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ESTABLISHING EFFECTIVE AND ECONOMICAL TRAFFIC SURVEILLANCE IN TONGA

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Abstract

The Pacific Islands are seriously challenged by the growth in wealth and the expansion of international material possessions. On the roads traffic has grown dramatically and the types of vehicles now using Island roads has greatly changed. With the importation of cheap second hand vehicles designed for freeway speeds serious safety issues have grown proportionally with the increasing numbers. In this research we consider the prohibitive costs of traditional traffic controls to economy and propose a light weight highly mobile aerial surveillance system that integrates with ground policing capability. Our research question was: How can road safety and security be enhanced with economical technologies? In addition to collecting and processing live data we have also designed a forensically ready system, and an information system to process the large amounts of data generated by the addition of these technologies into the traffic surveillance processes.

Keywords
Surveillance, Security, Road Safety, Economical Technology, Innovation

INTRODUCTION

Aerial surveillance has a long history of use in the military for monitoring activities on the ground (CambraBascca et al., 2013). Commercially, aerial surveillance is used for monitoring resources such as forests, crops, coast lines, aerial news gathering, and search and rescue. The surveillance activities have relied initially on the human eye and binoculars but now have moved towards sophisticated cameras and digital technologies. These images can be reviewed in real time or can be examined at a later date for forensic analysis and evidence. With regards to traffic surveillance in particular, the increase in the number of vehicles on road has led transport management agencies to seek the use of advanced technologies that can provide better information more cheaply in order to service informed decisions and road safety. This requires collection of precise and accurate information about the state of traffic, conformance, behaviours and road conditions. It is also required to get timely information in case of emergencies (accidents, and so on). In the case of accidents, the time of response is critical in victim survivability and with increased traffic volumes even emergency vehicles struggle to reach incident scenes in a timely fashion. Traditional surveillance methods do not prove to be time effective or cost effective. They can provide useful information about traffic flows but cannot provide useful information regarding traffic flows over a space of time including the vehicle trajectories, routing information and real-time movements (Cheng et al., 2012).

Traffic information is the foundation of traffic management, traffic control, and transportation planning. However, many rural and some urban road segments are not installed with any fixed traffic detectors due to the high cost and historically low volumes. In addition in many of the built-up city areas with high surveillance the motorists have learnt behaviour regarding fixed cameras and mobile vehicles, and have change their behaviour to only comply when a surveillance instrument is present. This is exactly why my research is aiming to see if the using of unmanned aerial vehicles (UAVs or drones) will be effective in the Kingdom of Tonga for improving the flow of information for the control of vehicle traffic. Additionally, mobile traffic sensors are not broadly used, which leads to low traffic information acquisition. As a new tool, UAV or civil drone has its unique advantages of flexibility and mobility, wide view scope, and low cost compared with traditional fixed systems. Hence, in this work, UAVs are introduced to monitor road segments and to identify the problems and challenges that would face a full implementation. At present UAVs have many limitations that require management. Some of the challenges are battery life, attenuation of signals, camera cost, large datasets, lack of training, and other issues that will be documented in this research.

This paper is structured to review the background context, look at visual data processing, consider the big data problem, and to propose an integrated visual surveillance system for traffic management. The research contribution is the problem evaluation and design solution proposed.

PROBLEM BACKGROUND

Tonga has very small islands with over one hundred thousand people in population. Consequently small lightweight UAVs even with their current capabilities of endurance are effective tools for monitoring behaviours on the road (Dijk et al., 2013). Tonga does not have any traffic lights even in the most populated areas and few fixed surveillance cameras. There appears to be a need for some kind of electronic device that will assist the Tonga Police in their traffic duties, that is economically effective and efficient. The objectives for this research are to match the suitability of current off-the-shelf drones under $5000 to the task of traffic surveillance (Cusack & Khaleghparast, 2005); and, then to propose the design for information management system. There are also other practical questions to be considered. For example, Are the weather conditions in Tonga suitable? What about from January to April in the hurricane season? Also there is the consideration of other applications of these lightweight surveillance devices. For example, are they useful for other needs such as searching, Agriculture, Fisheries, Fire department or any other commercial need. These are very important areas in Tonga also. The question is, are we able to adopt some kind of framework that will help our traffic conformance as well as the other needs using the civil drones? Because the most important issue here is the safety of the people and if the civil drone can economically add value they should be more widely used.

Traffic conformance audit on roads is maintained by a mixture of surveillance devices and techniques (Coifman et al., 2004; Goradia & Xi, 2012). A compliant vehicle is one which delivers the transportation service within a profile of measurable attributes that conform to the usage contract. These attributes include behaviour, speed, mechanical safety, registration, licensing and so on. The usage contract has a wide variety of requirements that cover different vehicles, human factors and situations. Traffic intelligence can be gathered from a wide range of sensor networks. The most important aspect of using this intelligence is reference. References are found when for example the speed of the vehicle is compared with the conformance contract. A bus or a truck for example has a different conformance contract than a motorcar. Similarly matters of weight, size, registration, and so on all fall within the spectrum of traffic surveillance and intelligence gathering. Each instance on the road has a different conformance contract and some contracts overlap. The overall result is that any data which is collected has to be assessed against the reference data or template. Consequently the information processing around sensor networks has to be tuned to automate the lower-level decision-making processes and to filter out compliant information (Kastrinaki et al., 2003; Ahmed et al., 2012). Persons deciding how to act require only selective information that is about variations to conformance.

When the information processing processes are automated information may be fed directly to law enforcement or an investigating officer. For example sensors on roads may indicate that a vehicle is overweight or over height or travelling with excessive speed or dangerously (Bakhtari et al., 2006; Amran et al., 2014). For this to happen the primary data has to be processed in such a way that the information provided for decision-makers is summative in nature and represents previous determinations against benchmarks. To achieve this level of sophistication highly intelligent information systems are required to support a sensor network. This would mean that when adding UAVs to a surveillance network that the extra intelligence data can be processed into useful information for the decision-makers effectively and efficiently. The software and the computational algorithms required have to be built into the information system to support the higher-level decision-making capability. In practical terms this means that a match between an image of a vehicle and a database is required in order to find information such as the current warrant fitness, the current owner and other useful information that can lead to those responsible for the conformance contract.

VISUAL DATA COLLECTION

A quad-copter drone was used to take video footages of vehicles travelling over city streets. These video footages were then used as the input of the data processing life cycle that was used to automatically process number plates and speed data. The data could be processed either on the drone motherboard, stored for later analysis or in our case we beamed directly back in real time to a laptop processing unit. We calculated vehicle speed and number plate recognition using the following processes.

Generally, a license plate detection system has to solve two problems: where a license plate is located and how big it is (Howell, 2015). Usually, the candidate position of characters in the license plate is first identified, and the bounding box of the license plate is determined later. There are many challenges in license plate detection in an open environment, such as various observation angles from cameras, background clutter, differently sized license plates, poor image quality from uneven lighting conditions, and multi-plate detection. In terms of drone traffic surveillance in Tonga, the increase in the number of road users today has led to evaluating the use of technologies for monitoring and control. However, the environment posed extra challenges for instance, the existence of tree branches over public roads, low overhead phone and power lines and tall coconut trees near roads. These can be major obstruction as they block the drone's view and hide vital evidence.

The Quad-copter that was used to take images for data collection purpose in this study used ISO-100, shutter 6400, EV-1 and Fnum-F2.8 camera settings. Figure 1 specifies the steps in image processing that we used. Step one deals with image acquisition, two deals with pre-processing processes which concerns with ways that increases the chances for success. Step three deals with partitioning of the image into parts or objects and step four concerns with the conversion of the input data into a form that is suitable for computer processing. Step five deals with the description of the image. This is concerning the extraction of the features that can be used to differentiate one object from the other. Step six deals with recognition of the image, assigning a label to an object based on its descriptors. Final step is concerned with the interpretation of the image to assign meaning to the recognised objects. We developed this model in the research and applied it to the actual processing of numberplates. The number plate processing required morphological processes, a conversion of the colour imagery from the drone camera to greyscale is, and then a cropping and a dilation of the image so that only the number plate could be fed through the character recognition algorithm. With the limited number (6) of characters on a number plate processing was very quick. When the system is connected to a reference database then immediate data match can be achieved to find the owner of the conformance contract.

The speak calculations could proceed in two fashions. The simplest way is to take time elapses as vehicles move between measured points. However the resultant is an average speed and the distance between the markers has to be sufficient that the entry image and exit image are distinct, and that the margins for visual error calculations are also factored. Consequently we opted for pixel by pixel image processing to calculate instantaneous speeds. Drone traffic surveillance provides many advantages for instance; low cost, easy to deploy, high mobility, large view scope, uniform scale, and so on (Goradia & Xi, 2012; The Economist, 2015). The drone can adjust its flying altitude in order to capture the target object from various angles in order to have the best image. However, data captured by drones contains much more complex information than traditional surveillance video. Footages captured by drone contain not only the traditional data such as traffic flow information but also 360^o level data for each vehicle such as vehicle's trajectory data, lane change data and the cars around data on the road. As a result, extracting a moving object from video frames is a challenge.

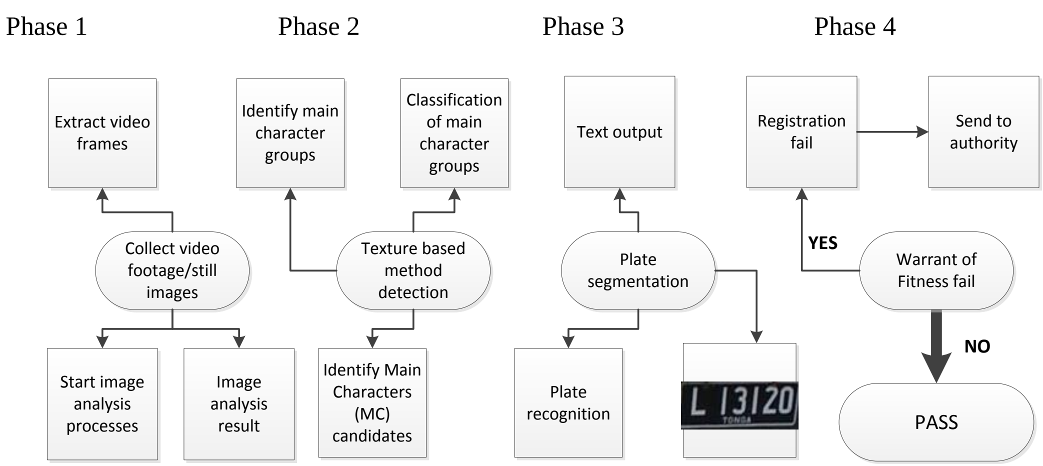

Figure 1: Four phases of image processing employed in this study.

Each vehicle's speed includes two directions – longitudinal and lateral. Usually the lateral value can be assumed to be 0 unless the vehicle makes a lane change. If that happens, the value will change accordingly but relatively small compared to the longitudinal speed. In terms of footage from the drone, any movements in the lateral direction can be the drone's camera motion. In order to minimize this type of errors, only the velocity of vehicle along the road longitudinal direction is considered, which can be expressed by

$$V_{Ion}\ {}^{1}/_{4}\, V_x \cos\vartheta + V_y \sin\vartheta$$

It is possible to acquire each pixel's velocity however, due to the variability nature of the optical flow at pixel level; the accuracy of the vehicle's speed obtained is questionable. As a result, the optical flow is used to detect the shape of each vehicle, and the value of V_{Ion} is converted into a binary value in the following equation where τ and σ are the maximum and minimum rational speeds.

$$F_{OF}(i,j) = \begin{cases} 1 & V_{Ion} \geq \tau \text{ and } V_{Ion} \leq \sigma \\ 0 & \text{otherwise} \end{cases}$$

This relates to the drone's altitude and its stability when the image is captured.

Figure 2: speed calculation images

Drones have proven to be beneficial, effective and efficient in observing and surveilling activities on the ground (Kovar, 2015; Paganini, 2015). However, calculating speed of moving vehicles from a moving camera such as those on drones in real-time is a difficult task due to the potential variability in moving frames, movement and vibration of the drone's camera in the air caused by wind force, the vehicle will change its position on the video as it is travelling so the angle will change accordingly. The settings of the drone's camera might also change such as its brightness values and colours. As a result, stationary and moving cameras call for different processing approaches. In our research we produce the computational algorithms for both instances but only did the calculations and practice for a stable drone. Hence, when the image from the drone's footage is acquired, the point of interest is characterised by its vector features composed of 128 values. The feature matching process started continuously in order to detect changing similarity points and to filter the most stable estimate. The filtering process delivers two images of the vehicle that are very close in time, and hence the distance covered by each image object can be simply computed.

BIG DATA PROBLEMS

The current technologies used for traffic surveillance seem to be inadequate, inasmuch as, purposely placed cameras can only photograph speeding vehicles or vehicles proceeding through red lights. Such images cannot give investigators information such as behaviour of the driver that leads to a traffic accident. For instance, were they weaving all over the road even though they were driving slowly? This type of question needs a different type of monitoring system. However, although there are many benefits of such system, the main challenge is managing big data issues (Rowlingson, 2004; Pooe et al., 2012). The small digital cameras are very efficient and they produce huge amounts of image and other metric data. Big data is a term used to describe sets of electronic data both structured and unstructured, that are large and complex. The current data processing techniques or methods, database applications and software are insufficient. The main issues of big data include capturing, searching, storage, analysis, query and updating and managing information privacy just to name a few. If this is the case then the question is, how big is big data? An example of big data might be Petabytes (1,024 terabytes) or Exabyte (1,024 petabytes) of data consisting of billions to trillions of records. From the data that was collected for this study, a 60 seconds of footage from the quad-copter equals to 446.25MB of video data, this was taken with ISO-100, shutter 6400, EV-1 and Fnum-F2.8 at 25 frames per second, a rate of 60Mbps. At this rate, a drone that can take 30 minutes of video, that is 446.25 x 30 = 13 Gigabytes and 387.5 Megabytes of data. This amount of data will multiply by the number of hours worked each day, and by the number of drones being used by the police department. In terms of storage, if the traffic surveillance system in Tonga employs five quad-copters, video footage streaming from five drones will be 133 Gigabytes and 875 Megabytes of data. Even for small to medium amounts of data the speed of extraction and access to specific segments of data can be hard to manage when the volumes get great. If the traffic surveillance system in Tonga employed five quad-copters, and they observe traffic behaviours every day but only at peak hours, 3 hours in the morning and 3 hours in the evening. Capturing six hours a day of streaming video data from five drones, that's 823 Gigabytes 250 Megabytes of video data. If 823,250 is multiplied by 365 days, that's over 293 Terabytes of data in one year.

A FORENSICALLY READY DRONE INFORMATION SYSTEM

The notion of digital forensic readiness is to meet the objectives for a system that is used in a digital investigation to maximise its ability to collect reliable evidence while minimising the cost (Beebe et al., 2005; Paganini, 2014). The forensic readiness objectives are designed to:

a) To gather admissible evidence legally and without interfering with business processes.
b) To gather evidence targeting the potential crimes and disputes that may adversely impact an organisation.
c) To allow an investigation to proceed at a cost in proportion to the incident.
d) To minimise interruption to the business from any investigation.
e) To ensure that evidence makes a positive impact on the outcome of any legal action.

The advantages of forensic readiness planning include:

Preparing for potential need for digital evidence. If an organisation has to go to litigation and if digital evidence is required, electronic evidence is required to be collected and stored in an appropriate manner so that it is readily available when requested and can be admissible in the court of law. In this process, incident response, disaster recovery and business continuity policies are improved by a forensic readiness policy or plan.

Minimising the cost of the investigation. In the case of a drone surveillance system, the evidence is already gathered, the investigator needs only to process, analyse and review the video footages. This enables faster and more efficient investigation process as a result, the cost of the investigation is minimised and interruption to businesses' normal operation is also minimised. Figure 3 illustrates the systems process architecture.

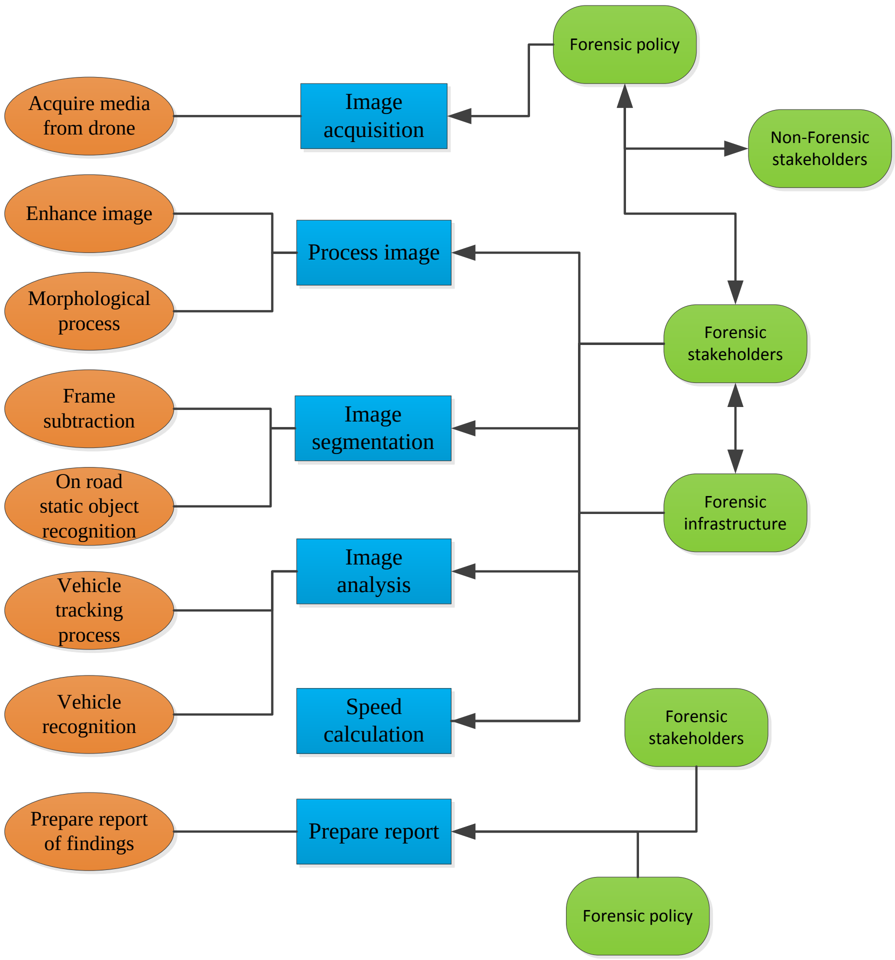

Figure 3: A forensic readiness processes for drone traffic surveillance information system

The requirement to process big data from a drone surveillance program for traffic conformance can be mitigated by an efficient and effective information systems architecture. We propose a structure that is supported by both technology and personnel that can efficiently and effectively mine the mountain of data delivered by both exception and by archival extraction. Real-time data is most efficiently processed by exception filters and this data can be rapidly transmitted to enforcement officers for further follow-up. Stored data requires both storage and mining capabilities. We propose in figure 4 an information systems architecture that maps operational and infrastructure readiness onto the response units liable to act on the information. The information itself has been categorised before extraction and prepared by due processes that are compliant by law and by policy for its usage. Such a system is a necessary addition to any new technologies that may be used for traffic control and conformance.

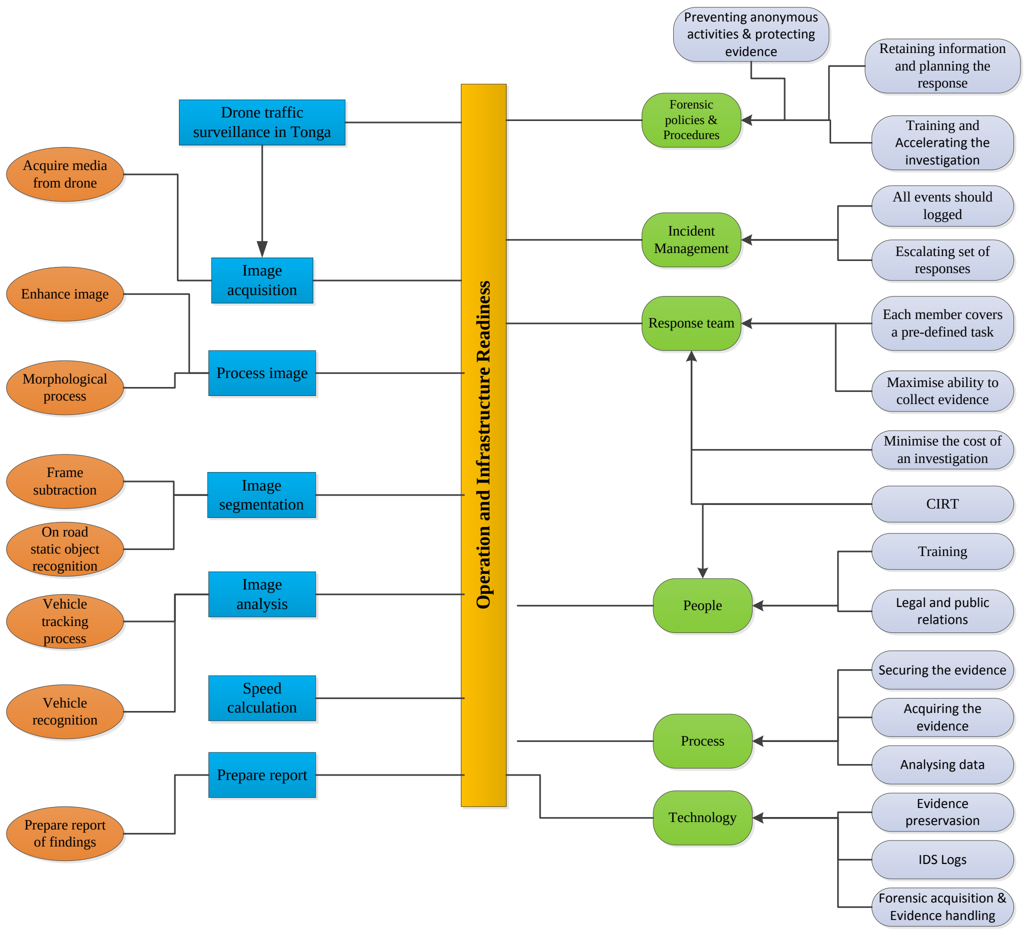

Figure 4: Information Systems architecture for drone data

CONCLUSION

The study was aimed to fill the identified gap in the literature and in practice by developing an information system that is forensically ready to use for drone traffic surveillance in Tonga. The relatively small size of each island and the intensity of traffic allowed lightweight and economical quad copters to be used in this research. The proposal is innovative and as a prototype has added value to current traffic monitoring and control systems. Further research is proposed into the efficient utilisation of the resource so that effective monitoring of vehicle behaviour can be achieved within stringent economic constraints for data. The systems reviewed and shown in this paper provide a cost-effective solution to the constraints imposed by the problem context.

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