

A Realtime Road Boundary Detection and Vehicle Detection for Indian Roads

Ajit Danti Professor & Director Dept. of Computer Applications Jawaharlal Nehru National College of Engineering

Shimoga, Karnataka, INDIA

Jyoti .Y. Kulkarni Asst. Professor Govt. First Grade College, Bijapur, Karnataka, INDIA P.S.Hiremath Professor & Chairman Department of P.G. Studies and Research in Computer Science Gulbarga University, Gulbarga, Karnataka, INDIA

ABSTRACT

Traffic conditions in Indian urban and sub urban roads are in many ways not ideal for driving. This is due to faded and unmaintained lane markings. Therefore driving sometimes becomes difficult. Due to inappropriate markings of the roads, it is difficult to track the lane marking using conventional lane marking algorithms. Therefore the issue of Lane tracking with road boundary detection and other vehicle tracking for Indian road conditions is addressed here. The technique is based on modified road boundary detection which first segments the road area based on color segmentation and Hough transform is applied to find out the near vertical lines. Even in the absence of prominent lanes in the road, the segmentation line itself acts as boundary line. Further optical flow based vehicle detection is integrated with the system. When compared with conventional hough transform based lane detection this technique is proven to be more efficient in terms of accuracy. The method is tested with OpenCV under real time environment with Live Video frames. Results show accurate detection of road boundary, lanes and other vehicles under different road textures and varying intensity conditions.

Keywords

Hough Transform, Color Segmentation, Boundary Detection, Optical flow, Vehicle Detection, OpenCV.

1. INTRODUCTION

Developing an automated driver guidance system is very important in the context of Indian road conditions. A driver finds it difficult to control the vehicle due to sudden path holes or bumps or sudden turns where the road signs are not very prominent or missing. Suppose if there is a system with integrated motion camera and an integrated onboard computer with the vehicle, a simple driver guidance system based on frame analysis of the motion can be developed and an alarm system can be developed accordingly, so that the driving can be made quite easier.

Road Image analysis is very important aspect for automated driver support system and Real-time qualitative road image analysis is the cornerstone for any modern transport system. So far, most of the analysis is done manually and the use of image processing technique for qualitative analysis is still at its early stage. Further, many of the algorithms are developed on image processing techniques and do not address the real time aspects like motion estimation and blurring. The qualitative description of a road scene can be used as a driver guidance system, thereby warning drivers to slow down or direct them to alternative routes.

An attempt has been made here to analyze a wider view of the path and evaluate the whole description of road status using real time video signal processing with OpenCV. This full frame processing application requires a low-cost frame grabber and a Pentium-based computer system for on-line real-time operations. A sample block diagram of the overall prospective is presented in figure 1.



Figure 1: Basic Block Diagram for Driver Guidance System

The automated driver guidance system has various aspects which include detection of the road boundary, potholes, road curves, road signs, junction detection and so on. Various techniques are proposed in this direction. Such core techniques are broadly classified into i) Techniques for detection of road profile ii) Detection of irregularity in the road profile like bump or zebra crossing iii) Detection of vanishing point of the road iv) Detection of traffic pattern of the road.

The preliminary steps followed in respect of classification of road images or frames are i) segmentation ii) road boundary detection iii) voting for the candidate problem iv) classification.



There are various segmentation techniques which are primarily categorized into i) color based segmentation ii) texture based segmentation iii) threshold based segmentation iv) contour tracking and active contour based segmentation. Various techniques also take the help of either local or global properties of the road to determine the road part. Once the road part is segmented from the rest of the image or frame, road boundary is obtained through mainly the edge profile of the road and using Hough transform. Some of the techniques also make use of supervised learning for extracting the road boundary.

Most of the existing works focus on detection of the features using Image processing toolbox and with Matlab. But in real time, speed of detection and the accuracy of detections are major issues in the performance of the driver guidance system. Therefore in this work, real time mechanism for detecting road boundary and on-road vehicles based on Opens is presented. The technique is not only highly accurate but at the same time is fast to suite the practice need of such a system.

2. RELATED WORK

[1] Proposes gray scale based processing of the road images for lanes, zebra crossing detection. The median filtering approach for detecting detail less image and further extracting the parts of roads like zebra crossing from contrast differential of the median filtered image with the original image is proposed. [2] Uses a new technique for detecting the vanishing lines using projection geometry. It deviates from the conventional approach of detecting the vanishing point from intersecting lines and proposes that the vanishing points are also to be considered as an object which is a property of projection plane of other objects. [3]Finds that the log color space i.e. $\log(R/G)$ and $\log(B/G)$ forms a straight line and is helpful for removing shadowed region from the road part for efficient road segmentation. The authors also use an entropy measure for road candidate selection and classification. [4] Uses an affine transformation to rectify the slant in the images. This is an important finding as it gives a strong mathematical model to project slanted or inclined roads to homographic plane which leads to better segmentation approach. [5] Uses a modified clustering technique for road segmentation. The technique first obtains the co-variance color matrix of the significant colors present in the image and normalizes it. Further the image pixels are classified based on each dominant color group or outside Mahalanobis distance. [6] Uses multiple color models to represent the road and its background. The background and road part color model is formed using sample of road and the background images. [7]Compares the work of [29] which proposes a Hough transform based approach for line intersection detection with that of [27],[28], where vanishing points are considered to be the statistical properties of the road, rather than a property of line intersection. Further, it proposes a conjugate translate transformation for detecting the vanishing lines in a 3-d plane. [8] Finds that the driving trajectory or the path is best represented in the polar coordinate system and the pixels falling in the trajectory point can be represented using a color model based on Gaussian mixture model. It also suggests a periodic up gradation strategy of the color model. Though proposed for an automated robot driving, it gives a good foundation for supervised learning and obtaining the most probable road part from the previous knowledge. In case of curved roads, most of the line based algorithms cannot function properly. Further, such algorithms for segmentation

also suffer due to illumination variation in the road image and also due to intensity variation. Such variations can be avoided by integrating contour tracking method where kalman filter is one of the most used methods. But due to non-dependency nature of various road curves a conditional density based tracking can replace a kalman filtering approach. This technique is observed and elaborated by [9]. The segmentation approach proposed in this paper is derived from the findings of [10]. [11] Observes that for faster processing and segmentation, it is important that the images are resized first. Resizing the images gain a processing speed improvement over other methods like median filtering. The resized images are converted into gray scale and edges are extracted and enhanced from the gray scale image. These edges are further classified for detection of the road boundary. [12] Proposes a new plane for image representation in a v-plane image. It observes that the segmentation result obtained from this plane is much better than the segmentation obtained over (x,y) plane of the image. [13] Uses a two-way model for detecting road boundary and also vanishing points. It uses a parallel technique of graph based segmentation and Hough transformation and road boundary extraction and further merges the points obtained by both the mechanism for extracting the road points and vanishing areas. [14] Considers segmentation as a classification problem and performs the same to detect road points based on prior knowledge. [15] Formulates a vanishing point algorithm by first segmenting the image and detecting each vertical and horizontal lines of each of the segments. Then the center of the image mass-data is calculated and lines are spread such that each line meets the segmented lines in right angle. It finds that if the parameter of the circle around the center point is estimated properly then it is sufficient to calculate the vanishing points. [16] Proposes a model algorithm for moving object tracking [24] specially moving cars against a road profile. It observes that a covariance based weight matrix can be used to classify the moving objects. The road profile in a video sequence will be more or less consistent and hence subtracting such point where the motion is detected gives an estimation of the road profile. [17] Supports the proposed methodology by claiming and justifying the RGB color model which is best suited for road segmentation and HLS [21] color model requires extra time for computation and H components are not suitable for detecting the road part. It uses a Euclidian distance based approach for finding the homogeneity of a region and further classifies the region as road or non road region based on color, area and shape information. [18] Proposes a dominant orientation technique for finding the vanishing points in non homogeneous roads like desserts. [19] Elaborates the properties of Gabor filter which in summery is a quantized conjugate plane of time-frequency such that each component occupies a distinct space in the coordinate system. The described filter coefficients are utilized by [23], as a feature vector for classifying road components. [20] Enhances the Fourier based road tracking algorithm developed by [30] for a multi spectral road data. [21] Uses gray level concurrence matrix and its features for classifying the independent clusters generated from a road image based on fuzzy rule set. This strengthens the idea of road segmentation approach by segmenting all the possible clusters and then selecting the candidate road clusters. But generating all the clusters and further classifying them by cluster wise classification rule is time consuming. Therefore the work emphasizes color model based singleton segmentation for the road part. [22] Uses a connected component based approach for extracting objects from the image and based on binary image processing. The



idea is adopted here for a post processing step of segmentation for improving the segmentation result. [28] presents an application of computer vision methods to traffic flow monitoring and road traffic analysis. The said application is utilizing image-processing and pattern recognition methods designed and modified to the needs and constraints of road traffic analysis. These methods combined together gives functional capabilities of the system to monitor the road, to initiate automated vehicle tracking, to measure the speed, and to recognize number plates of a car. Software developed was applied, approved with video monitoring system, and based on standard CCTV cameras connected to wide area network computers. Traffic signal lights are triggered using an inductive loop. At a traffic light, an automobile will be stopped above an inductive coil and this will signal a green light. Unfortunately, the device does not work with most motorbikes. Using a passive system such as a camera along with image processing may prove to be more effective at detecting vehicles than the current system. [29] Determines that the features of various motorbikes and automobiles are sufficient enough to classify it as traffic. [31] Introduces a visual zebra crossing detector based on the Viola-Jones approach. The basic properties of this cascaded classifier and the use of integral images are explained. Additional pre and post processing for this task are introduced and evaluated. [32] Proposes that the autonomous vehicle system is a demanding application for our daily life. The vehicle requires on-road vehicle detection algorithms. Given the sequence of images, the algorithms need to find on-road vehicles in real time. Basically there are two types of on-road vehicle (cars traveling in the opposite direction and cars traveling in the same direction).

3. METHODOLOGY

A. Segmentation

Color based segmentation is fast but suffer from inaccuracy in segmentation problem. But due to the speed of detection it is the best suited method for the proposed application. The immediate front part of the vehicle is bound to be road part and there could be a variation of about 10% in the color profile of the color values of the road. Hence the color information obtained from this part of the image should be a good descriptor for the image segmentation for road part extraction. But some of the background may also share the same color information like that of the road images. Therefore segmentation process must not only segment the road scene based on the color information but at the same time must also remove those pixels which are wrongly segmented due to color similarity.





There are various image segmentation techniques available for segmenting the color objects. Most of the algorithm works with clustering and finding out the occurrence of major objects with repetition. Image in figure 1 reveals that if a cluster based segmentation is applied on these images, then objects like the pedestrians or the vehicles or the sky in the background, all may get segmented. Hence, threshold based segmentation is required to separate the road image from the rest of the objects. Color based thresholding is difficult to adopt as the color and the texture of the road varies from scene to scene and from place to place. Therefore first, 100 images are read from the image database and a small road part is cropped from these images. R,G and B components of the cropped images are tabulated. It is observed that R,G and B values in the road part are defined by a color bound of 50 to 220. Further the pixels in the road part have very small deviation in R, G and B values. Therefore the following algorithm is developed for separating the road part.

Read the image pixel by pixel.

Extract R,G and B components from each pixel

Define distance between the color components of each pixel.

D1=/R-G //255

D2 = |G - B|/255

D3 = |R - B|/255

If D1,D2,D3<10% and 50<=*R*,*G*,*B*<=220

Mark the pixel as road pixel

From the current pixel take a block size of 50x50 pixel and move the block in current pixels neighborhood(Up,Down, Right, Left, Diagonal UP Left and Right, Diagonal Down Left and Right)

Classify the pixels in the blocks



If a block has more than 50% pixels being classified as road pixels and there exists atleast two such blocks

Then mark the current pixel as final_road_pixel

Else

Don't consider the current pixel as road pixel.

Repeat the steps till the entire image is marked.

Extract the marked image as the mask image and segment the road part from the original image using this mask.

The performance of this custom segmentation technique for the road image is observed to segment the roads with nearly 100% efficiency interns of road marking. Though some extra objects are also observed to have segmented along with the road based on the color composition of the objects, these objects are further filtered using a morphological technique.

Extracted road image is first converted into binary image. Most the objects falsely segmented are seen as smaller objects with span less than 100 pixels. Hence erosion is applied over the entire image with a square structuring element with 3x3 kernel. This process erodes the smaller noisy segmented objects from the image. But at the same time it also lightens the road part of the image. Now a dilation process is applied to fill the gaps in the road image with the same structuring element. It results in a smooth binary road image. This is superimposed over the original image to extract the road part.

This assumption may be considered as wrong for those road images where there are parallel roads as in case of multilane highways. In such roads morphological technique can not remove the detection of parallel roads and may lead to misdetection. Hence a unique method for extracting the current road part is adopted.

B. Road Boundary Detection

Conventional techniques use a Hough transform based technique for road boundary detection. In this first edges are obtained from the road image, followed by generalized Hough transform with lines that are perpendicular to the horizontal axes. As a preprocessing step, erosion and dilation are performed to connect components of the lanes.

This system suffers a setback in roads in the absence of any clear markings. To maintain the virtual lane, it is important that an alternative strategy be developed towards this direction. In this context an alternative method is proposed as elaborated below.

- 1. Segment the Road part with the help of methodology as suggested by A.
- 2. Extract binary road image and erode it with a structuring element of size 6x6.
- 3. Dilate the binary image with operator 9x9
- 4. Detect edges using canny edge operator with thresholds 150.

5. Apply generalized hough transform over the edge detected image.

Hough transformation (HT) maps a set of features in an input space to a set of parameters in an output parameter space as shown in figure.



Figure 3: Hough Transform for Lane detection

Here, $F: = \{ \{ x: f(\Sigma, x) = 0, x \in R2 \} : \Sigma \in \Omega \}$ (1)

Hough transformation in the current context can be defined as follows:

Let E` be some set of parameters in a parameter space essentially edges detected through canny edge operator, and

 $F = \{\{(X): f(\Sigma, X)=0, X \in R2\} : \Sigma \in \Omega\}$ be a family of patterns in R2 parameterized by Σ .

The HT maps the patterns in R2 to Rd using a function f: R2..... Rd and the problem is to find out the function f that maximizes the number of points $X \in R2$ that is mapped onto $\sum \in \Omega$.

The Lane Detection process through Hough Transformation can be considered in following steps:

- 1. Detect edges to Identify the line separated over image
- 2. Binding the lines so that they do not get parallels (horizontal to axis).
- *3. Calculating the high peaks.*
- 4. Identifying nonzero points in peaks.
- 5. Straitening the line and placing the point on the line.
- 6. Join these points.
- 7. Super impose the point joining over the original image.

C. Detection of Other Moving Vehicles

On Road vehicle detection is achieved through three phases as shown below.

- Pre–Processing
- Processing
- Post-Processing

Here preprocessing makes the acquired raw data into readable format for better processing of data inside computers. The preprocessing is done for removing the noise inside the data which is acquired from the cameras in order to make use of the same for further processing. Processing takes the help of the data which is completely checked from the preprocessing and manipulates the said data to get required detection from the frames. Post processing is utilized for checking the results absorbed from the processing. In case any changes are required can be verified and corrected.

Pre-processing:



The preprocessing is used for processing the raw data and to implement required transformations in order to utilize it for further processing. It shall be necessary to remove the noise from the raw data and then data should be normalized for several operations to organize the data frames for efficient performance. Pre processing block diagram is as shown below.



Fig 4: Pre-Processing Modules

As it is seen above, pre processing performs several modules to make required transformation for the traffic jam detection. First modules provide the real-time acquisitions of video data from the CCTV cameras. This data which is recorded will be a raw data accompanied with noise. For removing the noise, transformation of video is required and here we extract frame from the video till the last frame of the video is extracted completely. Now extracted frames from the raw video shall be converted into OpenCV readable format for applying several image processing techniques on all subsequence frames. Gray scale function is applied for every frame for efficient operations of image processing functions in OpenCV, where gray scale makes equalization of color form for all frames. Absorption of difference between the two subsequent frames of gray scale finds the difference and gives us the possible matrix vector values. These vector values with the gradient technique will provide the edge detection of moving objects or vehicles in sequences of frames; here we can find the location of moving objects in particular frames and optical flow direction of moving objects. To make a variation from the background and foreground the representation of frames will be in the form of binary format which is nothing but highlighting the mask information in the form of black and white color, 0's represent black color and 1's represent white color. Now binary frames which detect the motion and optical flow of the object will have unfilled gaps inside the frames. In order to fill these gaps for efficient detection and processing dilation is applied for structuring the pixels of detected objects.

Processing:

In the preprocessing stage it was possible for the detection of moving objects or vehicles location and flow of direction in sequence of frames. Now it is necessary to make main process for correlating the detected objects as moving vehicles only. Block diagram for processing section is as shown below.



Fig 5: Block diagram for Processing

From the above figure we come to know that features or contours play a main role in detection of traffic jam information from the frames. To know the traffic jams, first there a need to know the difference between the fore ground and background information which we were able to know from pervious preprocessing section. After knowing the motion and direction of moving objects, it is now necessary to track them along all the frames without any drawback. We also know there is a motion in particular sequence of frames along with location with the help of edge detection. Now Lukas-Kanade method is applied on every individual frames for identifying the required features of moving objects. This will help us to track the particular object along the sequence of frames. When we give image for features or contours conversion, there will be number of features all over the frame, and now the main difficult part would be to extract the required features or contours. Lucas-Kanade were able to extract the contours or features from the required moving object then; makes the calculation with common connected features or contours into a single group of contours or features to detect moving objects in subsequent frames. In this process there is a likelyhood of facing problems with unwanted detection like flying papers or leaves; which we should neglect to achieve efficient detection of algorithm. In such situation a filter shall be used to be applied for every frame to remove little or small motion formations. Finally the processing of this information and changes should be continuously updated for further processing.

Post-Processing:

In the post processing step, the detected vehicles are marked with circles and the result of road boundary detection is superimposed with this. Once a vehicle is detected, it must be tracked back in all the frames. This is performed by lucuskennedy method [36] as described in detail in the following section.



Lucas-Kanade Optical Flow Method:

`The Lucas-Kanade method is involved in feature extraction from the detected foreground objects inside the particular sequence of frames. This method was developed in 1981, where two persons' work is recognized as Lucas-Kanade method, those are Bruce D Lucas and Takeo Kanade [36]. These researchers made a combined work to develop one efficient technique to extract contours or features and to track them along all the sequence of frames in a video. To make differential assumption of optical flow between the two sequences of frames in image processing "Vision System" is achieved by Lucas-Kanade method [38]. This method strongly assumes that flow remains stable when it is closer to the nearer pixel, in same manner as optical flow mathematical equations are considered for all pixels, which are detected with motion reflection [38]. By several combinations of common pixels nearer to the flow, this will extract the features of the detected objects, and then provides the optical flow information of the objects.

Tracking Features:

The main task is to track the features along the sequence of the frames of video. Here the camera is fixed in a required region and this camera should be capable to track the features along the allocated region without losing the detection automatically [37]. The tracking of detected objects without losing detection of tracking from several variations of environment is essential. In order to achieve this task we need a robust system to track the features or contours along the frames of video. We have to consider few things before knowing the contours or features information. First the object tracking can be achieved when we know the location of motion in particular frames of video, where we gather motion of the object and location from the gradient based background subtraction methodology. Now based on the location of the objects information the features or contours make a small rectangles on moving pixel going through several combinations of equations belonging to the pixels. After motion detection, the object is tracked as it moves through the subsequent video frames [37]. The tracking is needed to deduce information about vehicle like its moving direction and mainly to jam condition. Tracking an object simply means identifying unique points or features on object and finally tracking those features as they move through subsequent frames [37].

For feature extraction, Lucas-Kanade Optical Flow method is utilized in this thesis work. The method is developed based on the Lucas-Kanade, where it takes arithmetical differential of the 2 frames which leads to detection of optical flow of moving object. Whole process to find optical flow depends on the central value of the pixel information, which is interrelated to the surrounded local variable [37].

Assuming that a specific point/feature in an image I(x, y, t) shifts to another position, then:

$$I(x, y, t) = I(x + dx, y + dy, t + dt)$$
(2)

First order Taylor Expansion

$$I(x, y, t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt \qquad (3)$$

Simplifying notations:

$$Ixdx + Iydy + Itdt = 0 \tag{4}$$

Dividing by *dt* and denoting

$$u = \frac{dx}{dt}, v = \frac{dy}{dt}$$
(5)

Assuming constant (u, v) in small neighborhood, the state space from equation above can be given as





Our goal is to minimize $\|A\vec{u} - b\|^2$. Multiplying both sides of Eqs. of above by A^T , we get:

$$\overrightarrow{u} = \left(A^T A\right)^{-1} A^T b \tag{6}$$

Where

$$A^{T}A = \begin{bmatrix} \sum I_{x}^{2} & \sum I_{x}I_{y} \\ \sum I_{x}I_{y} & \sum I_{y}^{2} \end{bmatrix}_{(7)}$$

 $A^T A$ represents the local neighborhood. We want this matrix to be invertible i.e. no zero eigen values. According to Shi/Tomasi method [39], a good feature r

contour is that for which $A^T A$ has big eigen values. So the aim of finding unique features or contours to find those points where $A^T A$ has higher eigen values [37].

Optical flow based direction tracking of the Moving objects

The optical flow gives a detailed information flow of moving objects in sequence of frames by making optimal estimation of motion from one frame to another frame. The main task of optical flow is to identify the number of moving objects in sequence of frames and to make optimal moving directions of the objects.





Fig 6: Motion Analysis Understanding



Fig 7.1: Optical Flow Estimation of Movement

The optical flow has constraints in order to make velocity vector information for every pixel in the frame. The optical flow function compromises the flow constraints by undergoing Lukas Kanade method which uses the gradient edge information in order to produce flow directions of moving object within a sequence of frames. First the optical flow in image processing represents the changes between two sequences of frames. It is known that optical flow process estimates flow information depending on the vector values for every pixel present in the frame, which are known as distance and velocity vector information of moving objects in the sequence of frames. The movement of single pixel can be observed with the help of following graphical representation.



(using d for displacement here instead of u)



The consideration of sequence of frames in time along with moving objects in view of camera gives us the interesting information, which is useful for analyzing and knowing the possible changes caused between sequences of frames by moving objects [35]. Various operations can be known based on the optical flow, like number of moving objects in a particular frame and then which direction objects are moving in sequence of frames. Finally the optical flow function uses two main variables as already mentioned, i.e, vector data V = (u, v). Here V represents the pixel information of the direction of moving object and how fast pixel varies due to moving objects from frame to frame information [35]. The frame intensity is represented by I(x, y, t), changes in intensity of frames is represented by time t along with x and y. From below equation it can be seen as to how a moving object varies its intensity value based on time, for example, point A with a time t after some time later to point B with extended time dt.

$$I(x + dx, y + dy, t + dt) = I(x, y, t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt + \cdots,$$
(8)

Above equation represents the moving object in sequence of frames, The x and y position at time t can be changed later to dx and dy. with dt of time in sequence of frames [35]. This is also represented as:

$$I(x, y, t + 1) = I(x + Vx, y + vy, t)$$
(9)

In this equation $\xrightarrow{V} = (Vx, Vy)$ that shows the velocity of vector. From the calculation of derivation, following constraint equation can be got for optical flow as shown below.

$$\left(\underset{vvl}{\longrightarrow} \cdot \underset{V}{\rightarrow} + \frac{\partial l}{\partial t} = 0 \right)$$
(10)

Here $\frac{1}{vl} = \left(\frac{\partial 1}{\partial x}, \frac{\partial 1}{\partial y}\right)$ is nothing but the gradient representation in frame. The above constraint for optical flow is a gradient constraint. It can be observed that the equation is with 2 unknown values which are not possible to solve. Now Lucas-Kanade will operate the optical flow based on the (u, v) point by assuming that the static motion in a defined surrounded pixels at the point Vu, v. The motion vector characteristics are known by variable $\theta = (a, b)$, now the deviation from the (u, v) can be handled by Lucas-Kanade search vector $\frac{1}{v}$ which will be solved by constraint equation solution as given below:

$$\underset{V}{\rightarrow} (u, v) = argmin \ with \ \theta \ \sum_{x, y \in \theta u, v} \left[\frac{\partial I}{\partial x} \cdot a + \frac{\partial I}{\partial y} \cdot b + \frac{\partial I}{\partial t} \right] 2 (11)$$

Once a vehicle contour is tracked in a frame, the vehicle is tracked through all the subsequent frames in which it is visible using the mentioned algorithm. This not only avoids a single object being repeatedly detected multiple times as independent objects in subsequent frames, also helps leveling the objects.



4. RESULTS



Fig 8: Misdetection of Hough Transform based Conventional Techniques due to improper markings



Fig 9: Appropriate Detection even in the absence of strong lane markings



Fig 10: Proper detection: 2



Fig 11: Road Segmentation and Vehicle Detection



Fig 12: Multiple lane, result of conventional system



Fig 13: Road Boundary detection in the proposed system



Fig 14: Detection of vehicle





Fig 15: Multiple Vehicle Detection



Fig 16: A Case of Lane Misdetection



Fig 17: Optical flow detected when moving vehicle comes very near



Fig 18: Successful boundary detection even when a vehicle is crossing the sight of the boundary

Analysis of the result:

For analysis of the efficiency of the algorithm, we considered still frame of 90 frames from a video and 20 such videos. Algorithm is simulated with the still video frames and manually labeled as correct or wrong detection. This is due to the fact that detection efficiency test on the video object is analytically difficult to define. Further we average the detection efficiency of vehicle detection, road boundary detection and lane detection. We analyzed the algorithm with two sets of methods: A) Segmentation with Texture map, Lane detection using Contours, Vehicle Detection using Morphology features B) Segmentation with Texture, Lane Detection using Hough Transform and Vehicle Detection based on correlation coefficient. Detection accuracy is tested against frame rate and number of vehicles on the road.



Figure 19: Efficiency of the Techniques

The graph clearly suggests that the proposed technique is better than the other two in terms of overall accuracy of the system. It is also apparent that as the number of vehicle increases, the accuracy decreases. This is mainly due to many motion objects and unclear road boundary. Low efficiency is also caused by less visibility of the road profile.





Figure 20: Efficiency of the techniques under different frame rate.

For these experiments, still frames are grabbed from the recorded motion video at different frame rate. Higher frame rate results in smooth transition from one frame to another frame. Therefore object detection result is far better in high frame rate. It is quite clear that the proposed algorithm performs well between medium to low frame rate.

5. CONCLUSION

Various image processing techniques have been proposed over the years for detection and classification of various road objects like lanes, zebra crossing, pot holes, bumps, vanishing points and so on. Different techniques are used for detection of such features. The goal of the work was to develop a fast and efficient technique for detecting the lanes, road boundaries and other vehicles on the roads in Indian roads. Indian rural and sub urban roads profile in a color model is inconsistent, hence making it very challenging task to extract the road part and detect any profile such as lanes. The other criteria considered are fast detection of the same. Therefore, in this paper a simplistic approach for the problem is proposed which is based on image processing in color domain and without any significant transform like Fourier Transform to speed up the detection. The frames are captured at the real time from moving vehicle. Therefore certain blurring effect is usual in such image or frames. But due to straight orientation of the camera such effects is minimized and hence does not require any specific deblurring algorithm. The results show promising efficiency in detection. Combining the results in color domain processing and gray scale processing of the images helps for detecting the profiles with utmost efficiency. The only drawback observed in the technique is that in cases of excessive number of vehicles, the accuracy becomes low. This problem can be considered as a significant direction for the future work.

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7. REFERENCES

- Gavrilovic Thomas, Ninot Jerome and Smadja Laurent, "Frequency Filtering and Connected Components Characterization for Zebra-crossing and Hatched Markings Detection," in Paparoditis N., Pierrot-Deseilligny M, Mallet C, Tournaire O. (Eds), IAPRS, Vol. XXXVIII, Part 3A – Saint-Mande, France, September 1-3, 2010.
- [2] Po-Lun Lai and Alper Yilmaz, "A New Approach for Vanishing Line Estimation," in ASPRS 2009 Annual Conference Baltimore, Maryland, March 9-13, 2009
- [3] Alvarez J. M., A. Lopez and R. Baldrich, "Illuminant-Invariant Model Based Road Segmentation," in Intelligent Vehicles Symposium, 2008 IEEE, pp. 1175-1180.
- [4] Ondrej Chum and Jiri Matas, "Planar Affine Rectification from Change of Scale," *in ACCV*, 2010.
- [5] J.D. Crisman and C.E. Thorpe, "UNSCARF-A Color Vision System for the Detection of Unstructured Roads," in Proceedings of IEEE International Conference on Robotics and Automation, California, April. 1991.
- [6] J.D. Crisman and C.E. Thorpe, "SCARF: A Color Vision System that Tracks Roads and Intersections," *in IEEE Transaction on <u>Robotics and Automation</u>, Feb. 1993, pp. 49-58.*
- [7] Stephen se, "Zebra-crossing Detection for the Partially Sighted," in Proceedings of the IEEE Conference, 2000, pp. 211-217.
- [8] Stuart Glaser, Eitan Marder-Eppstein, and William D. Smart, "Computationally Efficient Path-following Using Adaptive Color Models," 2008.
- [9] Michael Israd and Andrew Blake, "Contour Tracking by Stoichastic Propagation of Conditional Density," *in Proc. European Conf. Computer Vision*, Cambridge, UK, 1996, pp. 343-356.
- [10] Yang Ming, Lu Jianye, Wang Hong, Zhang Bo, "Visionbased Real Time Vehicle Guidance on THMR-V, Part I: Unstructured road detection," in Proceedings of the International Symposium on Test and Measurement (ISTM'01), Shanghai, pp. 365-368, June 1-3, 2001.
- [11] Nicolas Soquet and Didier Aubert, "Road Segmentation Supervised by an Extended V-Disparity Algorithm for Autonomous Navigation," in 2007 IEEE Intelligent Vehicles Symposium, pp. 160-165, June 2007.
- [12] Geng Zhang, Nanning Zheng, Chao Cui, Yuzhen Yan and Zejian Yuan, "An Efficient Road Detection Method in Noisy Urban Environment," *in Intelligent Vehicles Symposium*, pp. 556-561, June 2009.
- [13] Alberto Broggi and Simon Berte, "Vision-Based Road Detection in Automotive Systems: A Real Time Expectation-Driven Approach," *Journal of Artificial Intelligence Research*, pp. 326-348, 1995.
- [14] Mahzad Kalantari, Franck Jung, Jeanpierre Guedon, "Precise Automatic and Fast Method for Vanishing Point Detection," *in the Photogrammetric Record* 24, 127, 2009.



- [15] Wlodzimierz Kasprzak, "Adaptive Methods of Moving Car Detection in Monocular Image Sequences, Machine Graphics & Vision," vol. 9, no. 1/2, 2000, pp. 167 – 185.
- [16] Ming-Yang Chern, Shi-Chong Cheng, "Finding Road Boundaries from the Unstructured Rural Road Scene," in 16th IPPR Conference on Computer Vision, Graphics and Image Processing (CVGIP 2003), Kinmen 2003, pp. 786-793.
- [17] Christopher Rasmussen, "Grouping Dominant Orientations for Ill-Structured Road Following," in IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'04), vol. 1, 2004, pp. 470-477.
- [18] Tai Sing Lee, "Image Representation Using 2d Gabor Wavelets," *IEEE transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 10, pp. 959-971, Oct. 1996.
- [19] Vinay Pandit, Sudhir Gupta, K.S. Rajan, "Automatic Road Network Extraction Using High Resolution Multitemporal Satellite Images," *in Proceedings of IEEE IGARSS*, 2009.
- [20] Barna Saha, Arya mazumdar, Nikhil R Pal, "Bidirectional Fuzzy-Regression Model for Road-lines Detection," in IEEE Conference on Engineering of Intelligent Systems, Islamabad, 2006. pp. 1-6.
- [21] Hasan Fleyeh, "Color Detection and Segmentation for Road and Traffic Signs," *in Proceedings of the IEEE Conference on cybernetics and intelligent systems*, Singapore, Dec. 2004.
- [22] Chin-teng Lin, Yu-Chen Huang, Ting-wei Mei, Her-Chang Pu, Chao-Ting Hong, "Multi-objects Tracking System Using Adaptive Background Reconstruction Technique and its Application to Traffic Parameters Extraction," in IEEE International conference on Systems, Man, and Cybernetics, Oct. 2006, Taipei, Taiwan.
- [23] Zehang Sun, George Bebis and R. Miller, "On-Road Vehicle Detection Using Gabor Filters and Support Vector Machines," in 14th International Conference on Digital Signal Processing, Reno, NV, USA, 2002. pp. 1019-1022.
- [24] Shanming Lin and Jun Tang Xuewu Zhang and Yanyun Lv, "Research on Traffic Moving Object Detection, Tracking and Track-generating," in Proceedings of the IEEE International Conference on Automation and Logistics, Shenyang, China, August 2009.
- [25] Chuanzhao Han, Zhixin Zhou, Zhu Junjie, Ding Chibiao, "Road Extraction From High-Resolution Sar Image on Urban Area," in *IEEE Conference on Geosciences and Remote Sensing Symposium*, Denver, CO, IGARSS 2006, pp. 1454-1457.
- [26] Shang-Jeng Tsai and Tsung-Ying Sun "The Robust and Fast Approach for Vision-based Shadowy Road Boundary Detection," in Proceedings of the 8th International IEEE Conference on Intelligent Transportation Systems, Hualien, Taiwan, Sept. 13-16, 2005.

- [27] B. Brillault-O'Mahony. "New Method for Vanishing Point Detection," in Journal Computer Vision, Graphics, and Image Processing, vol. 54, Issue. 2, Sept. 1991.
- [28] R.T. Collins and R.S. Weiss "Vanishing Point Calculation as a Statistical Inference on the Unit Sphere," in Proceedings of the Third International Conference on Computer Vision, Osaka, Japan, Dec.1990, pp. 400-403.

Dr. Ajit Danti.

Professor & Director. Dept. of Computer Applications. Jawaharlal Nehru National College of Engineering, Shimoga, Karnataka, INDIA.

He has obtained PhD(Comp.Sc. & Tech) from Gulbarga University, Gulbarga in 2006, Karntaka, INDIA. Currently working as a Professor & Director. Dept. of Computer Applications. Jawaharlal Nehru National College of Engineering, Shimoga, Karnataka, INDIA. His research area of interests are Computer Vision, Image Processing and Pattern Recognition. He has published 20 research papers in peer reviewed International Journals.

Smt. Jyoti .Y. Kulkarni

Asst. Professor, Govt. First Grade College, Bijapur

&

Research Scholar, Department of Research in Computer Science, Dravidian University, Kuppam , Andhra Pradesh, INDIA.

She has obtained M.Sc degree in Information Technology from KSOU, Mysore in 2005 and M.Phil in Computer Science from Alagappa University, Karaikudi in 2007. Since 2009 she is working as Assistant Professor in Govt. Degree College, Bijapur Karntaka, India. She is working for her doctoral degree in Computer Science. Her research areas of interests are Image Processing and Pattern Recognition.

Dr. P.S. Hiremath

Professor and Chairman, Department of P. G. Studies and Research in Computer Science, Gulbarga University, Gulbarga-585106, Karnataka, INDIA.

He has obtained M.Sc. degree in 1973 and Ph.D. degree in 1978 in Applied Mathematics from Karnatak University, Dharwad. He had been in the Faculty of Mathematics and Computer Science of various Institutions in India, namely, National Institute of Technology, Surathkal (1977-79), Coimbatore Institute of Technology, Coimbatore (1979-80), National Institute of Technology, Tiruchinapalli (1980-86), Karnatak University, Dharwad (1986-1993) and has been presently working as Professor of Computer Science in Gulbarga University, Gulbarga (1993 onwards). His research areas of interest are Computational Fluid Dynamics, Optimization Techniques, Image Processing and Pattern Recognition. He has published 42 research papers in peer reviewed International Journals.