International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 11 (2015) pp. 30135-30152

http://www.ripublication.com

Single Moving Object Detection and Tracking Using Horn-Schunck Optical Flow Method

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Abstract

Object tracking in video sequencesis gaining much importance in computer vision. Many video surveillance system implemented template or pattern matching to track the moving object.However, template or pattern matching requires sample of pattern or template before it can track any object. Object tracking can be difficult if the surface of the object does not remain same from frame to frame, such as reflection of light. This paper proposes a new method to detect a single moving object in a multimedia file such as video through an approach called Optical flow which proves to be a more efficient method for tracking moving objects.Optical flow is a flexible representation of visual motion that is particularly suitable for computers for analyzing digital images. In this work the Horn & Schunck method is used to find the optical flow vectors which in turn pave a way for the detection and tracking of the single moving object in a video. Optical flow method introduced in this work proves to be more efficient method for object detection and tracking compared to existing methods of object detection tracking. A detailed study on the existing methods is presented. The proposed method was experimented with various videos and the results are also discussed.

Keywords: Object detection, tracking, optical flow, flow velocity

Literature Survey

The detection of moving object is important in many tasks, such as video surveillance and moving object tracking. The aim of object tracking and detection is to establish a correspondence between objects or object parts in consecutive frames and to extract temporal information about objects such as trajectory, posture, speed and direction. Tracking detected objects frame by frame in video is a significant and difficult task. [1]

The present day technology allows automatic detection based on predefined measures. In this foreground detection based moving object detection and vehicle tracking algorithm is implemented targeting a wide class of applications. An AVI file is read and it is decomposed into R, G and B components. Various operations are carried out and the moving objects are detected. Thresholds at various phases decide the possibility of identifying the moving object of certain sizes. Moving objects are also tracked in it. MATLAB is used for implementation of the algorithm [2]

Tracking in higher level applications requires the location and shape of object in every frame. Implementation of Matlab based moving object detecting algorithm, in which adjacent frame difference algorithm is applied, can be used for detecting moving objects in video from the aspects of video acquisition, feature extraction and frame segmentation, etc. In adjacent frame difference method, moving objects are extracted according to the differences among two or three continuous frames. [3]

Moving object detection involves identification of an object in consecutive frames whereas object tracking is used to monitor the movements with respect to the region of interest. Optical Flow is a concept which is used for object detection and tracking. Single object and multiple object movements in a frame with respect to the computed vectors are segmented with the help of threshold which is specified depending on the value mentioned. The extracted movements are tracked. A smoothing algorithm is used to estimate Moving object detection using image processing technique using Matlab Software.

The Optical Flow algorithms are mostly based on correlation, gradient and frequency information respectively. Some common algorithms for computing Optical Flow vectors are block matching for correlation, Lucas-Kanade and Horn &Schunck is for gradient and phase- based filtering for frequency. The Optical Flow vectors with the components u and v for each region are calculated. Optical Flow vectors are used to determine whether the pixels in the frame belong to movement or not that in turn helps in object tracking. [4]

Optical flow-based tracking algorithm incorporates physically-based constraints to extract motion data from video. The technique can accurately track a significant number of data points with a high degree of automation and efficiency. Many traditional methods of video data extraction from poor-quality video have proven tedious and time-consuming due to extensive user-input requirements.

To meet the drawbacks of traditional methods, Optical flow-based algorithm is proposed which functions with a minimal degree of user involvement. Points identified at the outset of a video sequence, and within a small subset of frames spaced throughout, can be automatically tracked even when they become occluded or undergo translational, rotational, or deformational motion. The proposed algorithm improves upon previous optical flow-based tracking algorithms by providing greater flexibility and robustness. [5]

The production of optical flow image using Horn &Schunck technique for finding the optimal parameters are done by combining parameters and the different types of displacements. . Different types of displacements used are small, medium and large. Optical flow is generally carried out through utilizing a brightness constancy constraint equation (BCCE), which makes use of spatiotemporal derivatives of image intensity. Methods utilizing the BCCE are referred to as differential techniques.

There are many different methods to estimate the optical flow, which can be divided into correlation, energy, phase and differential based method. The differential based method of estimating optical flow, based on partial derivatives of the image signal and the sought flow field and higher-order partial derivatives, can be solve using Horn &Schunck method and Locus Kanade method. [6]

Horn and Schunck algorithm is based on a differential technique computed by using a gradient constraint (brightness constancy) with a global smoothness to obtain an estimated velocity field. There are two main processes for the implementation of the HS algorithm. The first one is an estimation of partial derivatives, and the second one is a minimization of the sum of the errors by an iterative process to present the final motion vector.

The Horn & Schunck algorithm is a technique used to identify the image velocity or motion vector based on spatial temporal gradient technique which computes the image velocity from the derivatives of image intensity .To compute the partial derivatives convolution function is used. According to the characteristics of the Horn & Schunck algorithm, when applied with the BFB kernel it provides simplicity in the algorithm with reasonable performance and better quality, but the value of the smoothing weight (α) cannot be defined exactly because the suitable value is varying upon different image sequences. [7]

The Horn-Schunck algorithm assumes smoothness in the flow over the whole image. Thus, it tries to minimize distortions in flow and prefers solutions which show more smoothness.The differential method does not generate Optical Flow in case of stationary moving objects (same intensity) with respect to stationary camera.The filtering and segmentation algorithm needs to be improved with respect to computation time suitable for real time applications.The work with respect to moving background with moving object (dynamic) has not been discussed so far.

Introduction

A. Existing methods

i) Background subtraction

Background subtraction, also known as Foreground Detection, is a technique in the fields of image processing and computer vision wherein an image's foreground is extracted for further processing (object recognition etc.). Generally an image's regions of interest are objects (humans, cars, text etc.) in its foreground. After the stage of image preprocessing (which may include image denoising etc.) object localization is required which may make use of this technique. Background subtraction is a widely used approach for detecting moving objects in videos from static cameras. The rationale in the approach is that of detecting the moving objects from the difference between the current frame and a reference frame, often called “background image”, or “background model”. Background subtraction is mostly done if the image in question is a part of a video stream.

Figure 1 Background Subtraction

Advantages:

- Extremely easy to implement and use!
- All pretty fast.
- Corresponding background models are not constant, they change over time.

Disadvantages:

- Accuracy of frame differencing depends on object speed and frame rate!
- Mean and median background models have relatively high memory requirements.

ii) Template matching

Template matching is a technique in digital image processing for finding small parts of an image which match a template image. It can be used in manufacturing as a part of quality control,a way to navigate a mobile robot,or as a way to detect edges in images.

For templates without strong features, or for when the bulk of the template image constitutes the matching image, a template-based approach may be effective. As aforementioned, since template-based template matching may potentially require sampling of a large number of points, it is possible to reduce the number of sampling points by reducing the resolution of the search and template images by the same factor and performing the operation on the resultant downsized images (multiresolution, or pyramid, image processing), providing a search window of data points within the search image so that the template does not have to search every viable data point, or a combination of both.

iii) Local template matching

A possible solution is to reduce the size of the templates, and detect salientfeatures in the image that characterize the object we are interested in Extract a set of local features that are invariant to translation, rotation and scale. Perform matching only on these local features then analyze the spatial relationships between those features

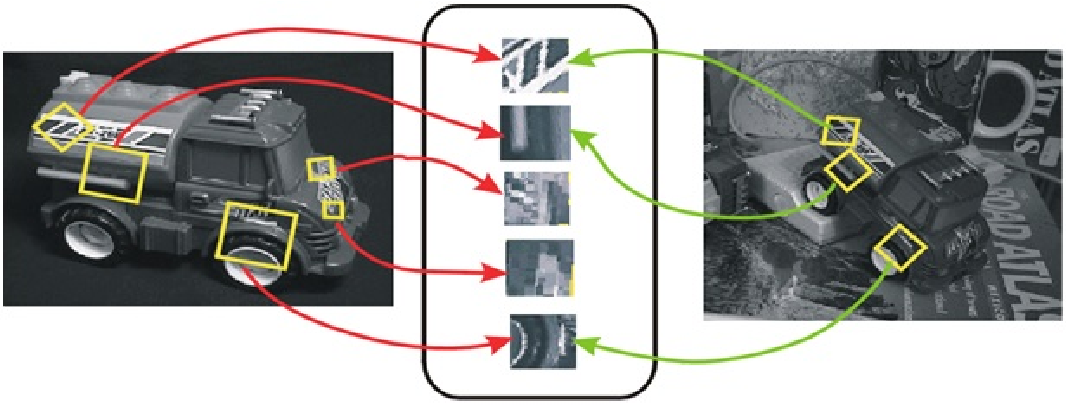

Figure 2 Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters.

Problems with template matching

- The template represents the object as we expect to find it in the image
- The object can indeed be scaled or rotated
- This technique requires a separate template for each scale and orientation
- Template matching become thus too expensive, especially for large templates
- Sensitive to noise, occlusions

B. Introduction to optical flow

Optical flow or optic flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer (an eye or a camera) and the scene.The concept of optical flow was introduced by the American psychologist James J. Gibson in the 1940s to describe the visual stimulus provided to animals moving through the world. James Gibson stressed the importance of optic flow for affordance perception, the ability to discern possibilities for action within the environment. Followers of Gibson and his ecological approach to psychology have further demonstrated the role of the optical flow stimulus for the perception of movement by the observer in the world; perception of the shape, distance and movement of objects in the world; and the control of locomotion. Recently the term optical flow has been co-opted by robotcists to incorporate related techniques from image processing and control of navigation, such as motion detection, object segmentation, time-to-contact information, focus of expansion calculations, luminance, motion compensated encoding, and stereo disparity measurement.

C. Estimation of the optical flow

Sequences of ordered images allow the estimation of motion as either instantaneous image velocities or discrete image displacements. Fleet and Weiss provide a tutorial introduction to gradient based optical flow. John L. Barron, David J. Fleet, and Steven Beauchemin provide a performance analysis of a number of optical flow techniques. It emphasizes the accuracy and density of measurements.

The optical flow methods try to calculate the motion between two image frames which are taken at times t and $t+\Delta t$ at every voxel position. These methods are called differential since they are based on local Taylor series approximations of the image signal; that is, they use partial derivatives with respect to the spatial and temporal coordinates.

For a 2D+*t* dimensional case(3Dor *n*-Dcases are similar) avoxel at location (x,y,t) with intensity I(x,y,t) willhave moved by , and between the two image frames Δx, Δy and Δt the following brightness constancy constraint can be given:

$$I(x,y,t) = I(x+\Delta x, y+\Delta y, t+\Delta t)$$

Assuming the movement to be small, the image constraint at I(x, y, t) with Taylor series can be developed to get:

$$I(x,y,t) = I(x,y,t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt + H.O.T$$

From these equations it follows that:

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

or

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

which results in

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

where V_x,V_y are the x and y components of thevelocity or optical flow of I(x,y,t) and , $\frac{\partial I}{\partial x}$ $\frac{\partial I}{\partial y}$ and are the derivatives $\frac{\partial I}{\partial t}$ of the image at (x,y,t) in the corresponding directions. I_x,I_y and I_t can be written for the derivatives in the following.Thus:

$I_xV_x+I_yV_y= -I_t$ or $\nabla I^T \cdot \vec{V} = -I_t$

This is an equation in two unknowns and cannot be solved as such. This is known as the aperture problem of the optical flow algorithms. To find the optical flow another set of equations is needed, given by some additional constraint. All optical flow methods introduce additional conditions for estimating the actual flow.

D. Methods for determining optical flow

- Phase correlation – inverse of normalized cross-power spectrum
- Block-based methods – minimizing sum of squared differences or sum of absolute differences, or maximizing normalized cross-correlation

- Differential methods of estimating optical flow, based on partial derivatives of the image signal and/or the sought flow field and higher-order partial derivatives, such as:
- Lucas–Kanade method – regarding image patches and an affine model for the flow field
- Horn–Schunck method – optimizing a functional based on residuals from the brightness constancy constraint, and a particular regularization term expressing the expected smoothness of the flow field
- Buxton–Buxton method – based on a model of the motion of edges in image sequences
- Black–Jepson method – coarse optical flow via correlation
- General variational methods – a range of modifications/extensions of Horn–Schunck, using other data terms and other smoothness terms.
- Discrete optimization methods – the search space is quantized, and then image matching is addressed through label assignment at every pixel, such that the corresponding deformation minimizes the distance between the source and the target image. The optimal solution is often recovered through Max-flow min-cut theorem algorithms, linear programming or belief propagation methods.

E. Uses of Optical Flow

Motion estimation and video compression have developed as a major aspect of optical flow research. While the optical flow field is superficially similar to a dense motion field derived from the techniques of motion estimation, optical flow is the study of not only the determination of the optical flow field itself, but also of its use in estimating the three-dimensional nature and structure of the scene, as well as the 3D motion of objects and the observer relative to the scene, most of them using the Image Jacobian.

Optical flow was used by robotics researchers in many areas such as: object detection and tracking, image dominant plane extraction, movement detection, robot navigation and visual odometry. Optical flow information has been recognized as being useful for controlling micro air vehicles.

The application of optical flow includes the problem of inferring not only the motion of the observer and objects in the scene, but also the structure of objects and the environment. Since awareness of motion and the generation of mental maps of the structure of our environment are critical components of animal (and human) vision, the conversion of this innate ability to a computer capability is similarly crucial in the field of machine vision.

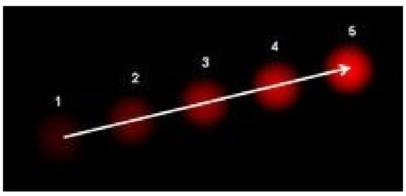

Figure 3 The optical flow vector of a moving object in a video sequence.

Consider a five-frame clip of a ball moving from the bottom left of a field of vision, to the top right. Motion estimation techniques can determine that on a two dimensional plane the ball is moving up and to the right and vectors describing this motion can be extracted from the sequence of frames. For the purposes of video compression (e.g., MPEG), the sequence is now described as well as it needs to be. However, in the field of machine vision, the question of whether the ball is moving to the right or if the observer is moving to the left is unknowable yet critical information. Not even if a static, patterned background were present in the five frames, could we confidently state that the ball was moving to the right, because the pattern might have an infinite distance to the observer.

Proposed algorithm

A. Horn & Schunck Algorithm

Optical flow is the distribution of apparent velocities of movement of brightness patterns in an image. Optical flow can arise from the relative motion of objects and viewer. Consequently optical flow can give the spatial arrangement of the objects viewed. Discontinuities in optical flow can help in segmenting images into regions to different objects.

The Horn &Schunck method computes optical flow by making an initial assumption that the optical flow has already been computed and the brightness of consecutive frames is assumed to be constant. Optical flow cannot be computed at a point in the image independently of neighboring points without using additional constraints, because the velocity field at each image point has two components while the change in image brightness at a point in the image plane due to the motion yields only one constraint. Thus additional constraints must be introduced to determine the optical flow.

Let the brightness at the point (x, y) in the image plane at time t be denoted by F(x, y, t). The brightness of a particular point in the pattern is constant, so that

$$\frac{dF}{dt} = 0$$

In optical flow two consecutive frames are compared at a time. The brightness of all the points of frames can be represented as a function as shown below

$$F(x, y, t) = F(x + dx, y + dy, t + dt)$$

The dx, dy and dt in the function of second frame represents the small change in brightness along x-axis, y-axis and with respect to time t. As per the initial brightness assumption, the consecutive frames are said to have almost the same brightness and the small change in the brightness dx, dy and dt is negligible.

Using chain rule of differentiation,

$$F(x,y,t) = F(x,y,t) + \frac{\partial F}{\partial x}\, dx + \frac{\partial F}{\partial y}\, dy + \frac{\partial F}{\partial t}\, dt$$

$$\Rightarrow \quad \frac{\partial F}{\partial x}\frac{dx}{dt} + \frac{\partial F}{\partial y}\frac{dy}{dt} + \frac{\partial F}{\partial t} = 0$$

If u = $\frac{dx}{dt}$ and v = $\frac{dy}{dt}$, an optical flow equation is obtained with two unknowns u and v. This is called aperture problem and it has to be solved to obtain the correct flow vectors.

$$F_x u + F_y v + F_t = 0$$

F_x, F_y and F_t are the partial derivatives in the x-axis, y-axis and time t. It is required to estimate the partial derivatives of brightness from the discrete set of image brightness measurements available. It is important that the estimates of F_x, F_y, F_t be consistent i.e. they should all refer to the same point in the image at the same time. Each of the estimates as shown below is the average of four first differences taken over adjacent measurements.

Fx ≈ $\frac{1}{4}$ { F i,j+1,k —Fi,j,k + Fi+1,j+1,k — Fi+1,j,k + Fi,j+1,k+1 — Fi,j,k+1 + Fi+1,j+1,k+1 — Fi+1,j,k+1}

Fy ≈ $\frac{1}{4}$ { F i+1,j,k —Fi,j,k + Fi+1,j+1,k — Fi,j+1,k + Fi+1,j,k+1 — Fi,j,k+1 + Fi+1,j+1,k+1 — Fi,j+1,k+1}

Ft ≈ $\frac{1}{4}$ { F i,j,k+1 —Fi,j,k + Fi+1,j,k+1 — Fi+1,j,k + Fi,+1j,k+1 — Fi,j+1,k+1 + Fi+1,j+1,k+1 — Fi+1,j+1,k}

In the above equations, k represents the previous frame and k+1 represents the current frame. The constraint on the local flow velocity is as expressed in the figure.

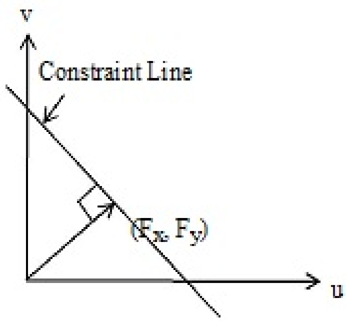

Figure 4 Constraint on local flow velocity

The component of optical flow in the direction of (F_x, F_y) is $-\frac{F_t}{\sqrt{F_x{}^2+F_y{}^2}}$. This is called the normal flow. The basic rate of change of image brightness equation constrains the optical flow velocity. The velocity (u, v) has to lie along a certain line perpendicular to the brightness gradient vector (F_x, F_y) in the velocity space. It is not possible to determine the iso-brightness contours at right angles to the brightness gradient. As a consequence the flow vectors (u, v) cannot be computed without introducing additional constraints.

In order to determine the optical flow, an additional constraint called the smoothness constraint is added. Smoothness constraint indicates that the neighbouring points in the objects have similar velocities and the velocity field of brightness patterns in the image varies smoothly almost everywhere. So, the optical flow vectors can be obtained by solving the following equation.

$$\iint[(F_x u + F_y v + F_t)^2 + \lambda(u_x{}^2 + u_y{}^2 + v_x{}^2 + v_y{}^2)]\, dx\, dy \qquad \text{----------- (1)}$$

In the above equation, the first part is the brightness constancy constraint and the second part is the smoothness constraint. This is called the smoothness factor which determines the amount of smoothness of the flow vectors. For the optical flow to be precise, the above equation must yield a value equal to or nearly equal to zero.

One way to express the additional constraint is to limit the flow velocity at a point and the average velocity over a small neighborhood containing the point. Equivalently this is minimizing the sum of the squares of the laplacians of the x- and y-components of the flow. These averages help in deriving at the final flow vectors. The laplacians of u and v are defined as

$$\nabla^2 u = \frac{\partial^2 u}{\partial^2 x} + \frac{\partial^2 u}{\partial^2 y} \qquad \nabla^2 v = \frac{\partial^2 v}{\partial^2 x} + \frac{\partial^2 v}{\partial^2 y}$$

A convenient approximation of laplacian takes the following minimized form,

$$\nabla^2 u \approx k(\bar{u}_{i,j,k} - u_{i,j,k}) \quad and \quad \nabla^2 v \approx k(\bar{v}_{i,j,k} - v_{i,j,k})$$

And the above equation (1) when differentiated with respect to dx and dy separately takes the form as shown below,

The discrete version of the laplacian is given as,

$(F_x u + F_y v + F_t)\, F_x + {}^2\, (u - \bar{u}) = 0$

$(F_x u + F_y v + F_t)\, F_y + {}^2\, (v - \bar{v}) = 0$

Where the local averages $\bar{u}$ and $\bar{v}$ are defined as follows,

$$\bar{u}_{i,j,k} = \frac{1}{6}\{u_{i-1,j,k} + u_{i,j+1,k} + u_{i+1,j,k} + u_{i,j-1,k}\} + \frac{1}{12}\{u_{i-1,j-1,k} + u_{i-1,j+1,k} + u_{i+1,j+1,k} + u_{i+1,j-1,k}\}$$

$$\bar{v}_{i,j,k} = \frac{1}{6}\{v_{i-1,j,k} + v_{i,j+1,k} + v_{i+1,j,k} + v_{i,j-1,k}\} + \frac{1}{12}\{v_{i-1,j-1,k} + v_{i-1,j+1,k} + v_{i+1,j+1,k} + v_{i+1,j-1,k}\}$$

With these the final flow vectors are obtained using the following formula,

$$u = \bar{u} - F_x \frac{P}{D} \qquad and \qquad v = \bar{v} - F_y \frac{P}{D}$$

Where $P = F_x\bar{u} + F_y\bar{v} + F_t$ and $D = \lambda^2 + F_x{}^2 + F_y{}^2$

At each point of the image a pair of equations is obtained which calculate the final flow vectors u and v which give the displacements and direction of each pixel in the x and y directions respectively. These flow vectors determine the motion in a sequence of images. The smoothness factor plays a major role in areas where the brightness gradient is small and avoids haphazard adjustments to the estimated flow velocity occasioned by noise in the estimated derivatives. The above equations are solved iteratively until convergence in order to obtain accurate values of flow vectors.

B. Detailed view of the Algorithm

Step 1: Calculating the derivatives F_x, $F_y$and F_t.The derivatives are calculated by applying amask using the convolution function. The convolution is mathematical operation which gives the summation of products. In image processing, it supresses high or low frequencies in the image to perform filtering that helps in smoothing, edge detection etc.

Fx=conv2(double(img2),double(0.25*[-1 1;-1 1]),'same') + conv2(double(img1), double(0.25*[-1 1;-1 1),'same');

In the above code, the partial derivative with respect to X direction is calculated. By applying the mask [-1 1; -1 1] on the image, the places in which the values of derivatives are high indicated the presence of edges in the object. By adding the derivatives of two images img1 and img2, the amount of displacement of the object in X-axis is obtained.

The above figure depicts the displacement of the moving object pixels in the X direction by showing the edges obtained from img1 and img2. In the same way, F_y

using the mask [-1 -1; 1 1]. F_t is calculated by applying the mask [1 1; 1 1] on img2 and the mask [-1 - 1; -1 -1] on img1.

Step 2: The averages of the flow vectors $u_{av}$and $v_{av}$are calculated. This is done byconvoluting the flow vectors u and v with the laplacian mask [1/12 1/6 1/12; 1/6 0 1/6; 1/12 1/6 1/12]. In the first iteration, the values of u_{av} and v_{av} remain zero as the computations will be made on the zero initialized flow vectors. The further iterations will be averaging out the values of flow vectors u and v. This averaging will help in deriving the flow vectors accurately.

Step 3: Substituting the $u_{av}$and v_{av}in the optical flow equation $P=(F_x*u_{av})+(F_y*v_{av})+Ft$. Inthe first iteration, since the value of u_{av} and v_{av} are zero, this equation will have the value of Ft. In the further iterations, the value of P will be the summation of the products of the displacements and the averages along X and Y direction and also F_t.

Step 4: The equation $D=^2+F_x^2+F_y^2$is solved. By squaring $F_x$and $F_y$thick edges in X and Ydirections are displayed. The smoothness factor smoothens the edges. This helps in obtaining a smooth flow i.e. all pixels belonging to the same region or object will have uniform motion. The fig 5.3 shows the variations in the image by squaring F_x ,F_y and then applying the smoothness factor .

Figure 5: The first part shows the F_x^2, second part is the F_y^2 and the last part is the summation of F_x&F_y with smoothness factor ^{2} applied

Step 5: The final flow vectors are calculated in the following way

$u = u_{av}-(F_x*(P))/D$ and $v = v_{av}-(F_y*(P))/D$

In the above equations, the displacement along X and Y axis i.e. F_x and F_y are multiplied with P so that the correct displacements along X and Y axis is obtained as shown in fig 5.4. Diving by D helps in smoothing out the values. Finally it is subtracted from the averages u_{av} and v_{av} to obtain the final flow vectors u and v.

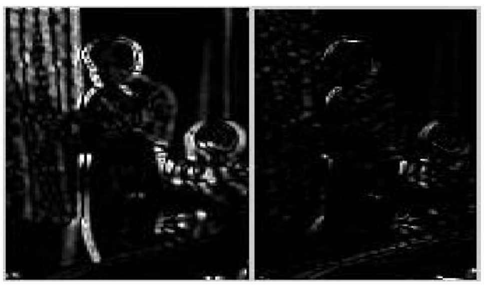

Figure 6: First one is F_x*P and second one is F_y*P

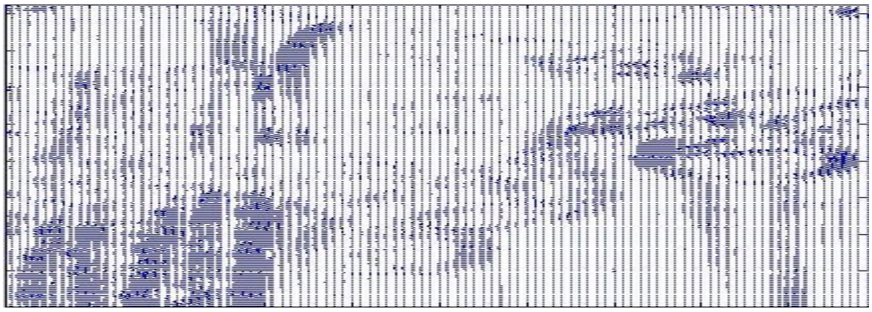

Figure 7: velocity plot of flow vectors u and v

C. Algorithmic module

Step 1: The control starts by accepting an input video and obtaining the video parameters such as the number of frames in the video, height and width of the frame.

Step 2: Initialise the first frame of the video to I and obtain its height & width.

Step 3: Display the image by setting the screen size.

Step 4: Select a portion of the displayed image I by using the getrect() function and obtain the coordinates and also the height and width of the selected rectangular portion.

Step 5: Set the smoothness weight lambda=10. Apply filtering and smoothen the image I.

Step 6: Obtain the second frame of the video and smooth it using filtering operation.

Step 7: Calculate the derivatives Fx, Fy and Ft.

Step 8: For a certain number of iterations, calculate the uav and vav and finally calculate the flow vectors u & v.

Step 9: Compute the Normal flow.

Step 10: Perform thresholding and segment the object and background.

Step 11: Display the frames, displacements Fx, Fy & Ft, the flow vectors and the thresholded image.

Step 12: Calculate the top-leftmost and bottom-rightmost corner of the moving object along X and Y-axis.

Step 13: Using these points track the object by drawing a box around it. Store the current frame to img1 and accept new frame for comparison.

Results

Snapshot 1

Figure 8: Selecting the Target Area

Figure 9: Single object Tracked

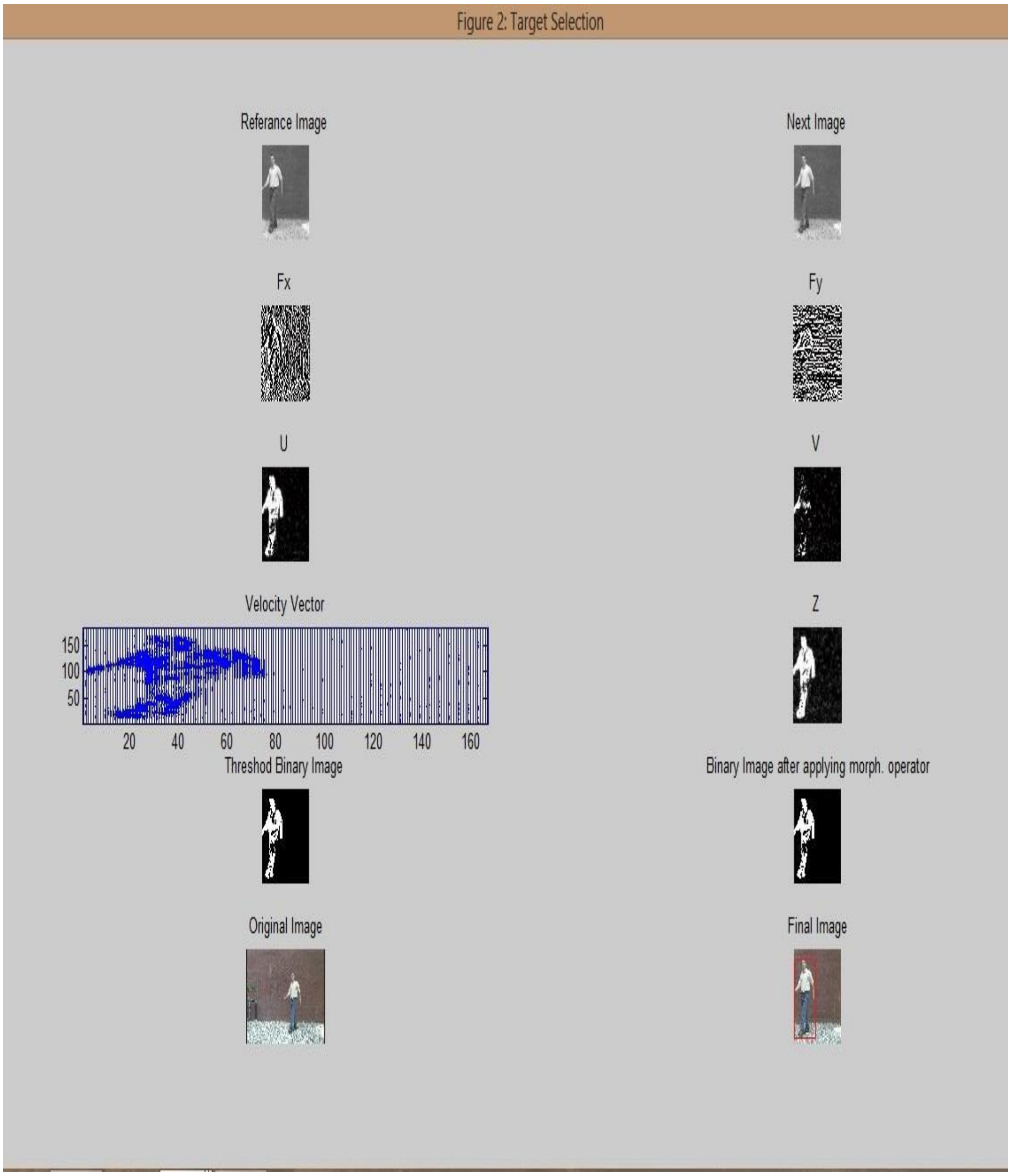

Figure 10: Displaying Tracked Object along with other values

Snapshot 2

Figure 11: Selecting Target Area of Rotating Object

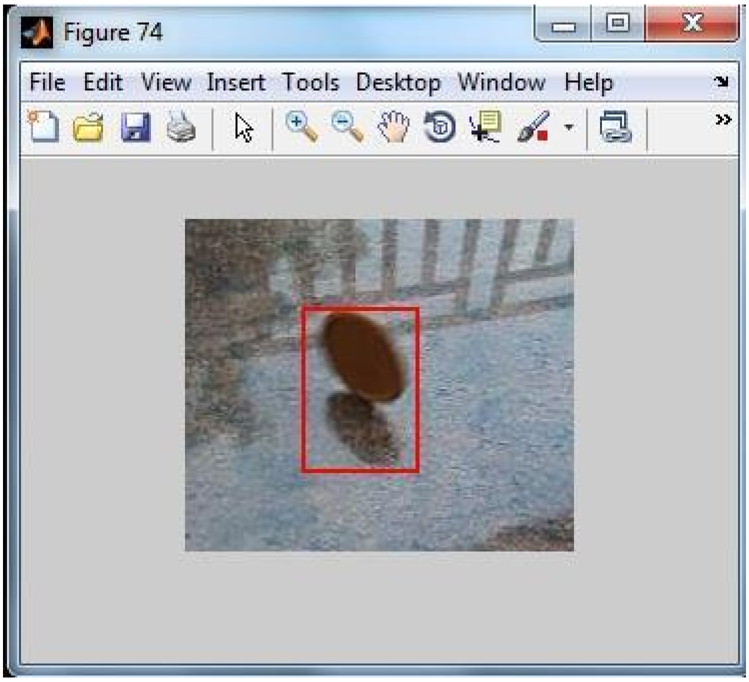

Figure 12: Tracking the Rotating Object

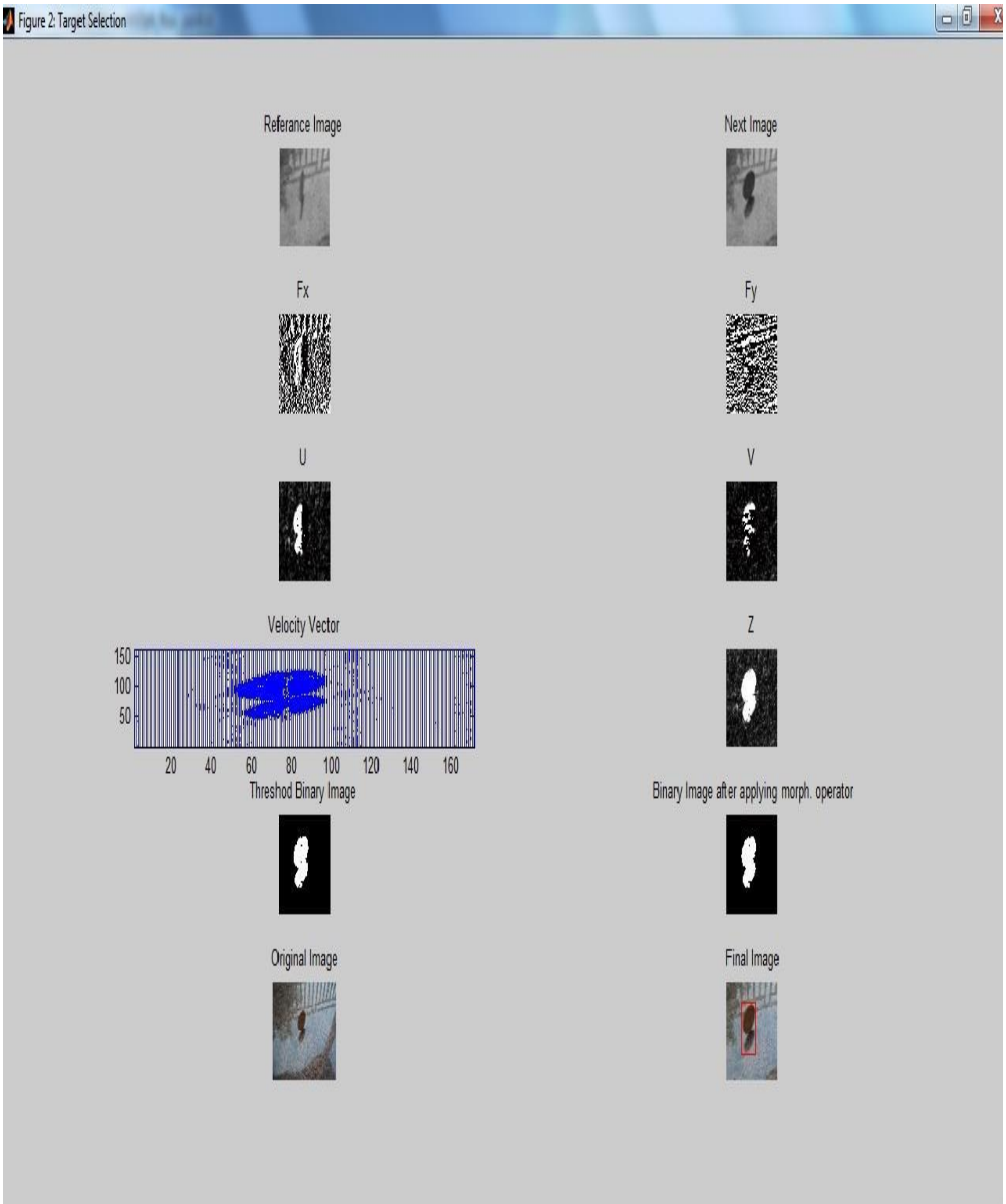

Figure 13: Displaying the Tracked Rotating Object with other values

Conclusion

The Horn & Schunck method of optical flow is a global method which introduces global constraints in order to obtain the flow vectors. The assumption of smoothness of flow over the whole image minimizes the distortions in the flow and prefers solutions which show more smoothness. Advantages of the Horn–Schunck algorithm include that it yields a high density of flow vectors, i.e. the flow information missing in inner parts of homogeneous objects is filled in from the motion boundaries. On the negative side, it is more sensitive to noise than local methods. In this work a single moving object is detected and tracked using the Horn & Schunck algorithm. Some of the future enhancements include, detecting only the object in case the moving object has a shadow, detecting multiple moving objects etc...

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