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Multi-Agent Event Detection Based Onmotion Information

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ABSTRACT
Multi-agent event recognition activity is a highly challenging task because of the difficulties in detecting humans in a crowd, which composes of various types of motion, background, appearance, illumination and clutter. This paper presents a method to detect multi-agent activity such as snatch theft using motion information. These motion based descriptors are composed of motion vector flow and directional motion histogram to capture the interaction between two persons in a video sequence. The simulation results show that the proposed feature vector has successfully detected snatch theft activity up to 90% accuracy, which corresponds to less than 10 % error rate.

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INTRODUCTION

Motion cue information has been widely used in many applications such as man-machine interaction, gesture-based remote control, sign language interpretation and video surveillance. The performance of these systems can potentially be improved by fusing motion information into the recognition module that focuses on movement information. Most existing works in multi-agent event recognition in a crowd, for instance snatch theft, fight and assault have used motion cues to extract the motion patterns from the scene. The most popular method extracts the movement information using optical flow of the motion vector (Ibrahim, N., *et al.*, 2012; Fischer, D. and R. Isermann, 2004) that estimates the pixels movement between successive frames through feature similarities. In the classification stage, feature vector or temporal sequence of the vectors is classified using general model, mainly by Hidden Markov Model (Goya, K., *et al.*, 2009; Liu, X., C.-S. Chua, 2006). Meanwhile, Liu *et al*. (2006) extracted individual motion trajectories to represent the cluster of object-centered motion patterns, which is used to detect rare trajectory pattern that signifies suspicious human activity. Tracking of the motion trajectories capture the temporal information and role of each agent. This paper proposes motion vector flow to detect multi-agent event recognition such as snatch theft. Motion vector flow is computed based on three different methods; differential, phase and energy. We consider a single camera system with a fixed viewing angle for the validation test. We apply phase based motion vector to the extracted human silhouette during motion segmentation process. Then, the motion vector flow is projected into directional motion histogram to construct four directions of sum of vector flow at the intersection point (the start and end point of agent interaction). Finally, the classification is done using support vector machine (SVM).

Proposed Methods:

In this section, we present the in-depth explanation of the proposed method. Generally, the proposed method composes of four stages.

A. Silhouette Edge Points Extraction:

The silhouette is obtained from a foreground segmentation process while the edge points are extracted from the silhouette by a Canny edge detector. The moving edge points are obtained through a combination of extracted silhouette and Canny edge image. Initially, the silhouette is extracted using background subtraction process method, which compares the current image with an updated background image. In this work, we implement the background subtraction method as described in Xu *et al.* (2005) that includes shadow removal technique. A sample of background subtraction result is shown in Figure 1(b). The moving edge points as

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shown in Figure 1(d) are obtained by combining Canny edge image in Figure 1(c) and foreground silhouette image in Figure 1(b). These steps are necessary to overcome bad segmentation problem due to noisy image before further motion analysis is performed.

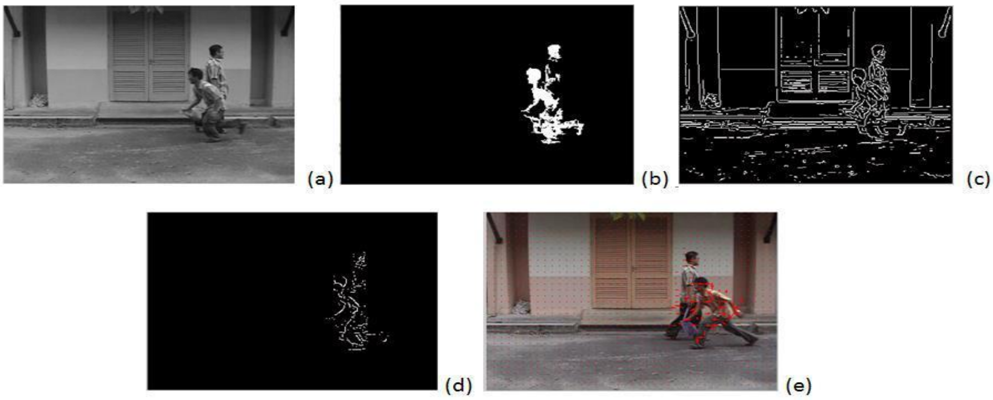

Fig. 1: (a) Original image, (b) background subtraction process, (c) Canny edge detection, (d) moving edge points and (e) motion vector flow

B. Phase Correlation motion vector:

For motion analysis, we utilize phase correlation to estimate the motion vectors between two successive frames for every local region. We apply phase correlation based on Fourier shift theorem as explained in [Castro and Morandi 1987]. We also implement Fast Fourier Transform (FFT) to increase the computational efficiency. Given that R_p^t and R_p^{t+1} are regions for two consecutive frames observed at position *p*, time *t* and *t+1*, respectively. The regions denoted as f_p^t and f_p^{t+1} are transformed to the frequency domain using discrete FFT. Then, normalize phase correlation is computed as follows:

$$\psi_p^{t+1} = \left(f_p^t \cdot f_p^{*,t+1}\right) / \left| f_p^t \cdot f_p^{*,t+1} \right| \tag{1}$$

note that complex conjugate of f_p^{t+1} is the Hadamard product of f_p^t and $f_p^{*,t+1}$. The normalized cross correlation ϕ_p^{t+1} is obtained by applying the Inverse Fast Fourier Transform (IFFT) for ψ_p^{t+1}. Thus, the estimated motion vector $(\Delta x, \Delta y)$ between R_p^t and R_p^{t+1} is given by $(\Delta x, \Delta y) = \arg\max_{x.y} \phi_p^{t+1}$.

C. Projected Directional Motion Histogram For Snatch Theft Event Detection:

In this step, each sequence of image will have its own motion field vectors, which is then classified into four directional motion components (positive and negative components of the horizontal and vertical motions). As shown in Figure 2, motion field is divided into right and left motions, which are drawn in *y*-axis, while up and down motions are plotted in *x*-axis. Thus, four histograms are generated to represent the projection of each component onto the perpendicular axes of the respective motion direction. The concatenate of accumulated features vector represents the directional motion distributions and summarizes the motion history of the images to generate distinguishable features between normal and snatch activity.

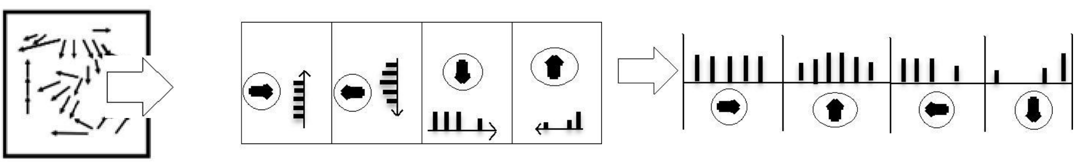

Fig. 2: Projected directional motion histogram as proposed by Hitoshi [Hitoshi 2008]. (a) Motion field vectors, (b) four components of motion directions, (c) concatenated directional motion histogram

A unique characteristic of normal and snatch activity can be observed at the intersection point, where SOV is computed across the image, t. Figure 3 illustrates the SOV for a sequence of images with and without human interaction activity. Individual motion vector flow for a single person (with no interaction) is constant, while sudden change in SOV at the intersection point is observed because of conflicting movement of multiple persons that interact with each other. The thresholds for the starting and ending points of the interaction are selected as follows:

$$T_{SOV} > 60 \tag{2}$$

where T_{SOV} is the selected threshold for SOV motion flow across the sequence of images, t.

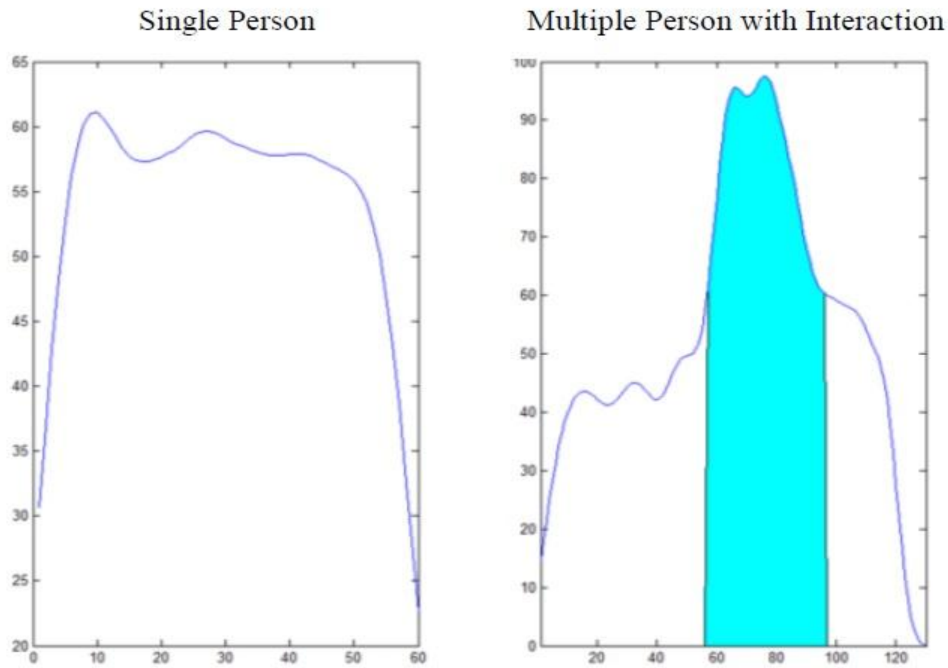

Fig. 3: The sequence of movements for single person and multiple-person with interaction activity. The shaded area shows the interaction region

D. Classification:

Support Vector Machine (SVM) is widely used in classification problem, which offers good performance with a fast computational time that can handle large data sets and robust to various feature sets and parameters. Several well-known kernel functions are analysed as listed in Table 1, where *x* is a test sample vector.

Table 1: Kernel functions

Linear	$K(x_i, x_j) = x_i^T x_j$
Polynomial of degree m	$K(x_i, x_j) = (x_i^T x_j + 1)^m$
Radial Basis Function (RBF)	$K(x_i, x_j) = e^{\frac{-\lVert x_i - x_j \rVert^2}{\alpha^2}}$

RESULT AND DISCUSSION

The proposed method works well for a dataset of 80 clips that consists of two-person interaction of normal and snatch activities. The total number of frame varies from 100 to 300 frames and the resolution is 320 x 240 pixels. The simulation output from the dataset (Ibrahim, N., *et al*., 2012) gave acceptable results in spite of low quality images (noise, high compression) and segmentation challenges. Table 2 shows the recognition results obtained from the dataset of 40 normal activity clips and 40 snatch theft activity clips that are tested on supervised SVM. The performance of phase-based motion vector flow algorithm is analysed in terms of sensitivity and specificity. The sensitivity metric defines the capability of the algorithm to detect snatch activity correctly while specificity is the percentage of true normal activity detection over total number of normal activity.

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They are defined as in equation 3 to 6, where TP is the number of true detection, FN is the number of false detection, while TN and FP are the total number of true and missed detection of normal activity respectively.

Sensitivity = TP / (TP+FN) (3)
Specificity = TN / (TN+FP) (4)
Accuracy = (TP+TN) / (TP+TN+FP+FN) (5)
Error Rate = (FP+FN) / (TP+TN+FP+FN) (6)

Table 2 shows the classification results using tree types of kernel. Both linear SVM and polynomial kernel with 2-degree classifier produce error rate greater than 10%. However, the RBF kernel managed to register higher accuracy with error rate less than 10%.

Table 2: Classification results using SVM classifier

SVM Kernel	Linear	Polynomial	RBF
		(m=3)	($\sigma = \pi$)
Sensitivity (%)	79.85	78.15	89.15
Specificity (%)	84.4	84.81	95.63
Accuracy (%)	82.24	81.62	94.59
Error Rate (%)	17.76	18.38	5.41

Conclusion:

In this paper, a phase-based method has been proposed to analyse motion vector flow for snatch event detection. The projected directional motion histogram captures the spatial distribution of motion history across the video, which is useful to detect silhouette changes, especially during human interaction. Preliminary recognition of snatch event detection has been carried out based on the proposed method, where it delivered good accuracy for both specificity and sensitivity. For the future work, we will use adaptive thresholding method to automatically initialize the starting and ending points of the interaction activity.

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REFERENCES

Asaad, H., S. Mubarak, 2007. Learning, detection and representation of multi-agent events in videos, J. Artificial Intelli., 171: 586-605.

Fischer, D. and R. Isermann, 2004. Mechatronic semi-active and active vehicle suspensions. Control Engineering Practice, 12(11): 1353-1367.

Goya, K., X. Zhang, K. Kitayama, 2009. A Method for Automatic Detection of Crimes for Public Security by Using Motion Analysis, Proc. of the Int. Conf. on Intell. Information Hiding and Multimedia Signal Process, pp: 736-741.

Ibrahim, N., M.M. Mustafa, S.S. Mokri, L.Y. Siong, A. Hussain, 2012. Detection of snatch theft based on temporal differences in motion flow field orientation histograms. Int. J. Adv. Comput. Technol., 4: 308-317.

Liu, X., C.-S. Chua, 2006. Multi-agent activity recognition using observation decomposed hidden Markov models. J. Image Vision Comput., 24: 166-176.