IMPROVING POLICING THROUGH TECHNOLOGY: A COMPARISON OF DRONE CAMERAS AGAINST TERRESTRIAL SCANNERS IN TRAFFIC ACCIDENT DATA COLLECTION

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ABSTRACT

This article presents the results of a field test of drone technology which is being used in the collection of traffic accident data as conducted by the Estonian Academy of Security Sciences in September 2019. The experiment is part of a larger research project which is investigating the viability of the use of new forms of technology in traffic police work, especially drone cameras. Drones have shown that they have the potential to support and enhance traffic accident data collection, and can therefore greatly enhance the legal processing of accident scenes. Additionally, drones are able to capture data at a comparatively quicker rate than are manual methods. Further investigation is required, however, to determine whether data that is collected by drones is sufficiently accurate for the purposes of carrying out measurement checks at accident sites.

The aim of the field test being presented here was to compare the accuracy and speed of data collection using the terrestrial scanner, a Leica C10 ScanStation, and a quadcopter drone, the Matrice 210v2 with 15 mm RGB, 45 mm RGB, and thermal infracted 13 mm cameras. Measurement accuracy was calculated in terms of data, both with and without geo-references, via the use of photogrammetry. Taking terrestrial scanner measurements as a benchmark, the experiment found the following: i) when drone data was geo-referenced, the difference between the benchmark and those measurements that were based on drone camera data ranged from 6.7–7.5 cm; without geo-referencing the error or difference was significantly higher, reaching at least 2 m; ii) when a local scale bar measurement was used, camera data accuracy remained high even without the data being geo-referenced.

Although geo-referencing can improve accuracy, the additional software and also hardware requirements add additional time and the requirement for a level of skill to the job of data processing. Results with local scale bar measurement, however, indicated the likelihood that geo-referencing may not be required to maintain accuracy rates. When considering these results, the article concludes that drone technology bears further study as an alternative to the currently-used manual methods.

INTRODUCTION

This article presents the results of a field test involving drone technology,[1] specifically in terms of the collection of data where it is related to the scene of a traffic accident, as conducted by the Estonian Academy of Security Sciences in September 2019. This field test focussed on the data collection process in low-light conditions, using an accident scenario in which a pedestrian has been hit by a private motor vehicle, with the accident having taken place in an urban setting. The field test is part of a larger area of research which is investigating the viability of new forms of technology in traffic police work, especially in the form of drone cameras, and how they may serve to complement existing accident scene documentation practices, especially in terms of measurements being taken by the use of photogrammetry. Currently, accident scene measurements are taken using manual methods, and the adoption of new forms of technology requires an assessment of that technology's use value, including a comparison of accuracy levels and speed against the current methods.

Drone photography, including photogrammetry via drone imagery, has shown itself to have the potential to be able to support and enhance aspects of data collection at the scene of traffic accidents, including the possibility of being able to improve the speed at which data is collected at the scene, as well as allowing the possibility of being able to re-visit and re-measure accident scenes after the initial measurements have been taken. In respect to this second point, the implementation of drone technology also has the potential to improve the accessibility of data for the legal processing of the scene of traffic accidents. Having said that, the usage value of drone photography and drone-data-based photogrammetry in traffic accident scene investigations, including the ability to assess data validity and measurement accuracy, has not fully been established and

[1] As a note regarding terminology, this article is referring to drone technology (or drones, in short), where the drone is 'an unmanned aircraft or ship that is guided by remote control or onboard computers' (Merriam-Webster, 2020). In existing research, drone technology is often also referred to as 'unmanned aerial systems' (UASs). UASs include an unmanned aerial vehicle (UAV), a ground-based controller, and a communications system between the two. This article considers these two ways of referring to the technology to be broadly equivalent, and so the use of these terms is largely interchangeable.

is still subject to testing. Whilst drones have generally proven to offer a rapid solution in terms of data collection, research questions remain regarding whether the speed of data collection may come at the cost of data accuracy, as well as questions remaining regarding the best method to be used for collecting data via drone which could further be used for photogrammetry. The field test described in this paper goes some way towards addressing these questions.

In that light, Section 1 introduces the context within which is located the broader research project to which this paper contributes. Section 2 describes the methodology used in the field test (2.1), and the results for that field test (2.2). The article concludes with a brief analysis of the relevance of those results within both the local and broader research context, including a discussion of further lines of research that have been indicated by the results of the field test.

1. RESEARCH CONTEXT

A significant barrier in terms of the uptake of specific new forms of technology in law enforcement practices, even for forms of technology that have widely been discussed as potential complements to current law enforcement practices, is a lack of research that serves to confirm the reliability and usage value of the relevant forms of technology. One such area, with which the field test described here is concerned, is data collection and measurement at the scene of a traffic accident.

The practice of manually carrying out data collection at the scene of a traffic accident, and especially the measurement of accident scenes, is common around the world. However, this approach is both time-consuming and labour-intensive, which in turn can have indirect negative consequences. Along these lines, research that has been conducted by the US Department of Transportation, and the National Highway Traffic Safety Administration (Blincoe *et al,* 2015), indicates that service providers can incur significant monetary costs through increased fuel usage and time lost due to an accident scene being closed off so that manual data collection can take place. Studies by Dukowitz (2020), Kamnik et al (2019), and the Purdue University (Sequin, 2019), indicate that traffic jams and delays that result from an accident scene investigation can lead to secondary accidents; with the Purdue study finding that secondary crashes increase by up to a factor of 24 during the time in which law enforcement officials are collecting data. Similarly, Dukowitz indicates that the possibility of a secondary crash occurring increases by 3% for every minute that the scene of an accident is sealed off, whilst law enforcement officials and towing and recovery personnel are themselves most vulnerable during that same period (Dukowitz, 2020).

In addition to these costs in terms of time and labour, as well as the physical threat to human life, the common methodology of using a tape measure or a measuring wheel, with manual note-taking, and the use of handheld cameras to document the scene, are all practices that are prone to human error (see Shinar *et al,* 1983; similarly, see also Griffard, 2019, p 53, which shows that attention has been draw to potential problems both in terms of erroneous data collection and data insertion when it comes to a criminal investigation that makes use of the data).[2]

Despite these apparent issues with manual data collection and measurements at the scene of an accident, few technological alternatives have been considered as being possible complements to existing practices or as ways of enhancing this area of law enforcement (see, for example, Pagounis *et al,* 2006; Osman & Tahar, 2016). Reasons for this include the resilience of the current methodology in the face of various environmental conditions, such as wind, rain, or low levels of lighting, plus which the ease of use of the relevant tools – the way in which they can be used and their levels of reliability – is somewhat robust, and has a comparatively low level of expertise required when it comes to processing the data that is collected. No additional personnel are required for such data processing (for an in-depth analysis of the conditions in which drones could be used, see Padua *et al,* 2020). Moreover, the current methods provide a degree of standardisation in the data collection process across international borders with relative ease (for a European initiative as an example, see SAU – Urban Accident Analysis System, 2007).

Two forms of technology that a growing body of research is testing and assessing as potential complements to the existing manual practices involve terrestrial laser scanners and drone technology. Of particular interest and emphasis within this research is the possibility of using such forms of technology to make possible the process of taking measurements at scenes of accidents to be conducted via photogrammetry.

Terrestrial laser scanners send a laser beam towards numerous points on three-dimensional objects, measuring the distance between the collected data points and the equipment itself. The data produced by this can, in turn, be used to generate a point cloud which, with the use of the appropriate software, is suitable for topographical mapping and spatial analysis (Oguchi *et al,* 2011). Additionally, this model can allow officials to effectively re-visit and re-measure the site at a later date. The scale of the speed and accuracy of point cloud creation – as reported by Oguchi et al (2011) – is between 10^4–10^6 points per second with an accuracy of 10^{-1}

[2] The authors recognise that human error may occur in part as a result of external factors such as, for example, rapidly changing weather conditions, low-level lighting, and so on.

to -10^{0}cm. In this light, there is evidence (Kersten *et al,* 2008) that laser scanners have an exceptionally high level of accuracy of measurement.[3] In relation to this, there has already been some uptake of this technology in traffic policing practice in the USA (such as, for example, by the North Carolina Department of Transportation, 2017, p 3),[4] and there have been further suggestions that scanners could be employed in crime scene investigation to reach and record points of a crime scene that a standard camera cannot (Tedinnick *et al,* 2019). Barriers to any wider adoption of this technology, especially in traffic policing, however, involve the relatively complicated nature of the technology and the comparatively high level of expertise that is required when it comes to processing the resultant data (although, as Rosell-Polo *et al,* 2019 point out, there is a growing number of user-friendly software applications that provide enhanced opportunities to use the data). In addition, laser scanners are expensive and are better suited for use in areas with less vegetation and a flat surface (Guisado-Pintado *et al,* 2019).[5]

Currently, the primary use of drones at traffic accident scenes, especially in the USA where they are most widely used, has been in terms of providing additional documentation of the accident scene in the form of photographs (especially aerial photographs) that can later be used in the investigation process (Bergal, 2018; Eyerman *et al,* 2018; John Hopkins University, 2018).[6] In light of the limitations that have been mentioned when it comes to employing laser scanners in traffic policing, there is now a growing body of research into the potential shown by drone technology – in combination with photogrammetry software – to also be

[3] Every terrestrial scanner has a defined margin of error that is confirmed by the manufacturer. The scanner being used in this field test was confirmed to have a 4mm margin for error.

[4] The Leica C10 ScanStation model terrestrial laser scanner has been tested for police use in Estonia, and is in some instances also used for 3D modelling. However, due to the absence of a certified methodology for carrying out measurement duties at the scene of a traffic accident, it cannot be used in taking measurements at accident scenes.

[5] There is a growing body of research (especially that which has been considering the use of technology in terms of vegetation, snow, cliffs, etc, when it comes to monitoring and analysis), which has been investigating the simultaneous use of drone technology and TLSs as complementary forms of technology, with drones providing better access, and scanners greater accuracy (see, for example, Cooper *et al,* 2017; Bartoš *et al,* 2019; Yakar *et al,* 2014; Šašak *et al,* 2019).

[6] In a survey conducted in the U.S in March 2019., it was reported that drones are also being used for surveying work, public education and outreach work, emergency response work, and daily traffic control and monitoring, as well as for scientific research and when inspecting high-mast light poles (Bergal, 2018).

able to provide assistance when it comes to data collection and taking measurements at scenes of accidents. One comparative strength of this form of technology is the possibility of being able to attach more than one type of camera to a single drone, thereby providing a greater variety of data to be collected.[7] Additionally, drones are comparatively easy to operate, as well as cheaper to acquire and maintain than are terrestrial laser scanners (Kamnik *et al,* 2019; Perez *et al,* 2019). It is also suggested that the ability to operate the drone from the roadside when taking measurements on site may contribute to the increased safety of the officer who is responsible for operating the drone (Queensland Police, 2019). Finally, the technology may deliver additional value to current practices by enabling the re-measurement of the scene of the accident without it needing to be revisited, as well as allowing for views of the scene of the accident that would not be possible otherwise (such as in terms of providing an overhead 'bird's-eye' view). Employing drone technology in the collection of data from scenes of accidents is limited by weather conditions and the physical features of the specific site of the accident. However, the aspects of the technology that are mentioned above suggest that it may, nonetheless, have significant advantages over terrestrial scanners as a complementary method to existing practices.

That said, there are a number of concerns with the employment of drone imagery via photogrammetry that have so far curbed their use in terms of measurement purposes. Firstly, the camera being used needs to be suitably calibrated so that any data that is collected is not distorted in any way. This calibration, in turn, demands proper flight planning. Experiments that have been conducted by Su et al (2016) do, however, show that a rapid mapping system could be developed that would be suitable for these purposes. Secondly, different cameras and data collecting altitudes can provide photographs that are of differing levels of quality (which is calculated based on the number of pixels in each image), which can distort the size of objects, and their edges, and make the taking of measurements somewhat difficult. Field tests that have been conducted by Jurkofsky (2015) used circular targets for reference in an attempt to overcome this limitation, but that research suggests that the accuracy of photogrammetry can be compromised if such reference targets are not

7 In the field test being reported in this paper, for example, three different cameras were used on one drone.

used. Furthermore, when using drone camera photos for photogrammetry, the margin of error for the measurements needs to be established separately for each individual scene of accident. This contrasts with laser scanner imagery where the margin of error for measurements that are carried out via the scanner is pre-established by the manufacturer. One approach to overcoming this problem, and one which is already in use, is to georeference the images and any objects that are captured on the images. Using GNSS, this method situates the points at which the drone image is taken onto a world map. This geo-referencing can be carried out either with designated points marking the area at which the data is collected or with the built-in technology of the drone that is being used to take the pictures. The distance between the objects on the photograph, the length of objects, and so on, can be measured according to the designated points (in terms of the position of the point cloud) on the world map and the distance between those points.[8] An alternative is to use a local object of a specific size as a benchmark measure. It is the viability of this process as well as that of the geo-referencing approach that the current research is intended to assess.

Taking all of these issues into consideration, a significant barrier to the adoption of this measurement technology is the lack of evidence that the combination of drone technology and photogrammetry software can provide measurements that are of sufficient accuracy for the purpose of traffic policing and scene of accident analysis (John Hopkins University, 2018, p 57). Two current articles that address this gap are Padua et al (2020), and Kamnik et al (2019). Both of which take the similarity of data results that have been collected by means of conventional methods and those which have been collected using drone technology to be indicative of the feasibility of drone technology for use in traffic accident investigations. It is to this short list of research into accuracy that the field test described here contributes, with a specific focus on the local law enforcement context in Estonia in which the field test was conducted.

Police involvement in traffic accidents (which involve motor vehicle-related collisions) in Estonia is required when a person is harmed or when the parties involved in the collision and/or the owners of other objects that have been involved and damaged in such a collision are

[8] For the methodological concerns see, for example, Zhou *et al,* 2017; Oniga *et al,* 2020.

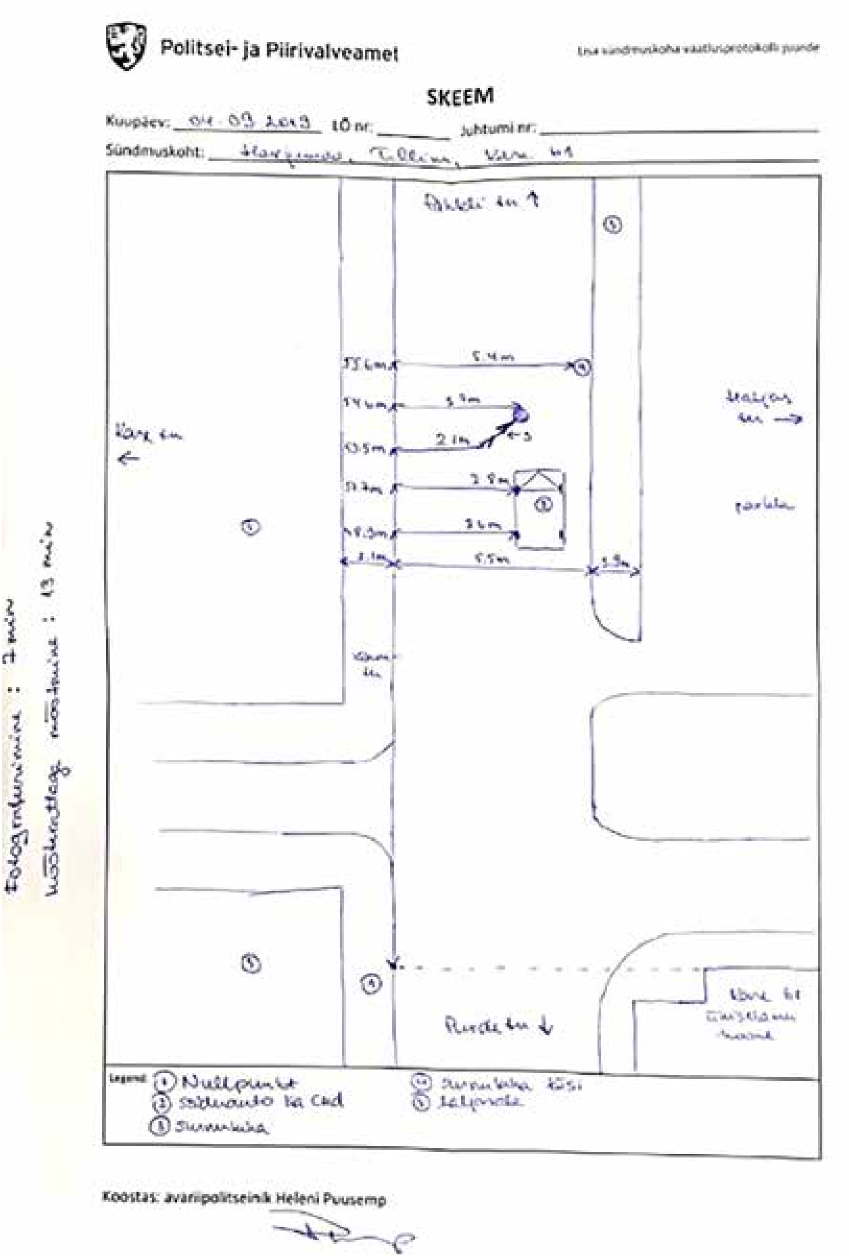

FIGURE 1: Data collection from the traffic accident – initial report at the scene of the accident, produced via the field test.

unable to agree upon the amount of damage that has been done and/or which party is responsible for the accident.[9] In keeping with practices in other countries, accident site data in Estonia is collected manually. Manual data collection precludes the ability to re-create or re-measure the scene of the accident. Therefore, it is of crucial importance that any data which is collected at the scene be as comprehensive as possible. This involves producing an accurate representation of the scene which is suitable for subsequent investigative work in the office and an analysis of the accident. In this light, manual data collection in Estonian traffic policing includes the task of measuring the relevant features of the accident site and providing a schematic representation or memo drawing of the scene (as illustrated in Figure 1). Having conducted this process, the police officers involved will return to their office to draw up a more detailed image of the collision site (a process that is illustrated in Figure 2), which provides the primary material for the investigation, in addition to photographs from the scene of the accident and statements from the parties that were involved in the accident.

In line with earlier comments, the process of carrying out manual data collection and accident site measurement which is currently followed in Estonia is somewhat time-consuming, while potentially also leading to subsequent issues with traffic management – including secondary accidents – and is prone to human error, particularly so with large or complex accidents where producing the detailed plan that is required for the subsequent investigation can be extremely complicated.[10] In addition, a pressing underlying issue that is specific to Estonia is the bearing of demographic changes in a broader sense on current policing practices, where a decreasing population is predicted to lead to a significant reduction in the working age population and, so too, to potential shortfalls in policing staff levels (Ministry of the Interior of Estonia, 2020; Ministry of the Interior of Estonia, 2019). At the same time, a decrease in the relative

[9] In March 2020, Statistics Estonia (Statistics Estonia, 2020a) reported that in 2019, there were a total of 1,406 traffic accidents reported, which means an average of 118 a month and four a day; according to the Estonian Road Administration, by 1 September 2020, there have already been 889 traffic accidents in this year involving human victims (The Republic of Estonia Road Administration, 2020).

[10] When it comes to secondary traffic accidents, the authors recognise the difference in the scale of road traffic in the USA (where the primary body of research originates that is referenced in this article) and in Estonia, but consider the aforementioned concerns regarding the safety of law enforcement officers, etc, to be a pressing concern in Estonia nonetheless.

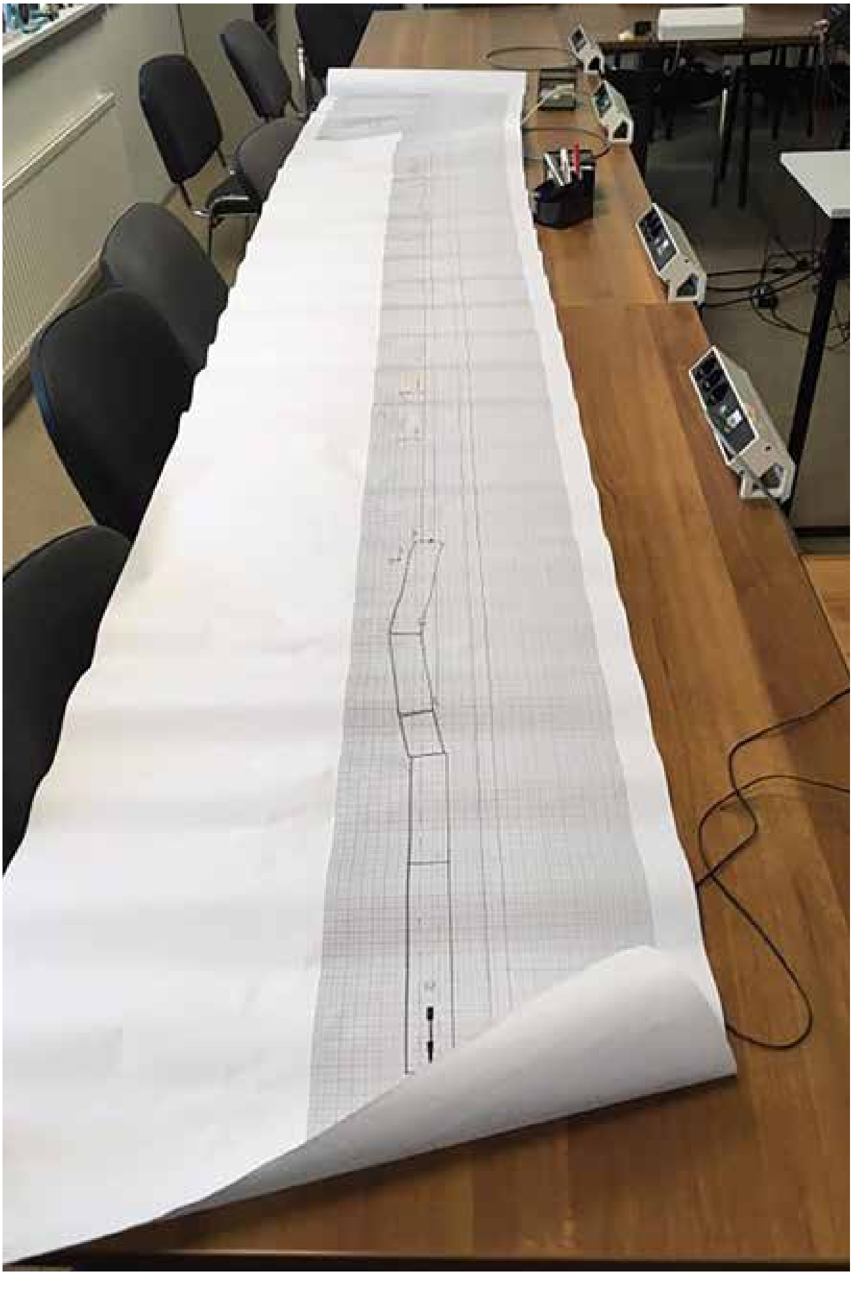

FIGURE 2: Traffic accident report – detailed report, drawn up in the office according to the initial report from the scene of the accident (the report shown involves a rail accident that took place in Raasiku in 2014).

working age population of Estonia need not result in a similar change to the driving population. The population in Estonia, as in Europe more generally, is aging with corresponding rises in life expectancy levels. In line with this trend, it is to be expected that in the future the share of the population that is eligible to drive will continue to increase (Eurostat, 2019). Related to this, economic growth and improving economic welfare has resulted in continued growth in the number of passenger cars being sold in Estonia, with the last five years alone seeing the number of privately driven motor vehicles on the road increasing by 100,000 (Statistics Estonia, 2020b). These demographic and economic shifts may then produce reductions in the number of available traffic police at the same time as there is an increased need for traffic policing, including being able to respond to and investigate scenes of accidents.[11] Considering these shifts, it is vital to policing across the board in Estonia that policing practices be modernised when and where that is suitable and possible – including in the provision of traffic policing.[12]

Within the local context described, the Estonian Academy of Security Sciences launched a research project in 2019 which aimed to assess the potential of employing photogrammetry that can be facilitated by drone along with the process of collecting data via drone as an additional means of measuring details at traffic accident sites. To do so, this ongoing project is conducting a series of field tests,[13] which will compare the image quality of various cameras that are attached to drones which are being employed at a specific accident site to test the efficacy of using (drone) cameras in different lighting conditions,[14] while also testing the efficacy of using (drone) cameras in different settings,[15] and in simulated scenarios,[16] and to analyse the accuracy of measurements that are taken via photogrammetry with and without geo-referenced data. In the remainder of

[11] Thanks are given here to an anonymous reviewer for pushing the need to discuss both aspects of the significance of demographic and economic changes.

[12] The authors take into consideration the possibility that the technological solutions being tested here may be of limited use in Estonia due to the local weather conditions, the density of the population, the large number of rural roads, and other local factors.

[13] At the time of writing, seven field tests have been conducted.

[14] Field tests are conducted in daylight as well as under low-lighting conditions, both with additional lighting and without.

[15] Some field tests simulate built up urban areas, others rural settings and/or larger roads.

[16] Some simulations model accidents in which a pedestrian is hit, while others simulate collisions between cars.

this article, the findings from one field test are presented, which took place on 5 September 2019 on the premises of the Estonian Academy of Security Sciences in Tallinn. The aim of this specific field test was: i) to compare the accuracy and speed of data collection by a specific model of terrestrial scanner and a quadcopter drone which was equipped with RGB and thermal infracted cameras; and ii) to compare the accuracy of the drone data measurement process via photogrammetry with and without geo-referenced data. In the next section (2.1), the methodology used to conduct the field test is described, and in 2.2, the results of the test are presented.

2. FIELD TEST

2.1 METHODOLOGY

The aim of the field test being presented here was to compare the accuracy and speed of data collection using the terrestrial scanner, Leica C10 ScanStation, and the Matrice 210v2 quadcopter drone with 15 mm RGB, 45 mm RGB, and thermal infracted 13 mm cameras. The field test was conducted in low-light conditions during the early hours of 5 September 2019 on the premises of the Estonian Academy of Security Sciences in Tallinn. The field test simulated a densely-built urban area in which the scene of the accident is surrounded by buildings, posts, wires, and other components of a built-up infrastructure. The simulated accident involved one private motor vehicle and a pedestrian, with the latter being represented by a life-size dummy that was employed at the scene of the accident to simulate someone who had been hit by the vehicle, and was now lying in the road a couple of metres in front of the vehicle.

Data gathering was conducted using a Leica C10 ScanStation terrestrial scanner and a Matrice 210 v2 quadcopter drone with 15 mm RGB, 45 mm RGB, and thermal infrared 13 mm cameras. Data was geo-referenced using the RTK GNSS Trimble Catalyst DA1 service with a 10 cm accuracy. For drone data processing and ready-to-use data product development, use was made of the Agisoft Metashape photogrammetry software; CloudCompare software was used for terrestrial scanner data merging. On-scene lighting was provided by two of the police department's portable lighting equipment units, a Solaris Duo 40,000 Lumens Rechargeable LED Lighting System.

Accordingly, five different ready-to-use data products were produced. The first was a handwritten sketch of the scene of an accident (data product-0) in which important measurements were described (see Figure 1). In addition to the sketch, following the data gathering protocol for an accident site, the scene of the accident was photographed using a handheld camera. As with the conventional process, the data collection process from the scene of a road traffic accident is complemented with a more detailed sketch on millimetre paper which will be drawn later (see Figure 2). The measurements that were taken in this process were done using a handheld measuring wheel and were rounded to the nearest tenths of a decimal place, e.g. from 2.11 m to 2.1 m (see Figure 1).

In addition to the manually-produced data product, a Leica C10 ScanStation laser scanner was used to gather data to create a high accuracy point cloud that was later used as the benchmark when it came to comparing the accuracy of drone camera data against the manual product.[17] Data product-1 was generated with the data that had been obtained by means of the laser scanner (the maximum scope for error for the Leica

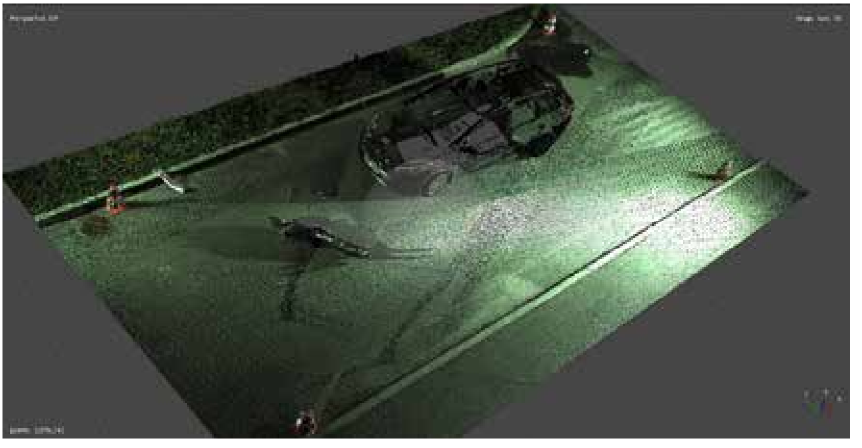

FIGURE 3: A Leica C10 laser scanner point cloud, with benchmark data that has been geo-referenced using RTK GNSS.

FIGURE 4: A 15 mm focal length RGB camera point cloud and orthomosaic, geo-referenced using RTK GNSS.

17 The use of laser scanner measurements as a benchmark is in keeping with the methodology used in similar research from other countries, such as Jurkofsky, 2015; Kamnik *et al*, 2019.

C10 scanner is 4 mm if the distance being measured is geo-referenced using the aforementioned RTK GNSS (see also Figure 3)).

The second data product (data product-2) and the third (data product-3) were point clouds and orthomosaics that were derived from drone data from the 15 mm and 45 mm focal length RGB cameras. Both of these

FIGURE 5: A 45 mm focal length RGB camera orthomosaic and point cloud, geo-referenced using RTK GNSS.

FIGURE 6: A 45 mm focal length RGB camera point cloud, geo-referenced using a scale bar.

data products were also geo-referenced using RTK GNSS (figures 4 and 5). The fourth data product (data product-4) was also derived from the 45 mm focal length RGB camera on the drones, but this was geo-referenced using only the drone's on-board GNSS which has a level of accuracy up to 1.5 m (Figure 5). The fifth data product (data product-5) is identical to the fourth apart from its being geo-referenced with a scale bar (Figure 6).

Once generated, the five ready-to-use data products were then compared, being assessed with a focus upon accuracy and the speed of data collection. The accuracy of the data products that were produced via the use of the drone (data products 2, 3, 4, and 5) was assessed by way of two different methods, both of which have been used in prior research to assess the available options in terms of the use of drone imagery in measuring road traffic accident scenes via photogrammetry. One method was to assess the accuracy of geo-referenced data products (data products 2, 3, and 4) against the benchmark terrestrial scanner measurements (data product-1) in a global context. For the purpose of this assessment, the CloudCompare software was employed, with calculations made for how far the neighbouring points from each of the relevant data products (i.e. the point clouds) as derived from drone data were from the benchmark point cloud that was generated from the terrestrial scanners. The second method was used to assess the accuracy of data product-5, by employing a local scale bar on the image for subsequent measurement.

2.2 RESULTS

The results represented in Table 1 show the time taken to gather the measurements that were used to generate each data product. The results show that using just a drone alone with its own geo-referencing equipment takes significantly less time when it comes to generating a data product than does manual measurement, a laser scanner, or using additional geo-referencing technology. The same speed can also be achieved as when using a drone's built-in geo-referencing technology when using a local scale bar to produce the data product. As shown by the field test results that are presented in Table 1, whilst the drone flight for data gathering takes the same amount of time (five minutes) whether or not the data is geo-referenced, the time taken in setting up the RTK GNSS equipment

TABLE 1: List of ready-to-use data products that were produced as part of the current field test and the time taken to produce each of them.

Data product	Data product name	Time	Place
0	Measuring wheel measurements and photographing	20 minutes	II
1	Terrestrial scanner	50 minutes	III
2	Drone and 15 mm RGB camera, with RTK GNSS geo-referencing	20 minutes	II
3	Drone and 45 mm RGB camera, with RTK GNSS geo-referencing	20 minutes	II
4	Drone and 45 mm RGB camera, with drone GNSS geo-referencing	5 minutes	I
5	Drone and 45 mm RGB camera, with scale bar geo-referencing	5 minutes	I

for geo-referencing purposes increases the data collection time by as much as fifteen minutes. The use of a terrestrial scanner is significantly more time-consuming than the other methods that were used in the field test.[18] The last column in Table 1 ranks the data product in terms of product creation speed.

The remaining results describe the percentage of drone data for each data product that is within, respectively, 5 cm, 10 cm, or 15 cm accuracy of the benchmark product. For data product-5, the assessment was carried out in a two-dimensional setting with the benchmark data being employed in this case coming from those measurements that were carried out using a handheld measuring wheel and a measuring tape. The model was referenced using one measurement – the height of the dummy – and its accuracy was assessed via the use of four independent distances that were measured with a measuring wheel. The results describe how close (in terms of metres) were the distances that were measured via the drone's data model to the benchmark measurements from the measuring wheel.

Figure 7 describes the accuracy assessment of data product-2 against the terrestrial scanner data. The results show that approximately 80% of the drone data has a margin of error that is less than 10 cm, and 95%

[18] The authors recognise that newer terrestrial scanners are significantly quicker in terms of taking the measurements and providing the relevant data for the data product than is the scanner used in the field test (the latest technology can take around fifteen minutes to gather the relevant data).

of it that is less than 15 cm. Figure 8 describes the accuracy assessment for data product-3 against the terrestrial scanner. As illustrated by the data presented in the figures, the results for data product-3 are similar to those for data product-2, with an average error for product-2 being 6.7 cm and an average error for product-3 being 7.5 cm, a difference that is not statistically significant in the current context (it can be noted that data product-3 has a greater number of points and pixels and so generates a higher resolution representation of the scene than does product-2; however, this has no bearing upon the results of the field test).

Figures 9, 10, and 11 describe the accuracy of data product-4. These figures reveal a significant loss in accuracy when only the drone's onboard GNSS device is used, in contrast to data products-2 and 3, both of which are geo-referenced using RTK GNSS. The average margin of error for data product-4 which uses only the onboard GNSS equipment is 4.81 m, whilst data products-2 and 3, which were geo-referenced using separate units, had margins of error that were only between 6.7 cm and 7.5 cm. This 4.81 m average margin of error can largely be explained by inaccurate elevation data, for which the average margin of error is approximately 4 m. However, even when limited to two-dimensional data and so excluding the elevation data, the margin of error is approximately two metres

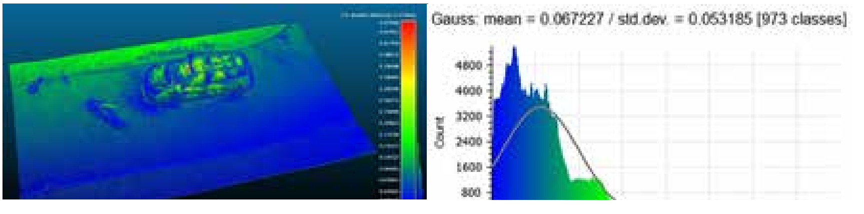

FIGURE 7: An accuracy assessment of a 15 mm focal length RGB camera point cloud (data product-2, RTK GNSS geo-referenced), against terrestrial scanner benchmark data.

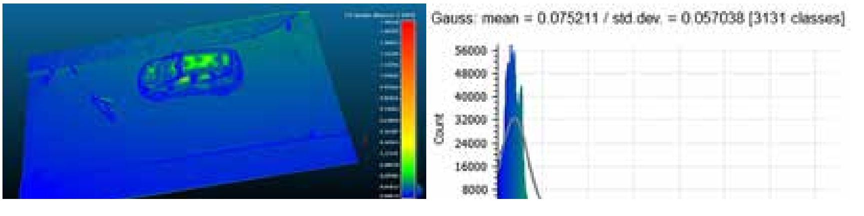

FIGURE 8: An accuracy assessment of a 45 mm focal length RGB camera point cloud (data product-3, RTK GNSS geo-referenced), against terrestrial scanner benchmark data.

FIGURE 9: An accuracy assessment of a 45 mm focal length RGB camera point cloud (data product-4, geo-referenced using the drone's onboard GNSS), against terrestrial scanner benchmark data.

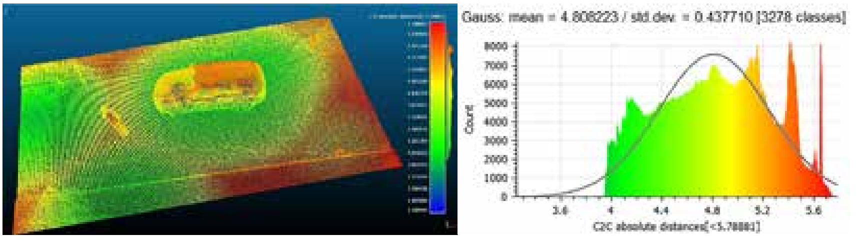

FIGURE 10: An accuracy assessment of a 45 mm focal length RGB camera point cloud (data product-4, geo-referenced using the drone's onboard GNSS), against terrestrial scanner benchmark data in the three-dimensional direction (x, y, and z).

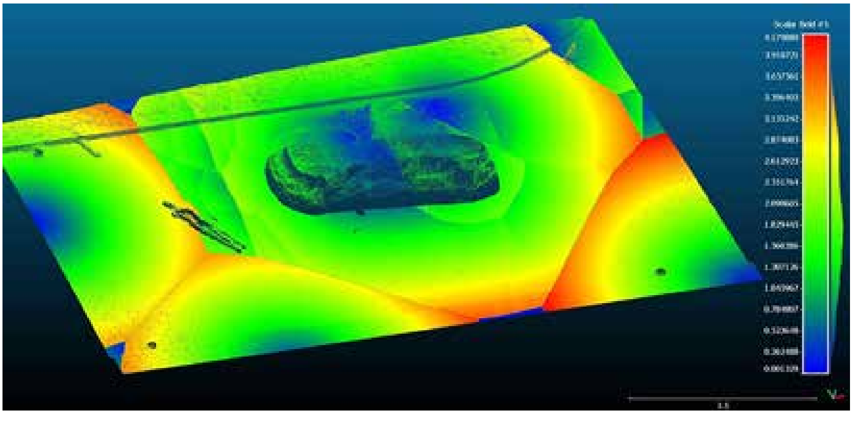

FIGURE 11: An accuracy assessment of a 45 mm focal length RGB camera point cloud (data product-4, geo-referenced using the drone's onboard GNSS), against terrestrial scanner benchmark data in the two-dimensional direction (x and y).

(Figure 11). This means a figure that is around 25 times higher than those for data products-2 and 3.

Figure 12 describes data product-5. This is created from the inaccurate GNSS drone data that was employed in the production of data product-4 but which has been geo-referenced using a local scale bar (a control scale bar) with only one measurement – the dummy – taken by means of measurement tape (1.81 m). In the global geographical context, data product-5 is inaccurate to the same average margin of error as data product-4 (4.81 m). However, when accuracy is assessed without geographical context, and taking into consideration only those measurements that have been taken from the local scene of an accident (i.e. involving only the local context), it can seen that the model measurements that were taken of the dummy exhibit no margin of error at all. That is, the photogrammetry software reports the dummy to be as tall as it was actually measured with the tape measure: 1.81 m.

Taking the dummy's height as a local scale bar, data product-5 includes a further four measurements of distance which were taken at the test site. These additional measurements, which mimic the manual measuring process (data product-0), are not initially geo-referenced, thereby avoiding the accuracy problems that occur with the drone's built-in GNSS system. Accordingly, as the results show, the average margin of error in terms of measurements taken using the local independent scale bar is 8.8 cm. This is only slightly less accurate than measurements that were taken using geo-referenced data in data product-2 and 3, where RTK GNSS was used for geo-referencing. There the respective errors that could be identified were at 6.7 cm for data product-2 and 7.5 cm for data product-3.

FIGURE 12: A 45 mm focal length RGB camera point cloud (geo-referenced using a scale bar), showing the measurement of the control scale bar (on the left) and the check scale bar (on the right).

Table 2 further presents the results of measurements that were taken using drone imaging (data product-5), using control and check scale bars and comparing these results with the manual measurements that were taken by the traffic police (data product-0). As the results that are presented in the table show, the distances that were measured for data product-5 using the local scale bar (a dummy with a height of 1.81 m) which are presented in the second column, and the measurements that were recorded for data product-0, which are presented in the third column, show a difference in measurements, ie. a margin of error when comparing product-5 to product-0 of up to 10cm. However, the average margin of error when comparing the manual measurements that were taken with the use of photogrammetry was at 8.8 cm.

TABLE 2: Summary of the measurement results, comparing the use of a local scale bar for measurements that were taken via a photograph (data product-5) and a manual data-collecting process (data product-0).

Scale bar	Distance (measured)	Distance (model)	Error
Control point 5_point 7	1.81 m	1.81 m	1.11022e-15 m
Check point 1_point 2	2.51 m	2.6 m	9 cm
Check point 3_point 4	2.7 m	2.8 m	10 cm
Check point 5_point 6	2.2 m	2.1 m	10 cm
Check point 7_point 8	3.64 m	3.7 m	6 cm
Average			8.8 cm

A brief note should be given here on a limitation in terms of the field test that has been described and in the results that are presented in Table 2: the level of accuracy for the measurements in data product-5 was only assessed from the four points and only in two dimensions (replicating the manual measurements that were taken in data product-0). In contrast, the accuracy of data products-2 and 3 are assessed on a three-dimensional scale and without limits to the reference points (see the relevant point clouds in Figure 7 and Figure 8). To be able to properly assess the comparative accuracy of the use of a local scale bar, the relevant data product should include measurements taken in three dimensions (ie. x, y, and z).

Finally, Table 3 provides a summary of all of the data that was collected, presenting the time taken to collect the measurements and the level of accuracy calculated for each data product. Accordingly, the table sorts the methods used into an order that is based on the time taken to collect the data (see Column 4 in Table 3), and based on the accuracy of the measurements (see Column 6 in Table 3). The experimental results that are presented in the table show that when collecting data with drones, completing the process using separate geo-referencing equipment takes significantly more time than does using built-in geo-referencing alone. Yet, when comparing the two methods of geo-referencing data to the measurements from the terrestrial scanner, the separate geo-referencing technology provides significantly more accurate data. At the same time, using a local scale bar in applying photogrammetry for data that is collected by drones can provide an alternative to geo-referenced data, as the results of the measurements that are taken in this field test show that the errors of margin differ from between 1.3 cm and 2.1 cm.

TABLE 3: Summary of the data collection times and accuracy levels for each data product.

Model number	Model name	Time	Place	Accuracy error	Place
0	Measuring wheel measurements and photographing	20 minutes	II	-	-
1	Terrestrial scanner	50 minutes	III	0 cm (globally geo-referenced)	-
2	Drone and 15mm RGB camera, with RTK GNSS geo-referencing	20 minutes	II	6.7 cm (globally geo-referenced)	I
3	Drone and 45mm RGB camera, with RTK GNSS geo-referencing	20 minutes	II	7.5 cm (globally geo-referenced)	II
4	Drone and 45mm RGB camera, with drone GNSS geo-referencing	5 minutes	I	481 cm (globally geo-referenced)	IV
5	Drone and 45mm RGB camera, with scale bar geo-referencing	5 minutes	I	8.8 cm (locally geo-referenced), 481 cm (globally geo-referenced)	III

CONCLUSIONS

As has been shown in the discussion in Section 1, whilst there is a growing body of research into new means of carrying out data collection and measurements at accident sites, that research is still ongoing and the methods being used are still under investigation. The larger research project to which this paper belongs is examining the potential for adopting photogrammetry via drone as a form of technology that is complementary to current practice. The results of the field test that are described here offer some support in that direction.

The results of the field test that have been described in the previous section provide specific data points on the accuracy of specific technological solutions that can be used in relation to data collection and taking measurements at scenes of accidents (corresponding to the five data products), as well as on the time taken to capture the relevant measurements when employing those forms of technology. As discussed in earlier sections, the motivations behind the study of the efficacy of photogrammetry via drone technology are to enhance accuracy, provide additional opportunities to process data, such as in terms of re-measuring the scene of an accident, provide additional viewpoints and, possibly, to reduce the time taken to complete the entire process. More specifically in the Estonian context, ongoing demographic changes, and therefore, changes to the available workforce, add a greater sense of urgency to the need to identify forms of technology that will fit in with these criteria. Considering the multi-dimensional nature of these requirements, however, the specific data points that result from the current field test cannot be taken alone when it comes to establishing the suitability or otherwise of the relevant forms of technology. Having said that, there are some inferences that seem reasonable to make based upon the data provided.

Firstly, so long as global geo-referencing is not required, the model that best balances accuracy and speed appears to be data product-5, which was considerably faster in terms of processing than all of the other viable methods (ie. data products-1, 2, and -3), with only marginal losses in terms of accuracy. Data product-4 took the same amount of time to process as data product-5, but was by far the least accurate, marking it out as an unsuitable candidate for use in this field of operations, either in place of or complementary to existing practices. Addition to costs in terms of time, the Leica C10 ScanStation laser scanning system that was used to generate data product-1, as well as the RTK GNSS system that was used in data products-2 and 3, are significantly more expensive, as well as requiring additional training to deploy, than are the equipment and resources required for the local scale bar method that was employed to generate data product-5. Again, whilst not providing conclusive evidence that would satisfy the criteria needed to justify the uptake of drone technology, it seems reasonable to infer that there are at least some considerable advantages to the use of the local scale bar use, i.e. the possibility of being able to use photogrammetry for accident site measurements at a considerably lower cost than when geo-referencing the data.

That said, there are two significant limitations to this method that are worth recognising before further study is conducted. Firstly, over and above speed, time, and cost, geo-referenced measurements can add additional value when it comes to further analysis and investigation, e.g. via the production of metadata that can make possible the identification of wider accident patterns. The local scale bar method that was used to generate data product-5 would not allow such an option. Secondly, as briefly mentioned above, drone technology in general is subject to several use limitations, e.g. weather conditions, plus the physical features of the accident site and the site type, both of which are extremely significant when it comes to the possibility of being able to fly a drone in any specific case (Padua *et al,* 2020). (For further analysis of UAV use for photogrammetry within the context of Baltic weather, see also Suziedelyte Visochiene *et al,* 2016.) Moreover, as was the case in the field test described here, additional lighting is needed to produce high quality photos, and erecting such lighting at the accident site can add additional time (which was not measured here, but see John Hopkins University, 2018, p 57 for further discussion), which may significantly extend the time required for measurements to be taken and data collection to be completed.

Having noted these limitations on the available technology, however, the paper can put forward the opinion that the positive comparisons and inferences that have been noted above and which have been supported by the field test that has also been described in this paper provide solid grounds for the further study of the suitability of the use of a local scale bar in relation to data collection and measurements at the scene of a traffic accident.

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