Master's Thesis
Electrical Engineering Signal Processing
JUN 2013

Robust lane detection and object tracking

In relation to the intelligence transport system

Muhammad Shafique
Muhammad Fahim
Prashant Pydipogu

School of Engineering
Blekinge Institute of Technology
SE – 371 79 Karlskrona
Sweden

This thesis is submitted to the School of Engineering at Blekinge Institute of Technology in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering. The thesis is equivalent to 22 weeks of full time studies.

Contact Information:
Author(s):

Muhammad Shafique
Address: Lindbloomsvagen LGH 98, 1101 Ronneby, Sweden
E-mail: shafique_malik@hotmail.com

Prashant Pydipogu
Address: Lindbloomsvagen LGH 98, 1101 Ronneby, Sweden
E-mail: prashant.paul87@gmail.com

Muhammad Fahim
Address: Lindbloomsvagen LGH 98, 1103 Ronneby, Sweden
E-mail: fahim_engineer@yahoo.com

Examiner:
Mr.Sven johansson
School of Engineering

School of Engineering
Blekinge Institute of Technology
SE – 371 79 Karlskrona
Sweden

Internet : www.bth.se/com
Phone : +46 455 38 50 00
Fax : +46 455 38 50 57

ABSTRACT

Every person in this world is concerned about being safe. Increasing safety and reducing road accidents, thereby saving lives are one of great interest in the context of Advanced Driver Assistance Systems. Among the complex and challenging tasks of future road vehicles is road lane detection or road boundaries detection. In driving assistance systems, obstacle detection especially for moving object detection is a key component of collision avoidance[1]. Many sensors can be used for obstacle detection and lane detection, such as laser, radar and vision sensors. The most frequently used principal approach to detect road boundaries and lanes using vision system on the vehicle. The detecting all kinds of obstacle on the road, mainly include IPM (Inverse Perspective Mapping) method. The system acquires the front view using a camera mounted on the vehicle then applying few processes in order to detect the lanes and objects. A versatile methodology is used in order to detecting the lanes and objects.

In our research we have developed a simple heuristic method which is more robust in both lane detection object detection and tracking in video. In this method we use clustering methodology to group the detected points in case of lane detection. Heuristic gives effective results in detection and tracking of multiple vehicles at a time irrespective to the distance.

Keywords: Heuristic method, lane detection, object detection and tracking, clustering methodology, least square, LibSVM

ACKNOWLEDGMENT

We would like to Praise the Almighty God for giving us the enough strength and good spirit to carry out this thesis work successfully.

We would like to show our sincere gratitude towards our thesis supervisor Mr. Sven Johansson, for his continuous support and good feedback throughout our thesis. His supervision and support made us to complete our thesis successfully.

We would like to show our respect and whole hearted thanks to our parents and friends for their support and giving us physical and moral strength to complete our education.

We would be very thankful to our Co-students for their co-operation during the thesis work.

Prashant, Fahim, and Shafique

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

IPM	Inverse Perspective Mapping
ITS	Intelligent Transportation Systems
NGPP	Near Ground Point Projection
SNR	Signal to Noise Ratio
TFALDA	Three-Feature Based Automatic Lane Detection Algorithm
LDA	Lane Detection Algorithms
LOIS	Likelihood of Image Shape
ROI	Region of Interest
VioLET	Video-Based Lane Estimation and Tracking
PROMETHEUS	Program for European Traffic with Highest Efficiency and Unprecedented Safety
UBM	Universitaet der Bundes-wehr Munich
KL	Karhunen Loeve
SIFT	Scale Invariant Feature Transform
USA	United State of America
MRF	Markov Random Function
HMM	Hidden Markov Model
WB	Wald Boost
TLD	Top Level Domain
CPU	Central Processing Unit
ITS	Intelligent Transport Systems
IBM	International Business Machines
RGB	Red, Green, Blue
CMYK	Cyan Magenta Yellow and Key (black)
HIS	Hue Saturation and Intensity
KLT	Kaehunen-Loeve Transform
NC	Normalized correlation
GA	Genetic algorithms
EGFO	Evolutionary Gabor Filter Optimization
SHT	Standard Hough Transform
HG	Hypothesis Generation
HV	Hypothesis Verification
PCA	Principal Component Analysis
SVM	Support Vector Machines

CONTENTS

Contents

1 INTRODUCTION

Everybody in this world is concerned about safety. The people those who go out from one place to other, expect to reach safely. Without any sudden incidents which may come through externally by road accidents while travelling. We can avoid the road accidents by using improved driving assistances. Vehicle crashes remain the leading cause of accidental death and injuries in most traffic congested countries e.g. UK, USA, and Asian countries claiming tens of thousands of lives and injuring millions of people each year. Most of these transportation deaths and injuries occur on the nation's highways. Therefore, a system that provides a means of warning the driver to the danger has the potential to save a considerable number of lives. One of the main technologies involves in these tasks is computer vision, which become a powerful tool for sensing the environment and has been widely used in much application by the intelligent transportation systems (ITS)[1].

In order to increase safety and reducing road accidents, people are spending lots of money for the advancement in the driving techniques which ensures the safety. The technology makes man to think more to improve the safety to save the lives. The automobiles are more conscious of providing safety feathers like seat belts, air bags and strong body structures which provide the passive safety that may reduce the effects of an accident. Avoiding accidents and saving lives are one of great interest that all researchers and Automobile companies work on.

In Advanced Driver Assistance Systems in order to achieve the desired safety on roads, the complex and challenging tasks of future road vehicles are road lanes detection or boundaries detection (white and black lines on roads) and Obstacles detection (cars, pedestrians, trees, etc) especially for moving object detection is a key component of collision avoidance in driving assistance systems.

Many sensors can be used for lane detection and obstacle detection, such as laser, radar and vision sensors. Detecting all kinds of obstacles on the roads mainly include IPM (inverse perspective mapping) method. The system acquires the front view using a camera mounted on the vehicle then applying few processes in order to detect the lanes and objects. A versatile methodology is used in order to detect the lanes and objects. Cars equipped with intelligent system like road lane detection and obstacle detection makes vehicles safer, which is vital in decrease number of victims or injured people by car accidents. Principal approaches to detection are using vision system on the vehicle.

In our research we have developed a simple heuristic method to improve the robustness of lane detection and object detection and tracking in relation to intelligent transportation system. In Heuristic method clustering methodology is used to group the detected points and a best fit line in the mean square sense to detect the lanes. Which are compared with other methods gives better lane detection. This method is briefly explained in Chapter-3. From which you can assume the lane detection plays a vital role for safety of lives in moving vehicles on roads.

On the other hand object detection and tracking the proposed heuristic method is more effective for detect and track of single or multiple vehicles at a time without any means of distortion and collision. This is compared with other important methods are explained briefly in Chapter -4. Object detection and tracking with respect to distant is other important aspect to ensure the safety on roads.

1.1 Motivation

There are many researchers who have worked and are working on creating and developing many techniques in intelligent transportation systems with advanced driving assistances system which are able to ensure the safety in the roads and congested traffic conditions. The road accidents are the main causes for the sudden death in this world. Even though we have many good and advanced techniques in this world, we are left over with something to make it better than before. There are chances from different angles. The road lane detection and object detection is also the other important way that we can improve the safety in roads.

Vehicle crashes remain the leading cause of accident death and injuries in Malaysia and Asian countries claiming tens of thousands of lives and injuring millions of people each year. Most of these transportation deaths and injuries occur on the nation's highways. The United Nations has ranked Malaysia 30th among countries with the highest number of fatal road accidents, registering an average of 4.5 deaths per 10,000 registered vehicles[1]. It is not only limited to one country most of the traffic congested countries like U.S, India, other Asian countries have many calculation of deaths and injuries.

In intelligent transportation systems with improved technologies, the vehicles are made more sophisticated with better infrastructure. But the way to move on the roads by means of lane and object detection aspect is neglected by many automobile companies and the ways to improve these aspects does not change from many years. Lane detection and object detection plays vital role for accidents. For human vision and human intelligence the task of lane detection and object detection changes due to variations in the road conditions. Sometimes it is very easy to detect with the human eyes but in some conditions due to externals effects the human intelligent have detection problems.

Due too many external conditions that appears for the lane detection and obstacle detection which may lead for the accidents. They are conditions such as appearances such as change of Light conditions at Night vision, shadows caused by building and trees, existence of surrounding objects, Mismatching of lanes, and lane changes in curved roads[2].

So in our research we provide the way to improve the lane detection and object detection in vehicles is import ants then rest of the other categories that may avoid the many road accidents. Lane should have to be detected clearly even with the external factors in consideration. The object detection will provide driving person confidences even in the different lighting and different environments situations by improved techniques to detect the objects. Thought you can provide the safety in roads to achieve a safer environment and in traffic congested conditions.

In our thesis we have motivated to improve the intelligent vehicle assistances with improving the SNR quality for lane and object detections as an important aspect to avoid the road accidents and improving the safety on roads.

1.2 Aims and Objectives

The aim of this thesis is to avoid accidental deaths and provide a better safety on roads, by use of advanced technologies in driving assistances system. The clear idea of the important aims and objectives of this thesis is explained with the help of block diagram.

General Block diagram of Research Thesis:

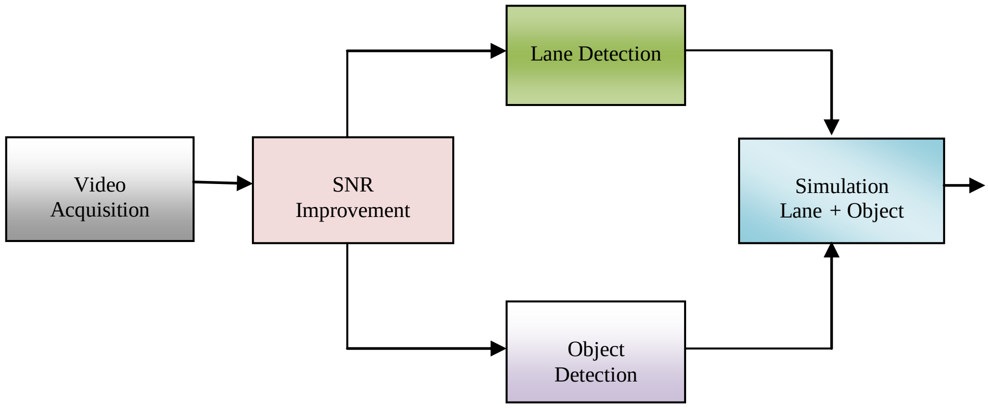


Figure 1 General Block diagram of proposed Research

1.2.1 Video Acquisition

There are many sources for the video acquisition in field of signal processing. The main important one is vision based approach. Here camera is mounted on the vehicle which is capable of reaching real time performances in detection and tracking of structured road Boundaries (Painted or Unpainted Lane markings) with slight curvature, which is robust enough in presence of shadow conditions. Also rear view camera based moving object detection algorithm which helps detection of moving object when the vehicle is passing it also very effectively used for backup aid and parking assist application.

1.2.2 SNR Improvement

Improving the SNR plays a vital role. As in clear the computer vision, avoids the blurring of video and improves the quality of the image frames in the process of the detection. Here we use the SNR improvement which is collaboration of both road boundaries and objects. These are detected by a camera mounted on vehicle in the form of series of images. Thus received data will be a noisy data. In order to reduce noise we will pass the series of images through certain filtering and modeling process, so thus obtained result is the improvement in SNR. This increases the quality of the images which will be very effectively used for further lane and object detection.

1.2.3 Lane detection

Lane detection is one of the methods which use the principle of vision based lane detection. As the name itself indicates is a process of detecting as well as recognizing the lanes where the ground traffic circulates. For driving advanced driving assistances the lane detection is one of the essential functions. The lane detection has become very specific term that implies the utilization of certain perceptive sensors, certain processing units, and certain algorithms to perform this functionality.

The lane detection is processes which have to be effective with the following. There are many factors which affects the lane detection. The Good quality of lane should not be affected by shadows of which can be caused by appearances of trees, buildings and other aid boards, the existences of surrounding object, the change of light condition, the dirt left on the road surface etc[2].

We humans has still some problems in detection of road lanes marks, detection should also have to assume the curved roads instead of assuming only that the roads are straight. Balancing the image which detects the lane should assume the parallelism of both sides of the lane marking to improve the detection in the existence of noises in images. Despite of existence of many research works on lane detection. The difficulties of lane detection always exist. So far there is no such technique that can boast of detecting lanes successfully. This can say that lanes can be visible by us humans[3].

So in this research we consider the lane detection which satisfies all the affects which I mentioned above will be explained clearly in Chapter3.

1.2.4 Object detection

To detect various moving objects such as vehicles and pedestrians, the ego motion of host vehicle is firstly estimated by A robust NGPP (near ground point projection) method. Then a novel point based moving object detection method is proposed which can detect fast motion as well as slight motion in the bird-eye image. Finally, a region based motion compensation method is used in order to filter out the false detection results caused by the error matching points.

In driving assistance systems, obstacle detection especially for moving object detection is a key component of collision avoidance. Many sensors can be used for obstacle detection, such as laser, radar and vision sensors. In the last few years vision sensors have been more and more popular as they giving more information about the scene. Vision sensors can be divided into normal cameras with a limited view and fish-eye cameras [4]. The latter have much wider application prospect in backup aid and parking assist systems as their much larger field of view. For driving assistance systems using visual sensors, feature based object detection algorithms are often used for detecting some specific kinds of objects such as pedestrians and vehicles as explained in article [4]. This kind of approach is applicable for the appearances of objects are known beforehand and not change much. In backup aid applications, al l kinds of obstacles can possess potential threatens to host vehicle. So this kind of algorithm is not suitable. For detecting all kinds of obstacle on the road, IPM (inverse perspective mapping) method is often used [4].

The simulated results of the lane detection and object detection are collaborated in the final stage of the system which gives the expected results of the system.

1.3 Research Questions

1- What are the main problems by using Hough based detection (Gray scale method and Color segmentation method) in case of lane detection?
2- How to overcome the detected problems from question-1 by using our proposed method?
3- What are the main problems by using fish eye camera, Gabor filter optimization and real time multiple object detection in case of object detection and tracking?
4- How to overcome the detected problems from question-3 by using our proposed method?

1.4 Thesis Outline

The organization of this research thesis will be as follows:

Chapter 1: We so went on with brief introduction about lane and object detection, motivation for research and aims and objectives of the implementing this thesis.

Chapter 2: Background of the SNR improved in the depth sensor data. Different ways represent of lane and object detection with relation to moving vehicles.

Chapter 3: Worked Simulation and results of the lane detection. Versatile methodologies used in order to get the results of lane detection.

Chapter 4: Worked Simulation and results of the object detection. Versatile methodologies used in order to get the results of object detection.

Chapter 5: Simulated results of both lane and object detection and comparing the results of versatile methodologies of lane detection and object detection suggesting the best method to improve the lane and object detection.

Chapter 6: Conclusion.

2 BACKGROUND

This chapter provides information about lane detection, object detection which is used for the road safety, safety is the top priority for all road lane detection systems because of this reason most of the cars accident will occur due to the miss leading of the vehicle path by the driver. Therefore now a day's many different vision-based lane detection algorithms and object detection algorithms for visibility of roads have been developed to prevent a crash of the vehicles on the road.

2.1 Lane Detection

Lane detection is a well-researched area of computer vision with applications to autonomous vehicles and driver assistance systems. This is partly because, despite the apparent simplicity of the white markings on a dark road, making it very difficult to identify the markings on different types of roads. These difficulties are of an occlusion in the shadow of other vehicles, changes in the roadway itself, and different types of road markings. A lane detection system must collect all types of markers roads confusion and filtered to give a reliable estimate of the path of the vehicle's position[5].

Lane detection plays an important role in driver assistance systems. In general, the steps of lane detection localize lane boundaries in the images of the specified path, and can help to estimate the geometry of the floor and lateral position ego vehicle on the road, Lane detection in intelligent cruise control environments for Lane Departure Warning, modeling the way, and so on.

Lane detection algorithms detect lane markings and the edges of the road, and estimate the vehicle position in the lane. Lane detection provides a framework for the support of many other single-camera based Mobil eye functions as vehicle detection; in this case, it contributes to the correct position of the vehicle in the same lane. Provided that the road markings visible and that their testimony is not hindered by the presence of clutter, acknowledge shadows, rain, snow or other disturbances on the road, the LDA recognizes the majority of white, blue and yellow markings across the world, and is Mobil eye system is approximately 99% of cases[6].

Different types of marks, such as solid, dashed, Bott points are double and triple road markings validated and integrated into production successfully. In addition, recognizing the LDA roadside (road edges) unmarked, such as grass or gravel banks, for more information on the adjacent track to support the strategy of caution and refine the OEM requirements. Also developed a system of permits for better separation of ambiguous markings, road markings double, triple, markings, etc., and the system has been refined and adapted to meet the variation found in different countries correctly. The authorization mechanism can also use the color information for better separation.

The LDA was tested in a series production programs in Europe, North America, Africa, the Middle East and Asia and has been validated on several continents and in a wide range of scenarios, including bright sunlight and weather around the world. In construction areas where there are many overlapping brands, the system is not available. Lane markers of different colors (e.g. blue markings Korean) has successfully developed and operated on the same input a monochrome imager as all other functions.

Mobil eye currently working on a back-LDA with existing units (rear-facing cameras) already in production for recycling applications. This increases the LDW function in difficult situations, such as when entering a tunnel or drivers support in situations where, for example, the sun blinds front camera, and there are reflectors on road seams and tar caused the overall system performance is improved[6].

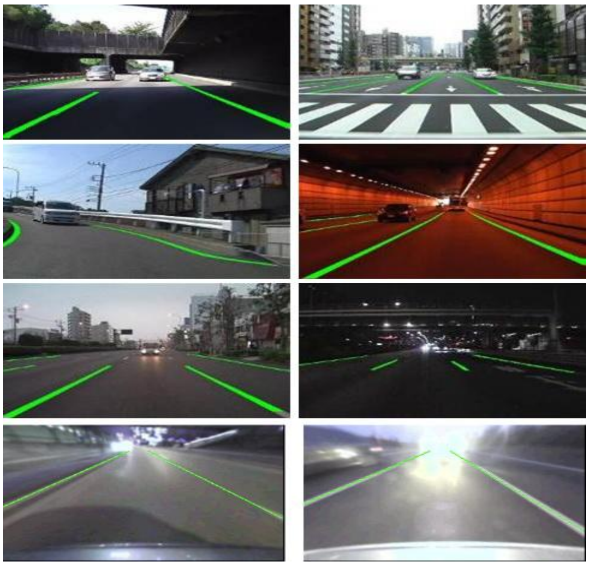


Figure 2 Examples of lane detection

2.1.1 Features of lane marking

- Adapts to various types of roads.
- Color, style and width of markings recognition.
- Detects all road markings in the picture.
- Integrated navigation system, see the track ego lane change and offer advice.
- Adapts to different weather and light condition[7].

2.1.2 Types of Road Lines

- **Continuous centre lines**

You can cross a continue center line to enter or leave a road, but cannot overtake.

- **Broken center lines**

You are allowed to overtake across a broken centre line or broken centre line.

- **Continuous edges lines**

Boundary lines (edges lines) are used to select the edge of the road. The area to the left edge of the line is the axis of the road which is also called shoulder of the road. This is not just an extra lane for vehicles to travel in. But, cyclists may also travel on the shoulder road. Vehicle also used the road edges lines in case when vehicle entering or leaving the road, stopping at the side of a road, turning at an intersection etc[8].

2.2 Related Work on Lane Detection

A complete survey on the state of the art is out of the scope of this project. The search was thus limited to IEEE database with the keywords: “lane tracking in video” in May 11th, 2013. This search retrieved a total of 99 papers, from which 14 were journal papers and the remaining 85 are conference papers. After reading all the titles and abstracts, 51 papers were considered to be of interest, from which 4 are journal papers and 47 are conference papers. Publication years range from 1992 to 2012. From these, it was only possible to access the full version of the 14 works that are briefly described in the following paragraphs.

Schneiderman and Nashman [9] describe a visual processing algorithm that supports autonomous road following. There are three stages of computation: extracting edges; matching extracted edge points with a geometric model of the road, and updating the geometric road model. All processing is confined to the 2-D image plane. No information about the motion of the vehicle is used. The algorithm also requires that lane markings be present and well marked.

Litkouhi, Lee and Craig [10] developed a theory for the design of a lane estimator and a lane controller. The roadway curvature and the relative positioning of the vehicle within its lane are estimated using Kalman filtering. Inputs to the estimator are vehicle kinematical variables provided by a vehicle directional control model, and lane boundary information provided by a video camera model. Although the developed model uses as input lane information, its detection is not discussed in this particular paper.

Taylor et al [11] lane extraction system is based on a parameterized model for the appearance of the lanes in the images. This model captures the position, orientation and width of the lane as well as the height and inclination of the stereo rig with respect to the road. Their work differs from ours in the premise that they have stereo vision, while here only information from one camera is available.

Betke, Haritaoglu and Davis [12] analyze color videos taken from a car driving on a highway. The system uses a combination of color, edge, and motion information to recognize and track the road boundaries, lane markings and other vehicles on the road. The system recognizes and tracks road boundaries and lane markings using a recursive least squares filter. The algorithm here presented could not be adapted to our situation since in relies on color information, while the video here processed is in grayscale.

In 2004, Jung and Kelber [13] addressed the problem of lane detection and lane tracking. A linear model is used to approximate lane boundaries in the first frame of a video sequence, using a combination of the edge distribution function and the Hough transform. A linear-parabolic model is used in the subsequent frames: the linear part of the model is used to fit the near vision field, while the parabolic model fits the far field. The proposed line detection procedure is applied independently to each lane boundary. In our work, information of the dependencies between the lines is used to improve the detection results.

Fletcher, Petersson and Zelinsky [14] develop and evaluate a road scene monotony detector. Again, although the method uses information about lanes, its detection is not discussed in this work.

Hsieh et al. [15] present an automatic traffic surveillance system to estimate important traffic parameters from video sequences using only one camera. An automatic scheme to detect all possible lane dividing lines by analyzing vehicles' trajectories is proposed. Video data differs from ours in the sense that it is assumed to be static, while ours is set in the moving car.

Maire and Rakotonirainy [17] describe a system that analyses videos of driving sessions collected by on-board Web-cameras. The system detects and tracks lane markings in order to estimate the relative position of the vehicle with respect to its lane. The analysis of the video recording is performed in reverse temporal order. Although having several benefits when compared to forward analysis, it makes it not suitable for an on-line system.

McCall and Trivedi [18] developed the "video-based lane estimation and tracking" (VioLET) system. The system is designed using steerable filters for lane-marking detection. Unlike the present work, several sensors, like front camera, vehicle speed, vehicle steering and vehicle and road model, are used as input.

Isa [19] used image processing to perform some experimental studies on dynamics performance of lateral and longitudinal control for autonomous vehicle. The paper presents an algorithm of vehicle lane detection and tracking based on color cue segmentation, canny edge detection and Hough transform. Again, we stress that the information available for the present project is in grayscale and thus color information could not be used.

Borkar, Hayes and Smith [20] also describe a lane detection system. The camera captured image undergoes pre-processing in the form of temporal blurring and grayscale conversion. Then, Inverse Perspective Mapping is applied to remove perspective and transform the image into a bird’s-eye view. An adaptive threshold converts the grayscale image into binary and then a low-resolution Hough transform is computed to find a set of candidate lane markers. The candidate markers are further scrutinized in a matched filtering stage to extract the lane marker centres. Random Sample Consensus is used to estimate parameters for fitting a mathematical model through the recovered lane markers. Finally, the Kalman filter predicts the parameters of each lane marker line from one frame to the next. A color camera installed below the rear-view mirror is used to capture video.

Cheng and Chiang [21] developed an automatic lane following navigation system for the intelligent robotic wheelchair. The system was developed to work in a barrier-free environment and used video paint line detection as the basis of automatic tracking navigation. It is clear that these conditions do not hold in our application.

More recently, a video-based lane detection using a fast vanishing point estimation method was proposed by Benligiray, Topal and Akinlar[22]. The first step of the algorithm is to extract and validate the line segments from the image. In the next step, an angle based elimination of line segments is done according to the perspective characteristics of lane markings. Remaining line segments are extrapolated and superimposed to detect the image location where majority of the linear edge features converge. The location found by this operation is assumed to be the vanishing point. Subsequently, an orientation-based removal is done by eliminating the line segments whose extensions do not intersect the vanishing point. The final step is clustering the remaining line segments such that each cluster represents a lane marking or a boundary of the road. The properties of the line segments that constitute the clusters are fused to represent each cluster with a single line. Although this work was found only after our implementation was developed, several of the ideas here presented seem to match ours. Our work differs, however, in the fact that the vanishing point does not need to be explicitly computed.

Finally, Gopalan et al. [23] used a learning approach towards detection and tracking of lane markings. They propose the following: 1) a pixel-hierarchy feature descriptor to model the contextual information shared by lane markings with the surrounding road region; 2) a robust boosting algorithm to select relevant contextual features for detecting lane markings; and 3) particle filters to track the lane markings. At the core of the approach is the importance placed on the quality of data. There can be instances such as foggy or rainy road conditions where the visual inputs alone are insufficient to detect lane markings. In the present work we tried to overcome this difficulty by using information of the previous frames of the video. We point the interested reader to more complete surveys like the one in[18].

The GOLD system developed by Broggi, it uses an edge-based lane boundary detection algorithm [24] hardware and software architecture based on stereo vision for use on moving vehicles to improve road safety. Based on a full-custom massively parallel hardware, detect generic obstacles (Without constraints on symmetry or shape) and the lane position in a structured environment (with painted lane markings) at a rate of 10 Hz.

Kreucher C. propose in [25] LOIS the algorithm (Likelihood of Image Shape) has been shown to find robust markings, even in the presence of observation of occlusion and a plurality of light conditions. He uses the algorithm to follow the laws of the road through a sequence of images, and a warning of a crossing is Imminent.

Mellon University developed a system called AURORA [26] the lane marks observed on structured roads as highways and city streets. The lateral position of the vehicle calculated from the detected line marker. If the car begins to stray from the path, alerts the driver with audible and visual alarms AURORA. We are also an active intervention in the form of the vehicle's steering and speed device that collision avoidance strategies aggressive.

Real time vision-based lane detection method is presented to find the position and type of lanes in each video frame [27] proposed a method for lane detection effective combination of filter functions edge-Link channels. The first filter means candidates are sought in the region of interest (ROI). During the research, a broad edge linking algorithm circuit slot marginal land used to produce the filter width for wider access board and serves as a way to research the edge orientation and tape are used to filter the channels marked border pair link candidates. A linear model based method has been developed for detecting the tracking markers in real time. To estimate the linear model is robust filtering capabilities such as efficient roads and edges, color, width and direction are combined to follow the markings on the parameters of the linear model is used to represent traces are calculated. Lane position can be determined from the linear model parameters and Lane Departure can be calculated. A diagram of the overall management of the Lane Departure proposed method of detection is shown in Figure3.

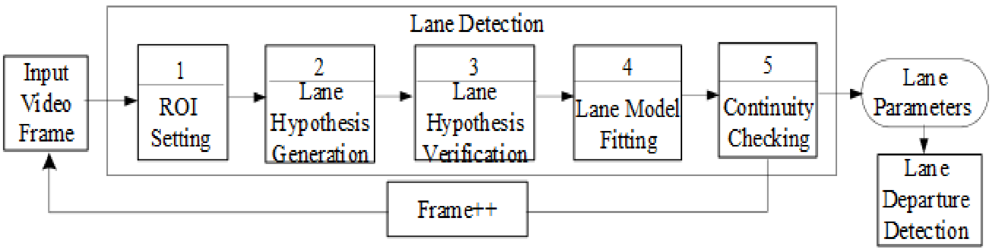


Figure 3 Lane detection block diagram

Image characteristics of the lane that comes with a new method for lane detection and tracking can accurately extract [28] by contrast gray image and processing binary .the filter strengthening increasingly application track binary information. Smooth Gaussian image Canny operator, processed for the detection of channel outlines, when the corner detection method is used for the image coordinates of the corners, finally RANSAC is used to get the optimized lane step by step, the lane parameters used to obtain more accurate track of and extraction of the curve is more perfect. The method not only improves the accuracy of path discovery, but also ensures the safety of the vehicle.

TFALDA is a lane detection algorithm proposed by yam et al [29] TFALDA which stands for Three-feature based automatic lane detection algorithm presented, suitable for rapid automated detection of lane boundries in different environments without tedious manual initialization or prior information on the way. The strength of the algorithm is to merge all three of the main characteristics of a lane boundary, and control of the temporal evolution. TFALDA could develop into a solid wide variety road conditions by optimizing the parameters of an evolutionary algorithm, instead of manually testing and improving. The lanes can be detected inverse perspective transformation in an image plane view from the steering angle next road and / or the information needed to control the direction of the channel's output can be obtained directly.

2.3 Object Detection

Object detection is a well-researched area of computer vision with applications to autonomous vehicles and driver assistance systems.

Every minute on average number of lives Dies, at least one person in a vehicle accident. Vehicle accidents were also injured at least 10 million people every year, two or three million of them seriously. It is expected. To reduce the damage and the severity of the accident to the hospital bill, property damage and other costs of up to 1-3 percent of global gross domestic product, is primarily an accident discovered an active research area among automobile companies , suppliers and universities. Several national and international projects have been launched in recent years to life to explore new technologies to improve the regulation of safety against accidents. Vehicle accident statistics show that the main threats a driver is facing are from other vehicles. Therefore Development of automotive driver assistance systems on board to cause the driving environments and communication collision with other vehicles has attracted many Attentions. In these systems, robust and reliable vehicles Detects of the first step. Vehicle detection and tracking -A large number of applications, including platooning (i.e. vehicles Traveling at high speed and short distance) quit and go (vehicles traveling in lowspeeds and close distance in cities) and autonomous driving[30].

Vehicle detection based on the vision for driver assistance systems have received considerable attention over the past 15 years. There are at least three reasons for the blooming research in this area: 1) Surprisingly, both human and economic losses from traffic accidents caused 2) the availability of possible technology accumulated over the last 30 years, research in computer vision, and 3) the exponential growth of processor speed has paved the way for the operation.

To build autonomous vehicles, many government institutions, automobile companies and suppliers, and R&D companies have launched various projects around the world, where a large number of research institutions working together. These looking at the research on intelligent vehicles globally, Europe's pioneering research, followed by Japan and the United States[30].

In Europe, the PROMETHEUS project (Program for European Traffic with Highest Efficiency and Unprecedented Safety) start search in 1986.More than 13 vehicle manufacturers and research institutes from 19 European countries were involved. Several vehicles and prototypes have been developed and demonstrated in the wake of Prometheus. In 1987, the UBM (Universitaet der Bundes-wehr Munich) test the VaMoRs vehicle's longitudinal direction and transverse direction of fully autonomous vehicles computer vision on a free part of the 20 km highway with a speed up to 96 km / h was used to show input both transverse and longitudinal control. This was seen as a first step[30].

2.4 Related Work on Object Detection

SENSING of vehicle detection and traffic conditions while driving preceded important safety driving, accident avoidance, and automatic driving and pursuit[31] detecting and tracking vehicle forward with a video camera in the vehicle. Introduced the HMM to vehicle identification during tracking, so that the likelihood of a decision framework that follows less affected by temporary thresholds. The joint probability of the picture and velocities to separate the dynamic HMM estimated from the target vehicles in the background-way positions. The use of coherence functions temporal motion extends the identification and tracking of vehicles.

A noval system for detecting and tracking vehicles from a camera mounted on the vehicle presented. The heart of the system is high vision algorithms to control the WB detector and the TLD tracker, real-time process scheduling.[32] The system is running in real-time (10Hz) on a single CPU core. New record for system evaluation board is designed to monitor featured of the vehicles. All data were collected on the Italian motorways, which includes a variety of light conditions and signaling the amount of data which show in below figure 4, has an approximate ground truth estimated from laser scans with visual data. The data and the reality of difficult terrain will be available to the public.

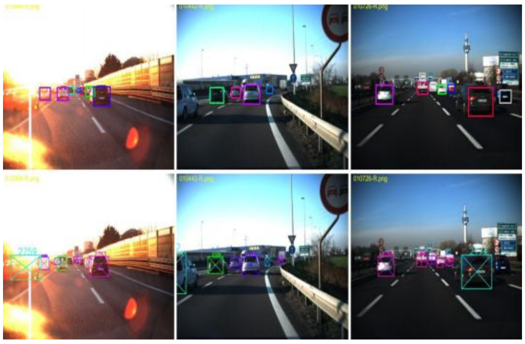


Figure 4 (a) Sunset (b) Curve (c) 4-lanes motorway

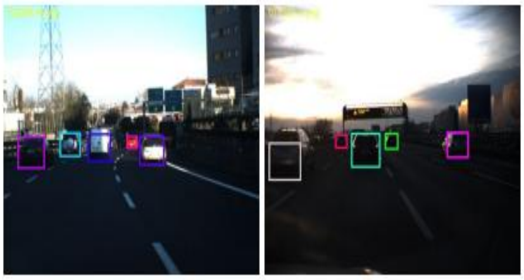


Figure 5 (a) Long range, variable light (b) Dusk conditions

The sensor fusion method is better than the method by using a single sensor [33] In this algorithm data association is performed on the capacity level primitives such recognition is greater than the recognition capacity of the sensor. The below figure 6 is a flowchart of the proposed algorithm. First calculate the primitive data from each sensor. Second connect the primitive image data with SLR primitive data. Call this fusion vector combined data. Fusion vector is treated as a virtual sensor. Fusion Vector dimension is compressed with a Karhunen-Loeve expansion (KL expansion). Third, compare the ROI dictionary vector fusion, which are prepared in advance discrimination.

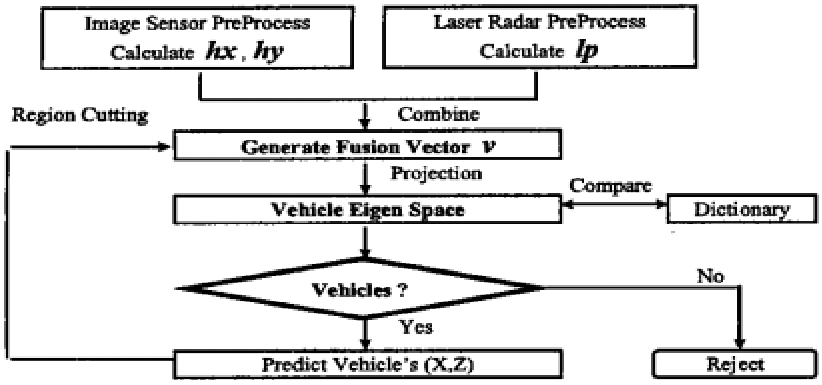


Figure 6 sensor fusion method flow chart.

Alonso et al [34] proposed strategy for vehicle detection which is based on classification of multidimensional probability measures for robustness and effectiveness are achieved considering the combination of three morphological characteristics of vehicles shadows, symmetry and corners.

The proposed approaches of these aspects are the effective combination testing phase of methods which are based on model-based and appearance-based. Thus achieve simple and stronger results. The proposed strategy is based on efficient computation of the probability of heterogeneous model in determining a method for classification, which is likely to match the assumptions vehicles. The production phase of the proposed approach selects region of interest (ROI) with adaptive knowledge-based split-and-related segmentation and propose candidates for each ROI sub-regions, which are classified in the testing phase. For this purpose, a minimum rating of Mahalanobis distance is used in an area of multi-dimensional function. In this work, the criteria used are probability measures in the form of a simplified model of three morphological features-region candidate vehicles shadows, symmetry and corners. In this way, the classification result of each candidate identified as belonging to the class of vehicle or a vehicle that is not also a measure of confidence.

A block diagram of the proposed vehicle detection approach is presented in Figure 7. The hypotheses generation phase.

- **Generation of hypotheses**
  In charge to select those image regions likely to hold vehicles.
- **Verification of hypotheses**
  Whose objective is to verify the presence of vehicles, among the selected area.

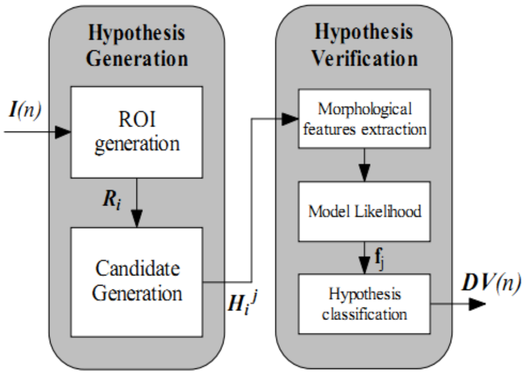


Figure 7 Block diagram of vehicle detection approach.

Method Scale Invariant Feature Transform (SIFT) with mean-shift tracking Algorithm. The method determines a region Interest (ROI), including the blind spot receiving successive frames in a side view camera. Information on the topology of the prominent areas derived from Statistical model used to identify impaired candidate Situations in ROI and SIFT Algorithm just to check if the candidate area contain an automobile[35].

Car tracking algorithm based on clipping technology in the field of adaptive filtering algorithms. A clipping technique allows controlling the noise source in predicting the positions of the vehicles. The version of the LMS algorithm, the LMS QX namely, which has a better tracking capability in relation to the clipped LMS (CLMS) of adaptive filtering algorithm. QX LMS algorithm for the estimation of a noisy chirp-signal is used for system identification and tracking applications in the car[36].

2.5 SNR Improvement for visibility of Road

Visibility is an important factor for road safety. Every year a number of accidents occur due to poor visibility and high speeds. due to poor vision in bad weather, considerable number of airborne particles with the significant size and distribution of media participants that absorb and scatter light environment and is reflected by significant items, and to the point display position is not as clear as if there are no object presence, and in foggy weather, people actually tend to show that excessive speed can cause overestimation.

Recently, perception sensors (cameras, radar, etc.) are introduced for monitoring the surveillance system. These sensors are designed to operate in a variety of situations and conditions (light, weather, etc.) with a pre-determined threshold rate of change. When using perception sensors rather than the meteorological visibility sensor, through dealing with hazy or fog image, has a great hot topic in the study. Many countries and institutions, such as Japan, USA, began to study on the subject. AerotechTelub and Dalarma University under the Swedish National Road Agency have done some associated research on the topic [37].

2.6 Related Work on SNR Improvement for visibility of Road

To solve some problem for enhanced the visibility [38] provide an automated method which requires only a single input image. Unlike current methods, which use a single image, the proposed method is not needed, the geometric information of the input image, without user interaction. The method is based on two important observations: First, images with better visibility (or clear images day) more contrast than images plagued by bad weather, on the other hand Air light whose variation is depend due to distance of objects for the viewer to be smooth. Based on these observations, they develop a cost function in the context of Markov random (MRF), which can be optimized efficiently by techniques such as graph cuts or belief propagation. The method can be used for both color and grayscale. Short description as follow first estimate the atmospheric light, from where can get the light chromaticity. With light chromaticity, remove the bright colors of the input image. Estimate the cost of the data and the cost of smoothness for each pixel. The data cost is calculated from the contrast of a small patch cropped from the image, and the smoothness cost is calculated from the difference of two neighboring pixels. These data and the costs of building complete regularity MRF optimized use of existing inference methods, produces estimated values of the Air light. Based on the estimated Air light, shows the scene with better visibility.

The optical model usually used in dealing with bad weather.

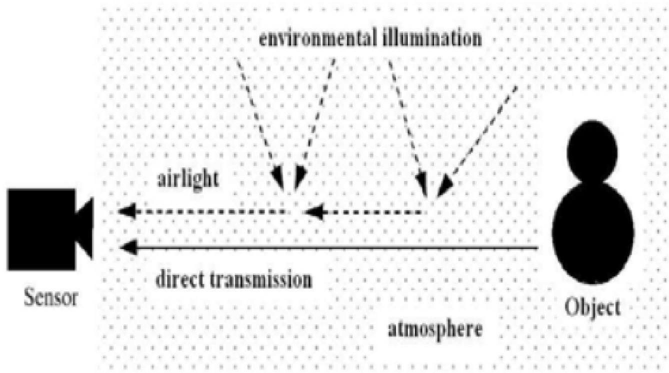


Figure 8 Optical model

3 ROAD LANE-DETECTION BASED ON HEURISTIC ALGORITHM

3.1 Introduction

With increasing traffic density, the demand for higher security and greater comfort for the car driver arises. Therefore new technologies are required. One of these is computer vision, which can be used to support the driver in complex situations in order to increase his security and comfort. A possible function to be used in future driver support systems is automatic object and lane marker detection. For these applications active sensors like radar shows significant problems in the near vicinity of the sensor[39]. As an alternative, video can be applied for object detection, which is the subject of this paper. Discovering markers road lane in a noisy video stream captured by the camera mounted on the car in the cloudy environment where it is difficult to recognize white lines on the road to stay in exactly lanes due to wrong way lane detection, many researchers and companies car introduce Intelligent transport systems (ITS) work with smart infrastructure towards having safer environment and reduce traffic problems [39] .This fact helps us to embed a system driver assistant in the vehicle to keep the vehicles on the track and prevent road leaves. Analyzing an image or a few images as frames of a video to mark the lane called Lane detection [40], which provides information to the embedded intelligent systems that track lane and steer the vehicle. There are many methods for lane detection in which one of the methods is to use the SP line and equalizing the SP line[41][42]. These methods model lane by dividing the captured image to any sub images. The second method is to use an artificial vision-based lane detection using the Hough transform and linear parabolic installation [43]. As we mentioned, there are many methods implemented for lane discovered in that two of them are Hough-based detection, color-based detection. Hough-based detection and Color-based detection is effective, but there are some problems when we use them individually to detect unwanted lines or not detect any existing lines of Hough-based detection and sensitive to the scene condition for Color-based detection.

One of the main pre-processing steps of these types of applications is lane detection. We have developed a simple heuristic method for detection of lanes in video. The method starts by thresholding each frame (or a combination of the current frame with the previous one) by keeping only the brightest regions of the image. Some of the detected regions are then eliminated having as basis some properties like area, orientation and eccentricity. A clustering methodology is used to group the detected points and a best fit line (in the mean squares sense) is then fitted to the remaining points. In order to check the coherence of the retrieved lines, some checks are made. Lines that are too close are merged; if more than 4 lines are detected, the 4 most similar to the ones detected in the previous frame are kept; if there are big jumps in the lines from one frame to the next ones, the corresponding line is eliminated; and if less than 4 lines are detected, lines from the previous frame are retrieved. Finally, if the lines are not being updated for 12 frames they are either not displayed (in the case of the outside lanes) or the line is replaced with a line between the two adjacent lines (in the case of the inside lanes).

3.2 Research Methodology

Vehicles equipped with intelligent transportation system we proposed Heuristic Algorithm to detect lanes. Firstly, we describe Hough-based detection and Color-based detection individually and look at their results. In order to do Hough-based detection, we send image to convert into gray scale, applying Region of Interest (ROI), using global thresholding, using edge detection, and finally find lines by Hough Line Transform. In order to do Color-based detection, we send captured images to color segmentation and noise reduction step. In Color-based detection; we extract more data from lines and their boundaries. Next, we describe our proposed method, which uses the extracted data from video stream and improves the efficiency of lane detection.

The result of lane detection using Heuristic Algorithm is considerably better than method that is just based on Hough Line Transform.

We have developed a simple heuristic method for detection of lanes in video. In Heuristic Method a clustering methodology is used to group the detected points and a best fit line in the Mean Square Squares sense is then fitted to the remaining points.

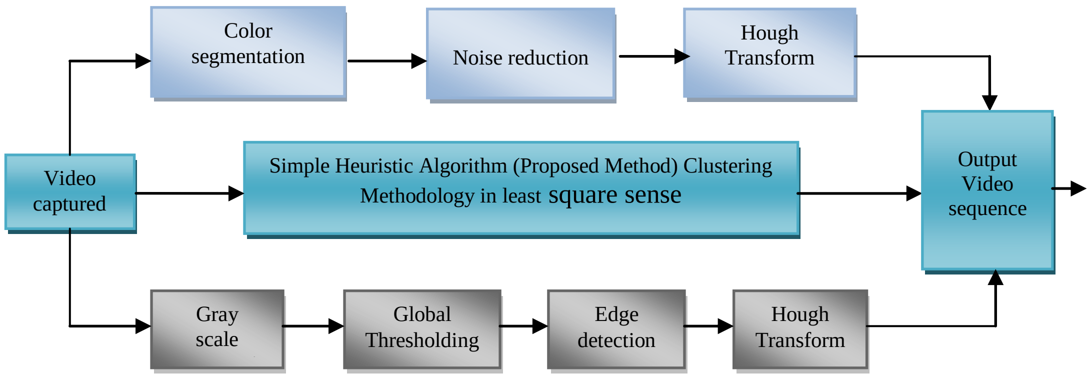


Figure 9 Block diagram of lane detection methodology

3.3 Hough-based Detection

In this section we will explain the lane detection by using gray scale method and edge detection and will examine the results by using this method .The Hough based detection includes the four parts as shown in the gray block diagram figure 9.

3.3.1 Defining and Conversion of ROI into Gray Scale

In this step, the captured color image is converted to gray scale to make method faster, less computational, and less sensitive to scene condition [44]. In our proposed method, captured series of images received from a camera on top of a car would be processed. The camera is adjusted in a way that the vanishing point of road should be placed on the top of ROI, shown in figure 10. Based on camera place adjustment, only part of the bottom of the captured image would be valuable for processing and it causes short time processing and less memory usage.

Figure 10 Converting to Gray Scale and ROI Selection

3.3.2 Optimum Global Thresholding

Single global thresholding does not effectively segment an image containing phenomenon like illumination. By using Optimum Global Thresholding with the help of Otsu's method, we could solve this problem of illumination, and make method less sensitive to scene conditions [45]. The main principle of Otsu's method is choosing threshold to maximize the interclass variance of the black and white pixels [46]. The interclass variance is given as Eq1.

$$\partial^2_{B} = P_1\left(m_1 - m_g\right)^2 + P_2\left(m_2 - m_g\right)^2 \ldots\ldots\ldots(3.1)$$

Here,

$P_i = Probability\ of\ pixel\ associated\ with\ class\ C_i$

$m_i = Mean\ value\ of\ pixel\ associated\ with\ class\ C_i$

$m_g = Global\ Mean\ value$

In the optimum thresholding method, we convert an intensity image to binary image, which is fed as the input to the edge detection step. There has been used many edge detector, canny, sobel etc. but here we will deal with Canny edge detector.

3.3.3 Canny Edge Detection

By applying the optimum global thresholding to selected part of image, ROI, we have binary image as the input for this step. In this step, to find lane boundaries in the image we use one of the edge detection methods called Canny Edge Detection and the detected boundaries are shown in figure 11.

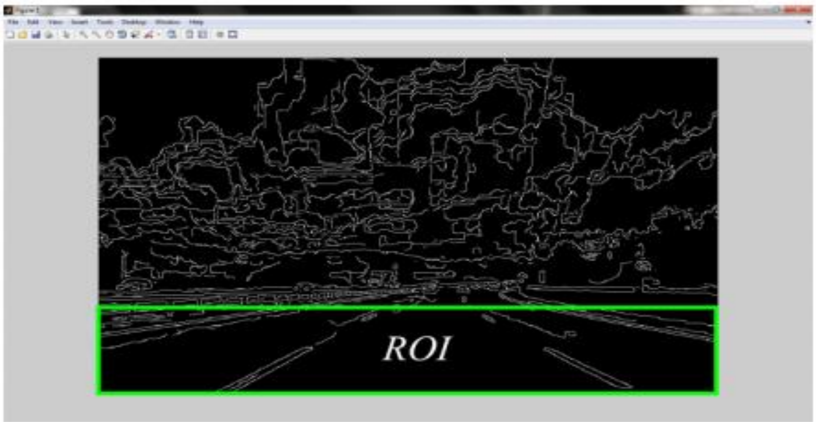


Figure 11 Canny Edge Detection

Canny Edge detector most commonly used for step edges due to Optimal, then is corrupted by white noise. The objective is the edges detected must be as close as possible to the true edges the number of local maxima around the true edge should be minimum.

Canny edge detection basically uses gradient vector of an intensity image. Lane boundaries have high contrast in the image, and this feature yields high values of gradient vector by which we can find the edge direction, which is orthogonal to gradient vector. Many edge detection methods are based on this principle, but the efficiency levels are different. One of the best and efficient methods is canny edge detection [8]. The most important characteristics of canny method are that the error rate of this method is low because this algorithm uses double thresholding, hysteresis thresholding [8]. Hysteresis threshold, double thresholding, suppresses the pixels that are not related to edges. Therefore, the detected edge is really close to true place. We should also mention that canny edge detector is very sensitive to noise; therefore, we smooth the image by a low pass filter to reduce the effect of noise [41].

Let $f(x, y)$ denote the input image $G(x, y)$ denote the Gaussian function than,

$$G(x, y) = \frac{e^{-(x^2+y^2)}}{2\partial^2} \text{ ……… (3.2)}$$

We form a smooth image $fs(x, y)$ by convolving G and f : $fs(x, y) = G(x, y) * f(x, y)$

3.3.4 Hough Line Transform

“The Hough transform is a general technique for identifying the Locations and orientations of certain types of features in a digital Image. Developed by Paul Hough in 1962 and patented by IBM, the transform consists of parameterizing a description of a feature at any given location in the original image’s space. A mesh in the space defined by this parameter is then generated, and at each mesh point a value is accumulated, indicating how well an object generated by the parameters defined at that point fits the given image. Mesh points that accumulate relatively larger values then that described features may be projected back onto the image, fitting to some degree the features actually present in the image.”

A method for finding global relationships between pixels, for example if we want to find straight lines in an image we apply edge enhancement filter e.g. Laplacian set a threshold for what filter response is considered a true ‘’Edge Pixel’’ extract the pixels that are on straight line using the Hough Transform.

3.3.4.1 Finding straight lines

Consider a pixel in position (X_k, Y_k) equation of a straight line,

$$Y_k = m \; X_k + b..........(3.3)$$

Set b=- m(X_k, Y_k) and draw this (single) line in”mb-space”Consider the next pixel with position (X_j, Y_j) and draw the line b=- m(X_j + Y_j) ”mb-space” (also called parameter space). The points (m’, b’) where the two lines intersect represent the line y=m’x+b’ in”xy-space” which will go through both (X_k, Y_k) sdcand (X_j, Y_j). Draw the line in mb-space corresponding to each pixel in XY-space. Divide mb-space into accumulator cells and find most common (m’, b’) which will give the line connecting the largest number of pixels.

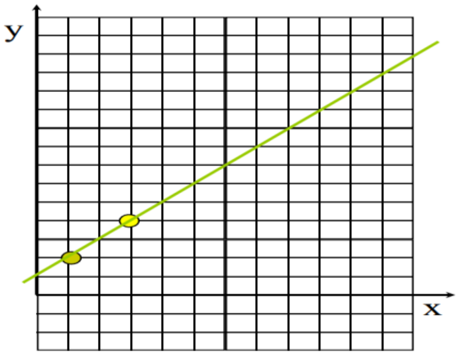


Figure 12 Hough Transform (a) x-y space

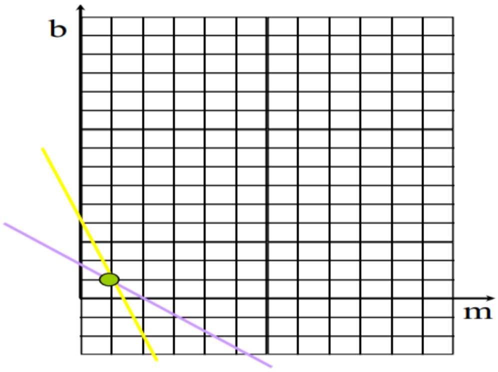


Figure 13 Hough Transform ab space

In reality we have a problem with y=mx +b because m reaches infinity for vertical lines, so we use

$$x\cos\theta + y\sin\theta = \rho..........(3.4)$$

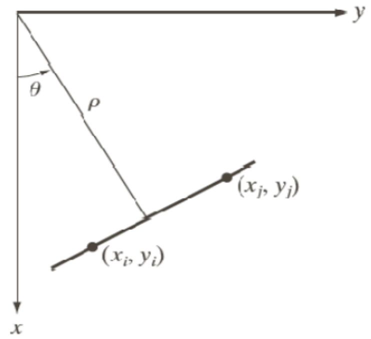


Figure 14 (ρ, θ) parameterization of line in XY plans

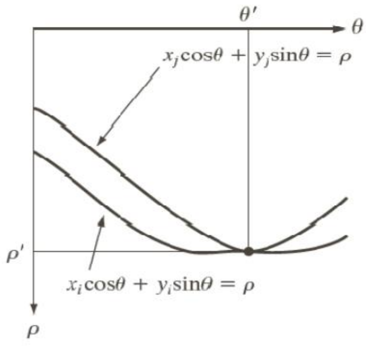


Figure 15 Sinusoidal curve in the (ρ_θ) plane

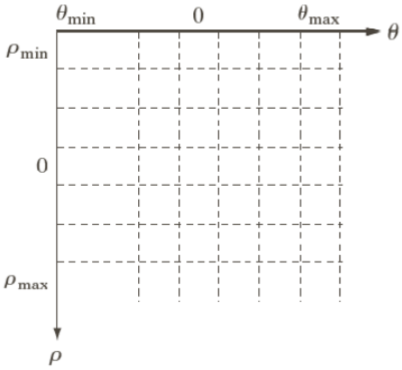


Figure 16 division of (ρ_θ) plane into accumulator cell

By using Hough Transform for a too big cell and we merge quite different lines too small and noise causes lines to be missed ,count the peaks in the Hough array, treat adjacent peaks as a single peak ,search for points close to the line and iterate the procedure:

Detecting shapes or features in a digital image is important for some purposes like detection of straight lines. In order to find lines in an image, we use standard Hough line transform that is one form of Hough Transform. For detecting the lines, we consider the output of Edge detection step as the input of Hough line detection, and this transformation finds lines in an image based on figure 14,15,16 describes that every point in Hough space is a line in Euclidean space and vice versa. By using this basic we detect the lines in an image obtained from edge detection step, and it is shown in Figure 17.

Figure 17 Line Detection Using Hough Line Transform

3.4 Color-based Detection

In Color-based detection, we extract more information about the lines and line boundaries based on their color Information to improve the efficiency of detection. We perform color-based detection on the same ROI shown in Figure 10 the color-based detection has two parts. First step is Color Segmentation, and second step is Noise Reduction.

3.4.1 Color Segmentation

The process that an image is divided to multiple segments is called segmentation. Color segmentation helps us to identify the boundaries and objects in an image based on desired color. Color images could be modeled with many color space like RGB, CMYK, and HSI. Every color space could be converted to other by using some formulas. In our proposed algorithm, the acquired image is in RGB and we convert it to HSI color model as we use HSI color model [46]. In lane detection using HSI model, saturation component S and intensity component I are more important than hue component H, and give us more consequential information [47].

The reason that we use HSI color space model with ordinary threshold value in our method is that in order to detect lanes in lane detection using RGB color space model we should use all three components R, G, and B, and they are all important for processing to detect the lanes. But when we use HSI color space model, just saturation S and Intensity I are important for processing to detect the lanes because of their considerable variations. This feature cause less computations and we have faster algorithm to detect the lanes [47].Usually, captured image from the roads contains white lines and gray background of road. High contrast between gray color of road and white color of lines cause higher values of saturation S and intensity I components rather than hue component H. This feature leads us to detect the lanes using HSI color space model based on information of saturation S and Intensity I. The segmented white lines in ROI based on color information of lines are shown in Figure 18.

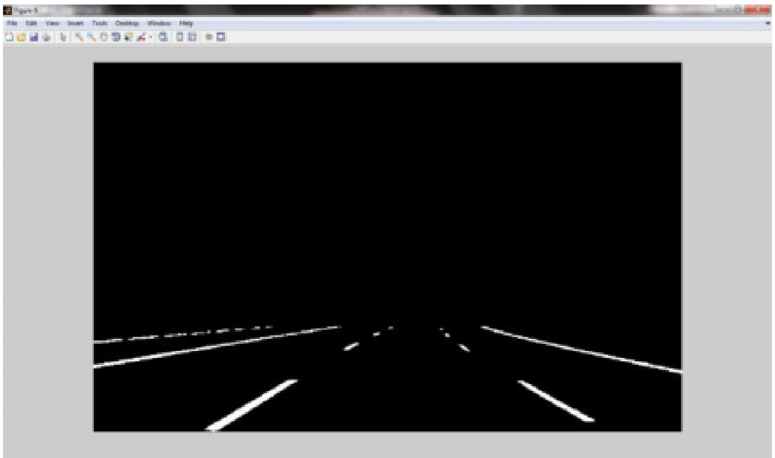


Figure 18 color segmentation

3.4.2 Noise Reduction

After detecting the lanes in an image using color segmentation, the segmented image contains noise. Therefore, proposed algorithm should be tolerant to noise. In this part, we remove noise and make our proposed algorithm noise tolerant [39].In order to remove noise from the segmented image, we use Morphological operation. We first do Opening operation to remove small objects that are responsible for the noise, and then Closing operation to make the lane boundaries clearer and softer [44]. Then we put some operations to remove some small and unrelated objects [41][43]. The output after removing the noise from segmented image is shown in Figure 19.

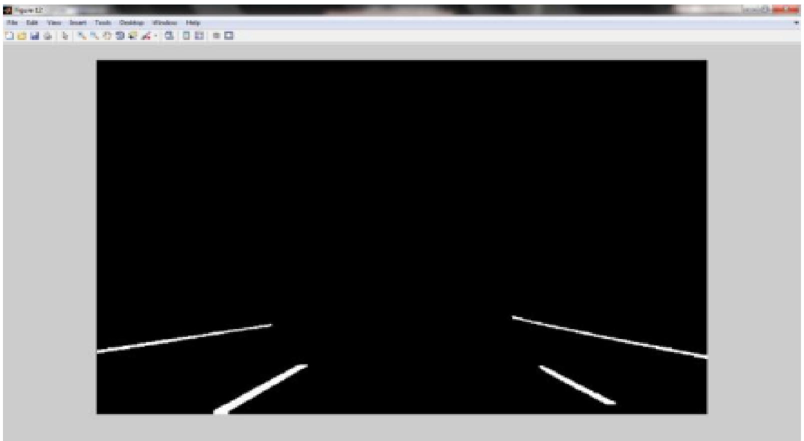


Figure 19 color segmentation

3.5 Simple Heuristic Algorithm (Proposed Method)

Lane, boundary detection is the problem of estimating the geometric structure of the lane boundaries of a road on the images captured by a camera. To be an intelligent vehicle, lane boundary is necessary information, so the system and the algorithm should be as simple and fast as possible. In this research, we propose a new method based on simple Heuristic Algorithm clustering method and this method will be applicable in complex environment. In this System, we have developed a simple heuristic method for detection of lanes in video. The method starts by thresholding each frame (or a combination of the current frame with the previous one) by keeping only the brightest regions of the image. Some of the detected regions are then eliminated having as basis some properties like area, orientation and eccentricity.

3.5.1 Clustering Methodology

A clustering methodology is used to group the detected points and a best fit line in the mean least squares sense is then fitted to the remaining points. In order to check the coherence of the retrieved lines, some checks are made. Lines that are too close are merged; if more than 4 lines are detected, the 4 most similar to the ones detected in the previous frame are kept; if there are big jumps in the lines from one frame to the next ones, the corresponding line is eliminated; and if less than 4 lines are detected, lines from the previous frame are retrieved. Finally, if the lines are not being updated for 12 frames they are either not displayed (in the case of the outside lanes) or the line is replaced with a line between the two adjacent lines (in the case of the inside lanes)[39].

3.5.2 Least Square

Least squares method is used to detect the lane mark point in such a way that a collineation is given for a point $P_2 = \left(X_2, Y_2\right)^T$ in the right image that can be obtain from a point $P_1 = \left(X_1, Y_1\right)^T$ in the left image when this point lies in the area of interest so,

$$\boldsymbol{X}_2 = \frac{\left(r_{11} + n_1 t_1\right) X_1 + \frac{F_x}{F_y}\left(r_{12} + n_2 t_1\right) Y_1 + F_x\left(r_{13} + n_2 t_1\right)}{\frac{1}{F_x}\left(r_{31} + n_1 t_3\right) X_1 + \frac{1}{F_y}\left(r_{32} + n_2 t_3\right) Y_1 + \left(r_{33} + n_3 t_3\right)} \quad \ldots\ldots\ldots\ldots\ldots \text{(3.5)}$$

$$\boldsymbol{Y}_2=\frac{\frac{F_y}{F_x}\left(r_{21}+n_1t_2\right)X_1+\left(r_{22}+n_2t_2\right)Y_1+F_y\left(r_{23}+n_3t_2\right)}{\frac{1}{F_x}\left(r_{31}+n_1t_3\right)X_1+\frac{1}{F_y}\left(r_{32}+n_2t_3\right)Y_1+\left(r_{33}+n_3t_3\right)} \text{ .... (3.6)}$$

F_x : Camera constant in pel for x-direction.

F_y : Camera constant in pel for y-direction.

In Matrix form:

$$\underline{R}=\begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}, \vec{t}=[t_1 \quad t_2 \quad t_3]^T, \vec{n}=[n_1 \quad n_2 \quad n_3]^T \text{ .... (3.7)}$$

From equations (3.5) and (3.6) two linear equations in η can be derived for each measurement i.

$$\boldsymbol{X}_{2,i}=\frac{k_{0,i}X_{1,i}}{r_{33}}\frac{n_1}{F_x}+\frac{k_{0,i}Y_{1,i}}{r_{33}}\frac{n_2}{F_y}+\frac{k_{0,i}}{r_{33}}n_3+\frac{k_{2,i}}{r_{33}} \text{ .... (3.8)}$$

$$\boldsymbol{Y}_{2,i}=\frac{k_{1,i}X_{1,i}}{r_{33}}\frac{n_1}{F_x}+\frac{k_{1,i}Y_{1,i}}{r_{33}}\frac{n_2}{F_y}+\frac{k_{1,i}}{r_{33}}n_3+\frac{k_{3,i}}{r_{33}} \text{.............. } (3.9)$$

with each point,

$$k_{0,i}=F_xt_1-t_3X_{2,i} \text{ .... (3.10)}$$

$$k_{1,j}=F_yt_2-t_3Y_{2,i} \text{ .... (3.11)}$$

$$k_{2,i}=r_{11}X_{1,i}+\frac{F_x}{F_y}r_{12}Y_{1,i}+F_xr_{13}-\frac{1}{F_x}r_{31}X_{1,i}X_{2,i}-\frac{1}{F_y}r_{32}X_{1,i}X_{2,i} \text{ ....(3.12)}$$

$$k_{3,i}=\frac{F_y}{F_x}r_{21}X_{1,i}+r_{22}Y_{1,i}+F_yr_{23}-\frac{1}{F_x}r_{31}X_{1,i}X_{2,i}-\frac{1}{F_y}r_{32}X_{1,i}X_{2,i} \text{ ....(3.13)}$$

The least mean square error,

$$e^2=\sum(e_{x,i}^2+e_{y,i}^2)\rightarrow \textit{Minimum least square error}\text{.......(3.14)}$$

has to be minimized with,

$$\boldsymbol{e}_{x,i}=\frac{1}{r_{33}}\left(k_{0,i}X_{1,i}\frac{n_1}{F_x}+k_{0,i}Y_{1,i}\frac{n_2}{F_y}+k_{0,i}n_3+k_{2,i}\right)-X_{2,i} \text{ .... (3.15)}$$

$$\boldsymbol{e}_{y,i}=\frac{1}{r_{33}}\left(k_{1,i}X_{1,i}\frac{n_1}{F_x}+k_{1,i}Y_{1,i}\frac{n_2}{F_y}+k_{1,i}n_3+k_{3,i}\right)-Y_{2,i} \text{ ....(3.16)}$$

So we get the Matrix equation,

$$\begin{bmatrix} \sum_i k_{5,i} X_{1,i}^2 & \sum_i k_{5,i} X_{1,i} Y_{1,i} & \sum_i k_{5,i} X_{1,i} \\ \sum_i k_{5,i} X_{1,i} Y_{1,i} & \sum_i k_{5,i} Y_{1,i}^2 & \sum_i k_{5,i} Y_{1,i} \\ \sum_i k_{5,i} X_{1,i} & \sum_i k_{5,i} Y_{1,i} & \sum_i k_{5,i} \end{bmatrix} \cdot \begin{bmatrix} \frac{n_1}{F_x} \\ \frac{n_2}{F_y} \\ n_3 \end{bmatrix} = \begin{bmatrix} \sum_i k_{4,1} X_{1,i} \\ \sum_i k_{4,1} Y_{1,i} \\ \sum_i k_{4,1} \end{bmatrix} \text{....(3.17)}$$

$$With, k_{4,1} = -k_{0,i} k_{2,i} - k_{1,i} k_{3,i} + r_{33} \left(k_{0,i} X_{2,i} + k_{1,i} Y_{2,i} \right) \text{......... (3.18)}$$

$$k_{5,1} = k_{0,i}{}^2 + k_{1,i}{}^2 \text{...........(3.19)}$$

This can be solved easily for the required road plane vector n_k, in figure 20 a typical result of our proposed algorithm is shown. Nearly all lane markers - although lying in the road plane - have been detected as object so the difference image of the left and the compensated image which has been calculated from the right image with the final collineation parameters P are presented.

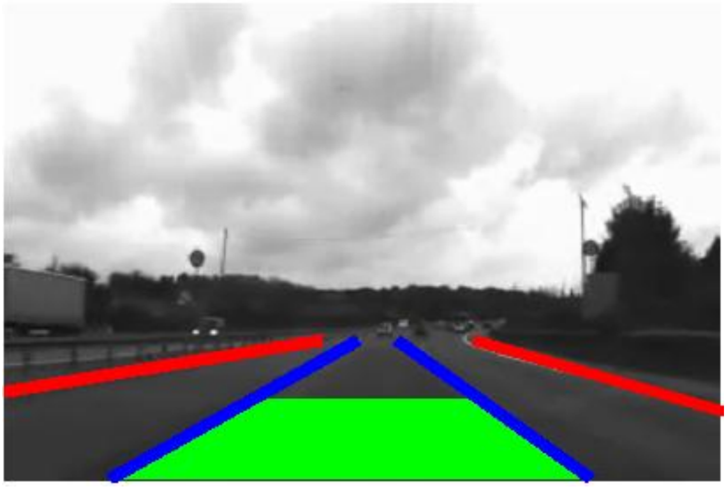


Figure 20 Simple Heuristic Algorithm

3.5.3 Advantages of Algorithm

This system demands low computational power and memory requirements, and is robust in the presence of noise, shadows, pavement, and obstacles such like cars, motorcycles and pedestrians conditions. The result images can be used as pre-processed images for lane tracking, road following or obstacle detection moving across lanes in order to overtake vehicles and avoid obstacles, searching for the correct and shortest route to a destination[39].

As we mentioned, Hough-based detection [44] and Color-based detection [46] are efficient, but there are some problems when we use them individually like detecting unwanted lines or not detecting some existing lines for Hough-based detection and sensitive to scene condition for Color -based detection. By using proposed method, we solve the problem of sensitivity of Color-based detection and detecting missing lines in Hough-based detection. We compare two methods based on our experimental results, and tabulate their detection rates in different scene conditions in Ch.5.

4 VEHICLE-DETECTION AND TRACKING BASED ON HEURISTIC ALGORITHM

4.1 Introduction

Object detection and tracking differ with each other, the word detection is only limited just finding out obstacles which are in front of camera such as (vehicles, pedestrians etc). Where as in tracking the obstacles are followed according to the distance and specified if the objects are closer as per distance. Object detection plays a vital rule in intelligent transport system to make it more vulnerable to cause accidents. Detection of different kinds of moving objects on road, such as vehicles and pedestrians is very important in backup aid and parking assist applications. The detection of moving object may be varied according the way to detect and track the objects. The detection and tracking using fixed camera mounted on moving vehicle is more interesting where there presents of the motion of objects, relative motion between cameras with the environment. The other hand it is by detecting using stationary camera.

Vision system is principle method used for detection. Which most commonly used for different methods for the detection and tracking there are many researchers who had worked and are working in vision based object detection. Here we stated some of the previous methods which are used for vehicle detections and tacking but infect due to the advancement of technologies there are problems and draw backs of these methods. Due to which there are many theories improved to overcome the drawbacks for the previous method. We have effectively proposed a method which shows the best results for object detection and tracking which also overcomes the drawbacks of previously stated methods.

Some of the methods which are briefly explained below are fish eye camera, Gobar filter optimization, and real time multiple vehicle detection and tracking. These method are widely used method which are been compared to the method with the proposed method.

4.2 Research Methodology

In Object detection and tracking to increase the robustness of the vehicle we proposed Simple Heuristic method in intelligent vehicle system, which is more effective for detect and track of single or multiple vehicles at a time without any means of distortion and collision. This is compared with other important the proposed simple heuristic method gives the accurate results in detection and tracking multiple vehicles at a time. In fish eye camera using NGPP (Near Ground Point Projection) [4] methodology for detects the objects and the motion compensation method is used track the moving objects minimizing the error matching point pairs .Secondly Gabor filter optimization is other method for detection of objects which uses the normal camera this method to detect the vehicles uses Gabor filter optimization which is based on optical sensors. The third method which we can see is the Real Time method which uses the normal camera, detector and process coordinator to track the object.

In our research we used simple heuristic method which uses the normal camera for the object detection and tracking by using Lib-SVM toolbox which makes the object detection and tracking more efficient when compared to other methods.

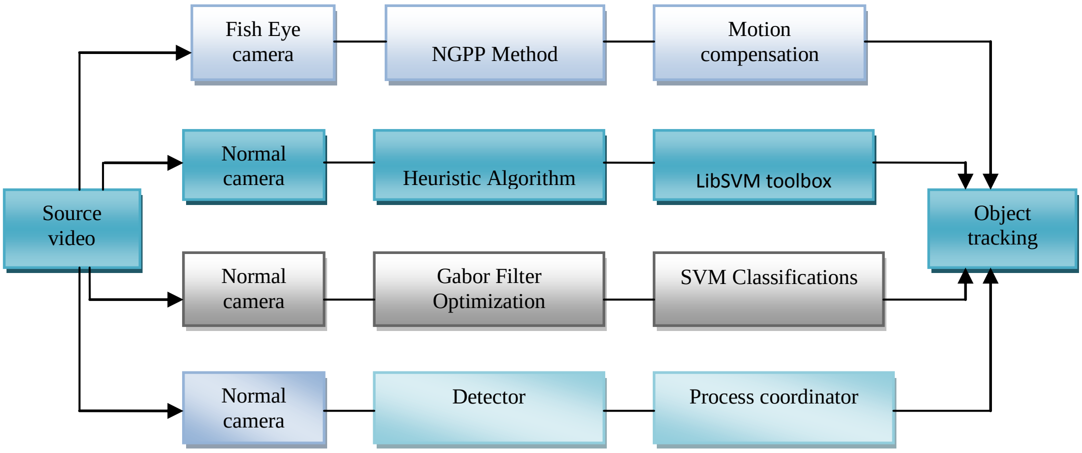


Figure 21 General Block diagram of object detection methodology

4.3 Object Detection by using Fish Eye Camera

Fish eye camera has a large field of view. First and foremost camera intrinsic and extrinsic parameters are known and are assumed to be calibrated and detect the region of moving object for each image. The regions are represented as the small grids which are setting according to the image size and used in the ego motion estimation. In current time t both the detection results at time t-1 and the consecutive images t and t-1 are input into our system. The KLT (Kaehunen-Loeve Transform) [4] method is employed which is the linear transformation to select and match feature points between two images because of its accuracy and efficiency. These matching point pairs are greatly used in the following steps to their length. For detection moving feature points, orientation and distance, the point pairs are clustered into different groups according to their length. Every image we see contains some form of structure. As a result, there is some correlation between neighboring pixels. If one can find a reversible transformation that removes the redundancy by de-correlating the data, then an image can be stored more efficiently.

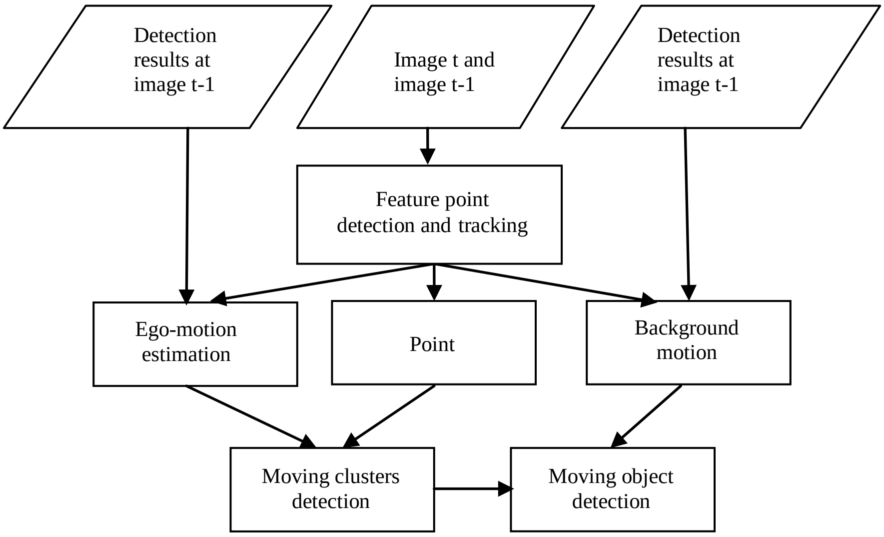


Figure 22 flowchart moving object detection method

4.3.1 Normal camera vs. fish-eye camera

Imaging model of normal camera is based on pinhole camera model while imaging model of fisheye camera model can be considered as a model of spherical projection. Both camera modals are shown in figure 23 and 24.

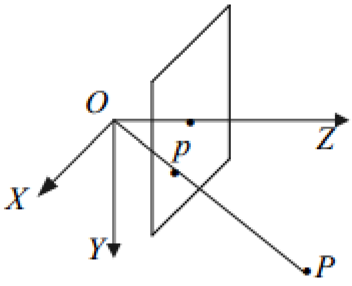


Figure 23 pin-hole model

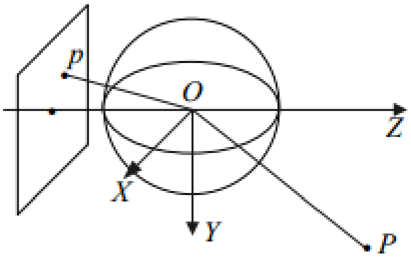


Figure 24 large FOV camera model

For normal cameras, the normalization vector p_s of P can be computed by

$$p_s = (\frac{X}{Z}, \frac{Y}{Z}, 1) \text{.............(4.1)}$$

For fish eye camera, the normalization vector p_s of P can be computed by

$$\begin{Bmatrix} x_s \\ y_s \\ z_s \end{Bmatrix} = k \begin{Bmatrix} X \\ Y \\ Z \end{Bmatrix}, k > 0, x_s^2 + y_s^2 + z_s^2 = 1 \text{.............(4.2)}$$

$$p_s = \frac{1}{\sqrt{X^2 + Y^2 + Z^2}} (X, Y, Z) \text{.............(4.3)}$$

According to image coordinate p is (u, v), so the projection of p to P can be written as

$$P(u, v) = M(p_s(x_s, y_s, z_s)) \text{.............(4.4)}$$

Here M is a mapping rule.

$$p_s(x_s, y_s, z_s) = M^{-1}(P(u, v)) \text{..........(4.5)}$$

4.3.2 Ego-motion parameters computation

To calculate the Ego-motion parameters, the proposed method is robust NGPP[4].In this process, the near ground pairs of points used for parameter estimation.

Select the near ground feature point of the below image, where there is no movement of the selected object. The picture is evenly distributed into grids. The projection distances between the grid floor and Camera are calculated.

Figure 25 original fish-eye image

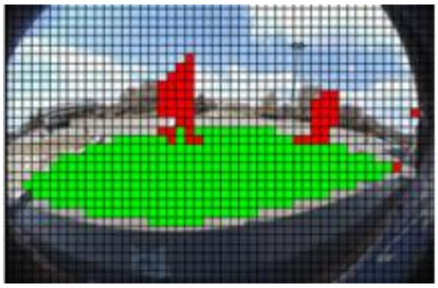


Figure 26 background region detection

Fisheye camera mounted on the rear of the vehicle and parallel to the ground plane. Two coordinate systems are defined in successive images, as in the figure 27 below.

The relationship between $(x^t, y^t, z^t) = (x^{(t-1)}, y^{(t-1)}, z^{(t-1)})$ in below equation.

$$\begin{pmatrix} x^t \\ y^t \\ z^t \end{pmatrix} = r \begin{pmatrix} x^{t-1} \\ y^{t-1} \\ z^{t-1} \end{pmatrix} + \begin{pmatrix} T_x \\ T_y \\ T_z \end{pmatrix} \ldots\ldots\ldots\ldots (4.6)$$

$$r = \begin{pmatrix} C_\gamma C_\beta & C_\gamma C_\beta S_\alpha - S_\gamma C_\alpha & C_\gamma S_\beta C_\alpha + S_\gamma S_\alpha \\ S_\gamma C_\beta & S_\gamma S_\beta S_\alpha + C_\gamma C_\alpha & S_\gamma C_\beta C_\alpha - C_\gamma S_\alpha \\ -S_\beta & C_\beta S_\alpha & C_\beta S_\alpha \end{pmatrix} \ldots\ldots\ldots.. (4.7)$$

Assumed $\alpha = 0,\ \Upsilon = 0,\ and\ T_\Upsilon = 0$

So,

$$\begin{pmatrix} x^t \\ y^t \\ z^t \end{pmatrix} = \begin{bmatrix} C_\beta & 0 & S_\beta \\ 0 & 1 & 0 \\ -S_\beta & 0 & C_\beta \end{bmatrix} \begin{pmatrix} x^{t-1} \\ y^{t-1} \\ z^{t-1} \end{pmatrix} + \begin{pmatrix} T_x \\ 0 \\ T_z \end{pmatrix} \ldots\ldots\ldots..(4.8)$$

Ground point motion equation is given by:

$$\begin{bmatrix} x^t - x^{t-1} \\ z^t - z^{t-1} \end{bmatrix} = \begin{bmatrix} z^{t-1} & 1 & 0 \\ -x^{t-1} & 0 & 1 \end{bmatrix} \begin{pmatrix} \beta \\ T_s \\ T_z \end{pmatrix} \ldots\ldots\ldots\ldots(4.9)$$

The initial median threshold is set to be the error squares of LLS method using all ground features points as input[4].

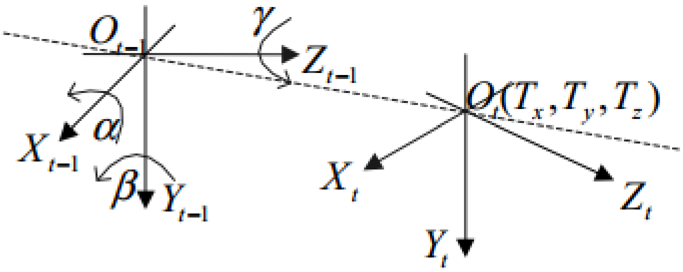


Figure 27 Camera coordinates system

4.3.3 Moving point's detection

Cluster of point's pair is defined as,

$$C = \left\{(P_t^i, P_{t-1}^i)\right\}, i \in \{1, \ldots, N\} \ldots\ldots\ldots(4.10)$$

Two pairs of points meet the following condition,

$$\sqrt{\left(u_t^i - u_t^i\right)^2 + \left(v_t^i - v_t^i\right)^2} \le D \ldots\ldots\ldots\ldots(4.11)$$

$$Min\left\{\left|\frac{l_t^i - l_t^j}{l_t^i}\right|, \left|\frac{l_t^i - l_t^j}{l_t^j}\right|\right\} \le L, l_t^i = \sqrt{\left(u_t^i - u_{t-1}^i\right)^2 + \left(v_t^i - v_{t-1}^i\right)^2} \ldots\ldots\ldots(4.12)$$

$$f_{angle}(P_t^i - P_{t-1}^i, P_t^j - P_{t-1}^j) \le \theta$$

where

$$f_{angle}\left(a,b\right) = arccos\frac{a.b}{|a|.|b|}$$

The points have same color if they belong to same cluster.

4.3.4 Find Moving clusters detection

After regrouping, the point pair's ammunition less than three pairs of points are removed from the cluster to remove the connectors for error. Then a new classification method used to separate the moving cluster and the other clusters.

For 3D coordinates as described above five statistical values can be calculated by following equation

$$d_{t-1}^i = Z_{t-1}; \ldots\ldots\ldots\ldots(4.13)$$

$$d_t^i = Z_t; \ldots\ldots\ldots\ldots (4.14)$$

$$e_{t-1}^i = max\left\{| u_{t-1}^i - u_{t-1} |, | v_{t-1}^i - v_{t-1} |\right\} ;\ldots\ldots\ldots.(4.15)$$

$$e_t^i = max\left\{| u_t^i - u_t |, | v_t^i - v_t |\right\};\ldots\ldots\ldots\ldots(4.16)$$

$$a^i = f_{angle} \ (p_t^i - p_{t-1}^i,\ p_t - \ p_{t-1});\ldots\ldots\ldots.(4.17).$$

4.3.5 Motion Compensation method

To avoid the error matching point pairs to be identified as moving points, background motion compensation method is used. The idea behind using motion compensation to offset first the effects of the global movement and then find the motion region.

Normalized correlation (NC) value is calculated between each pair of grids. Which can be define as follows[4]:

$$NC(I_t^i, I_{t-1}^i) = \frac{\sum_{y=1}^{n}\sum_{x=1}^{m}\left(I_t^i(x,y) - \overline{I_t^i}\right)\left(I_{t-1}^i(x,y) - \overline{I_{t-1}^i}\right)}{\sqrt{\sum_{y=1}^{n}\sum_{x=1}^{m}\left(I_t^i(x,y) - \overline{I_t^i}\right)^2}\sqrt{\sum_{y=1}^{n}\sum_{x=1}^{m}\left(I_{t-1}^i(x,y) - \overline{I_{t-1}^i}\right)^2}} \ldots\ldots (4.18)$$

Where I_t^i and I_{t-1}^i are the i^{th} grid in image t and t-1 respectively and the size of the grid is mxn.

The use of fish-eye camera provides vision, but also involves large image distortions that complicate the task difficulty. In this study, the detection of objects that are suitable for in- vehicle fisheye cameras and most moving objects contained in the motion. So far only two consecutive images (frames) are used, a further improvement by using a sophisticated tracking for monitoring a multiple of images obtained. Given the risk of collision is another further work.

4.4 Vehicle Detection by Using Gabor Filter Optimization:

The EGFO approach combines filter design with filter selection through integration of genetic algorithms (GA) with an incremental clustering approach. Genetic algorithms can search in the space of filter parameters and filter effectively removes excess clustering. In particular, the filter design were performed using GAs , an overall optimization approach, that encodes the parameters of the Gabor filter in a chromosome, and uses the genetic operators optimize[48].

4.4.1 GABOR FILTER Specification

Gabor filters used for various applications in image analysis including, edge detection, image coding texture analysis handwritten digit, face detection, vehicle detection and image retrieval[48].

g (x, y) is 2- D Gabor filter which can be represented as a Gaussian function modulated by a complex sinusoidal signal.

g (x, y) can be formulated by:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp[-\frac{1}{2}(\frac{\tilde{x}^2}{\sigma_x^2} + \frac{\tilde{y}^2}{\sigma_y^2}) \exp[2\pi jWx] \ldots\ldots\ldots. (4.19)$$

$$\tilde{x} = x\cos\theta + y\sin\theta$$

$$\tilde{y} = -x\sin\theta + y\cos\theta$$

Where σ_x and σ_y are the scaling parameters of the filter and determines the effective size of neighborhood of a pixel.

$\theta(\theta \in (0,\pi))$ Specifies the orientation of the Gabor filter and W is the radial frequency of the sinusoid[48].

The Fourier transform of the Gabor function is below.

$$G(x, y) = \exp[-\frac{1}{2}(\frac{(u-W)^2}{\sigma_x^{\ 2}} + \frac{v^2}{\sigma_v^{\ 2}} \ldots\ldots\ldots\ldots(4.20)$$

Where $\sigma_u = \dfrac{1}{2\pi\sigma_x}, \sigma_v = \dfrac{1}{2\pi\sigma_y}$. Is the fourier domain which the filter modifies each frequency components of the input image.

Gabor filters follow two main directions: "filter design approach" method and the "filter bank approach.

To show the proposed approach of filter design, redundant statistical Gabor features and SVM is used.

4.4.2 Gabor Filter Operation

As an input image I (x, y), Gabor feature extraction by fold I (x, y) is performed with a set of Gabor filters[48].

$$r(x, y) = \iint I(\xi,\eta) g(x-\xi, y-\eta) d\xi d\eta \ldots\ldots\ldots(4.21)$$

In the above equation I(x,y) is in input image.

where

x,y $\in \Omega$ (Ω the set of image point) is convolved with g(x,y) (2-D Gabor function).

While the crude reaction Gabor filter can be used directly as functions, is a kind of post-processing is usually applied (e.g., Gabor energy features, thresholded Gabor features, and moments based on Gabor features.

First, each sub-image is scaled to fixed size of 32 × 32. There is overlap in nine sub windows. Each sub frame consists of sixteen 8 × 8 patches distributed, the plates 1, 2, 5 and 6, the first consist 16 x 16, 2, 3, 6 and 7, the second, 5, 6, 9 and 10 of the fourth and so on. Gabor filter is then applied separately to each sub window. The motivation for extracting Gabor has several potentially redundant sub windows overlap of the error due to the sub window (eg sub-images containing partially extracted object or background) which compensates for feature extraction.

The levels on the responses of Gabor filters collected from each sub-window and represent through three stages: the mean μ_{ij}, the standard deviation σ_{ij}, and theskewness k_{ij}. Suppose by using N = 6 filters. The application of the filter bank to each of the nine sub-windows results in a vector format 162 having in the following form.

$$\left[\mu_{11}\sigma_{11}k_{11}, \mu_{12}\sigma_{12}k_{12} \ldots\ldots\mu_{69}\sigma_{69}k_{69}\right] \ldots\ldots\ldots (4.22)$$

4.4.3 SVM classifier

SVM are mainly two classes of classifiers, which proved an interesting and systematic manner the limits of linear or non-linear decision boundaries given the example of two classes [48].

$$(x_1,, y_1)(x_2,, y_2)\ldots(x_l,, y_l), x_i \in R^n y_i \in \{1,+1\} \ldots\ldots\ldots\ldots (4.23)$$

The discriminating hyper plane is defined as.

$$f(x) = \sum_{i=1}^{l} y_i a_i k(x, x_i) + b \ldots\ldots\ldots(4.24)$$

The Gaussian radial basis kernel, which is used is given by

$$k(x - x_i) = exp\left(\frac{\left\|x - x_i\right\|^2}{2\delta^2}\right) \ldots\ldots\ldots\ldots (4.25)$$

By using this method the average error in this case is reduced significantly is compared to the feature extraction method the average error rate is more with clustering and less without clustering using a threefold cross validation, the main advantage of using clustering Is that, it gives a more compact set of filter that is critical in real time system[48]. However by using EGFO method we have to face unwanted detection under various obstacles like detection of bridges, sign boards on the road Experimental shown in chapter-5.

4.5 Real time multiple vehicle detection and tracking

In computer vision based on fixed camera mounted on vehicle on vision system is the principle used to in real time the detecting and tracking the moving vehicles. The camera mounted on the moving car is much challenging than that of stationary camera. There the relative motion of between camera and objects and the environment plays a vital role[49].

The various vision based system approaches are recognised to detecting and tracking the moving cars. In our system we detect the multiple cars at a time. Which does not need any initialization by a human operator .but recognizes the cars it tracks automatically it does not rely in having to estimate road parameters.

The real time vision system multiple vehicle detection and tracking is explained with the help of the block diagram.

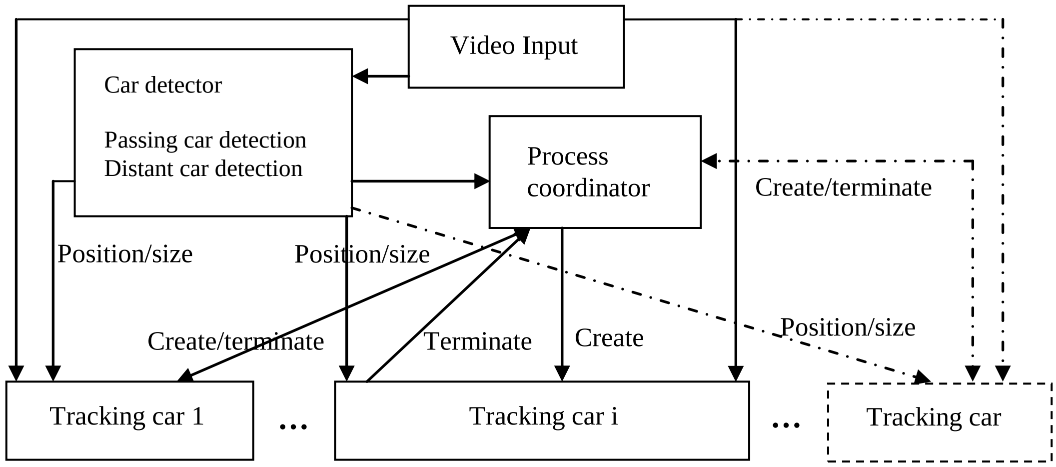


Figure 28 The hard real-time vision system for car detection and tracking.

The block diagram is derived into three important blocks they are car detector, process coordinator and tracker. The video input is taken with the camera mounted on the moving vehicle in the form of images to detect and track. Once the car is detected the process coordinator creates a tracking process for car and provides the information of the tracked car till it is in the surveillance of the camera. The process coordinator also specified with initial parameters for the position and size of the car that for the detected car is not tracked by any other process. The tracker analyzes the history of the tracked areas in the previous image frames and determines how likely it is that the area in the current image contains a car. Process of detection and tracking will go on from single car to the N no of cars.

This vision system utilizes the real time system Maruti. Here we are employed with different tasks of distant car detection and tracking according to the single image frame .It is a dynamic hard real time system that which is either scheduled and executes them if the resources needed are available or rejects them. Other important feature of Maruti is it can switch from usual cyclic execution to a different operational mode. That improves the safety in congested traffic places.

The process coordination has two tracking processes which if tracks the same object close to each other in the image when the car passes other car it occludes the process. Which leads to low values terminate problem.

Real time programming language is high level based on C. Maruti is programming language is programmed in UNIX.

4.6 Object Tracking Based on Heuristic Algorithm

As we discussed three methods of object detection in detail that are of interest in our research in detail, the use of fish-eye camera provides large field of view as a result we get large image distortion that complicate the task difficulty, so to overcome this problem we suggested a normal camera for object detection with reduced complexity Heuristic Algorithm that gives better results in case of fish eye camera.

In this second method of car detection of interest by using EGFO Method although the average error reduced significantly, but the we have experienced some unwanted detection, by using our proposed algorithm we have overcome this problem.

In third method of vehicle detection of interest this vision system utilizes the real time system Maruti.The process coordination has two tracking processes which if tracks the same object close to each other in the image when the car passes other car it occludes the process. Which leads to low values terminate problem. By using Heuristic Algorithms we have overcome this problem even for multiple detection.

4.6.1 Vehicles detection procedure

LibSVM is itegrated software developed by Chih-Chung Chang and Chih-Jen Lin for Support Vector Classification, regression, and distribution estimation. It supports mulit-class classification.

Support vector Machine (SVM) are supervised learning Model with associated learning algorithms that analyze data and recognize patterns used for classification and regression analysis. In case of object tracking SVM is trained with algorithm by using features extraction of objects on road.

The main features of the Support Vector Machine Program are fast Optimization Algorithm, shrinking Heuristic, catching of Kernel evaluation. Troubleshoot classification and regression problems. Handles thousands of support vectors. It uses sparse vector representation. Allow to restart from specified vector of dual variables. It also solves ranking problems.

Support Vector Machines classifier (using the LibSVM toolbox [50]) is used to decide whether the current car candidate is in fact a car or not by using the following features extraction from each candidate regions H_i^j, namely;

f_0: Shadows

Shadows are considered to be based on vertical profile analysis, for each frame vertical line is scanned bottom to up looking for gray value transition from road to vehicle shadows expected darker than road gray value .The shadow model measure is constructed as:

$$f_0 = \frac{d_u}{h-(d_d - d_u)} \quad \text{.........} \ (4.26)$$

Where

d_u is the vertical distance of the top boundary of the detected shadow to the top boundary of the candidate area and, d_d is the vertical distance of the bottom boundary of the detected shadow to the top boundary of the candidate area and h correspond to the height of the candidate area[34].

f_1: Symmetry

The symmetry value f_1 is obtained as the sum of symmetric values computed for each pixel belonging to central column x_c of the candidate region H_i^j [34]:

$$f_1 = \sum_{y=0}^{h} s(y)$$

Where

H is the height of the rectangular hypothesis region

$$s(y)=\frac{\int_0^w H_e^2(x,y)dx-\int_0^w H_0^2(x,y)dx}{\int_0^w H_e^2(x,y)dx+\int_0^w H_0^2(x,y)dx} \text{ ……………………… (4.27)}$$

$$H_e(x,y)=\frac{H(x,y)+H(-x,y)}{2} \text{ and } H_0(x,y)=\frac{H(x,y)+H(-x,y)}{2} \text{ …………(4.28)}$$

Where

H_e = the normalized even part of the hypothesis region.

H_0 = the normalized odd part of the hypothesis region.

w = is the width of the hypothesis region.

f_2 : Corners

Four corners are strictly needed to describe a vehicle; robustness against outliers is achieved increasing the number of detected corners. Considering C_p the coordinates of the four corners of the rectangular candidate region H_i^j and is measured as[34]:

$$f_2=1-\frac{1}{4}\sum_{p=0}^{4}D(C_p)\ n_k \text{ …………(4.29)}$$

Where

$$D(C_p)=\min\left\{d(C_p,\hat{C}_p)\right\},\forall p,m$$

$D(C_p)$ is the minimum of the normalized distances between each C_p and the detected corners $\hat{C}_m$.

C_p is the bounding box of hypothesis H_i^j , and the detected corner $\hat{C}_m$.

f3: Area of the region of interest[34];
f4: Mean intensity of the region of interest[34];
f5: Centroid of the region of interest[34];
f6: Distance between the region of interest centroid and its weighted centroid.

Shows the final detections superimposed on the original frame.

Figure 29 Final car detection on frame 453.

Finally, a last coherence check is made where the candidate regions that intersect are merged. Further experimental results are shown in CH-5.

5 EXPERIMENTAL RESULTS

5.1 Introduction

For lane detection this search was thus limited to IEEE database with the keywords: “lane tracking in video” and “Object tracking in video” in May 11th, 2013. This search retrieved a total of 99 papers, from which 14 were journal papers and the remaining 85 are conference papers. After reading all the titles and abstracts, 51 papers were considered to be of interest, from which 4 are journal papers and 47 are conference papers. Publication years range from 1992 to 2012. From this research various method have been described, but our research mainly focus on latest research Hough based transform by using gray-scale method and colour segmentation method which is a part of our subject Digital image processing, same video is used for both Hough based transform and proposed method and will see their experimental results and comparison in case of lane detection.

5.2 Hough based detection by using MATLAB

This reference method is used for experimental results and comparison; we may proceed by using a single frame of video and may implement the methodology for multi-frames.

The video used for the experiment have the information:

Video Parameters=15.00 frames/ second, RGB24 320x240. Total video frames available=1807

The experiment start with extraction of frame#1 and RGB image is converted into gray scale image as shown in figure 30.

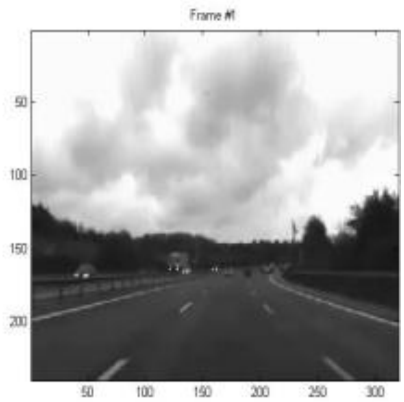


Figure 31 Gray scale image

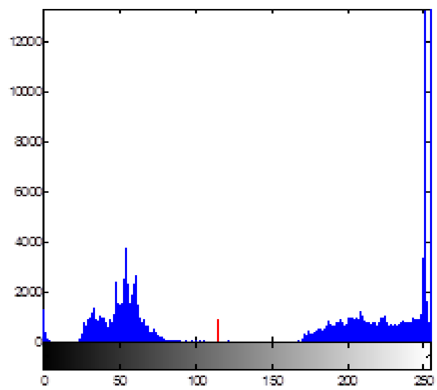


Figure 30 Histogram of image

Gray scale image is converted into binary image (Black and white) and to remove extra objects which have lower than 80 pixels by applying Otsu’s threshold method as shown in figure 32 and 33.

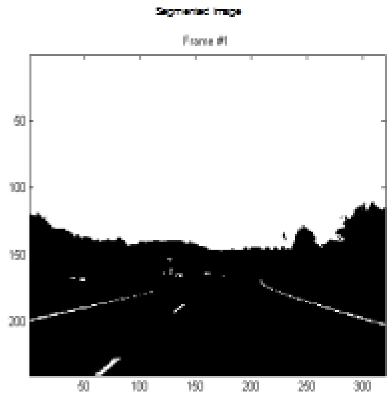


Figure 32 black and white

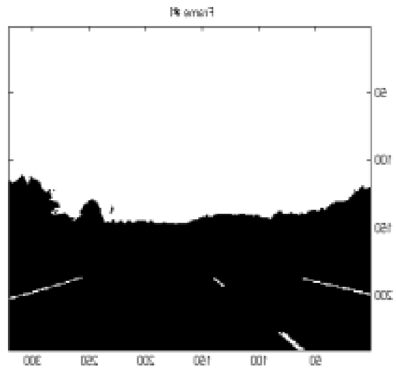


Figure 33 Binary (Otsu's threshold method)

Find edges in intensity image takes an intensity or a binary image I as its input, and returns a binary image BW of the same size as I, with 1's where the function finds edges in I and 0's elsewhere. The Canny method finds edges by looking for local maxima of the gradient of I. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is therefore less likely than the others to be "fooled" by noise, and more likely to detect true weak edges. The parameters you can supply differ depending on the method you specify.

BW = edge (I, 'canny') specifies the Canny method BW = edge (I,'canny', THRESH) specifies sensitivity thresholds for the Canny method. THRESH is a two-element vector in which the first element is the low threshold, and the second element is the high threshold. If we specify a scalar for THRESH, this value is used for the high threshold and 0.4*THRESH is used for the low threshold. If we do not specify THRESH, or if THRESH is empty ([]), edge chooses low and high values automatically as shown in figure 34.

Figure 34 Canny Edge Detection.

To detect the road line Hough transform is used, Hough implements the Standard Hough Transform. Hough is designed to detect lines. It uses the parametric representation of a line: rho = x*cos (theta) + y*sin(theta).The variable rho is the distance from the origin to the line along vector perpendicular to the line. Theta is the angle between the x-axis and this vector.

The Standard Hough Transform (SHT) is a parameter space matrix whose rows and columns correspond to rho and theta values respectively. The elements in the SHT represent accumulator cells. Initially, each cell is set to zero. Then, for every no background point in the image, rho is calculated for every theta. Rho is rounded off to the nearest allowed row in SHT. That accumulator cell is incremented. At the end of this procedure, a value of Q in SHT(r,c) means that Q points in the XY plane lie on the line specified by the theta(c) and rho(r). Peak values in the SHT represent potential lines in the input image.

[H, THETA, RHO] = hough (BW) computes the SHT of the binary image BW,THETA (in degrees) and RHO are the arrays of rho and theta values over which the Hough transform matrix, H, was generated.

[H, THETA, RHO] = hough(BW,PARAM1,VAL1,PARAM2,VAL2) sets various parameters. Parameter names can be abbreviated, and case does not matter. Each string parameter is followed by a value as indicated below: 'RhoResolution' Real scalar between 0 and norm (size (BW)), exclusive. 'RhoResolution' specifies the spacing of the Hough transform bins along the rho axis.

```
% Selected suitable angles
    a1=-79:1:-30;a2=30:1:80;a=[a1,a2];
    [H,theta,rho] = hough(BW,'RhoResolution',.5,'Theta',a);
    %[H,theta,rho] = hough(BW),a,a;
    peaks = houghpeaks(H,
8,'Threshold',0.20*max(H(:)));%,'NHoodSize',round(size(H)/40));
    lines = houghlines(BW, theta, rho, peaks,'FillGap',10,'MinLength',35);
```

So we get the lane detection by using Hough transform as shown in figure 35.

Figure 35 Hough Based detection

5.3 Heuristic Algorithm based detection by using MATLAB.

As seen in the related work section in CH 2, no work was found to suit the present application. A new methodology was thus developed. In this section, an illustrated description of the developed method is made. Two frames will be used through this chapter: frame 1 (to exemplify the case where no previous information exists) and frame 453 (to exemplify the case where previous information does exists). The frames are shown in figure 36(a) and 37(b).

Figure 36 (a) Frame 1

Figure 37 (b) Frame 453

The method starts by thresholding each frame by keeping only the brightest regions of the image. The value of the threshold was empirically set to 0.58 of the Otsu threshold [51]. The result of this step is shown in figure 39(a) and 38(b).

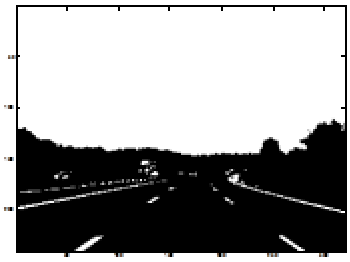


Figure 39 (a) Frame 1

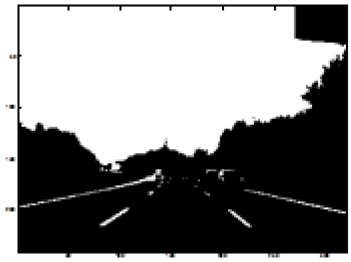


Figure 38 (b) Frame 453

If previous information is available, the difference between the current frame and the previous frame is computed and thresholded with the Otsu method [51]. The two white regions, of the thresholded frame and of the difference of frames are combined into one black and white image, as depicted in figure 40(a), 41(b), 43(c) and 42(d).

Figure 40 (a) Previous frame

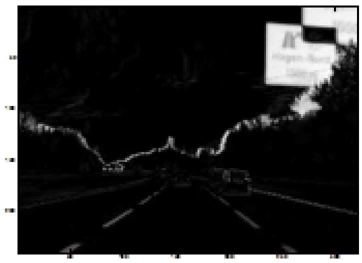


Figure 41 (b)Difference of frames

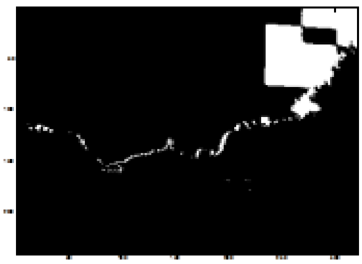


Figure 43 (c) Thresholded difference

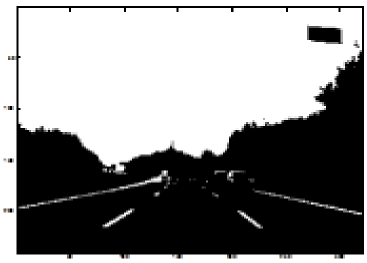


Figure 42 (d) Black and White result

Some of the detected regions are then eliminated having as basis some region properties. Only regions with eccentricity bigger or equal to 0.95, area between 20 and

890, and orientation absolute value between 10 and 48 are kept. Results are presented in figure 44(a) and 45(b).

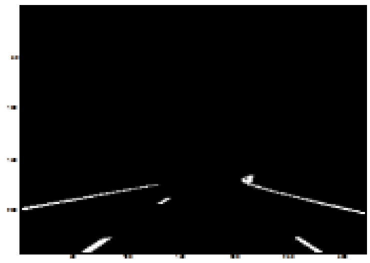


Figure 44 (a) Frame 1

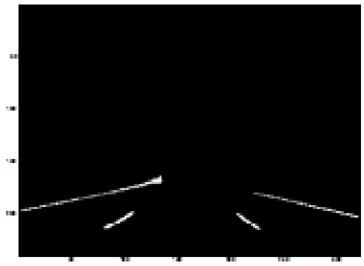


Figure 45 (b) Frame 453

A clustering methodology is used to group the detected points. The algorithm for the selection of the best number of clusters is outlined in Algorithm 1.

Algorithm 1 – Selection of best number of clusters

```
for nr_clust = 1 : maximum number of regions
    IDX = clusterdata(X,nr_clust); % cluster

    for line=1:nr_clust
        [line,S] = polyfit(X(p,1),X(p,2),1); % adjust a line
        [y,delta] = polyval(line,X(p,1),S); % compute error
    end

    if new_error < error
        selected_k = nr_clust; % select k with minnimum error
    end
end
return selected_k
```

After the best number of clusters is selected, data is clustered and a best fit line (in the mean squares sense) is fitted to each cluster of points. Illustration can be seen in figure 47(a) and 46 (b).

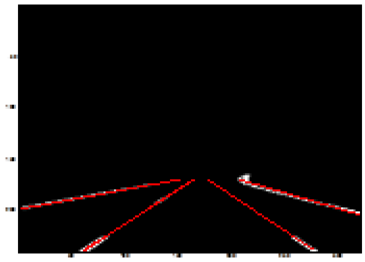


Figure 47 (a) Frame 1(5 clusters were selected)

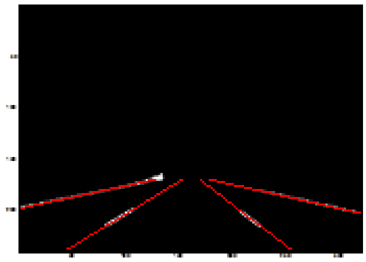


Figure 46 (b) Frame 453 (4 clusters were selected)

In order to check the coherence of the retrieved lines, 4 coherence tests are made.

Coherence test 1: Lines that are too close are merged. In the working examples, Frame 453 passed the test, while in Frame 1 two lines were merged.

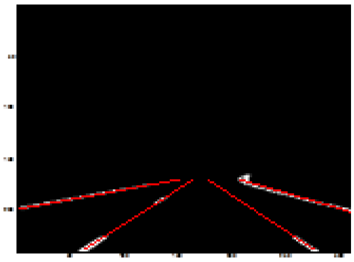


Figure 48 Coherence Test

Figure 48 – Coherence test 1 illustrated in Frame 1. While previously 5 lines were detected, now only 4 lines remain.

Coherence test 2: If more than 4 lines are detected, the 4 most similar to the ones detected in the previous frame are kept. This test cannot be performed when no previous information is available, thus it is not applied to Frame 1. Since Frame 453 passed this test, it is illustrated with Frame 9 (figures 49, 50 and 51).

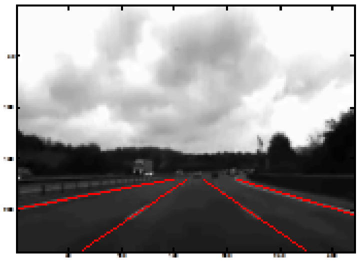


Figure 49 Final detection on previous frame

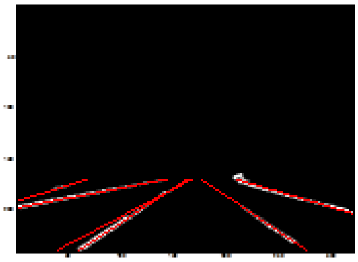


Figure 50 Detection on frame 9 before coherence test 2

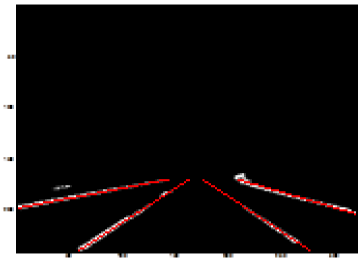


Figure 51 Detection on frame 9 after coherence test 2

Coherence test 3: If there are big jumps in the lines from one frame to the next ones, the corresponding line is eliminated. This test cannot be performed when no previous information is available, thus it is not applied to Frame 1. Since both Frame 9 and Frame 453 passed this test, it is illustrated with Frame 337 (figure 52(a) and figure 53(b)).

Moreover, if two lines are related to the same line in the previous frame, the line further away to the corresponding one in the previous frame is eliminated. Since Frames 9, 337 and 453 passed this test, it is illustrated with Frame 613 (figure 54(c) and 55(d)).

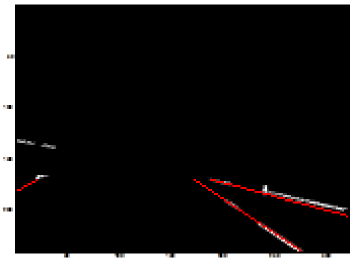


Figure 52 (a) Detection on Frame 337 before coherence test 3

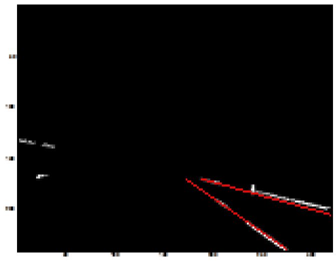


Figure 53(b) Detection on Frame 337 after coherence test 3

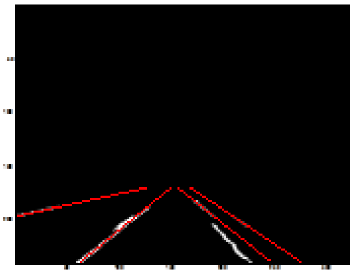


Figure 54 (c) Detection on Frame 613 before coherence test

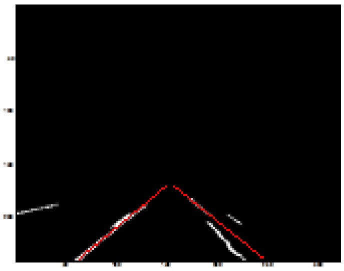


Figure 55 (d) Detection on Frame 613 after coherence test 3

Coherence test 4: If less than 4 lines are detected, lines from the previous frame are retrieved (figure 56 (a) and 57 (b)).

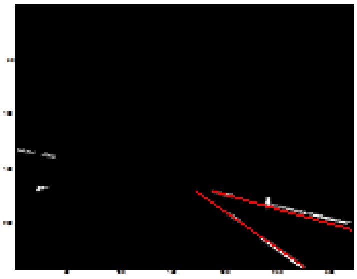


Figure 56 (a) Detection on Frame 337 before coherence test 4

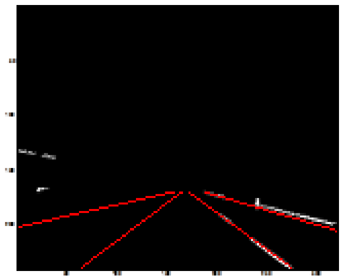


Figure 57 (b) Detection on Frame 337 after coherence test 4

Finally, if the lines are not being updated for 12 frames they are either not displayed (in the case of the outside lanes) or the line is replaced with a line between the two adjacent lines (in the case of the inside lanes). Final results for some representative frames are shown in (figure 58(a), 59(b), 60(d) and 61(c)).

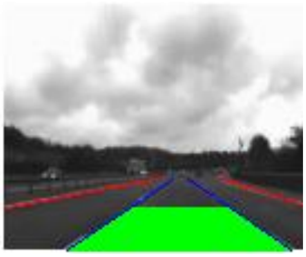


Figure 58 (a) Frame 1

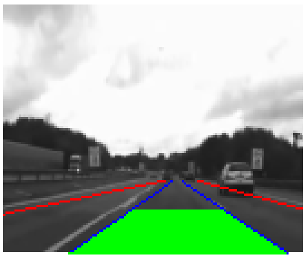


Figure 59 (b) Frame 337

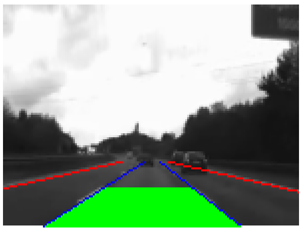


Figure 61 (c) Frame 453

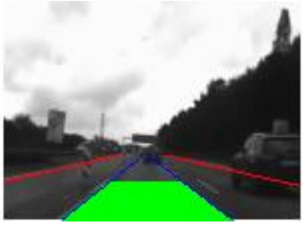
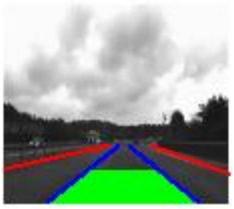
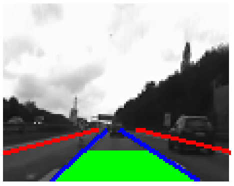
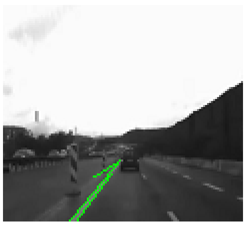
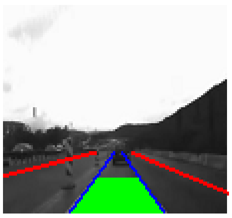


Figure 60 (d) Frame 613

5.4 Algorithms comparison

In TABLE - 1, comparing of the images processed with two algorithms in different scene conditions is shown. It is apparent that Heuristic algorithm is more efficient than standard Hough-based line algorithm to detect the road lines. As it is shown in TABLE -1, some lines in Hough -based detection are not detected or unwanted lines are detected, but in proposed method by clustering methodology in least square sense of white lines, we make our detection considerably efficient to detect the lines.

Frame #	Hough Based detection	Heuristic Algorithm(Proposed) Method	Algorithms difference
1			Proposed method is more robust in lane detection as compared to Hough based detection as shown in cloudy environment. Reduced complexity, easy to implement and more robust to noisy environment.
600			Hough based algorithm is not efficient enough and some lines were not detected or either wrongly detection while by using heuristic algorithm easy and flexible for multiple lines detection also in shadow environment as shown.
1300			Hough based detection by using colour segmentation based algorithm extract some more information of lines based on their colour information although efficient in lane detection but more sensitive to scene conditions as shown clear environment.

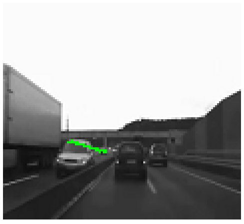
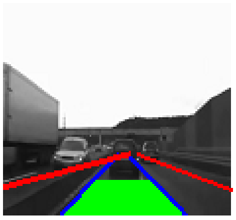
1805			Proposed algorithm could detect those missing lines in Hough based algorithm reasonably and is more tolerant to noise and scene condition ,for more precautions extreme boundaries lines are marked red and the lane where vehicle move are set by draw poly inside the blue lines .

Table 1 Comparing Algorithms

From TABLE5.1,it could be easily figured out that proposed algorithm is more tolerant to scene condition and noise rather than standard Hough-based algorithm, because it uses more data and pixel information.

5.5 Vehicle Detection by using Gabor Filter optimization, Fish-Eye Camera And Multiple Vehicle Detection In Hard Real Time

Gabor Filter Optimization:

Vehicle detection system based on optical sensors which are two basic steps: 1) hypothesis generation (HG), where the position of the vehicles in image are hypothesized and 2) hypothesis verification (HV) tests to verify the presence of vehicle in an image (Figure 62). The purpose of the HG step is to give some candidates places for further exploration. Three basic categories: 1) knowledge based, 2) stereo vision based, and 3) motion based. Using methods based on the knowledge of a priori knowledge about the location of vehicles in an image: a) symmetry b) shadow, c) texture d) Horizontal / vertical edges, and e) color. An approach to the stereo vision using inverse perspective mapping to estimate the locations of vehicles and obstacles in the images. In the phase of HV tests are conducted to verify the accuracy of each hypothesis. HV methods can be divided into two categories: 1) template based and 2) appearance-based[48].

Models methods based on predefined models of vehicle class and perform a correlation between an input image and model. Methods based on appearance can learn the characteristics of the class of vehicle with a set of training images to detect changes in the appearance of the vehicle.

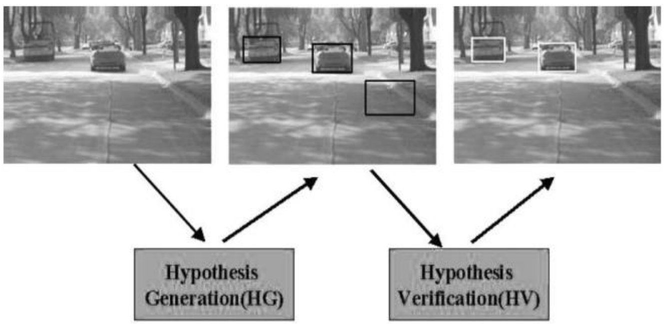


Figure 62 Two-step vehicle detection strategy.

The structure of a vehicle detection system associated with the supervised learning includes two main steps: 1) extracting a set of extracting a number of features (e.g., PCA features, wavelet features , Gabor features, etc.) And 2) training a classifier (e.g., NNs , SVMs, modified quadratic discriminant function, etc.) with the extracted features and non-vehicle between classes of vehicles. A key issue in this approach is to select a number of appropriate characteristics. In most cases, the relevant functions are unknown. Often, a large number of features are extracted in order to better represent the goal, but without explicitly using a strategy function point election, many of them can be redundant or irrelevant to the classification task. Therefore, the classification performance is not optimal.

To investigate the use of Gabor features for vehicle detection, showing its superiority over other functions such as PCA and wavelet features. Like other generic may bank of Gabor filters used for feature extraction. For classification to improve, it would be very important to choose an optimal set of features and thus an optimal set of Gabor filters.

Figure 63 Unwanted detection

The main drawback by using EGFO method is incorrect detection under severe occlusion like detection of sign board on the road etc.

Fish Eye Camera:

In case of using fish –eye camera algorithm is evaluated on real sequences which Captured by a fisheye camera whose area of interest is 185 degrees. The camera adjustment is to the rear of host vehicle and moves with it. Images under different scene conditions are taken. The moving object whose size is larger than 30 ×30 pixels is considered as targets that need to be detected. For every target if the manually labeled region and the detected region are overlapped than ten percent of the manually labeled region, the target will be considered to be detected correctly. If a detected region isn't overlapped with any manually labeled target region it will be considered to be a false detected region. The frame in which there is one false detected region or more will be considered as a false detection frame. But this system cannot work very well in some complex scenes, such as bad weather, night and etc[4]. Also use of fish eye camera brings a large field of view which results in great image distortion as shown in figure 64.

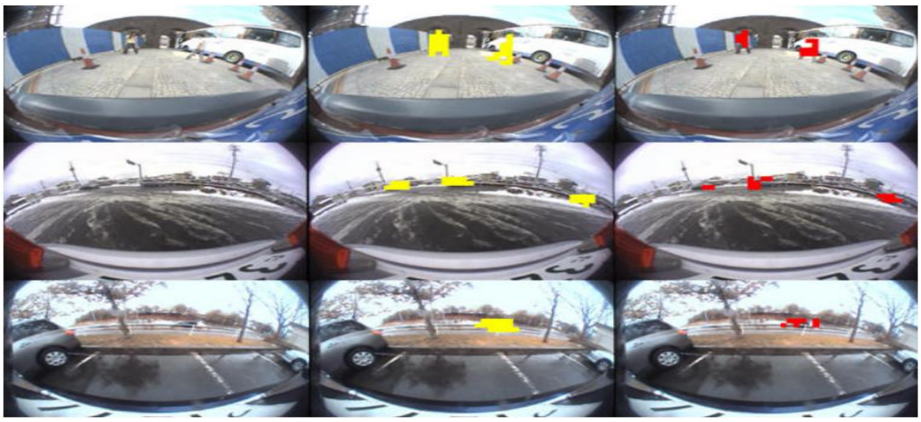


Figure 64 Vehicle detection by using fish eye camera

Real time multiple vehicle detection and tracking:

In case of multiple vehicle detection in hard real time have developed and implemented a hard real- time vision system that recognizes and tracks multiple cars from sequences of gray-scale images taken from a moving car. This vision system can track more than one car at a time, recognizes the cars automatically, and relies only on simple low-cost hardware. However this work does not address driving situations with difficult lighting conditions and congested traffic. Although it detects multiple cars but if it track cars which are close to each other which occludes the process resulting low terminate problem[49].

5.6 Vehicle Detection based on Heuristic Algorithm by using LibSVM in Matlab

For cars, the negative of each frame is first computed by the operation 1 – Frame (assuming the frame's grey values are normalized to the interval [0, 1]). Then a binarization with a fixed threshold of 0.93 is made on the negative of the frame. Illustrative plots for frame 453 are shown in Figure 65(a) and 66(b)

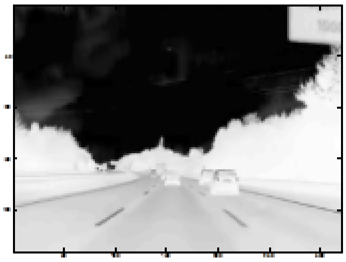


Figure 65 (a) Negative frame

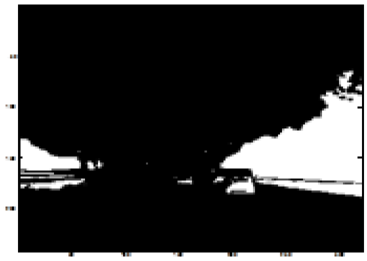


Figure 66 (b) Thresholded frame

For each region on the binarized image, the corresponding bounding box was computed and initial car candidates are determined by a square with size length corresponding to maximum between the width and height of the corresponding bounding box. Only regions with side bigger than 7 pixels are kept. Illustration of this step can be seen in Figure 67(a) and 68(b).

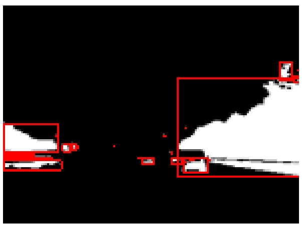


Figure 67 (a) Regions detected by thresholding

Figure 68 (b) Square bounding boxes

Cars detected on the previous frame are
current frame. Some features are extracted from each candidate region, as mention in ch.4 Using the these features, a Support Vector Machines classifier using the LibSVM toolbox is used to decide whether the current car candidate is in fact a car or not. Figure 69 shows the final detections superimposed on the original frame.

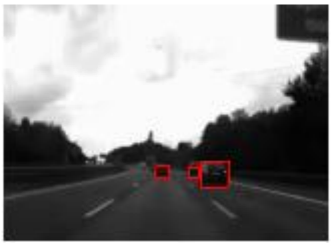


Figure 69 Final car detection on frame 453.

Finally, a last coherence check is made where the candidate regions that intersect are merged.

5.7 Robust Lane detection and object tracking simulated results

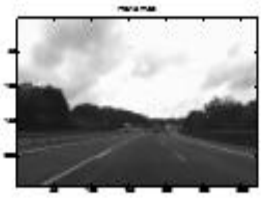
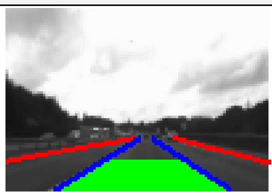
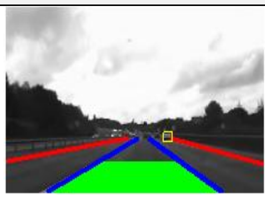
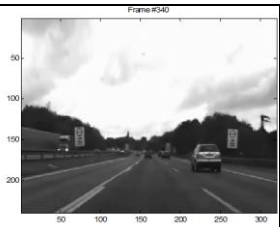
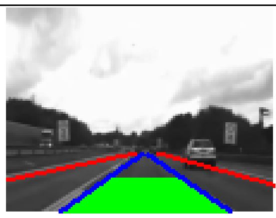
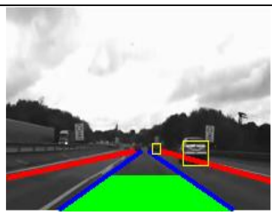
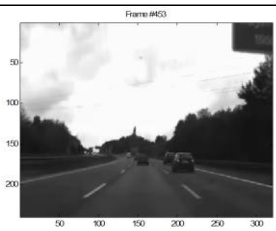
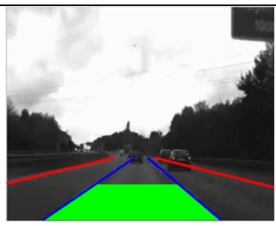
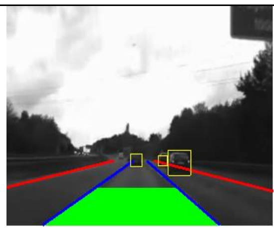
Frame #	Source video	Lane detection	Object detection	Detection
150				**Single**
340				**Double**
453				**Multiple**

Table 2 Simulated result

6 CONCLUSION

Robust lane detection and object tracking is an important application of Intelligent Transport System. To avoid victims and number of accidents in heavy traffic countries like USA, China, Malaysia, UK, where it becomes difficult for the driver to exact location and detection of line and cars especially during cloudy environment than it is important to make Intelligent Transport System more robust and as well in other way lane detection and object tracking is one of important future application of auto drive vehicle.

Up till Now so many different vehicle companies and researchers have used different ways and develop different algorithms under different conditions to make the Intelligent Transport System more robust to noise and detection but they usually operate under certain type of scene conditions and more complex to implement under different conditions.

As in case of lane detection we described and implemented the Hough-based detection, and had a look on the results. We saw that Hough based algorithm is not efficient enough and some lines were not detected. Then, we described the color-based detection algorithm and extracted some more information of lines based on their color information to make Hough-based detection more efficient. In this case some unwanted lines are detected although with complexity reduction.

As in case of object detection the use Fish eye camera brings a large field of view resulting great image distortion and in case of Gabor Filter optimization some unwanted objects are detected.

For instance, in our research we have developed a Heuristic Algorithm which is more robust in case of lane detection when compared with other methods of lane detection with reduced complexity, more tolerant to scene condition and also easy to implement in any noisy environment. In the same manner it is also in object tracking. Multiple vehicles are detected on the same time without any distortions and overcome all the drawbacks when compared with other methods. This method is very effective in all the conditions and more robust in object tracking with reduced complexity and easy to implement under different scene conditions, that significantly gives more strengthen to Intelligent Transport System.

Our proposed algorithm was implemented in MATLAB R2012a on a DELL computer with CPU of Intel ® Core™ 2 Duo with the processor frequency of 2.0 GHz and RAM of 4.00 GB. We have processed captured images collected from PHD student at BTH Karlskrona who has already used this video for another algorithm that are in RGB24 320x240 with 1807 total number of frames.

As future work, a formal evaluation of the performance should be made. Moreover, the robustness of the algorithm will be tested by applying it to other video sequences. Another line of work would be to generalize the lane detection to curves. In the car analysis, we believe that the detection algorithm is robust enough, but results could be improved by using more advanced tracking methodologies.

7 REFERENCES

[1] A. A. Assidiq, O. O. Khalifa, R. Islam, and S. Khan, “Real time lane detection for autonomous vehicles,” in *Computer and Communication Engineering, 2008. ICCCE 2008. International Conference on*, 2008, pp. 82–88.

[2] H. Li and F. Nashashibi, “Lane Detection (Part I): Mono-Vision Based Method,” 2013.

[3] S. Zhou, Y. Jiang, J. Xi, J. Gong, G. Xiong, and H. Chen, “A novel lane detection based on geometrical model and gabor filter,” in *Intelligent Vehicles Symposium (IV), 2010 IEEE*, 2010, pp. 59–64.

[4] H. Yu, W. Liu, S. Zhang, H. Yuan, and H. Zhao, “Moving Object Detection Using an In-Vehicle Fish-Eye Camera,” in *Wireless Communications Networking and Mobile Computing (WiCOM), 2010 6th International Conference on*, 2010, pp. 1–6.

[5] “http://cvrr.ucsd.edu/LISA/LaneDetection.htm - Google Scholar.” [Online]. Available: http://scholar.google.se.miman.bib.bth.se/scholar?q=http%3A%2F%2Fcvrr.ucsd.edu%2FLISA%2FLaneDetection.htm&btnG=&hl=sv&as_sdt=0%2C5. [Accessed: 18-May-2013].

[6] “http://www.mobileye.com/technology/applications/lane-detection/ - Google Scholar.” [Online]. Available: http://scholar.google.se.miman.bib.bth.se/scholar?q=http%3A%2F%2Fwww.mobileye.com%2Ftechnology%2Fapplications%2Flane-detection%2F&btnG=&hl=sv&as_sdt=0%2C5. [Accessed: 18-May-2013].

[7] “http://www.neusoft.com/solutions/1234/ - Google Scholar.” [Online]. Available: http://scholar.google.se.miman.bib.bth.se/scholar?q=http%3A%2F%2Fwww.neusoft.com%2Fsolutions%2F1234%2F&btnG=&hl=sv&as_sdt=0%2C5. [Accessed: 18-May-2013].

[8] “http://www.tmr.qld.gov.au/safety/queensland-road-rules/road-rules-refresher/lines.aspx - Google Scholar.” [Online]. Available: http://scholar.google.se.miman.bib.bth.se/scholar?q=http%3A%2F%2Fwww.tmr.qld.gov.au%2Fsafety%2Fqueensland-road-rules%2Froad-rules-refresher%2Flines.aspx&btnG=&hl=sv&as_sdt=0%2C5. [Accessed: 18-May-2013].

[9] H. Schneiderman and M. Nashman, “Visual processing for autonomous driving,” in *Applications of Computer Vision, Proceedings, 1992., IEEE Workshop on*, 1992, pp. 164–171.

[10] B. B. Litkouhi, A. Y. Lee, and D. B. Craig, “Estimator and controller design for lanetrak, a vision-based automatic vehicle steering system,” in *Decision and Control, 1993., Proceedings of the 32nd IEEE Conference on*, 1993, pp. 1868–1873.

[11] C. J. Taylor, J. Malik, and J. Weber, “A real-time approach to stereopsis and lane-finding,” in *Intelligent Vehicles Symposium, 1996., Proceedings of the 1996 IEEE*, 1996, pp. 207–212.

[12] M. Betke, E. Haritaoglu, and L. S. Davis, “Highway scene analysis in hard real-time,” in *Intelligent Transportation System, 1997. ITSC’97., IEEE Conference on*, 1997, pp. 812–817.

[13] C. R. Jung and C. R. Kelber, “A robust linear-parabolic model for lane following,” in *Computer Graphics and Image Processing, 2004. Proceedings. 17th Brazilian Symposium on*, 2004, pp. 72–79.

[14] L. Fletcher, L. Petersson, and A. Zelinsky, “Road scene monotony detection in a fatigue management driver assistance system,” in *Intelligent Vehicles Symposium, 2005. Proceedings. IEEE*, 2005, pp. 484–489.

[15] J.-W. Hsieh, S.-H. Yu, Y.-S. Chen, and W.-F. Hu, “Automatic traffic surveillance system for vehicle tracking and classification,” *Intell. Transp. Syst. Ieee Trans.*, vol. 7, no. 2, pp. 175–187, 2006.

[16] J.-W. Hsieh, S.-H. Yu, Y.-S. Chen, and W.-F. Hu, “Automatic traffic surveillance system for vehicle tracking and classification,” *Ieee Trans. Intell. Transp. Syst.*, vol. 7, no. 2, pp. 175–187, 2006.
[17] F. Maire and A. Rakotonirainy, “Analysis of driving session videos by reverse temporal order processing,” in *Computer Graphics, Imaging and Visualisation, 2006 International Conference on*, 2006, pp. 255–261.
[18] J. C. McCall and M. M. Trivedi, “Video-based lane estimation and tracking for driver assistance: survey, system, and evaluation,” *Intell. Transp. Syst. Ieee Trans.*, vol. 7, no. 1, pp. 20–37, 2006.
[19] K. Isa, “Experimental Studies on Dynamics Performance of Lateral and Longitudinal Control for Autonomous Vehicle Using Image Processing,” in *Computer and Information Technology Workshops, 2008. CIT Workshops 2008. IEEE 8th International Conference on*, 2008, pp. 411–416.
[20] A. Borkar, M. Hayes, and M. T. Smith, “An efficient method to generate ground truth for evaluating lane detection systems,” in *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, 2010, pp. 1090–1093.
[21] W.-C. Cheng and C.-C. Chiang, “The development of the automatic lane following navigation system for the intelligent robotic wheelchair,” in *Fuzzy Systems (FUZZ), 2011 IEEE International Conference on*, 2011, pp. 1946–1952.
[22] B. Benligiray, C. Topal, and C. Akinlar, “Video-Based Lane Detection Using a Fast Vanishing Point Estimation Method,” in *Multimedia (ISM), 2012 IEEE International Symposium on*, 2012, pp. 348–351.
[23] R. Gopalan, T. Hong, M. Shneier, and R. Chellappa, “A learning approach towards detection and tracking of lane markings,” *Intell. Transp. Syst. Ieee Trans.*, vol. 13, no. 3, pp. 1088–1098, 2012.
[24] M. Bertozzi and A. Broggi, “GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection,” *Ieee Trans. Image Process.*, vol. 7, no. 1, pp. 62–81, 1998.
[25] C. Kreucher, S. Lakshmanan, and K. Kluge, “A driver warning system based on the LOIS lane detection algorithm,” in *Proceedings of IEEE International Conference on Intelligent Vehicles*, 1998, pp. 17–22.
[26] M. Chen, T. Jochem, and D. Pomerleau, “AURORA: a vision-based roadway departure warning system,” in *1995 IEEE/RSJ International Conference on Intelligent Robots and Systems 95. “Human Robot Interaction and Cooperative Robots”, Proceedings*, 1995, vol. 1, pp. 243–248 vol.1.
[27] Q. Lin, Y. Han, and H. Hahn, “Real-time lane departure detection based on extended edge-linking algorithm,” in *Computer Research and Development, 2010 Second International Conference on*, 2010, pp. 725–730.
[28] G. Keyou, L. Na, and Z. Mo, “Lane Detection Based on the Random Sample Consensus,” in *2011 International Conference on Information Technology, Computer Engineering and Management Sciences (ICM)*, 2011, vol. 3, pp. 38–41.
[29] Y. U. Yim and S. Oh, “Three-feature based automatic lane detection algorithm (TFALDA) for autonomous driving,” *Ieee Trans. Intell. Transp. Syst.*, vol. 4, no. 4, pp. 219–225, 2003.
[30] Z. Sun, G. Bebis, and R. Miller, “On-road vehicle detection: a review,” *Ieee Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 5, pp. 694–711, 2006.
[31] A. Jazayeri, H. Cai, J. Y. Zheng, and M. Tuceryan, “Vehicle Detection and Tracking in Car Video Based on Motion Model,” *Ieee Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 583–595, 2011.
[32] C. Caraffi, T. Vojir, J. Trefny, J. Sochman, and J. Matas, “A system for real-time detection and tracking of vehicles from a single car-mounted camera,” in *2012 15th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2012, pp. 975–982.
[33] H. Takizawa, K. Yamada, and T. Ito, “Vehicles detection using sensor fusion,” in *2004 IEEE Intelligent Vehicles Symposium*, 2004, pp. 238–243.

[34] D. Alonso, L. Salgado, and M. Nieto, “Robust Vehicle Detection Through Multidimensional Classification for on Board Video Based Systems,” in *IEEE International Conference on Image Processing, 2007. ICIP 2007*, 2007, vol. 4, pp. IV – 321–IV – 324.
[35] S. Jeong, S.-W. Ban, and M. Lee, “Autonomous Detector Using Saliency Map Model and Modified Mean-Shift Tracking for a Blind Spot Monitor in a Car,” in *Seventh International Conference on Machine Learning and Applications, 2008. ICMLA ’08*, 2008, pp. 253–258.
[36] H. S. Yazdi, M. Lotfizad, and M. Fathy, “Car tracking by quantised input LMS, QX-LMS algorithm in traffic scenes,” *Vis. Image Signal Process. Iee Proc. -*, vol. 153, no. 1, pp. 37–45, 2006.
[37] C. Zhao-zheng, L. jia, and C. Qi-mei, “Real-Time Video Detection of Road Visibility Conditions,” in *2009 WRI World Congress on Computer Science and Information Engineering*, 2009, vol. 5, pp. 472–476.
[38] R. T. Tan, “Visibility in bad weather from a single image,” in *IEEE Conference on Computer Vision and Pattern Recognition, 2008. CVPR 2008*, 2008, pp. 1–8.
[39] C. Rossig, R. Herrmann, and M. Hotter, “Continuous estimation of the road plane for measuring obstacles using a stereo rig,” in *Image Processing and Its Applications, 1997., Sixth International Conference on*, 1997, vol. 1, pp. 394–398.
[40] S. Sehestedt, S. Kodagoda, A. Alempijevic, and G. Dissanayake, “Efficient lane detection and tracking in urban environments,” in *Proc. European Conf. Mobile Robots*, 2007, pp. 126–131.
[41] Y. Wang, D. Shen, and E. K. Teoh, “Lane detection using spline model,” *Pattern Recognit. Lett.*, vol. 21, no. 8, pp. 677–689, 2000.
[42] C. Nuthong and T. Charoenpong, “Lane detection using smoothing spline,” in *Image and Signal Processing (CISP), 2010 3rd International Congress on*, 2010, vol. 2, pp. 989–993.
[43] N. Ben Romdhane, M. Hammami, and H. Ben-Abdallah, “An Artificial Vision-Based Lane Detection Algorithm,” in *2nd International Conference on Computer Science and its Applications, 2009. CSA ’09*, 2009, pp. 1–6.
[44] A. A. Assidiq, O. O. Khalifa, R. Islam, and S. Khan, “Real time lane detection for autonomous vehicles,” in *Computer and Communication Engineering, 2008. ICCCE 2008. International Conference on*, 2008, pp. 82–88.
[45] Y. Wang, D. Chen, and C. Shi, “Vision-based road detection by adaptive region segmentation and edge constraint,” in *Intelligent Information Technology Application, 2008. IITA’08. Second International Symposium on*, 2008, vol. 1, pp. 342–346.
[46] *Digital Imaging Processing and Analysis: Human and Computer Vision Applications With CVIPtools*. CRC Press, 2010.
[47] T.-Y. Sun, S.-J. Tsai, and V. Chan, “HSI color model based Lane-Marking detection,” in *Intelligent Transportation Systems Conference, 2006. ITSC’06. IEEE*, 2006, pp. 1168–1172.
[48] Z. Sun, G. Bebis, and R. Miller, “On-road vehicle detection using evolutionary gabor filter optimization,” *Intell. Transp. Syst. Ieee Trans.*, vol. 6, no. 2, pp. 125–137, 2005.
[49] M. Betke, E. Haritaoglu, and L. S. Davis, “Multiple vehicle detection and tracking in hard real-time,” in *Intelligent Vehicles Symposium, 1996., Proceedings of the 1996 IEEE*, 1996, pp. 351–356.
[50] C.-C. Chang and C.-J. Lin, “LIBSVM: A library for support vector machines,” *Acm Trans. Intell. Syst. Technol.*, vol. 2, no. 3, pp. 27:1–27:27, 2011.
[51] N. Otsu, “A Threshold Selection Method from Gray-Level Histograms,” *Ieee Trans. Syst. Man Cybern.*, vol. 9, no. 1, pp. 62–66, 1979.