Monitoring in High Density Crowd Movements Using Particle Advection

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Abstract

Today, trying to understand what kind of behaviour the crowd shows by studying the data from surveillance systems is an important topic for researchers of computer vision. The aim of this study make the motion data that is at pixel level and that is obtained by optical flow method a more meaningful data set with the particle advection method. In other words, the aim is to monitor the motion data by converting the 3D optical flow data set to a 2D data set. With this respect, evaluating how the crowd motion changes throughout the video by focusing only on the moments where there is motion can be carried out easily.

Keywords – optical flow, particle advection, motion detection, crowd analysis

1. Introduction

Studies that are carried out in order to understand the flow of the crowd and to define what kind of sampling they generate by processing the videos obtained from surveillance systems and by revealing some characteristics of the crowd are called crowd analysis. Crowd analysis is a study field that is used in order to meet the demands of different areas and anticipate as well as solve the problems that might occur.

Managing crowds, designing public spaces, environmental planning by virtual spaces, abnormal behaviour detection, designing smart spaces, etc. are among the topics that crowd analysis focuses. [1]

Monitoring how the crowd moves, noticing the creation of a dangerous crowd, managing a crowd in case of panic, determining a person in crowd, and tracking such people using the surveillance videos are among the important topics of literature.

An uncontrolled crowd may lead to vital damages. By observing the general flow and behaviour of the crowd, precautions can be taken against abnormal conditions.

Crowd analysis problems were tried to be solved by algorithms developed for object tracking in the first years but it was seen that tracking people in high density videos is fairly difficult and that this is a solution that needs burdensome and excessive calculations.

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Fig. 1. Some images in the literature used in the study of crowd analysis

In the following studies, it was tried to grasp the general features of the crowd rather than focusing on the people in the crowd as a whole (Holistic approach).

In their study, Hu, Saad, & Shah [2] worked on understanding and assessing the movement pattern by benefiting from the momentary location data of the movement rather than tracking people in the long-term. In the result of the study, there were clear resemblances between the pattern designed by the system and the pattern manually drawn.

With a method developed in another study, the segmentation of high density crowds and dynamic detection on irregularities that might occur in time were aimed. [3]

In his study, Solmaz B, [4] helped identify the crowd being observed. With this method, the system could identify that the crowd show movements in one of the five classes specified by author.

Different from other studies, Rodriguez M. tried to observe similarities by comparing the known behaviour in the crowd movement database. [5]

Crowd analysis has been able to made use of various problem solving technique used in different disciplines. For example, Mehran R benefited from streaklines, mostly used in fluid dynamics in observing the limits of the behaviour. [6] In another study, he used the social factors that influence the walking patterns of pedestrians and determined abnormal conditions in the crowd. [7]

At this level, the general aim of the studies mentioned as well as of the ones in the literature is to obtain the movement data from the videos and assess it. In this study, the focus is on how to obtain movement data out of videos using optical flow method, what format it is, and how this data can be assessed with particle advection method.

2. Methods

Some methods that were used in order to obtain some characteristics of the crowd and to observe how the crowd moves clearly will be explained in a priority order.

2.1. Optical Flow

This is a method used in order to obtain movement data in a video [8] [9] [10]. In this method, the direction and the speed of object movements in consequent frames at pixel level can be obtained (shown in Fig. 2). This method is usually used for obtaining the movement data at lower speeds and at high density. It is seen that the method proves to return better results in videos with these qualifications.

When we take the prerequisite that the light source does not change in time and that the change is not more than 1 pixel (in relocations more than 1 pixel, the pyramid method is recommended but this is not included in this article [11]) into consideration, we can have this equation, provided that the pixel at (x,y) location in t time can relocate as much as (dx,dy) in t+1 time period.

$$\frac{dI}{dt} = o \quad \Rightarrow \quad I(x, y, t) = I(x + dx, y + dy, t + dt) \qquad (1)$$

When the process is proceeded using Taylor series;

$$I(x, y, t) = I(x, y, t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt + H.O.T \qquad (2)$$

$$Ix\, u + Iy\, v = -It \qquad (3)$$

The general formula of the optical flow is obtained. ($Ix = \partial I/\partial x$, $Iy = \partial I/\partial y$, $It = \partial I/\partial t$, $u = dx/dt$, $v = dy/dt$).

In equation (3) that is obtained as the movement data of a single pixel, there are known values such as lx, ly, and lt values but also unknown values such as u and v values. The aim of the optical flow is to find the u and v values.

At this level, a solution was developed benefiting from the method developed by Lucas-Kanade for optical flow. [9] Lucas-Kanade calculated the velocity of a pixel taking into consideration of the fact that a pixel moves at the same velocity with neighbouring pixels. That is to say, when calculating the movement of a pixel that has a 3x3 neighbouring scheme, we obtain 9 equations in order to find the two unknowns of u and v in equation (3), thinking that all the neighbouring pixels move at the same velocity.

$$\underbrace{\begin{bmatrix} Ix_1 & Iy_1 \\ Ix_2 & Iy_2 \\ \vdots & \vdots \\ Ix_9 & Iy_9 \end{bmatrix}}_{\substack{\mathbf{A} \\ 9x2}} \underbrace{\begin{bmatrix} u \\ v \end{bmatrix}}_{\substack{\mathbf{d} \\ 2x1}} = \underbrace{\begin{bmatrix} -It_1 \\ -It_2 \\ \vdots \\ -It_9 \end{bmatrix}}_{\substack{\mathbf{b} \\ 9x1}} \qquad (4)$$

The neighbouring window chosen as 3x3 in the sample can be chosen at different sizes depending on the condition of the problem.

While preferring a smaller size of window value can help us obtain the details in an image, these details might lead to image

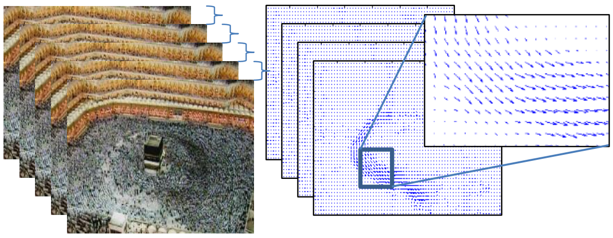


Fig. 2. Optical Flow

confusion and the load of the system might increase. Moreover, it may also lead to the loss of general flow data of the video. On the other hand, a larger sized neighbouring window can capture the movements at larger scale and helps us obtain the general flow of the movement, yet the bottlenecks or small movements might not be noticed. There is a trade off in question. Therefore, the size of the neighbouring window is another problem to think about.

When the equation (4) is solved using minimum least squares method:

$$\underset{2x2}{(A^T A)}\ \underset{2x1}{d} = \underset{2x1}{A^T b}$$

$$\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_y I_x & \sum I_y I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = -\begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix} \qquad (5)$$

There are four basic steps to be taken in obtaining optical flow using Lucas-Kanade method.

1. Noise reduction is applied in frames
2. Ix, Iy, and It are calculated
3. u and v values are found by calculating the equation (5).
4. Due to the fact that optical flow values are independent from each other and that they might Show differences from the general flow, the resulting values (u,v) are applied a median filter.

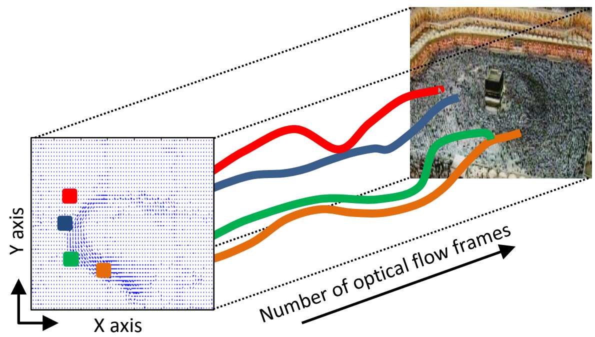


Fig. 3. Particle Advection

Algorithm 1: Lucas-Kanade Optical Flow Algorithm
Input: Set of input image frames S
Output: Optical flow vectors [u,v]

```
Begin: A= set 2x2 zero matrix
       b= set 2x1 zero matrix
       d= set 2x1 zero matrix
       NWS= floor(Neighbor Window Size)-1
       [Ix,Iy]=gradient(f1)
       It=f1-f2
for i=1+NWS to X_ size of(f1)
    for j=1+NWS to Y_ size of(f1)
        A= set 2x2 zero matrix
        b= set 2x1 zero matrix
          for m=i-NWS to i+NWS
              for n=j-NWS to j+NWS
                  A(1,1)=A(1,1)+Ix(m,n)*Ix(m,n)
                  A(1,2)=A(1,2)+Ix(m,n)*Iy(m,n)
                  A(2,1)=A(2,1)+Iy(m,n)*Ix(m,n)
                  A(2,2)=A(2,2)+Iy(m,n)*Iy(m,n)

                  b(1,1)=b(1,1)+ Ix(m,n)*It(m,n)
                  b(2,1)=b(2,1)+ Iy(m,n)*It(m,n)
              end
          end
        d=PseudoInverse(A)*(-b)
        u(i,j)=d(1,1)
        v(i,j)=d(2,1)
    end
end
```

2.2. Particle Advection

Optical flow provides the data related to where a pixel will be heading to on the next frame. Particle Advection, on the other hand, is a method used in order to observe (understand) how a pixel moves throughout the video.
At this level, particles that are located on every pixel in the first frame of the video are being directed by the time domain pixel level 3D movement data (WxHxT, W= x side resolution of frame, H= y side resolution of frame, T=time, as shown in Figure 2) that is obtained by optical flow. At the end of the process, the time domain 3D optical flow data is obtained as 2D movement data. This process is called particle advection and the distance covered by each particle is called particle trajectories [12] [13] [14] [15].

For n number of frame, time domain optical flow value is;

$V(t) \rightarrow t=1,2,3\ldots\ldots n-1.$

If we consider the data set created in each frame of the video as $S=\{f_1,f_2....,f_n\}$, the optical flow value between f_1 and f_2 can be expressed as,

$$\mathbf{V}(1) = [u(1), v(1)] \tag{6}$$

The velocity of a pixel at x,y location as,

$$\mathbf{V}(x,y) = [u(x,y), v(x,y)] \tag{7}$$

i= 1,2,3…..N particle number and the particle at x,y location at t time can be shown as $x_i(t),y_i(t)$.

A grid is located on f_1 in S data set, namely each pixel in the first frame and the particles are moved according to optical flow data. Ideally, a grid is made up as N=WxH. Particle advection can be formulized according to notation expressed above.

$$x_i(t+i) = x_i(t) + u[x_i(t), y_i(t)] \tag{8}$$
$$y_i(t+i) = y_i(t) + v[x_i(t), y_i(t)] \tag{9}$$

The track that each particle keeps throughout the video;

$$t_i = \{(x_i(1), y_i(1)), (x_i(2), y_i(2)), \ldots\ldots, (x_i(n-1), y_i(n-1))\} \tag{10}$$

and the data set that creates the motion data in the video more meaningfully and that is created with the accumulation of each particle is;

$T_t^{t+T} = \{t_1, t_2, t_3, \ldots\ldots, t_N\}.$

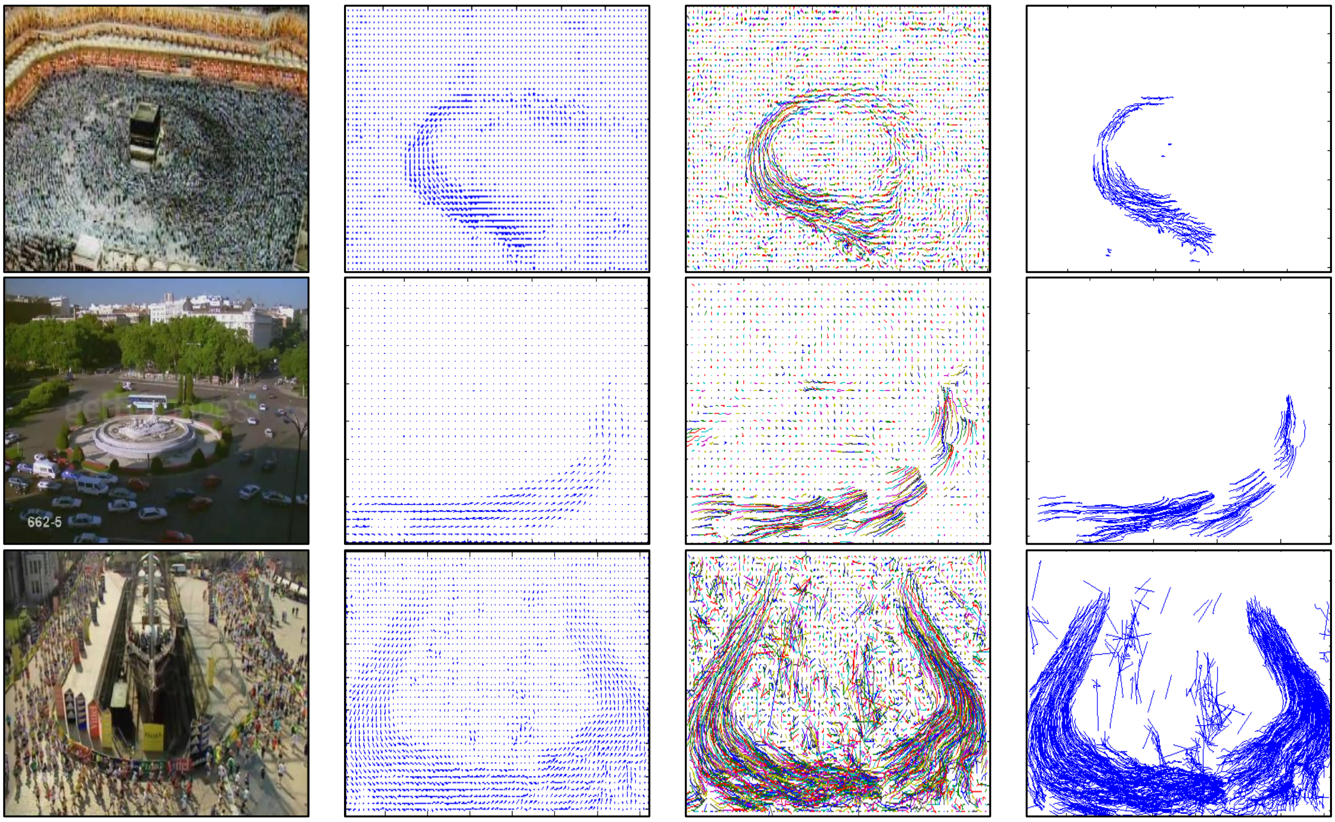
Algorithm 2: Particle Advection Algorithm
Input: Set of Optical flow frames
Output: Set of Particle Trajectories

```
Begin: i = number of particles
       t = number of optical flow frames
       t(i).x(1) = 1th x position of grid
       t(i).y(1) = 1th y position of grid

for i=1 to number of particles
    for t=1 to number of optical flow frames
        xi(t+1) = xi(t) + (u[xi(t), yi(t)])
        yi(t+1) = yi(t) + (v[xi(t), yi(t)])
        t(i).x(t+1) = xi(t+1)
        t(i).y(t+1) = yi(t+1)
    end
end
```

3. Conclusion

This study was carried out as a preliminary study in realizing some purposes like assessing and understanding the behaviour of crowds. For this reason, a dataset that represents the moving areas in the video was created using optical flow and particle advection. Thanks to this dataset, stable and moving parts in the video was easily determined.
The results that were obtained for three scenarios and with the help of the application we developed are shown in Figure 4. In Figure 4, N-1 optical flow (b column) that were obtained from N number of frame (a column) out of the video as well as one 2D particle advection (c column) were shown as result. In the d column in the figure, the result that we display the particles over a threshold defined by trial and error for each image by taking the movement length of each particle was shown. This result is a successful result that can represent the moving areas in the video. In addition to this study, in the future studies, what kind of pattern the crowd creates will be defined by extracting the characteristics of the areas in motion. As a result of this, abnormal situations can be identified and the behaviour that the crowd shows can be understood.



a) b) c) d)

Fig. 4. The results obtained as a result of the processes that are done on the video. a) a frame from the video that the system processed b) the motion data of tow consequent frames (Optical Flow) c) Obtaining the time dependent 3D optical flow data in 2D (Particle Advection) d) Projection the data set created throughout the video by eliminating the moving ones under the threshold (Particle Trajectories)

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