Snatch Theft Detection using Low Level Features

Norazlin Ibrahim, Siti Salasiah Mokri, Lee Yee Siong, M Marzuki Mustafa and Aini Hussain

***Abstract*— In practice it is difficult to diagnose events based on the ability to segment the individual persons in a crowd.. The used of low level features is seemed to be more effective to identify the abnormality situation. This paper presents the detection of snatch theft in pedestrian crowd movement. It is based on the features extracted from the computation of optical flow for sequence of video frame. Kalman filter is used to detect the start and the end of of possible snatching events. The event is classified based on the distribution of the optical flow vectors before and after the events using vector matching and SVM classification. The algorithm has been tested on simulated events, and showed a good detection rate of snatch theft events..**

Index Terms—snatch theft, optical flow, Kalman filter, SVM

I. Introduction

Petty theft such as snatch thefts are increasing drastically especially in the global economic downturn. An efficient surveillance system is needed to monitor the suspicious action to enable quick response to such activities can be made.. Even though, CCTV is widely used to monitor high risk public areas, the images are used more towards as a post event investigation when a criminal happened. Online monitoring and detection is the solution; while human observation is still the best way to accurately detect suspicious event or behavior, it has the disadvantages of cannot be alertfor a long time gazing at the monitor and human can monitor a few numbers of the camera at one time. Cost of employing personnels to do this mundane task can also is a factor against human.

The focus of this research is to detect snatching activity in pedestrian movement in which the detection of human activities is done on low level and high level feature extraction. For high level feature extraction, the main aim is to find the shape of an individual object. It is easy to identify human activities such as walking, standing, sitting and crawling if the object is segmented individually. In general, human gaits can be easily identified via the perimeter of the edge. Problem arises if he/she is in a crowd or when an occlusion happens. Thus, the crowd–behaviors need to be identified.

This problem poses a big challenge when individual segmentation for snatching detection is no longer valid. The focus of this research is mainly on low level feature extraction. The features are extracted from optical flow computation in sequence of video frames. It will only detect the abnormality of the event instead of tracking each activity in the area of interests.

II. Previous works

Previously, background subtraction had been applied and successfully identified individual activities [2]. This technique can estimates the congestion density over time in the crowd [5]. However, it is unable to detect anomaly movement. Optical flow has been used to track an individual in the crowd but the tracking is based on the assumption that certain movements such as running, jumping or crawling are considered abnormal [3]. This proves that optical flow can be used to identify crowd surveillance.

Many researchers have used the features of optical flow to extract the data in detecting anomalies without knowing each individual activity. E.L. Andrade et.al have used optical flow features from the crowd and used Hidden Markov Models to detect anomaly events at exit location and when people falling down[4][6]. Another recent approach in real–time crowd motion analysis is carried out by N. Ihaddadene and Chabane Djeraba by estimating sudden change of variations from the set point of interest [13].

The detection of change in an overhead imaginary has triggered an attraction to detect abnormalities over a big area albeit under the influences of illumination. Chris Clifton [11] has developed a predictive modeling to identify unusual changes in images. It is done using neural network training method. A research by P Reisman. O. Mano, et.al uses the x-axis of the graph corresponds to the position on the scanline by using Hough transform while the y-axis is the probability of that pixel that makes the detection of human and vehicles in the crowd is possible [12].

The discussed techniques that have the ability to detect the anomalies are based on the distribution of density. The implementations are good throughout certain specific locations and indoctrinated cases. The contribution of anomalies detection recently is more toward classification field and is not from the feature extraction itself.

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III. Feature Extraction Framework

Generally, snatching activities happen in hush roads. They involve a few numbers of people~~s~~. Commonly, as snatching crime takes place, the perpetrator will observe the scenario and walk towards the victim. At a certain point of time, as the perpetrator close at hand with the victim, there will be an abrupt change when the perpetrator starts to snatch. After the snatch, there will be another change that is when the perpetrator starts to run away from the victim. As for the victim, there will be intermediate changes such as stand still, confuse, puzzled, drop down or running towards the perpetrator. If there is one or more vigilant persons around, they will help to chase after the perpetrator or to assist the victim. All this will induce a precipitous change in the movement pattern before and after the snatching process.

Movement analysis starts with the computation of optical flow vector. There are a number of techniques used to compute optical flow in the sequence of images such as differential based, phased based, energy based and etc. In this research, differential technique namely Horn Schunk technique is used [7]. Albeit a lot of enhancements have been done by comparison between traditional (Horn Schunck) and new Brox's[10] technique, traditional method is prefered due to the assimilating global smoothness constrains that will result in smoother optical flow vector with considerably short time. Although the utilization of Brox technique results in smoother optical flow, the execution time is higher [8].

In this research, the sum of optical flow for every sequence of frame is computed. If there are 2 peoples move~~d~~ independently , the sum of optical flow will depend on individual flow vector. However, when it comes to the intersection point between 2 people~~s~~, the value of optical flow vector will imperceptibly lowered. This concept could be seen from Figure 1 where the skeleton's flow for movement before intersection is higher compared to during intersection.

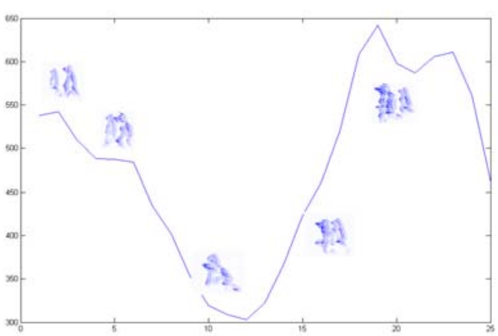

Figure 1: The value of sum of optical flow for 25 sequences frame

The snatching activity happens only when human movements are toward each other; not when the individuals are scattered separately. For a consistent movement, the flow is normally constant before and after the intersection, but it is observably different if there is snatching activity. The flow will be abruptly distracted after the intersection. The start and end of intersection are shown in Figure 1. Kalman filter technique is used to find the frames where it starts to intersect and when the intersection ends. This technique has been introduced based on [2].

Mathematically, the approach of a signal is normally performed as

$$x(k+1) = Ax(k) + w(k); \tag{1}$$

Where $x(k)$ is a state vector, A is the changes state metric and $w(k)$ is noise in assortment covariance Q_w. The signal $y(k)$ is measured and assume as the linear form state vector and the noise is defined as.

$$y(k+1) = Cy(k) + r(k); \tag{2}$$

C is an observer metric and $r(k)$ is the noise movement with covariance Q_r .The sum of optical flow for sequences of frame is performed as refer to Figure (1). The value of slope $d(k)$ for sum of optical flow in k sequence time is pivoted on equation (3).

$$SOF_{k+1} = SOF_k + T_s d_k \tag{3}$$

where Ts is the sampling time. The sum of optical flow (SOF) for every frame is presented from the magnitude calculation of optical flow and it will deformed by noise of r_k

$$y_k = SOF_k + r_k; \tag{4}$$

With the assumption that the slope d_k of SOF changes smoothly, the model is transfigured as equation below.

$$d_{k+1} = \alpha d_k + w_k \tag{5}$$

The Kalman filter is used to predict the condition for current data (c) based on previous data (p)

$$\hat{x}_{k(p)} = A\hat{x}_{k-1(c)}; \tag{6}$$

where A is the changes metric. The involvement of covariance error is clarified as

$$\mathrm{P}_{k(p)} = \mathrm{A} * \mathrm{P}_{k\text{-}1(c)} * \mathrm{A}^{\mathrm{T}} + \mathrm{Q}_{\mathrm{w}}; \tag{7}$$

The Kalman filter gain matrix is computed as

$$\mathrm{K} = \mathrm{P}_{k(p)} * \mathrm{C}^{\mathrm{T}} / (\mathrm{C} * \mathrm{P}_{k(p)} * \mathrm{C}^{\mathrm{T}} + \mathrm{Q}_{\mathrm{r}} \tag{8}$$

To update the predicted data, then ~~is.~~

$$\mathrm{P}_{k(c)} = \mathrm{P}_{k(p)} - \mathrm{K} * \mathrm{C} * \mathrm{P}_{k(p)}; \tag{9}$$

And the updated predict condition is assigned as

$$\mathrm{X}_{k(c)} = \mathrm{X}_{k(p)} + \mathrm{K} * (\mathrm{y}_k - \mathrm{C} * \mathrm{X}_{k(p)}), \tag{10}$$

The value of state in sum of optical flow data is defined as $x_k = [d_k \quad JOF_k]$. As relates to (3) and (5), the changing state is performed as

$$x_{k+1} = Ax_k + \zeta_k \tag{11}$$

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where $A = \begin{bmatrix} \alpha & 0 \\ T_s & 1 \end{bmatrix}$ and $\zeta_k = \begin{bmatrix} w_k \\ 0 \end{bmatrix}$

The observer equation that refers to equation (4) is defined as $y_k = C_{xk} + r_k$; and C is $[0 \quad 1]$

With activated A and C, Kalman filter step is then implemented based on equation (7) to (10). The performance of the filter depends on the value of α and $\gamma = \frac{\sigma_w^2}{\sigma_r^2}$. To choose the value of start intersection and end intersection, we pick α =1 and $\gamma = 0.1$.

In order to discern the abnormality of the movement, the distribution of angles of the start and end intersection are compared. The cosinus vector matching is executed. The computation is in n dimensional vector, which produces cosinus angle in between of 2 comparison vectors. The calculation is based on the equation below [9].

$$Matching = \cos(\theta) = \frac{A.B}{\|A\|\|B\|} \qquad (12)$$

The vector A performs as angle dissemination before the intersection and B is after the intersection. The output of the matching is between 0 and 1 in which the value near 1 show that the identical is high while 0 means it is distracted.

In order to ensure that this feature extraction is able to detect high accuracy of abnormality, supervised SVM classifier is implemented.

The entire steps mentioned earlier is simplified in Figure 2

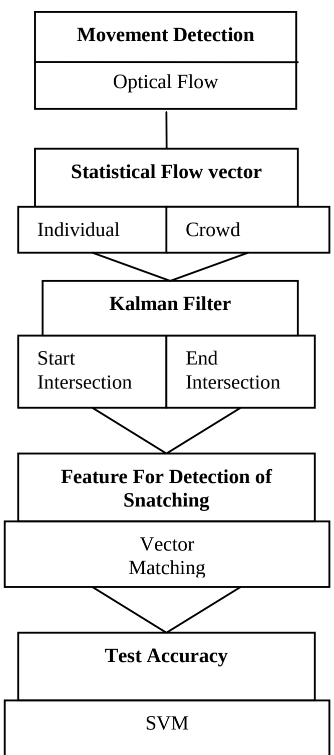
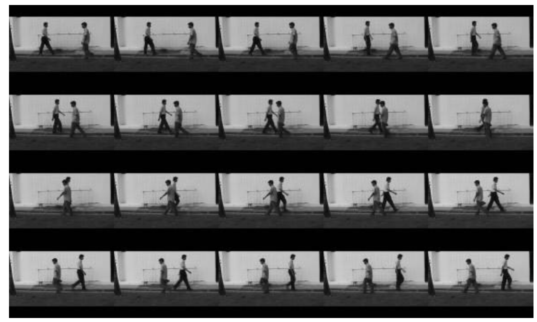


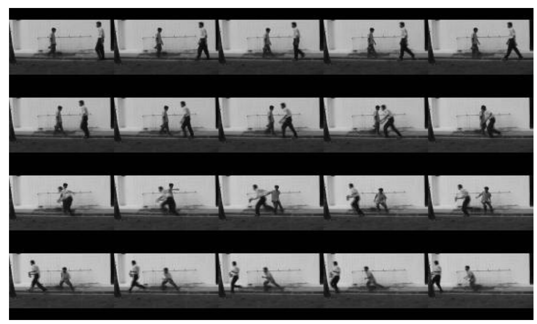
Figure 2: The flowchart of detection technique

IV. EXPERIMENTS AND RESULTS

In order to implement the techniques previously discussed, several models of movements that perform normal situation of intersection and familiar snatching movement are acted out. The movements are presented in one and two ways outlines. Figure 3(a) and 3(b) correspondingly shows no snatching (normal) activity and snatching (abnormal) activity when two persons are moving towards each other.



(a)



(b)

Figure 3: The sequence of movement 3(a) without snatching activity and 3(b) with snatching activity

The optical flow is implemented to detect the movement. The sum of optical flow is computed for each frame where the movement is either walking or running individually or in a crowd. The flow vector skeleton for the movement via the sum of optical flow is shown in Figure 4.

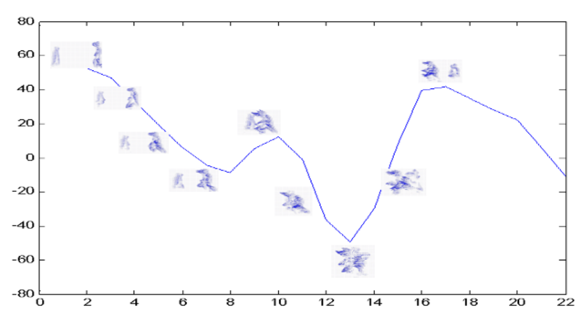


Figure 4: The sum of optical flow and the skeleton flow for the movement in Figure 3(b)

The start of the intersection is predicted based on Kalman's filter with the chosen parameters are α =1 and $\gamma = 0.1$. The start of the intersection is chosen when the slope of the graph meets a certain range. In this video, the slope is set between

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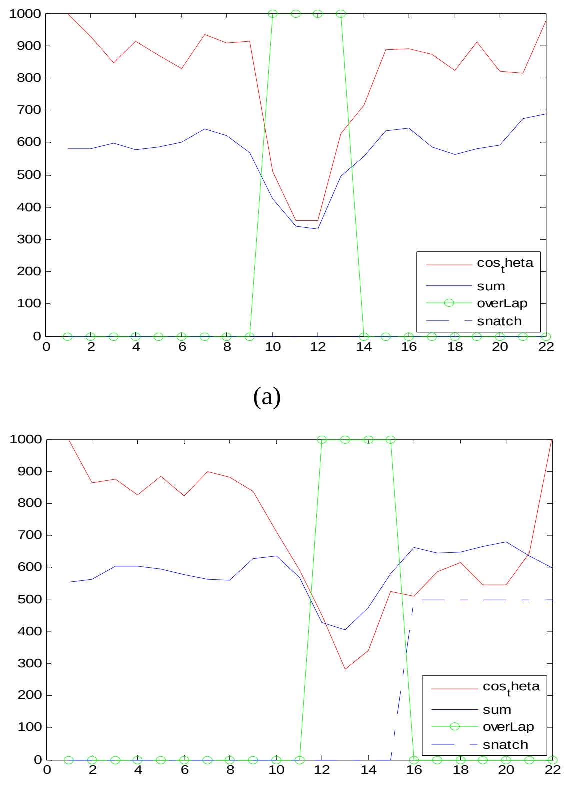
-15 to -50 for start intersection while for the end intersection, it is between 15 to 50. When the sum of optical flow slope meets the start of the intersection value, where it starts to overlap, it will change the state to 1. When the slope is increasing to a positive value, it will change the state back to 0. This is denoted by the green line in Figure 5 for both snatching and normal movements.



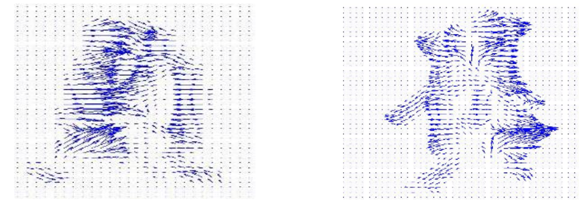
(a)

(b)

Figure 5: Sum of optical flow, vector matching, detection of overlap for sequence of the frames in (a) normal and (b) snatching movements.

When the starts of intersection and end of intersection have been detected, the flow vector in the start and end of intersection frames are compared. When there is no snatching activity happens the flow for the two frames should be consistent and will be distracted if there is snatching activity. This can be illustrated by the angle distribution histogram in comparison to the flow vector for the 2 activities (snatching and without snatching) as shown in Figure 6 and 7.

When a snatching activity is detected, the distracted angles can be visibly seen and the rate of distraction is done by using cosinus vector matching in start and end of the intersection frames. The cosinus vector matching technique can also be applied on every sequence as shown in Figure 5. In this figure, if there is a large difference between the two frames (start and end of intersection), with a certain threshold value, a snatch activity is demonstrated.



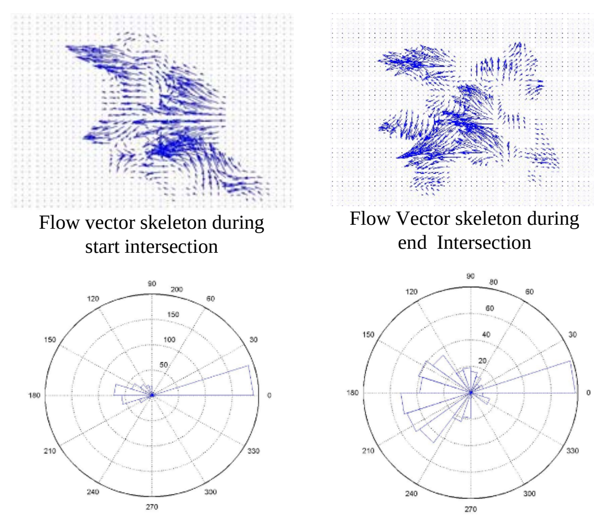
Flow vector skeleton during start intersection

Flow Vector skeleton during end Intersection

Angle distribution during start intersection

Angle distribution during end intersection

Figure 6: The flow vector and angle distribution in start intersection and end intersection for normal movement



Flow vector skeleton during start intersection

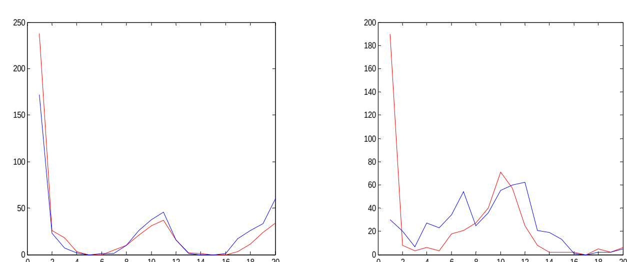
Flow Vector skeleton during end Intersection

Angle distribution during start intersection

Angle distribution during end intersection

Figure 7: The flow vector and angle distribution in start of intersection and end of intersection for snatching movement

From the distribution of angle of both snatching and not snatching activities, it shows that the values will approximately the same when no snatching happens. This is proven in Figure 8.



(a)Normal activities

(b)Snatching activities

Figure 8: The comparison of angle distribution for normal and snatching activities.

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For classification purpose, supervised SVM is implemented to evaluate the accuracy of snatch or not snatch activity for the extracted features. The data is not taken based on one area but multiple areas including indoor and outdoor, which are very dynamically changed. When tested to 260 data, the efficiency is approximately 91%.

V. Conclusion

A significant output of this research is that the use of low level feature extraction is a turning point to avoid complicated segmentation of human movement. The ability to detect abnormality based on angle distribution from start intersection and end intersection creates advantages in term of execution time and storage of data. The experiment proves that SVM technique is able to classify more than 90% of the test data.

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