A Vision Based Lane Marking Detection, Tracking and Vehicle Detection on Highways

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Abstract- Changing street conditions is an important issue in the applications in mechanized route of vehicles essentially because of vast change in appearance in lane markings on by variables such substantial movement and changing daylight conditions of the specific time of day. A path identification framework is an imperative segment of numerous computerized vehicle frameworks. In this paper, we address these issues through lane identification and vehicle recognition calculation to manage testing situations, for example, a lane end and flow, old lane markings, and path changes. Left and right lane limits will be distinguished independently to adequately handle blending and part paths utilizing a strong calculation.

Vehicle discovery is another issue in computerized route of vehicles. Different vehicle discovery approaches have been actualized yet it is hard to locate a quick and trusty calculation for applications, for example, for vehicle crashing (hitting) cautioning or path evolving system .Vision-based vehicle recognition can likewise enhance the crash cautioning execution when it is consolidated with a lane marking identification calculation. In crash cautioning applications, it is vital to know whether the obstruction is in the same path with the sense of self vehicle or not.

Keywords- *Computer vison-Lane marking, Vehicle detection, tracking.*

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I. Introduction

Identifying and restricting paths from a street picture is an essential segment of numerous smart transportation framework applications. Lane marking identification plays a key role in variety of application like autonomous vehicle navigation, collision detection & warning, lane departure warning etc. Because of a continuous imperative and, then, moderate processor speed, the path markings have been identified construct just in light of basic slope changes, and a significant part of the more seasoned work has displayed results on straight streets and/or roadways with clear path markings or with a nonappearance of impediments out and about. As a contrasting option to a dream based methodology, one may utilize a worldwide situating framework (GPS) with a geographic data framework (GIS.For instance, it is vital to identify the street bend since it can produce a false-crash cautioning, yet most GPS-based frameworks experience the ill effects of separating whether the vehicle entered an exit ramp or not. Late endeavors manage bended streets, and powerful discovery results on testing pictures, for example, diverting shadows or a main vehicle, have been accounted for. Sunlight may differ in its intensity anytime which cause system output to vary continuously.Detecting moving vehicles in video is fundamental in many autonomous video surveillance systems. Task becomes even more difficult when outdoor scene has inconsistent lighting and background movement.

In this paper, an algorithm is presented the algorithm which will overcome these aspects and aims to develop robust lane marking & vehicle detection framework. Proposed framework achieves the goal in two steps: first focuses on lane marking identification and second on vehicle detection on road.

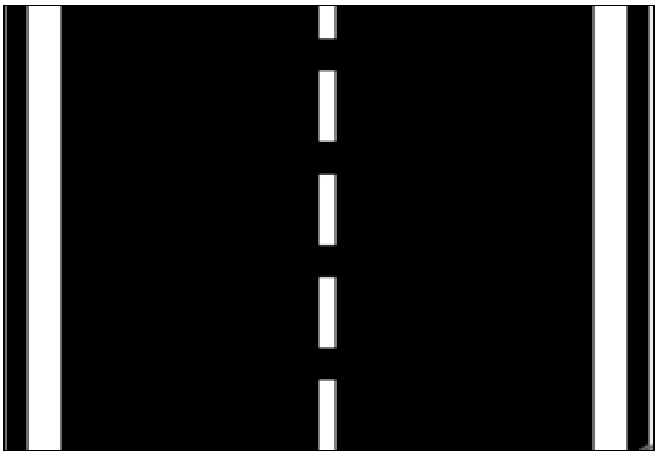

Fig. 1 Sample road image.

Fig. 2. Sample road traffic image

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II. LITERATURE REVIEW

One option may be to utilize a worldwide accepted framework (GPS) with a geographic data framework (GIS). Be that as it may, the GPS has a confinement on the spatial and fleeting determination, and point by point data is regularly lost or not upgraded as often as possible in GIS. Distinguishing street path markings utilizing picture investigation has been a zone of dynamic examination in the course of the most recent two decades. The late study paper by McCall and Trivedi [2] gives a far reaching outline of existing methodologies. The vast majority of the strategies propose a three-stage process: 1) separating components to introduce path markings, for example, edges [3], composition [4], shading [5], and recurrence space highlights [6]; 2) post preparing the extricated elements to evacuate anomalies utilizing procedures like Hough Transform [7] and dynamic programming [8],and 3) following the distinguished path markings utilizing a Kalman channel [9] or molecule channels [10], [11] by accepting movement models, for example, steady speed or quickening for the vehicle. There are additionally strategies that utilization stereo cameras (e.g., [12] and [13]) to authorize comparability of focuses saw from both cameras. All the more as of late, there has been an expanded spotlight on building continuous frameworks [14] on testing urban situations [15], [16], including evening time driving conditions [17], and on giving functionalities, for example, path takeoff cautioning [28] and path reservation on roadways [19]. Machine learning techniques with a solitary characterization limit, for example, neural systems and bolster vector machines [10], have likewise been utilized for location. Be that as it may, two primary parts of this issue have not yet been attractively addressed:1) Since the visual properties of path markings experience self-assertively extensive varieties, utilizing neighborhood components to depict their appearance and taking in the choice limit from a solitary classifier may not be hearty and adaptable. 2) The supposition of a pre specified movement model for the vehicle separates when the vehicle shows an arbitrary movement design. This is especially basic in the situation, in which we are intrigued, where the inputs are gotten just from the visual sensor. There have been different endeavors to recognize vehicles continuously or non-constant [20]. A considerable lot of the bland hindrance identification work likewise manages pictures of vehicles [21]. While such calculations can give great location rate notwithstanding for pictures with entangled foundations, the majority of them are off by a long shot to realtime. A large portion of the past realtime vehicle location endeavors depend on movement or stereo investigation. The movement based methodologies utilize the way that the picture movement of an obstruction (generally on a vertical plane) is not the same as that of the ground (on a flat plane) [22]. In any case, such a distinction is generally much littler than a pixel and it takes no less than a second of following to recognize the contrasts between them [22].

III. LANE MARKING DETECTION

Lane marking detection on highways of poor quality is a difficult task under different scenarios. In particular driving environments

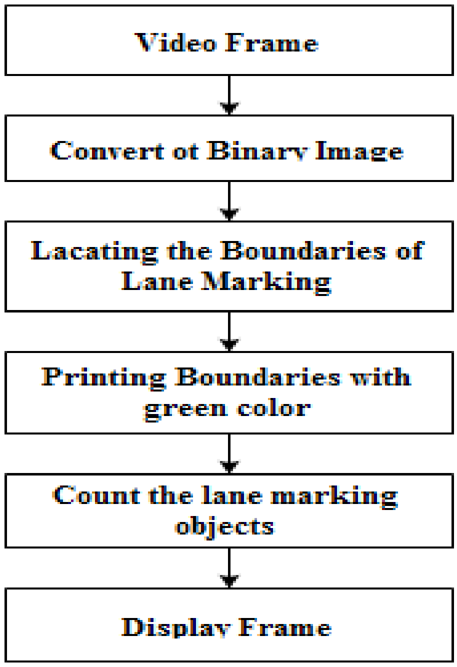

Fig. 3. Flow of the lane marking detection framework.

lane markings are not uniform. So ,It is an important task to find the lane markings on road for automated vehicle. Here we are representing the robust way achieve this task using image processing tools. Very first traffic videos are captured on road at daytime with clear sunshine. Lane markings are continuous as well as dashed lines. Below algorithm performs the specified task:

1. Read the video
2. Extract the frames from video.
3. Read the first frame
4. Convert it to the gray scale
5. Remove small objects from binary frame.
6. Plot the boundaries of lane marking object
7. Measure properties of frame regions.(MajorAxisLength, MinorAxisLength, BoundingBox,Area).
8. Locating & counting the lane objects.
9. Display the frame

IV. VEHICLE DETECTION

Vehicle detection and tracking has an important role in autonomous vehicle navigation system. The main task of the system is to recognize the moving objects from road surfaces from each frame of video. it is difficult to recognize the moving vehicles in different lighting conditions. In this system the camera is fixed as in highway monitoring systems. Detection is integrated with tracking. System focuses on finding the exact location of moving vehicle from the video and representing them in box. Below algorithm performs the specified task:

1. Import Video and Initialize Foreground Detector
2. read the next video frame
3. morphological filter for noise removal
4. Detect the foreground in the current video frame
5. Detect the connected components with the specified minimum area, and compute their bounding boxes
6. Draw bounding boxes around the detected cars
7. Display the number of cars found in the video frame
8. display the results

V. EXPERIMENTAL RESULTS

To test the proposed method of lane marking detection & vehicle detection. The road is typical with all kind of markings needed to carry the work. It includes continuous, dashed lines with white as well as yellow color. Fig. 2b presents the result of input frame in Fig.2a.Algorithm was accurate to find out all the 10 lane markings from input frame.

Figure 2a. sample input frame from video taken on NH-4 (Pune-Bangalore Road)

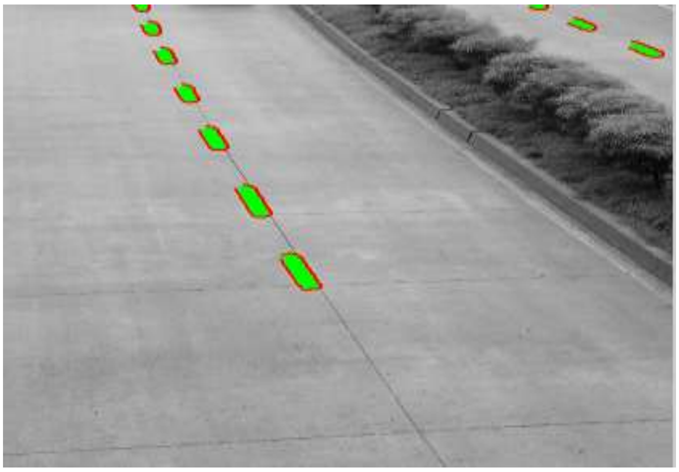

Figure 2b. Output of the algorithm for the input image 2a

We tested the algorithm on a 4 video clips taken on NH-4(Pune-Bangalore Road, Kolhapur-Ratnagiri Road). The video clip is in an AVI format of 920 × 088 image resolution. The video quality is good. Video contains all the road conditions like splitting, merging, changing lanes. The proposed algorithm was run at 10 frames/s with a total of 350 frames. The program was implemented in MATLAB on Microsoft Windows 7 using computer vision toolbox. Example results are shown in Fig.2b Fig.3b is the result of vehicle detection algorithm for which Fig.3a is input frame. Result shows the accuracy of the algorithm. Only 3 false cases (vehicles) were there in input frame.

Fig. 3a Sample frame from a sample traffic video.

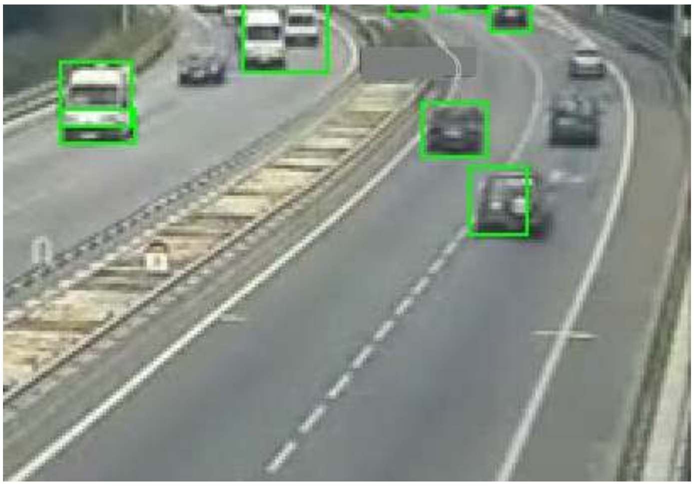

Fig. 3b Output of the algorithm for input frame 3a.

Result of lane marking identification framework is shown in Figure 2b.Lane markings are highlighted by green color and lane marking boundaries are highlighted by red color. The frame is taken from sample input video. Resulting frame has detected 10 lane marking which is 100% of input frame in Figure 2a.Table 1 shows the statistics of the experiments made on lane marking identification framework. Table represents the experimental results on 4 different frames. The average lane marking detection accuracy is near about 90%.

Sr. No	Lane Marking Detection Statistic			
	Frame	*Present No of Lane Marking*	*Detected No of Lane Marking*	*Accuracy %*
1	Frame 1	10	8	80%
2	Frame 2	10	10	100%
3	Frame 3	9	8	88%
4	Frame 4	7	6	85%

Table 1. Lane marking detection algorithm experimental statistics

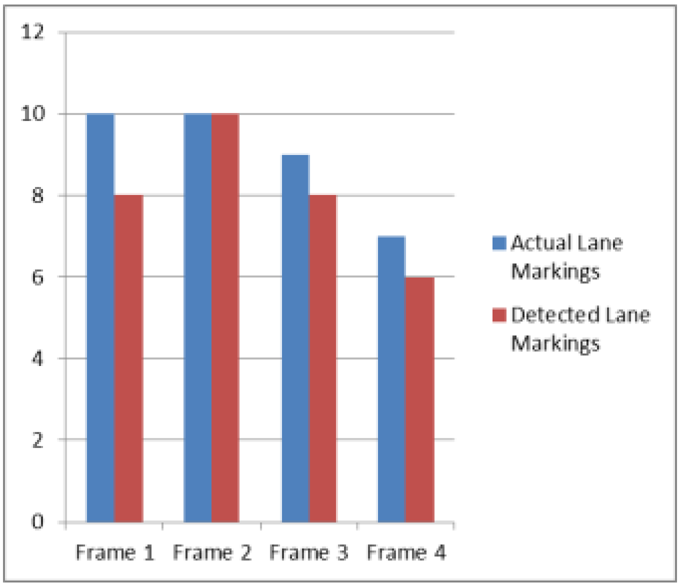

Fig. 4 Graph showing the statistics of tested lane marking v/s detected lane markings.

Experimental result of vehicle detection framework is shown in Figure 3b.Detected vehicles are highlighted by green color box covering the vehicle. The frame is taken from sample input video. Resulting frame has detected 9 vehicles successfully. The rate of detection is more than 70 %.False detection is observed in some frames. Table 2 shows the statistics of the experiments made on vehicle detection framework. Table represents the experimental results on 4 different sample videos.

VI. CONCLUSION & FUTURE WORK

A robust detection of road markings & vehicle detection using camera is an important task for many autonomous vehicle guidance system. This paper presents an approach towards lane marking detection and vehicle detection. The system provides a solution to detection in all kind of traffic. The application can be made more powerful by including real-time detection with increased accuracy. One advancement can be made to this work is to find the exact distance of next vehicle so as to collision alarm system.

Sr No	Vehicle Detection Statistics			
	Video	*No of present vehicles*	*Detected Vehicles*	*Accuracy %*
1	Video 1	12	10	83 %
2	Video 2	12	9	75 %
3	Video 3	8	6	75 %
4	Video 4	9	7	77 %

Table 2. Vehicle detection algorithm experimental statistics

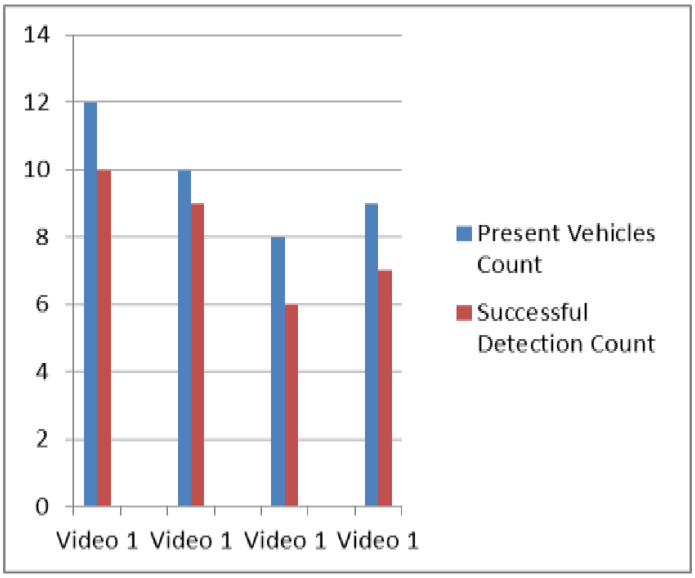

Fig. 5 Graph showing the accuracy of the vehicle detection algorithm

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