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An Innovative Pedestrian Behavior Detection System for Identifying Unusual Activity in Academic Environments

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ABSTRACT

In this paper, we propose an efficient method for the detection of student unusual activity in the academic environment. The proposed method extracts motion features that accurately describe the motion characteristics of the pedestrian's movement, velocity, and direction, as well as their intercommunication within a frame. We also use these motion features to detect both global and local anomalous behaviors within the frame. The proposed approach is validated on a newly built proposed student behavior database and three additional publicly available benchmark datasets. When compared to state-of-the-art techniques, the experimental results reveal a considerable performance improvement in anomalous activity recognition. Finally, we summarize and discuss future research directions.

1. INTRODUCTION

Today, public and private prominent areas are monitored with surveillance cameras due to increased security concerns. It is a difficult task to monitor pedestrian behavior by human supervision. The current problem with the traditional approach is that it is difficult to detect and separate suspicious activities from real-time video, and this procedure is extensive and time-consuming. Due to the current limitations of the system, we need an intelligent video surveillance system that can automatically recognize suspicious behavior in real time. Many researchers and practitioners in the fields of computer vision and video analysis have dedicated their efforts in recent years to recognizing human movement and behavior in video frames [1]–[3]. In recent years, researchers have concentrated increasingly on the detection of suspicious activity in high-density areas. Traditional systems cannot detect and track pedestrians in high density areas due to full or partial occlusion of objects, changes in item size, changes in ambient lighting, and other factors. Many authors have attempted to detect abnormal behaviour in overcrowded environments using texture- based information, such as time gradients [4], dynamic texture characteristics [5] and the spatiotemporal frequency properties [6], [7]. Other groups concentrate on optical flows, which recognize motion features in video frames directly, such as multi-scale pedestrian features [8], fuzzy clustering based features [9], behavioural model for pedestrian detection [10], convolutional neural networks (CNN) features [11], weighted autoencoder based features [12], trajectory based features [13], student object behavioral features [14], multi-target association based features [15], [16]. Previous research has shown that the technique of motion is beneficial, and we believe that the present methods can still be improved. It is essential to provide data on objects of different sizes, motion direction, speed, and inter-frame interactions. We can increase proposed method performance if we analyze the facts concerning this movement. In the proposed motion pattern-based method, we distinguish moving pedestrian using motion information, orientation, pedestrian size, and interaction within the video sequence, specifically in highly dense regions. Figure 1 illustrate the student suspicious behavior examples. Figure 1(a) depicts the unusual activity of student in which student stealing the mobile phone of another student. Figure 1(b) depicts the student dispute behavior in the lab. A small active segment of an anomalous area is classified as a local area. Meanwhile, a global region refers to the area where strange behavior is observed. In the literature, various ways to identify the region's unusual activity have been introduced.

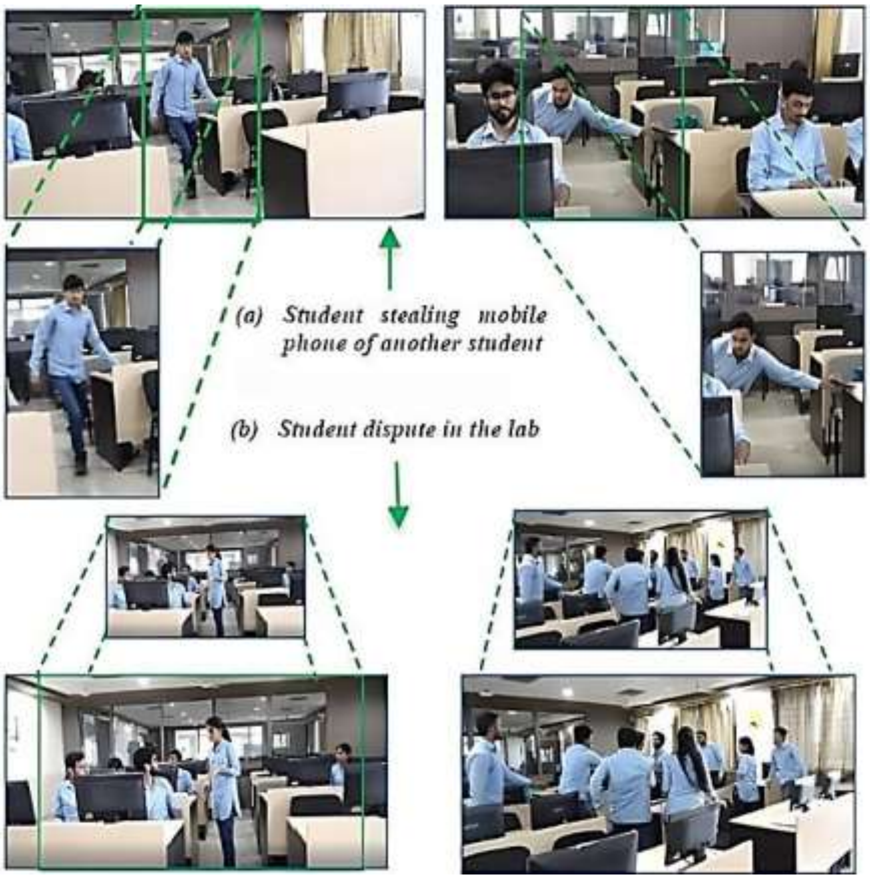

Figure 1. Student suspicious behavior examples (a) student steal the mobile phone of another student (specific area) and (b) student dispute in the lab. (full frame)

Li *et.al.* [15] presented a social force map-based strategy for detecting worldwide anomalous activity. They placed a particle grid across the optical flow field and computed the interaction force between each particle. Tufek and Ozkaya [11] described a method for detecting erroneous local motions in a scene. To detect anomalies in the immediate area, they created a saliency feature map employing optical flow features at various sizes. A comprehensive framework for detecting abnormal activity is required for a real-time monitoring system. The proposed contribution is outlined: i) at the pixel level, we proposed a unique approach for detecting behavioral patterns in academic environment; and ii) on our proposed database as well as other benchmark datasets, such as the University of Minnesota anomaly detection datasets, we assessed the effectiveness of the proposed motion-based method. The following is how the rest of the contribution is organized: The existing contribution in this area is outlined in section 2. We propose a motion feature-based suspicious activity detection in section 3. Section 4 covers a new pedestrian behavior database developed in an academic setting, as well as results and performance comparison with other relevant methodologies. The last section concludes with a research direction.

2. LITERATURE SURVEY

Researchers in a smart video surveillance system have recently become interested in the unusual activity detection. Gaddigoudar *et al.* [17] describe the difficulty of understanding and modelling behavior in surveillance video. In an unsupervised learning framework, violations are discovered using likelihood ratio analysis and pedestrian legal action categories. Mehmood [18] presented a method for detecting anomalies in a spatiotemporal environment. They showed an atomic event for a single object in a scene that includes the object's position, movement, direction, and velocity. To characterize valid occurrences, they use an aggregation of three partitioned atomic events. In crowded scenes, it's hard to comprehend moving pedestrians. Therefore, the aforementioned strategies aren't appropriate.

The multi-scale pedestrian detected using a deep learning architecture. The CNN features are used for classification of pedestrians in highly dense regions. The different issues and challenges addressed using author approaches are scale and illumination variation. Other recent research groups have concentrated on moving pedestrian motion orientation and speed information. The Kanade Lucas-Tomasi (KLT) approach [9] is employed by Zhang *et al.* [19], in which corner points are used to display pedestrians that are moving and cluster the motion information features in the controlled environment. The author used two types of historical and self-history descriptors, as well as neighbouring object histories, to detect abnormalities in a scene [10]. Chebli and Khalifa [20] presented a method for identifying the number of humans in an image without the use of a camera. They exploited foreground relationships as well as an optical-flow motion pattern. They calculated the dynamic energy of using optical flow to distinguish between walking and running activities, as well as crowd exponential distribution patterns.

Other academics have focused on understanding and modelling crowd behavior [21]–[24]. Several strategies were used to detect worldwide anomalous activity by modelling the crowd's behavior. Wang and Hou [22] author used the social force model to characterize crowd behavior [22]. The moving object optical flow pattern is computed for pedestrian detection in the crowded environment [14], [25]. The behavior classification of pedestrians performed by social force was also determined using latent Dirichlet allocation (LDA). Minguez *et al.* [26] use interactive energy potentials to study social behavior and its behavior. Zhang *et al.* [19] used the KLT feature-based pedestrian tracker. In this motion, characteristics are computed using temporal distinct points. It calculates interaction energy potentials based on the velocities of spatiotemporal interest points to see if they will collide soon [27]. Other research groups, on the other hand, have concentrated on detecting local aberrant activity. Quantifiable is a term used in [11] to describe the global rarity of picking uncorrelated motions from a spatial context. They calculated the index across numerous channels with varying velocities and directions.

Using the associated saliency map, they were almost able to detect local aberrant behavior. Zaki and Sayed [28] the author used motion intensities for creating a motion heat map and compared it to local motion fluctuations. Direkoglu [5] the author proposed a texture feature-based abnormal activity recognition in highly dense areas. Finally, crowd behavior analysis was performed using moving objects, optical flow patterns and directional information. Papathanasopoulou *et al.* [29] the author proposed an approach for highly dense areas for extracting the moving objects within the cluster of frames. Although the aforementioned strategies have been shown to be useful in studies, they are usually limited to detecting unusual activity in a local or global location. We contend that joint contemplation of the motion flows pattern, variable item sizes, and interactions between neighboring objects in a frame can reflect pedestrian activities in a high-density scene, resulting in improved performance in detecting unusual activity. We proposed an effective technique for dealing with the aforementioned issues and challenges with clustering of motion patterns in consecutive frames. We begin by extracting motion features at different scales and directions with sequences of frames. Furthermore, we also used motion analysis to identify abnormal activities within a scene.

3. PROPOSED METHODOLOGY

We describe a strategy for identifying and localizing abnormal activity in high-density zones in this section, which incorporates the motion component. We detected fast and slow movement of a pedestrian's unusual activities in the local and global regions of the scene. Figure 2 depicts the general architecture of the suggested technique. Each frame is broken down into blocks, and motion data is retrieved to generate motion characteristics at the pixel and block levels. The motion feature extraction process is divided into following stages:

- First, within a series of frames, the motion characteristics of moving pedestrians are extracted at spatial plane coordinates and block by block incrementally in different orientation and scale.
- After integrating the motion information single feature matrix is generated that represents both spatial and temporal characteristics.
- To classify the activity k-means clustering for each zone applied to identify the global and local region.

- The euclidean distances computed across the frames. Again, the directional motion pattern are the distinct feature values for the detection of abnormal behavior in academic environments.
- Once a frame has been categorized as unusual, we use pixel-level localization to determine the specific location of the unexpected behavior. The process will continue until the video sequence is complete.

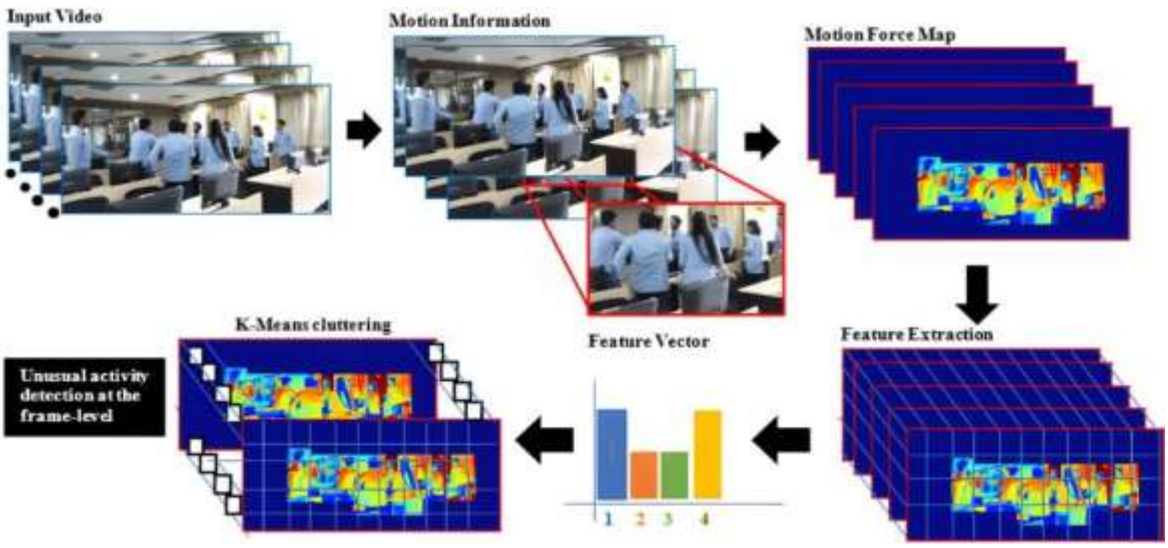

Figure 2. Proposed framework architecture to represent moving object behavior in academic environment

A method for detects an unusual human activity by processing each frame of the video sequence, the proposed method first extracts the optical flows of the pixels within each block of frame represented in (1).

$$B_i = \frac{1}{J}\sum_{j=0}^{n} f(x, y)_i^j \tag{1}$$

Where, B_i denotes the i^{th} block optical flow, pixel size is represented by J, i^{th} block j^{th} pixel optical flow represented by $f(x, y)_i^j$. Next, the threshold T_d for the block computed using the motion vector B_i and block width S represented in (2).

$$T_d \leftarrow B_i \, x \, S \tag{2}$$

The angle between the feature vector Θ_{ij} computed using $E_{(i,j)}$

$$\Theta_{ij} \begin{cases} 1 & E_{(i,j)} < T_d \\ 0 & therwise \end{cases}$$

The motion feature extraction process defined by (3).

$$MF = \frac{MF\,(\Theta B_i) + ED_{(i,j)}}{B_i} \tag{3}$$

Where in MF is the motion feature map, $E_{(i,j)}$ Euclidean distance between object i and j. Next, we have described motion feature extraction briefly in the algorithm.

In addition, clustered at frame level defined the motion region in a frame, each cluster optical flow of a pixel in a different direction being considered as the feature vector. Whenever distance between blocks decreases, the probability of unexpected behavior in the corresponding block decreases. If a larger value distance is determined, then we can classify anomalous actions in consecutive frames. As a result, if the distance is over a set limit of the constant threshold value, the current scene is recognized as an unusual activity frame. Next, we describe the experimental results.

Algorithm: Motion information extraction for detection of unusual human activity from video.

Inputs: ***V***, *the input video sequence*
n, *Last frame of video*
S, *Block width*
K, *Each frame block size*
f, *the frame of the input video sequence*
B, *Motion vector*
Output: $\boldsymbol{MF}$, *the motion Features*

Read each frame of video
for $f = 1$ **to** N **do**
  Process each block of frame
  for $i = 1$ **to** K **do**
    Compute the threshold for each block
    $T_d \leftarrow B_i \; x \; S$
      Process adjacent block in a frame
      for $j = 1$ **to** K **do**
        Compute the centroid from the bounding box points. represented by: (cX; cY)
        Append centroid in centroid dictionary
        If *i not equal j* **then**
          Compute the distance across the consecutive block
          $ED_{(i,j)} \leftarrow EucliDist(B_i, B_j)$
          Compute distance and compare against threshold
          if $|ED_{(i,j)} < T_d|$ **then**
            Compute Angle Θ_{ij} *between* B_i *and* B_j
          if $-\Theta B_i < \Theta_{ij} < \Theta B_j$ **then**
            $MF \leftarrow MF(\Theta B_i) + ED_{(i,j)}/B_i$
          end if
        end if
      end if
    end for
  end for
end for

4. RESULTS AND DISCUSSION

We validated the proposed approach accuracy on public datasets, as well as the suggested student behavior dataset and the University of Minnesota anomaly detection datasets. The experiments and proposed deep learning framework were carried out using a single NVIDIA graphics processing unit (GPU) and an Intel Core i7 3.4GHz processor with 32GB random-access memory (RAM) and a 32GB NVIDIA graphics card, all of which were configured using CUDA-optimized architecture and the open source computer vision library (OpenCV) deep learning framework. The suggested method is compared to the state-of-the-art unusual activity detection methods [29], [30], social force models [31], sparse representation-based method [32], and mixture of dynamic textures-based method [32]. True positive (TP), true negative (TN), false positive (FP), false negative (FN), equal error rate (ERR), true positive rate (TPR), true negative rate (TNR), and area under curve (AUC) are some common performance measuring metrics. We have computed these metrics using (4), (5), (6), and (7). These metrics are computed for the performance comparison.

$$TPR = \frac{TP}{TP+TN} \tag{4}$$

$$TNR = \frac{TN}{FP+FN} \tag{5}$$

$$AUC = \frac{1}{2} * (TPR + TNR) \tag{6}$$

$$ERR = 1 - \frac{1}{2} * (TPR + TNR) \tag{7}$$

First, we have performed experiments on University of Minnesota anomaly detection dataset. Figure 3 shows the receiving operating curve (ROC) for the proposed and existing approach presented in [31], [32]. Similarly, we have computed the ROC for the proposed student behavior dataset in Figure 4. After analysing the ROC curve, the proposed framework is efficient and outperformed the method available in the literature. For quantitative comparative analysis, we have computed ERR for the existing and proposed method as shown in Table 1 and Table 2 for both the datasets. We observed that the proposed method gives less error rate, comparatively, on both the datasets, i.e., 16.1% and 18.1% respectively. Again, AUC for the existing and proposed method as shown in Table 3 and Table 4 for both the dataset. As illustrated in the table AUC for the proposed method is 73.2% and 72.1%. It shows that the proposed motion pattern-based approach is more efficient, robust, and accurate on both the dataset and is comparatively better than existing approaches of the suspicious behavior.

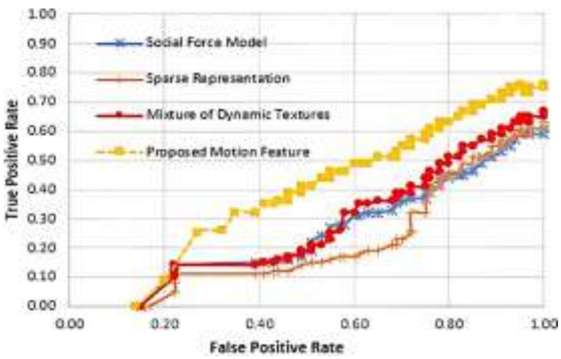

Figure 3. FPR and TPR for the existing and proposed motion feature map-based method for University of Minnesota anomaly detection dataset

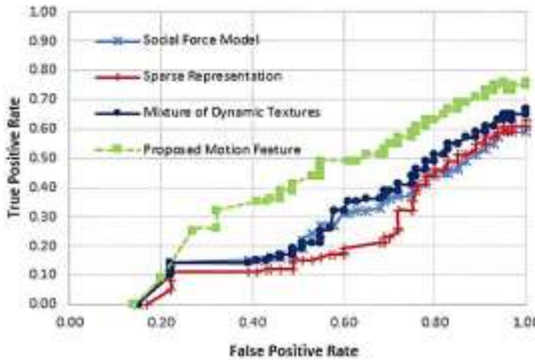

Figure 4. FPR and TPR for the existing and proposed motion feature map-based method for proposed student behavior dataset

Table 1. ERR for the existing and proposed motion feature map-based method on University of Minnesota anomaly detection dataset

Methodology	Ped. 1	Ped. 2	Avg.
Social Force Model [32]	36.5%	35.0%	35.7%
Sparce Representation [31]	35.6%	35.8%	35.7%
Mixture of Dynamic Texture [32]	22.9%	22.9%	22.9%
Proposed Motion Feature based method	21.1%	18.1%	16.1%

Table 2. ERR for the existing and proposed motion feature map-based method on student behavior dataset

Methodology	Ped. 1	Ped. 2	Avg.
Social Force Model [32]	37.5%	34.0%	36.7%
Sparce Representation [31]	32.6%	35.8%	33.7%
Mixture of Dynamic Texture [32]	24.9%	23.9%	23.5%
Proposed Motion Feature based method	22.1%	19.2%	18.1%

Table 3. AUC for the existing and proposed motion feature map-based method on University of Minnesota anomaly detection dataset

Methodology	Ped. 1	Ped. 2	Avg.
Social Force Model [32]	40.9%	27.6%	34.2%
Sparce Representation [31]	32.6%	22.4%	27.5%
Mixture of Dynamic Texture [32]	59.3%	56.8%	58.0%
Proposed Motion Feature based method	64.9%	81.5%	73.2%

Table 4. AUC for the existing and proposed motion feature map-based method on proposed student behavior dataset

Methodology	Ped. 1	Ped. 2	Avg.
Social Force Model [32]	50.8%	63.4%	57.1%
Sparce Representation [31]	74.5%	70.1%	72.3%
Mixture of Dynamic Texture [32]	35.6%	35.8%	35.7%
Proposed Motion Feature based method	63.4%	80.2%	72.1%

5. CONCLUSION

In this paper, we have proposed a novel method to detect the unusual human activities in an academic environment. Due to the spatial and temporal features of motion features, we can classify frames as normal or abnormal activity of the pedestrian and also able to locate regions of abnormal activity within the frame as local or global region. We conducted experiments on the University of Minnesota anomaly detection datasets and the proposed student behavioural dataset. The proposed method was confirmed to be effective, surpassing other competing methods in the literature. However, the purpose of this research is to detect abnormal actions in an academic environment, for which cameras generally cover a large area. In future, same method can be used for the different scenarios of student behaviour such as the student examination cheating scenarios, student dispute in the campus, etc. Again, scale, rotation, and illumination changes can also be address if the proposed approach enhance with the additional features such as scale, rotation, and illumination invariant feature.

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