Detection, Counting and Classification of Moving Objects by Using Real Time Traffic Flux through Differential and Rule Based Analysis

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ABSTRACT

This paper is focussed on detection, counting and classification of moving objects using differential and graphical techniques. The basic idea used is variation in the traffic flux density due to presence of objects in the scene. Accurate Traffic flux estimation will play vital role in object detection, counting and classification. The designed technique is evaluated with 15 different video sequences and weighed thoroughly with simple confidence measures. In the present work we have achieved real time analysis with normal video rate. And for object classification computation we are taking specific frame gap which saves computational time. The result produced with this analysis is extremely good and beneficial in real time traffic control, detecting and classifying objects in urban areas. The vehicle counting achieved with an accuracy of 94% under varied road conditions. In the normal condition the average accuracy achieved is near to 97%.

Keywords: Traffic Flux, Object Detection, Objects Classification, Differential and Graphical Techniques, Dynamic Selection, Ego-Motion.

1. INTRODUCTION

Most of the motion picture analysis presently available, takes considerable computational time, although we have high-speed computational technology. Real time view analysis will be very challenging as it involves the time component. Here, in this work an attempt is made to introduce a robust, simple and statistical solution to this difficult problem. Two stages of solution have been designed, tested and implemented in the present work. Firstly, to reduce the numbers of frames used for analysis, dynamic selection of images were made. Here, the frame-to-frame difference is obtained and a threshold has been fixed to register a subset of images to be used for analysis out of the 15/30 frames available for every second. This results considerable saving of computation and time. The selected subset is compared with the reference template, which is selected background image. This is done under different illumination conditions. In the second phase of the work, reference frame is constantly subtracted from the dynamically selected subset. This leads to the separation of object pixel, which is corresponding to moving vehicles and the background pixel, which are not altered. Counting object pixel in a frame leads to the traffic flux estimation. To make the design illumination invariant, a section of the background is taken as reference, which will not be affected by the traffic flow. Comparing the illumination of that block of reference with present picture will decide which background reference must be considered, for the purpose of analysis. Since it is small matrix pixel, time constraints of computation have been tackled. This novel and simple statistical algorithm is tested over real image sequence. Discrimination of object pixel and background pixel has shown good repeatability

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over many real sequences of images. Threshold is fixed and used to discriminate the low, medium and high traffic flux. There is a plot for traffic flux density; it's basically % flux density versus number of frames. The vehicle detection and classification is carried out by using this plot. Suppose if there is any object in the scene, then there is a certain range of flux density will produce according to object volume (size). Obviously the object pixel count is directly reflecting the presence of vehicles as well as type. By analyzing flux density in various cases, we can classify the objects (pedestrian, two wheeler, four wheeler and heavy vehicles).

Traffic flux is a generic term and it is nothing but the change in object pixel against the frame number. This embeds enormous information about the moving objects in the scene. By analyzing this percentage flux density variation, we can classify the objects. Hence, accurate Traffic flux estimation will play a very vital role in object detection and classification [14, 15]. The presence of object in the scene contributes a definite increase in flux. Similarly, exit of object from the scene decreases the flux. The plot of the same results in a stochastic variation graph. Presence of different vehicles/object in the scene creates different patterns in terms of change in percentage flux and slope. This forms the clear cut basis for the analysis of moving object/vehicles, counting and classification of the sane. Object classification is done by comparing percentage flux density, if there is only one vehicle at a time in the scene. Suppose if there are more objects at a time in the scene, in this case we have to analyze percentage flux density to classify the objects and we have methodology for classification. Suppose if there are multiple vehicles simultaneously enter into the scene still contribution by each of them are different along with different exit time. However, the accuracy of detection, counting and classification is cent percent when a single object or series of objects present in the video stream. The designed technique is evaluated with 15 different video sequences. The results obtained are encouraging and also establishes that even multiple entry and exit does not result in largely reduced accuracy. Very good result is achieved by combining logical statements with multiple threshold values. The module being much generalized, therefore, it fits into the applications of various areas, such as detecting speed violators on highways, vehicle count, weather forecasting, cloud tracking, satellite image processing for surveillance, biomedical analysis and so on.

2. Related Work

The review of the literature pertaining to the present topic is presented to the readers. In [1] authors worked on comparison of different approaches of optical flow estimation. Comparison is done on the basis of accuracy and computational complexities. They have concluded differential technique is best suited for the competition of optical flow and hence the dynamic scene analysis. Entropy based features are used in [2], to check for the existence of vehicles and then tracking is achieved. Though this takes less computational time it suffers serious occlusion problem. Fusion of images and vector maps technique is used in [3] to discriminate vehicles from objects in the scene. This is suitable for military applications as overall system is complicated and expensive. A comparison of edge element association EEA and marginalized contour approaches for 3D model based vehicle tracking in traffic scenes is implement in [4]. Tracking failures of two approaches, however, usually do not happen at the same time frames which can lead to insights into relative strengths and weakness of the two approaches. Since both the models are to be implemented on every frame computational time frame increases. Recursive optical flow estimation- Adaptive filtering approach is used in [5]. This is modification over Horn and Schunck[6] algorithms as it uses only parts of images. Hence sequence of images is used with adaptive filtering technique. The result achieved here is good at cost of linearly growing computational complexities because convergence to be achieved. In [7] authors present a new method for tracking rigid objects using a modified version of the Active Appearance Model. It works well with partial and self occlusion of objects. The layered representation is more flexible than standard image transforms and can capture many important properties of natural image sequences [8]. The study reveals that increased computational time and complexities are the hurdles in achieving real time analysis at video rate. This fact motivated us to develop the simple technique presented in this paper. The algorithm developed in this work computes the simple differences required and avoids time consuming iterative part in the optical flow analysis. Wherever possible certain parameters are evaluated and supported with sufficient sample sequences. Result establishes that they work well with the inherent problem of natural video traffic sequences. This paper emphasizes on the time and computational complexities of the developed simple algorithms, as there is a need of estimating the traffic flux in real time. In the present work we are concentrating on the accuracy of vehicle count and classification. In the end, it is important to ascertain the conditions under which these results were obtained. Traffic flux estimation critically depends on the changes in the intensities of the I^{th} image with respect to the reference image at all spatially uniformly spread pixels. One of our assumptions is that the intensities of the moving vehicles are preserved during the travel in the view path.

2.1 General Motion

In general, an observed motion does not have the simple structure of the spatially constant motion as assumed. Although motions are not constant in space still can make sense. Despite of different processing algorithms, three stages processing is essential to perform computing the motion in spatio-temporal domain.

1. Pre-filtering or smoothening with low-pass or band pass filters in order to extract signal structures of interest and to enhance the signal to noise ratio.

2. The extraction of basic measurements, such as spatio-temporal derivatives or local correlation surfaces

3. The integration of these measurements to produce 2D flow field, which often involves assumptions about the smoothness of the underlying flow field.

The algorithm description and analysis assumes an affined camera where perspective effects are limited to changes in overall scale. No camera calibration parameters are required since the assumptions are made as mentioned before. Camera used is of resolution 1024×1024 with a video rate of 30 frames per second. To reduce the time of computations, the same has the resolution of the image is scaled down to 200×200 without loosing much of the information. The above size reduction saves computation.

2.2 Differential Methods

Differential techniques compute motion related information from spatio-temporal derivatives of image intensity. The differential technique developed by Horn and Schunk[6] has been the most widely used algorithm for the optical flow computation.

Suppose we have a continuous image where E(x,y,t) refers to the gray-level of (x,y) at time t representing the dynamic image as a function of position and time permits it to be expressed as a Taylor series:

$E(x+u\delta t,y+v\delta t,t+\delta t)=E(x,y,t)+E_x\delta x+E_y\delta y+E_t\delta t+O(\partial^2)$

Where E_x, E_y, E_t denote the partial derivatives of E. The u(x,y) and v(x,y) are the components of optical flow. We can assume that the immediate neighborhood of (x,y) is translated some small distance ($\delta x,\delta y$) during the interval δt; that is, we can find δx, δy, δt such that

$E(x+u\delta t,y+v\delta t,t+\delta t)=E(x,y,t)$

The above equation is also known as brightness conservation equation. If δx, δy, δt are very small, the higher order terms in the equation vanishes. Dividing by δt and taking the limit $\delta t\to 0$, leads to the following expression.

Therefore, the brightness constraint equation is given by,

$E_x\, u + E_y\, v + E_t = 0$

Assuming the global smoothness of the brightness changes in the images, one can model the motion field applying the higher order derivatives of the data conservation equation. Iterative solutions of these two or more equations or certain regression methods applied on the relevant set of equations yield the components of the velocity vector field. In the present work we have computed the following differences and are used suitably.

$$\frac{dx}{dt}, \frac{dy}{dt}, \frac{\partial E}{\partial t}$$

Experimentally, it is found that thousands of iterations are needed until convergence is achieved if a second order smoothness criterion is applied on the other hand the first 10-20 iterations usually leave an error smaller than the required accuracy, and the rest of the iterative process is then very gradual [9,10]. Therefore first order difference is chosen for the analysis.

3. Algorithm

Line - by- line algorithm is presented below.

1. Selection of reference image in an image sequence: Image with no traffic in the identified sequence is considered as the reference image.
2. Dynamic selection of reference/background images. Compute normalized difference, $d_{nor}(i,j)= (1/N \times M) \sum_{I\{\}} d_I(i,j) - d_{I+1}(i,j)$
3. Selection of Background Image for computation of flux:

   If $E_r = \Sigma \mid d_I(i,j) - d_{I+1}(i,j) \mid \le \varepsilon_1$, then skip one image I=I+1

   If $E_r = \Sigma \mid d_I(i,j) - d_{I+1}(i,j) \mid > \varepsilon_1$ and $< \varepsilon_2$ then skip three images I=I+2

   If $E_r = \Sigma \mid d_I(i,j) - d_{I+1}(i,j) \mid > \varepsilon_2$ and $< \varepsilon_3$, then skip five image I=I+3

   Where $\varepsilon_1 < \varepsilon_2 < \varepsilon_3$ Further this set can be re-ascertained.
4. Selected image is passed though spatial low pass filter.
5. Find difference image between incoming video frame and background image.
6. using multiple thresholds create binary image
7. Compute the normalized average brightness of the segmented region and compute flux as a percentage with reference background.

8. Vehicle Count :

Slope=(Φn+1-Φn)=x

Φn+1=present flux density value for specific frame period Φn=previous flux density value

Sign=sig(x)=y

{ **1** if yn+1=1and yn=-1

Vehicle={ **0** if yn+1=-1and yn=1

{ 0 if yn+1=1 and yn=1

{ 0 if yn+1=-1 and yn=-1 .

9. Object classification :

Φ ➔ percentage flux density

Classification: P ➔ Pedestrian

T ➔ Two wheeler

F ➔ Four wheeler

H ➔ Heavy vehicles

Case(i) if $\Phi p_i \le \Phi \le \Phi p_f$

Pcount = 0

Pecount = Pcount+1

Pedcount =Pecount

10. Step nine is repeated for other type of vehicles with different slopes, rate of change of slopes and end flux values.

4. Implementation

Following general considerations and assumptions are made in order to implement the computer vision based system for traffic flux estimation.

- Camera is positioned at a fixed location with predetermined focus. This is in order to eliminate ego-motion problem.
- Video sequences are taken from the top to minimize occlusion also perspective oblique view to validate the result.
- Fixed number of frames with fixed camera resolution.
- Both color and black and white videos are used.
- Monocular video is the input for processing.

The block diagram of the implemented system is shown in Fig.1. The video input is given to the system with an input video rate at 30 frames per second. Frames are separated using frame grabber software. Further frames are converted to BMP format for the purpose of analysis. Pre processing follows which encompasses the low pass filters and spatial threshold operations. Cumulative and Normalized difference between frames are computed and used to establish the traffic flux.

At first we will consider a continuous family of images on some time period and derive expressions for traffic flux in terms of spatial and temporal derivatives of this continuous image sequence with $\varphi\,[0, I] \times \Omega \rightarrow$ R(s, t) $\rightarrow$ E(x, y); Here Ω is the image domain. We will always denote the sequence parameters by r and s respectively, where as x and y respectively stands for the spatial co-ordinates. We assume φ to be smooth in time and space.

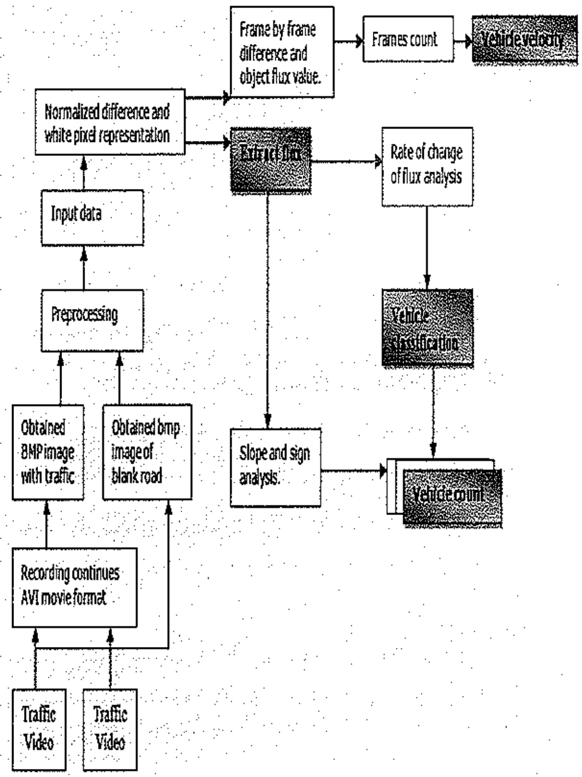

Figure 1

5. Discussion On Results

In order to test the above-developed algorithm, several sets of natural image sequences are used. Real image sequences, recorded in MPEG2 format have been used with camera, in fixed position to capture the aerial view of the road. Different natural traffic videos are taken in situations where obstacles are found in the line of view, vehicle shadows, building shadows in the path and oblique view of the traffic. The first set of images is taken in order to establish the reference images under different illumination condition from morning to evening. Four such reference frames have been identified under supervision.

In the present work, a platform has been created so that complete automation of dynamic and intelligent traffic control devoid of human intervention. The incorporated dynamic selection of background images supports the selection of required frames [12]. Subtraction of images in the raw data form helps to generate boundary between moving objects in the scene with the background. After subtraction the image is negated. Four levels of threshold is implemented to mark the difference between two images and assigned with different colors in the output image [11]. From the results obtained it is evident that the implemented algorithm is separating object from the back ground pixels, detection and classification of objects in almost all the cases. Also, it works satisfactorily when there is a change in illumination, obstacles found in the image path and building shadows.

Description of different cases	Vehicle count	visual analysis	Accuracy (%)
Case1: video with proper illumination	58	56	96.50%
Case2: video with cloudy illumination	37	35	94.50%
Case3: video with twilight illumination	25	27	92.50%
Case4: video with obstacle in the path	65	69	94.20%
Case5: video with building shadows	35	37	94.60%
Case6: video with fog and smoke	23	25	92.00%
Average Accuracy			94.04%

Confidence Measure: One of our major investigations has been the identifying confidence measure to establish the validity of the results. This provides means of determining the reliability of the computed object classification. Traffic flux computed is verified using tesselation method. Vehicle classification is verified through DFT technique and visual analysis.

Table1: Results of Object Classification in a Typical Case

Objects/vehicles	count	Error positive	Error negative	Accuracy (%)
Pedestrian	10	0	0	100%
Two wheeler	8	1	0	88.00%
Four wheeler	6	0	0	100%
Heavy vehicles	3	0	0	100%
Average				**97.00%**

6. Conclusions

The work carried out has produced very good and consistent results. The small deviations with different video streams taken under different situations are minimum and do not really hampers traffic analysis. Following are the limitations observed by the authors at this juncture and further finds the scope to continue the work.

1. The shadows of the vehicles and buildings in the field of view are causing subtle variation in the traffic flux and vehicle count computation.
2. If the color of the vehicle and the color of the road (Reference image) are same it may lead to marginally varied traffic (approximately 5-6%) flux and as well as vehicle count computation.
3. With the present computational facility maximum size of the color image that can be handled in real time is 200 pixels by 200 pixels.

4. Variation in illumination condition causes subtle variation in estimated traffic flux and vehicle count.
5. Depletion in accuracy to detect and classify the objects when there are multiple objects present having simultaneous entry and exit because of resulted effect on percentage flux.

7. Presentation And Display Of Results

The first level result shows the computation of traffic flux under six different natural conditions. The results are shown in figure 2. It consists of traffic flux graph, sample frames and table consisting of traffic flux values and the difference of flux. Peaks and valleys are indicated as +1 and -1. Further the change of sign increments the vehicle count. All images are of 200*200 sizes. Here result shown for only one pair of images in the sequence. Such computation is being done for all the images in the video input to the system. The result presented ensures the correctness of the computation as it is more near to the visual estimation value, which uses tessellation method. In figure 3, second set of result shows the vehicle classification. Four different types of object/vehicles have been presented along with their flux graph.

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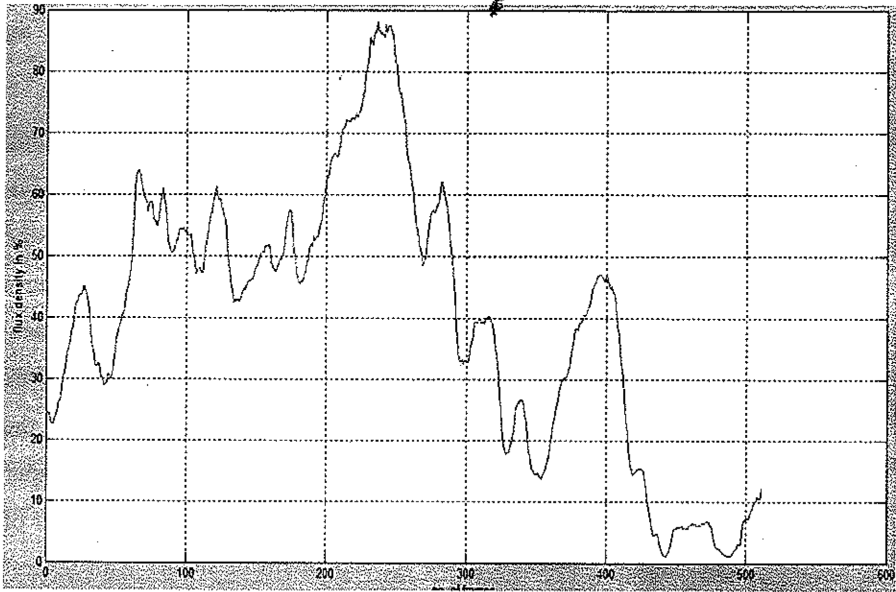
Author's Biography

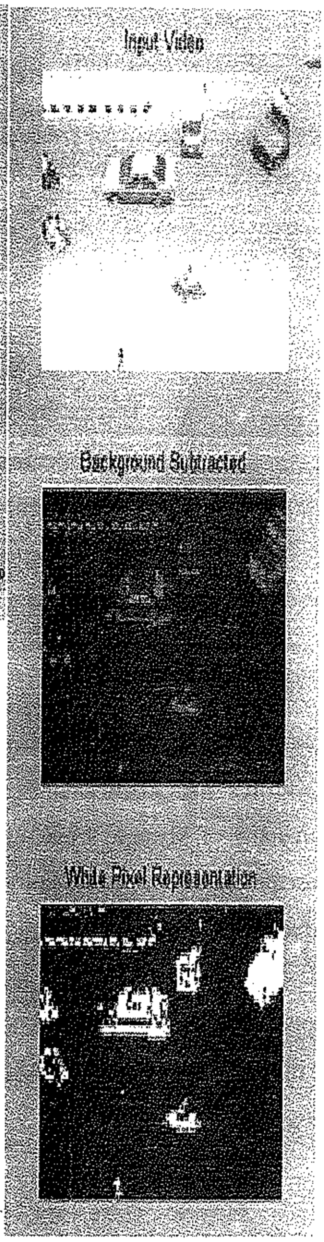
Prof.H.S.Mohana Obtained B.E Degree in Electical and Electronics Engineering from University of Mysore during 1986. Since then serving technical education field in various capacities. Obtained M.E from University of Roorkee, presently IIT ROORKEE with the specialization in Measurement and Instrumentation. Worked as chairmen and Member of Board of Examiner and Board of studies with several universities which include, University of Mysore, Kuvempu University and VTU. Presented research findings in 12 National Conferences and in 4 International conferences held across the world. Recognized as AICTE expert committee member in the inspection and reporting continuation of affiliation and Increase in intake of the Engineering Colleges. Completed, one AICTE/MHRD-TAPTECH project, and one AICTE/MHRD- Research project successfully. Coordinated TWO ISTE Sponsored STTP for the technical college teachers.

Dr. Aswatha Kumar. M has obtained B.E Degree from University of Mysore in Electronics and communication Engineering. Since then serving technical education field in various capacities. Obtained M.E from IISc Bangalore in ECE Department. Carried out research under the guidance of Professor B. N. Chattergi at IIT Kharagpur and obtained PhD. Worked as chairmen and Member of Board of Examiner and Board of studies with several universities which includes, University of Mysore, Kuvempu University and VTU.Chaired technical sessions at many National and International conferences. Presented research findings in 35 National Conferences and International conferences held across the world. Organized, many National and International conferences. Completed, many AICTE/MHRD-TAPTECH project, and one AICTE/MHRD- Research project successfully. Working as referee for reputed National and International Journals. Worked as technical consultant for many industries and banks. Presently, five research scholars pursuing research work.

Result Images and Graphs

For two similar IMAGES resultant subtracted image is shown





FLXDEN %	SLOP	SGN	(1->-1)VEHS
16.8	0.0		0
16.2	-1.1	-1	1
19.1	2.9	1	0
23.5	4.4	1	0
19.3	-4.2	-1	1
19.5	0.2	1	0
16.0	-3.5	-1	1
16.1	0.1	1	0
15.4	-0.7	-1	1
14.5	-0.9	-1	0
17.0	2.5	1	0
15.0	-2.0	-1	1
19.1	4.1	1	0
18.1	-1.1	-1	1
21.4	3.4	1	0
21.5	0.1	1	0
19.8	-1.7	-1	1
20.4	0.5	1	0
18.1	-2.3	-1	1
26.9	8.8	1	0
27.3	0.4	1	0
26.5	-0.8	-1	1
45.3	18.8	1	0
43.5	-1.8	-1	1
50.4	6.9	1	0
48.0	-2.4	-1	1
32.0	-15.0	-1	0
17.2	-14.8	-1	0
20.1	2.9	1	0
19.0	1.1	1	1
19.1	0.1	1	0
19.8	0.7	1	0
20.0	0.2	1	0
17.5	-2.5	-1	1
18.3	0.3	1	0
50.5	-2.8	-1	1
17.1	1.5	1	0
16.3	-0.8	-1	1
20.1	3.8	1	0
19.0	-1.1	-1	1
22.9	3.9	1	0

FRMS	FLXDEN%	SLOP	SGN	(1->-1)VEHS
205	21.3	-1.6	-1	1
210	25.2	3.9	1	0
215	24.8	-0.4	-1	1
220	26.2	1.4	1	0
225	25.3	-0.9	-1	1
230	28.5	3.2	1	0
235	27.4	1.1	1	1
240	25.8	-1.6	-1	0
245	24.8	-1.0	-1	0
250	25.0	0.3	1	0
255	22.2	-2.8	-1	1
260	21.0	-1.2	-1	0
265	24.3	3.3	1	0
270	22.1	-2.2	-1	1
275	26.4	4.3	1	0
280	24.8	-1.6	-1	1
285	24.7	-0.1	-1	0
290	25.0	0.3	1	0
295	23.0	-2.0	-1	1
300	14.5	-0.5	-1	0
305	13.1	-1.5	-1	0
310	14.2	1.2	1	0
315	13.2	-1.0	-1	1
320	14.9	1.7	1	0
325	16.2	1.3	1	0
330	11.2	-5.0	-1	1
335	04.3	-1.9	-1	0
340	10.8	1.5	1	0
345	11.9	1.1	1	0
350	10.5	-1.4	-1	1
355	08.8	-1.7	-1	0
360	09.2	0.4	1	0
365	08.0	-1.2	-1	1
370	12.0	4.0	1	0
375	13.3	1.3	1	0
380	12.0	-1.3	-1	1
385	17.2	5.2	1	0
390	15.0	-2.2	-1	1
395	19.2	4.2	1	0
400	17.8	-1.4	-1	1
405	18.0	0.2	1	0

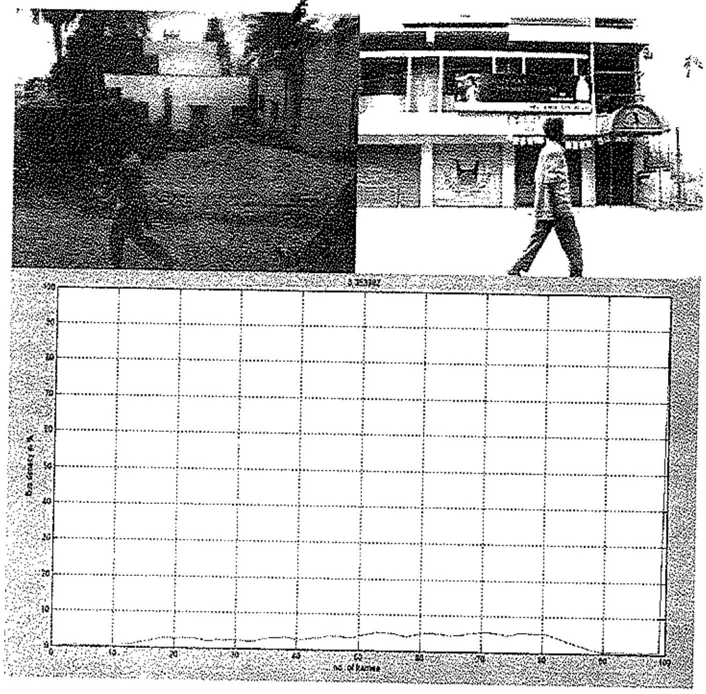
FRMS	FLXDEN%	SLOP	SGN	(1->-1)VEHS
410	15.9	-2.1	-1	1
415	14.5	-1.4	-1	0
420	15.0	0.5	1	0
425	07.9	-7.1	-1	1
430	08.5	0.6	1	0
435	07.5	-1.6	-1	1
440	05.4	-2.4	-1	0
445	04.4	-0.7	-1	0
450	05.5	1.1	1	0
455	04.0	-1.5	-1	1
460	05.4	1.4	1	0
465	06.7	1.1	1	0
470	06.1	-0.6	-1	1
475	07.9	1.8	1	0
480	04.7	-3.2	-1	1
485	05.8	1.1	1	0
490	03.9	-1.9	-1	1
495	03.8	-0.1	-1	0
500	04.6	0.8	1	0
505	03.0	-1.6	-1	1
510	06.8	3.8	1	0
515	05.2	-1.6	-1	1
520	06.2	1.0	1	0
525	04.3	-1.9	-1	1

38 VEHICLES

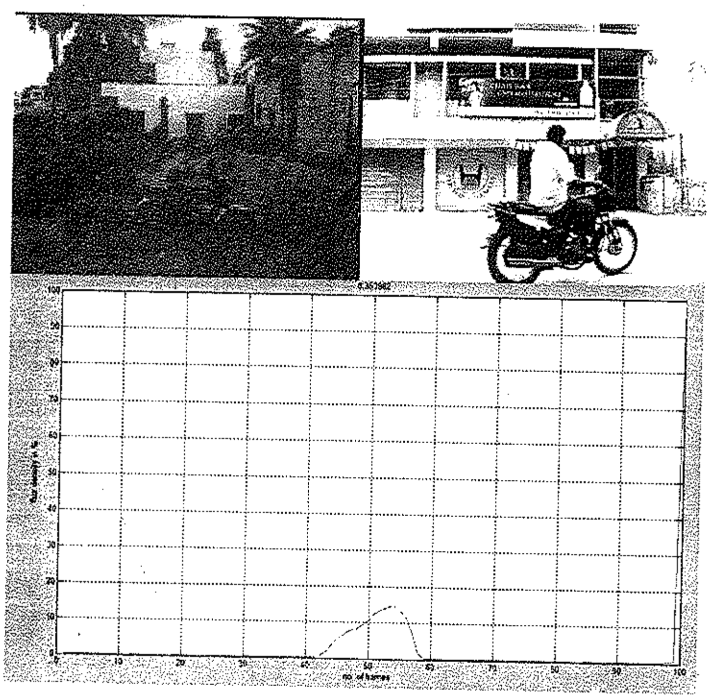
Figure 2 : Output Graph and Vehicle Count

Result Images and Graphs for Classification

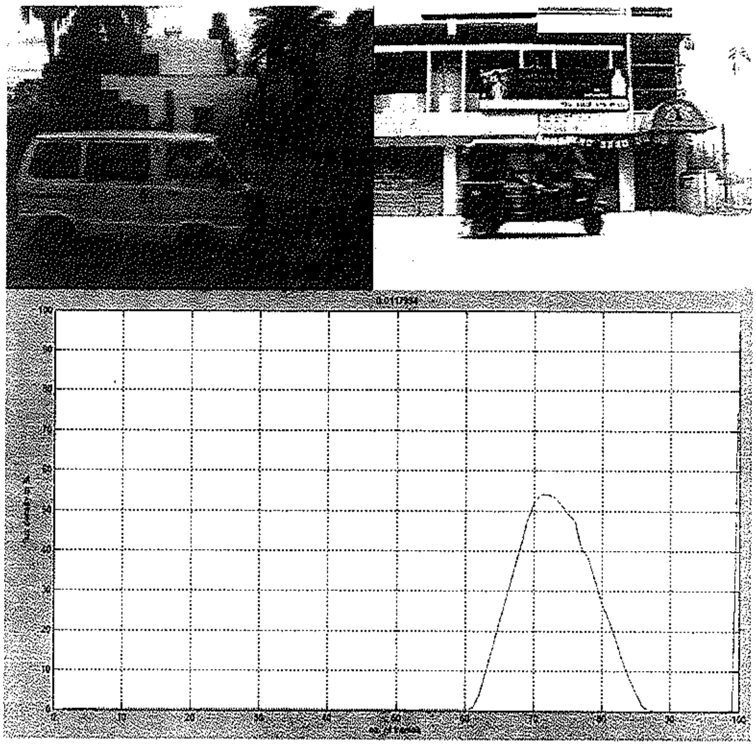
Pedestrian



Two Wheelers



Four wheelers



Heavy Vehicles

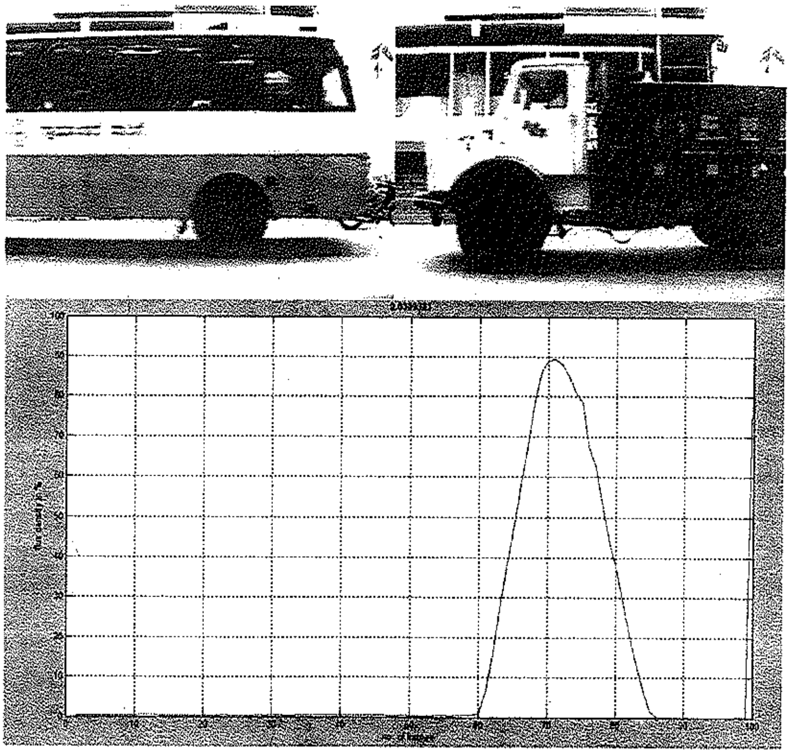


Figure 3 : Output Graph and Object Classification