International Journal of Emerging Technologies in Engineering Research (IJETER)
Volume 4, Issue 5, May (2016) www.ijeter.everscience.org

A Vision Based Traffic Analysis for Highway Vehicle

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Abstract – In this paper, we describe a novel algorithm that counts and classifies highway vehicles based on regression analysis. This algorithm requires no explicit segmentation or tracking of individual vehicles, which is usually an important part of many existing algorithms. Therefore, this algorithm is particularly useful when there are severe occlusions or vehicle resolution is low, in which extracted features are highly unreliable. we would like to process low quality videos by skipping this module. In our collected videos, multiple vehicles could be occluded and thus form a large foreground segment. Three different regressors are designed and evaluated. Experiments show that our Regression based algorithm is accurate and robust for poor quality videos, from which many existing algorithms could fail to extract reliable features.

Index Terms – Highway vehicle, image warping, cascaded regression. List of Keywords that are used in the article should be written.

1. INTRODUCTION

Video cameras could be used to record the traffic information constantly or continuously. We are thus able to analyze the traffic videos in real time and discover any information of interest. One fundamental task is to count the vehicles passing by in a given time period and classify the vehicles into different categories at the same time. The counting and classification results could be useful in many different applications. For example, they could be used to measure traffic density, traffic flow, and even emissions in terms of pollutants and greenhouse gases.

Counting and classification also could be done by other sensors such as radar, infrared, and inductive loop detectors. Although some sensors could be more accurate, they could also. be intrusive and need a higher maintenance cost. For example, we may need to embed weighing sensors in road to measure vehicle weight and classify vehicle size. Comparing with other sensors, vision-based systems could be non-intrusive and could obtain much richer traffic information. However, current vision based systems could be less accurate and more sensitive to operating conditions (e.g., weather). These problems make vision-based systems challenging and important research topics in the area of intelligent transportation systems.

A typical vision-based traffic analysis system could consist of many components such as foreground segmentation, shadow removal, feature extraction, and tracking [1]. In order to count and classify vehicles, there is often a module to detect and separate individual vehicles for each foreground segment. This module could be conducted after feature extraction or tracking. For example, if feature points could be extracted robustly across multiple image frames, it is possible to fit explicit 2D/3-D vehicle models.

2. SCALE INVARIANT FEATURE TRANSFORMRELATED WORK

A set of Scale Invariant Feature Transform (SIFT) features [6] are extracted and matched in the follow-up image frames in order to improve tracking performance. The SIFT features are also detected, tracked, clustered in the foreground blobs in [7]. Horizontal and vertical line features are extracted in [8] to build a 3-D vehicle model assuming the vehicle is not occluded. Similarly, by predicting and matching image intensity edges [9]. fit a generic 3-D vehicle model to multiple still images. Simultaneous tracking can also be done during the shape estimation in a video. proposed a vehicle classification algorithm that uses the feature based on edge points and modified SIFT descriptors. Two classification tasks, cars versus minivans and sedans versus taxies, are tested with good performance.

2.1 Histograms of Oriented Gradients

A 3-D extended Histograms of Oriented Gradients (HOG) feature for detection and classification of individual vehicles and pedestrians is proposed by combining 3-D interest points and HOG. The 3-D vehicle models are pre reconstructed by the methods. The similar idea is applied that lanes couldbe detected easily. However, image warping itself has not been applied directly to detect unclassified vehicles. Moreover, only four reference points used in these algorithms are often not enough to model non-straight road segments.

2.2 Regression analysis

Regression analysis has been applied to count people in which is similar to our proposed algorithm. There are mainly two differences between two algorithms. First, the detection of unclassified vehicles is quite different from the crowd segmentation d. The crowd segmentation is done by a mixture of dynamic textures. In the mixture model, the observed variable is the sampled video frames, and the hidden variable encodes the dynamics. Another hidden variable is a mixture component that is used to handle in homogeneous videos. In the first part of our algorithm, we apply a nonlinear warping algorithm on foreground segments in the previous frame. A projective transformation is applied to reduce perspective distortion.

2.3 Weighted normalized cross correlation

Weighted normalized cross correlation (WNCC) is used to compare transformed patches with the corresponding patches in the current frame. Secondly, the regression frameworks of two algorithms are different. In This algorithm, we build a three level cascaded regression Frame work as we have three different vehicle classes. More importantly, to our knowledge, regression analysis has not been applied before for counting and classifying highway vehicles.

3. PROPOSED MODELLING

Smart Traffic Analyzer is using the powerful Artificial Intelligence and Image processing Algorithm.and Recognition, Detection, Enumerating, classification the different vehicle type. Calculating road/street traffic volume, vehicle average speed.

3.1 Detection of Unclassified Vehicles

A warping method used to detect unclassified vehicles is based on the mesh grid. For simplicity, let us assume the traffic flow is from bottom to top. It is straightforward to extend the warping method to other different traffic flows. First, we check if there are any foreground segments in the bottom region of the previous image frame. This is done by comparing the current image frame with the background image. If the area of foreground segments is larger than the minimum area of a small size vehicle (computed from the training set), then we compute a bounding box that includes these foreground segments. The mesh vertices in the bounding box are the original mesh grid. Secondly, we conduct a complete search from the bottom region to the top region. When we decrease the *y* coordinate, we can find a new set of vertices that is a shift of the original mesh grid along the highway road. This new set of vertices is the targets mesh grid. Two sets of values are used to fit two smoothing splines. The spline fitted by vertical positions is a modeling of the foreshortening effect along the road direction.

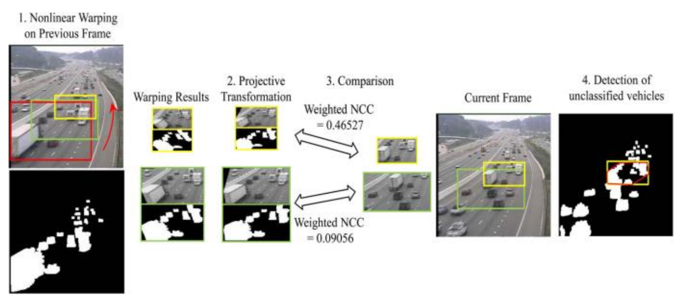
3.2 *Feature Extraction*

A set of low level features that could present weak linear relations to the vehicle count. These features include 1) segment area; 2) segment length along the road direction; 3) segment width;4) segment perimeter associated with the number of pixels on the segment boundary; 5) horizontal edge length within the segment (i.e., segment boundary is not included); 6) texture coarseness.

First, they are normalized (e.g., rescaled)based on the smoothing spline estimated . A reference line with *y* coordinate close to the image bottom is chosen for the normalization. Secondly, as traffic trajectory is known or has been estimated, segment length and width are not sensitive to the road direction. Thus, they are computed by projection on to the road direction and the direction perpendicular to the road direction.

3.3 Cascaded Regression

We are interested in three different vehicle classes (i.e., large, medium, and small size) corresponding to truck/bus, SUV/minivan, and sedan, respectively. There are two reasons for using three different classes.



3.3 An example of warping and detection processes.

A set of linear regressions to estimate relations between emission factors and diesel contribution for a Houston tunnel. Different classes of vehicles are manually counted by observers on traffic videos that have been captured. This algorithm is designed to automatically estimate counts and emissions in real time. Secondly, as our cameras only capture low resolution and low frame rate videos, it would be difficult to detect many different classes, and even specific models of highway vehicles. There are four different classes, cars/jeeps, light duty trucks, medium-duty trucks (i.e., trucks with two axles and six tires), and heavy duty trucks (trucks with threeor more axles), are used in the system. regression analysis is often applied to build a mapping from an input variable to a continuous output variable. It has been widely used in the area of image processing. The simplest regression could be the linear regression that is a linear combination of the input variables.

4. RESULTS AND DISCUSSIONS

Smart Traffic Analyzer(STA)can be integrate with Milestone XProtect (Enterprise, Professional and Corporate)Using the Milestone XProtect DirectShow Filter (Milestone DX) to loading the video stream. fig 4 The Milestone XProtect DirectShow filter is a Microsoft DirectShow-style source filter delivered by Milestone Systems. You may use it to get hold of the actual decoded uncompressed data for individual video frames.

Fig 4 Smart traffic analyzer

In the roadway vehicle will be detected and the size of the vehicle will be measured and moving the vehicle tracking. Fig 4.1 saves the changes of all segment.

Fig 4.1 Measure the Size of Vehicle

Vehicle count and record data every hour of the day and night Detecting the accident and unusual stopping vehicle including large object failing from the back of truck. Fig 4.2 Detecting of unusual changes in vehicle speed to detecting emergencies on road such as frozen and slippery of the road. The count estimates using standard Poisson regression and ground truth of small size vehicles over a moderate traffic video.

If the cascaded regression framework is not applied for small and medium vehicles (i.e., the counts of different vehicles in one segment are mutually independent), the counting and classification performance is further reduced. The video length is close to 30 minutes. We can find that these two distributions. This indicates that our estimation can be used to approximate the traffic density distribution.

Fig 4.2 Detecting the Vehicle

Ability to used different video source including all standard type of IP cameras and Analog cameras.

5. CONCLUSION

In this paper, we present a counting and classification algorithm for highway vehicles. Given a set of low level features, we apply a cascaded regression model to count and classify vehicles directly. We have tested this algorithm on low quality videos that last more than one hour. We show that this algorithm can deal with the traffic with severe occlusions and very low vehicle resolutions. This algorithm is suitable for vision based systems that are non-intrusive and can be mounted many places near highways. This algorithm could be further applied for estimation of traffic density and vehicle emissions.

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