Computer Engineering and Intelligent Systems
ISSN 2222-1719 (Paper) ISSN 2222-2863 (Online)
Vol.4, No.8, 2013

Identification and Classification of Moving Vehicles on Road

Suresh Babu Changalasetty[1*], Ahmed Said Badawy[1], Wade Ghribi[1], Haytham Ibrahim Ashwi[1], Ahmad Mohammed Al-Shehri[1], Ali Dhafer Ali Al-Shehri[1], Lalitha Saroja Thota[2], Ramakanth Medisetty[3]
1. Department of Computer Engineering, College of Computer Science, King Khalid University, Abha, Saudi Arabia
2. Department of Computer Science, College of Arts and Science, Khamis Mushayt, King Khalid University, Abha, Saudi Arabia
3. Department of Computer Science and Engineering, Vardhaman College of Engineering, JNTU, Hyderabad, India
* Email of the Corresponding author: sureshbabuchangalasetty@gmail.com

Abstract
It is important to know the road traffic density real time especially in cities for signal control and effective traffic management. In recent years, video monitoring and surveillance systems have been widely used in traffic management. Hence, traffic density estimation and vehicle classification can be achieved using video monitoring systems. The image sequences for traffic scenes are recorded by a stationary camera. The method is based on the establishment of correspondences between regions and vehicles, as the vehicles move through the image sequence. Background subtraction is used which improves the adaptive background mixture model and makes the system learn faster and more accurately, as well as adapt effectively to changing environments. The resulting system robustly identifies vehicles, rejecting background and tracks vehicles over a specific period of time. Once the (object) vehicle is tracked, the attributes of the vehicle like width, length, perimeter, area etc are extracted by image process feature extraction techniques. These features will be used in classification of vehicle as big or small using neural networks classification technique of data mining. In proposed system we use LABVIEW and Vision assistant module for image processing and feature extraction. A feed-forward neural network is trained to classify vehicles using data mining WEKA toolbox. The system will solve major problems of human effort and errors in traffic monitoring and time consumption in conducting survey and analysis of data. The project will benefit to reduce cost of traffic monitoring system and complete automation of traffic monitoring system.
Keywords: Image processing, Feature extraction, Segmentation, Threshold, Filter, Morphology, Blob, LABVIEW, NI, VI, Vision assistant, Data mining, Machine learning, Neural network, Back propagation, Multi layer perception, Classification, WEKA

1. Introduction
Closed-circuit television cameras are becoming increasingly common on freeways and are used for traffic management; the cameras allow operators to monitor traffic conditions visually. As the number of cameras increase, monitoring each of them by operators becomes a difficult task hence videos are recorded and such the videos are usually only monitored after an event of interest (e.g. an accident) has been known to occur within a particular camera's field of view. Manually reviewing the large amount of data they generate is often impractical. Thus, algorithms for analyzing video which require little or no human input are a good solution. With suitable processing and analysis it is possible to extract a lot of useful information on traffic from the videos, e.g., the number, type, and speed of vehicles using the road. Automatic detecting and tracking vehicles in video surveillance data is a very challenging problem in computer vision with important practical applications, such as traffic analysis and security. A vehicle tracking and classification system is described as one that can identify moving objects as vehicles and further classifies the vehicles into various classes.

2. Importance of the project
It is important to know the road traffic density and vehicle class for effective traffic signal control system and management and to estimate time for reaching from one location to another on traffic roads. In traffic zones, ban on big vehicles from road in school zone or sensitive areas may be done. The road design (width, thickness etc) also depend on traffic volume and type of vehicles.

3. Existing system
Existing method of traffic monitoring involves traffic count and classify the vehicle is done manually by employing number persons. Traffic monitoring is also done by installing cameras at various places. Several other vehicle detectors such as loop, infrared, ultrasonic, and microwave detectors are also existing but costly and require maintenances.

4. Proposed System

The system uses a single camera mounted usually on a pole or other tall structure, looking down on the traffic scene to capture video frames. With suitable image processing and analysis using LABVIEW it is possible to extract a lot of useful information on traffic from the videos, e.g., the number, type, class etc. To perform this task segmenting the video into foreground objects of interest (the vehicles) and the background (road, trees) is required. We consider image/video segmentation with initial background subtraction, object tracking, and vehicle classification in WEKA toolbox of data mining.

5. Related Work

A vehicle tracking and classification system made by Lipton et al., [1] identifies moving objects as vehicles or humans, but however it does not classify vehicles into different classes. A vision-based algorithm was developed for detection and classification of vehicles in monocular image sequences of traffic scenes are recorded by a stationary camera. The processing is done at three levels: raw images, region level, and vehicle level. Vehicles are modeled as rectangular patterns with certain dynamic behavior [2].

Daniel et al., [3] presents the background subtraction and modeling technique that estimates the traffic speed using a sequence of images from an uncalibrated camera. The combination of moving cameras and lack of calibration makes the concept of speed estimation a challenging job. Toufiq P. et al., in [4] describes background subtraction as the widely used paradigm for detection of moving objects in videos taken from static camera which has a very wide range of applications. The main idea behind this concept is to automatically generate and maintain a representation of the background, which can be later used to classify any new observation as background or foreground. In [5], background subtraction also involves computing a reference image and subtracting each new frame from this image and thresholding the result. This method is an improved version of adaptive background mixture model, it is faster and adapts effectively to changing environments. Karmann and Brandt [6] discuss the segmentation approach using adaptive background subtraction that uses Kalman filtering to predict the background. Segmentation requires vehicles to be accurately separated from the background with minimal amount of initialization.

Chen et al., [7], [8] have addressed the issues regarding unsupervised image segmentation and object modelling with multimedia inputs to capture the spatial and temporal behavior of the object for traffic monitoring. D.Beymer et al., [9] proposes a real time system for measuring traffic parameters that uses a feature-based method along with occlusion reasoning for tracking vehicles in congested traffic areas. Here instead of tracking the entire vehicle, only sub features are tracked. This approach however is very computationally expensive. Cheng and Kamath [10] compare the performance of a large set of different background models on urban traffic video. They experimented with sequences filmed in weather conditions such as snow and fog, for which a robust background model is required. Kanhere et al., [11] applies a feature tracking approach to traffic viewed from a low-angle off-axis camera. Vehicle occlusions and perspective effects pose a more significant challenge for a camera placed low to the ground.

The moving-target identification and feature-aided tracking approach described in [12] combines kinematic association hypotheses with accumulated target classification information obtained from high range resolution (HRR), inverse synthetic aperture radar (ISAR), and synthetic aperture radar (SAR) signatures, to obtain improved classification and association. The vehicles are detected using mathematical modeling in [13]. In [14], rule based reasoning is used for vehicle detection, in which the results highly depend on the rules decided by humans. Automatic Traffic Density Estimation and Vehicle Classification for Traffic Surveillance System using Neural Networks were done with real traffic videos obtained from Istanbul Traffic Management Company (ISBAK) [15].

Different classification techniques have been employed after the moving objects are detected in order to identify the moving object. In [16], support vector machines is used to identify if the detected moving object is a vehicle or not. Vibha L et al., [17] developed a framework for detecting the knowledge like vehicle identification and traffic flow count. The framework is made to monitor activities at traffic intersections for detecting congestions, and then predict the traffic flow which assists in regulating traffic. The algorithm for vision-based detection and counting of vehicles in monocular image sequences for traffic scenes are recorded by a stationary camera [17]. Highway toll control requires automated and real-time classification of fast-moving motor vehicles. Julius Stroffek et al., [18] made a modular software solution to the technical problem of how to classify vehicles on a highway with a tollgate equipped with a laser scanner with an angular resolution of 1^0 and a frame rate of 75 Hz. The software identifies individual vehicles and passes a set of descriptors to the classification process itself. The classification algorithm uses the shapes of vehicles, in the form of three-dimensional (3-D) reconstructions of scanned vehicles together with a series of inferred feature descriptors.

6. Methodology

Initially, a video clip is read and segregating into number of frames. Each frame is then considered as an independent image, which is in RGB format and is converted into Gray scale image. In the proposed project, we assume a stationary background for all video sequences. The next phase is identifying the foreground dynamic objects (vehicle), which is obtained by subtracting background image from the given input video frame. The difference between the frames at certain intervals is computed to detect the moving object as shown in Fig 2. The vehicle attributes (width, height, perimeter and area) are obtained by feature extraction technique of image processing. These features are feed into a classifier model to classify the vehicle as big or small by neural network architecture as depicted in Fig 3. The total architecture for vehicle classification system used in proposed project is shown in Fig 1.

7. Materials and methods

The vehicle identification and classification system was implemented in following steps

- Grabbing traffic video clip using by NI smart camera and image acquisition
- Obtaining image frames from video clip in LABVIEW environment
- Back ground image registration in LABVIEW
- Fore ground object (vehicle) detection in LABVIEW
- Image processing and vehicle attributes feature extraction with vision assistant in LABIEW
- Vehicle classification by WEKA data mining tool kit

(i)LABVIEW is graphical programming software that allows for instrument control, data acquisition, and pre/post processing of acquired data. With Graphical Programming Environment there is no need to write lines of program code. LABVIEW relies on graphical symbols rather than textual language to describe programming actions. With LABVIEW platforms big projects can be developed with less man power, less time and less cost when compared with normal project development with other platforms

(ii)NI Vision Assistant module of LABVIEW provides step-by-step instructions for prototyping a vision application. Vision Assistant is a tool for prototyping and testing image processing applications. To prototype an image processing application, build custom algorithms with the Vision Assistant scripting feature. The scripting feature records every step of the processing algorithm. After completing the algorithm, you can test it on other images to make sure it works.

(iii)WEKA (Waikato Environment for Knowledge Analysis) is a popular suite of machine learning software written in Java, developed at the University of Waikato, New Zealand. WEKA workbench is a collection of state of the art machine learning algorithms and data preprocessing and data mining tools.

8. Experiments and Results

The road with traffic was identified at ballat city center of Abha, Saudi Arabia and arrangements are made on top of a building with NI smart cameras at a fixed point in a clear day light environment. The duration of traffic video recorded for about 2 minutes. The next step is to divide the video clip into image frames. For this purpose a LabVIEW VI for converting AVI file to a series of JPEG images is show in Fig 4. The video clip in avi format is sent as input to the VI. The output generated is a set of images as depicted in Fig 5.

The stationary image without vehicles is selected as background image registration is shown in Fig 6. The image with vehicle (Current image) is selected from set of images is shown in Fig 7. The LABVIEW VI for comparing and finding difference between two images to identify vehicle in image is shown in Fig 8. We have to give current images as input. We get the image of only road with cars in image out window. The output is a gray scale image is presented in Fig 9. Save the image for further image processing and feature extraction in LABVIEW vision assistant module.

After the vehicle detection step, the image is in gray scale. Load image into Vision Assistant module of LABVIEW by open image and give file path of the image as shown in Fig 10.

(i)Step – I : Threshold -Select ranges of pixcel values in gray scale images, after applying threshold the image is converted into binary image. To perform this step, in grayscale tab select threshold function. The screen shot after applying the threshold value on the grayscale image is shown in Fig 11.

(ii)Step – II Particle filter - Removes or keeps particles in an image as specified by the filter criteria. To perform this step, in binary tab select particle filter function. Fig 12 shows screen shot after applying the particle filter on binary image.

(iii)Step – III Advance morphology - performs high level operations on blobs in binary images. To perform this step, in binary tab select Advanced Morphology function. First remove small particles in the image by selecting the option remove small objects. The screen shot after applying the particle filter on binary image is presented in Fig 13. Next step is to ccompute the Convex Hull of Objects in Convex option. Fig 14 shows a screen shot after applying convex hull on binary image.

(iv)Step – IV Particle analysis - Displays measurement results for selected particles measurements performed on the image in Fig 14. To perform this step, in binary tab select Particle Analysis function select the feature width, height, perimeter, area of the object (vehicle) to the measurements in pixcels.

The vision assistant script file with all steps is presented in Fig 15 and Fig 16 shows a LABVIEW VI block diagram for image processing and feature extraction for vehicle images.

After performing feature extraction, the data is sent to excel sheet and recorded. Table 1 presents summarized features extracted from vehicle images from different frames.

Building neural network classifier model and use is performed in three steps:

- Preparation of training data set from extracted features
- Build classifier model in WEKA
- Vehicle classification

(a)Training data - We had selected some images from the total set of images. By manual observation we select eight images. These vehicles image features are extracted and categorized as big and small and tabulated in an excel sheet and used as training dataset as shown in Table 2. The training data set is used to build the vehicle classifier model.

(b)Build classifier model - WEKA toolbox is used to for the vehicle classification system with data mining classification techniques, Multi-Layer Perceptron (MLP). The training data set is passed to WEKA data mining tool kit and different parameters are set. In this classifier model a Back-propagation neural network algorithm is used. A training set of input patterns is presented to the network. The network computes its output pattern, and if there is an error – or in other words a difference between actual and desired output patterns – the weights are adjusted to reduce this error. A two hidden layer neural network model is constructed. Fig 17 shows the neural network vehicle classifier model build in WEKA. The model constructed is used to classify unknown vehicles in running phase to classify various vehicles identified in Table 1.

(c)Vehicle classification - The unknown data set is prepared for the vehicles of unknown class. This is prepared from the Table 1 by removing sno, frame-id, vehicle-id and putting one column class. The last column class is marked as ? (Table 3). The unknown data set is passed as input to the vehicle classifier model (shown in Fig 17) build in WEKA tool kit. The output file is generated and interpreted. In the output file the predicted class attribute is generated for all the data samples which are the class of vehicle. Table 4 displays the results of vehicle classes in WEKA.

9. Conclusions and Future work

The vehicle classification system is use to automate the process of traffic monitoring system by making identification and classification of moving vehicles on road. The system uses LABVIEW for image processing of vehicle sample images to extract the features (area, perimeter, width, length). The features were passed as input to WEKA data mining toolkit to build a classifier model to classify new vehicles. Automatic traffic density estimation and vehicle classification through video processing is very important for traffic management especially in mega cities. The benefits of the system are reduce human effort and errors in traffic monitoring, reduce the cost of traffic monitoring system, reduce the time in conducting survey and analysis of data and complete automation of traffic monitoring system. New VIs in LABVIEW are be added to vehicle classification system for calculating traffic counting and density.

References

[1]. A. J. Lipton, H. Fujiyoshi and R. S. Patil, Moving Target Classification and Tracking from Real-time Video, IEEE Workshop Applications of Computer Vision, 1998, pp. 8–14

[2]. Gupte S., Masoud O., Martin R. F. K. and Papanikolopoulos N. P., Detection and Classification of Vehicles, IEEE Transactions on Intelligent Transportation Systems, vol. 3, no. 1, March, 2002, pp. 37– 47.

[3]. Dailey D. J., Cathey F. and Pumrin S., "An Algorithm to Estimate Mean Traffic Speed Using Uncalibrated Cameras", IEEE Transactions on Intelligent Ttransportations Systems, vol. 1, no. 2, pp. 98-107, June, 2000

[4]. Toufiq P., Ahmed Egammal and Anurag Mittal, A Framework for Feature Selection for Background Subtraction, IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06), 2006

[5]. P. Kaewtra Kulpong and R. Bowden, An Improved Adaptive Background Mixture Model for Real-time Tracking with Shadow Detection, In Proceedings of 2nd European Workshop on Advanced Video-Based Surveillance Systems, Sept. 2001

[6]. K. P. Karmann and A. Von Brandt, Moving Object Recognition using an Adaptive Background Memory, In Proceedings of Time-Varying Image Processing and Moving Object Recognition, vol. 2, V.Capellini, Ed., 1990

[7]. Chen S. C., Shyu M. L. and Zhang C., An Unsupervised Segmentation Framework for Texture Image Querie, IEEE COMPSAC, Chicago, Illinois, USA, Oct 2000.

[8]. Chen S. C., Shyu M. L. and Zhang C., An Intelligent Framework for Spatio-Temporal Vehicle Trackin,

IEEE Conference on Intelligent Transportation Systems, California, USA, Aug 2001
[9]. D. Beymer, P. McLauchlan, B. Coifman and J. Malik, A Real-time Computer Vision System for Measuring Traffic Parameter, IEEE Conference. Computer Vision and Pattern Recognition, Puerto Rico, June, 1997, pp. 496–501.
[10]. S. Cheung and C. Kamath, Robust Techniques for Background Subtraction in Urban Traffic Vide, In Video Communications and Image Processing, SPIE Electronic Imaging, San Jose, January, 2004
[11]. N.Kanhere, S.Pundlik and S.Birchfield, Vehicle Segmentation and Tracking from a Low-Angle Off-Axis Camera, IEEE Conference on Computer Vision and Pattern Recognition", San Diego, June, 2005.
[12]. Duy H. Nguyen, John H. Kay, Bradley J. Orchard, and Robert H. Whiting, Classification and Tracking of Moving Ground Vehicles, LINCOLN LABORATORY JOURNAL, VOLUME 13, NUMBER 2, 2002
[13]. Z. Zhu and G. Xu, VISATRAM: A real-time vision system for automatic traffic monitoring, Image Vis. Comput., 18(10), 781– 794, 2000
[14]. R.Cucchiara, M.Piccardi, and P.Mello, Image analysis and rule-based reasoning for a traffic monitoring system, IEEE Trans. Intell. Transp. Syst., 1,(2), 119–130, 2000
[15]. Celil Ozkurt and Fatih Camci, Automatic Traffic Density Estimation and Vehicle Classification for Traffic Surveillance System using Neural Networks, Mathematical and Computational Applications, Vol. 14, No. 3, pp. 187-196, 2009.
[16]. J. Zhou, D. Gao, D. Zhang, Moving vehicle detection for automatic traffic monitoring, IEEE Trans. Vehic. Tech., 56(1), 51-59, 2007
[17]. Vibha L, Venkatesha M, Prasanth G Rao, Suhas N, P Deepa Shenoy, Venugopal K R, L M Patnaik, Moving Vehicle Identification using Background Registration Technique for Traffic Surveillance, Vol I, IMECS 2008, 19-21 March, 2008, Hong Kong.
[18]. Julius Stroffek, Eduard Kuriscak, Petr Marsalek, Highway toll enforcement Real-time lassification of Motor Vehicles, IEEE Vehicular Technology Magazine, Dec 2010.

Authors Profile

Suresh Babu Changalasetty received Ph.D in Computer Science and Engineering from Acharya Nagarjuna Univeristy, Guntur, AP, India. He has 14 years of teaching experience. His research areas of interest include Bioinformatics, Data Mining and Image Processing. He is currently Associate Professor in Dept of Computer Engineering, College of Computer Science, King Khalid University, Abha, Saudi Arabia

Ahmed Said Badawy received Ph.D in Communication Engineering from Alexandria University, Egypt. He has 21 years of teaching experience. His research areas of interest include Digital Signal Processing, Signal separation, CDMA and Embedded systems. He is currently Assistant Professor in Department of Computer Engineering, College of Computer Science, King Khalid University, Abha, Saudi Arabia

Wade Ghribi received his B.Sc and M.Sc degree in Computer Science & Engineering from the Department of Computer Systems and Networks, National Aerospace University Kharkov, Ukraine in 2002 and 2003. He received PhD degree from Computer Engineering Faculty, Kharkov National University of Radio electronics, Kharkov, Ukraine during 2003-3007. He is currently working as Assistant Professor in the college of Computer Science at King Khalid University, Abha, and KSA. His research interests include Digital System Design and Digital Signal processing

Haytham Ibrahim Ashwi, Ahmad Mohammed Al-Shehri and Ali Dhafer Ali Al-Shehri students of Department of Computer Engineering, College of Computer Science, King Khalid University, Abha, Sausi Arabia

Lalitha Saroja Thota received M.Tech Software Engg from JNTU, Hyderabad, India. She is pursuing Ph.D in Computer Science and Engineering from Acharya Nagarjuna Univeristy, Guntur, AP, India. She has 5 years of teaching experience. Her research areas of interest include Bioinformatics and Data Mining. She is currently Lecturer in Department of Computer Science, College of Arts and Science, Khamis Mushayt, King Khalid University, Abha, KSA

Ramakanth Medisetty pursuing B.Tech degree in Computer Science and Engineering from Vardhaman College of Engineering, JNT University Hyderabad, India

Table 1 Features extracted from vehicle images from different frames

sno	frame-id	vehicle-id	bounded-width	bounded-height	perimeter	particle&hole-area
1	c50	v1	77	44	183	1836
2	c100	v1	109	76	260	3576
		v2	101	72	249	3483
3	c183	v1	71	40	172	1685
		v2	77	45	181	1779
		v3	94	78	295	3004
4	c263	v1	71	82	269	2430
		v2	84	90	280	2626
		v3	77	52	194	2350
		v4	101	78	263	3885
5	c353	v1	64	37	151	1641
		v2	69	40	160	1728
		v3	72	42	176	1877
6	c460	v1	55	35	151	1590
		v2	65	41	158	1688
		v3	105	81	274	4393
7	c568	v1	72	37	202	1360
		v2	94	61	227	2833
8	c662	v1	80	51	215	2418
		v2	77	47	192	2221
		v3	116	105	310	3854
9	c741	v1	71	45	183	2141
10	c790	v1	65	29	146	896
		v2	84	74	220	2104
11	c871	v1	68	46	158	1396
		v2	87	79	233	2289
12	c931	v1	86	52	204	2307
		v2	83	69	255	2512
13	c993	v1	79	46	181	2108
		v2	83	48	193	2216
		v3	86	52	204	2307
		v4	83	69	255	2612
14	c1093	v1	95	71	245	3312
15	c1211	v1	110	55	220	3165
16	c1319	v1	121	62	236	3204
17	c1401	v1	77	39	177	1685
		v2	85	51	198	2688
18	c1480	v1	84	48	199	2252
19	c1550	v1	84	54	207	2233

Training dataset prepared for vehicles

bounded-width	bounded-height	Perimeter	particle&hole-area	Veh-class
215	165	559	7856	Big
165	101	365	5688	Big
105	81	274	4393	Big
116	105	310	3854	Big
77	39	177	1685	Small
79	46	181	2108	Small
83	69	255	2612	Small

Table 3: Unknown dataset prepared for vehicles

bounded-width	bounded-height	Perimeter	particle&hole-area	Class
77	44	183	1836	?
109	76	260	3576	?
101	72	249	3483	?
71	40	172	1685	?
77	45	181	1779	?
94	78	295	3004	?
⋮	⋮	⋮	⋮	⋮

Table 4: Predicted class of vehicles

bounded-width	bounded-height	perimeter	particle&hole-area	class	Predicted class
77	44	183	1836	?	Small
109	76	260	3576	?	big
101	72	249	3483	?	big
71	40	172	1685	?	Small
77	45	181	1779	?	Small
94	78	295	3004	?	Small
71	82	269	2430	?	Small
84	90	280	2626	?	Small
77	52	194	2350	?	Small
101	78	263	3885	?	big
64	37	151	1641	?	Small
69	40	160	1728	?	Small
72	42	176	1877	?	Small
55	35	151	1590	?	Small
65	41	158	1688	?	Small
105	81	274	4393	?	big
72	37	202	1360	?	Small
94	61	227	2833	?	Small
80	51	215	2418	?	Small
77	47	192	2221	?	Small
116	105	310	3854	?	big
71	45	183	2141	?	Small
65	29	146	896	?	Small
84	74	220	2104	?	Small
68	46	158	1396	?	Small
87	79	233	2289	?	Small
86	52	204	2307	?	Small
83	69	255	2512	?	Small
79	46	181	2108	?	Small
83	48	193	2216	?	Small
86	52	204	2307	?	Small
83	69	255	2612	?	Small
95	71	245	3312	?	Small
110	55	220	3165	?	Small
121	62	236	3204	?	Small
77	39	177	1685	?	Small
85	51	198	2688	?	Small
84	48	199	2252	?	Small
84	54	207	2233	?	Small

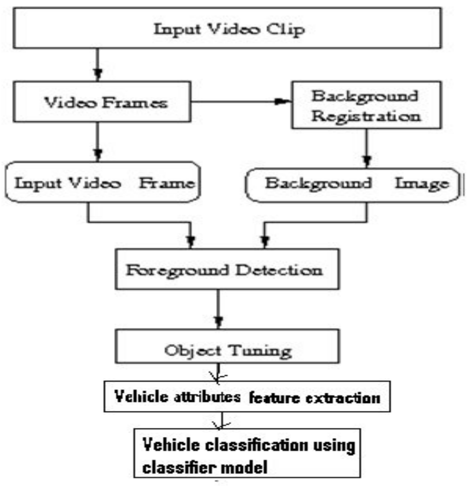

Fig 1 Architecture for Vehicle Classification system

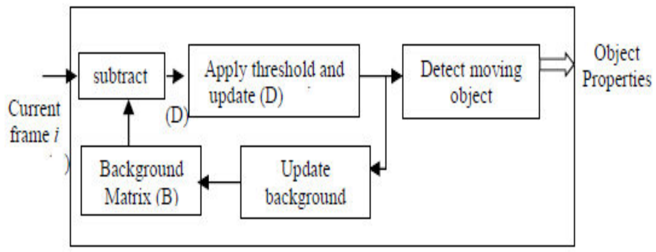

Fig 2 : Moving Object Detector Flow

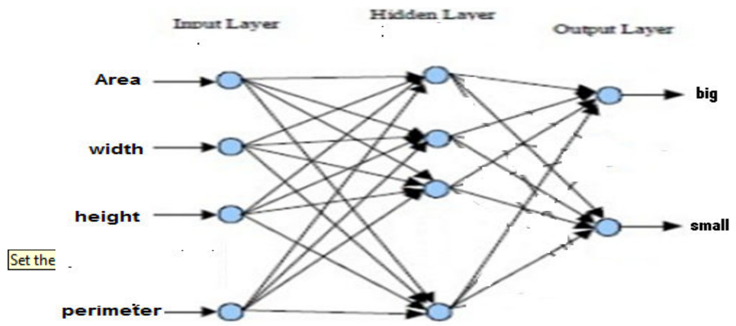

Fig 3 Neural Network Architecture for Project

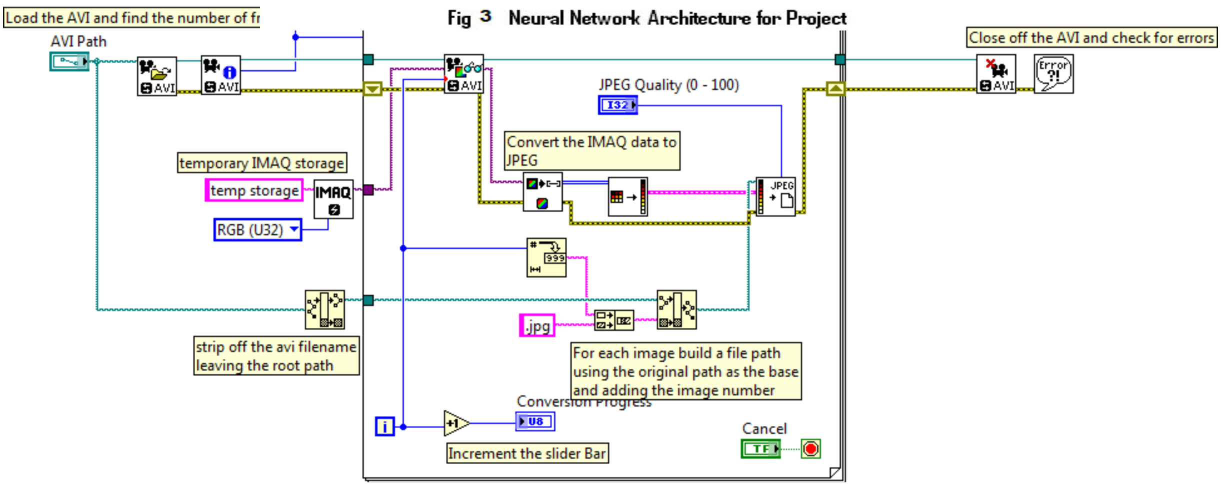

Fig 4: LABVIEW VI Block diagram of AVI file to images

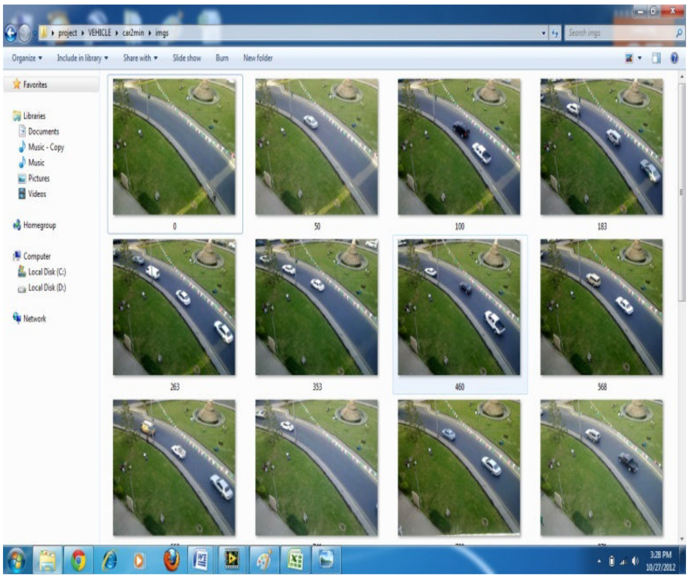

Fig 5: Images used in vehicle project

Fig 6: Back ground image

Fig 7: Image with vehicle (current image)

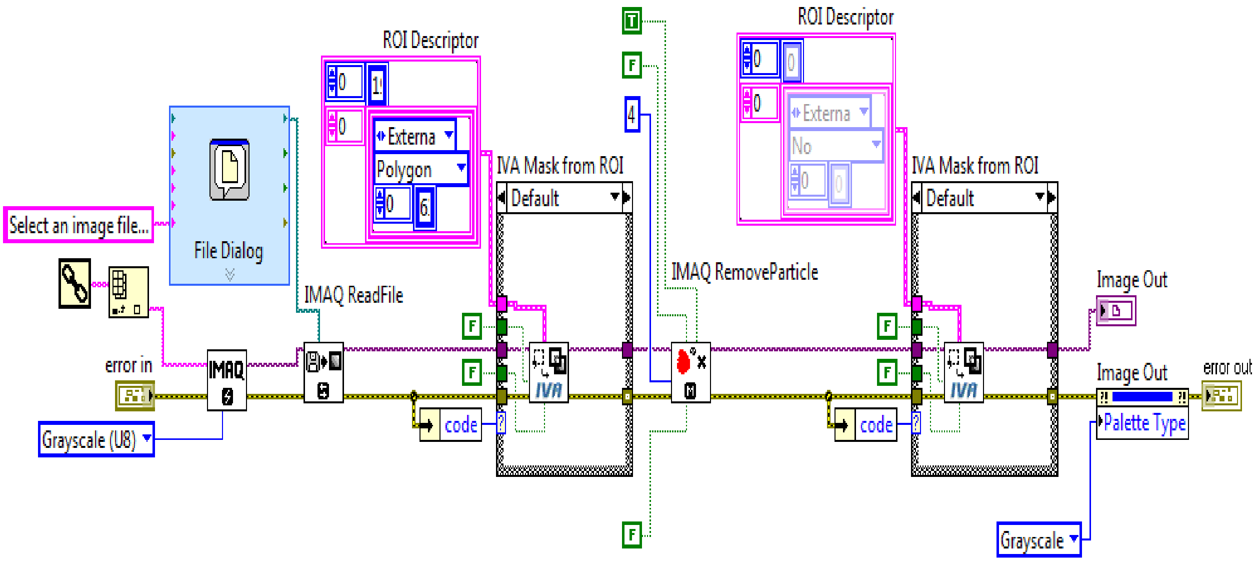

Fig 8 : LABVIEW VI Block diagram to detect the vehicles on road

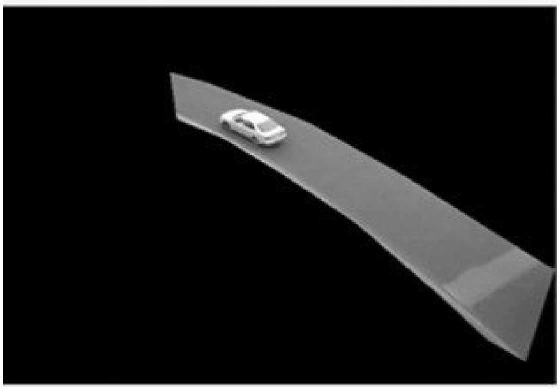

Fig 9 : Vehicle identification in LABVIEW

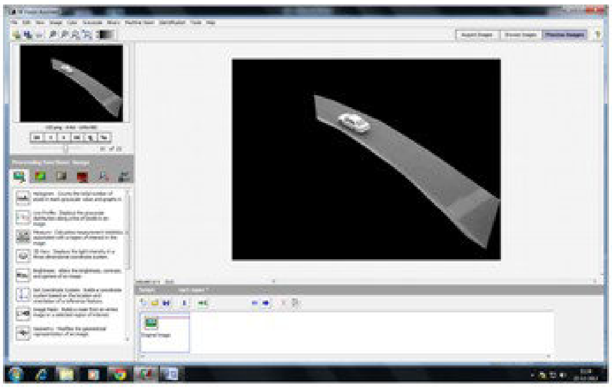

Fig 10: Grayscale image loaded in LABVIEW Vision Assistant module

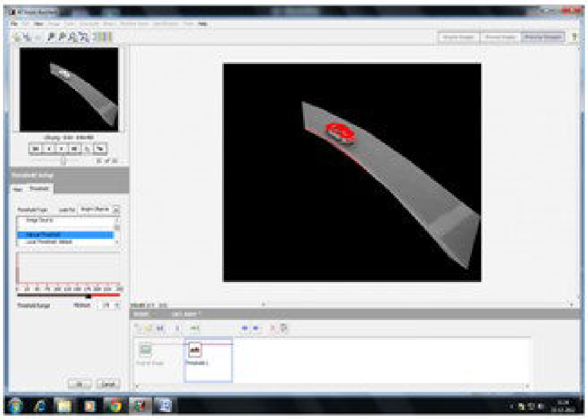

Fig 11: Screen shot after applying the threshold value on the grayscale image

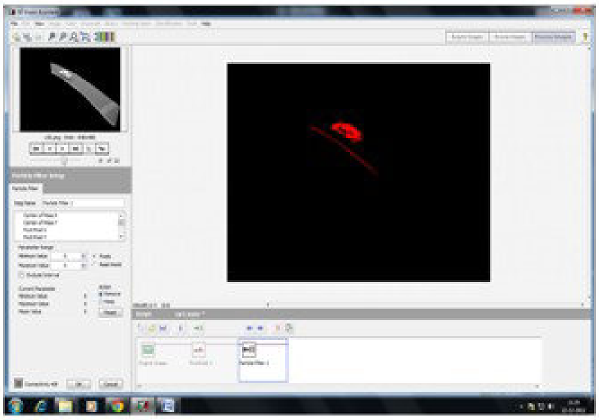

Fig 12: Screen shot after applying the particle filter on binary image

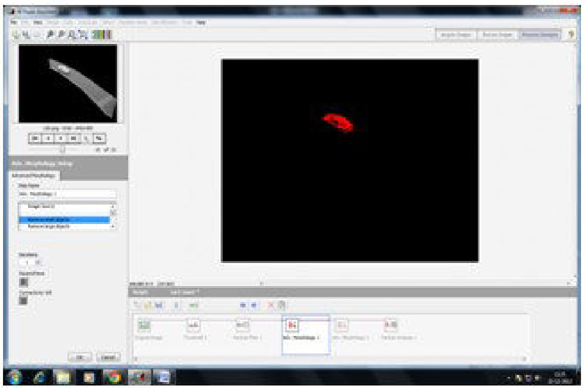

Fig 13: Screen shot after applying morphology – remove small particles

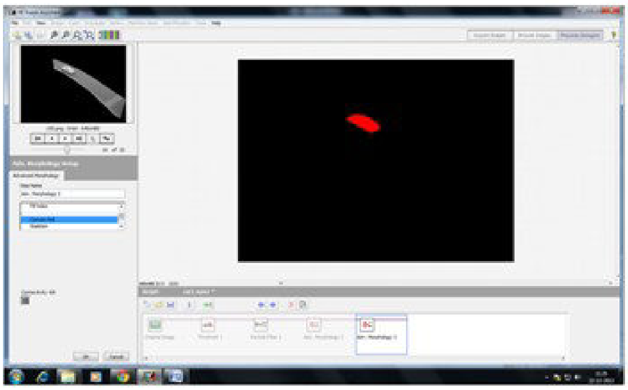

Fig 14: Screen shot after applying morphology - convex hull

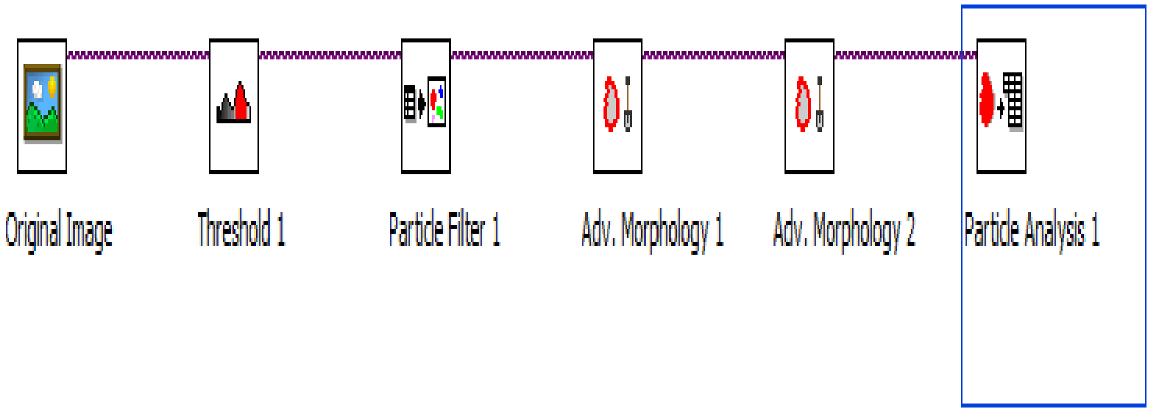

Fig 15:Vision assistant script file image processing and feature extraction for vehicle images

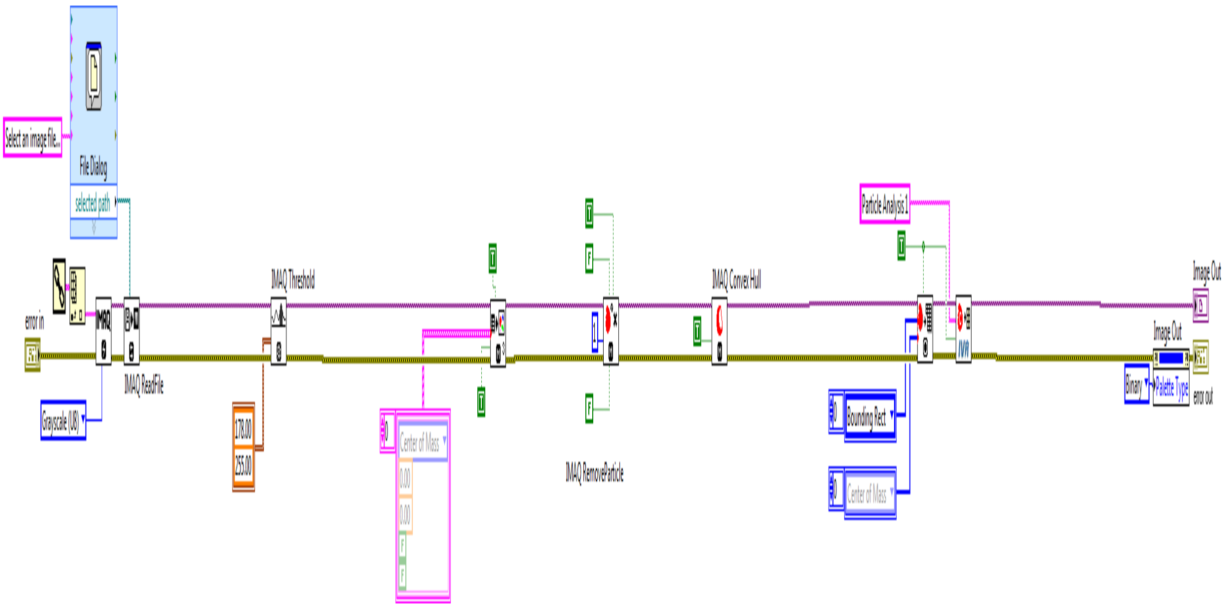

Fig 16: LABVIEW VI block diagram for image processing and feature extraction for vehicle images

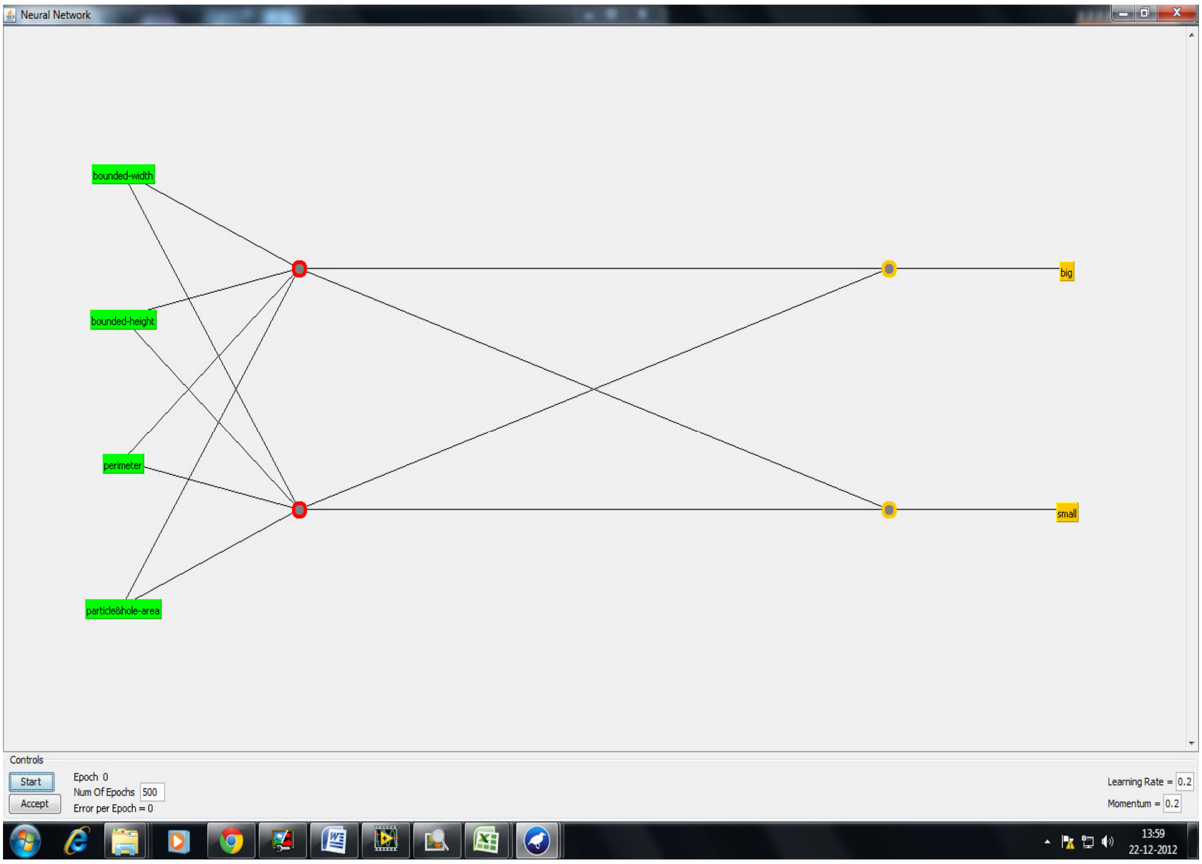

Fig 17: Neural network classifier model for vehicle classification in WEKA