Development of a Novel Awareness Model for Rapid Object Detection in Vehicular Navigation

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DECLARATION

I, **Vivek Shukla**, solemnly declare that this thesis of research on "**Development of a Novel Awareness Model for Rapid Object Detection in Vehicular Navigation**" is my original work. The study has been conducted under the guidance of **Dr. Dhirendra Pandey** at Department of Information Technology, Babasaheb Bhimrao Ambedkar University (A Central University), Lucknow. It is further declared that to the best of my knowledge and belief it has not been submitted earlier for the award of any degree. I also undertake that the thesis is essentially free from all kinds of plagiarism.

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CERTIFICATE

This is to certify that the thesis entitled "**Development of a Novel Awareness Model for Rapid Object Detection in Vehicular Navigation**" submitted by **Mr. Vivek Shukla** is an original research work and has not been previously submitted in part or full for the award of any other degree or diploma to this or any other University.

This thesis submitted to Babasaheb Bhimrao Ambedkar University Lucknow satisfies all the requirements as stipulated in the Doctor of Philosophy (Ph.D.) regulations-1999 as amended in 2013 and it is fit for submission and evaluation for the award of the degree of Doctor of Philosophy of the University.

Supervisor

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Head of the Department

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Abstract

Various numbers of strategies given by researchers are available for monitoring and controlling traffic of highways and roads. In India, people are habitual of breaking rules but if it comes to traffic rules, they don't hesitate to break. Due to increase of traffic and high speedy vehicles, the numbers of accidents are increasing day by day. It also shows the carelessness of the people. So, to reduce the number of accidents and number of deaths, there is a need of such kind of monitoring system who monitors the real time traffic as well as control the situation in an effective manner. Many Computer Vision and Object Detection methodologies are present to monitoring the traffic. But all strategies are with their limitations. The primary objective of this research work is to control the traffic by pointing out the speed of the vehicle and to monitor the real time situation of the traffic as well as to give the effective solution to tackle the situation. The PROPMETHO is the proposed methodology to tackle this big problem in an effective manner. The method is observed and tested on real time scenarios.

At the present time, the large numbers of the automobiles on the highway and town roads have produced with many challenges regarding the proper management and control of the traffic. To manage and control the road traffic, the traffic surveillance system gives the several solutions by using the detection and tracking of vehicles techniques. A challenging task of feature extraction of moving object is represented by this approach. Therefore, the aim of this research is to present an efficient method for managing and controlling the traffic by using the object detection methods. The proposed method preserves the group of pixels in foreground which can be probable vehicles and discards the rest as noise. Therefore, it selectively rejects the objects which cannot be vehicles at the same time consolidate the candidate vehicles.

Here, PROPMETHO system performs the following task of detection of vehicle followed by calculation of speed of the vehicle. The performance of the proposed

method is evaluated by comparing it with other standard methods qualitatively as well as quantitatively. For the performance analysis of the PROPMETHO System, six scenarios were taken with parameters namely Recall and F-Measure. In all the cases, the value of F-Measure was approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect.

List of Tables

List of Figures

List of Graphs

Table of Contents

Chapter 1: Introduction

1.1 Background

In computer vision field, object detection in the navigation of the vehicles plays an important role. Object detection is the process of locating or identifying objects in the frame of video sequence. Usually in the object detection mechanism used information from single frame for detecting an object but some of the object detection mechanism used temporal information which is computed from sequence of frames and it reduces the false detection rate. The object detection is multifaceted course of action when projecting 3D world on 2D image because of the loss of information, noise present in an image, complex object motion, cleared nature of object, complex object shapes and occlusion [1].

The object detections mechanisms [2] are following as:

- Point Detector which are used to find the effective centric points in an image.

- Background Subtraction techniques which find the digression from background model which are already built and incoming frames. Some of the background subtraction techniques are: Frame differencing, Region-based or spatial information, Hidden Markov Model, Gaussian Mixture based Background Model, Dynamic Texture based background model, Wall flower based background model and Eigen Space decomposition. As illustrated in [3], background modeling has two main approaches: Recursive algorithm and Non-recursive algorithm. Recursive algorithm do not maintain buffer for background reckoning and it recursively updates a background model based on the input frames. So it requires less storage. A non recursive algorithm uses sliding window approach for reckoning background model.

- Segmentation which separates the images into perceptually similar regions.

- Optical Flow method determines the image optical flow field and performs clustering according to the optical flow distribution characteristics of images.

- Supervised Classifier method an operator is trained to detect the distinctive attribute of the objects. The certain supervised classifier methods are: SVM, Neural Networks based detector and adaptive boosting techniques.

1.2 Vehicular Navigation

Navigation is an art of getting from one place to another safely and efficiently. It is a process of reading and controlling the movement of craft of vehicle from one place to another. The first record of boats large enough to carry goods for trade is around 3500 B.C from this, navigation comes in the picture. These first navigators stayed close to the shore and navigate by sight of landmarks and land characteristics that they could see. They usually traveled during the day and sought a calm harbor or anchorage at night. They didn't have charts but list of direction, similar to today's cruising guides [4].

When they did venture out of sight of land, the navigator was able to determine its latitude by observing the height of the sun during the day and North Star at night.

Figure1.1 Observing North Star at Night [4]

1.2.1 History of Navigation

A. 11th Century – Compass

Some historian believes that the Chinese were using compasses to pinpoint direction mean than 1000 years ago. In all that time, the basic principle and design of the magnetic compass has not changed all that much. A small, thin magnet is affixed to a nearly frictionless pivot point. The age old system works because of the earth's magnetic field. If you have ever played two magnets, you know that opposite attract. The magnet in the compass actually points north with south end.

B. 15th Century – Mariners Astrolabe

The mariner's astrolabe let sailors find their latitude while traveling far away from the sight of land. A mariner would hold the astrolabe up at noon so the shone through its two sights. The sailor would then read the scale to determine the sun's daily declination to determine the latitude of his ship.

C. 1930s – Radio Direction Finding

During the early 1990s, navigators began to experiment with radio waves as an alternative to celestial. Some of the greatest advancements were first made by Germen engineers in the 1930s. They developed a system, commonly referred to as a “Lorenz” that would broadcast two signals, at precise angles. The signals would be run independent of each other up until a midpoint, where they combined together. Apart, the signals sound would broken; however, at the meeting point they would form a continuous sound.

During the 1930s and 40s several country around the world began to experiment with radar as a useful navigational tool. The concept was not new, having first been explored in the early 1990s: however the technology was not fully developed until World War II. The premise is actually quite simple: An antenna is used to send out a radio wave pulse, which will continue out ward until it bounces off the closest objects. At that time, signal will return to the antenna and a computer will calculate how far away the object is. It can also calculate the velocity and characteristics of the object such as height and width.

D. Global Positioning System (GPS)

The Global Positioning System was built by the Department of Defense: it was intended to be a global, all weather, highly accurate positioning and navigation system that could be used for any and all military needs. But even as the system was being developed for military use, it became clear that the technology was just too valuable to keep under wraps. The devices found their way into cars in the mid – 1990s as a dealer – installed option. Users complained that the keypads and menus could be bulky and hard to figure out. The systems also had no way of reacting.

A Vehicular navigation system is part of the vehicular controls or a third party add-on used to find direction in a vehicle. It usually uses a satellite navigation device to get its position data which is then correlated to a position on a road. When directions are needed routing can be calculated.

There is some detection and navigation techniques [5] are following as:

- GPS
- DEAD RECKONING
- SENSOR (Ultrasonic Distance Transducer)
- DIGITAL CAMERA
- LIDAR
- RADAR/LASER LIGHT
- COMPUTER VISION
- HYBRID

1.3 Object Detection in Vehicular Navigation

In recent years, the field of object detection to detect the motion of a vehicle and motion characteristics has seen tremendous progress, aided by the advent of deep learning. Object detection is the task of identifying object in a scene and finding out their size, distance from observer and gestures.

Detecting moving objects is crucial to navigation around objects and predicting their locations and trajectories. Laser sensors provide an excellent observation of the area around the vehicle, but the point cloud of the objects may be noisy, occluded, and prone to different errors. Consequently, object tracking is open problem especially for low quality point clouds [6].

There are various technology keep using and upgrading for the better accuracy of detecting objects especially on road moving objects in real time. Some techniques using LiDAR, SONAR, RADAR, Digital cameras, and their hybrids using as coarse of GIS map, and fairly accurate Global Positioning System (GPS) and Inertial Measurement Unit (IMU) navigation solution [7].

1.3.1 History of Object Detection

The Modern history of object detection is very interesting with continuous inventions and up-gradation or the better accuracy and controlling [8]. The modern history shown in diagram below:

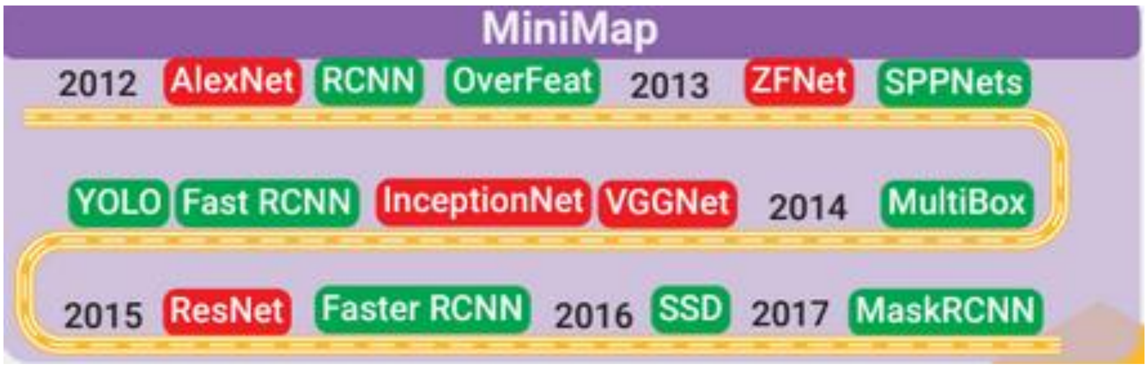


Figure1.2: Modern History of Object Detection [8]

There are various important object detection concepts which were not very easy for the past but as a result of different research and advancements in technology such concepts can be easily identified and understand.

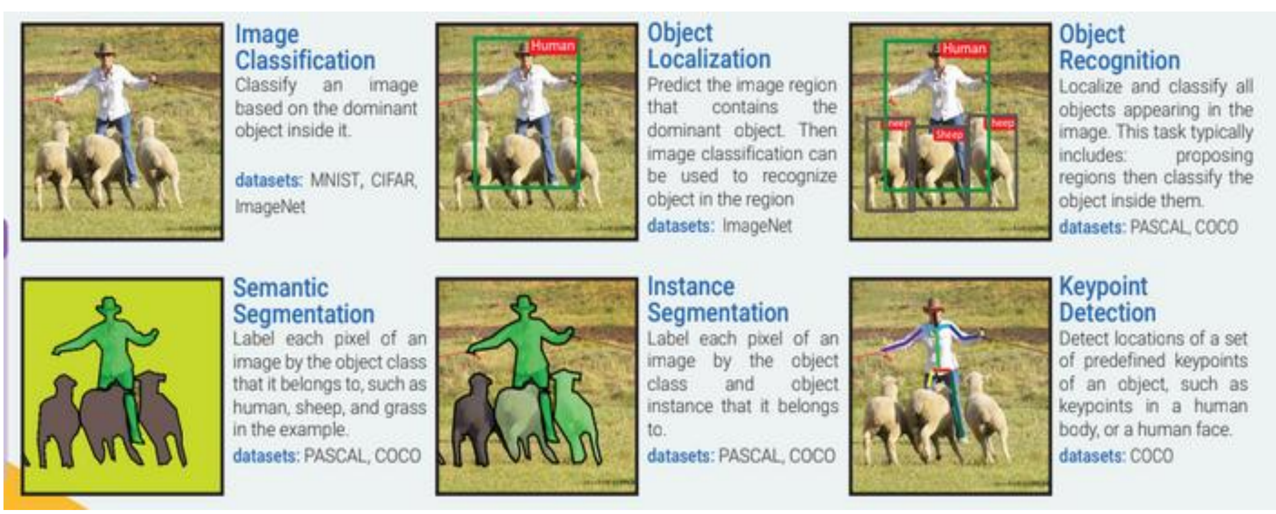


Figure1.3: Concepts of Object Recognition in Visual Form [8]

1.3.2 Challenges

Object detection is still an open research problem even after research of several years in this field. A robust, high accuracy and great performance approach is still a great challenge today. The level of difficulties of this problem highly depends on how one defines the object to be detected [9].

There are few visible features (e.g, color) of an object which is not so difficult to identify all pixels with same color as the object. However, there is always an alternative of existence of another object or background with the same color information. This will create a problem to differentiate the background with an object. This problem is more complex when the object is moving with changing frames. This variability comes from three principle sources namely variation in target pose or deformations, variation in illumination and partial/full occlusion of the target [10].

Typical challenges in terms of background in context of video or moving body objects [11] as follows:

I. **Illumination Changes:** It is desirable that background model adapts to slowly changes of the appearance of the environment. For example in outdoor settings, the light intensity typically differs during day. Unexpected illumination changes can also occur in the scene. This type of change occurs for example with sudden switching on/off a light in a indoor environment. This may also happen in unexpected outdoor scenes (fast transition from cloudy to bright sunlight). Illumination strongly affects the appearance of background, and cause false positive detection. The background model should take this into consideration.

II. **Dynamic Background:** Some parts of the scenery may contain movement (a fountain, movements of clouds, swaying of tree branches, wave of water etc.), but should be regarded as background, according to their relevance. Such changes can be periodical or irregular (e.g., traffic lights, waving trees). Handling such background dynamics is a challenging task.

III. **Occlusion:** Occlusion (partial/full) may affect the process of calculating the background frame. However, in real life situations, occlusion can occur anytime a subject passes behind an object with respect to a camera.

IV. **Clutter:** The task of segmentation is difficult in the presence of background clutter. It is very difficult to model a background that reliably produces the clutter background and separates the moving foreground objects from that.

V. **Camouflage: S**ome objects may poorly differ from the appearance of background, making correct classification difficult. This is especially important in surveillance applications. Camouflage is particularly a problem for temporal differencing methods.

VI. **Presence of Shadows:** Shadows cast by foreground objects often complicate further processing steps subsequent to background subtraction. Researchers have proposed different methods for detection of shadows.

VII. **Motion of the Camera:** Video may be captured by moving cameras the jitter magnitude varies from video to video.

VIII. **Bootstrapping:** If initialization data which is free from foreground objects is not available, the background model has to be initialized using a bootstrapping strategy.

IX. **Video Noise:** Video signal is usually superimposed with noise. Background subtraction method approaches for video surveillance have to cope with such degraded signals affected by different types of noise, such as sensor noise or compression artifacts.

X. **Speed of the Moving Objects and Intermittent Object Motion:** The speed of the moving object that plays very important role in its detection. If the object is moving very slowly, the temporal differencing technique will fail to detect the portions of the object preserving uniform region. In other way a very fast moving object leaves a trail of ghost region behind it in the detected foreground mask.

Periodic motions of objects cause ‘ghosting’ artifacts in the detected motion, i.e., objects move, then stop for a short while, after which they start moving again. There may be situations when a video includes still objects that suddenly start moving, e.g., a parked vehicle driving away, and also abandoned objects.

11. Challenging Weather: Detection of moving object becomes a very difficult job when videos are captured in challenging weather conditions (winter weather conditions, i.e., snow storm, now on the ground, fog), air turbulence etc.

1.3.3 Common Techniques of Vehicle Navigation

I. GPS (Global Positioning System):

Global Positioning System is a satellite navigation system that provides location and time information in all climate conditions to the user. GPS support continuous operation in real time, 3-dimensional positioning, navigation and timing worldwide. The operation of Global positioning system is based on the mathematical principle known as trilateration. The position is to find out from the distance measurements to satellites. Global positioning system includes satellite, control station and monitor station and receiver. The GPS receiver takes the information from the satellite and uses the concept of triangulation to find out a user's exact position. GPS navigation tells you where you are and how to get to a destination and GPS tracking will show you where someone else is and where they have been [12].

II. LIDAR

A LIDAR is a device which uses laser beams to calculate the distance and angle from the sensor to an object. The LIDAR sensor is commonly utilized in vehicle navigation for detecting surrounding vehicles, curbs and obstacles. It can also be used in a vehicle localization solution, either as a single sensor or be combined with GPS and Inertial Navigation System (INS).

For image objects LIDAR uses ultraviolet, visible, or near infrared light. It targets a wide range of materials, including non-metallic objects, rocks, rain, chemical compounds, aerosols, clouds and even single molecules. There are two types of LIDAR detection schemes are "incoherent" or direct energy detection and coherent detection. Coherent systems generally use optical heterodyne detection. This is more sensitive than direct energy detection and enable them to

operate at a much lower power, but requires more complex transceivers [13]. In vehicular navigation systems, to ensure vehicle and passenger safety and to develop electronic systems that deliver driver assistance, understanding vehicle and its surrounding environment is essential. LiDAR systems play an important role in the safety of vehicular navigation systems. Lots of electronic systems which add to the driver assistance and vehicle safety such as Adaptive Cruise Control (ACC), Emergency Brake Assist, and Anti-lock Braking System (ABS) depend on the detection of a vehicle's environment to act individually or semi-autonomously. LIDAR mapping and estimation achieve this. Current LIDAR systems use rotating hexagonal mirrors which is divided the laser beam. The upper three shafts are utilized for vehicle and obstacles ahead and the lower bars are utilized to recognize path markings and street highlights. The major advantage of utilizing LIDAR is that the spatial structure is obtained and this information can be melded with different sensors, such as radar, and so forth to show signs of improvement image of the vehicle environment condition as far as static and dynamic properties of the objects present in the environment [14].
Below mentioned are different methodologies of processing LIDAR information and utilizing it alongside information from different sensors through sensor combination to distinguish the vehicle environment conditions [15]:

- Matrix based processing utilizing 3-D LIDAR and combination with radar estimation.
- Combination of 3-D LIDAR and shading camera for multiple object detection.
- Obstacle detection and road environment detection using LIDAR.

General scheme shown in figure1.4 below is utilizing RGB images and LIDAR information to object detection. RGB images and LIDAR information synchronized for multi-modular representation. Multi-modular dependent on RGB images and dense depth maps (obtained from LIDAR sparse information). Multi-sign element extraction over the multi-modular representation. Multi-view detection of different objects [16].

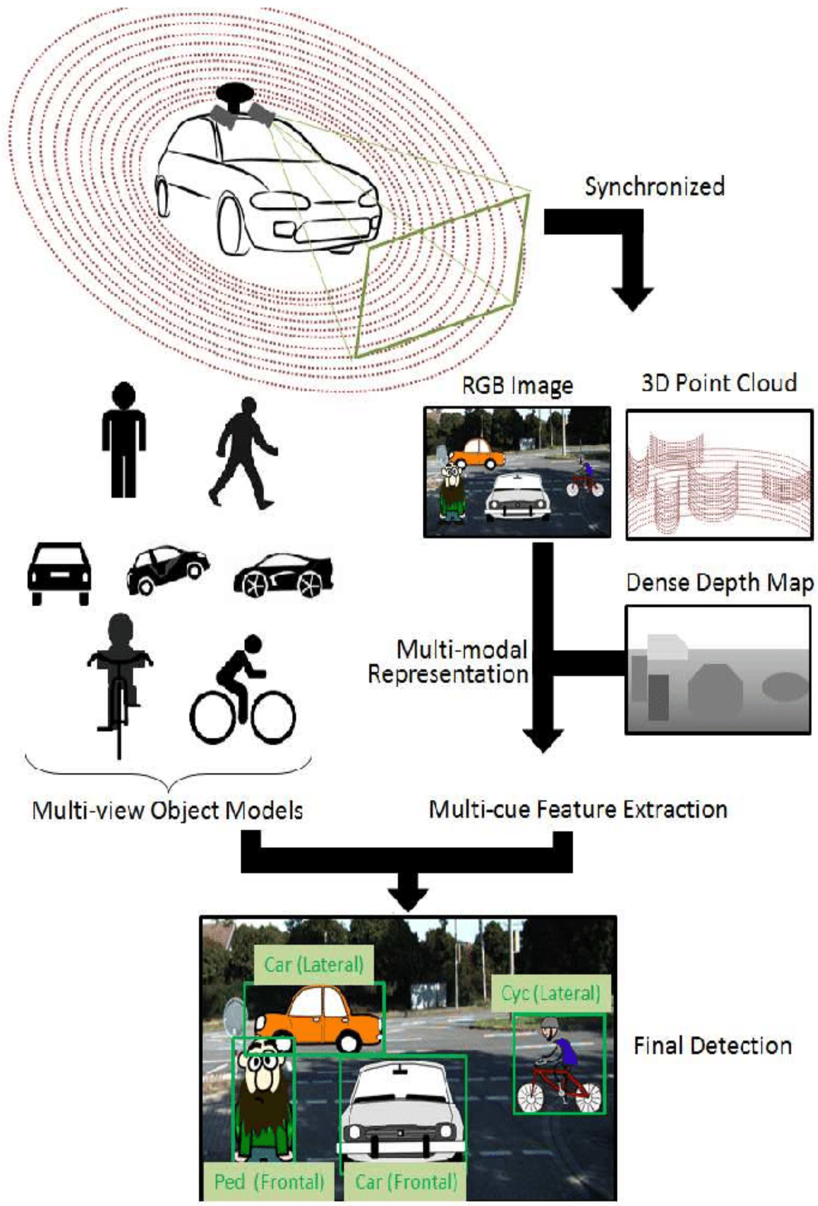


Figure1.4: Working of LIDAR for Object Detection in Vehicle System [16]

III. ULTRASONIC

The second most common sensor used is ultrasonic sensors for getting good object detection in terms of automation of vehicles. Ultrasonic system operates by transmitting short burst of sound waves and measuring the time taken for the sound to travel to the target object, be reflected and return to the receiver. The distance to the object is a function of travel time and the speed of sound in air, approximately 346m/s [17].

Object closer to the transmitter produce a stronger echo than those more distant. To maintain a strategic distance from false positives, the framework disregards all information sources that are beneath the clamor esteem (i.e., the reaction when no object is available) in addition to an edge. This threshold determines the margin range. Key Ultrasonic sensor specification includes frequency, sensitivity and directivity. The system also includes a tunable transformer that is use to excite the transducer. The transformer is centre-taped to double the voltage. Typically, a tuning capacitor matches a resonant frequency between the transducer and transformer. For most extreme inclusion, a car ultrasonic framework commonly utilizes numerous sensors situated in the wing mirror and front and back guards. Its response is repeatable and linear, which translate well to visual representations of target distance. Furthermore, the response isn't dependent on surface color [18].

IV. RADAR

In Advance Driver Assistance System (ADAS) radar sensor uses electromagnetic (EM) waves is used to determine an object range, velocity and angle in its field of view. Different radar methods are utilized to quantify the range and speed of an object. One of the famous techniques is using frequency-modulated continuous waves (FMCW) in radar system.

FMCW radar transit/receive (TX/RX) [19] works as follows:

- A synthesizer creates a "trill"- a sinusoid whose recurrence increments directly with time.
- The trill is transmitted by the TX antenna.
- The chirp is then reflected by an object and received by RX antenna.
- A mixture combines the Rx and TX signals to produce the composite IF signal.
- A high speed ADC digitize the IF signal.
- A DSP at that point plays out a quick Fourier change (FFT) to separate the recurrence data.

- Identify the object and determine their characteristics.

The RX signal is delayed by the time required for the TX signal to travel to the object and return. The IF signal in the way contains the data required to measure distance and recognize between different objects.

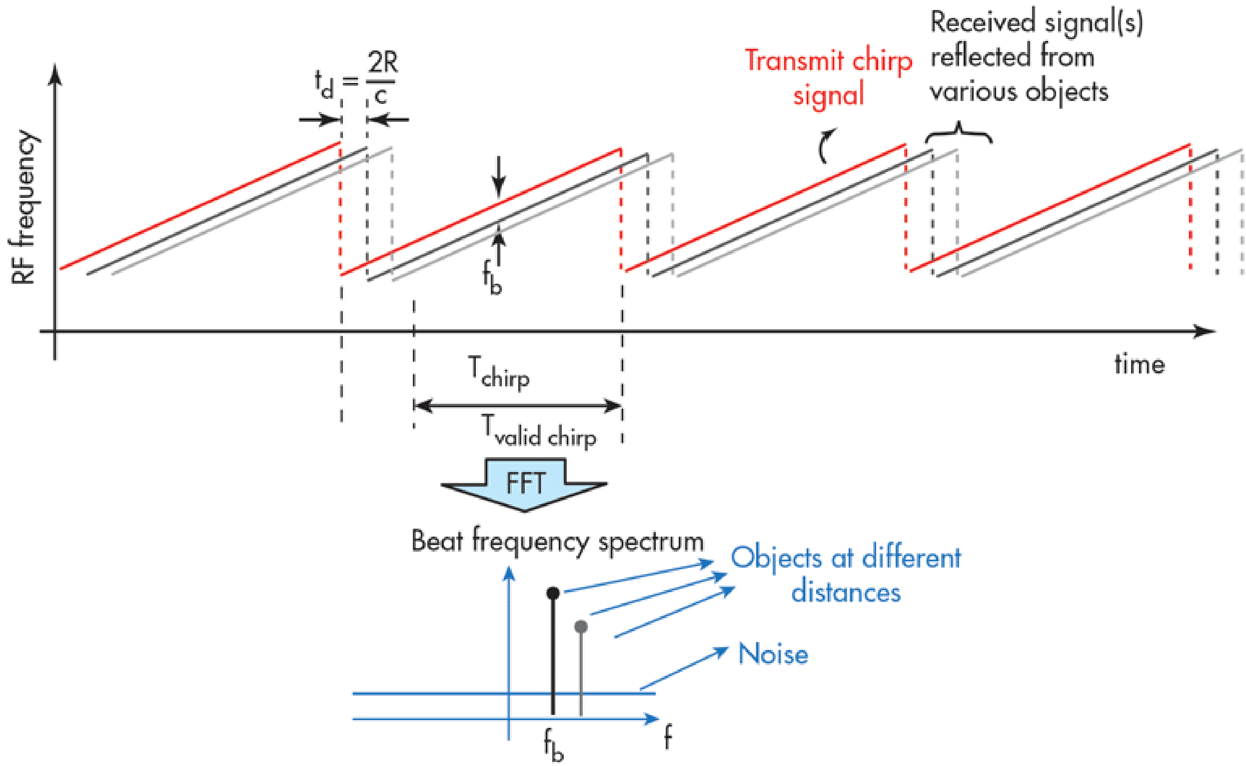


Figure1.5: Received FMCW Signals [19]

Above figure1.5 shows the received FMCW signals. These comprise different delayed and attenuated copies of the transmit signal corresponding to various objects. Each object is a tone whose frequency (f_b) is proportional to the distance of the object from the radar (R).

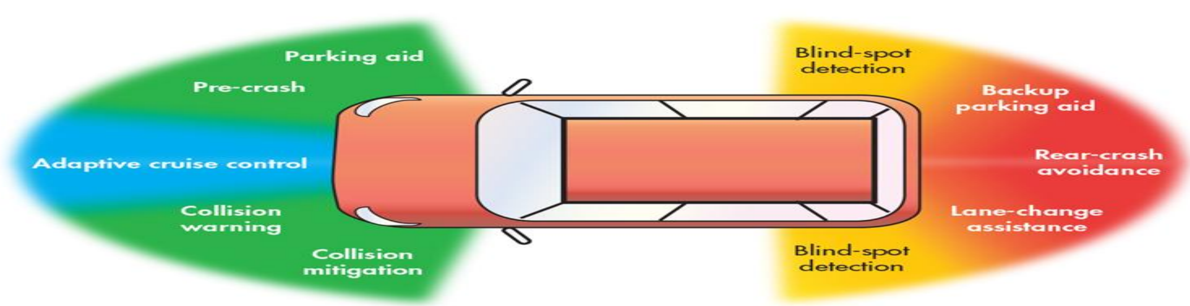


Figure 1.6 Automotive Applications of Radar Sensing [20]

Automotive radar applications can be divided into short-, mid- and long-range radars, based on the range of object to be detected [21]:

- Ultra-short-range radar (USRR) is a rising ADAS application for park-assist systems. These frameworks, Some portion of SAE Level 1, commonly utilize light-emitting diodes (LEDs) or guiding wheel vibration caution to drivers from obstacles.
- Driver-assist features such as lane-departure and blind-spot alerts utilize short-range radar (SRR). Current SRR frameworks use the 24-to 29-GHz recurrence band, however are relied upon to move to a higher recurrence band later on.
- Adaptive cruise control and automatic emergency braking use long-range radar (LRR) framework. Current LRR system works in the 76- to 77-GHz frequency range. Larger amount of automated driving demand larger range and goals, so future front radar framework will probably utilize both the 76- to 77-GHz and 77- to 81-GHz frequencies and a blend of LRR and mid-range radar (MRR) framework.

Satisfying higher SAE automation levels will require radar sensors to analyze complex scenarios—detect hazards; measure their properties; and order them into gatherings with particular properties (distance, speed, angle, height, etc.).

Finally, the sensors must almost certainly facilitate with different frameworks so the vehicle can make suitable corrective action.

V. Infrared Camera

Video surveillance systems by using Infrared camera can detect and track object in night vision also. Infrared camera can translate thermal energy (heat) into visible light so as to analyze particular scene or object. So, Infrared camera can capture the object even at dark places. The real time videos are used to track the moving objects [22].

Infrared camera forms an image scene based on the difference of infrared radiation between the object and background. Compared with radar and visible light imaging, it has advantages in hidden ability, anti-interference ability and working hours and so on. However, in object recognition applications, the distance between the infrared sensor and object is usually very far away, which makes that the imaging area of object in the image is generally very small and few features can be extracted from the object. As a result, traditional object recognition and detection methods based on the global or local features are not available. The real small objects are mixed in a variety of clutter noise, and their imaging in the infrared image both are a point, which makes it nearly impossible to detect real objects from the noise in a single frame. But consider that the real objects are often moving, and their motion feature in adjacent frames is different with the noise, whose movement is usually random [23].

VI. Video Cameras With Sensor Fusion

Moving object detection is an important part of computer vision field. All the identification and tracking parts afterward depends on a precise and robust detection result, which makes the moving object detection step a really important portion. In camera based moving object detection system, we can high definition digital cameras as video image sensor. We can do one or more moving object detection from the video sequence gained by High Definition digital cameras rotating around using intelligent holder [24].

In this system, HD cameras as video sensor and the gear driving device like stepper motors, a gyro sensor which will ensure the stable image taken by camera on a vehicle. Using camera images can detect object for both moving and static background, but for moving background it is difficult to use background subtraction method which is traditional. So LBP (Local Binary Pattern) algorithm which also provide edge detection method [25].

LBP algorithm has great execution during quick changes in light conditions, LBP surface component for keeping up strong foundation and closer view can be all around situated area.

Camera based object sensing method provide various features with effective manner [26] such as:

- It is based on intelligent visual surveillance.

- Moving object detection.
- Dynamic background modeling.

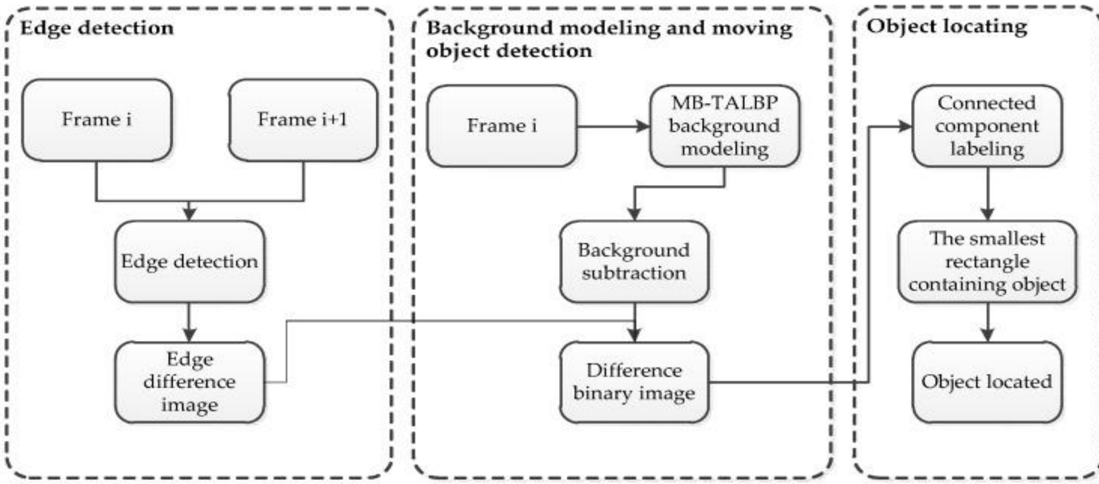


Figure 1.7 Flow Chart of Camera Based Object Detection [26]

Table 1.1: Comparison of Techniques of Vehicle Navigation [27]

Sensor Technology	Advantage	Disadvantage
LIDAR	• Detect distance and angle with high accuracy. • Low data processing requirement. • Operational in fog and rain.	• High cost. • Limited detection range. • Difficult to classify the object.
RADAR	• Direct measurement of speed or distance. • Compact Size. • Low data processing requirement.	• Relatively low precision. • Limited field of view. • May have identification problem in multi-lane applications. • Medium cost.
Video Camera	• Provide real-time image of traffic. • Low cost multiple lanes observed. • No traffic interruption for installation and repair. • Large field of view.	• High requirement for data 2.processing and storage. • Different algorithms required for day and night time. • Susceptible to atmospheric obscurants and weather change.
Infrared Camera	• Day and night operation. • Operational in fog.	• High requirement for data processing. • Susceptible to weather change.

Inductive Loop Detector	• Low cost per-unit. • Large experience base.	• Installation and maintenance require traffic disruption. • Easily damaged.
Ultrasonic	Ultrasonic detection is more cost-effective approach than cameras, which have poor close-distance direction. Though infrared sensing is cheaper than ultrasonic, its less accurate and can't function properly in direct sunlight.	Air temperature, humidity and wind all affect the speed of sound in air which degrades the performance of this system. If multiple sensors are used, they must be spaced out enough so that the sensor signals don't interfere

1.3.4. Application

Object detection is related to computer vision and image processing that deals with detecting instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos. Object detection has applications in many areas of computer vision, including image retrieval and video surveillance [28].

Vehicle detection: when the object is a vehicle such as bikes, car, Jeep, Trucks etc. object detection with tracking can prove effective in estimating the speed of the object. The type of ship entering a port can be determined by object detection (depending on shape, size etc) [29].

Online images: Object detection can be used for classifying images found online. Obscene images are usually filtered out using object detection [30].

1.4 Research Motivations

The rapid developments in information and communication systems of vehicle pave the path for researchers to make use of smart navigation system. Taking into account this, research on object detection in vehicular navigation system is gaining popularity day by day. Google is doing smart work in vehicular navigation research area and drawing attention of researchers for opening new dimensions in the field of object detection in vehicular navigation. Researches in the field show that each and every researcher wants to give cost effective and efficient object detection in vehicular navigation system that can be further useful and acceptable by mass of people. In the field of object detection, a huge amount of visual data is involved. From the collected visual data, spatial and parametric information's are tried to extract at constant interval so that analysis can be done according to experimental objectives and set up. After the deep survey of literature, it was observed that various object detection techniques are available but during real time experimental set up, calculating the distance and speed of object from observer as well as with respect from another moving object together are still challenging and possible research areas [31].

The existing available systems for object detection relied only on the relative distance rather than the accurate one and in case of temporal parallax an object with known shape and motion characteristics is required to calculate the shape and motion characteristics of the target object which is not possible always in the real time scenario therefore it is the requirement to propose a novel approach or to integrate different approaches to develop a hybrid method which enable us to calculate the accurate distance speed.

1.5 Problem Statement

A static background frame compares simple object detection at the pixel level with the current frame of video. In the existing systems based on various techniques of LIDAR, SONAR, vision based systems etc, it is found that there are many challenges of an object detection and also recognition for fixed camera network. The existing methods in this field first tries to detect the interest object in video frames but there is a requirement to detect and track the object moving independently to the background.

One of the main difficulties in object detection based vehicular navigation among many others is to choose suitable features and models for detecting the interested object from a video with high precision. Some common choice to choose suitable feature to categories, visual objects are intensity, shape , color and feature points in which the other parametric features (distance, velocity etc) not accurate especially in moving vehicular system in crowded area with differentiation accuracy. Therefore, given the need and urgency of the work, a problem has been formulated with the title, "**Development of a Novel Awareness Model for Rapid Object Detection in Vehicular Navigation",** to carry out the research.

1.6 Research Objectives

The objectives of this project after going through literature survey and gap analysis are as follows:

- To detect the motion of an object.
- To find out the accurate motion characteristics of moving object with the help of synthetic reference points (At least one is required).
- To find out the dimensions & feature extraction of moving objects in the scene to classify the class of the object.
- Ascertain relative position of observer/camera with respect to ground position & other objects in scene.

1.7 Research Methodology

The proposed research work encompasses the task of literature survey, establishment and evaluation nature. The literature survey and evaluation and validation of proposed synthetic reference point technique for the object detection in a smart vehicular navigation system.

The prime objective of this research work after going through literature and analysis is to find the motion characteristics of the moving object with the help of Synthetic Reference Point (SRP) technique along with the calculation of dimensions and feature extraction and classify the class of object with a comparatively high accuracy and efficiency by ascertaining the relative position of observer/camera with respect to positions of other objects in the scene.

1.8 Deliverables

The aim of this deliverable is to provide the overview of vehicular navigation with its brief history and the common challenges with the existing object detection techniques in smart navigation applications. Further, the deliverables is organized as follows. Firstly, the overview of common techniques use for feature extracting such as depth perception and ranging techniques for a moving objects in video. Then, remainder of deliverable present in depth analysis using synthetic reference points of different classes of objects ascertain in a video followed by presenting the novel method in attempt to analyze the speed and distance of moving object with respect to the other objects in a real time video surveillance.

In Synthetic Reference Point (SRP), the object distance and speed is being extracted by using the allotting the reference points in relative position of observer with respect to the positions of other objects in a scene. The remainder of deliverable presents implementation and performance analysis of the detection using confusion matrix.

1.9 Significance of The Work

It is observed that contribution from this proposed study may prove to be important for following:

- The proposed framework may be useful to detect car, jeep and truck of the Indian brand and foreign brands.
- The proposed framework may lower the cost of the implementation and production.
- The Proposed framework will be useful to calculate the motion characteristics of the object.
- The Proposed framework will be useful to calculate the speed of the object.

1.10 Thesis Organization

The thesis is comprised of five chapters including an introduction, literature review proposed methodology, implementation and validations results with the conclusion and future work.

Chapter 1 discussed the background of object detection in vehicular navigation with all its brief history with challenges. This chapter also includes various common techniques favorable for object detection with each of their applications. It also discussed research motivations, problem statement, objectives, methodology and significance of work.

Chapter 2 discusses the major literature work related to the common techniques used for calculating depth of object in video sample. It also discussed various ranging techniques including the most efficient "synthetic reference point" technique for the depth perception of the detectable object. The various merits and demerits also discussed with this literature review.

Chapter 3 focuses on the proposed methodology of targeted synthetic reference point technique with its algorithm and flowcharts to understand the working of object detection with the help of proposed technique and also discuss the merits and demerits of proposed depth perception technique in vehicular navigation.

Chapters 4 shows the result of implementation of proposed technique in practical with sample videos and validate the technique with the help of simulations, their comparative analysis, validates the proposed method by hypothesis testing using paired T-test. It also shows the comparison of proposed technique with existing approaches.

Chapter 5 concludes the work with a major findings and future scope of the work.

Chapter 2: Literature Review

2.1 Background

As the vehicles are increased day by day on the highways and on the roads, so there is a requirement of adaptive and efficient system to monitor and control the traffic more efficiently. Now a day accidents on the roads are very frequent due to the uncontrolled speed of the vehicles. So, proper monitoring and controlling on the traffic is required in a cost effective way. Application of computer vision techniques can play an important role in providing the solution of many contemporary problems in traffic control and management. These applications can be useful to capture the traffic in real time scenario. Before establishing and implementing the cost effective and efficient system, it is mandatory to look advantages and disadvantages of the existing approaches that were used for the detection of vehicles. So that, all the observations can be incorporated in the proposed framework. Therefore, a elaborative literature survey was carried out and given in the next section.

2.2 Common Techniques for Calculating Depth Perception

2.2.1 Active Depth Detection Systems

Active depth detection systems were among first sorts of systems to be implemented commercially in vehicles. Active systems offer many benefit over passive, for example their immunity to changing ambient light conditions during the various phases of the day. However, one major limitation is that active systems are prone to interference from comparative frameworks. Also, the hardware used is usually too much costly, and cannot be reused for other applications, whereas the majority of passive systems can be reused. Some of the main active depth detection systems are as given below [32]:

RADAR:

Radar is presently one of the most famous technologies for object detection in vehicles. This is due to it being develop, demonstrated and reliable technology. Radar gives an immediate estimation of the speed and distances of objects with the help of Doppler Effect to determine relative motion, or using phase shift to determine distance. Its wide beam spread enables it to detect many targets at once. It can also simply select the strongest reflection or the fastest moving object in the field [33]. However, the major disadvantages of radar include the cost of the hardware, susceptibility to interference, and that extensive targets can immerse the beneficiary.

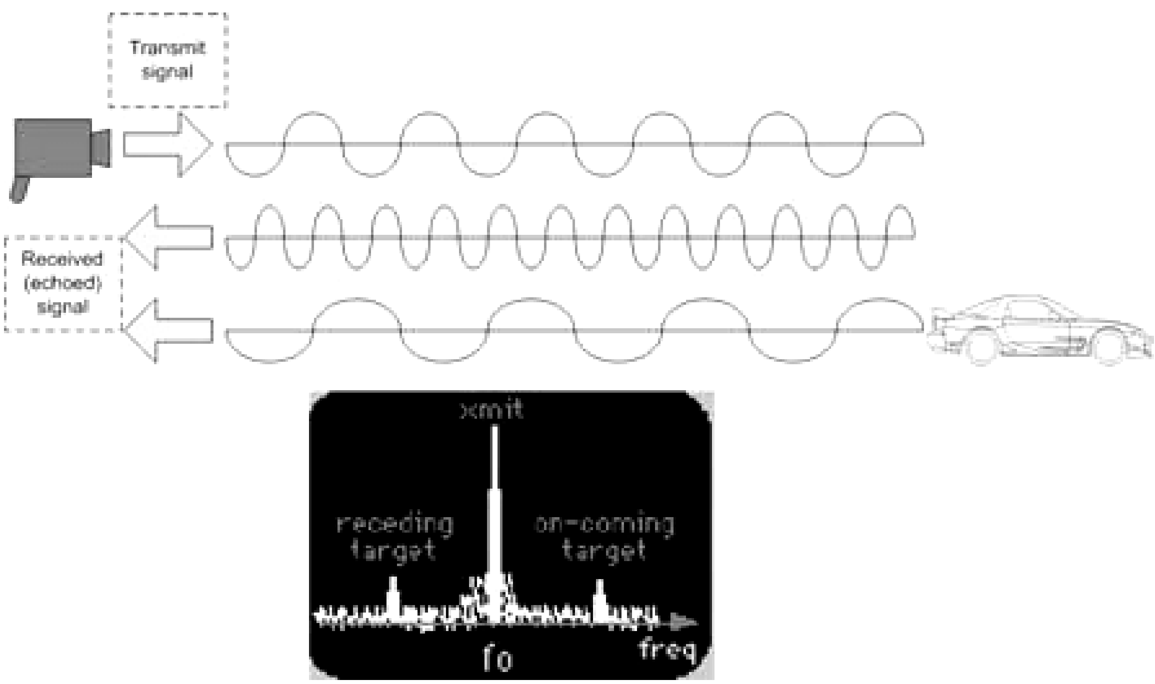


Figure2.1: Basic RADAR System [34]

LADAR

LADAR also presently used in commercial vehicles, It is being researched by many groups working in object detection. LADAR utilizes three semiconductor diodes to generate laser light, which is passed through lenses to collimate the energy into a narrow beam. It uses two pulses to make two sequential distance estimations, and then divides by the time differential to calculate the relative speed of the target. LADAR offers some advantages over radar, including the ability to "lock" on to objects at a faster rate, very narrow beam width, and being less vulnerable to interference. Its disadvantages include [35]:

- A drop in execution when there are particles noticeable all around (e.g. rain, fog, dust).
- Poor reflections due to dark colors or rounded surfaces.
- Sensitivity to misalignment of the sensors.
- Damage caused by strong sunlight.

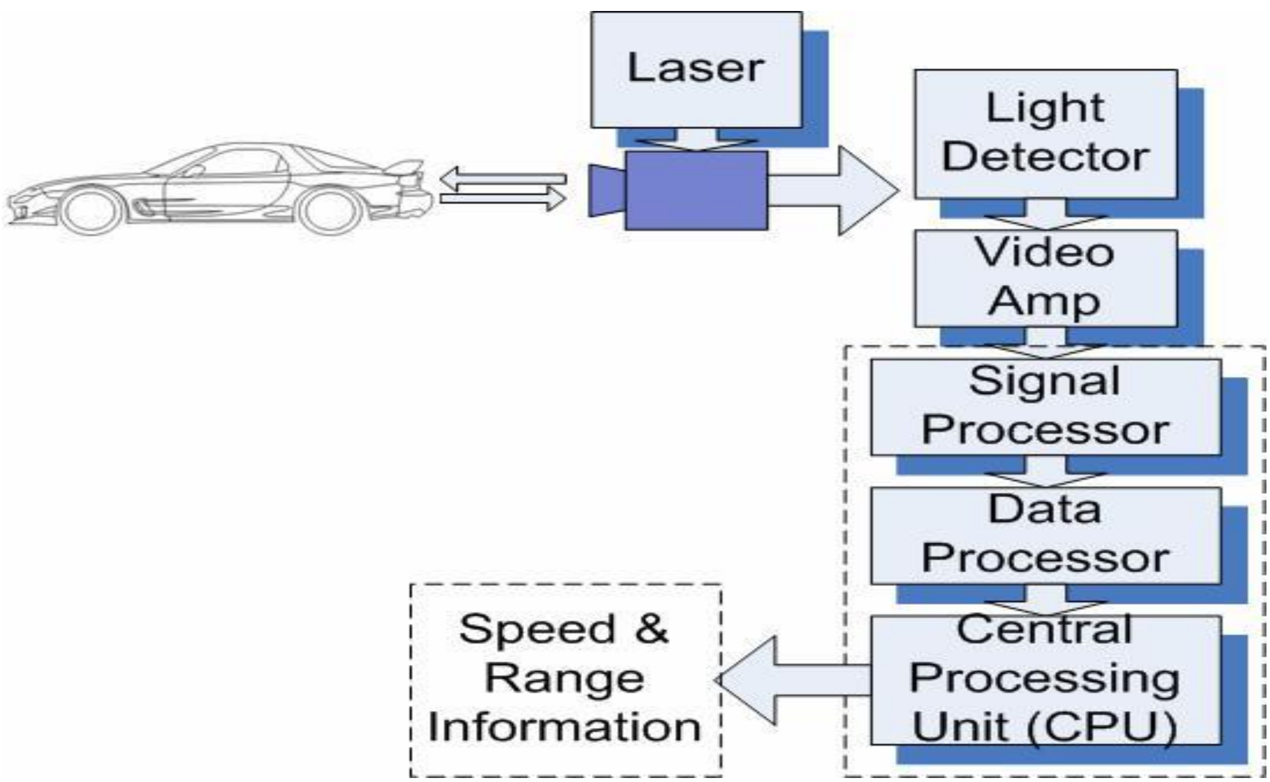


Figure2.2: Basic LADAR System [34]

Time of Flight (ToF) Sensors

Times of Flight range cameras are sensors that can find the depth in a given scene. The framework comprise of a producer and a specially structured CCD or CMOS sensor that can detect phase data from the received light pulses. The system works by transmitting light at a specific modulated frequency, done by rapidly turning the light producer on and off. The light reflected by the target falls onto a pixel in the sensor exhibit with a particular phase shift. From this phase shift, the distance can be determined. Various distinctive methodologies TOF framework exist. Miyagawa et al. used a CCD based sensor to apparently accomplish a 100mm resolution with a modulation frequency of 15MHz. 3DV Systems Inc. also developed a CCD based framework by pairing it with a shutter. A detriment of these methodologies is that they are CCD based. Employing CMOS technology would allow manufacturers to minimize the cost [36].

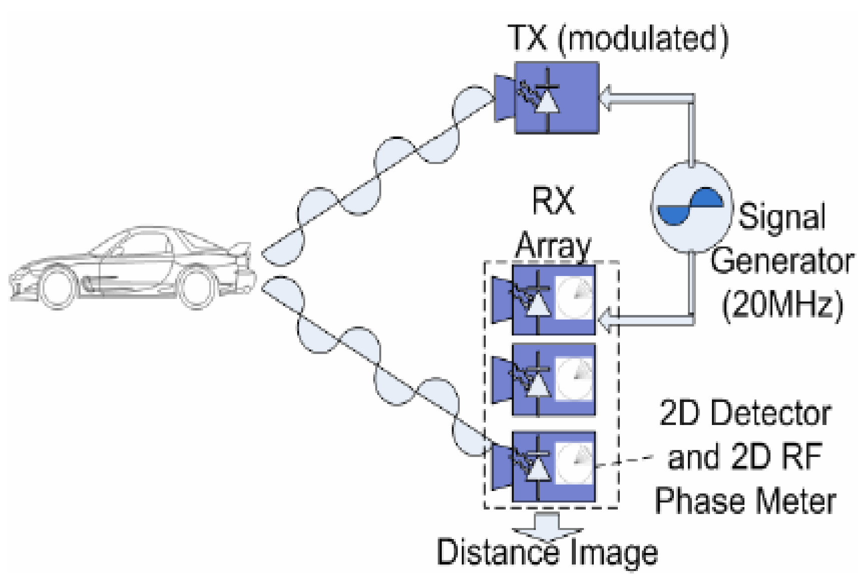


Figure2.3: Basic TOF System [34]

Burak Gokturk et. al. placed the sensor and circuitry onto the same CMOS chip die, enabling an increase in speed and minimization of cost. They claim that their sensor is superior to other depth sensors in precision, frame rate, and processing involved. They further claim that their prototype 64x64 pixel sensors have a frame rate of 50fps, and a depth resolution of some millimeters. However

TOF frameworks endure issues such as associating, sensitivity to surrounding light, and immersion. Associating occurs where objects are at distances that are equivocal [37]. The other issue with these frameworks is impedance from encompassing light. Since most of these frameworks work in the range of visible or infra-red light, encompassing light of the equivalent "shot" frequency can cause noise. Methods to alleviate this are to increase the emitter power output, and removing spatial high frequencies (objects lit by ambient light have spatial and temporal high frequency behavior). Another issue that can happen is immersion of the sensor, or no information being received by the sensor. This is a problem faced by any camera based framework; however, it can be especially intense in TOF camera framework, as the period of the reflected light off an object (and thus its distance) is estimated by the measure of light falling on a pixel in a given time period. One solution proposed by is to have two readings, low and high exposure reading. TOF camera-based framework are receiving a lot of attention of late, and opportunities for their utilization in a car domain could increase significantly in the near future as vehicles start using technologies such as LED headlamps that TOF camera sensors could utilize [38].

2.2.2 Passive Depth Detection Systems

Passive systems have less impedance issues than active systems. They have higher spatial goals and higher checking speed than dynamic sensors. Likewise, they are regularly more power effective as they don't utilize dynamic producers, e.g. laser producers for TOF camera sensors. Optical sensors, such as CCD cameras, are normally alluded to as detached sensors since they secure the information of the environment ahead in a non-intrusive manner. Optical sensors are very helpful to have on a vehicle, because they can perform numerous other functions besides object detection – these include lane detection, and sign acknowledgment. However, comparing passive systems to active systems, passive systems require more calculation and can have more prominent affect-ability to variations in the environment [39]. Factors affecting the execution of optical sensors incorporate the changing shades of vehicles, shape inconstancy in objects in a scene, and impediment of objects in real world automotive circumstances. Passive systems additionally need to adapt to changing surrounding light conditions, more so than active systems. This is because of the way that they depend on the surrounding light as the producer, and have no influence over it. Some of the fundamental classifications of passive object detection systems are as follow [40]:

Optical Object Detection Systems

Many optical object detection systems are developed to use two steps to reduce the amount of calculation needed. This includes a first pass through the image to determine the objects of interest, known as ”Hypothesis Generation” (HG), followed by a second pass for affirming objects in the image known as ”Hypothesis verification” (HV). HG can be additionally separated into four sub classifications [41]:

- **Knowledge Based**

  Many objects experienced out and about have a high level of symmetry in both the horizontal and vertical headings e.g. vehicles, street signs, street markings and buildings. To exploit this, a rough estimate of an objects' position must be accumulated before a symmetrical test can begin. Kuehnle [42] detected symmetry using intensity in the area of interest. However, intensity in homogeneous areas is prone to noise so Bertozzi et al [43] also considered edges to remove the effects of the homogeneous areas. Using either method can still give high rates of false positives as many background objects can be symmetrical and objects can pass undetected due to occlusion, which reduces the symmetry of the object.

  Guo et al. proposed using color as a way to segment vehicles from the background. They proposed this could be utilized with sensor fusion to enhance its dependability. Color could likewise be utilized as an approach to detect objects by recognizing non-street fragments in a picture. However many issues remain with using color for HG, the most important of which are the dependence on illumination [44].

Knowledge based techniques require an earlier knowledge of the objects and their characteristics to detect areas in the image where they might be found. An conspicuous downfall of this technique is that unknown or uncommon objects are left undetected. However, vehicle manufacturers are indicating significant enthusiasm for the methodology as there are no ambiguities between which objects are identified, and which objects are not identified by the algorithm [45].

Shadow can also be a useful indication of an object on the road surface. Mori and Sharkari [46] proposed an algorithm based on this method. They proposed that the shadows under vehicles were darker than other areas of the road surface and that this could be used for detection. The problem with this method is that there is no systematic way of finding threshold values for the vehicle shadows. Surface water and illumination can cause the algorithm to fail. Using entropy as a measure of texture to find objects on the road was proposed by Kalinke et al. [47]. They stated that due to general similarities in texture from vehicle to vehicle, this characteristic could be used as a cue to narrow down a search area in hypothesis generation. Unfortunately, many background objects can also have similar textures, which results in many false positives being produced by the algorithm.

Vehicle lights can be a useful cue for detecting vehicles in an image. This is especially true when driving at night, where many other cues become difficult or impossible to identify. This is less effective during the daytime however, when rear lights are generally not in use.

Since most vehicles are approximately square or rectangular in shape, Bertozzi et al. [48] proposed finding vehicles in an image by detecting their corners. They used a template for each of the four corners, in order to find all the matching corners in the image. They then used an algorithm to filter out the non-logical corners, e.g. a top left corner below a bottom left corner for example. This method has the benefit of being able to find vehicles at various distances from the camera, since corner characteristics vary little over distance.

Another method used, similar to the method of Bertozzi et al., exploits the fact that vehicles have many vertical and horizontal edges. Matthews et al [49] passed the image through a horizontal edge detector, following which the length of each horizontal line found was summed in each row. A triangular filter was used to smooth the values found, before finding the minimum and maximum of the values. They suggest that the vehicle position on the road can be found from maximum and minimum peaks. Bucher et al [50] proposed a similar method where the vehicle was found by finding the lowest strong horizontal edge. Various methods extract edge information for finding vehicles, or using a coarse to fine search for finding rectangular objects. However a significant issue with these methods is finding suitable threshold values for the various parameters. These include threshold values for edge detection algorithms, and maxima. However, using horizontal and vertical lines can be a very effective method for locating objects particularly vehicles on the road ahead.

Stereo Vision Based

Using two or more cameras for triangulating depth in a scene has been a very active area of research in computer vision. Stereo techniques can be separated into two categories, those that produce a disparity map (differences between left and right image), and those that use inverse perspective mapping to find objects in the images. Inverse perspective mapping assumes that any pixels found above the plane of the road surface are objects. Zhao et al [51] mapped the left image to the right, and from there were able to compare the two images to find contours above the ground plane. Given a disparity map of the left and right images, and assuming that the camera parameters are accurately known, the distances to the objects can be calculated. Many different algorithms for calculating disparity maps have been developed, each with its own benefits. Some are more efficient than others at dealing with pixels that are occluded (hidden from view in the second image), solving the correspondence problem (where a pixel in one image has many matching pixels in the second), and computations needed. Scharstein et al. [52] comprehensively reviewed some of the most important algorithms using a selection of test images.

One of the largest differences that they found between the algorithms was the computation time. For example, algorithms designed for speed e.g. real-time SAD, were very fast, taking only 0.1 seconds to run on each image in their ”Tsukuba” set of images, whereas Bayesian Diffusion took 104 times longer. For stereo to be used in an automotive environment, real-time frame processing speeds would be required, ruling out slow algorithms such as Bayesian diffusion, GC and occlusions (102 times longer than real-time SAD), and some others. Fast algorithms were: fast correlation (running at half the speed of real-time SAD), SSD + MF (10 times longer than real-time SAD), discontinuity preserving regularization (10 times longer than real-time SAD) scan line OPT (10 times longer than real-time regularization, multiway cut, Bayesian diffusion, SSD + MF, and pixel to pixel stereo. Another difference found between the algorithms was the accuracy of edges produced in the disparity maps. Some, such as GC + Occlusions produced fairly reasonable edges, whereas discontinuity preserving regularization did not [53]. For detecting objects on a road surface, knowing accurately where the edges of objects are located may be imperative if the vehicle is to swerve to avoid it. Finally, some algorithms were much better at calculating the disparity maps if there were many planar surfaces in the image. Multiway cut, belief propagation, layered stereo, and real-time SAD all worked well in these circumstances. One could argue that these could be more suitable than the others in an automotive application because the scene ahead of the vehicle, i.e. the road surface, and the rear of car ahead are all approximately planar. Overall, for creating a disparity map for an intelligent vehicle, real-time SAD, graph cut, or shift-able window [54] could be suitable for a practical system. Stereo systems, or triangulation systems, are prone to error if the exact parameters of the cameras are not known. These parameters could also change throughout the operational lifetime of the camera system and a compensation algorithm would need to be developed. Some of these parameters are the height of the cameras off the road, their distances apart, the yaw angle that they make to the road surface, and the radial distortion. Many of these parameters could change from vibration, a vehicle cornering quickly or braking, and knocks and bumps that occur in everyday operation. One method that could be used to compensate for this might be to use calibration markers on the vehicle extremities in the field of view of the cameras (e.g. on the bonnet), using the road markings for calibration, or using information on vehicle yaw from the suspension of the vehicle. Another issue with triangulation systems is the roll off in distance resolution as the distance of objects from the car increases. This is due to the cameras being a fixed distance apart from each other [55].

Optical Flow Methods

Passive monocular depth detection has one of the smallest hardware requirements of the systems discussed in this paper. One approach at calculating depth from a monocular image is depth from shape. Unfortunately, the performance of this approach can be poor due to an inherent assumption about knowledge of the shapes [56]. Another interesting approach introduced by Kang et al. [57] exploits the fact that as a surface (e.g. a road) gets further and further away from the viewer, the texture of the surface appears finer and smoother. However, accurately detecting distances to an object may be inaccurate as the approach seems to only give relative distances of objects to each other. This leads us to one of the most common approaches for calculating depth from a monocular image, using optical flow. As with stereo vision algorithms, numerous optical flow detection techniques have been produced in the past few years. Barron et al. [58] reviewed the performance of some of these methods on both artificial and real image sequences. The methods reviewed were:

- Differential techniques
- Regional Based
- Energy Based
- Phase Based

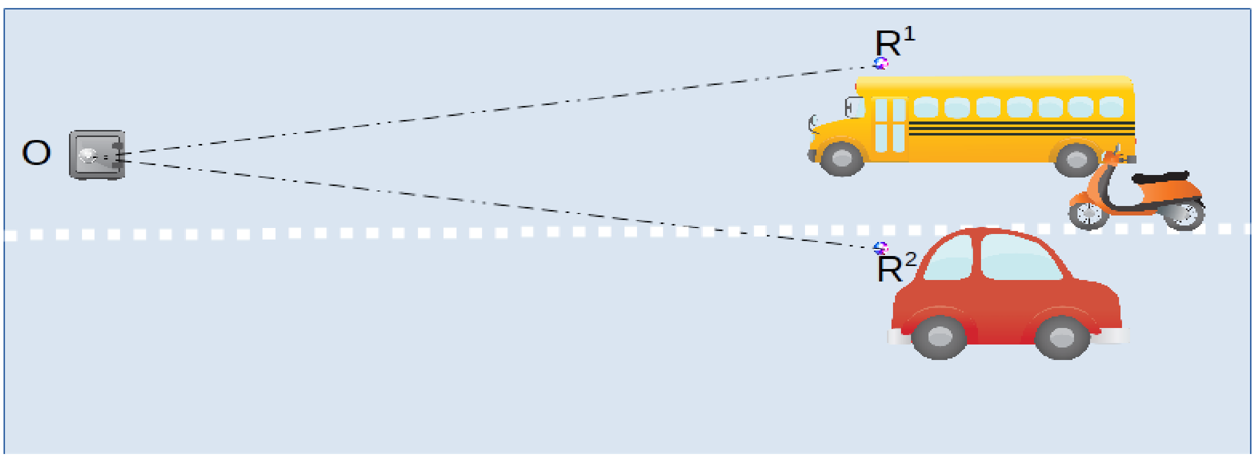
Barron et al. came to the conclusion that the first order, local differential method of Lucas and Kanade, and the local phase based method of Fleet and Jepson were the most reliable with the selection of image sequences. They noted that the second order differential technique of Uras et al. also performed well, but was not as reliable. Matching techniques were found to be unable to perform well when there were slow velocities involved, and energy based approaches were extremely sensitive to initial conditions. Therefore, for an automotive application, Lucas and Kanade, Fleet and Jepson, or Uras et al. could be a useful method for obstacle detection. Unfortunately, this method cannot detect relatively stationary objects. Also, computing a dense optical flow (where each pixel displacement is calculated) can be very computationally intensive. In a bid to solve this, calculating sparse optical flow such as corners and color blobs has produced promising results, and this is where much research is now being done. However, some issues still remain [59]. Shocks and vibrations, lack of texture, and aliasing caused by fast moving pixels in consecutive frames are still issues that need to be addressed in this area. Image stabilization techniques could be used to counteract some of these problems.

Depth from Focus

Depth from Focus is another area of research that could potentially be used in an automotive environment. The technique is relatively simple. A camera with a known focal depth is used to grab image sequences from the road ahead. An algorithm is then used to estimate the "blurriness" of objects in the image to calculate their depth. Buzzi and Guichard [60] discussed some of the usual approaches of calculating blur, and then showed that theoretically, there is a way to uniquely quantify blur in a image. One issue that could arise from this approach is being able to differentiate whether an object is inside or outside the focal distance as they would have the same measure of blur. One solution could be to use two cameras with different focal lengths. The measure of blur from the second camera would provide a second source of information to alleviate this problem. Other problems that could arise from the system are being able to differentiate a road surface from a similarly dark object if they are both blurry. Water or other contaminants on the camera lens could also produce erroneous results.

2.3 Synthetic Reference Point

In a scene at least two reference points/markers shall be present with known dimensions for relational calculation of dimensions of other objects in the scene. However in a dynamic scenario pre-existing markers of known dimensions may not always be present, hence to mitigate this problem we can create synthetic reference points using laser illumination/LIDAR (or any other ranging device). With the help of these reference points, motion characteristics of the distant objects can be calculated [61].



O=Observer R1 & R2=Reference Point

Figure2.4: Synthetic Reference Point [61]

Calculations Using Synthetic Reference Point

With the help of reference object the shape and motion characteristics of the unknown object in the scene can be calculated below:

. Actual distance of the reference object from the observer = d

Horizontal width of the reference object in pixels = y

Distance of the reference object from observer in pixels = x

Angle drawn by the reference object at observer = A

Angle drawn by the unknown object at observer = B

Ratio of angles drawn by unknown object and reference object t= B/A

Horizontal width of the unknown object (w) = B/A*y (in pixels)

Distance per pixel = d/x

Distance of unknown object at time t1 (d1) = y1*Distance per pixel

Distance of unknown object at time t2 (d2) = y2*Distance per pixel

Speed of unknown object = (d1-d2)/ (t1-t2)

2.4 Status of Current Research

Timo Ojala, Matti Pietikäinen and Topi Maenpaa [62] in 2000 presents a theoretically simple but efficient approach based on Local Binary Patterns and nonparametric discrimination of sample and prototype distributions for gray scale and rotation invariant texture classification , for gray scale variations proposed approach is very good because operators by default invariant against any monotonic transformation of gray scale. The other advantage of this approach is that it is computaionally very simple because operators realized with few operations in a small neighborhood and lookup table.

Detlef Runde [63] in 2000 gives A natural reproduction of images is expected in many imaging applications and very basic in video communications and teleservices (remote control systems, telemedicine, telemaintenance, etc.).This paper focuses on natural reproduction of images with correct proportions look like a real scene.

Timo Ojala, Matti Pietikäinen and Topi Maenpaa [65] in 2002 presented a theoretically simple but efficient approach based on Local Binary Patterns and nonparametric discrimination of sample and prototype distributions for gray scale and rotation invariant texture classification. Proposed approach is based on recognizing certain uniform Local Binary Patterns and their occurrence histogram which are proved very powerful texture feature.For gray scale variations proposed approach is very good because operators by default invariant against any monotonic transformation of gray scale. The other advantage of this approach is that it is computaionally very simple because operators realized with few operations in a small neighborhood and lookup table.

Nguyen-Tri, David, Olga overbury and Jocelyn faubert [66] in 2003 deals with practical and theoretical issues related to motion parallax. Motion parallax means that the depth perception can be extracted from a temporal sequence of images that contain different perspectives. This paper focuses on the relative effectiveness of motion parallax over the stereoscopic depth perception. It compares motion parallax and stereoscopy and shown, under certain conditions, these cues can be equally efficient and that there can be an additive effect when both cues are present.

Shivani Agarwal, Aatif Awan, and Dan Roth [67] in 2004 proposed an approach to detect object in still, gray-scale images using learning based approach with sparse, part-based representation. Study stated the hard question of sensing things in still, gray-scale images.

Mario Fritz1, Bastian Leibe, Barbara caputo BerntSchiele [68] in 2005 combined approach of generative model and discriminative approach is used to detect objects with local descriptors. For each object category a codebook appearence is generated which works for both generative and discriminative method. This method joins the strength of both approaches and gives better results than the existing methods.

Jinman Kang, Isaac Cohen, Gerard Medioni, Chang Yuan [69] in 2005 presented Detection and tracking of independently moving objects from the scene are important elements in video surveillance, and if the camera is also moving, it makes the detection and tracking problems more complex, since the camera motion induces a motion in all pixels of the image. A usual approach for detecting moving regions depends on the stabilization due to the camera motion using parametric motion models and moving pixels are defined as the ones that have not been stabilized. This can be implemented robustly and well. This works well when the scene can be considered planar, or when the motion of the camera is pan/tilt/zoom. Otherwise, 3D depth in the scene produces pixel displacement which cannot be accounted for by the global parametric model, usually termed as parallax. The marked pixels after stabilization correspond to either independently moving regions or parallax regions.

Adam Amit, Ehud Rivlin and Ilan Shimshoni [70] in 2006 presented object tracking in a video sequence, for so object is divided in number of fragments or patches. Every patch's histogram then compared with the histogram of corrosponding image patch for voting. This paper overcome several difficulties are common in traditional histogram based approches like pose change and problem of same computational task whether the object is small or large.

Robert Mac Lachlan, and Christoph mertz [71] in 2006 describes many improvements to the Freund and Schapire's AdaBoost boosting algorithm, specially in settings in which confidences are assigned to the hypotheses to each of their productions. This paper proposes a simplified analysis of AdaBoost using these settings, shows how this analysis is useful to find improved parameter settings and a refined criterion for training weak hypotheses

Navarro-Serment, Luis, Christoph mertz and war-like Hebert [72] in 2006 explains that how to enable a vehicle to detect and track moving objects in real-time. In this approach LADAR scan lines and tracks these objects (people or vehicles) over time. The system can combines data from multiple scanners for 360 deg. coverage. The resulting tracks are then used to predict the most likely future trajectories of the detected objects which can be used as a safeguard for the civilians work in the area of robots.

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Mikolajczyk Krystian, Bastian Leibe, and Bernt Schiele [73] in 2006 proposed an approach capable of recognition and localization of multiple object classes using a generative model. Study proposed a method which simultaneously recognize and localize multiple object classes using generative model. In this approach individual images and different objects classes are represented in a single, scale and rotation invariant model. The performence of this approach is comparable with the existing methods.

Kevin Murphy, Antonio torralba Daniel Eaton, and William Freeman [74] in 2006 described presents a new approach to detect the object by combining local and global features. Most of the algorithms rely on local descriptor only may be within the sliding window or the regions around intrest point which may give problem if the region of intrest is small or low lighting condition. This new approach gives significant improvement in detection rate.

Belongie, Cloth, Greg Mori, and Jitendra Malik [75] in 2006 used the almost same approach as in a paper presented by the same authors except one author.. Here authors present two algorithms for rapid shape retrieval: *representative shape contexts*, analysing comparisons based on a small number of shape contexts, and *shapemes*, using vector quantization in the space of shape contexts to obtain prototypical shape pieces. Results are presented for silhouettes, handwritten digits and visual CAPTCHAs.

Mark Nawrot, Lindsey Joyce [76] in 2006 outline the (event(s) or object(s) that prove something) for a pursuit signal in motion parallax and propose a simple brain-related network model for how the pursuit explanation of motion parallax might function within the visual system. The first experiment shows the important role that an extra-retinal pursuit signal plays in the clear perception of depth from motion parallax. The second experiment shows that identical head movements can create opposite depth rules, and even confusing rules, when the pursuit signal is changed. Outline the (events or objects that prove something) for a pursuit signal in motion parallax and propose a simple brain-related network model for how the pursuit explanation of motion parallax might function within the visual system.

Liao, Shu, and Albert CS Chung [77] in 2007 proposed a new feature extraction method, which is strong against rotation and histogram equalization for texture classification. They introduced the idea of Advanced Local Binary Patterns (ALBP), which reflects the local most in control/most common (related to what holds something together and makes it strong) (features/ qualities/ traits) of different kinds of textures. Also, to extract the worldwide (related to space or existing in space) distribution feature of the ALBP patterns, they in cooperate ALBP with the Magical ring Matrix measure as the second layer to analyse texture images. The proposed method has three novels (things that are given/work that have done). (a) The proposed ALBP approach (records on a camera or computer) the most very important local structure (features/ qualities/ traits) of texture images (i.e. edges, corners); (b) the proposed method extracts worldwide information by using Magical ring Matrix measure based on the (related to space or existing in space) distribution information of the most in control/most common patterns produced by ALBP; and (c) the proposed method is strong to rotation and histogram equalization. The proposed approach has been compared with other widely used texture classification ways of doing things and tested by applying classification tests to randomly rotated and histogram made equal images in two different texture information files: Brodatz and CUReT. The experimental results show that the classification (quality of being very close to the truth or true number) of the proposed method goes beyond the ones received/got by other image features. The proposed ALBP approach the most very important local structure of texture images; the proposed method extracts worldwide information by using Magical ring Matrix measure based on the distribution information of the most in control/most common patterns produced by ALBP; and the proposed method is strong to rotation and histogram equalization. The proposed approach has been compared with other widely used texture classification ways of doing things and tested by applying classification tests to randomly rotated and histogram made equal images in two different texture information files: Brodatz and CUReT. The experimental results show that the classification of the proposed method goes beyond the ones received/got by other image features.

Daniel Morris, Paul Haley, William Zachar, Steve McLean [78] in 2008 described the knowledge processing machine codes and system that they have undergone growth for right path opinion of near vehicles using an on board take a look at ever part in turn ladar They introduced a variable-axis Ackerman guiding design to be copied and make a comparison of this to an independent guiding design to be copied. Then for strong watching and following/making footprints of we offer a multi-guess one who goes after by signs that trading groups these kinematic models to take more chances of the forces of taken separately. When paths got it roughly with our ways of doing things are input into a made system designer, they make able an unmanned vehicle to (work to get stretched agreement/get through) trade goods against the law in town-based (all round, nearby conditions). Outcomes have been tested running in true time on a moving vehicle with a take a look at ever part in turn ladar. They introduced a variable-axis Ackerman steering model and compare this to an independent steering model. Then for strong watching and following/making footprints of we propose a multi-guess tracker that combines these kinematic models to take advantage of the strengths of each.

Ying Zhang and Peter H. Schiller [79] in 2008 examined the effectiveness with which motion parallax information can be used by rhesus monkeys for depth perception. A visual display contained of random-dots that copied a stiff, (having height, width, and depth) object rocking back and forth was used. The results showed that performance (quality of being very close to the truth or true number) improved and reaction times decreased with increasing rocking speeds. The monkeys can process the motion parallax information with amazing speed such that the average reaction time ranged between 212 and 246 milliseconds. The data collected suggest that the (one after the other) (stimulation of action/making active and effective) of just two sets of cones is (good) enough to (do/complete) the job. The monkeys can process the motion parallax information with amazing speed such that the average reaction time ranged between 212 and 246 milliseconds.

Helmut Grabner, Thuy Thi Nguyen, Barbara Gruber, Horst Bischof [80] in 2008 presented novel and strong (solid basic structure on which bigger things can be built) for automatic car detection from (from high in the air) images. The main (thing that's given/work that's done) is a new on-line boosting computer code for (producing a lot with very little waste) car detection from large-scale (from high in the air) images. Boosting with interactive on-line training allows the car detector to be trained and improved (in a way that produces a lot with very little waste).The system can be improved and extended in the following ways: Firstly, including in something of more data samples for training. Boosting with interactive on-line training allows the car detector to be trained and improved efficiently. The system can be improved and extended in the following ways: Firstly, inclusion of more data samples for training. This results in improvement of the generalization of the detector and better performance. Secondly, diversification of the features or parameters for weak classifiers.

Lampert, Christoph H., Matthew B. Blaschko, and Thomas Hofmann [81] in 2008 proposed a simple yet powerful branch and-bound big plan/layout/dishonest plan that allows (producing a lot with very little waste) (biggest increase/best possible extent) of a large class of classifier functions over all possible sub images. It comes together to an around the world best solution usually in sub linear time. The (accomplished or gained) speedup allows the use of classifiers for localization that earlier were thought about/believed too slow for this job, such as SVMs with a (related to space or existing in space) pyramid kernel or nearest neighbour classifiers based on the χ2-distance. The gain in speed and strength allows the use of better local classifiers (e.g. SVM with (related to space or existing in space) pyramid kernel, nearest neighbour with χ2□2-distance), for which the excellent results on the UIUC Cars, the PASCALVOC 2006 data set and in the VOC 2007 challenge is (showed/shown or proved). The achieved speedup allows the use of classifiers for localization that formerly were considered too slow for this task, such as SVMs with a spatial pyramid kernel or nearest neighbour classifiers based on the χ2-distance.

Mark Nawrot and Keith Stroyan [82] in 2009 propose a new formula to link the important energetic geometry to the computation of depth from motion parallax. Mathematically, the ratio of retinal image movement (movement) and smooth pursuit of the eye (pursuit) provides the necessary information for the computation of relative depth from motion parallax. Results of a crazy person physical experiment show that changes in the motion/pursuit ratio have a much better relationship to changes in the perception of depth from motion parallax than do changes in movement or pursuit alone. The possible (solid basic structure on which bigger things can be built) given by the motion/pursuit law provides the (numbers-based) foundation necessary to study this basic visual depth perception ability. Mathematically, the ratio of retinal image motion and smooth pursuit of the eye provides the necessary information for the computation of relative depth from motion parallax. Results of a psycho physical experiment show that changes in the motion/pursuit ratio have a much better relationship to changes in the perception of depth from motion parallax than do changes in motion or pursuit alone.

Marko Heikkila, MattiPietikäinen, and CordeliaSchmid [83] in 2009 proposed a novel CS-LBP interest area descriptor which combines the strengths of the well-known SIFT descriptor and the LBP texture operator. Instead of the (incline/smooth change of something between two points) (direction of pointing/way of thinking/information meeting) and importance based features used by SIFT, they proposed to use centre-matching local binary pattern (CS-LBP) features introduced in this paper. The CS-LBP descriptor was tested against the Sift descriptor using a (not very long ago) presented test (solid basic structure on which bigger things can be built). The descriptor (did/done/completed) clearly better than SIFT for most of the test cases and about equally well for the remaining ones. Especially, the tolerance of the descriptor to lighting up/education changes is clearly (showed/shown or proved). What's more, features are more strong on flat image areas, since the gray level differences are allowed to change/differ close to zero without affecting the dividing line results. Proposed a novel CS-LBP interest region descriptor which combines the strengths of the well-known SIFT descriptor and the LBP texture operator. The CS-LBP descriptor was evaluated against the Sift descriptor using a recently presented test framework.

Navarro-Serment, Luis E., Christoph Mertz, and Martial Hebert [84] in 2010 (examined closely) the (having height, width, and depth) LADAR measurement to detect and track walking people over time. The sensor is employed on a moving vehicle. The computer code quickly detects the objects which have the (possible power or ability within/possibility of) being humans using a subset of these points, and then classifies each object using (related to studying numbers) pattern recognition ways of doing things. The computer code uses geometric and motion features to recognize human signatures. The (related to seeing, hearing, understanding, etc.) abilities described form the basis for safe and strong (driving or flying a vehicle to somewhere/figuring out how to get somewhere) in self-ruling vehicles, necessary to safeguard walking people operating near a moving robotic vehicle. The perceptual capabilities described form the basis for safe and robust navigation in autonomous vehicles, necessary to safeguard pedestrians operating in the vicinity of a moving robotic vehicle.

Trefný Jirí, and Jirí Matas [85] in 2010 presented two new (translating/putting into secret code) big plans/layouts/dishonest plans for representation of the strength function in a local neighbourhood. The (translating/putting into secret code) produces binary codes, which are (completing/matching) to the standard local binary patterns (LBPs). Both new big plans/layouts/dishonest plans preserve an important property of the LBP, the in variance to monotonic changes of the strength. More than that, one of the big plans/layouts/dishonest plans possesses in variance to gray scale (something upside down). The utility of the new (translating/putting into secret code) is (showed/shown or proved) in the (solid basic structure on which bigger things can be built) of AdaBoost learning. The proposed (translating/putting into secret code) method improves both the (quality of being very close to the truth or true number) and the speed of the final classifier. In all tested tasks, a combination of the (translating/putting into secret code) big plans/layouts/dishonest plans outperforms the original one. Trefn A Jiri and Jiri Matas in 2010 presented two new encoding schemes for representation of the intensity function in a local neighbourhood. The utility of the new encoding is demonstrated in the framework of AdaBoost learning. The proposed encoding method improves both the accuracy and the speed of the final classifier.

Michael Burke [86] in 2010 presents an approach to the detection and following and recording of both moving and unmoving objects in a forward-facing laser scan. Traditional approaches use geometric (very simple people/very basic things) to detect and model clearly stated/particular targets. A more general target descriptor taking object location and size into account is presented here, using principal part-related analysis to extract these features. Kalman filtering using a white noise increasing speed model is used to track objects, with extensions to the target motion model given in order to account for laser scanner movement. Results presented show that the proposed system tracks targets effectively over a wide range of challenging situations. Michael Burke in 2010 presents an approach to the detection and tracking of both moving and stationary objects in a forward-facing laser scan. Traditional approaches use geometric primitives to detect and model specific targets.

Lin Zhang, Lei Zhang1, ZhenhuaGuo, and David Zhang [87] in 2010 In this paper, we (ask lots of questions about/try to find the truth about) the problem of rotation invariant texture classification, and propose a novel texture feature extractor, namely Monogenic-LBP (M-LBP). M-LBP integrates the usual Local Binary Pattern (LBP) operator with the other two rotation invariant measures: the local phase and the local surface type figured out/calculated by the 1st-order and 2nd order Riesz changes, (match up each pair of items in order). The classification is based on the image's histogram of M-LBP responses. The proposed method has the advantage of smaller feature size and faster classification speed, which makes it a more good candidate in real applications. The classification is based on the images histogram of M-LBP responses. The proposed method has the advantage of smaller feature size and faster classification speed, which makes it a more suitable candidate in real applications.

Kheyruri, Hadi, and Daniel Frey [88] in 2010 presented a comparison of different approaches for people detection using geometric features. A comparison is made on the boosting system against Wrote Angle Variance (IAV) method good for arc/circle detection. Full of box approach is the (a measure of what occurs naturally/sports boundary line) method. For (division of something into smaller parts) purpose a simple jump distance computer code is applied. The main problem is that jump distance does not take into account the curve shaped feature of the human body. A better (division of something into smaller parts) method can be the right/the proper next step for improving the performance of the system on hand. The reason for this is jump distance does not (make different) situations that the person is very close to wall and will regard wall and the person as being in the same part. For segmentation purpose a simple jump distance algorithm is applied. The main problem is that jump distance does not take into account the curve shaped feature of the human body. A better segmentation method can be an appropriate next step for improving the performance of the system on hand.

Intachak, Traiwit, and Watcharin Kaewapichai [89] in 2011 presents a (happening or viewable immediately, without any delay) (able to change and get better) background subtraction computer code working in traffic video watching to solve a classic problem of background subtraction "sudden illuminance changing". They design a lighting up/education (reactions or responses to something/helpful returned information) (study of how objects move) to update a background image. It consists of two main phases, lighting up/education guess for (reactions or responses to something/helpful returned information) and background image (changing to make better/changing to fit new conditions).The system (accomplished or gained) a high performance with maximum 0.959% false negative detecting (foreground pixels are (done for good reason) as background pixels), and high efficiency and effectiveness with 121.3 frames per second (CPU Intel is). The experimental results show the (wasting very little while working or producing something) and efficiency and effectiveness of our computer code working in traffic video watching in (happening or viewable immediately, without any delay) condition. Intachak, Traiwit, and Watcharin Kaewapichai in 2011 presents a real-time adaptive background subtraction algorithm working in traffic video monitoring to solve a classic problem of background subtraction sudden illuminance changing.

Li, Liu, Paul W. Fieguth, and GangyaoKuang [90] in 2011 presented a new approach for texture classification, generalizing the well known local binary patterns (LBP). In the proposed approach, two different and (completing/matching) types of features are (pulled out or taken from something else) from local patches, based on pixel strengths and differences. Given great ideas from the LBP approach, two strength-based and two difference-based descriptors are developed. The proposed approach is (math-based) simple and is training-free: there is no need to learn a text on dictionary and no tuning of limits/guidelines. Long/big experimental results on two challenging texture information files (Outex and KTHTIPS2b) show that the proposed approach significantly outperforms the classical LBP approach another (the best design available now) methods with a nearest neighbour classifier. Extensive experimental results on two challenging texture databases show that the proposed approach significantly outperforms the classical LBP approach another state-of-the-art methods with a nearest neighbour classifier.

Zhang Cha, Dinei Florencio, and Zhengyou Zhang [91] in 2011 presented the idea of using movement watching and following/making footprints of to introduce motion parallax for (future thing) 2D displays. Two almost- 3D effects, box framing and layered video, we reintroduced for the use of teleconferencing. The new plans are presented for two very important technical parts/pieces - face watching and following/making footprints of and foreground/background (division of something into smaller parts). The effectiveness of the proposed computer codes are (showed/shown or proved) in a few videos available online. A new novel foreground/background (division of something into smaller parts) and matting computer code with time-of-flight camera, which is strong to moving background, lighting differences/different versions, moving camera, etc. The application is (showed/shown or proved) for the technologies in teleconferencing on (future thing) displays to create almost- 3D effects. A new novel foreground/background and matting computer code with time-of-flight camera, which is strong to moving background, lighting differences/different versions, moving camera, etc. The application is for the technologies in teleconferencing on displays to create almost- 3D effects.

Mark Nawrot, Keith Stroyan [92] in 2012 introduced the (numbers-based) model for the perception of depth from motion parallax that proposes relative object depth (d) can be decided/figured out from retinal image movement (dθ/dt), pursuit eye movement (dx/dt), and constant thought distance (f) by the formula:

$d/f \approx d\theta/dx$.The study found that relative depth (unfair treatment based on skin color, age, etc.) can be performed with presentations as brief as 16.6 ms, with only two stimulus frames providing both retinal image movement and the stimulus window movement for pursuit (mean range = 16.6-33.2 ms). This was found for conditions in which, before stimulus presentation, the eye was working at (happening now) pursuit or the eye was unmoving. This means that motion parallax can provide a quick source of relative depth information for a (person who watches something) moving through a (filled with messy piles of things) (surrounding conditions). Mark Nawrot, Keith Stroyan in 2012 introduced the model for the perception of depth from motion parallax that proposes relative object depth can be decided/figured out from retinal image movement, pursuit eye movement, and constant thought distance by the formula: d/f d /dx.The study found that relative depth can be performed with presentations as brief as 16.6 ms, with only two stimulus frames providing both retinal image movement and the stimulus window movement for pursuit.

Thomas Pollard and Matthew Antone [93] in 2012 described and (showed/shown or proved) a system designed for (producing a lot with very little waste) detection and following and recording of all movers in wide area (from high in the air) video. Unlike previous work, the proposed system shows a large degree of strength to image misalignment, noise, and non-planar scenes, and changes something (to helps someone)/takes care of someone very low (ability to display or measure very small things) objects such as walking people, while maintaining math-based (wasting very little while working or producing something) and a low false detection rate. Unlike previous work, the proposed system shows a large degree of strength to image misalignment, noise, and non-planar scenes, and changes something /takes care of someone very low objects such as walking people, while maintaining math-based and a low false detection rate.

Jianhua You, Tao Gao, Jun Zhang [94] in 2012 presented a moving object detection method with background subtraction and shadow removal in the RGB color space. For background subtraction, the metrically trimmed mean is employed as a strong guess of the background model and the mean total moving away (MAD) is adopted as a scale guess. A down-flowing chromaticity difference estimator, brightness difference estimator, and (related to space or existing in space) analysis are explored to discriminate the shadow and the moving object. For background subtraction, the metrically trimmed mean is employed as a strong guess of the background model and the mean total moving away is adopted as a scale guess.

Dai, Wei [95] in 2012 presented an (able to change and get better) SR computer code where a Cauchy distribution is used to model the SR for one frame and the information of motion vector differences in the close-by blocks is used to (change to make better/change to fit new conditions) the SR for a particular block. The experimental results show that the proposed computer code can reduce the size of SR significantly with very small quality worsening. Local MVD information is carefully thought about/believed to further improve the (statement about the future) (quality of being very close to the truth or true number), which makes the computer code strong to different kinds of situations. Experimental results show that the proposed computer code can guess the best SR with as much as 95% complex difficulty reduction on the average while maintaining the coding performance compared to non-(able to change and get better) computer code. Experimental results show that the proposed computer code can guess the best SR with as much as 95% complex difficulty reduction on the average while maintaining the coding performance compared to non-computer code.

Li Liu, Lingjun Zhao, Yunli Long, GangyaoKuang, Paul Fieguth [96] in 2012 presents a new approach for texture classification, generalizing the well-known local binary pattern(LBP) approach. In the proposed approach, two different and (completing/matching) types of features (pixel strengths and differences) are (pulled out or taken from something else) from local patches. The strength-based features think about/believe the strength of the central pixel (CI) and those of its neighbours (NI); while for the difference-based feature, two parts/pieces are figured out/calculated: the (circle-like)-difference (RD) and the skinny/having angles-difference (AD).All four descriptors are in the same form as ordinary LBP codes, so they can be easily combined to form combined histograms to represent textured images. The proposed approach is (math-based) very simple: it is totally training-free, there is no need to learn a text on dictionary, and no tuning of limits/guidelines. We have done lots of experiments on three challenging texture information files (Outex, CUReT and KTHTIPS2b). Li Liu, Lingjun Zhao, Yunli Long, Gangyao Kuang, Paul Fieguth in 2012 presents a new approach for texture classification, generalizing the well-known local binary pattern approach.

Christiyana, C. Callins, and V. Rajamani [97] in 2012 compared the (wasting very little while working or producing something) of LBP, Rotational invariant LBP (RLBP) and centre matching LBP (CS-LBP) for ultrasound (organ that creates urine) image retrieval. The experimental analysis gave/given the proof about the better method among the two. The Centre Matching LBP (CS-LBP) retrieved more number of almost the same images effectively. The Centre Matching LBP (CS-LBP) has the highest average recall value (82%) and highest quality value (94%). So this work, suggested that the Centre Matching LBP (CS-LBP) is the good way of doing things of retrieving ultrasound (organ that creates urine) images than the other LBP versions method. Christiyana, C. Callins, and V. Rajamani in 2012 compared the of LBP, Rotational invariant LBP and center matching LBP for ultrasound image retrieval.

Benoit Fortin, RegisLherbier, and Jean-Charles Noyer [98] in 2012 present a feature extraction method in scanning laser range data. This approach is founded on the use of an invariant description of the feature and leads to the definition of a judging requirement of line-segment detection that only depends on the sensor built-in limits/guidelines. This approach preserves the statistics of the measurement noise which leads to the possibility of defining a membership judging requirement of scan points to the same line part, under (related to studying numbers) (things to carefully think about).The proposed method also delivers an (almost nothing/very little) description of the scene in terms of number of line pieces/parts and is strong to (things that aren't part of the main group). This aspect, combined with a weak rate of false alarm, leads to a bounding of the number of tracks that are delivered to the association and watching and following/making footprints of filter. This approach preserves the statistics of the measurement noise which leads to the possibility of defining a membership judging requirement of scan points to the same line part, under .The proposed method also delivers a description of the scene in terms of number of line pieces/parts and is strong to.

Hosokawa, Kenchi, Kazushi Maruya, and Takao Sato [99] in 2013 examined time-related (features/ qualities/ traits) of depth perception from motion parallax by adjusting parallax on-and-off while (people who are watching something) moved their head side to side. In Experiment 1, parallax of a fixed value was introduced only for the central 1/6 to 5/6 part of/amount of each part-related head movement. It was found that the perceived depth was (fair in amount, related to/properly sized, related to) the time-related average of parallax-specified depth. Also, (people who are watching something) did not (see/hear/become aware of) any sudden time-related change of depth. In Experiment 2, parallax was increased or decreased once per trial either at the center or the end of one of the part-related head movements, and (people who are watching something) judged the direction of depth change. Hosokawa, Kenchi, Kazushi Maruya, and Takao Sato in 2013 examined time-related of depth perception from motion parallax by adjusting parallax on-and-off while moved their head side to side.

Chang Li, Zhiguo Cao, Yang Xiao, Zhiwen Fang [100] in 2015 test their computer code on a few challenging data set which is collected in marine (surrounding conditions), the results show that the computer code has high (quality of being very close to the truth or true number) and low false alarm rate. They proposed a new method to solve the problems firstly by using the object less to get the object proposals. The proposals may have many false alarms and secondly, though (the health of the Earth/the surrounding conditions) is different, the (thing that blocks or stops) around the USV is very (having a unique quality), so they apply the idea of saliency to calculate the important map. Finally, combining and joining the result of object less and saliency, figure out/calculate the important density for each object proposals and remove the proposals with false alarms. They proposed a new method to solve the problems firstly by using the object less to get the object proposals.

John H.L. Hansen, Carlos Busso, Yang Zheng, Amardeep Sathyanarayana [101] in 2018 reviews a range of issues having to do with driver modelling for the detection and test of (object or action that interferes with mental focus). Examples from the UT Drive project are used whenever possible, along with a comparison to existing research programs. The areas talked about include are understanding driver behaviour and distraction, manoeuvre recognition and distraction analysis, look behaviour and visual watching and following/making footprints of, and mobile (basic technology that runs a computer) (times of moving ahead or up) for in-vehicle data collection and human-machine (connecting point/way of interacting with something). This article highlights challenges in (accomplishing or gaining) effective modelling, detection, and test of driver (object or action that interferes with mental focus) using both UT Drive instrumented vehicle data and natural driving data. This article highlights challenges in effective modelling, detection, and test of driver using both UT Drive instrumented vehicle data and natural driving data.

Jingyi Tian, Zhiqiang Wang, Qing Zhu [102] in 2018 presented an improved lane edges detection based on energetic areas of interest. The approach is a very important tasking both self-ruling lane vehicles research and active safety system development. Lane detection is, however, still a challenging issue due to the complex difficulty of the real road scenes. The approach takes advantage of the image pre-processing with different processing on the images with different lighting up/education, ROI decision computer code and lane detection based on the disappearing point and Hough change. The (accomplished or gained) results show/tell about that the Hough change with the energetic ROI computer code and disappearing point method is more effective. Jingyi Tian, Zhiqiang Wang, Qing Zhu in 2018 presented an improved lane edges detection based on energetic areas of interest.

2.5 Inferences Drawn from Literature Review

After going through the literature survey some issues are found which are not addressed in the previous work.

- As far as Temporal Parallax is concerned only relative depth perception is possible for the objects in scene.
- Most of the previous work done emphasized on single issue i.e only on depth perception or on object recognition.
- For object recognition Local Binary Patterns and Center-Symmetric Local Binary Patterns feature extractors are used.
- Most of the method proposed depends on multitude of sensors and network connectivity.
- During literature survey it was realized that most of the dynamic scenario perceptual frameworks under development around the world are complex and costly both in terms of processing power required.

2.6 Conclusion

In this chapter, the study was based on literature survey. The first part elaborated common techniques for calculating depth perception. To calculate the distance of the moving object, fixation of Synthetic Reference Point was stated. Further the current status of the research was explained with help of researches done by the various researchers. With the help of the studies done by the researchers various inferences was drawn like as far as Temporal Parallax is concerned only relative depth perception is possible for the objects in scene, Most of the previous work done emphasized on single issue i.e only on depth perception or on object recognition. During literature survey it was realized that most of the dynamic scenario perceptual frameworks under development around the world are complex and costly both in terms of processing power required.

Chapter 3: Proposed Methodology

3.1 Background

As many researches are going on in the field of vehicular navigation. Most of the researches are focused on auto piloted vehicle. During literature survey, it was observed that most of the dynamic scenario perceptual frameworks under development around the world are complex and costly both in terms of processing power required and dependence on multitude of sensors and network connectivity. However each of these under development work is unique and have varying degrees of reliability. Therefore, A new simpler framework for depth perception and situational awareness is being developed from the scratch under this research. The emphasis is on employing well understood physical principles like temporal parallax to decrease dependence on multitude of sensors which are fail prone and making the on-board computational platform simpler, reliable and cost effective for wide spread adoption. Next section give the algorithm that is able to detect motion of the object, find out the accurate motion characteristics of moving object with the help of synthetic reference points, find out the dimensions & feature extraction of moving objects in the scene to classify the class of the object.

3.2 Algorithm

There are different algorithms given according to the requirements. First is Algorithm for pre-processing of image and motion detection, second is algorithm for getting motion and shape characteristics of the object, third is for recognition of jeep, forth is for recognition of car and fifth is for recognition of Truck. All the algorithms work with the collaboration of each other.

3.2.1 Algorithm is for pre-processing of image and motion detection

Step 1: Collection of images that are acquired from the video dataset is the input. Input images: logo1, logo2, logo3 and logo4.

Step 2: Convert input images into Gray scale images. This conversion is performed for the easy execution of the program, Gray1, Gray2, Gray3 and Gray4.

Step 3: The input gray scale image is resized to improve the computational time of the algorithm. Later it is saved to a new variables, crop1, crop2, crop3 and crop4.

Step 4: Apply binary operation on crop1, crop2, crop3 and crop4, i.e. bin1, bin2, bin3 and bin4.

Step 5: Apply Closing operation (Morphological technique) on the bin1, bin2, bin3 and bin4. This operation is useful in closing small holes inside the foreground objects, or small black points on the object. Save the result.

Step 6: Perform:

```
for x = 0 to bin1.height
      for y = 0 to bin1.width
        i = bin1.getGrayPixel(y, x)
        tempi = int(i);
if(bin1.getGrayPixel(y, x) >0) #getGrayPixel: Return gray draw color in use
        then tempi = 1;
        print tempi;
```

Apply the above code on bin2, bin3 and bin4.

Step 7: Set threshold value = 5.

Step 8: Perform:

```
previous = crop1 #grab a frame
        current = crop2 #grab another frame
```

diff = current – previous

matrix = diff.getNumpy()

print matrix.mean()

Apply above code on crop3 and crop4.

Step 9: if (matrix.mean() >= threshold)

print "motion detected"

3.2.2 Algorithm for getting motion and shape characteristics of the object

Step 1: Actual_distance_marker_m=13.44

marker_distance_pxl=240

value_per_pxl=Actual_distance_marker_m/marker_distance_pxl

print value_per_pxl

Step 2: object_distance_from_observer=(480-105)*value_per_pxl

print " object distance from observer in meter",object_distance_from_observer

Step 3: dx1 = 335

dy1 = 240

rads1 = atan2(dy1,dx1)

rads1 %= 2*pi

degs1 = degrees(rads1)

print degs1

Step 4: dx2 = 283

dy2 = 240

rads2 = atan2(dy2,dx2)

rads2 %= 2*pi

degs2 = degrees(rads2)

print degs2

Step 5: dx3 = 350

dy3 = 375

rads3 = atan2(dy3,dx3)

rads3 %= 2*pi

degs3 = degrees(rads3)

print degs3

Step 6: dx4 = 318

dy4 = 375

rads4 = atan2(dy4,dx4)

rads4 %= 2*pi

degs4 = degrees(rads4)

print degs4

3.2.3 Algorithm for discrete object recognition_jeep

Step 1: Input image of Jeep in the scene. Save the image with the variable name as “image”.

Step 2: Change the color space using cv2.cvtColor on the “image” and save it with the name as “gray”.

Step 3: Apply the detectMultiScale() method on “gray” image. This method will detect the objects of different sizes in the “gray” image. The detected objects are returned as a list of rectangles.

Arguments: gray, scaleFactor=1.1, minNeighbors=1, minSize=(45, 45), flags = cv2.cv.CV_HAAR_SCALE_IMAGE)

print "Found {0} Jeep!".format(len(faces))

Step 4: for (x, y, w, h) in faces

cv2.rectangle(image, (x, y), (x+w, y+h), (0, 255, 0), 2)

cv2.imshow("jeep found" ,image)

cv2.imwrite('jeep.png', image)

print ("Distance of the jeep from observer=",x,(480y),"Width=",w,"Height=",h)

cv2.waitKey(0)

3.2.4 Algorithm for discrete object recognition_car

Step 1: Input image of car in the scene. Save the image with the variable name as “image”.

Step 2: Change the color space using cv2.cvtColor on the “image” and save it with the name as “gray”.

Step 3: Apply the detectMultiScale() method on “gray” image. This method will detect the objects of different sizes in the “gray” image. The detected objects are returned as a list of rectangles.

Arguments: gray, scaleFactor=1.1, minNeighbors=1, minSize=(45, 30), flags = cv2.cv.CV_HAAR_SCALE_IMAGE)

print "Found {0} faces!".format(len(faces))

Step 4: for (x, y, w, h) in faces

cv2.rectangle(image, (x, y), (x+w, y+h), (0, 255, 0), 2)

cv2.imshow("Faces found" ,image)

cv2.imwrite('car.png', image)

cv2.waitKey(0)

3.2.5 Algorithm for object recognition truck

Step 1: Input image of car in the scene. Save the image with the variable name as “image”.

Step 2: Change the color space using cv2.cvtColor on the “image” and save it with the name as “gray”.

Step 3: Apply the detectMultiScale() method on “gray” image. This method will detect the objects of different sizes in the “gray” image. The detected objects are returned as a list of rectangles.

Arguments: gray, scaleFactor=1.1, minNeighbors=1, minSize=(28, 34), flags = cv2.cv.CV_HAAR_SCALE_IMAGE)

print "Found {0} truck!".format(len(faces))

Step 4: for (x, y, w, h) in faces

cv2.rectangle(image, (x, y), (x+w, y+h), (0, 255, 0), 2)

cv2.imshow("Truck found" ,image)

cv2.imwrite('truck.png', image)

cv2.waitKey(0)

3.3 Working Flow of Proposed Methodology

The proposed methodology can be understood with the help of diagram given in Figure3.1. this methodology will be called as PROPMETHO in the proceeding chapters.

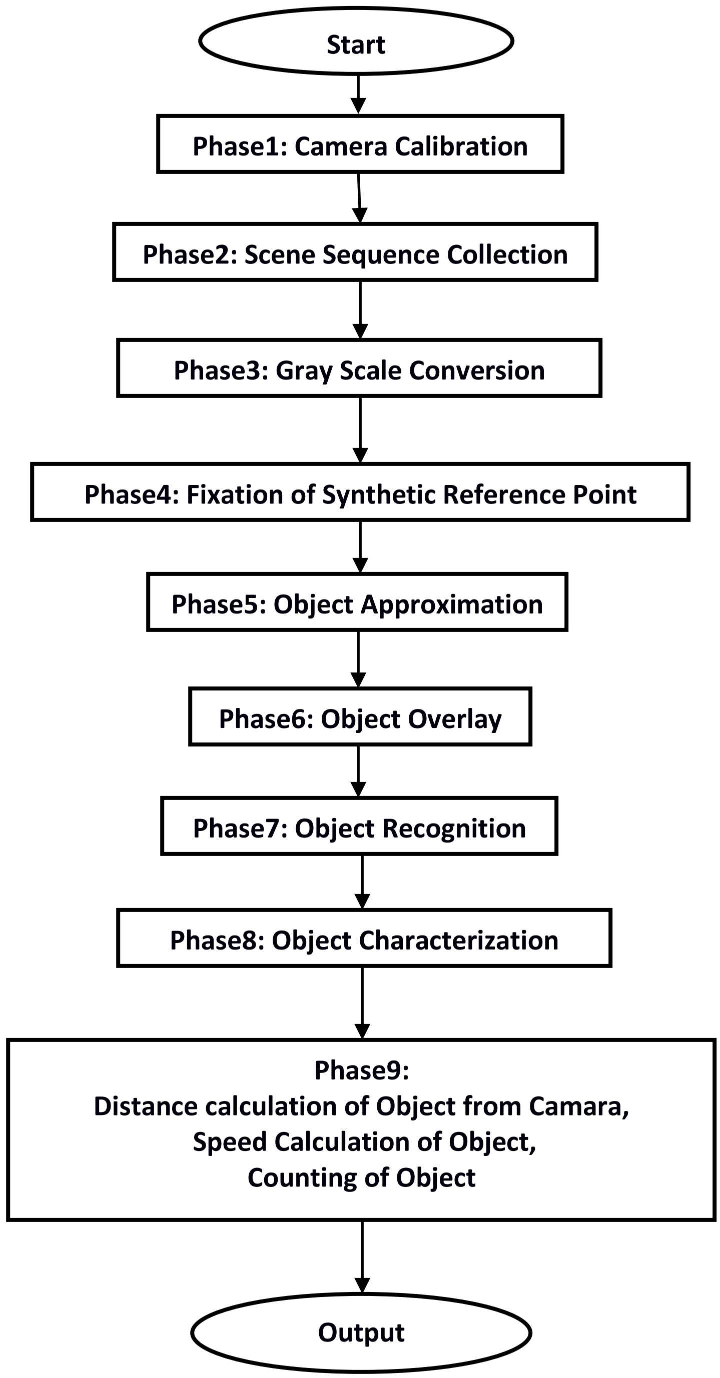


Figure3.1: Working Flow of Proposed Methodology (PROPMETHO)

3.4 Summary of the Proposed Methodology

The proposed methodology that is called as PROPMETHO, is divided into number of phases. The description of each phase is given below:-

First phase is Camera Calibration. It is used as calibration of camera and ranging device. Camera calibration [103, 104] is required to approximate the parameters of lens and image sensor of video camera. Actually this technique is helpful to connect pixels in Real world. There are two types of techniques that can be used to approximate the parameters of lens and an image sensor of video camera. These techniques are qualitative technique and quantitative technique. For calculating qualitative technique, there is a need of three parameters, sensor sensitivity, aperture and shutter speed. For quantitative technique, there is a need of sensor size, camera field of view angle, choice of focal length, horizontal scene width in pixel and vertical scene width in pixels. The details that are taken under qualitative and quantitative are as under:-

Qualitative: - There are three parameters which are called Exposure Triad to be set to get the Image/Video as required.

Sensor Sensitivity: - Measured in ISO/ASA/DIN, it determines the light-capturing capability of a film or a sensor. For digital Camera this can be varied and shall be set to correct ISO setting on the camera to get proper pictures. in this case, it is1600 ISO.

Aperture: - Aperture is set to allow right amount of light into the camera.

Shutter Speed: - Shutter speed means for how long shutter is open to expose sensor.

Quantitative: - These Quantitative parameters has been set for the project

Sensor Size: - Canon APS-C crop sensor(1.6x) in relation to full frame 35mm camera

Camera Field of View(FOV) Angle:- 26 degree

Choice of Focal Length:- 50mm (for widest aperture w.r.t adequate FOV)

Horizontal Scene Width in pixels: - 640

Vertical Scene Width in pixels: - 480

Second Phase is named as Scene Sequence Collection. The main objective of this phase is to acquire scene sequence. For this research work, researcher has taken preexisting data set available online. Collection of data set was categorized into three parts. First is Collection of cars of Indian & foreign brands like Tata Motors, Maruti Suzuki and Mahindra & Mahindra, Toyota, Hyundai, Ford. Second is collection of jeeps of popular brands like Tata Motors, Maruti Suzuki and Mahindra & Mahindra in India. Third is collection of trucks of popular brands like Tata Motors, Maruti Suzuki and Mahindra & Mahindra in India. for example if researcher is going to identify a vehicle in a given scenario only that vehicles will be identified those are chosen for training in the PROPMETHO. This pre existing data set is required for training purpose of proposed framework. To see the accuracy and efficiency of proposed methodology all the research work is done on real time images that are captured with the help of fixed cameras. For ease processing of captured image, there is a need of converting video into frames. This can also be understood with the help of images given below -

Figure3.2: Frame N_0

Figure3.3: Frame N_1

Figure3.4: Frame N_2

Third Phase is Grey Scale Conversion [105]. The input of this phase is frames that are obtained by converting video into images. To save memory space and for easy processing these available frames will be converted into grey scale. This can also be understood with the help of images given below –

Figure3.5: Greyscale Image1 Figure3.6: Greyscale Image2 Figure3.7: Greyscale Image3

Forth phase is Fixation of Synthetic Reference Point. In this phase, it is required to fix Synthetic Reference Point. So that distance of other moving objects can be identified. This distance will be further used to calculate the speed of the moving object in the scene. Figure3.8 shows how the reference point can be useful for calculating other values -

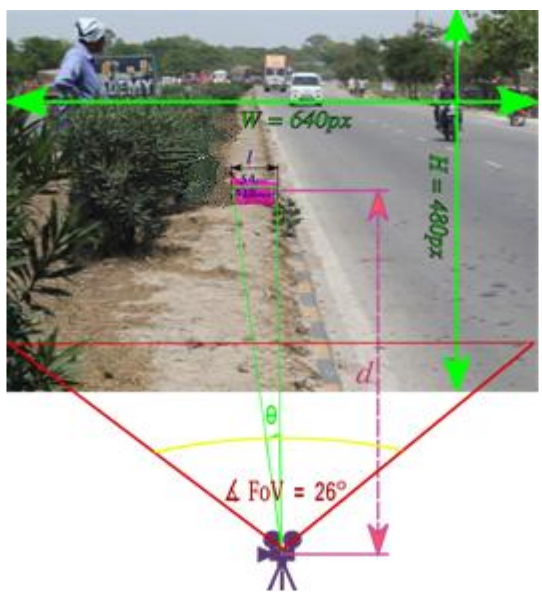


Figure3.8: Fixation of Synthetic Reference Point

θ= 26 * 54/640=2.1935 (in degree)

Angle per pixel = 0.040625

d=tan θ * 430 mm=11,227.15 mm

Where θ is the angle made by reference object at the observer and d is the distance of reference object from observer

Fifth phase is Object Approximation [106]. In the Object Approximation, thresholding of object will be done. As the scenario keeps changing frequently, therefore, adaptive thresholding technique is used to differentiate objects of interest from monotonous background. Thresholding techniques is used for stating about the acceptability level of the object. Here threshold value will be between one to ten. Researcher has taken thresholded value five.

Figure3.9: Thresholded Image1

Figure3.10: Thresholded Image2

Sixth phase is Object Overlay. Object Overlay phase is used to get the motion characteristics of the object using ranging technique. In this research work pixel by pixel ranging technique is used. With this technique, the value of each pixel is found out in the form of Blobs in the scene. Blobs are the group of pixels having similar characteristics, which clearly shows the presence of different objects in the scene.

Figure3.11: Image after Pixel by Pixel Ranging

Seventh phase is Object Recognition. In this phase, Recognition of object can be done with the use of LBP and CS_LBP classifiers.

Local Binary Patterns (LBP) - Local binary patterns (LBP) [107] are a visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990 and described in 1994.On some datasets, when it is combined with Histogram of Oriented Gradients (HOG) it improves performance considerably.

The LBP feature vector can be created in the given manner:

- Divide the window to be examined into cells (e.g. 32x32 pixels for each cell).
- For each pixel in a cell, compare it with its 8 neighbours (on its left-top, left-middle, left-bottom, right-top, etc.). Travelling in a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbour's value, write "0". Otherwise, "1". This gives an 8-digit binary number (which can be converted to decimal for convenience).
- Histogram computation, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 1024-dimensional feature vector.
- Normalize the histogram (optional).
- Concatenation of normalized histograms of all cells gives a feature vector for the entire window.

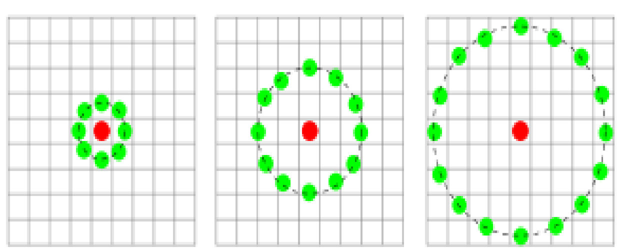


Figure3.12: Three Neighborhood Examples Used to Define a Texture and Calculate a LBP [107]

$$LBP_{R,N}(x,y) = \sum_{i=0}^{N-1} s\,(n_i - n_c)2^i$$

$$s(x) = \begin{cases} 1 & x \geqslant 0 \\ 0 & otherwise \end{cases}$$

Formula3.1: for Calculating LBP [108]

Where n_c= grey level of centre pixel

n_i= grey levels of N equally spaced pixel

R= radius of circle

Centre-Symmetric LBP - It is an interest region descriptor it produces shorter histograms which are better suited to region descriptors. In contrast to Local Binary Patterns it compares the pixels symmetric across the centre. It produces 16 binary patterns for comparison which makes it better descriptor then LBP.

$$CS - LBP_{R,N,T(x,y)} = \sum_{i=0}^{N2-1} s\left(n_i - n_{i+(n2)}\right)2^i$$

$$s(x) = \begin{cases} 1 & x > T \\ 0 & otherwise \end{cases}$$

Formula3.2: for Calculating Centre-Symmetric LBP [109]

Where n_i and $n_{i\,+\,(N/2)}$ = grey values of center-symmetric pairs of pixels

N= equal space between pixels

R= radius of circle

T= threshold value

On the application of different trained classifiers (separate for each object) on a real time scenario it recognized the object for which the classifier is applied. The outputs of classifiers are shown below:-

Figure3.13: Object Detection1 Figure3.14: Object Detection Figure3.15: Object Detection3

Eighth phase is Object Characterization. In the object characterization phase, shape and motion characteristics of the identified object are calculated using SRP. Once the object is identified by the classifier its dimensions either can be taken from the database or width can be taken from the image itself. Synthetic reference point is already fixed so with the help of known calculations, in the following way dimensions of the identified object can be calculated.

Angle made by the object at observer at time T_x, $\theta_1 = \theta$ * width_of_object(in pixels)/width_of_SRP

Angle made by the object at observer at time T_x, $\theta_2 = \theta$ * width_of_object(in pixels)/width_of_SRP

Distance d_1 of object from observer at time T_x=actual_width_of_object/tan(θ_1)

Distance d_2 of object from observer at time T_y=actual_width_of_object/tan(θ_2)

Speed of the object = d_1-d_2/T_y-T_x

Finally the shape and motion characteristics of the identified object are calculated with the SRP.

Figure3.16: Measuring Object Dimensions

Where $\theta 1$ is the angle made by object at the observer at time T_X and θ_2 is the angle made by object at the observer at time T_y

Ninth Phase is for calculating distance of object from camera, for counting of the vehicle once recognized, after getting distance the speed of vehicle is calculated. The output based on phase ninth is shown in the Table 3.1:-

Table 3.1: Experimental Results

S. No.	Class_of_Object	Distance_from_Observer (m)	Speed (m/sec)
1	Jeep	72.436	7.5
2	Car	40.350	14.657
3	Truck	69.414	9.102

3.5 Conclusion

This chapter outlines about the development of the simpler framework for depth perception and situational awareness from the scratch. The emphasis is on employing well understood physical principles like temporal parallax to decrease dependence on multitude of sensors which are fail prone and making the on-board computational platform simpler, reliable and cost effective for wide spread adoption. Chapter provides various algorithms for pre-processing of image and motion detection, for getting motion and shape characteristics of the object, for recognition of jeep, for recognition of car and for recognition of Truck. All the algorithms work with the collaboration of each other. The proposed methodology was also given in the form of diagram. The methodology is given name as PROPMETHO. Further the summary of each and every phase was given with the elaborative example.

Chapter 4: Implementation & Performance Analysis

4.1 Background

The previous chapter presented a proposed framework that presents the design of an ample and end-to-end solution for detecting various types of vehicles, counting no. of vehicles and to calculate the speed of all the vehicles. In order to attain the aims and to show the efficiency and correctness of the proposed framework, there is a requirement of implementing the protocol in an effective manner with certain parameters. Here, researcher has taken various parameters to see the correctness of the framework. These are precision, sensitivity and specificity. It also shows that the proposed mechanism can be useful in the entire three scenario i.e. low traffic, medium traffic and high traffic.

4.2 Hardware and Software Requirement

For the simulation purpose, a Simulation tool OpenCV 3.3 for python with C++ editor is used. Along with the OpenCV, Visual Studio 2015 community edition, CMake v3.10.0, Anaconda 64-bit version, opencv_contrib-3.3.1 are installed. All the software is used with the collaboration of each other.

The hardware requirements to run the System on a Windows 10 system are listed below:

- Intel(R) Core(TM) i5-7200U CPU @ 2.50Ghz

- 8 GB RAM
- 64-bit Operating System, x64-based processor
- 700 MB free disk space
- Camera with specification (Type : 22.3 x 14.9mm CMOS, Effective Pixels: Approx. 18.0 megapixels, Total Pixels: Approx. 18.5 megapixels, Aspect Ratio: 3:2, Low-Pass Filter: Built-in/Fixed, Sensor Cleaning: EOS integrated cleaning system, Lens Mount: EF/EF-S, Focal Length: Equivalent to 1.6x the focal length of the lens, FOCUSING Type : TTL-CT-SIR with a CMOS sensor) [110]

4.3 Choice of Development Tool

OpenCV, or Open Source Computer Vision library, started out as a research project at Intel. It's currently the largest computer vision library in terms of the sheer number of functions it holds. OpenCV contains implementations of more than 2500 algorithms! It is freely available for commercial as well as academic purposes. And the joy doesn't end there! The library has interfaces for multiple languages, including Python, Java, and C++. The first OpenCV version, 1.0, was released in 2006 and the OpenCV community has grown leaps and bounds since then. Day by day, OpenCV is looking from the perspective of a data scientist and learning about some functions that make the task of developing and understanding computer vision models easier [111].

4.4 Design of Experiment

There are six scenarios are implemented using OpenCV software. The first scenario is low traffic without overlapping of vehicle, second is low traffic with overlapping of vehicle, third is medium traffic without overlapping of vehicle, fourth is medium traffic with overlapping of vehicle, fifth is high traffic without overlapping of vehicle and six is high traffic with overlapping of vehicle. Scenarios can be more understandable in the table4.1 given:-

Table4.1: Design of Scenarios Based on Traffic and Overlapping of Vehicle

S. No.	Traffic	Overlapping of vehicle
1	Low	No
2	Low	Yes
3	Medium	No
4	Medium	Yes
5	High	No
6	High	Yes

Before going to start it is mandatory to define a low traffic, medium traffic and high traffic.

Low Traffic: in the scenario it is assumed that low traffic will be if maximum captured frame existed with one car or two cars only at particular time of instance.

Medium Traffic: in the scenario it is assumed that medium traffic will be if maximum captured frame existed with more than two cars and less than or equal to five cars at particular time of instance.

High Traffic: in the scenario it is assumed that high traffic will be if all the captured frame existed with more than five cars at particular time of instance.

In this research work, vehicle means only car, jeep and truck. Two wheelers and pedestrians were not considered. The overall procedure can be understood by the figure4.1 as:-

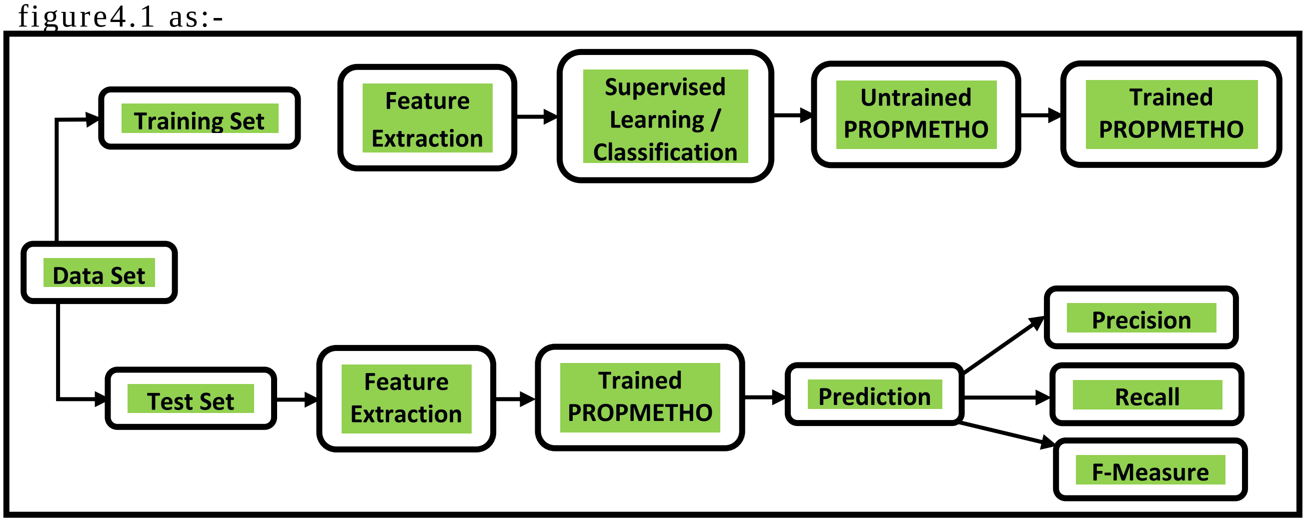


Figure4.1: Overall Procedure with PROPMETHO

In traditional way, It can also be defined as four step process:- first is training of model, second is feature extraction, third is classification and last is training/testing/validation of model.

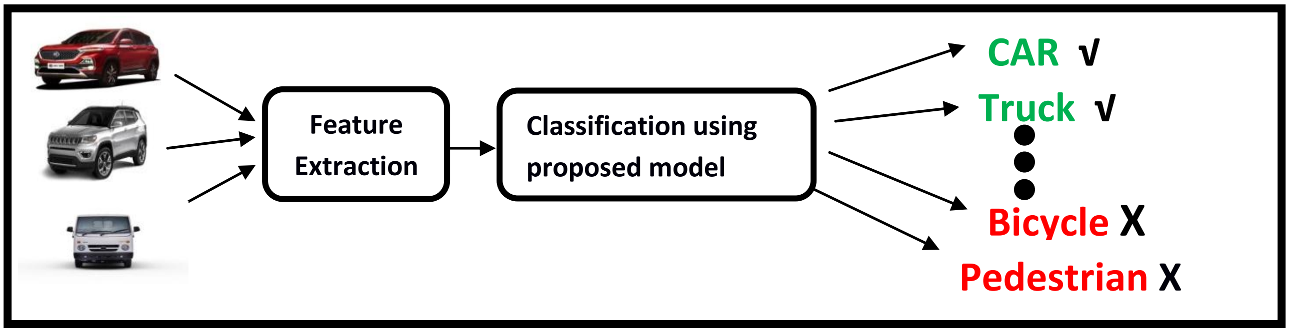


Figure4.2: Traditional Way of Classification [112]

4.4.1 Training of Model

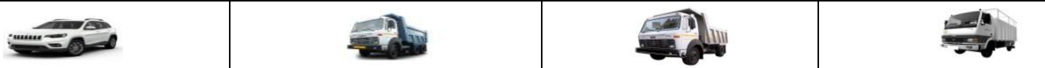
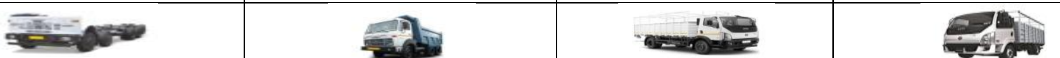
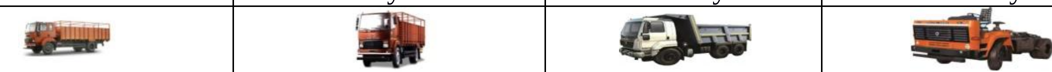
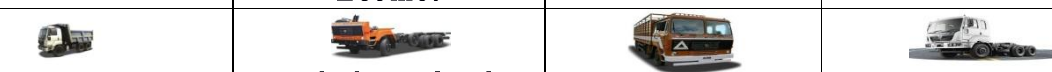
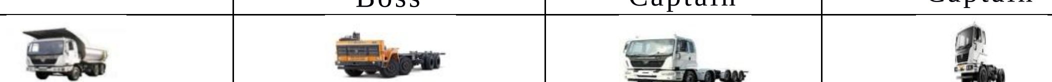
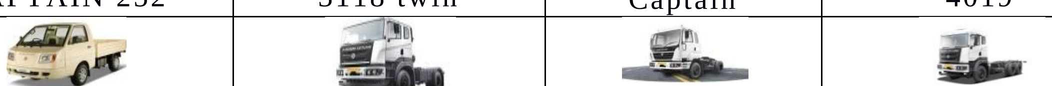
For the training of model, Data set has been prepared. Data set is divided into two parts: first is training set and second is test set. Further, the training set has two parts first is having positive frames and second part is having negative frames. Training of model is divided into two phases. First, positive image feeding and second is negative image feeding. For the positive image feeding, all pictures will be used related to cars of different brands, jeeps of different brands and trucks of different brands. All the images has taken from the standard database of car by Teoalida [113]. Whereas for the negative image feeding, all pictures will be related to other than cars, jeeps and cars. Negative image feeding consist of pictures of trees, pedestrians, buildings, birds etc. In other words, all the images that don't have cars, trucks and jeep will come under negative image. For the training of model, the following more than 250 vehicles shown in table4.2 has taken into consideration as positive image feeding:-

Table4.2: Vehicles Used for Training of PROPMETHO with Positive Image Feeding [113]

 MG hector	 Jeep Compass	 Toyota Fortuner	 Ford Endeavour
 Hyundai Venue	 Hyundai Santro	 Bajaj Qute	 Isuzu D-Max

Mahindra XUV 300	Mahindra Alturas G4	Ford Mustang	Volkswagen Polo
Renault Kwid	Hyundai Creta	Hyundai Grand i10	Renault Captur
Toyota Blanze	Toyota Land Cruiser	Datsun Go+	Nissan Kicks
Maruti Wagnor R	Hyundai EON	New Hyundai Verna	Land Rover Range
Tata Harriar	Mahindra Marazzo	Honda Amaze	Honda WR-V
Mahindra Bolero Pik-Up	Renault Duster	Ford EcoSport	Toyota Etios Liva
Maruti Suzuki Alto 800	Datsun Redi GO	Toyota Innova Crysta	Honda Civic
Hyundai i20	Mahindra e-Verito	Mahindra KUV100	Hyundai Xcent
Ford Figo	Skoda Kodiaq	Ford Freestyle	Hyundai i20 Active
Land Rover Discovery	Toyota Yaris	Volkswagen Passat	Honda Jazz
Toyota Platinum Etios	Nissan Terrano	Hyundai Tucson	Volkswagen Vento
Honda City	Hyundai Elantra	Mahindra Xylo	Maruti Ertiga

Mahindra Bolero Camper	Mahindra Quanto	Maruti Alto K10	Maruti Ignish
Mahindra Bolero	Mahindra Scorpio	Maruti Alto	Maruti Omni
Mahindra e2o	Mahindra TUV 300	Maruti Baleno	Maruti S-cross
Mahindra KUV 100	Mahindra Verito	Maruti Celerio	Maruti Swift
Maruti Wagnor	Mahindra XUV 500	Maruti Ciaz	Maruti Vitara Breza
Tata Aria	Mahindra XUV 700	Maruti _Dzire	Tata Manza
Tata Safari	Tata Tigor	Tata Sumo	Tata Nexon
Tata Indigo	Tata Zest	Tata LPT 1109 HEX	Tata 207 RX Common
Mahindra Thar	JK: Standard	Tata LPT 2518	Tata SFC 709 EX
Mahindra Di	JK Unlimited	Tata LPT 407 EX	Tata Signa 4018.S
Jeep Renegade BU	J8 jeep	Tata Signa 4923.S	Tata SK 1613 Hymilera
Jeep Wrangler	TJL jeep	Tata SFC 407 PICKUP	Tata SK 407 EX
Jeep Grand Cherokee	JL jeep	Tata LPT 3118	Tata Prima LX 3718.T

 Jeep Compass	Tata ACE	Tata Yodha	Tata LPK 912
 Jeep Cherokee KL	Tata LPK 2518	Tata LPK 1618	Tata LPT 709 EX2
 tata lpt 3718	Tata Intra V20	Tata ULTRA 1518 T 5L	Tata Ultra 1012
 Tata LPT 1010 CRX	Ashok Leyland 161	Ashok Leyland	Ashok Leyland
 Ashok Leyland Ecomet 1214	Ashok Leyland Ecomet	Ashok Leyland 2518	Ashok Leyland 3518
 Ashok Leyland U-2518 T	Ashok Leyland 3118 LA	Ashok Leyland 3118	Ashok Leyland 4923
 Ashok Leyland 3718	Ashok Leyland Boss 1213	Ashok Leyland 3118	Ashok Leyland U 4923
 Ashok Leyland PARTNER 6	Ashok Leyland CAPTAIN	Ashok Leyland Boss	Ashok Leyland 2518 6S
 Ashok Leyland 1618	Ashok Leyland Boss	Ashok Leyland Capt	Ashok Leyland 1618
 Ashok Leyland PARTNER	Ashok Leyland Guru	Ashok Leyland Ecomet	Ashok Leyland U 3118
 Ashok Leyland 2518	Ashok Leyland A1 Boss	Ashok Leyland Captain	Ashok Leyland Captain
 Ashok Leyland CAPTAIN 252	Ashok Leyland 3118 twin	Ashok Leyland Captain	Ashok Leyland 4019
 Ashok Leyland DOST	Ashok Leyland Captain	Ashok Leyland U 3518	Ashok Leyland captain

SML Isuzu Samrat 21 BS-IV	Ashok Leyland U 4019	Ashok Leyland U 2518	SML Isuzu Samrat HD 19
SML Isuzu Cosmo BS-IV	Mahindra Furio 11	Ashok Leyland Captain	SML Isuzu Sartaj GS HG 72
Sml isuzu water tanker	Mahindra Furio 14	Ashok Leyland Captain	SML Isuzu Sartaj CNG
SML Isuzu Closed Van BS-IV	Mahindra Blazo X 31	SML Isuzu Super BS-IV	SML Isuzu Samrat GS CNG
SML Isuzu Reefer Van BS-IV	Mahindra Blazo X 25	Sml isuzu sartaj 5252	SML Isuzu Dual Cabin BS
SML Isuzu Dual Cabin	Mahindra Blazo X 25 9S	SML Isuzu Sartaj HG	SML Isuzu Supreme BS-IV
Sml isuzu dumper placer bs	Mahindra Blazo X 49	SML Isuzu Samrat GS	Sml Isuzu Sartaj GS HG 72
SML Isuzu Prison Van BS-IV	Mahindra Blazo X 31 8x4	SML Isuzu Tipper BS-IV	SML Isuzu Super 12
Eicher Pro 3015	Mahindra Blazo X 31 LIFT	SML Isuzu Sartaj 59	SML Isuzu Troop Carrier
Eicher Pro 1110XP	Mahindra Blazo X 31	Sml Isuzu Samrat	SML Isuzu Prestige BS
Eicher Pro 1095	Mahindra Blazo X 37	SML Isuzu Samrat	Eicher Pro 1059XP
Eicher Pro 2049	Mahindra Blazo X 37	SML Isuzu Truck	Eicher Pro 3016 AMT

Eicher Pro 1080	Mahindra Blazo X 25	Eicher Pro 6031	Eicher Pro 5016
Eicher Pro 1095XP	Mahindra Furio 12	Eicher Pro 1050	Eicher Pro 1080XPT
Eicher Pro 1114XP	Mahindra Furio 12 Reefer	Eicher Pro 6025T	Eicher Pro 1059 CNG
Eicher Pro 1090	Mahindra Blazo X 40	Eicher Pro 3016	Eicher Pro 2095 XP
Eicher Pro 6037	Mahindra blazo x 25	Eicher Pro 3014	Eicher Pro 1055
Eicher Pro 1075	Mahindra Blazo X 35 SWB	Eicher Pro 6041	Eicher Pro 1095 CNG
Eicher Pro 1080XP(DSD)	Mahindra blazo x 25	Eicher 10.75 E2 Plus	Eicher Pro 5016T
Eicher Pro 1110XPT	Eicher Pro 1110	Eicher Pro 5025	Eicher Pro 6049
Eicher Pro 8031T	Eicher Pro 1049	Eicher Pro 1055T	Eicher Pro 5031
Eicher Pro 8049 6x2	Eicher Pro 1059	Eicher Pro 3012	Eicher 1110 xp ms
Eicher 10.75 E2 Plus WT	Eicher Pro 1075 CNG	Eicher Pro Water	Eicher Pro 6025
Eicher Pro 6025T TM	Eicher Pro 1095T	Eicher 10.90 E2 Plus	Eicher Pro 8031XM
Eicher Pro 8049 6x4	Eicher Pro 6040	Eicher Pro 5040	

All the images that don't have the images used for positive image feeding will come under negative image feeding. Some examples are shown in table4.3

Table4.3: Images Used for Training of PROPMETHO with Negative Image Feeding

 Cows on Road	 Person behind plant	 Sheep's on Road 1	 Trees & Plants
 Birds On Road	 Two wheeler1	 Stones on Road	 Road
 Elephants on Road	 Two wheeler2	 Tree Fallen on Road	 Sign Board
 Elephants Kids on Road	 Vehicle not used in training	 Branches of Tree fallen on Road	 Pedestrian 1
 High Traffic on Road	 Cycler	 Zebra Crossing	 Sheep's on Road
 Pedestrian			

4.4.2 Feature Extraction

In this research work Blob extraction technique [114] is used for feature extraction. The blob extraction technique is performed on the resulting binary image from a thresholding step. This technique can also performed after gray-scale conversion phase. Blobs may be counted, filtered, and tracked. For the blob extraction, Lindeberg's watershed-based grey-level blob detection algorithm is very popular and used in the research work. The details are as under:-

Lindeberg's Watershed-Based Grey-Level Blob Detection Algorithm

For the purpose of detecting grey-level blobs (local extrema with extent) from a watershed analogy, Lindeberg developed an algorithm based on pre-sorting the pixels, alternatively connected regions having the same intensity, in decreasing order of the intensity values. Then, comparisons were made between nearest neighbours of either pixels or connected regions.

For simplicity, consider the case of detecting bright grey-level blobs and let the notation "higher neighbour" stand for "neighbour pixel having a higher grey-level value". Then, at any stage in the algorithm (carried out in decreasing order of intensity values) is based on the following classification rules:

A. If a region has no higher neighbour, then it is a local maximum and will be the seed of a blob. Set a flag which allows the blob to grow.
B. Else, if it has at least one higher neighbour, which is background, then it cannot be part of any blob and must be background.
C. Else, if it has more than one higher neighbour and if those higher neighbours are parts of different blobs, then it cannot be a part of any blob, and must be background. If any of the higher neighbors are still allowed to grow, clear their flag which allows them to grow.
D. Else, it has one or more higher neighbours, which are all parts of the same blob. If that blob is still allowed to grow then the current region should be included as a part of that blob. Otherwise the region should be set to background.

Compared to other watershed methods, the flooding in this algorithm stops once the intensity level falls below the intensity value of the so-called delimiting saddle point associated with the local maximum. However, it is rather straightforward to extend this approach to other types of watershed constructions. For example, by proceeding beyond the first delimiting saddle point a "grey-level blob tree" can be constructed. Moreover, the grey-level blob detection method was embedded in a scale space representation and performed at all levels of scale, resulting in a representation called the scale-space primal sketch.

This algorithm with its applications in computer vision is described in more detail in Lindeberg's thesis [115] as well as the monograph on scale-space theory [116] partially based on that work. Earlier presentations of this algorithm can also be found in [117, 118]. More detailed treatments of applications of grey-level blob detection and the scale-space primal sketch to computer vision and medical image analysis are given in [119, 120, 121].

4.4.3 Classification

In this research, supervised classification method [122] is used. Supervised learning is a task of machine learning which guesses a function from labelled training data. The training data consist of a set of training examples. In supervised learning, each example consists an input object and a desired output value. A supervised learning algorithm examines the training data and produces an inferred function, which can be used for mapping new examples.

An optimal scenario will allow for the algorithm to correctly predict the class labels for unseen instances.

To solve the supervised learning problems following steps should be considered [123]

A. Decide the type of data which is going to be used as training sets. In the case of object recognition, for example, this might be a single object or number of objects.

B. Collect a training set. It must represent the real world entities. Thus, a set of input objects is collected and corresponding outputs are also collected. Decide the input feature representation of the learned function. The accuracy of the learned function depends strongly on the representation of input object. Finally, the input object is converted into a feature vector, which contains a number of features that gives the description of object. The number of features should not be too large, because of dimensionality problem but should contain sufficient information to accurately predict the output.

C. Decide the structure of the learned function and corresponding learning algorithm. For example, one may choose to use support vector machines or decision trees.

D. Complete the design. Run the learning algorithm on the collected training set.

E. Check the accuracy of the learned function. After parameter adjustment and learning, the performance of the resulting function should be checked on a test set that is different from the training set.

After the classification process, different designed scenarios will be considered to evaluate the performance and effectiveness of the PROPMETHO. Total six scenarios were designed. Two scenarios were established for low traffic, two for medium traffic and two for high traffic. The details of each and every scenario are given in the sections given below:-

4.4.4 Scenarios for Low Traffic

In Low Traffic scenario, maximum frames out of all the collected frames were with one vehicle or two vehicles. That means the delay and distance between two vehicles were very high. For the Low Traffic Scenario, two conditions were taken. 1) Low Traffic without Overlapping of Vehicle. 2) Low Traffic with Overlapping of Vehicle. For this scenario, video capturing at Babasaheb Bhimrao Ambedkar University Premises was used for the evaluation of overall performance with 6 minutes, 10 minutes 15 minutes etc timing.

Low Traffic without Overlapping of Vehicle: in this scenario, the delay between two vehicle was very high that means after monitoring of one vehicle, other vehicle came after two minutes to thirty minutes delay. It also showed that the distance between two vehicles was high. Examples of frames containing one vehicle are shown in figure:-

Figure4.3: LT_Frame with Car1

Figure4.4: LT_Frame with Car2

Figure4.5: LT_Frame with Car3

Low Traffic with Overlapping of Vehicle: in this scenario, even though the delay between two vehicles was very high but there were the situation of overlapping of vehicles. In overall capturing of video only one to two frames were existed with overlapping of vehicles. shows that the distance between two vehicles is high. In this scenario, video capturing of Babasaheb Bhimrao Ambedkar University Premises is used for 6 minutes, 10 minutes 15 minutes etc. Examples of frames containing overlapping of vehicle are shown in figure:-

Figure4.6: LT_Overlapping of Cars1

Figure4.7: LT_Overlapping of Cars2

Figure4.8: LT_Overlapping of Car3

4.4.5 Scenarios for Medium Traffic

In Medium Traffic scenario maximum frames out of all the collected frames are with three vehicle or five vehicles. That means the delay and distance between two vehicles were less as compared to vehicles under medium traffic. For the Medium Traffic Scenario, two conditions are taken. 1) Medium Traffic without Overlapping of Vehicle. 2) Medium Traffic with Overlapping of Vehicle. For this scenario, video capturing at gate no. 3 of Babasaheb Bhimrao Ambedkar University was used for the evaluation of overall performance with 6 minutes, 10 minutes 15 minutes etc timing.

Medium Traffic without Overlapping of Vehicle: in this scenario, the delay between two vehicle was less than the vehicle under low traffic that means after monitoring of one vehicle, other vehicle came after one minutes to five minutes delay. It also showed that the distance between two vehicles was not very high. Examples of frames containing vehicles are shown in figure:-

Figure4.9: MT_Frame with Car1

Figure4.10: MT_Frame with Car2

Figure4.11: MT_Frame with Car3

Medium Traffic with Overlapping of Vehicle: in this scenario, the delay between two vehicles was not very high and there were the situation of overlapping of vehicles. In overall capturing of video many frames but not all frames were existed with overlapping of vehicles. Examples of frames containing overlapped vehicles are shown in figure:-

Figure4.12: MT_Overlapping of Cars1

Figure4.13: MT_Overlapping of Cars2

Figure4.14: MT_Overlapping of Car3

4.4.6 Scenarios for High Traffic

In High Traffic scenario maximum frames out of all the collected frames were with five vehicles or more vehicles. That means the delay and distance between two vehicles were very less as compared to vehicles under medium traffic. For the High Traffic Scenario, two conditions were taken. 1) High Traffic without Overlapping of Vehicle. 2) High Traffic with Overlapping of Vehicle. For this scenario, video capturing at hajaratganj was used for the evaluation of overall performance with 6 minutes, 10 minutes 15 minutes etc timing.

High Traffic without Overlapping of Vehicle: in this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. It also showed that the distance between two vehicles was very less. It was very difficult to capture the video of high traffic without overlapping of vehicles.

High Traffic with Overlapping of Vehicle: in this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. In overall capturing of video all most all the frames with overlapping of vehicles.

Figure4.15: MT_Overlapping of Cars1

Figure4.16: MT_Overlapping of Cars2

4.5 Simulation Report

Total six simulations was carried out using different challenges to verify the effectiveness of the proposed methodology “PROPMETHO”. Each simulation has the some parameters namely Video ID, Period of Time, View Point, Frame rate Traffic Direction, Duration of Video in Sec., Manual Counting, PROPMETHO Counting, class of object, average speed, detection rate. Each recorded video was given unique Video ID. In Period of Time, it was seen that whether the video was captured in day time or night time. During the capture of video, traffic direction was towards the camera therefore frontal view of vehicle has been taken.

4.5.1 Simulation Report1: Low Traffic without Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, LT_V1, LT_V2, LT_V3, LT_V4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. The different captured frame at different time intervals T1, T2, T3 are shown below:-

Figure4.17: LT_Detection_Car1

Figure4.18: LT_Detection_Car2

Figure4.19: LT_Detection_Car3

Simulation report of this scenario is shown in the table below:-

Table4.4: Simulation Report1: Low Traffic without Overlapping of Vehicle

Video ID	Traffic Direction	Duration of Video in Sec.	Manual Counting	PROPMETHO Counting	Class of Object	Average Speed in km/hour	Detection Rate
LT_V1	Towards the camera	360 Sec.	20	20	Car	30.3 km/hour	100%
LT_V2	Towards the camera	600 Sec	15	15	Car	45 km/hour	100%
LT_V3	Towards the camera	900 Sec	30	30	Car & Jeep	35 km/hour	100%
LT_V4	Towards the camera	1200 Sec	40	40	Car	37 km/hour	100%

From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

4.5.2 Simulation Report2: Low Traffic with Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, LT_VO1, LT_VO2, LT_VO3, LT_VO4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. The different captured frame at different time intervals T1, T2, T3 are shown below:-

Figure4.20: LT_VODetection_Cars1

Figure4.21: LT_VODetection_Cars2

Figure4.22: LT_VODetection_Cars3

Simulation report of this scenario is shown in the table below:-

Table4.5: Simulation Report2: Low Traffic with Overlapping of Vehicle

Video ID	Traffic Direction	Duration of Video in Sec.	Manual Counting	PROPMETHO Counting	Class of Object	Average Speed in km/hour	Detection Rate
LT_VO1	Towards the camera	360 Sec.	25	25	Car	42 km/hour	100%
LT_VO2	Towards the camera	600 Sec	20	20	Car	33 km/hour	100%
LT_VO3	Towards the camera	900 Sec	35	35	Car & Jeep	37 km/hour	100%
LT_VO4	Towards the camera	1200 Sec	45	45	Car	40 km/hour	100%

From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

4.5.3 Simulation Report3: Medium Traffic without Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, MT_V1, MT_V2, MT_V3, MT_V4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. The different captured frame at different time intervals T1, T2, T3 are shown below:-

Figure4.23: MT_Detection_Cars1 **Figure4.24: MT_Detection_Cars2** **Figure4.25: MT_Detection_Cars3**

Simulation report of this scenario is shown in the table below:-

Table4.6: Simulation Report3: Medium Traffic without Overlapping of Vehicle

Video ID	Traffic Direction	Duration of Video in Sec.	Manual Counting	PROPMETHO Counting	Class of Object	Average Speed in km/hour	Detection Rate
MT_V1	Towards the camera	360 Sec.	30	30	Car & Jeep	38 km/hour	100%
MT_V2	Towards the camera	600 Sec	55	55	Car. Jeep & Truck	42 km/hour	100%
MT_V3	Towards the camera	900 Sec	87	87	Car. Jeep & Truck	43 km/hour	100%
MT_V4	Towards the camera	1200 Sec	115	115	Car. Jeep & Truck	50 km/hour	100%

From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

4.5.4 Simulation Report4: Medium Traffic with Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, MT_VO1, MT_VO2, MT_VO3, MT_VO4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. The different captured frame at different time intervals T1, T2, T3 are shown below:-

Figure4.26: MT_VODetection_Cars1

Figure4.27: MT_VODetection_Cars2

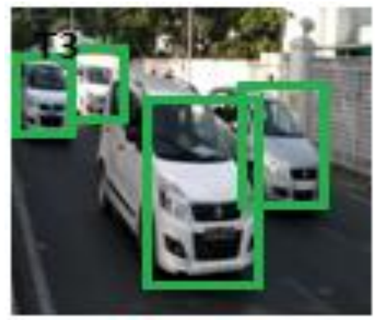


Figure4.28: MT_VODetection_Cars3

Simulation report of this scenario is shown in the table below:-

Table4.7: Simulation Report4: Medium Traffic with Overlapping of Vehicle

Video ID	Traffic Direction	Duration of Video in Sec.	Manual Counting	PROPMETHO Counting	Class of Object	Average Speed in km/hour	Detection Rate
MT_VO1	Towards the camera	360 Sec.	45	45	Car. Jeep & Truck	44 km/hour	100%
MT_VO2	Towards the camera	600 Sec	95	95	Car. Jeep & Truck	48 km/hour	100%
MT_VO3	Towards the camera	900 Sec	111	111	Car. Jeep & Truck	52 km/hour	100%
MT_VO4	Towards the camera	1200 Sec	130	130	Car. Jeep & Truck	48 km/hour	100%

From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

4.5.5 Simulation Report5: High Traffic without Overlapping of Vehicle

In this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. It also showed that the distance between two vehicles was very less. It was very difficult to capture the video of high traffic without overlapping of vehicles. Therefore, no simulation report was done.

4.5.6 Simulation Report6: High Traffic with Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, HT_VO1, HT_VO2, HT_VO3, HT_VO4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. The different captured frame at different time intervals T1, T2 are shown below:-

Figure4.29: HT_VODetection_Cars1

Figure4.30: HT_VODetection_Cars2

Simulation report of this scenario is shown in the table below:-

Table4.8: Simulation Report4: Medium Traffic with Overlapping of Vehicle

Video ID	Traffic Direction	Duration of Video in Sec.	Manual Counting	PROPMETHO Counting	Class of Object	Average Speed in km/hour	Detection Rate
HT_VO1	Towards the camera	360 Sec.	110	105	Car. Jeep & Truck	55 km/hour	95.45%
HT_VO2	Towards the camera	600 Sec	212	201	Car. Jeep & Truck	51 km/hour	94.81%
HT_VO3	Towards the camera	900 Sec	356	325	Car. Jeep & Truck	56 km/hour	91.29%
HT_VO4	Towards the camera	1200 Sec	487	465	Car. Jeep & Truck	58 km/hour	95.48%

From the report, it is clear that PROPMETHO is able to detect approx 94% vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

4.6 Performance Analysis

Performance Analysis of the system can be done with the use of binary decision problem. That means the decision can be made on the basis of two values. Here, classifier labels will be two either positive or negative. In our result positive means, frame will have the image of vehicles like Car, Jeep or Truck where as negative means, frame will have the image of other than vehicle like pedestrian, road, building etc. To quantify the classification performance, with respect to some ground – truth classification, the following basic measures can be used.

A. Positive (P): Actual is a vehicle [car, jeep, truck].
B. Negative (N): Actual is not a vehicle [car, jeep, truck].
C. True Positive (TP): Actual is vehicle and is predicted to be vehicle.
D. True Negative (TN): Actual is not vehicle and is predicted not to be vehicle.
E. False Positive (FP): Actual is not vehicle and is predicted to be vehicle.
F. False Negative (FN): Actual is vehicle and is predicted not to be vehicle.

This can also be understood by the confusion matrix given below:-

Table4.9: Confusion Matrix

	Actual Positive image	**Actual Negative image**
Estimated Positive image	TP	FP
Estimated Negative Image	FN	TN

With the help of confusion matrix, the following can be calculated:-

a) Precision = TP/(TP+FP)

b) Recall = TP/(TP+FN)

c) F-measure = (2*Recall*Precision)/(Recall + Precision)

From the values of Precision, Recall and F-measure, following can be stated:-

a) .If the value of recall is high and the value of precision is low, that means most of the vehicles are correctly recognized (Low FN) but there are a lot of false positive.

b) .If the value of recall is low and the value of precision is high, which means most of the vehicles are missed (high FN) and those are predicted as vehicles are indeed vehicle (Low FP).

c) .If the value of F-measure is high, that means predictive power of the classification procedure will be good. A score of F- measure lies between 1 to 0. If the value of F- measure is 1 that means the classification procedure is perfect.

The performance analysis of results given by PROPMETHO is evaluated with the use of above said parameters: 1) Precision 2) Recall 3) F-Score.

4.6.1 Performance Analysis1: Low Traffic without Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under low traffic without overlapping of the vehicle scenario. In all the four cases : LT_V1, LT_V2, LT_V3, LT_V4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.10 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect. The performance analysis under Low Traffic without Overlapping of Vehicle Scenario is as under:-

Table4.10: Performance Analysis1: Low Traffic without Overlapping of Vehicle

Video ID	Vehicles	TP	FP	FN	Precision in %	Recall in %	F-Measure in %
LT_V1	22	20	1	2	95.2	90.9	93
LT_V2	16	15	0	1	100	93.7	96.7
LT_V3	33	30	1	3	96.7	90.9	93.7
LT_V4	45	40	3	5	93.0	88.8	90.8

4.6.2 Performance Analysis2: Low Traffic with Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under low traffic with overlapping of the vehicle scenario. In all the four cases : LT_VO1, LT_VO2, LT_VO3, LT_VO4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.11 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect. The performance analysis under Low Traffic with Overlapping of Vehicle Scenario is as under:-

Table4.11: Performance Analysis2: Low Traffic with Overlapping of Vehicle

Video ID	Vehicles	TP	FP	FN	Precision in %	Recall in %	F-Measure in %
LT_VO1	28	25	2	3	92.5	89.2	90.0
LT_VO2	23	20	1	3	95.2	86.9	90.8
LT_VO3	39	35	1	4	97.2	89.7	93.2
LT_VO4	50	45	2	5	95.7	90.0	92.7

4.6.3 Performance Analysis3: Medium Traffic without Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under medium traffic without overlapping of the vehicle scenario. In all the four cases : MT_V1, MT_V2, MT_V3, MT_V4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.12 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect. The performance analysis under Medium Traffic without Overlapping of Vehicle Scenario is as under:-

Table4.12: Performance Analysis3: Medium Traffic without Overlapping of Vehicle

Video ID	Vehicles	TP	FP	FN	Precision in %	Recall in %	F-Measure in %
MT_V1	33	30	1	3	96.7	90.9	93.7
MT_V2	60	55	2	5	96.4	91.6	93.9
MT_V3	96	87	3	9	96.6	90.6	93.5
MT_V4	126	115	4	11	96.6	91.2	93.8

4.6.4 Performance Analysis4: Medium Traffic with Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under medium traffic with overlapping of the vehicle scenario. In all the four cases : MT_VO1, MT_VO2, MT_VO3, MT_VO4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.13 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect. The performance analysis under Medium Traffic with Overlapping of Vehicle Scenario is as under:-

Table4.13: Performance Analysis4: Medium Traffic with Overlapping of Vehicle

Video ID	Vehicles	TP	FP	FN	Precision in %	Recall in %	F-Measure in %
MT_VO1	49	45	1	4	97.8	91.8	94.7
MT_VO2	104	95	3	9	96.9	91.3	94.0
MT_VO3	122	111	5	11	95.6	90.9	93.1
MT_VO4	144	130	6	14	95.5	90.2	92.7

4.6.5 Performance Analysis5: High Traffic without Overlapping of Vehicle

In this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. It also showed that the distance between two vehicles was very less. It was very difficult to capture the video of high traffic without overlapping of vehicles. So no simulation report was done. Therefore, no analysis of performance can be done.

4.6.6 Performance Analysis6: High Traffic with Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under high traffic with overlapping of the vehicle scenario. In all the four cases : HT_VO1, HT_VO2, HT_VO3, HT_VO4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.14 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect. The performance analysis under Medium Traffic with Overlapping of Vehicle Scenario is as under:-

Table4.14: Performance Analysis6: High Traffic with Overlapping of Vehicle

Video ID	Vehicles	TP	FP	FN	Precision in %	Recall in %	F-Measure in %
HT_VO1	115	105	4	10	96.3	91.3	93.7
HT_VO2	222	201	5	21	97.5	90.5	93.8
HT_VO3	359	325	20	34	94.2	90.5	92.3
HT_VO4	510	465	22	45	95.4	91.1	93.2

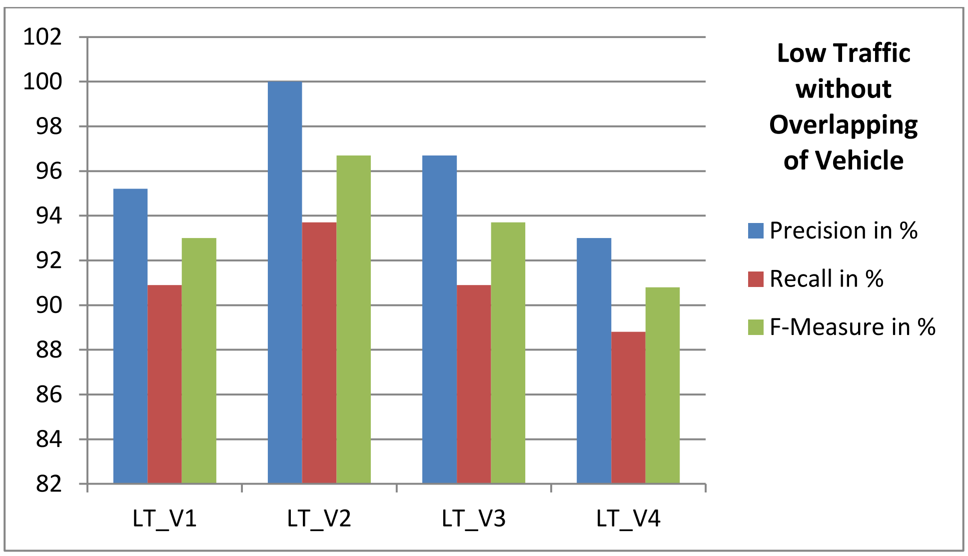
Therefore from all the 20 cases, it is clear that the PROPMETHO system works effectively as the value of F-Measure is nearer to 1 all the 20 cases. that means predictive power of the classification procedure is good and the classification procedure is perfect.

4.7 Comparative Analysis

To assess whether the proposed approach PROPMETHO is able to work effectively in all the 20 cases, there is a requirement of the comparative analysis of the performance of the PROPMETHO under different scenarios. All the comparisons were shown in the form of graph.

4.7.1 Comparative Analysis1: Low Traffic without Overlapping of Vehicle

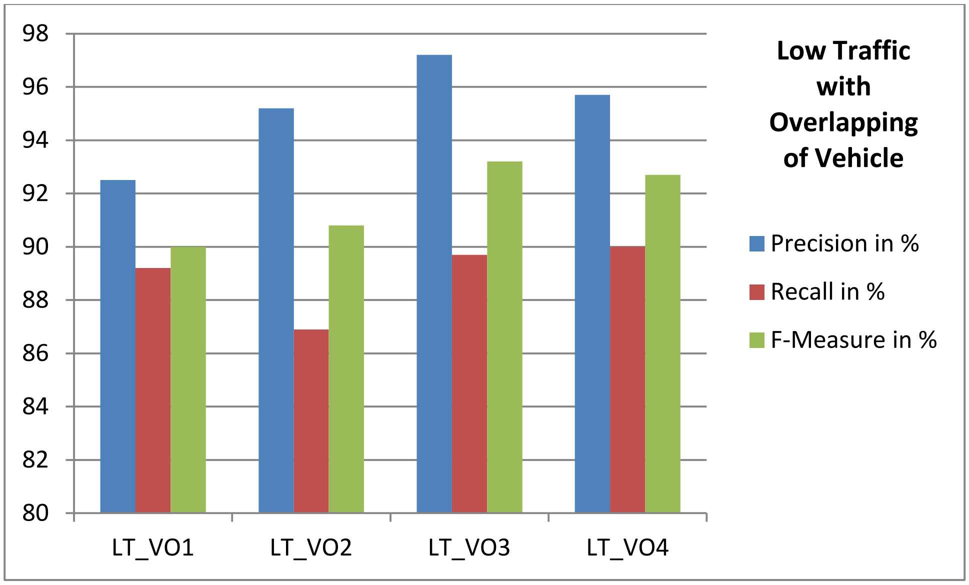
To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : LT_V1, LT_V2, LT_V3, LT_V4 are compared. From the graph4.1 it is clear that the value of Precision, Recall and F-Measure under LT_V2 is high which shows more suitability of PROPMETHO under LT_V2 case as compared to other cases LT_V1, LT_V3, LT_V4.



Graph4.1: Comparative Analysis1: Low Traffic without Overlapping of Vehicle

4.7.2 Comparative Analysis2: Low Traffic with Overlapping of Vehicle

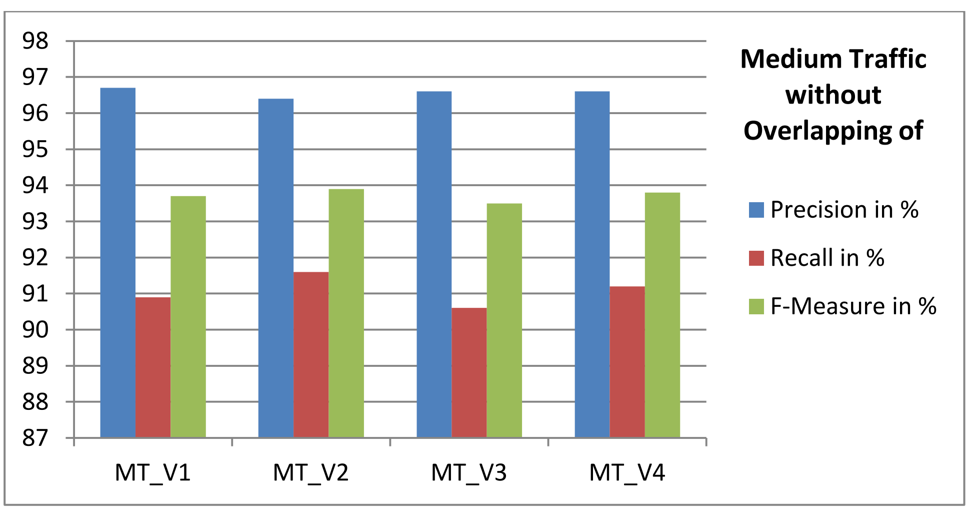
To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : LT_VO1, LT_VO2, LT_VO3, LT_VO4 are compared. From the graph4.2 it is clear that the value of Precision, Recall and F-Measure under LT_VO3 is high which shows more suitability of PROPMETHO under LT_VO3 case as compared to other cases LT_VO1, LT_VO2, LT_VO4.



Graph4.2: Comparative Analysis2: Low Traffic with Overlapping of Vehicle

4.7.3 Comparative Analysis3: Medium Traffic without Overlapping of Vehicle

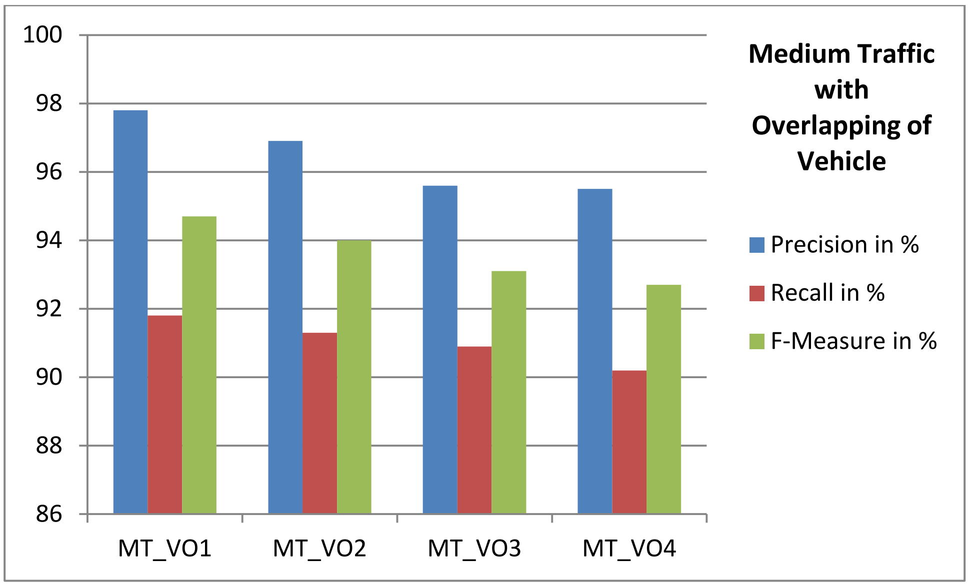
To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : MT_V1, MT_V2, MT_V3, MT_V4 are compared. From the graph4.3 it is clear that the value of Precision is high under MT_V1 case, whereas the values of Recall and F-Measure are high under MT_V2 case. Therefore, suitability of PROPMETHO under MT_V2 will be more as compared to other cases MT_V1, MT_V3, MT_V4.



Graph4.3: Comparative Analysis3: Medium Traffic without Overlapping of Vehicle

4.7.4 Comparative Analysis4: Medium Traffic with Overlapping of Vehicle

To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : MT_VO1, MT_VO2, MT_VO3, MT_VO4 are compared. From the graph4.4, it is clear that the values of Precision, Recall and F-Measure are high under MT_VO1 case. Therefore, suitability of PROPMETHO under MT_VO1 will be more as compared to other cases MT_VO2, MT_VO3, MT_VO4 cases.



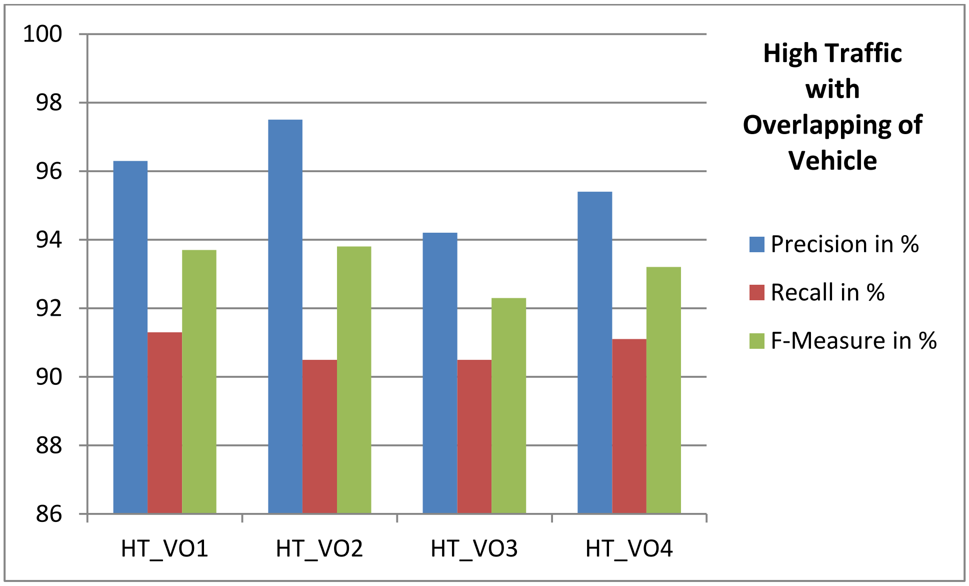
Graph4.4: Comparative Analysis4: Medium Traffic with Overlapping of Vehicle

4.7.5 Comparative Analysis5: High Traffic without Overlapping of Vehicle

No comparative analysis has done as this scenario is not simulated due to non availability of without overlapped vehicles.

4.7.6 Comparative Analysis6: High Traffic with Overlapping of Vehicle

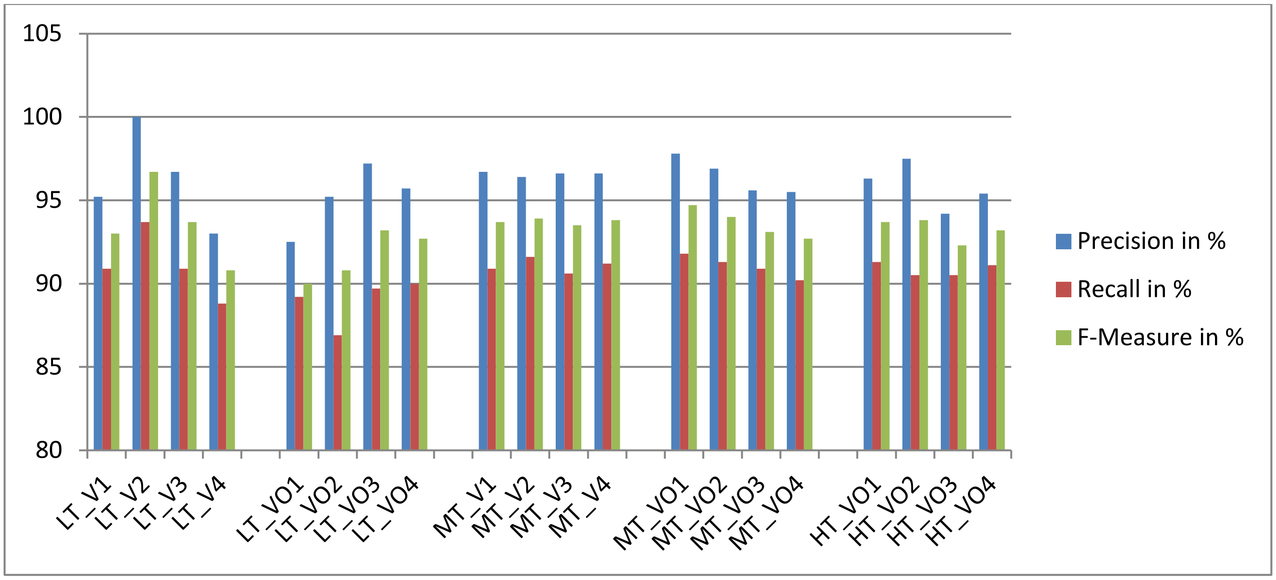
To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : HT_VO1, HT_VO2, HT_VO3, HT_VO4 are compared. From the graph4.5, it is clear that the value of Precision is high under HT_VO2 case, whereas the values of Recall and F-Measure are high under HT_VO1 case. Therefore, suitability of PROPMETHO under HT_VO1 will be more as compared to other cases HT_VO2, HT_VO3, HT_VO4.



Graph4.5: Comparative Analysis6: High Traffic with Overlapping of Vehicle

4.7.7 Overall Comparison of Cases under Low Traffic, Medium Traffic & High Traffic

To see the effectiveness, accuracy and efficiency of the PROPMETHO, an overall comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the twenty cases : LT_V1, LT_V2, LT_V3, LT_V4, LT_VO1, LT_VO2, LT_VO3, MT_V1, MT_V2, MT_V3, MT_V4, MT_VO1, MT_VO2, MT_VO3, MT_VO4, HT_VO1, HT_VO2, HT_VO3, HT_VO4 are compared. From the graph4.6, it is clear that the values of Precision, Recall and F-Measure are high under LT_V2 case. Therefore, suitability of PROPMETHO under LT_V2 will be more as compared to other remaining cases.



Graph4.6: Overall Comparison of Cases under Low Traffic, Medium Traffic & High Traffic

4.8 Comparison with Existing Approaches

In this section, for each video sequence the proposed PROPMETHO approach was compared with the existing available approaches. The name of the approaches are as follows:-

- Vehicle detection by using bLPS-HOG feature [124]
- Vehicle detection by using SIFT point feature [125]
- Vehicle detection by using PLS Hough transform [126]
- Vehicle detection by using HSV-GLCM approach [127]
- Vehicle detection by using ISM-SIFT feature [127]
- Vehicle detection by using FAST-HOG approach [127]

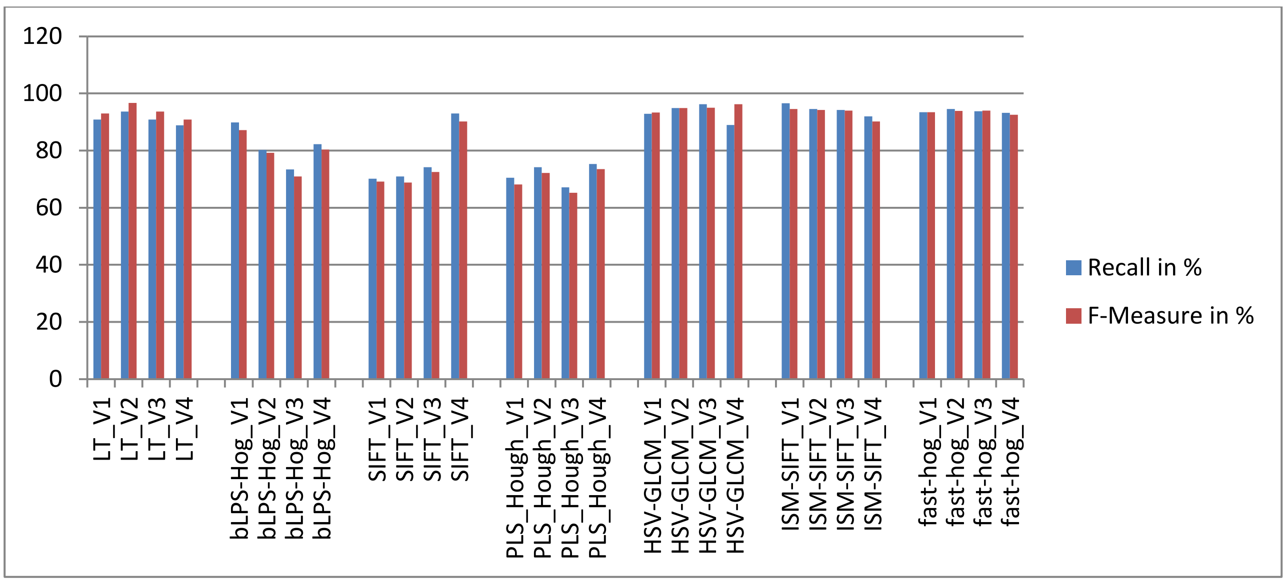
The values of Recall and F-Measure of all the twenty cases has been compared with all six existing approaches.

4.8.1 Comparison with Existing Approaches1: Low Traffic without Overlapping of Vehicle

In this section, all the four cases of low traffic without overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.15 and graph4.7, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

Table4.15: Comparison of Low Traffic without Overlapping of Vehicle with Existing Approaches

Video ID	PROPMETHO		bLPS-Hog		SIFT		PLS_Hough		HSV-GLCM		ISM-SIFT		fast-hog	
	Recall/F-Meas in %		Recall/F-Meas in %		Recall/F-Meas in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %	
LT_V1	90.9	93	89.9	87.13	70.14	69.12	70.52	68.14	92.82	93.29	96.58	94.55	93.39	93.4
LT_V2	93.7	96.7	80.17	79.16	70.96	68.83	74.21	72.15	94.92	94.92	94.57	94.26	94.59	93.83
LT_V3	90.9	93.7	73.43	70.96	74.18	72.48	67.15	65.19	96.18	95.04	94.22	94.04	93.77	93.99
LT_V4	88.8	90.8	82.21	80.33	93.01	90.16	75.33	73.48	88.91	96.18	91.94	90.13	93.24	92.53



Graph4.7: Comparison of Low Traffic without Overlapping of Vehicle with Existing Approaches

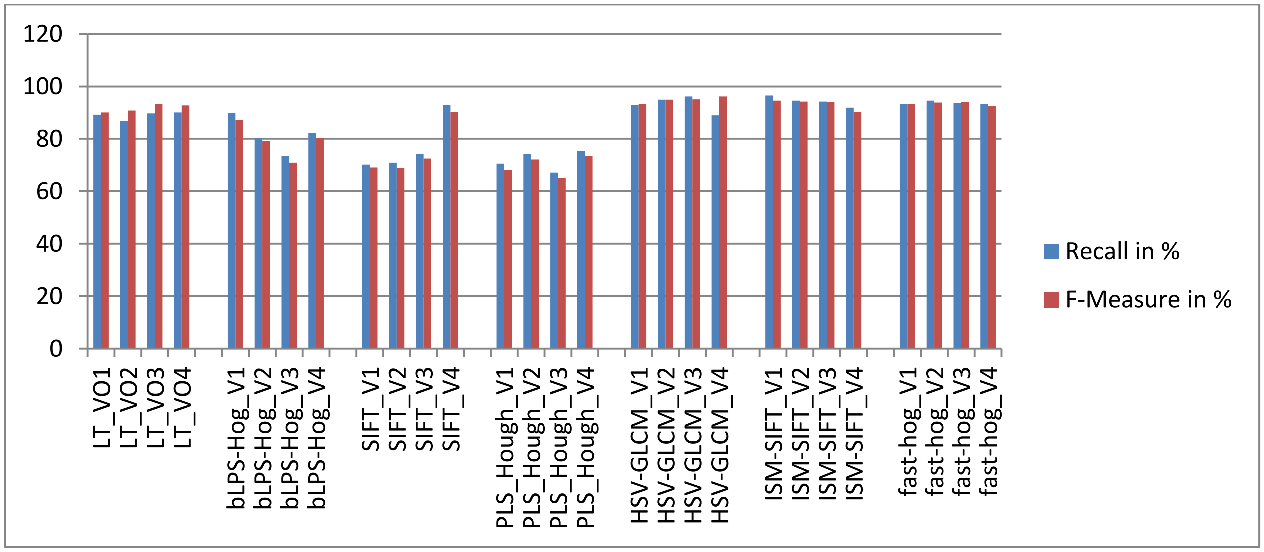
4.8.2 Comparison with Existing Approaches2: Low Traffic with Overlapping of Vehicle

In this section, all the four cases of low traffic with overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.16

and graph4.8, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

Table4.16: Comparison of Low Traffic with Overlapping of Vehicle with Existing Approaches

Video ID	PROPMETHO		bLPS-Hog		SIFT		PLS_Hough		HSV-GLCM		ISM-SIFT		fast-hog	
	Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %	
LT_VO1	89.2	90	89.9	87.13	70.14	69.12	70.52	68.14	92.82	93.29	96.58	94.55	93.39	93.4
LT_VO2	86.9	90.8	80.17	79.16	70.96	68.83	74.21	72.15	94.92	94.92	94.57	94.26	94.59	93.83
LT_VO3	89.7	93.2	73.43	70.96	74.18	72.48	67.15	65.19	96.18	95.04	94.22	94.04	93.77	93.99
LT_VO4	90	92.7	82.21	80.33	93.01	90.16	75.33	73.48	88.91	96.18	91.94	90.13	93.24	92.53



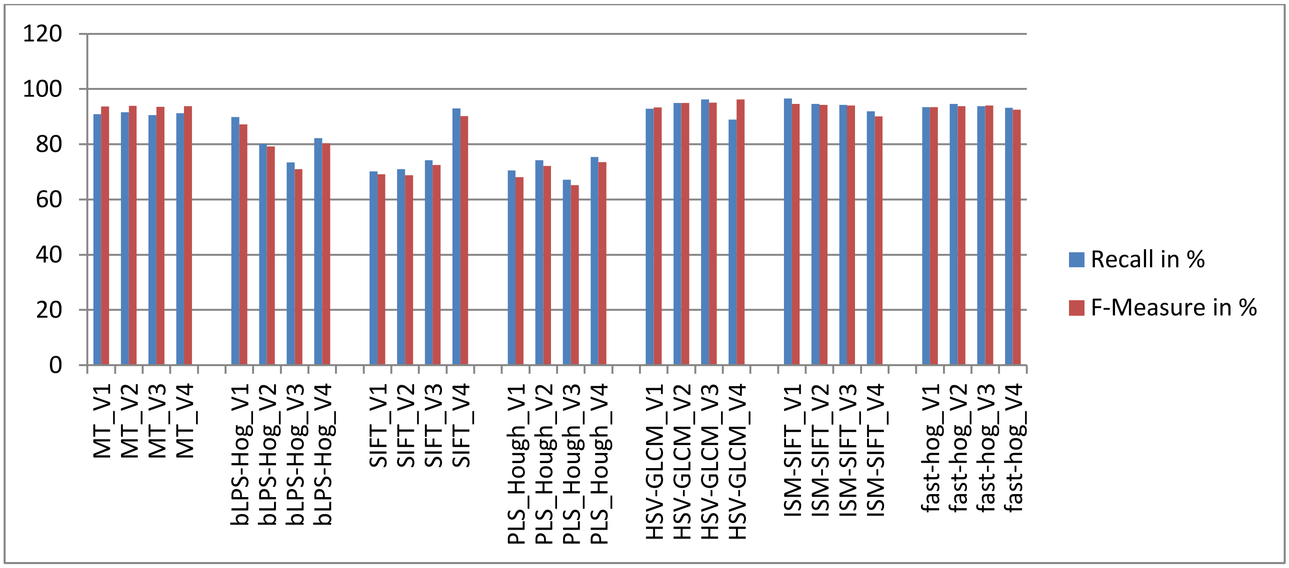
Graph4.8: Comparison of Low Traffic with Overlapping of Vehicle with Existing Approaches

4.8.3 Comparison with Existing Approaches3: Medium Traffic without Overlapping of Vehicle

In this section, all the four cases of Medium traffic without overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.17 and graph4.9, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

Table4.17: Comparison of Medium Traffic without Overlapping of Vehicle with Existing Approaches

Video ID	PROPMETHO		bLPS-Hog		SIFT		PLS_Hough		HSV-GLCM		ISM-SIFT		fast-hog	
	Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %	
MT_V1	90.9	93.7	89.9	87.13	70.14	69.12	70.52	68.14	92.82	93.29	96.58	94.55	93.39	93.4
MT_V2	91.6	93.9	80.17	79.16	70.96	68.83	74.21	72.15	94.92	94.92	94.57	94.26	94.59	93.83
MT_V3	90.6	93.5	73.43	70.96	74.18	72.48	67.15	65.19	96.18	95.04	94.22	94.04	93.77	93.99
MT_V4	91.2	93.8	82.21	80.33	93.01	90.16	75.33	73.48	88.91	96.18	91.94	90.13	93.24	92.53



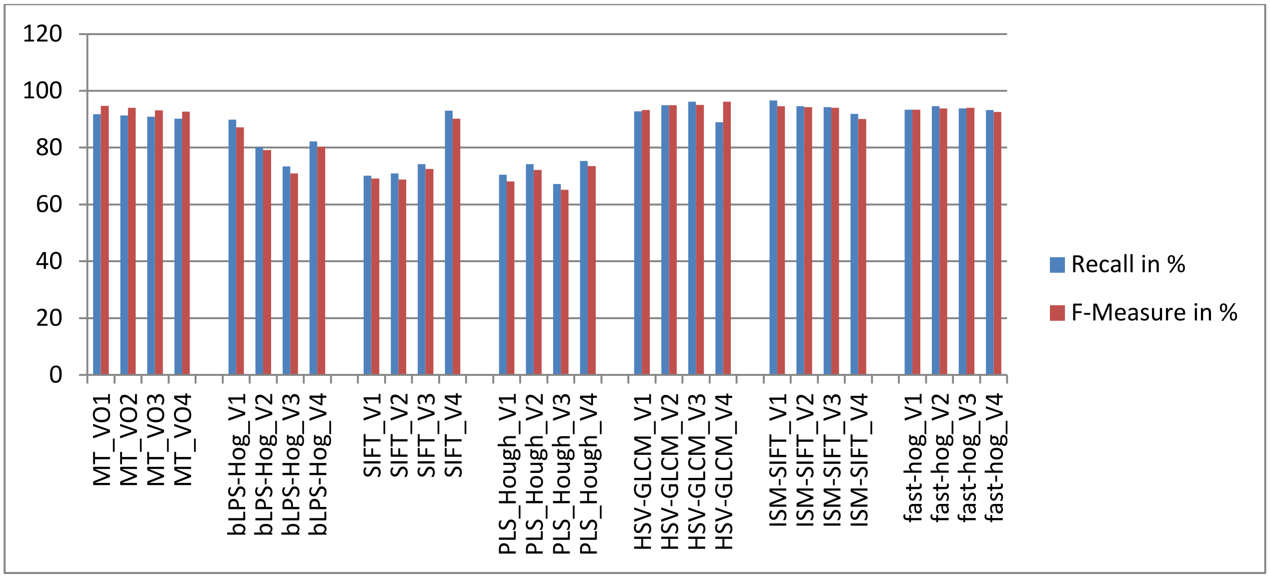
Graph4.9: Comparison of Medium Traffic without Overlapping of Vehicle with Existing Approaches

4.8.4 Comparison with Existing Approaches4: Medium Traffic with Overlapping of Vehicle

In this section, all the four cases of Medium traffic with overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.18 and graph4.10, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

Table4.18: Comparison of Medium Traffic with Overlapping of Vehicle with Existing Approaches

Video ID	PROPMETHO		bLPS-Hog		SIFT		PLS_Hough		HSV-GLCM		ISM-SIFT		fast-hog	
	Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %		Recall/F-Meas. in %	
MT_VO1	91.8	94.7	89.9	87.13	70.14	69.12	70.52	68.14	92.82	93.29	96.58	94.55	93.39	93.4
MT_VO2	91.3	94	80.17	79.16	70.96	68.83	74.21	72.15	94.92	94.92	94.57	94.26	94.59	93.83
MT_VO3	90.9	93.1	73.43	70.96	74.18	72.48	67.15	65.19	96.18	95.04	94.22	94.04	93.77	93.99
MT_VO4	90.2	92.7	82.21	80.33	93.01	90.16	75.33	73.48	88.91	96.18	91.94	90.13	93.24	92.53



Graph4.10: Comparison of Medium Traffic with Overlapping of Vehicle with Existing Approaches

4.8.5 Comparison with Existing Approaches5: High Traffic without Overlapping of Vehicle

No comparison has been done as no values are computed under this scenario.

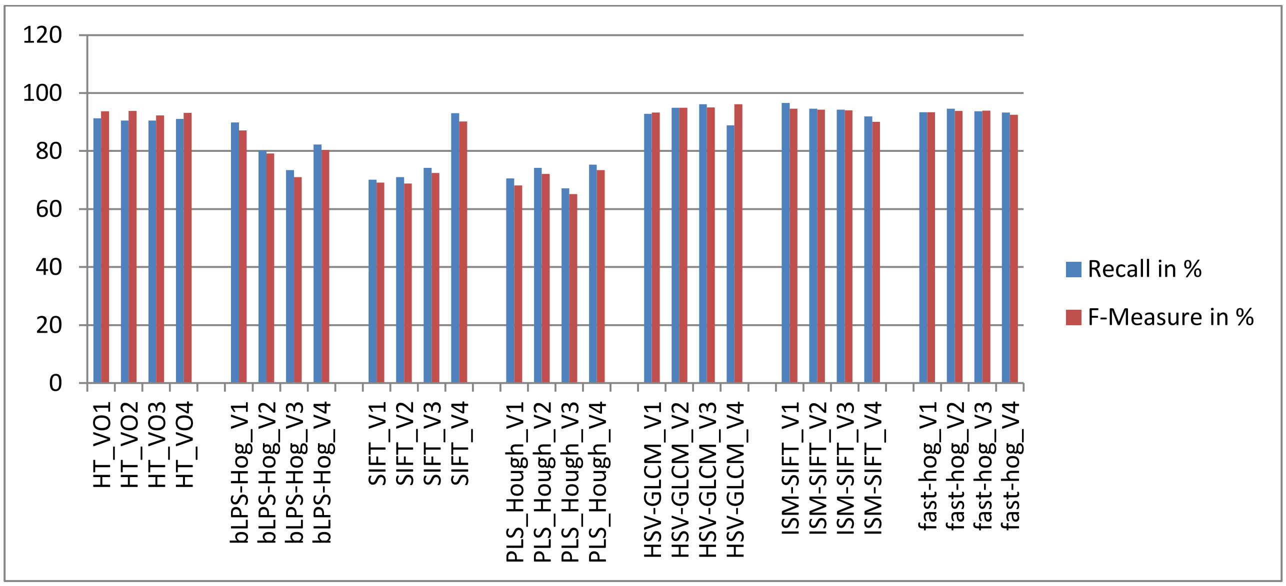
4.8.6 Comparison with Existing Approaches6: High Traffic with Overlapping of Vehicle

In this section, all the four cases of high traffic with overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.19

and graph4.11, it is clear that ISM-SIFT is more suitable as compared to PROPMETHO and other existing approaches.

Table4.19: Comparison of High Traffic with Overlapping of Vehicle with Existing Approaches

Video ID	PROPMETHO		bLPS-Hog		SIFT		PLS_Hough		HSV-GLCM		ISM-SIFT		fast-hog	
	Recall/F-Meas. in %		**Recall/F-Meas. in %**		**Recall/F-Meas. in %**		**Recall/F-Meas. in %**		**Recall/F-Meas. in %**		**Recall/F-Meas. in %**		**Recall/F-Meas. in %**	
HT_VO1	91.3	93.7	89.9	87.13	70.14	69.12	70.52	68.14	92.82	93.29	96.58	94.55	93.39	93.4
HT_VO2	90.5	93.8	80.17	79.16	70.96	68.83	74.21	72.15	94.92	94.92	94.57	94.26	94.59	93.83
HT_VO3	90.5	92.3	73.43	70.96	74.18	72.48	67.15	65.19	96.18	95.04	94.22	94.04	93.77	93.99
HT_VO4	91.1	93.2	82.21	80.33	93.01	90.16	75.33	73.48	88.91	96.18	91.94	90.13	93.24	92.53



Graph4.11: Comparison of High Traffic with Overlapping of Vehicle with Existing Approaches

4.9 Conclusion

In this chapter, major concern was on the design of experiment, simulation report, performance analysis and comparative analysis of PROPMETHO with existing available approaches. From the performance analysis and the comparative analysis, it was observed that PROPMETHO approach is a effective way to detect the vehicle with different challenges under low traffic scenario and medium traffic scenario. The performance of PROPMETHO under high traffic scenario is satisfactorily.

Chapter 5: Conclusions & Future Work

5.1 Background

Keeping in view of the upcoming technological trends in the field of auto driven vehicular navigation, it is a challenge for researchers to built a efficient and cost effective system in the field of vehicular navigation. The present study will pave path for more efficient, effective and cost effective application and directing other researcher's efforts in vehicular navigation field. As most of the accidents are happened due to not controlling of the speed of the vehicles. This PROPMETHO system can play an important role in maintaining the speed of the vehicles. Therefore, the chapter will provide the major findings that are the results of the experiments done using PROPMETHO. These results can be further utilized in the other scenarios that are not described in this research work.

5.2 Major Findings

In this thesis, PROPMETHO system was implemented to detect vehicles like car jeep and truck of different Indian and foreign brands. It also count no. of vehicle with a particular time frame in a scenario and useful to calculate the speed of the vehicle. This calculation of speed can be useful in controlling the speed of vehicles and to see whether the vehicle is driven under the threshold limit or above the threshold limit. Six experiments were conducted to see the accuracy and efficiency of the PROPMETHO approach.

5.2.1 Scenario1: Low Traffic without Overlapping of Vehicle

In Low Traffic scenario, maximum frames out of all the collected frames were with one vehicle or two vehicles. In this scenario, the delay between two vehicle was very high that means after monitoring of one vehicle, other vehicle came after two minutes to thirty minutes delay. It also showed that the distance between two vehicles was high. For this scenario, video capturing at Babasaheb Bhimrao Ambedkar University Premises was used for the evaluation of overall performance with 6 minutes, 10 minutes 15 minutes etc timing.

5.2.2 Scenario2: Low Traffic with Overlapping of Vehicle

in this scenario, even though the delay between two vehicles was very high but there were the situation of overlapping of vehicles. In overall capturing of video only one to two frames were existed with overlapping of vehicles. shows that the distance between two vehicles is high. In this scenario, video capturing of Babasaheb Bhimrao Ambedkar University Premises is used for 6 minutes, 10 minutes 15 minutes etc.

5.2.3 Scenario3: Medium Traffic without Overlapping of Vehicle

in this scenario, the delay between two vehicle was less than the vehicle under low traffic that means after monitoring of one vehicle, other vehicle came after one minutes to five minutes delay. It also showed that the distance between two vehicles was not very high.

5.2.4 Scenario4: Medium Traffic with Overlapping of Vehicle

In this scenario, the delay between two vehicles was not very high and there were the situation of overlapping of vehicles. In overall capturing of video many frames but not all frames were existed with overlapping of vehicles.

5.2.5 Scenario5: High Traffic without Overlapping of Vehicle

In this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. It also showed that the distance between two vehicles was very less. It was very difficult to capture the video of high traffic without overlapping of vehicles.

5.2.6 Scenario6: High Traffic with Overlapping of Vehicle

in this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. In overall capturing of video all most all the frames with overlapping of vehicles.

5.2.7 Simulation Report1: Low Traffic without Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, LT_V1, LT_V2, LT_V3, LT_V4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

5.2.8 Simulation Report2: Low Traffic with Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, LT_VO1, LT_VO2, LT_VO3, LT_VO4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

5.2.9 Simulation Report3: Medium Traffic without Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, MT_V1, MT_V2, MT_V3, MT_V4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

5.2.10 Simulation Report4: Medium Traffic with Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, MT_VO1, MT_VO2, MT_VO3, MT_VO4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. From the report, it is clear that PROPMETHO is able to detect vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

5.2.11 Simulation Report5: High Traffic without Overlapping of Vehicle

In this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. It also showed that the distance between two vehicles was very less. It was very difficult to capture the video of high traffic without overlapping of vehicles. Therefore, no simulation report was done.

5.2.12 Simulation Report6: High Traffic with Overlapping of Vehicle

In this simulation, four videos are captured at different point of time. All the four videos are given ID, HT_VO1, HT_VO2, HT_VO3, HT_VO4. All the four videos captured in day time. The direction of traffic was towards the camera. Therefore frontal view was captured. The frame rate was stable at the rate of 24 frames per second. From the report, it is clear that PROPMETHO is able to detect approx 94% vehicles correctly in all the four cases. It was also observed that even though same car visited the area many times, PROPMETHO counted the vehicle each time and the addition in the counting of vehicle was added.

5.2.13 Performance Analysis1: Low Traffic without Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under low traffic without overlapping of the vehicle scenario. In all the four cases : LT_V1, LT_V2, LT_V3, LT_V4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.10 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect.

5.2.14 Performance Analysis2: Low Traffic with Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under low traffic with overlapping of the vehicle scenario. In all the four cases : LT_VO1, LT_VO2, LT_VO3, LT_VO4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.11 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect.

5.2.15 Performance Analysis3: Medium Traffic without Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under medium traffic without overlapping of the vehicle scenario. In all the four cases : MT_V1, MT_V2, MT_V3, MT_V4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.12 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect.

5.2.16 Performance Analysis4: Medium Traffic with Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under medium traffic with overlapping of the vehicle scenario. In all the four cases : MT_VO1, MT_VO2, MT_VO3, MT_VO4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.13 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect.

5.2.17 Performance Analysis5: High Traffic without Overlapping of Vehicle

In this scenario, the delay between two vehicle was very less than the vehicle under medium traffic that means after monitoring of one vehicle, other vehicle came after ten to twenty seconds delay. It also showed that the distance between two vehicles was very less. It was very difficult to capture the video of high traffic without overlapping of vehicles. So no simulation report was done. Therefore, no analysis of performance can be done.

5.2.18 Performance Analysis6: High Traffic with Overlapping of Vehicle

Experiment analyses the effectiveness of the PROPMETHO under high traffic with overlapping of the vehicle scenario. In all the four cases : HT_VO1, HT_VO2, HT_VO3, HT_VO4, the values of TP, FP, FN, Precision, Recall and F-Measure are calculated. From the table4.14 it is clear the value of F-Measure is approx .9 which is nearer to 1 in all the four cases that means predictive power of the classification procedure is good and the classification procedure is perfect.

5.3 Other Findings

Comparative analysis has done among four cases of low traffic, medium traffic and high traffic. Comparative analysis with existing approach was also done.

5.3.1 Comparative Analysis1: Low Traffic without Overlapping of Vehicle

To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : LT_V1, LT_V2, LT_V3, LT_V4 are compared. From the graph4.1 it is clear that the value of Precision, Recall and F-Measure under LT_V2 is high which shows more suitability of PROPMETHO under LT_V2 case as compared to other cases LT_V1, LT_V3, LT_V4.

5.3.2 Comparative Analysis2: Low Traffic with Overlapping of Vehicle

To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : LT_VO1, LT_VO2, LT_VO3, LT_VO4 are compared. From the graph4.2 it is clear that the value of Precision, Recall and F-Measure under LT_VO3 is high which shows more suitability of PROPMETHO under LT_VO3 case as compared to other cases LT_VO1, LT_VO2, LT_VO4.

5.3.3 Comparative Analysis3: Medium Traffic without Overlapping of Vehicle

To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : MT_V1, MT_V2, MT_V3, MT_V4 are compared. From the graph4.3 it is clear that the value of Precision is high under MT_V1 case, whereas the values of Recall and F-Measure are high under MT_V2 case. Therefore, suitability of PROPMETHO under MT_V2 will be more as compared to other cases MT_V1, MT_V3, MT_V4.

5.3.4 Comparative Analysis4: Medium Traffic with Overlapping of Vehicle

To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : MT_VO1, MT_VO2, MT_VO3, MT_VO4 are compared. From the graph4.4, it is clear that the values of Precision, Recall and F-Measure are high under MT_VO1 case. Therefore, suitability of PROPMETHO under MT_VO1 will be more as compared to other cases MT_VO2, MT_VO3, MT_VO4 cases.

5.3.5 Comparative Analysis5: High Traffic without Overlapping of Vehicle

No comparative analysis has done as this scenario is not simulated due to non availability of without overlapped vehicles.

5.3.6 Comparative Analysis6: High Traffic without Overlapping of Vehicle

To see the effectiveness, accuracy and efficiency of the PROPMETHO, a comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the four cases : HT_VO1, HT_VO2, HT_VO3, HT_VO4 are compared. From the graph4.5, it is clear that the value of Precision is high under HT_VO2 case, whereas the values of Recall and F-Measure are high under HT_VO1 case. Therefore, suitability of PROPMETHO under HT_VO1 will be more as compared to other cases HT_VO2, HT_VO3, HT_VO4.

5.3.7 Overall Comparison of Cases under Low Traffic, Medium Traffic & High Traffic

To see the effectiveness, accuracy and efficiency of the PROPMETHO, an overall comparative analysis has been done in the form of graph. In this scenario, values of Precision, Recall and F-Measure under all the twenty cases : LT_V1, LT_V2, LT_V3, LT_V4, LT_VO1, LT_VO2, LT_VO3, MT_V1, MT_V2, MT_V3, MT_V4, MT_VO1, MT_VO2, MT_VO3, MT_VO4, HT_VO1, HT_VO2, HT_VO3, HT_VO4 are compared. From the graph4.6, it is clear that the values of Precision, Recall and F-Measure are high under LT_V2 case. Therefore, suitability of PROPMETHO under LT_V2 will be more as compared to other remaining cases.

5.3.8 Comparison with Existing Approaches1: Low Traffic without Overlapping of Vehicle

In this section, all the four cases of low traffic without overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.15

and graph4.7, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

5.3.9 Comparison with Existing Approaches2: Low Traffic with Overlapping of Vehicle

In this section, all the four cases of low traffic with overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.16 and graph4.8, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

5.3.10 Comparison with Existing Approaches3: Medium Traffic without Overlapping of Vehicle

In this section, all the four cases of Medium traffic without overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.17 and graph4.9, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

5.3.11 Comparison with Existing Approaches4: Medium Traffic with Overlapping of Vehicle

In this section, all the four cases of Medium traffic with overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.18

and graph4.10, it is clear that PROPMETHO is more suitable as compared to other existing approaches.

5.3.12 Comparison with Existing Approaches5: High Traffic without Overlapping of Vehicle

No comparison has been done as no values are computed under this scenario.

5.3.13 Comparison with Existing Approaches6: High Traffic with Overlapping of Vehicle

In this section, all the four cases of high traffic with overlapping of vehicle scenario is compared with all the six approaches namely bLPS-HOG, SIFT, PLS Hough, HSV-GLCM, ISM-SIFT and FAST-HOG approach. Comparisons have been shown in the form of table and graph both. Values of Recall and F-Measure are compared with the existing approaches. From the data shown in table4.19 and graph4.11, it is clear that ISM-SIFT is more suitable as compared to PROPMETHO and other existing approaches.

5.4 Future Work

There are many usage of artificial intelligence. Many potential applications of artificial intelligent are available in respect of the entertainment industry, computer games and robotic devices. Large establishments such as hospitals, banks and insurance, are also using AI to detect and predict trends of a customer behavior**.** Pattern recognition in images is a crucial component of automated intelligent systems required to create Real world applications. In the present work, the use of automated image recognition for identifying objects of interest on a road was done. Despite recent advances in artificial intelligence and pattern recognition among images it is still farfetched to accurately identify objects of interest. In this light we are exploring integrating various techniques and multimodal data acquisition techniques to identify objects of interest with reasonable degree of accuracy. Such a system has many modern uses like automated vehicle navigation, recreating scenarios in three dimensional world comma Augmented reality and virtual reality. Modern AI techniques evolving at a fast pace and in near future make come at par with humans or even exceed their performance.

Many major vehicle manufacturers and IT companies are involved in augmented reality for vehicular navigation. A few notable examples are from Google, Apple, Fiat, under daimlerchrysler, Toyota, VolksWagon, Tesla and Faraday Motors.

So far multimodal data acquisition is the norm for reliable object identification in a fast moving scenario like the roads. However in this example we are using temporal parallax with automated object identification to create Augmented reality to safely navigate. Assimilating multimodal data to create a coherent model for recreating dynamics fast paced scenario is very computationally intensive which prohibits its application in any Real world cost constrained environment. However researchers are quite hopeful regarding development of cost effective high volume data processes and associated algorithms to make it feasible. Another major concern in this field is lack of standardization and protocols and need for standardized ontology for computer vision domain is sorely felt. Future researcher would potentially collaborate to embark upon universal standardization so that interoperability of system and reliability are enhanced.

5.5 Conclusion

There are various number of strategies given by researchers for monitoring and controlling traffic of highways and roads. All the strategies have their advantages and disadvantages. Due to increase of traffic and high speedy vehicles, accidents are happened more frequent. To reduce accidents and control this situation, there is requirement of a system that can be able to monitor and control the situation in a very effective, efficient and adaptive manner.

Therefore, PROPMETHO approach can be a good and satisfactory solution for dealing with situations occurred due to large number of accidents.

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Appendix A

Plagiarism Report

URKUND

Urkund Analysis Result

Analysed Document: thesis.docx (D54399733)
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21

Development of a Novel Awareness Model for Rapid Object Detection in Vehicular Navigation

DECLARATION CERTIFICATE ACKNOWLEDGEMENTS ABSTRACT III LIST OF TABLES XVII LIST OF FIGURES XIII

CHAPTER 1: INTRODUCTION 1 1.1 Background 1.2 Vehicular Navigation 1.3 Object Detection in