known_pts)

        ID1, ID2, ID3 = known_IDs[0], known_IDs[1], known_IDs[2]
        for ID_unknown in unknown_pts:
            A = {"lat" : known_pts[ID1]["lat"],
                "long" :  known_pts[ID1]["long"],
                "dist" : None}

            B = {"lat" : known_pts[ID2]["lat"],
                "long" : known_pts[ID2]["long"],
                "dist" : None}

            C = {"lat" : known_pts[ID3]["lat"],
                "long" : known_pts[ID3]["long"],
                "dist" : None}

            pt1 = (known_pts[ID1]["x"], known_pts[ID1]["y"])
```

```
            pt2 = (known_pts[ID2]["x"], known_pts[ID2]["y"])
            pt3 = (known_pts[ID3]["x"], known_pts[ID3]["y"])

            pt_unknown = (unknown_pts[ID_unknown]["x"], unknown_pts[ID_unknown]["y"])

            A["dist"] = distance_between_2d_pts(pt1, pt_unknown)*meters_per_pixel
            B["dist"] = distance_between_2d_pts(pt2, pt_unknown)*meters_per_pixel
            C["dist"] = distance_between_2d_pts(pt3, pt_unknown)*meters_per_pixel

            unknown_pts[ID_unknown]["lat"], unknown_pts[ID_unknown]["long"] = trilateration(A, B, C)
            lat, lon = round(unknown_pts[ID_unknown]["lat"], 2), round(unknown_pts[ID_unknown]["long"], 2)

            if frame_ctr%fps == 0:
                current_minutes = current_time//60
                current_seconds = current_time%60
                output_list.append([current_minutes, current_seconds, ID_unknown, unknown_pts[ID_unknown]["lat"], unknown_pts[ID_unknown]["long"]])
                if ID_unknown not in output_dict:
                    output_dict[ID_unknown] = []

output_dict[ID_unknown].append([unknown_pts[ID_unknown]["lat"], unknown_pts[ID_unknown]["long"]])

            cv2.putText(img,
                        "lat: " + str(lat)  + " lon: " + str(lon),
                        (unknown_pts[ID_unknown]["x"], unknown_pts[ID_unknown]["y"]),
                        font,
                        0.5,
                        (0, 0, 255),
                        2,
                        cv2.LINE_AA)


    cv2.imshow('Result',img)
    frame_ctr += 1
    # output_video.write(img)
    k = cv2.waitKey(30)

    if k == ord("q"):
        break
# output_video.release()

out_file = open("output_5.csv", "w")
line = "ID,lat,long\n"
out_file.write(line)

for ID in output_dict:
    for pt in output_dict[ID]:
```

```
        line = ID.replace('"', "") + "," + f'{pt[0]},{pt[1]}\n'
        out_file.write(line)

out_file.close()


out_file = open("time_output_5.csv", "w")
line = "Minute,Seconds,ID,lat,long\n"
out_file.write(line)

for row in output_list:
    line = ""
    for col in row:
        line += str(col) + ","

    line = line[:-1]
    out_file.write(line + "\n")

out_file.close()
```

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