Statistical Profile Generation for Traffic Monitoring Using Real-time UAV based Video Data

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Abstract— The eye-in-the-sky alternative to collecting real-time temporal/spatial data using small unmanned helicopters is proposed to: monitor traffic, evaluate and assess traffic patterns and provide accurate vehicle counts. Collected real-time visual data are converted to traffic statistical profiles and used as continuously updated inputs to existing traffic simulation models improving calibration, accuracy (in terms of variable parameter values) and future traffic predictions. Functionality of simulation models is enhanced, and reliability is improved. The proposed approach offers significant advantages over conventional methods where historical and outdated data is used to run poorly calibrated traffic simulation models.

Keywords – unmanned helicopters, visual data, traffic monitoring, traffic simulation models.

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I. INTRODUCTION

Small unmanned helicopters offer a novel, viable and cost-effective solution to the problem of collecting spatial and temporal real-time, dynamic, video-based traffic network data. Assuming that helicopter modeling control and navigation issues have been solved, it has been shown that a team of such small tele-operated / semi-autonomous unmanned helicopters, each equipped with a fully autonomous pan-tilt camera vision system may be used to: track individual vehicles; track the fastest moving captured vehicle; ‘lock in’ a specific vehicle dictated by a human operator who views captured video data; provide vehicle counts; monitor traffic over an intersection or road segment or specific traffic network; evaluate and assess traffic patterns, and improve traffic management [1], [2]. Most importantly, such a system may be used for emergency response where helicopters fly to the scene of an accident and provide visual data to emergency response team who can then make timely informed decisions. In short, aerial vehicles are being used for traffic data collection and surveillance [1].

The novel idea presented in this paper focuses on the fact that collected video data may be incorporated into traffic simulation models improving real-time traffic monitoring and control. Video data may be used to evaluate traffic patterns over chosen areas, study possible network enhancements, update and calibrate traffic simulation models such that real-time changes in an urban traffic system will be captured and discrepancies between actual/simulated traffic conditions will be minimized.

The way to implement this idea is by converting collected video data into ‘useful traffic measures’ that can be combined to obtain essential statistical profiles for traffic patterns. In essence, following the proposed approach, traffic parameters such as mean-speed, density, volume, turning ratio, origin-destination matrix, to name a few, may be derived accurately and be used to improve prediction of traffic behavior in real-time. Emergency response strategies and control of traffic using adaptive intersection signal control, ramp metering or variable message signs can also be planned and optimized in real-time. Derived parameters being dynamically updated may serve as inputs to commercial traffic simulation models.

It is important to emphasize that traffic simulation models play an important role in managing and evaluating traffic networks. Traffic engineers rely on accurate prediction of future traffic trends based on outputs from such models. Hence, calibration and update of these models becomes a very important and critical concern. Since current sensors such as inductive loops are unable to provide detailed data for such models, and since data collection following conventional techniques is a highly exhaustive and intensive procedure, mostly historical out-of-date data is used for calibration of these models. Therefore, the proposed alternative method is justified.

At this stage of the research, the helicopter (helicopters) is (are) assumed to hover over intersection areas, or above
a specific street segment, that is, the source is fixed. Thus, only a certain region of the network is visible to the camera. At a later stage, multiple helicopters will fly at the same time to cover a wider area of the network. The images will be superimposed to obtain a complete picture of the network.

Section II discusses related research, while Section III summarizes on-board and on-the-ground processing fundamentals. Section IV focuses on the generation of statistical profiles, and Section V presents results.

II. RELATED WORK

The increase in number of vehicles on roadway networks has encouraged transport management agencies to allow use of technology advances and innovative solutions to obtain data of traffic trends to monitor and control traffic in real-time. Current methods such as detectors embedded in pavements or pneumatic tubes, and cameras mounted on towers have proven to be expensive and time-consuming. Moreover, these methods provide point-based data since only a certain point or region of the network is targeted. UAVs provide the “bird’s eye view” obtaining temporal-spatial data for network surveillance.

Satellites were initially considered for traffic surveillance purposes, but the transitory nature of satellite orbits make it difficult to obtain the right imagery to address continuous problems such as traffic tracking [7]. Also, cloud cover hampers good image quality on days with bad weather. Manned aircrafts are deemed expensive for traffic surveillance studies and are non-operational in severe weathers as well as potentially unsafe environments due to presence and safety concern of operators. Unmanned helicopters on the other hand, can fly at low altitudes and do not involve risk of operators. They may be employed for a wide range of transportation operations and planning applications such as incident response, monitor freeway conditions, traffic signal control coordination, traveler information, emergency vehicle guidance, vehicle tracking on intersections, measurement of typical roadway usage, and estimation of Origin-Destination (OD) flows [3].

On-going research projects propose technologies that improve surveillance techniques for traffic management. Travel time estimation algorithms such as Extrapolation method and Platoon matching have been developed based upon measurable point parameters such as volume, lane occupancy etc. image matching algorithms are used to match vehicle images or signatures captured at two consecutive observation points. Other techniques use image sensors to measure traffic flow parameters [4], [5].

III. HARDWARE, ON-BOARD/OFF-LINE PROCESSING

Each helicopter is equipped with custom made vision systems for on-board and on-the-ground data processing, pan-tilt cameras for dynamic tracking and car-following, other sensors and mission specific controllers for robust hovering over intersections and assigned target areas. A custom made system is shown in Figure 1.

Helicopters like the one shown in Figure 1 may be used to fly to and hover over chosen intersections for simultaneous video data collection, and to collect video data over surface street segments, traffic corridors, or highway segments. The used (fully functional) vision system has on-board and on-the-ground processing capabilities for image stabilization, object extraction, localization, motion estimation, grouping, network geometry extraction, vehicle tracking and traffic patterns, on top of and in addition to a robust helicopter control system.

![Figure 1. Custom-made Unmanned Helicopter with On-board Vision system and controllers.](image)

Figure 2 shows the different modules involved in the image processing process [1]. The stabilization module overcomes vibrations inherent in a VTOL vehicle. The motion extraction module gathers information from the Inertial Measurement Unit (IMU) to extract the moving objects from the images, the configuration of which is relative to the camera. The feature extraction module is used to select features from the image sequence that are likely to provide as much information as possible, such as edges and lines that can be matched to automobiles or to the silhouette of the road. The feature grouping module groups the features generated by the feature extraction module to allow for scene interpretation.

![Figure 2. Block diagram of the image processing modules](image)

To fully exploit the capabilities of the helicopter (mobile) platform, the vision system is designed to adapt to different environmental setups. The environmental setup selection module contains algorithms to achieve this automatically. The structures containing the grouped features are tracked in the vehicle tracking module through the image sequence to estimate the trajectory each vehicle followed. Finally, the traffic statistics module receives all the information created in the system and converts it to statistical measures. This module is able to count the total number of vehicles or turning vehicles at...
intersections based on the estimated vehicle trajectories and the extracted local network geometry.

IV. GENERATING STATISTICAL PROFILES

Collected video data are exploited to obtain detailed information about the traffic flow in general. Related traffic parameters are formulated and modified based on information extracted using aerial video data.

Figure 3 shows the proposed and utilized conceptual framework. The real world traffic network block depicts the physical traffic network. The gray blocks depict the utilization of unmanned helicopters and the on-board/on-the ground image processing system. Traffic parameters are generated and fed to a traffic simulation model, which will then be used for modeling traffic conditions. Once the model is calibrated to accommodate a current traffic pattern, measures of strategic effectiveness are incorporated to make improved decisions in real-time.

Capacity and Occupancy:

Capacity of a link may be determined based on the space headway and acceptable gap:

\[ d = l_i + \sum_{j=1}^{n} (l_i + g_a) \]  

Thus, the total capacity of the link becomes \( I + n_o \). Also, the occupancy of the link using temporal data from a static image may be given as:

\[ o = \frac{n}{1+n_o} \]  

Statistical conversion involves placement of “virtual detectors” (VDs) at the beginning and end of each link as shown in Figure 5.

These VDs act as ‘point detectors’ where each vehicle entry is recorded helping in determining the path of the vehicle. This in turn is helpful to calculate the turning movement and the origin-destination (O-D) matrix.

Mean Speed on Network

Mean speed, \( s \), may be calculated by observing the travel time of individual vehicles through the link:

\[ s = \frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{m} \frac{d_i}{t_{i,j}} = \frac{d_i}{n} \sum_{j=1}^{n} \sum_{i=1}^{m} \frac{1}{t_{i,j}} \]  

with \( d_i = VD_2 - VD_1 \).

Flow

Flow, \( f \), is given by the number of vehicles passing through a certain point in the network in a given time period (T):
Therefore, the dynamic occupancy of a link is defined based on the traffic flow $f$ and speed $s$ as follows:

$$o = \frac{f \cdot L}{s}$$  \hspace{1cm} (6)

Density

Calculating density of a particular link or network has proven to be very difficult given that point detectors are unable to keep track of vehicles currently present on a link. Video data enables us to calculate density using spatial, temporal, as well as (pseudo)-spatial-temporal methods.

To calculate spatial density, a virtual detector of width $\Delta x$ is placed at any point on the link as shown in Figure 6.

![Figure 6. A Virtual Detector of $\Delta x$ to calculate spatial density](image)

The spatial density $k_s$ can be calculated as:

$$k_s = \frac{\sum_{j=1}^{n} \sum_{i=1}^{\Delta x} t_{i,j}}{T \cdot \Delta x}$$  \hspace{1cm} (7)

$$k_s = \frac{\sum_{j=1}^{n} \sum_{i=1}^{\Delta x} \frac{1}{S_{i,j}}}{T \cdot \Delta x}$$  \hspace{1cm} (8)

Temporal density is calculated using a Virtual Detection Frame ($VDF$) as shown in Figure 7. This method, in fact, uses a single still-image at one time and calculates the vehicles present inside the $VDF$.

![Figure 7. A Virtual Detection Frame to calculate temporal density](image)

Using a $VDF$ of length $d_{fr}$, the equation for temporal density $k_t$ becomes:

$$k_t = \frac{1}{d_{fr}} \sum_{j=1}^{n} n_j$$  \hspace{1cm} (9)

(Pseudo-) Spatial-Temporal Density

Based on the two calculated measurements, the spatial-temporal density may be obtained by repeating the procedure over a time period $T$. Thus, temporal density is calculated for each time unit for a period of time $T$ (for example: one hour), and the average density $k_{st}$ can be calculated as:

$$k_{st} = \frac{1}{T} \int \left( \frac{1}{d_{fr}} \sum_{j=1}^{n} n_j \right) dt = \frac{1}{T \cdot d_{fr}} \int \left( \sum_{j=1}^{n} n_j \right) dt$$  \hspace{1cm} (10)

Turning Movement/Origin-Destination

It is essential for traffic planners to know an estimate of number of vehicles passing through an intersection. It is also necessary to know the ratio of turning vehicles (left, through or right) for signal timing and control purposes. Presently, turning movements are calculated using manual count only. This ratio can however be calculated by tracking every individual vehicle through an intersection, using the tracking algorithm. As mentioned earlier, $VDs$ are assigned at start and end points of links. Each vehicle in the network is tagged with its identity number, $id$, time of arrival and position at each $VD$ it goes through. For example, Figure 5 depicts an intersection with eight $VDs$ to record the movement of vehicles.

A vehicle that enters the network through $VD_1$ and turns left will be assigned the path $VD_1-VD_2-VD_7-VD_8$ and so on. Thus, to find the turning movement for all vehicles with tag $VD_2$, the path of each vehicle must be checked. Thus, the turning movement will be given by the ratio $VD_2 \Rightarrow VD_7:VD_2 \Rightarrow VD_3:VD_2 \Rightarrow VD_6$.

$OD$ matrix is essential to analyze the travel behavior for a given network. $OD$ studies are beneficial for observing traffic patterns, as they are indicative of the driver’s preferred path from a specific origin to a specific destination. Vehicles will be also tracked from the moment they enter the network until they leave it as shown in Figure 8.

![Figure 8. A network with multiple OD nodes](image)

Each node acts as both an origin and a destination. When a vehicle enters the network through a node, it gets tagged by its source of origin. Its path is followed, and
finally when it leaves the network, it gets assigned with the destination point. Travel time of each vehicle for every OD pair will be observed and tabulated. Assuming \( n_{on, dn} \) be the number of vehicles with origin \( on \) and destination \( dn \). Figure 9 shows an instantiation of an OD matrix that can be formed from Figure 8. Same type of table can used to represent the travel time \( t_{on, dn} \) for vehicles to enter and exit the network.

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Figure 9. OD Matrix for small network

In case of large networks, each origin or destination node for a zone will be considered as a centroid of the zone [6]. With current technology, estimating this centroid point is not accurate. With help of aerial data, it will be easier to accurately calculate centroid of the zone based on density of the zone.

**Delay**

Delay is a very important component of traffic behavior. A network with minimum delay implies a free flow network with low travel times. Delays can be either recurrent (due to bottlenecks, peak-hours) or temporal (due to an incident/accident etc). Delays can be accounted due to increased occupancy of the network which leads to speeds lower than free flow speed \( s_f \). It is rather very hard to calculate delays using conventional methods of loop detectors. Considering that every vehicle is recorded for time and position through the network, delay may be calculated as:

\[
\text{Delay} = \frac{n_s f_s}{\sum \sum \frac{1}{t_{i,j}}} - d = \frac{n_s f_s - d \sum \sum \frac{1}{t_{i,j}}}{s_f \sum \sum \frac{1}{t_{i,j}}} \quad (11)
\]

Depending on application, other relevant parameters may be defined and measured/estimated.

**V. RESULTS AND RECOMMENDATIONS**

Statistical profiles generated using the previously derived equations serve as inputs into simulation models to update the traffic parameters in real-time. Such procedure leads to better and optimized results from these models, which will improve the accuracy of simulated results as well as diminish discrepancies between observed and simulated traffic data.

Virtual detectors are implemented as colored boxes in the image processing algorithm. Each lane has its own corresponding box, which is responsible for detecting every vehicle passing through it. The boxes can be either automatically placed after the system recognizes the road environment; or the experimenter can manually place the box to the desired detection region. It is critical that the boxes do not overlap the same region of interest, and the same vehicle should not be counted by both the VDs. Still, there can be exceptions when a vehicle tries to change lanes in the detection zone. Figure 10 illustrates how these detectors are implemented based on the proposed approach. The colored boxes show VDs for different lanes. It may be noted that because of instability factor of the helicopter, these boxes seem to be shifted across the lanes in figure 10. This leads to one vehicle being counted by two detectors, which leads to vehicle count error. Further image stabilization will produce much better and accurate results.

Figure 10. Colored boxes show implementation of virtual detectors in the image processing technique.

Synchro is used to simulate a traffic network on the USF campus. Network geometry was validated using the Google Earth software, while special attention was paid to turning lanes. Volumes calculated from the obtained data are inputs to the simulation model. Figure 11 presents the real traffic network built using Synchro 6.

Figure 11. The USF campus network using Synchro

Data was collected using an unmanned helicopter with a fully autonomous pan-tilt vision system with one camera mounted on the helicopter hovering over the intersection of Alumni Dr. and Leroy Collins Drive in the morning hour from 7:00 AM to 8:00 AM. Counts/volumes were extracted and input into Synchro to update the traffic behavior. Figure 12 shows the volume, average speed, and turning movement on the observed area.

Figure 12. Real traffic network data collected using unmanned helicopter for Synchro model.
It can be observed that the traffic follows a certain trend depending on the direction of travel. Since the data is for only one hour (due to limitation of flying time), and cover only one intersection, major deviations in traffic are not noticeable. Though, it has to be pointed out, that this effort is to show that important information can be extracted out from readily available video data. In the future, the flying time and the observable area can be increased massively.

Future work needs to be done with multiple helicopters hovering on different intersections collecting data simultaneously. The combined data needs to be input into the simulation model to generate an overall profile of the traffic network. Also, work needs to be done on calculating statistics when the helicopter is in a moving state, that is, the image source is also moving.

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