VEDIO BASED OBJECT RECOGNITION AND TRACKING

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Abstract

Automated motion detection and tracking is challenging task in traffic surveillance. Here system is developed to gather useful information from stationary camera for detecting moving objects in digital videos. Optical flow is the pattern of apparent motion of objects in a visual scene caused by the relative motion between an observer and the scene. There are many methods to extract optical flow, yet there is no platform that brings out comparison on the performance of these methods. Hence comparison between the results obtained by the application of two major optical flow algorithms on different sets of image sequences is brought out. The image sequence is spatially filtered using bank of Gabor filter Horn Schunck and Lucas Kanade algorithms are used for computation of optic flow velocity vectors. Computed vectors are segmented using intensity based thresholding. Image enhancement techniques consisting of morphological operations to remove unwanted objects and pixel connectivity helps to enhance the segmented objects that mean rectangular shaped vehicles. The technique works well on most of these videos under sunny condition.

Index Terms: Optical Flow (Horn Schunck & Lukas Kanade), Morphological operations, Complex response of Gabor filter.

I. INTRODUCTION

Here system is developed to gather useful information from real time camera for detecting moving objects in digital videos. Image changes are due to the relative motion between the scene and the camera. There are 3 possibilities:

(1)Camera still, moving scene
(2)Moving camera, still scene
(3)Moving camera, moving scene

Vehicle detection is very challenging due to huge variabilities includes in below:

(1)Vehicles may vary in shape, size, and color.
(2)Vehicle appearance depends on its pose,
(3)Complex outdoor environments such as illumination conditions, cluttered background, and unpredictable interactions.

In the hypothesis Generation step, the algorithm hypothesizes the locations of vehicles in an image. In the Hypothesis Verification (HV) step, the algorithm verifies the presence of vehicle in an image. The goal of computer vision is to make useful decisions about physical objects and scenes based on sensed images. Tracking can be defined as problem of the estimating trajectory of an object in image plane. It moves around a scene of a video. The tracker assigns consistent labels to tracked objects in different frames of a different video. Additionally, depending on the tracking domain, a tracker can also provide area, such as orientation or shape of an object, object-centric information. Its aim is to detect a moving object or several ones in a video. Tracking algorithm is used for analyzing the video frame by frame. The goal of algorithm is to determine interesting moving target objects and tracking of such objects from frame to frame and to find its location. An object detection algorithm must have the ability to recognize the variation in visual appearance. Motion estimation is the process to find the motion vectors of a real world 3D scene captured projected into 2D plane. Detection and motion estimation of object is based upon comparing two frames. For finding the moving objects segmentation refers to segregating the objects detected in the image in groups depending on its size, shape and various characteristics. The process of locating the moving object in sequence of frames is known as object tracking. Object tracking is more equivalent to the recognition step in image processing. Tracking can be performed by using feature extraction of object and detecting the objects in sequences of frames.

The process in locating the object which is moving in instance of time is known as video tracking. Video tracking can be a time saving process due to the quantity of data that are contained in video. Mapping of target can be especially difficult when objects are moving relatively fast to the frame rate and another problem is when tracked object changes orientation over time. Video tracking is to combine objects in successive video frames. The goal of moving vehicle detection is to separate moving vehicles from background, and its detection result has a great impact on post image processing. At present, moving vehicles detection method from video are mainly temporal difference between two consecutive frames, image subtraction with background and optical flow estimation. Due to the higher detection accuracy of optical flow, it is more suitable for multiobjective moving analysis. Through optical flow estimation, motion parameters of moving objects can be obtained and at the same time, phenomena of occlusion and Overlapping of objects may be avoided as far as possible. Optical flow presents an apparent change of moving object's location or deformation between frames. The Optical flow is a pixel-level representation model for motion patterns, in which each point in the image is assigned a motion vector and it is known as a motion vector field. As it is an ill-posed problem, so far a wide variety of constraints between frames have been introduced in optical-flow modeling. Such constraints are based on image brightness and velocity. In particular, assumption of image brightness constancy between frames is one of the mostly used constraints. Moreover, a motion smoothness constraint is incorporated to enhance the detection accuracy and stability of the estimation. Optic flow techniques are widely used in various applications like motion estimation, Biometrics and film industry.

Motion vectors are computed with the help of optic flow computation. Horn Schunck and Lucas Kanade algorithms are used for computation of optic flow velocity vectors. Computed vectors are segmented using intensity based thresholding. Image enhancement techniques consisting of morphological operations to remove unwanted objects. Vectors are passed to Gabor filter bank parameter which gives complex response in real and imaginary part.

II. THE TRACKING ALGORITHM

The proposed methodology for vehicle detection and tracking will be a flow depicted below.

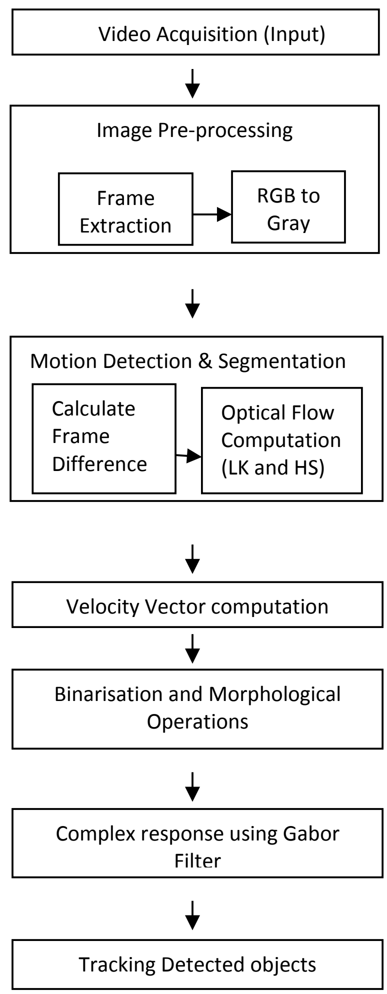


Fig 1. Block Diagram of Proposed work

Input information captured from the mobile camera is analyzed effectively and processed for making the decision. Then frame extraction from input video sequence. Some pre-processing operations have to be done for making the scene ready to process. Due to the camera's auto white balance and the effect of sudden environment intensity changes, the mean of every frame is calculated on gray-scale format. Segmentation operation based on back-ground subtraction using frame difference. The optical flow estimation is the essential part of the algorithm, velocity vectors are computed using LK and HS techniques. In order to segment the moving object, resultant optical flow vectors used to determine whether pixel in frame belongs to movement or not. Threshold is dynamic parameter change from one frame to another. Once velocity vectors are computed some morphological operation needs to perform such as "erosion". Now the motion objects are detected, but many of them are not interested. The pedestrians or waving flags are the example of these unwanted motions. Binarisation of velocity vectors according to energy content that is useful to extract the ROI. With the help of complex response of Gabor filter specification we calculate real and imaginary part. This is named as "Gabor transformed Image". Finally bounding boxes around the rectangular shaped vehicles is the last.

III. PHASES USED IN OBJECT TRACKING

A. Pre-processing Phase

Video is the technology of electronically capturing, recording, processing, storing, transmitting, and reconstructing a sequence of still images representing scenes in motion. An image is a rectangular grid of pixels. It has a definite height and a definite width counted in pixels. A video usually consists of scenes, and each scene includes one or more shots. A shot is an uninterrupted segment of video frame sequence with static or continuous camera motion, while a scene is a series of consecutive shots that are coherent from the narrative point of view.

Before performing any video processing operation the quality of the frame is very essential. In this phase improving the quality of frame is taken into the consideration. An outdoor video sequence is taken as input. The video processing carried out using MATLAB. The video is imported into the environment using function mmreader. Numbers of frames are extracted. For RGB to Gray scale conversion each frame applies on "Gaussian Filter". It helps to intensify or reduce certain image detail that enables easier and faster evaluation. It can used to further process on individual frames. Lighting context to describe the condition of environment lighting, which is reflected in the measurable light intensities. In addition to ambient lights, image intensities also depends on camera parameters such as exposure time, camera gain etc. Since vehicle detection will be performed in the image domain, it is more tangible to define the lighting context from the space that integrates all of the above imaging parameters. The histogram, being the distribution of pixel values of an image, reflects its overall intensity level and is considered to be a viable indicator of the lighting context. A number of vehicles along with their histograms is considered. Here observed a strong correlation between the distribution of the pixel values and the lighting conditions that indicates histogram is the good indicator to determine the lighting context.

B. Segmentation Phase

Background subtraction is a popular method to detect an object as a foreground by segmenting it from a scene of a surveillance camera. The camera could be fixed, pure translational or mobile in nature. Background subtraction attempts to detect moving objects from the difference between the current frame and the reference frame in a pixel-by-pixel or block-by-block fashion. The reference frame is commonly known as 'background image', 'background model' or 'environment model'. A good background model needs to be adaptive to the changes in dynamic scenes. Updating the background information in regular intervals could do this.

To classify the foreground object from the background operation is performed by background modeling technique, i.e. frame differencing. It takes less processing time. In this step, the captured color image is converted to gray scale to make method faster, less computational, and less sensitive to scene condition. In our proposed method, captured series of images received from a camera would be processed. Difference of two images shows moving objects that means calculate frame difference.

Read the first input frame and consider it as background frame. Convert the background frame to gray scale. Set the threshold value, and then set the variables for frame size such as width and height of background frame. Perform the following processing starting form the second frame till the end of last frame in the video. Step is to Read the frame then convert the frame to grey scale, then find the frame difference between current frame with previous frame (Diff_frame = frame t – frame t-1). Now makes the current frame as previous frame and next frame as current frame. Repeat until end of frame in video. Eliminate Background changes with histogram thresholding.

Difference of two images that means frame difference shows moving object. Here use a reference background image (previous frame) for comparative purpose. Then current frame (containing target object) is compared to reference image pixel by pixel. Places where there difference are detected and classified as moving objects.

C. Feature Extraction (Optical Flow Algorithm)

This is based on frame difference and optical flow based methods such as Horn Schunck and Lucas Kanade. The object detection is performed by extracting the features of each object. Every object it has its own specific feature. Here feature extraction is implemented using optical Flow algorithm which is used to detect and point out object in each frame sequence. In this method, the pixels are calculated based on vector position and it is compared in frame sequences for the pixel position. Motion is correspond to vector position of pixels. Here ROI is resultant optical flow vectors are used to determine whether a pixel belongs to movement or not. Pixels are moving then calculate a velocity vector that means motion vectors which gives magnitude and direction.

The object detection is performed by extracting the features of each object. Based on the dimension of every object it has its own specific feature. The Motion field assigns a velocity vector to each pixel in the image. These velocities are induced by the relative motion between the camera and the 3D scene. The motion field can be thought as the projection of the 3D velocities on the image plane. However Motion field ≠ Optical flow.

Motion field is the projection of 3D motion vectors on image plane and Optical flow field is apparent motion of brightness patterns. Consequently optical flow can give important information about the spatial arrangement of the objects viewed and the rate of change of this arrangement. In general the motion is correspond to vector position of pixels. It has the advantage over approaches which attempt to find flow everywhere in the object. The optical flow which is used to detect and point out object in each frame sequence. The Optical Flow is a motion detection technique which specifies how much each image pixels moves between adjacent images in the presence of either camera motion or dynamic background. Lukas-Kanade and Horn-Schunck are a differential technique used to solve aperture problem and compute image velocity from spatiotemporal derivative of image intensities.

I) Horn-Schunck Technique (Dense OF)

The gradient-based methods are primarily based on the image flow constraint equation, which is derived from the brightness constancy assumption as well as the first-order Taylor series approximation. When one used only the image flow constraint equation alone, it is insufficient to compute the OF, because each equation involves two different variables. Also, a regularization approach is introduced by Horn and Schunck that it employed a first order smoothness assumption to constrain the flow field and solve the flow. The unsatisfactory performance of Horn and Schunck's regularization method is mainly due to the insufficient number of iterations of their numerical method in the experiments. In addition, HS method can still generate very accurate OF as long as sufficient iterations (i.e., several thousands) are applied. However, the gradient-based methods suffer from some problems, such as illumination variations, image motion in vicinity of motion discontinuities (i.e., due to smoothness assumption), image aliasing, and noise. According to the assumptions of the first-order Taylor approximation and the intensity conservation, the OF's basic equation is as follows:

$$I_x v_x + I_y v_y = -I_t \qquad \text{----------(1)}$$

Here I(x,y,t) represents the continuous space-time intensity distributing function of a given image. I_x and I_y are the x gradient and y gradient of image I respectively. In addition, I_t represents partial differentiation towards the time, and (v_x, v_y) indicates the components of the image velocity field. There is single linear equation with two unknowns this is called

"Aperture Problem". This Aperture Problem getting solved using Lukas kanade used Least Square method locally and smoothness constrains based on Horn-Schunck approach globally. The minimization of the sum of the errors in the equation for the rate of changes of image brightness and the measure of smoothness in the velocity flow. The minimization is to be accomplished by finding suitable values for optical flow velocity (v_x, v_y). small motion is important means (v_x & v_y are less than 1 pixel). Extraction of Optical Flow at the pixel level can be computed from an image sequence by making some assumptions as intensity values are unchanged, Location of a point between two successive frames changes by only a few pixels, A point behaves together with its neighbours.

In the Horn and Schunck's study, they declared that the OF problem involves minimizing a combination of the OF constraint and a smoothness term. Smoothening is done by taking laplacian. They proposed the regularization method that it involves minimizing an energy functional of the following form,

$$e = \int_D (\nabla I . v + \frac{\partial I}{\partial t})^2 + \lambda^2 \left[(\frac{\partial v_x}{\partial x})^2 + (\frac{\partial v_x}{\partial y})^2 (\frac{\partial v_y}{\partial x})^2 + (\frac{\partial v_y}{\partial x})^2 \right] dxdy \qquad \text{----------(2)}$$

Where D (domain) is the region of the whole image, λ expresses relative effect of the second added error term. λ is a parameter controlling the degree of smoothness in the flow field. Also, smoothness weight $\lambda > 0$ serves as regularization parameter. Larger values for λ lead to smoother flow fields. In dense flow fields, this regularization is a clear advantage over local methods.

II) Lucas-Kanade Technique (Sparse OF)

Horn-Schunck's method introduces a regularization term and it is a global method. Lucas kanade method is to solve the problem on small local windows, where the motion vector is assumed to be constant. The LK method involves minimizing the equation of the following term,

$$\min E = \sum W^2 (\nabla I . v + \frac{\partial I}{\partial t})^2 \qquad \text{----------(3)}$$

To solve it, we let,

$$A = \begin{bmatrix} \frac{\partial I_1}{\partial x_1} & \cdots & \frac{\partial I_1}{\partial y_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial I_N}{\partial x_N} & \cdots & \frac{\partial I_N}{\partial y_N} \end{bmatrix} \qquad \text{----------(4)}$$

$$v = \left[\frac{\partial x}{\partial t}, \frac{\partial y}{\partial t} \right]^T = [v_x, v_y]^t \qquad \text{----------(5)}$$

$$W = diag(W(x_1 y_1) \ldots\ldots (W x_N y_N)) \qquad \text{----------(6)}$$

$$b = - \begin{bmatrix} \frac{\partial I_1}{\partial t} \\ \vdots \\ \frac{\partial I_N}{\partial t} \end{bmatrix} \qquad \text{-----------(7)}$$

Using such notations, we have

$$A^T W^2 A v = A^T W^2 \qquad \text{-----------(8)}$$

So, the flow for the image pixel can be solved,

$$v = (A^T W^2 A)^{-1} A^T W^2 b \qquad \text{------------(9)}$$

Here, $A^T W^2 A$ is Gradient Co-variance matrix, these is useful to extract feature points and those feature points useful for calculating eigenvalues and eigenvectors. Here we calculate mean of all the values. Extraction of feature points on the current video frame given their coordinates on the previous frame. Extraction of the feature points is the key to effectively track the moving object.

D. *Image Enhancement*

Morphological processing can solve an image processing problem, view the image processing toolbox Dilation and Erosion. Morphological operations are performed to extract significant features from images that are useful in the representation and description of the shapes in the region. Mostly used in image segmentation and pattern recognition.

Morphology is a broad set of image processing operations. The process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image on the same size. The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image. In the proposed system we used both morphological erode, respectively, to remove portions of the road and unwanted objects. The Optical flow vectors obtained are segmented using "Threshold Techniques". Thresholding function is used to convert the gray image to binary so that the objects of interest can be highlighted. Here Threshold value is not fixed, it is updated. Everytime it gets comparing with frame difference value and proceeds further.

E. Gabor Filter

The method of ruling image displacements which is easiest to understand is the feature-based approach. This finds features (for example, image edges, corners, and other structures well localized in two dimensions) and tracks these as they move from frame to frame. The act of feature extraction, if done well, will both reduce the amount of information to be processed (and so reduce the workload), and also go some way towards obtaining a higher level of understanding of the scene.

Motion vectors are computed by using optical flow methods but Gabor functions have achieved impressive results when used for object recognition. The magnitude of Gabor coefficients normally used for object recognition. Gabor filters are very popular in various image processing applications such as texture segmentation, target detection, fractal dimension management, document analysis, edge detection, retina identification, images coding and image representation. These Gabor wavelets provide a complete image representation.

Gabor filters are extremely useful for variation with 2-D spatial position. In addition to accurate time-frequency location, they also provide robustness against varying brightness and contrast of images. The success of the developed algorithm highly depends on the Gabor filter parameters; namely f, η, γ and θ. The selection of these parameters affects not only the accuracy of the developed algorithm, but also the size of templates to be stored in the database. Furthermore, the size of the selected Gabor filter directly affects the speed of the algorithm. Effects of the filter parameters and the filter size on accuracy, speed and template size have been taken into account and these parameters and the size are tuned. The size and the parameters of the Gabor filter have been determined, Gabor filter coefficients can be easily calculated.

$$\phi(x,y) = \frac{f^2}{\pi\eta\gamma} e^{\left(-\left(\frac{f^2}{\gamma^2}x_r^2+\frac{f^2}{\eta^2}y_r^2\right)\right)} e^{(j2\pi f x_r)} \quad \text{------------(10)}$$

Where,

$$x_r = (x-1)\cos\theta + (y-1)\sin\theta$$

$$y_r = -(x-1)\sin\theta + (y-1)\cos\theta$$

where,
r is rotation operation,
f is central frequency,
γ is sharpness along major axis,
η is sharpness along minor axis and
θ is orientation.

Moreover, since the size and the parameters are constant, Gabor filter coefficients are also constant. This means that the Gabor filter coefficients can be calculated offline, which speeds up the developed algorithm by eliminating the need in recalculating the filter coefficients.

After the Gabor filter has been determined, the extracted velocity vectors are convoluted with the Gabor filter. Since the Gabor filter is a complex filter, the result of the convolution is also complex, having real and imaginary parts.

IV. EXPERIMENTAL RESULTS

The simulation results obtained from MATLAB software are presented in this chapter. An outdoor video sequence is taken as input. Input of target model is video file which is in .avi format. The output of target model is observed on MATLAB version of R2010a software. Spatial resolution of video is 320x240. The target object is initialized as a rectangular region in an image. Detecting and tracking the objects which exceed the threshold value as moving objects. The object which is moving ahead is to be tracked first. These algorithms were tested on different sets of images.

Algorithm produced its results which are summarised below. Fig (a) is the original images, Fig (b) is the Frame differential component and Fig (c) is the resultant tracking motion vehicle which is highlighted by boundary box.

Video1 (a)

Video1 (b)

Video1 (c)


Video2 (a)

Video2 (b)

Video2 (c)


Video3 (a)

Video3 (b)

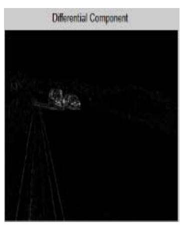
Video3 (c)


Video4 (a)

Video4 (b)

Video4 (c)


Video5 (a)



Video5 (b)

Video5 (c)

Fig.2. A Selected frame (a) input image, (b) frame differential component, (c) tracking motion vehicles with boundary box.

Algorithm produced its good results with sunny condition. For testing purpose we take input as night time video. The headlights and street lights/lamps are brighter than the other pixels. Separating the headlights and other lights sources is the only major hurdle in the detection. The headlight in the image can be used to detect the vehicle but separating it from other light sources is challenging task. Other light sources that interface with headlight detection are street lights, traffic signals, taillights of vehicle in other lane and distant light sources. Here pair of headlights intensity we need to utilize for the requirement of region of interest. Here testing this algorithm on night time video gets fail.


Fig.3. Night Time video for Testing Purpose

This can be improved by using another feature extraction (includes as PCA features, Wavelet features, quantized wavelet features, Gabor features, and combined wavelet and Gabor features) and classification algorithms and two popular classifiers such as SVMs and NNs. That part we consider in future scope.

Pixel Density in each frame is calculated. Graphical representation of frame count vs feature density (frame with vehicle detection) gives following results.

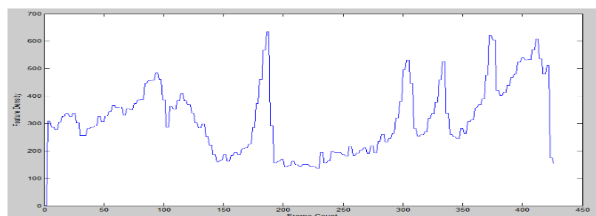


Fig.4 (a) Graphical Representation of HS method for video 1

Above graph shows with the horizontal as counting number of frames and vertical with vehicle detection information of Horn Schunck method with respect to Video1. In Horn Schunck method due to smoothening some of the information gets lost so here we cannot get sharp pick with respect to frame number. By considering frame numbers between 150-200, here vehicle is recognized and gets tracked, once vehicle is very close then we get pick value and if vehicle is far then there is no any pick.

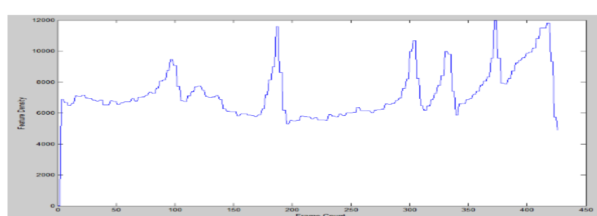


Fig.4 (b) Graphical Representation of LK method for video 1

Above graph shows counting number of frames and with respect to feature density of Lukas Kanade differential method of Video1. Considering frame numbers between 150-200, here vehicle is recognized and gets tracked, once vehicle is very close then we get pick value and if vehicle is far then there is no any pick. In Lukas Kanade method there is no any loss of information as simple mathematical and fast and easy computation is the main advantage over the Horn Schunck method. LK get sharp pick with respect to frame number.

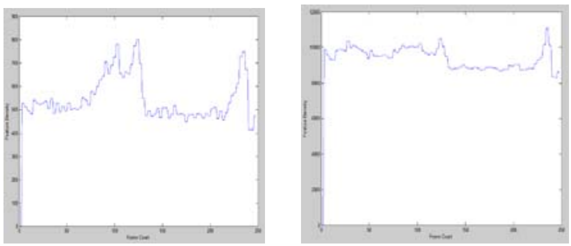


Fig.5 (a)(b)Graphical of Representation HS & LK method for video2

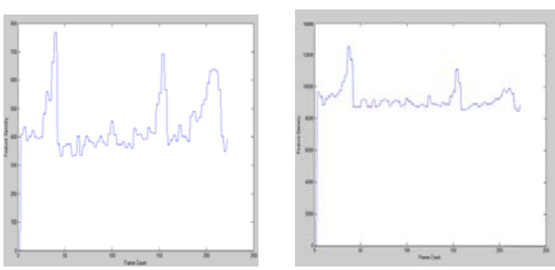


Fig.6 (a)(b)Graphical of Representation HS & LK method for video3

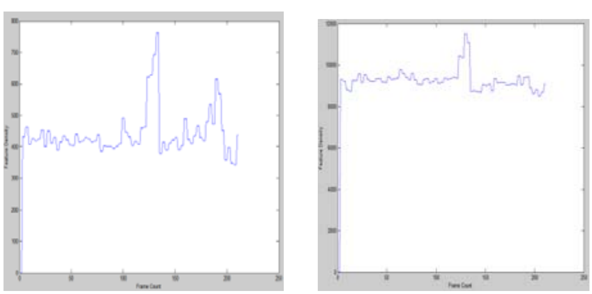


Fig.7 (a)(b)Graphical of Representation HS & LK method for video4

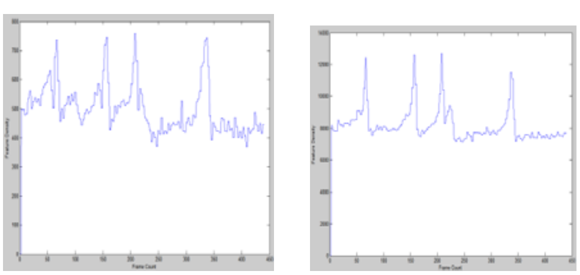


Fig.7 (a)(b)Graphical of Representation HS & LK method for video5

Based on the graphical results here we get vehicle recognition rate with respective frames. More the pixel density then more the accuracy and lesser in the error. If video started with vehicle the we get pick at starting with respective frame number and if vehicle is far then there is no any pick. The output of target object is observed on MATLAB R2010a software. By comparing both the methods such as Lukas kanade and Horn Schunck here we conclude that LK having simple mathematical operations. Easy and fast calculations. It calculates accurate time derivatives. HS method having more mathematical operations than LK method. Hence HS is more complicated than LK. In HS smoothening is done that reduces the information.

Table 6.1 Enlists that performance recognition rate by Lukas Kanade and Horn Schunck methods. Number of frames with respective videos are calculated.

Table 1 Performance Recognition Rate of the System

	Number of Frames	Recognition Rate Method 1 (HS)	Recognition Rate Method 2 (LK)
Video 1	426	49.514 %	60.479 %
Video 2	248	67.498 %	84.181 %
Video 3	222	56.519 %	72.81 %
Video 4	211	57.411 %	79.874 %
Video 5	440	65.595 %	64.436 %
Video 6	137	66.767 %	87.838 %
Video 7	300	74.742 %	69.085 %
Video 8	208	39.352 %	67.931 %
Video 9	159	70.558 %	83.0607 %
Video 10	182	53.478 %	75.86 %

By comparing both the methods such as Lukas kanade and Horn Schunck here we conclude that LK method tracks vehicles more accurately than HS.

V. CONCLUSION

When compared to Horn-Schunck algorithm, Lucas-Kanade algorithm improves the results and reduces noise giving more accurate and relatively better results. In Horn-Schunck algorithm, we optimize the function based on residuals from the brightness constancy. Here we improve the global smoothness but to reduce the mathematical complexity, we go for iterative method. In Lucas-Kanade method we use image patches and windowing methods with least squares technique. LK is easy and fast for execution as compared with HS. All different formats of videos such as night condition, foggy , rainy are not supported by this system. I have tested this algorithm with one night time video it will not show any results hence this algorithm is suitable only for sunny conditions. Moving object detection and tracking is evaluated for traffic monitoring (In case of breaks of traffic rules in monitored using cameras is tracked down easily), Video Surveillance (Designed to monitor the movement in an area to indentify moving object), vision analysis, vehicle navigation.

This work can be extended using Artificial intelligent and fuzzy logic variance. These techniques can be able to handle the inconsistency and wagenence of segmenting object and tracking even when quality of video is low.

REFERENCES

[1] Sepehr Aslani, Homayoun Mahdavi-Nasab, "Optical Flow based Moving Object Detection and Tracking for Traffic Surveillance", *IEEE Transactions On Broadcasting*, *International Journal of Electrical, Electronics Science and Engineering,* Vol. 7, No. 9, 2013.

[2] Weiming Hu, Tieniu Tan, Liang Wang, and Steve Maybank, "A Survey on Visual Surveillance of Object Motion and Behaviors", *IEEE Transactions On Systems, Man and Cybernetics-Part C:Applications and Reviews,* Vol. 34, No.3, August 2004.

[3] R. Revathi, M. Hemalatha, "Certain Approach of Object Tracking using Optical Flow", *International Journal of Computer Application, (0975 – 8887)*, Vol. 53, No. 8, September 2012.

[4] Sri Devi Thota, Kanaka Sunanda Vemulapalli, Kartheek Chintalapati, Phanindra Sai Srinivas Gudipudi, "Comparison Between The Optical Flow Computational Techniques," *International Journal of Engineering Trends and Technology (IJETT),* vol.4, ISSN.223-5381, Iss.10, Oct 2013.

[5] Smitha Gayathri. D, Dattatreya K. A, "Optical Flow Based Multiple Object Detection and Tracking System in Static and Dynamic Environment," *IOSR Journal of Electronics and Communication Engineering, (IOSR-JECE),* vol.9, Iss.1, Ver. V, pp.09-16 (Feb.2014).