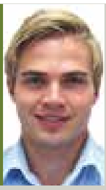
Drone-based traffic flow estimation and tracking using computer vision



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The autonomous drone-based traffic flow estimation system can effectively be separated into two parts. The first part consists of the computer vision system used to detect and calculate vehicle velocities for calculation of key traffic metrics. The second part involves the design of an autonomous target tracking and landing system for the unmanned aerial vehicle (UAV).

BACKGROUND

According to the National Traffic Information System, there are currently around 11 million registered vehicles on South African roads (National Department of Transport 2014). This number is increasing at an alarming rate, which requires that roads be upgraded continually. The study of traffic flow estimation is used to evaluate how well a particular road segment is accommodating traffic, as well as to determine the priority of road upgrades. Current traffic monitoring techniques make use of intrusive static sensors in the form of inductive loop detectors, IR detectors and radar guns (Thies *et al* 2013). Visual monitoring is often done manually with the operator watching hours of video footage while counting the cars as they pass through an area. Two of the significant problems associated with the above-mentioned techniques are that they are intrusive and time consuming. Traffic cameras are mounted around most urban areas and are used primarily for security reasons. In the City of Cape Town alone there are around 300 traffic cameras streaming live video directly to the Traffic Message Channel (TMC) database. The cameras cover the majority of the roads throughout Cape Town, and could therefore provide unparalleled access to essential video data.

AIMS AND OBJECTIVES

The project proposes a novel solution to automate traffic flow estimation using computer vision. It also introduces the notion of making the recording equipment mobile by using drone-based equipment, thereby negating the need for fixed recording installations. The results demonstrate measurement accuracies of 100% down to 81% from ideal to worst case conditions, and successful implementation of drone control algorithms.

SYSTEM DESIGN

The autonomous drone-based traffic flow estimation system can effectively be separated into two parts. The first part consists of the computer vision system used to detect and calculate vehicle velocities for calculation of key traffic metrics. The second part involves the design of an autonomous target tracking and landing system for the unmanned aerial vehicle (UAV).

TRAFFIC FLOW ESTIMATION

A main traffic flow algorithm is required to automatically detect the number of vehicles that pass through a given area, as well as to determine their relative velocities. Once the vehicles are detected and their velocities estimated, they are classified according to relative size (motorbikes, cars and trucks).

A particularly challenging aspect was to design a system that relied entirely on visual references. The idea was to design and implement a non-intrusive system that makes use of existing traffic cameras placed around a city. It is important to note that traffic cameras need not be the only source of video feed. The idea is to eventually incorporate an unmanned aircraft into the system that can autonomously fly to remote locations which might not currently have an established traffic camera network. The system is required to be extremely flexible in order to accommodate a variety of different video sources, and therefore relies heavily on highly adaptive computer vision techniques to compute all traffic metrics.

The key challenge to realising the system is to successfully identify and track objects in a video stream. The background subtraction (BS) technique, for use in computer vision, is designed to successfully differentiate a moving object from its corresponding static background scene. The system discussed in this article makes use of the BS technique for the detection and tracking of passing vehicles.

To conduct background subtraction, it is necessary to obtain a model of the static background scene. Background modelling consists of two primary phases – phase one is responsible for background initialisation, while phase two is aimed at updating the background model.

The use of the BS algorithm does not provide a complete solution with regard to object detection. A particular disadvantage of using the MoG (mixture of Gaussian) technique, is that the object shadows tend to be classified as part of the foreground. The reason for this is that shadows share the same movement patterns as the objects that create them. Shadows also tend to exhibit similar pixel intensity characteristics as the corresponding foreground objects (Lovell *et al* 2012). When two vehicles are in close proximity to each other, their corresponding shadows make them appear as a single object leading to reduced tracking and counting accuracy.

The shadow detection technique used in this system is based on the chromaticity characteristics of shadows. Chromaticity is a measure of colour that is independent of intensity (Lovell *et al* 2012). The idea behind the method of chromaticity is to detect shadows based on their pixel characteristics. Once the frame coordinates of the shadow pixels have been identified, the corresponding pixels are subsequently removed from the foreground mask (result of the background subtraction) before being put through a bilateral filter to minimise noise.

Traffic flow estimation theory does not only depend on the number of vehicles passing through a specific road location, but on the relative velocities of the vehicles as well. Vehicle velocities are usually obtained using radar guns, inductive loops and IR counters (National Research Council 2010). However, these methods are seen as intrusive, as additional hardware needs to be incorporated into the existing road structure. A particularly attractive alternative is to use the existing camera infrastructure to automatically compute relative vehicle velocities.

Optical flow tracking provides a way of determining pixel displacement between consecutive frames. Optical flow operates under two primary assumptions. The first assumption is based on the fact that the pixel intensities of an object should remain constant between consecutive frames (OpenCV 2011). The second assumption is that neighbouring pixels will have a similar motion to that of the pixel under observation (OpenCV 2011).

Autonomous traffic flow estimation is recognised as the fundamental core of this system. Determining the total vehicle count and respective vehicle velocities was a necessary step in computing traffic flow metrics. It was decided that the following metrics would be useful in describing uninterrupted traffic flow data:

- Time mean speed (TMS)
- Volume
- Flow rate
- Density
- Peak Hour Factor (PHF), and
- Level of service (LOS).

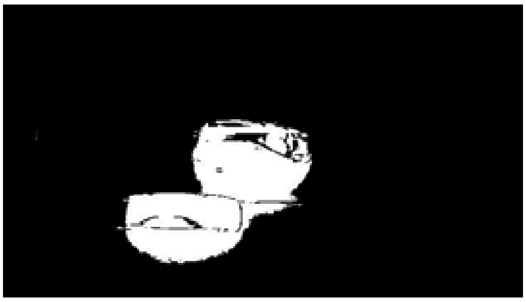

Figure 1: Raw background subtraction (BS) frame

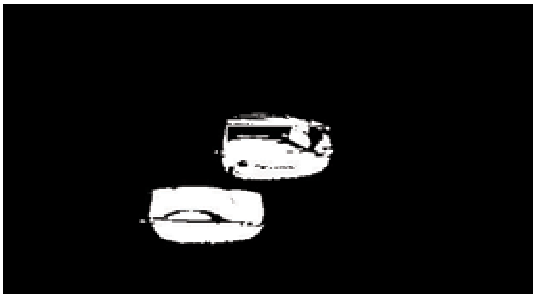

Figure 2: Shadow removal

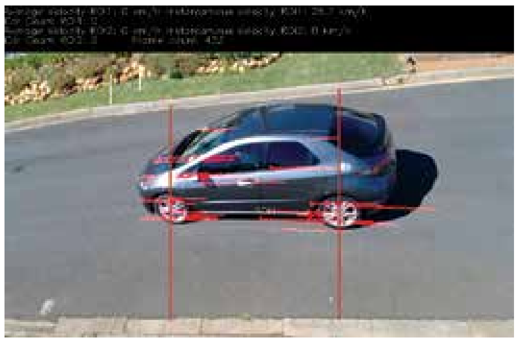

Figure 3: Optical flow vectors

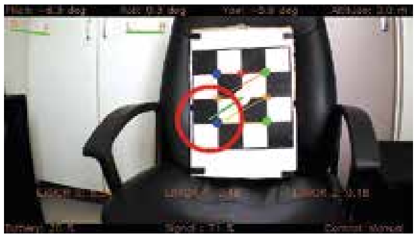

Figure 4: The drone's on-screen display once the target has been identified

Once the system is able to identify the number of vehicles moving through a particular road segment (background subtraction) and their corresponding velocities (optical flow tracking), the above-mentioned traffic flow metrics are then autonomously generated based on predetermined equations described by the Highway Capacity Manual (National Research Council 2010).

AUTONOMOUS AIRCRAFT

Autonomous aircraft is included to provide a novel form of autonomy for future traffic analyses. The idea is that the drone will eventually fly to pre-determined destinations using a GPS navigation system. Once the drone is within visual range of the landing platform, a unique identifier in the form of a checkerboard pattern will be used as a reference for the visual target tracking system. When the control system has stabilised the drone in front of the target, an autonomous landing system will land the drone on the platform below. The drone's front-facing camera can then be used as a mobile substitute for the static pole-mounted traffic cameras.

In order to detect whether a checkerboard shape is currently in the frame, each frame is converted to a greyscale image to maximise the distinction between the black and white checked squares. The frame is then put through a binary threshold function before a pattern recognition algorithm is used to identify the location of the checkerboard. Figure 4 shows the drone's on-screen display once the target has been identified. An algorithm, running on the ground station, determines the translation and rotation of the checkerboard in 3D space. This information is then used by a feedback PID control system to automate the drone's flight and ultimately stabilise it at a set distance from the target position.

RESULTS AND CONCLUSIONS

This article addressed two key challenges in the field of traffic flow estimation – laborious manual vehicle counting, and the need for multiple and fixed recording infrastructure. The former challenge was addressed by automating vehicle detection and automatic calculation of traffic flow metrics using computer vision techniques. The latter was addressed by introducing drone-based recording equipment that uses pole-mounted landing platforms making it especially useful in remote and fiscally-challenged areas. The results demonstrate that the solutions work with high accuracy, with detection ranging from 81% to 100%, and 100% landing accuracy for the drone.

A demonstration video of the complete system is available at: http://goo.gl/jT7lke

REFERENCES

http://dx.doi.org/10.13140/RG.2.1.1024.6888