Human Motion Detection for video surveillance by estimating Optical Flow

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Abstract – To obtain motion for arbitrary, real-world video sequences are a challenging but important task for both algorithm evaluation and model design. In this paper, we analyze a method for motion estimation that exploits the entire image information using the optical flow equation. Optical flow cannot be computed locally, since only one independent measurement is available from the image sequence at a point, while the flow velocity has two components a second constraint is needed. Paper presents experimental results obtained from the fast version of Classic + NL algorithm method for obtaining flow on Weizmann Action Database.
Keywords – Motion Estimation; Optical Flow.

I. INTRODUCTION

Motion analysis has been an essential component for many computer vision applications such as structure from motion, objects tracking/recognition, and advanced video editing. A variety of computational models, *e.g.* optical flow fields [1, 2], layers [2] and boundaries [3], have been developed to estimate the motion from a video sequence. It is important to evaluate the performance of various motion analysis algorithms to gain insight and design better models. However, little has been done for evaluating motion analysis algorithms compared to the tremendous effort put into developing these algorithms.

The optical flow cannot be computed at a point in the image independently of neighbouring points without introducing 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 motion yields only one constraint. Consider, for example, a patch of a pattern where brightness I varies as a function of one image coordinate but not the other. Movement of the pattern in one direction alters the brightness at a particular point, but motion in the other direction yields no change. Thus components of movement in the latter direction cannot be determined locally. One solution to this problem is to compute a regularized optical flow field. As the optical flow equation provides one equation for two unknowns, added constraints are needed. These can be smoothing constraints on the optical flow field itself. The main contribution of this paper is the analysis of fast version of Classic + NL method for obtaining optical flow from the image sequence. Their approach for motion estimation is based on three observations. First, humans are experts at segmenting layers in a video sequence because human being can easily recognize the moving objects and their relative depth relationships. Second, humans are sensitive to any differences between two images when these two images are displayed back and forth. Third, humans have knowledge of the smoothness and discontinuities of the motion that a moving object undergoes.

In fact, computer vision researchers have implicitly used these observations to inspect the accuracy of motion estimates when the ground truth is missing, and even to verify the correctness of ground-truth annotation [21].

II. PREVIOUS WORK

Motion between two frames is commonly described by a dense displacement vector field which links the location of each point in a given frame to its location in the next frame. Registering a model to an image and tracking of objects is a large field of research and there exists a multitude of methods. Modelling and estimating dense optical flow fields have been intensively studied in the literature. Starting with Horn & Schunck [5] and Lucas & Kanade [6], researchers have developed a variety of models for effective flow computation, including some recent work such as incorporating robustness functions [7], integrating gradient information [8], estimating a symmetric flow field [9], combining local and global flow [10], and reasoning about occluded/disoccluded pixels (outliers) [11].

The optical flow constraint is ill-posed as it provides one equation for two unknowns. Therefore additional constraints are required. These can be provided by additional smoothing constraints or by a predefined motion model to regularize the optical flow field. They have been successfully demonstrated in the context of face tracking [12], [13] using deformable meshes or for camera motion or person tracking using rigid or affine motion models. In [14] a method has been presented that uses optical flow in connection with radial basis functions to track less constrained deformations. Their method uses an iterative scheme to adapt the number of RBF centres to the degree of non-rigidity between the images.

III. OPTICAL FLOW

A. Optical Flow Computation:

Optical flow algorithms attempt to estimate the vector field, which describes spatial movements of every image point over time, and provides important information for motion analysis [20]. In order to track an object in a video sequence optical flow constraint equation can be used.

$$Ix\,(x_{i,}\ y_{i,}).dx\,(x_{i,}\ y_{i,}) + Iy\,(x_{i,}\ y_{i,}).dy\,(x_{i,}\ y_{i,}) = -\,I_t\,(x_{i,}\ y_{i,}) \quad \text{........ (1)}$$

Where $Ix\ (x_{i,}\ y_i)$ and $Iy\ (x_{i,}\ y_i)$ are the spatial derivatives of the image at pixel position $[x_{i,}\ y_{i,}]^T$ and $I_t\ (x_{i,}\ y_i)$ denotes the intensity change between two images. In order to be independent from lighting changes, first segment the objects of interest and work with gray scale images with pixel values 0 in the background and higher values for the foreground object. Here by filter both images with a moving average filter transforming the binary object borders into linear ramps. $D\ (x_{i,}\ y_i)$ denotes the displacement vector at position $[x_{i,}\ y_{i,}]^T$ that transforms the pixel $[x_{i,}\ y_{i,}]^T$ from the previous frame onto the pixel $[x'_i, y'_i]^T$ in the current frame:

$$di = [x'i, y'i]T - [xi, yi,]T \quad \text{........ (2)}$$

However, the solution to (1) is under-determined as each equation has two unknowns. Additional constraints can be provided by smoothing constraints on the optical flow field or by a predefined motion model. Finding the best transformation then amounts into minimizing the quadratic error.

$$E = \sum_{i=1}^{n} \Big\| I_x(x_b\, y_i) \cdot dx\ (x_b\, y_i) + I_y(x_b\, y_i) \cdot dy\, xb\, yi + Itxb\, yi2 \quad \text{........(3)}$$

B. Point - constrained optical flow:

The algorithm introduces constraints on the classical optical flow algorithm by setting motion vectors to known values for several characteristic points at the boundary of tracked object [15]. An assumption is made that it will influence and enhance the computation of the optical flow at neighbouring locations.

Because of the relaxation method applied in the algorithm the influence of fixed values will propagate to other points as well. The problem of approach presented above is that the influence of constrained points to their neighbourhood is limited. In order to overcome this difficulty instead of single point constraint, additional neighbourhood constraints in the small area around every constrained point can be used. Each constraint from the initial set of fixed vectors F contributes to such additional constraint by a factor that is inversely proportional to the squared distance of its location to the given point [21]. Equation for horizontal component is shown below, equivalent equation is used to calculate vertical component.

$$uif = \frac{\sum j \in F \frac{uj}{d(i,j)^2}}{\sum j \in F \frac{1}{d(i,j)^2}} \quad \text{........ (4)}$$

The additional constraints are not kept fixed in iterative process; they are combined with the results of the optical flow computation after each step of iterative process. Weight factor is used to balance influence of those constraints depending on distance from the fixed constraint as shown in the following equation:

$$u'_f = \propto\ u_i + (1 - \propto)\, u_{if} \quad \text{........ (5)}$$

Neighbourhood constraint region, the similar equation is used to calculate the vertical component of the vector field v.

IV. RESULTS AND DISCUSSION

The test involves jumping Daria video collected from Weizmann Action Database publically available at http://www.wisdom.weizmann.ac.il/ as shown in Figure 1. This video is processed to extract the frames. A computer with core i3 processor of 2.13GHz, with a RAM of 4GB is used in this work. It requires 0.32 minutes to calculate the flow and maximum flow comes out to be 14.8700.

Figure 1: First image frame of running Lena video

Figure 2 is the color coding image of the figure1.

Figure 2: Color coding image of video frame

Figure 3 shows the Vector field of the motion of the foreground object obtained for optical flow method [6].

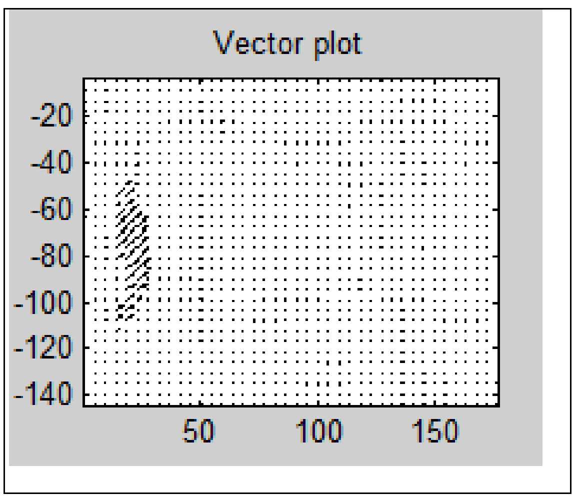

Figure 3: Vector field using Optical flow method

V. CONCLUSION

In this paper, authors have analyzed a method for estimation of the optical flow from the image sequence. This method is motivated by the fact that standard optical flow technique does not provide accurate displacement estimates. An accurate segmentation of boundary and estimation of its deformation can improve motion estimation.

Boundaries in consecutive frames are matched, and a set of point constraints is derived to enhance final computation of optical flow field. The presented method provides basis for further study and application of the method to three-dimensional objects.

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