Extended Abstract

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Title: An Advanced Framework for Traffic Parameters Estimation from UAV Video

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Introduction

Currently unmanned aerial vehicle (UAV) is at the heart of traffic sensing research due to its advantages such as low cost, high flexibility, and wide view range over traditional traffic sensing technologies *(2, 7, 8, 22)*. It opens up new opportunities for intelligent transportation systems by supporting efficient and reliable traffic monitoring and decision making. Under such context, an increasing trend of emerging research on UAV-based traffic detection can be observed. In many preliminary experiments, researchers just explored the possibilities of using UAV for traffic monitoring, thus, they focused on either UAV videos with static backgrounds *(11, 16, 18, 19)* or some straightforward research tasks (e.g., vehicle detection) that could be completed without handling ego-motion issue *(1, 5, 21)*. Recently, with the needs for more advanced ITS applications and great progress in video processing technologies, some new studies have been conducted on addressing the UAV ego-motion issue *(4, 6, 12-15, 20)*. Some of them have already achieved great progress on the extraction of aggregated macroscopic traffic parameters from moving UAVs *(12-15, 20)*. However, there is still a wide gap between the state-of-the-art methods and a complete framework that can automatically estimate both microscopic traffic parameters and lane-level macroscopic traffic parameters at the same time. In this paper, an advanced framework is proposed to fill this gap by addressing several key challenges. This framework is composed of three functional modules: core functional module, data storing module, and traffic parameters estimation module. The core functional module consists of two sub-modules, which are a new method for lane detection and an exclusive method for multiple vehicle tracking in UAV video. The integration of the two sub-modules enables the collection of various raw traffic data, which are then organized and stored in the data storing module for further processing. The traffic parameters estimation module is designed to calculate the macroscopic and microscopic traffic parameters, and to analyze individual vehicle behaviors. Experiments on real-world UAV video data and thorough analyses on the results demonstrate the promising performances of the proposed framework.

Methodology

The proposed framework is composed of three main modules: core functional module, data storing module, and traffic parameters estimation module. The core functional module contains two sub-modules, one for lane detection and another for multiple vehicle detection/tracking. The lane detection submodule has three steps: modified Canny edge detection *(3)*, Hough transform *(9)*, and DBSCAN clustering *(10)*. Color information is integrated into the standard Canny edge detection to filter our redundant lines by setting the hue channel and saturation channel. Hough transform is a standard process following Canny edge, and in the Hough space, we adopt DBSCAN clustering to further remove redundant lines and determine the number of lane boundaries. The multiple vehicle detection and tracking process follows a detection-based tracking pipeline, which contains three steps: detection, prediction, and association. In the vehicle detection step, the well-developed ensemble classifier in *(15)* is implemented. Sparse optical flow, which has demonstrated its great performance in UAV-based vehicle speed prediction, are selected as the prediction method in this study *(17)*. Specifically, for each box identified as a vehicle in the previous frame, motion vectors within the box are extracted using optical flow. The median motion vector within a vehicle bounding box is chosen as the vehicle motion in the current frame. The association process makes use of the metric intersection-over-union (IoU) considering the UAV's top-view perspective advantage. The data storing module takes inputs from the core functional module, and stores data that are necessary for traffic parameter estimation. For macroscopic traffic flow parameters, three fundamental metrics, i.e., speed, density, and volume, are estimated. For microscopic parameters, we extract vehicle position, vehicle speed, lane information, space headway, and time headway. Individual vehicles' behaviors can be further analyzed based on microscopic parameters and lane information.

Findings

Generally, the overall performance was promising that few false detections or missed vehicles showed up (see Figure 1). We carefully examined 600 representative video frames by hand to validate the effectiveness of the methodology. In this video clip, the UAV had irregular background movement patterns including rotation, cruising, and vibration.

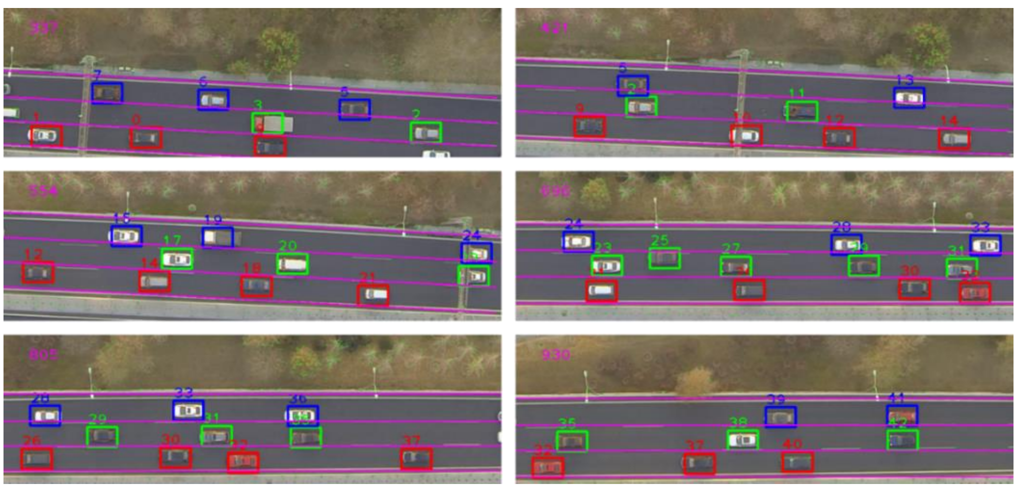

FIGURE 1 Example frames showing the results of lane detection and multiple vehicle detection/tracking.

Figure 2 presents some microscopic traffic parameters estimated from our method. It contains three charts, each of which displays a certain extracted parameter for all vehicles in a single chart. We name the charts as "vehicle-frame charts", which are formed by two dimensions: one is the frame number, or in other words, time dimension, and another is the vehicle ID. The vehicle-frame charts are literally matrices that are produced by stacking each vehicle's one-dimensional microscopic parameters throughout the whole video together. These charts record the number of vehicles, all vehicles' life periods, and some microscopic parameter for any given vehicle at any timestamp in a clear and straightforward way. The top vehicle-frame chart records all vehicles' life periods using a binary image, where the white part means vehicle with a certain ID is within the UAV view at a certain frame. In the middle of the figure, the vehicle-frame speed chart gives an impression of the speed information, where lighter color corresponds to higher speed. The vehicle-frame lane chart at the bottom shows each vehicle's lane information. There are three colors (red, blue, white) in this chart and each of them represents one of the three lanes. From this chart, the distribution of the number of vehicles on each lane and lane changing timestamps for any vehicle can be observed. A better understanding of individual vehicle behaviors is likely to be achieved by properly utilizing these vehicle-frame charts produced by our system.

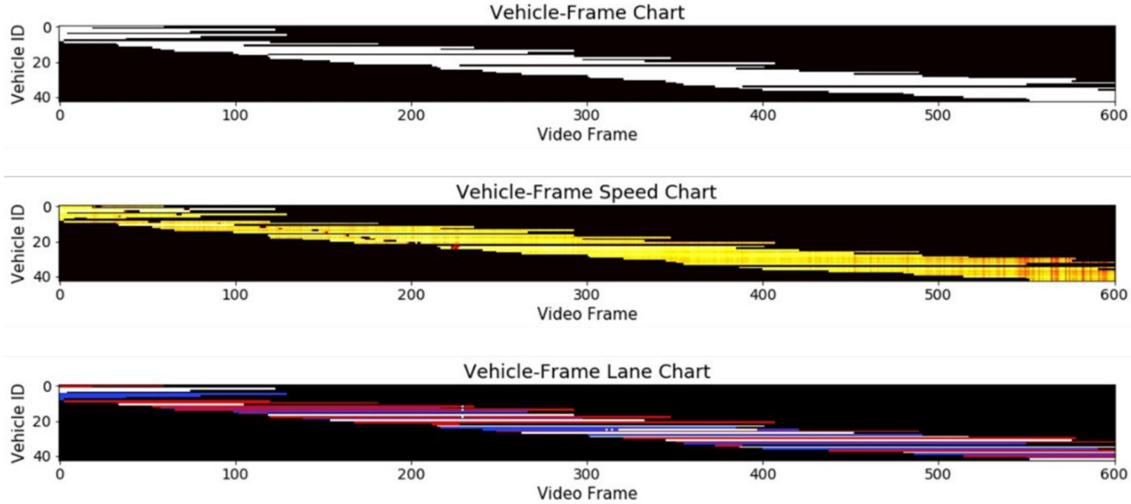

FIGURE 2 These are the vehicle-frame charts showing some of the microscopic information of all vehicles' in 2D matrices, where in each chart x-axis denotes the video frame number and y-axis the vehicle ID. White or colorful pixels mark vehicle appearances or certain values.

Since reporting instantaneous macroscopic traffic parameters frame by frame is not meaningful in practice, the averaged traffic speeds, densities, and volumes of all frames are computed and displayed in Table 1 for every lane. In this table, we also show the speed estimation accuracies and vehicle count estimation accuracies.

Table 1 Macroscopic traffic parameter estimation results and overall accuracy evaluation

	Lane #1	Lane #2	Lane #3
Estimated speed (mph)	32	33	28
Estimated density (pc/mi/lane)	26	33	38
Estimated volume (pc/h)	905	1200	1155
Speed estimation accuracy (%)	97.1	96.2	96.5
Count estimation accuracy (%)	100	95.4	98.8

Conclusion

In this paper, an advanced framework was developed to extract both macroscopic and microscopic traffic parameters from UAV videos with background motion. This framework was composed of three functional modules, which were core functional module, data storing module, and traffic parameters estimation module. In the core functional module, two sub-modules were designed for traffic lane detection and multiple vehicle detection and tracking. The algorithms and parameters settings in both sub-modules were specifically devised with the considerations of UAV video properties. The data storing module contained a couple of exclusive data structures for receiving outputs from the core functional module. These data were organized for efficient computation of traffic parameters. The traffic parameters estimation module was designed to calculate macroscopic and microscopic traffic parameters as well as to analyze individual vehicle behaviors by taking outputs from core functional module and data storing module. The proposed framework was implemented and tested on a challenging UAV video dataset. The experimental results turned out to be very encouraging based on comprehensive visualization, evaluation and analysis on the outputs and comparison with the state-of-the-art method. With the new framework, it has been demonstrated that UAV video could serve as a valuable data source for automatic collection of both macroscopic and microscopic traffic parameters. It could be a very important option for future ITS applications and transportation monitoring tasks.

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