

Review of Automobile Identification and Tracing

Ms. Varuni Chitransh, Prof Rahul Dubey

Abstract- In the recent times, it is noticed that increasing number of rear end accidents have been accredited due to distraction of the driver. Presence of quick advanced caution system can reduce the count and intensity of collisions. In this regard various advanced warning systems have been anticipated. But major challenge in this regard is identifying vehicle in varying environment. To combat such challenges a method is proposed here to design and apply real-time in-car video to sense and track the automobile further for safety. Concepts of probability are applied to identify occurrence of vehicle and their intensity distribution. Here temporal processing is done for target recognition. The motion conduct of scenes in video is modeled using Hidden Markov Model (HMM) which has been generally used in describing the sequential data.

Index Terms- Probability, Hidden Markov Model (HMM), 1-D Profiling, In-Car Video, Tracking, Feature Extraction.

I. INTRODUCTION

It is monitored that in-car video is the least intricate and most broadly applied arrangement on police cars where a camera is placed ahead. It accounts numerous traffic and road circumstances ahead and is meticulously crucial to cautious driving, traffic recording, and motor vehicle recognition [5]. Here the objective is to comprehend vehicles ahead or those being pursued and relentlessly track them on video.

Ms. Varuni Chitransh, Department of Electronics & Communication, Oriental Institute of Science & Technology, Bhopal, India (e-mail: vc.varuni.03@gmail.com).

Prof Rahul Dubey, Department of Electronics & Communication, Oriental Institute of Science & Technology, Bhopal, India (e-mail:rahul.dubey0686@gmail.com)

Customarily it is hard for a single moving camera to promptly generate the information for vibrant scenes devoid of making the use of stereo or other sensors' support. The foremost prevailing challenges are the recurrent alterations of vehicles in their forms, contours and colors [6]. The massive range of automobile samples is difficult to model or learn. Also, the automobile detection should be done involuntarily besides the video tracking. It is also required that vehicle identification must be mechanized besides the video tracking [7].

The approach used here primarily selects and detects the most regular low-level features of the vehicles which are tough against the variations of shape, lighting and occlusion [8]. Hence, it avoids the high-level sight modeling and learning, which are commonly erratic, time taking and unusual. Also, the focus has been made on the horizontal scene movement based on the arrangement of camera and vehicle driving procedure [9]. Various one dimension profiles are mounted up from the video frame to figure out the horizontal motion. Feature trajectories are tracked in such temporal profiles, this helps to classify vehicle and background in compact aspects.

The proposed technique highlights the feature extraction of the perceived vehicles which are afterwards profiled to the temporal domain to create condensed mode of data. Later, 1-D profiling of horizontal motion is done to identify the tracked traces as cars and backgrounds [11]. The vibrant environment of in-car video is also evaluated. The evaluation of their motion development is done by the implementation of HMM, where traces are tracked incessantly and then featured in temporal profile for motion. Afterwards posterior probability of presence of objective vehicle is computed using HMM.

II. LITERATURE REVIEW

A. Forward Collision Warning System with Single Camera:-

Forward Collision Warning (FCW) System is observed as very useful for the highway safety as it is able to play a crucial role for the purpose of reduction of the number and the severity of driving accidents. It has been studied that lack of attention by the driver is identified as the cause for 91% of driver related accidents, also if additional warning time of 0.5-second is provided to the car drivers than, about 60% of rear-end collisions can be averted.

A realistic solution to this trouble could be offered by a range sensor boarded on the vehicle. Though, the outlays of the conventional systems available today (typically based on Radar sensors) and their bounded performance (narrow field of view and poor lateral resolution) have avoided such systems from coming into the market. From a scientific viewpoint, combination of radar and vision is a striking approach. In such systems, the radar provides precise range and range-rate measurements whereas vision resolves the angular accuracy issue of radar. However this solution is expensive [5].

By using MobilEye vision based FCW system, the Time-to-Contact (TTC) and probable collision course can be evaluated directly from the dimensions and position of the automobile in the image. These measurements for a vision based system don't need computation of a 3D image of the scene. Particularly, there is no requirement for exact range measurements. In FCW system image scale change and image position are used for calculating TTC and to check whether the object is on the path of collision or not. Thus, it avoids need for complex calculations of distance and velocity. The warning speed of the system can be further improved for nearly 3seconds.



Fig 1: System Components of MobileEye AWS

B. Vehicle Detection for Automated Guided Vehicle:-

Automated object detection is very useful for robotics, navigation etc. Here vehicle identification is done by two-level approach. The methodology implemented is use of eigen space and Support Vector Machine (SVM) for classification. Initially hypothesis generation is done where probable automobiles are hypothesized by using vertical and horizontal edge maps to generate potential regions for probable area of vehicle presence. After this, hypothesis verification is done. Here the entire hypothesis is verified by using Principle Component Analysis (PCA) [2]

Traditional methods of hypothesis generation in monocular vision included moving of a search window over the image input and then classifying the vehicle using a classifier. A rough estimation is made for each vehicle with a definite size. Hence it is required that to-be-detected vehicle lies in the specific window while testing images.

For detection of all the vehicles an image pyramid is built by sampling the test images. The process is repeated till all the vehicles are scaled to the image window size at some layer in pyramid. Although the approach is simple but it requires a long time for processing; hence it is not suitable for driver assistance.

C. PCA- based vehicle organization framework:-

In intelligent transportation system vehicle classification has been a crucial issue to deal. In any traffic video, above system firstly segments the individual vehicles, then extracted vehicles are normalized so that all the vehicles get aligned in the same direction and measurement can be made on the same scale. Thus to classify the vehicles into various categories like trucks, passengers cars, vans etc proposed classification algorithms include Eigen vehicle and PCA-SVM. Initially a dimension based method is used to classify the vehicles. The dimensions information such as length, height etc is taken out. The cars of nearly equivalent dimensions are further classified into finer level. This is done by PCA [4]. PCA can be used in two ways- first as Eigen vehicle method which is similar to Eigen face technique. Second is PCA-SVM method in which representative vectors of vehicles are captured and then categorized by using One- Class SVM.

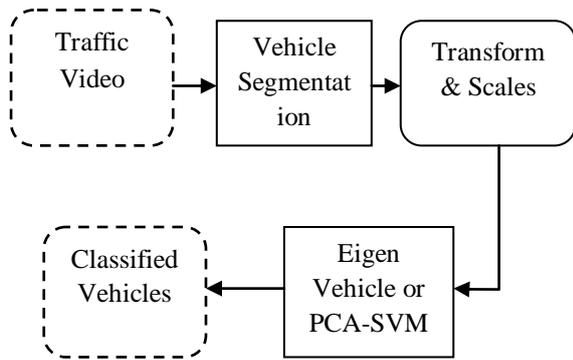


Fig 2: General system design for vehicle extraction and classification

D. Eigen faces for face recognition:-

The motive of facial recognition is differentiating input signal into several categories. The characteristic features such as presence of various facial features like eyes, nose, and mouth are at relative distance between these objects. These attributes are called as eigen faces in facial recognition realm. These attributes can be extracted by the mathematical tool called Principal Component Analysis (PCA) as expressed in [3].

If all the eigen faces are extracted from the original images, then the original image can be restructured accurately. But inclusion of all the features is not possible in all situations due to limited availability of computational resources. Therefore, only crucial aspects are included for facial recognition. Apart from extracting the face from the eigen face, it is also required to extract the weights from all the eigen faces and the face to be recognized.

E. Regulating the Route Panorama with condensed image slicing:-

Route panorama can be extorted out from the video string while obtaining an extended image of the street, while the camera translates along a smooth path. It is observed that distributed stances cannot be easily overlapped due to presence of disparities. Route Panoramas can be engendered by following methods. Firstly by 1-D slit scanning which results in parallel-perspective image. Secondly by 2-D image mosaicing is done which results in multi-perspective image. Due to effectiveness, slit scanning methodology is used to obtain route panoramas in urban area. Slit scanning does not require inter frame matching of video and requires well controlled mechanic movement of the vehicle [12].

One of the shortcomings is the deformation of shapes in parallel-perspective images. To make the outlook projection close to real, dynamic slit selection scheme is also examined. Instant jitters or certain speed changes caused due to measuring vertical camera motion. Image frame correspondence can be avoided using feature extraction and intensity. Hence to overcome all the shortcomings proposed methodology is condensed image slicing which traces the intensity accumulation in the frames horizontally.

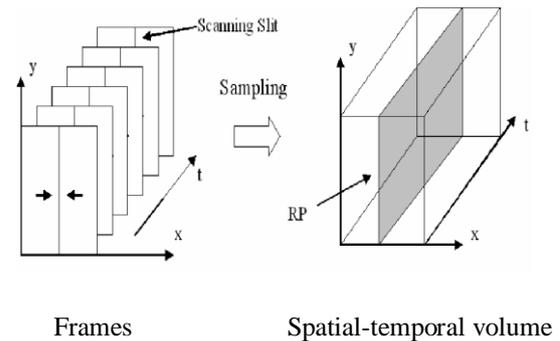


Fig 3: Route panorama attainment as the vehicle moves (left) and its location in a spatial-time volume of video (right).

III. PROPOSED METHODOLOGY

The real time extraction of characteristics of vehicle in video frame is done in order to manage various disparities of vehicle, we choose three types of basic features for reliable vehicle detection such as: horizontal line segments, corner points, and intensity peaks [1]. Later in order to pace up the processing for real-time object tracking and to obtain strong results besides trembling of a vehicle on variable road slope, it is required to vertically project the intensity/color $I(x, y)$ in every video frame, thus a 1-D profile:

$$T(x, t) = \sum_{y=-h/2}^{h/2} w(x, y) I(x, y, t) \quad (1)$$

Where h is height of the image.

The intensity profile represents the horizontal locations of the vertical characteristics and ignores all the horizontal characteristics. Hence, a compressed image is formed for understanding the horizontal movement in the video. Tracking of the intensity profile can be done by horizontal differentiation of $T(x, t)$. The edges are spotted in

another image $E(x, t)$ and maximum extent is set in search of adjacent trace points. Also, $\partial T(x, t)/\partial t$ are calculated to find the horizontal edges. This processing outcome in image position $x(t)$ and image velocity $v(t)$ is obtained for a trace, where

$$v(t) = x(t) - x(t-1) \quad (2)$$

Now a model is made for motion with probability in order to determine the state of a traced object with the HMM. For this two hidden states are assigned to a trace at any time instance t : car and background, which are denoted by C_t and B_t . The observations thus obtained are image position $x(t)$ and component of horizontal image velocity $v(t)$ of $u(x, y)$. Both of these are continuous distributions in the conventional HMM [12]. An array can be obtained from each trajectory which is tracked in the condensed profiles.

The traits of movement in the spatiotemporal image are most crucial indication in our vehicle identification process. The background is associated by the ego-motion of camera and its distance. As the front facing camera undergoes translation in the Z-direction, the condensed temporal image composed of 1-D profiles can also be obtained. In such spatiotemporal demonstrations backgrounds chase the hyperbolic trajectories growing from the projection of FOE (field of expansion) the bending of the course is elevated for objects close to the road and is small (i.e. flat trace is formed) for objects which are far from the road, and the image velocity is relative to the image position $x(t)$. The image velocity is high at scenes passing by at fast speed and is low at scenes in front. Whereas, the cars traced within the road may reside in the image frame even if they move unevenly in a meandering way. Now by tracking the trajectories for a short span of time the traces can be identified with some probabilities. This can be done by calculating the probability at every moment using HMM which is based on (x, v) series.

IV. CONCLUSION

As evident from [5] perceiving the automobile ahead and the upcoming traffic situations during driving are the crucial aspects in cautious driving, accident avoidance and mechanized driving and quest. But the major challenge in this regard is tracking vehicle ahead in varying environment and lighting. Due to increasing traffic density incidence of rear end collision are increasing and also the

warning systems being used so far are not complaint to quick variations of traffic.

Earlier implemented techniques of edge detection and segmentation are not compatible for working in misty environment and during night. To overcome all the problems stated above, system is intended which is proficient of recognizing vehicles in advance, moving in the similar route as our vehicle, by following them constantly with an in-car video. Here the designing and application of such real-time oriented algorithms and arrangements which are highly conforming to the road and traffic scenes based on domain-specific acquaintance on road, automobiles and command.

In-car video avoids the high-level scene modeling and learning, which are usually erratic, time taking and strange. Also, the focus has been made on the horizontal scene movement based on the arrangement of camera and vehicle driving procedure. Various one dimension profiles are mounted up from the video frame to figure out the horizontal motion. Feature trajectories are tracked in such temporal profiles, this helps to classify vehicle and background in compact aspects.

V. REFERENCES

- [1] Jazayeri, A.; Hongyuan Cai; Jiang Yu Zheng; Tuceryan, M., "Vehicle Detection and Tracking in Car Video Based on Motion Model, "Intelligent Transportation Systems, IEEE Transactions on, vol.12, no.2, pp.583, 595, June 2011.
- [2] Q. B. Truong, H. N. Geon, and B. R. Lee, "Vehicle detection and recognition for automated guided vehicle," in ICCAS-SICE, 2009, pp. 671-676, IEEE, 2009.
- [3] M. Turk and A. Pentland, "Eigen faces for Recognition", Journal of Cognitive Neuroscience, vol.3, no. 1, pp. 71-86, 1991.
- [4] Chengcui Zhang, Xin Chen, Wei-bang Chen, "A PCA-based Vehicle Classification Framework", Proceedings IEEE, International Conference on Data Engineering Workshops, 2006.
- [5] E. Dagan, O. Mano, G. P. Stein, and A. Shashua, "Forward collision warning with a single camera," in Intelligent Vehicles Symposium, 2004 IEEE, pp. 37-42, IEEE, 2004.

[6] H. Takizawa, K. Yamada, and T. Ito, "Vehicles detection using sensor fusion," in Proc. IEEE Intell. Vehicle, 2004, pp. 238–243.

[7] H. Schneiderman and T. Kanade, "A statistical method for 3D object detection applied to faces and cars," in Proc. IEEE CVPR, 2000, pp. 746–751.

[8] J. Chu, L. Ji, L. Guo, B. Li, and R. Wang, "Study on method of detecting preceding vehicle based on monocular camera," in Proc. IEEE Intell. Vehicle, 2004, pp. 750–755.

[9] D. Alonso, L. Salgado, and M. Nieto, "Robust vehicle detection through multidimensional classification for on board video based systems," in Proc. IEEE ICIP, Sep. 2007, vol. 4, pp. 321–324.

[10] L. Gao, C. Li, T. Fang, and Z. Xiong, "Vehicle detection based on color and edge information," in Proc. Image Anal. Recognition, vol. 5112, Lect. Notes Computer Science, 2008, pp. 142–150.

[11] X. Huang, M. Jack, and Y. Ariki, Hidden Markov Models for Speech Recognition. Edinburgh, U.K.: Edinburgh Univ. Press, 1990.

[12] G. Flora and J. Y. Zheng, "Adjusting route panoramas with condensed image slices," in Proc. ACM Conf. Multimedia, Augsburg, Germany, 2007, pp. 815–818.