

SEGMENTATION OF VEHICLES BASED ON MOTION ESTIMATION

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Abstract: Now a days predicting the motion has become important in our daily lives. Most of the traffic monitoring systems has been using the motion equipment for the estimation of motion of the particular vehicle. Motion Estimation and vehicles segmentation is an interesting solution for the efficient traffic monitoring system. Segmentation of moving vehicles in a scene is very much seen in applications such as robotics, video coding techniques, video surveillance, video indexing. One of the key elements of a traffic monitoring system is the motion analysis component, which segments vehicles from the scene and estimates the motion on the image plane. The objective of the paper is to find the methods that can be used efficiently to extract vehicles from the background in captured video frame and to apply the techniques of motion estimation and segmentation. We have applied Lucas Kanade algorithm to a reference frame and determined the motion vectors of the vehicles. We then extended this by applying segmentation to the reference frame to segment the vehicles from the background and then applied Lucas Kanade algorithm. Lukas Kanade algorithm is selected due to its efficiency in video coding standards and its simplicity for software implementations. This processed information will provide a brief information about the vehicle count, vehicle motion and turning rates at the cross road junction and also in video coding techniques.

Keywords: Motion estimation, Segmentation, video surveillance, video indexing, video coding.

I. INTRODUCTION

Time taken, noise removal and output information are the key factors in judging a system efficiency. Video is the combination of certain frames and each video is taken depending upon the frame rate. Frame rate is the number of frames in a second and it determines the efficiency of the system. Now a days, optical flow estimation in the frames of a video still remains a core challenge to determine all the parameters linked with the vehicle motion. Motion estimation is used to find the object trajectory in both the x and y directions and is an important method of analysing a video. It is used to find the vectors of motion of the vehicles and also used in the standard video coding technique for the efficient reduction of frames. Motion estimation is the estimation of motion vectors for a frame in the video either the past frame from the future frame or the future frame from the past frame. Segmentation is defined as separation of vehicles from the background by calculating the pixel difference between the background and vehicles. Video is taken in a cross road junction by using the static camera with certain height capturing all the vehicles at a cross road. We knew that for a video taken by a static camera the background will be constant and the pixel values at the vehicles continue to change continuously. With advancement in video capturing techniques many researchers are trying to reduce the time taken to process a video and extract more information from the captured video. An efficient traffic monitoring system should have less time to process the video, more information for the output video and less noise.

In this paper, we investigated different methods of segmentation after applying Lucas Kanade algorithm to the two successive frames of the video. The same is applied to the entire video. We also examined the difference between the time taken to perform Lucas Kanade with pyramidal decomposition of the frames and the normal application of Lucas Kanade algorithm. The proposed method firstly uses Lucas Kanade algorithm to the frames of the video to calculate the optical flow and the motion vectors. Using the output video we then performed various methods of segmentation to extract the background from the moving vehicles. We also performed Pyramidal decomposition of frames using Gaussian filter to highlight the low frequency components and then applied Lucas Kanade algorithm.

II. LITERATURE SURVEY

Chao-Jung Chen, Chung-Cheng Chiu have published a paper on “**The Moving Object Segmentation Approach to Vehicle Extraction**” using matlab in which the Intelligent traffic monitoring system is extended first time based on Moving vehicle segmentation using the threshold values. They have segmented the vehicles from the background based on the pixel differences. They have calculated the pixel differences and segmented the background which is motionless and constant for a given period time. The information provided by them is very much useful in vehicle counting, tracking, recognition and speed detection [1].

F. Bartolini, V. Cappellini have published a paper on “**Motion estimation and tracking for urban traffic monitoring**” in which traffic monitoring techniques based on image processing algorithms have replaced the classical inductive loops which are used to compute traffic density on a single lane at the cross road junction. In this paper the author have uses the static camera and acquired the images of the vehicles and determined the trajectories of the vehicle. The acquired image undergo block matching algorithm which compares a reference block with the captured image. The acquired image is divided into sub-blocks and each sub-block is compared with the all the sub-blocks in the next frame. Due to acquisition and environmental noise, many wrongly

estimated motion vectors appear over static uniform areas and system performance mainly depends upon the position of the camera [2].

In this paper we want to combine the two topics of motion estimation with pyramidal decomposition and segmentation. Firstly using matlab a video have been taken for processing and is divided into frames of certain frame rate. Pyramidal decomposition using Gaussian filter is then applied to all the frames to highlight the low frequency components in all the frames taken for processing. Lucas Kanade algorithm is then applied to all the frames of the video all the vector of the pixels in both X and Y directions, Orientation and magnitude can be noted from the workspace. After getting the output video the motion estimated video then undergo various segmentation process like thresholding, Blob analysis to segment the video into background and foreground parts. The acquired information is used in various applications like vehicle tracking, motion analysis, motion magnification, vehicle detection, turning rates etc.

III. METHODOLOGY

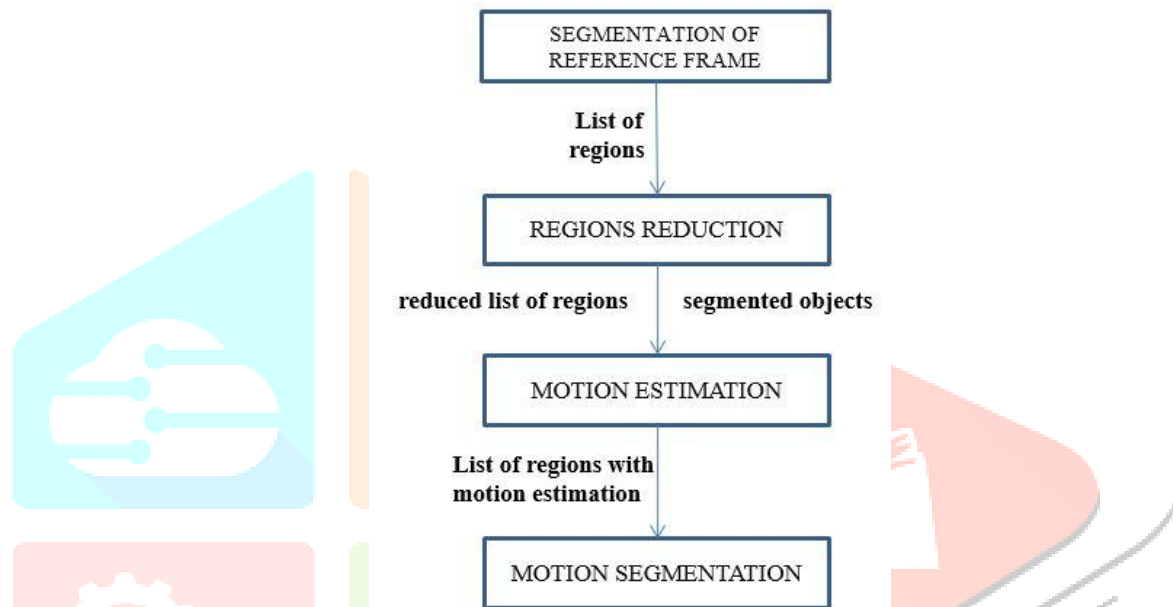


Figure 1 Work flow chart of the paper

Here Figure 1 depicts the work flow followed in this paper. Here the motion estimation process is the application of the Lucas Kanade algorithm

a) STEPS FOLLOWED FOR MOTION ESTIMATION

In our project, we followed the below mentioned steps for the estimation of motion between the adjacent frames in video sequence

- i. Input video is captured.
- ii. Conversion of video into frames.
- iii. Apply pyramidal decomposition to all the frames in the video and highlight the low frequency components.
- iv. The Lucas Kanade algorithm is applied to each and every frame.
- v. Reconstructing the video sequence.
- vi. Output video is observed.

b) STEPS FOLLOWED FOR SEGMENTATION BASED ON MOTION ESTIMATION

- i. Input video is captured.
- ii. Segmentation of video into frames.
- iii. Apply pyramidal decomposition to all the frames in the video and highlight the low frequency components.
- iv. Apply any segmentation technique to extract background from the moving vehicle on the road.
- v. And then the Lucas-Kanade algorithm is applied to each and every frame.
- vi. Reconstructing the video sequence.
- vii. Output video is observed.

IV. LUCAS KANADE ALGORITHM

This method try to calculate motion between two image frames which are taken at time t and t + delta (t).It uses differential method for motion estimation. A pixel at location (x, y, t) with intensity I(x, y, t) will have moved by (u, v, T) between two image frames

By the Taylor series expansion

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + \frac{\partial I}{\partial x} \Delta x + \frac{\partial I}{\partial Y} \Delta y + \frac{\delta I}{\delta t} \Delta t \quad (1)$$

Assume that the motion between the two frames is very small and can be neglected

From the above Eq.1

$$\frac{\partial I}{\partial x} \Delta x + \frac{\partial I}{\partial Y} \Delta y + \frac{\delta I}{\delta t} \Delta t = 0$$

or

$$\frac{\partial I}{\partial x} \frac{\Delta x}{\Delta t} + \frac{\partial I}{\partial Y} \frac{\Delta y}{\Delta t} + \frac{\delta I}{\delta t} = 0$$

Which results in

$$\frac{\partial I}{\partial x} V_x + \frac{\partial I}{\partial Y} V_y + \frac{\delta I}{\delta t} = 0$$

And finally results in

$$I_x V_x + I_y V_y = - I_t \quad (2)$$

$\frac{\partial I}{\partial x}, \frac{\partial I}{\partial Y}, \frac{\partial I}{\partial T}$ are the derivatives of the image at (x,y,t) in the corresponding directions. I_x, I_y, I_t can be written for derivatives.

Hence for all pixels it can be written in the format of AV=B and solve for V

From the above equation (2) we can solve the above matrices V_x, V_y

V. IMPLEMENTATION OF PROPOSED WORK FLOW

a) Reading of Input Video

The input video sequence that is taken for the estimation of motion between the adjacent frames in a video is shown below in the figure 2



Figure 2 Input video taken for processing

b) Conversion of video sequence into frames



Figure 3 Conversion of Video into frames

The input video is then splitted into number of frames depending upon the frame rate.

c) Metrics of Input Video

Table 1 Metrics of the input video

Property	Value
Bits per pixel	24
Frame rate	15
Height	120
Video format	RGB24
Width	160
Smoothness	1
Max iteration	10
Velocity difference	0

All the properties like frame rate, velocity difference, smoothness have been noted down in the table 1

d) After applying Pyramidal Decomposition to each frame



Figure 4 Application of Pyramidal decomposition to each frame

We have applied Gaussian filter four times for subsequent smoothing to highlight the low frequency components as shown in the figure 4. A low pass pyramid is made by smoothing the image with an appropriate smoothing filter and then subsampling the smoothed image, usually by a factor of 2 along each coordinate direction.

e) Performance metrics of Pyramidal Decomposition

Table 2 Performance metrics of pyramidal decomposition

No of Frames Applying Gaussian Filter	Mean	Median	Entropy
1	117.473	114	7.747
2	117.305	113	7.740
3	117.169	113	7.736
4	117.07	112	7.724

Gaussian filter is applied four times to all the frames and the low frequency components have been highlighted and all the performance metrics mean, entropy and entropy are noted down in the table 2.

f) After applying Lucas Kanade Algorithm to the two successive frames

Reading of two successive frames

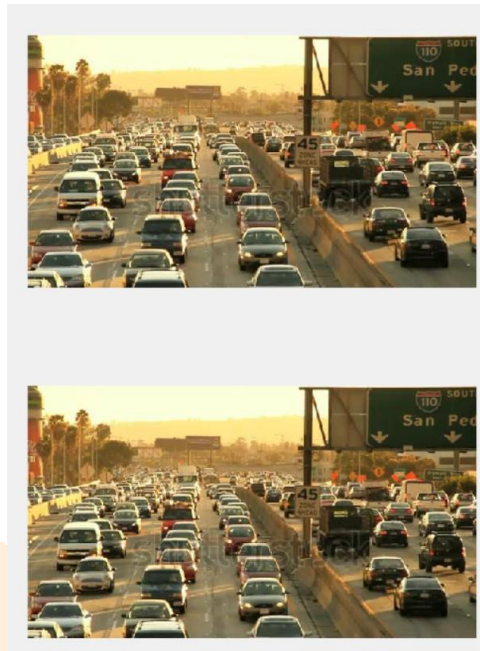


Figure 5 Reading of two successive frames in the video

Here two consecutive frames of a video have been taken as shown in the figure 5 and have been applied with Lucas kanade algorithm. We have applied Lucas kanade algorithm on the two frames to find the exact position where the each pixel in one frame has move to another frame.

g) After applying Lucas Kanade algorithm to the two successive frames



Figure 6 Result after applying Lucas Kanade algorithm to the two successive frames

We have applied the Lucas kanade algorithm to the two frames and we have identified the position of the each pixel in the next frame as shown in the figure 6.

h) After applying Lucas Kanade Algorithm to the entire video

The output video sequence after applying the Lucas-Kanade algorithm the frames in a video sequence is shown below in figure 7. The given algorithm is then applied for the video sequence we can notice the motion vectors for the moving objects from the video.



Figure 7 Motion vectors for the downloaded video after application of Lucas Kanade algorithm

The same algorithm for the each frame is then applied to the entire video and the motion vectors can be observed in blue color in the figure 7 and the time taken for elapsing with pyramidal decomposition and without pyramidal decomposition has been noted down.

i) Metrics of motion vectors in X and Y directions

Table 3 Metrics of motion vectors in x and y directions

Property	Value
V_x	120x160 single
V_y	120x160 single
Orientation	120x160 single
Magnitude	120x160 single

Here we have noted down all the velocity vectors in both x and y directions and the orientation for the each pixel position as shown in the table 3.

j) Performance metrics of video after applying Lucas Kanade algorithm

Table 4 Performance metrics of video after applying algorithm

Frame	Mean	Median	Entropy
RGB frame	123.209	124	6.94
Gray frame	123.566	123	6.81

Here we have noted down the mean, median and entropy values of both the RGB and the Gray frames in the Matlab as shown in table 4.

k) Motion Vector in X direction

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.7770e-04	3.6270e-04	8.9600e-05	8.4000e-05	1.7430e-04	2.5433e-04	2.3754e-04	4.1489e-04	1.0766e-04	2.2935e-04	3.8516e-04	3.3377e-04	8.2770e-04	0.0029	0.0041	0.0003
2.5703e-04	2.5996e-04	3.4510e-05	5.0027e-05	8.0830e-05	1.2451e-04	4.0883e-05	4.8290e-04	1.3099e-04	2.7004e-04	7.4856e-04	1.1640e-04	8.8230e-04	0.0017	0.0060	0.0064
3.5241e-04	8.0545e-05	5.4239e-05	2.0070e-05	1.0902e-05	8.4193e-05	2.6539e-04	4.2326e-04	3.0749e-04	1.1228e-04	3.4834e-04	3.8566e-04	5.8502e-04	0.0021	0.0540	0.0041
4.2056e-04	1.1288e-04	8.9620e-05	4.3082e-05	5.4190e-05	1.1764e-04	5.5713e-04	0.0010	6.1348e-04	3.8246e-04	3.9989e-04	3.9993e-04	5.0094e-04	8.7930e-04	5.7221e-04	0.0020
5.2790e-04	2.4811e-04	8.9390e-05	4.0315e-05	8.8960e-05	2.2583e-04	5.2771e-04	0.0011	0.0014	8.5914e-04	8.4056e-04	1.8250e-04	5.9423e-04	5.3330e-04	5.4332e-04	0.0013
6.3280e-04	3.1182e-04	1.5070e-04	1.0151e-04	1.3254e-04	1.2863e-04	4.8896e-04	8.2326e-04	8.8790e-04	8.2000e-04	6.0790e-04	3.8230e-04	5.9800e-04	8.1030e-04	0.0013	0.0008
7.4861e-04	3.5073e-04	2.5939e-04	2.0886e-04	4.1650e-04	4.7233e-04	3.1970e-04	5.7041e-04	6.1665e-04	6.7898e-04	9.1911e-04	3.1155e-04	2.4930e-04	3.8996e-04	9.7815e-04	0.0018
8.2865e-04	4.8530e-04	2.5920e-04	9.4480e-05	1.7837e-04	9.5821e-05	1.8101e-04	3.8212e-04	5.8519e-04	4.8584e-04	8.1483e-04	5.5833e-04	5.5396e-04	4.3810e-04	4.7990e-04	4.2042e-04
9.1530e-04	1.4036e-04	3.2139e-04	2.2311e-04	2.4310e-04	1.2996e-04	8.2733e-04	2.4004e-04	3.2019e-04	3.3400e-04	6.0823e-04	8.1790e-04	3.2424e-04	4.8421e-04	3.2038e-04	1.1790e-04
10.1947e-04	2.0484e-04	1.9800e-04	1.7463e-04	2.4311e-04	1.0330e-04	1.7118e-04	2.4984e-04	3.3377e-04	3.4240e-04	4.9502e-04	4.8984e-04	5.3294e-04	4.7194e-04	1.7547e-04	1.8471e-04
11.1772e-04	1.5956e-04	1.3896e-04	5.8793e-04	4.8838e-04	8.1709e-04	6.3311e-04	5.1998e-04	2.4284e-04	2.1777e-04	1.3021e-04	8.7640e-04	8.8240e-04	3.1009e-04	2.0865e-04	1.8046e-04
12.1570e-04	5.7875e-04	1.8990e-04	4.2471e-04	4.1403e-04	0.0011	8.4787e-04	7.0538e-04	3.2639e-04	3.8822e-04	4.2811e-04	3.3406e-04	0.0015	2.8794e-04	2.7014e-04	2.7963e-04
13.3489e-04	1.1704e-04	2.1910e-04	8.8270e-04	7.3230e-04	2.4500e-04	4.2753e-04	5.0319e-04	1.2793e-04	4.8899e-04	2.8838e-04	0.0017	8.2916e-04	3.8808e-04	5.3123e-04	4.1934e-04
14.1871e-04	3.3382e-04	4.0950e-04	8.3382e-04	0.0011	5.0898e-04	8.2848e-04	4.6323e-04	3.0681e-04	1.1798e-04	4.4890e-04	1.8864e-04	7.4717e-04	0.0021	0.0011	3.8219e-04
15.3413e-04	5.3382e-04	2.8511e-04	4.8607e-04	5.7234e-04	4.1588e-04	9.5033e-04	8.8931e-04	5.2426e-04	5.8829e-04	2.9171e-04	0.0010	5.4172e-04	0.0020	8.4579e-04	5.0272e-04
16.7478e-04	3.4670e-04	1.3790e-04	2.4870e-04	6.4733e-04	3.3590e-04	4.0666e-04	7.5738e-04	4.8939e-04	5.8793e-04	0.0012	0.0025	5.6386e-05	0.0014	8.2187e-04	6.7929e-04
17.3291e-04	9.9804e-05	3.3200e-04	4.0230e-04	2.3012e-04	1.2862e-04	2.2398e-04	4.3404e-04	1.8233e-04	2.8113e-04	6.8897e-04	0.0029	8.8717e-04	1.0598e-04	0.0015	0.0019
18.2495e-04	7.3995e-04	0.0011	7.4010e-04	8.2890e-04	3.3896e-04	4.1920e-04	3.9146e-04	1.8299e-04	7.2250e-04	0.0013	0.0012	4.8893e-04	6.4918e-04	3.8388e-04	0.0011
19.4358e-04	4.7950e-04	4.0320e-04	4.4722e-04	8.4433e-04	7.7850e-04	0.0014	8.8822e-04	2.5350e-04	1.8006e-04	6.2110e-04	0.0014	0.0013	9.3271e-04	0.0013	0.0015
20.0013	8.6485e-04	1.1901e-04	2.0886e-04	2.1474e-04	3.3277e-04	7.4784e-04	8.4323e-04	1.6814e-04	2.2077e-04	3.4831e-04	7.3894e-04	0.0012	0.0019	0.0012	0.0012
21.4267e-04	4.2256e-04	4.5750e-04	4.0113e-05	4.4870e-04	0.0015	6.1940e-04	0.0012	0.0011	2.1105e-04	3.8811e-04	3.4849e-04	0.0019	0.0024	0.0019	0.0013
22.3846e-04	3.8275e-04	3.5357e-04	4.8856e-04	5.2740e-04	2.5396e-04	7.6802e-04	0.0013	0.0023	8.4034e-04	0.0019	0.0016	0.0011	0.0043	0.0027	0.0015

Figure 8 Motion vectors in X direction

Motion vector in Y direction

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
-2.732e-04	9.217e-05	8.822e-05	2.984e-06	2.314e-05	5.4807e-05	3.902e-05	-1.328e-04	9.987e-05	2.091e-04	2.277e-04	1.118e-07	-2.002e-04	-7.269e-04	-0.0017	6.692e-04
-3.779e-05	5.991e-05	2.847e-05	1.920e-05	2.346e-05	3.737e-05	-1.988e-05	3.791e-04	1.292e-04	3.278e-04	3.902e-04	-1.661e-04	-6.762e-04	6.877e-04	-0.0014	-0.0012
-1.3817e-05	1.6586e-05	5.3803e-05	-8.5914e-06	1.0159e-05	3.9975e-05	-2.2055e-04	-4.1675e-04	-2.6718e-04	8.5984e-05	2.7995e-05	-3.4925e-04	5.4668e-04	-0.0013	-0.0022	-0.0023
1.3305e-04	1.2216e-04	8.6187e-05	2.5488e-05	2.2002e-05	-8.2415e-05	-4.3951e-04	-7.7009e-04	-6.6900e-04	-2.3817e-04	-2.3983e-04	-3.1082e-04	-3.3088e-04	-4.7725e-04	-5.6992e-04	-0.0014
7.8431e-05	1.0114e-04	8.1002e-05	3.9781e-05	6.8774e-05	-1.9131e-04	-4.4101e-04	-6.0584e-04	-0.0011	6.4314e-04	-4.0712e-04	-2.4109e-04	-3.3027e-04	-4.2737e-04	-4.9074e-04	-0.0012
5.5591e-05	1.6049e-04	1.2021e-04	9.7113e-05	8.8761e-05	-1.0020e-04	-6.0116e-04	-7.8771e-04	-3.2009e-04	-6.9721e-04	-4.5174e-04	-1.8733e-04	-3.0131e-04	-6.2999e-04	-8.7112e-04	-0.0019
7.4144e-04	6.4938e-05	2.0254e-04	2.0807e-04	3.9118e-04	-2.6647e-05	-3.0409e-04	-5.0786e-04	-5.9079e-04	-4.4456e-04	-8.2704e-04	-2.4819e-04	-1.6091e-04	-2.7193e-04	-4.9591e-04	-9.8442e-04
6.5644e-05	-1.6878e-04	1.4803e-04	8.8937e-05	1.5940e-04	2.4802e-05	-1.7223e-04	-5.8201e-04	-5.0044e-04	-3.2048e-04	-5.4878e-04	-3.2233e-04	5.2213e-05	-1.6319e-04	-2.5471e-04	-2.9142e-04
9.1311e-04	-4.3945e-05	2.3540e-04	6.8735e-05	1.1905e-04	4.2002e-05	2.2046e-05	-1.7979e-04	-2.1646e-04	2.6910e-04	-4.0046e-04	5.1479e-04	-2.1188e-04	5.2032e-04	-1.4465e-04	-6.6919e-05
1.0599e-05	-1.3914e-04	5.9171e-05	-7.9843e-05	2.2810e-05	1.3094e-05	5.8959e-05	-1.7624e-04	-2.1785e-04	-4.4004e-04	1.7371e-04	-3.3099e-04	-1.0311e-04	-1.9591e-05	4.3542e-06	-
11.7529e-05	6.6416e-05	-1.3780e-04	-5.9142e-04	-2.7137e-04	-2.1177e-04	-1.8309e-04	-1.0804e-04	-2.1160e-04	-1.5984e-04	-1.8826e-04	6.7966e-04	-4.3227e-04	-1.7172e-04	-3.3564e-05	5.3071e-05
8.1589e-05	4.0944e-05	-3.6607e-05	-4.0435e-04	-4.1042e-04	-5.7856e-04	8.4059e-06	3.4707e-05	-1.5017e-04	-2.0917e-04	2.5956e-04	2.2728e-05	-8.9021e-04	-1.1347e-04	1.0048e-05	7.3393e-05
13.1880e-04	5.9131e-06	-1.8016e-04	-6.0727e-04	-7.6443e-04	1.2411e-05	3.1459e-04	1.1342e-04	-7.5038e-05	1.3922e-05	1.8906e-04	-9.2944e-04	-8.4096e-05	1.7693e-04	2.9291e-04	8.4699e-05
5.9480e-05	2.7047e-04	3.3641e-04	-7.9919e-04	9.8403e-04	-4.0702e-04	5.8937e-04	3.0204e-04	-1.8402e-04	2.0411e-05	5.9191e-05	1.8211e-04	1.3701e-04	4.3917e-04	1.8762e-04	6.9049e-05
15.15413e-04	-5.3098e-04	-2.6849e-04	-3.7977e-04	-4.7131e-04	-3.4899e-04	-8.3811e-04	-4.9426e-04	-2.2608e-04	2.2020e-05	8.2337e-05	-2.5540e-04	8.1909e-05	-3.4063e-04	1.9952e-04	4.4801e-05
16.4.120e-04	-3.0471e-04	-5.5419e-05	-9.0789e-05	-4.9141e-04	-2.3037e-04	-3.3674e-04	-2.3144e-04	-1.6300e-04	3.8731e-04	9.0738e-04	-0.0014	1.2464e-05	-4.1331e-04	8.0871e-04	-3.9554e-04
17.1.781e-04	8.3340e-05	3.3226e-04	3.9185e-04	6.3421e-04	-4.3784e-04	-2.2089e-04	-2.0922e-05	-4.6790e-05	1.9700e-04	-1.9238e-05	-0.0015	-4.0212e-04	-1.9466e-04	6.0014	-0.0016
18.2.7912e-04	7.3805e-04	0.0011	2.3425e-04	8.0691e-04	2.3955e-04	4.9897e-04	2.8461e-05	7.6028e-05	3.7901e-04	-3.7664e-04	-0.0011	1.3402e-04	-6.3403e-04	3.0813e-04	-3.9181e-04
19.4.8957e-04	4.5544e-04	3.7327e-04	4.4891e-04	8.3959e-04	7.6884e-04	0.0014	5.6028e-04	2.4042e-04	6.5311e-05	-3.6549e-04	-0.0012	-5.1550e-04	-8.5239e-04	-0.0446e-04	-5.9327e-04
20.0.0013	6.4335e-04	1.0402e-04	2.1346e-05	-1.1838e-04	-1.1388e-04	2.9802e-04	-2.3341e-04	-6.6197e-05	-4.7911e-05	-7.6443e-05	-7.3093e-04	-0.0011	0.0019	-0.0011	-0.0010
21.4.1799e-04	2.8405e-04	-6.7289e-05	4.0296e-05	-3.2844e-04	-0.0013	-6.1830e-04	-0.3891e-04	-6.0716e-04	-1.1470e-04	2.9448e-04	-9.4789e-04	-0.0018	0.0024	-0.0019	-0.0013
22.2.6649e-05	6.8677e-05	3.9101e-05	4.1409e-04	5.6103e-04	2.7264e-04	-1.2349e-04	4.6173e-04	-2.9171e-04	2.9147e-04	-4.0271e-04	-8.7173e-04	-0.0014	-0.0021	-0.0015	-0.0012
23.1.2129e-04	-5.1979e-05	-1.4031e-04	3.9781e-04	4.9666e-04	1.3997e-04	-1.4704e-04	-2.0202e-04	-7.3544e-05	-2.7848e-04	-3.5579e-04	-6.8777e-04	-4.8889e-04	-0.0029	-0.0017	-0.0013

Figure 9 Motion vectors in Y direction

Here we can note down all the values of motion vectors in X and Y directions as shown in the figure 8 and figure 9, orientation and magnitude of all the pixel values in the frames of the video.

1) Extension of Motion estimation with Thresholding and Blob analysis



Figure 10 Segmented frame of Downloaded video by the method of Thresholding

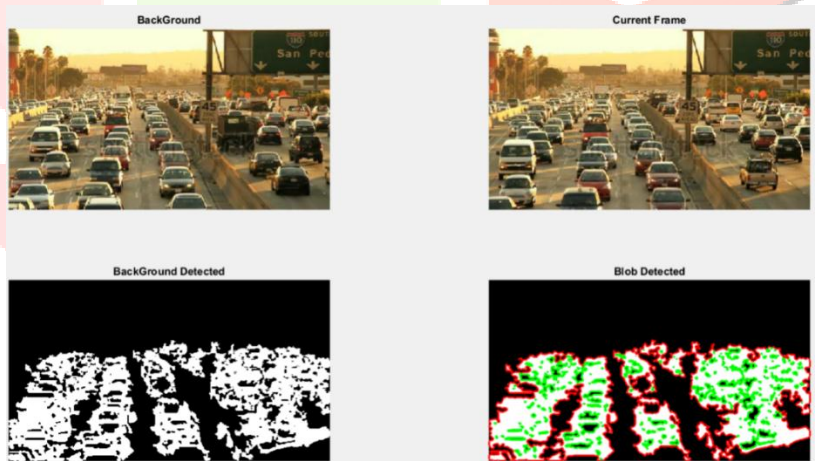


Figure 11 Segmented frame of Downloaded video by the method of Blob analysis

For the segmentation purpose we then applied the technique of Thresholding and Blob analysis to segment the moving vehicles and background as shown in the figure 11 and we have noted that elapsed time taken is 7.0147 sec. This algorithm can be further extended by using different techniques of segmentation.

m) Performance metrics of Lucas Kanade algorithm with and without pyramidal decomposition

Table 5 Performance metrics of algorithm with and without pyramidal decomposition

Method	Time elapsed
Lucas kanade Algorithm	6.0158 sec
Lucas Kanade Algorithm with pyramidal decomposition	5.0147 sec

We have compared the elapsed time of application of Lucas Kanade algorithm with and without Pyramidal decomposition and we found that it takes less time to perform Lucas kanade algorithm with pyramidal decomposition as shown in the table 5.

VI. CONCLUSION AND FUTURE SCOPE

Based on the results Lucas Kanade algorithm has been implemented for one frame and the performance is analysed and the same is applied to the video. We have performed Lucas Kanade algorithm with pyramidal decomposition to highlight the low frequency components. The metrics for each step have been taken and we have noticed that time elapsed for Lucas Kanade algorithm with pyramidal decomposition is less than the normal application of Lucas Kanade algorithm. The execution time taken by the algorithm is less than the conventional matching methods and block matching methods. The Lucas Kanade algorithm for motion estimation using Taylor series expansion works more efficiently with standard blob tracking method. The proposed algorithm is then extended with the various techniques of Segmentation to segment the vehicles and the background which is constant in the video taken by the static camera. We have segmented the video with the technique of thresholding and then we have applied Blob analysis to extract the vehicles from the video.

The concept is well extendable in applications like Intelligent Robots, Automatic Guided Vehicles, Enhancement of Security Systems to detect the suspicious behaviour along with detection of weapons, identify the suspicious movements of enemies on borders with the help of night vision cameras and many such applications. The proposed algorithm can be extended by applying various techniques of segmentation for the extraction of background. This concept is also extendable to see the subtle motions which cannot be seen with our naked eye. In order to see those subtle motions, the motion is estimated and then amplified. So in the applications like motion magnification this technique will be helpful to see the small motions.

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