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ANALYSING THE SUSPICIOUS BEHAVIOUR IN VIDEO SURVILLIENCE FOR CRIME DETECTION USING GAIT SPEED MONITORING

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Abstract
One of the most emergent research is suspicious behaviour monitoring in video surveillance. In recent past, crime detection is powerful topic to identify the abnormal events or crime events. This work focused on the suspicious behaviour analysis which helps to detect the crime events in terms of gait parameter. This work describes the following tasks. First, tracking the pedestrians from video data using MM track algorithm i.e. (calibration process). Second, extracting the gait parameters based on proposed modules: 1) spatial coordinate module contains the speed profiles which helps to measure the suspicious behaviour of pedestrian. 2) Fixed coordinate system module, it also measures the suspicious behaviour in different way based on the list of components and axis of the pedestrians. This step performs the major role in measure the suspicious behaviour among the pedestrians' movement for crime detection. Third, measure the suspicious behaviour in terms of walk ratio, Acceleration Auto Correlation (AAC) and gravity, dynamic, horizontal, vertical components of pedestrians as well this step θ value performs the validation role which is based on the reference range to validate the Walk Ratio value. The video helps to monitor the pedestrian's movement. This work is compared to the different pedestrian's detection technique such as DPM (Deformable Part Model) and Real Boost method foe efficiency in terms of true positive rate and pedestrian gait speed detection time parameters. Proposed work attains best result in both parameters.

Keywords:
Kapur's Entropy, Multilevel Thresholding, Teaching Learning based Optimization

1. INTRODUCTION

A set of systematic, analytical processes directed at providing timely and pertinent information relative to crime patterns and trend correlations to assist operational and administrative personnel in planning the deployment of resources for the prevention and suppression of criminal activities, aiding the investigative process, and increasing apprehensions and the clearance of cases. Within this context, crime analysis supports a number of department functions, including patrol deployment. The analyst monitors the actions of people, not machines; while criminals often adhere to habit, there is always the possibility they will deviate. In fact, a good criminal will deviate from habit frequently and intentionally. The predictions are not come true due to many other reasons

- The information used to formulate the prediction was inaccurate
- The analyst determination of the pattern/series was incorrect
- Targeted locations and/or date/time calculations were incorrect
- Suspect left the area or was arrested by another jurisdiction
- Suspect is deceased

Measure the suspicious activities helps in one of the part of crime detection. Suspicious behavior detection is one of the most actively studied areas of computer vision, such as video analysis and surveillance. Ordinary behavior refers to actions that do not attract people's attention when people perceive some sort of movement. Therefore, surveillance systems detect suspicious behavior using characteristic patterns for various behaviors, which are generally opposed to ordinary behaviors. There have been many studies on abnormal behavior detection using different approaches such as spatio–temporal features and machine learning techniques. As a high-dimensional feature is essential to better represent the suspicious behavior pattern, many methods based on spatio–temporal information such as optical flow, spatio–temporal gradient, the social force model, chaotic invariant, and sparse representation have been studied. It does not require any training learning process, so it has less computation, which can be used in real-time detection [1].

In recent day's video surveillance is important to identify the abnormal activities of human in order to maintain serene environment. In [2] analysed the movement trajectory of pedestrians, when tracked from video data, enables the automated analysis of individual's walking behavior. This work described the three tasks which are following: This paper describes the following tasks. First, to identify possible commonality in walking behavior between nearby pedestrians. This step is realized by proposing a new structural similarity measure of pedestrians' movement. Second, to provide a method for counting pedestrians in groups. A classification procedure accomplishes this task based on spatio-temporal criteria and the introduced movement similarity measure. Third, to show the feasibility of the method on a pedestrian group study from video data collected at a moderately dense pedestrian crosswalk in Vancouver, British Columbia. There are also some limitations to consider. The analysis does not adopt a proper definition of moderate pedestrian density as well the analysis does not incorporate their pedestrian attributes. There are various abnormal activities detection for various purposes.

In [3] proposed an automatic detection of abnormal events in the recorded video. Their work mainly focused on detection of human (Student) and their abnormal activities in academic zone. The proposed system consists of three phases 1. Motion Segmentation 2. Feature Extraction 3. Action Classification. Background subtraction method primarily used to segment the moving object. Feature extraction is carried out by Hu moments. Classification of normal and abnormal activities is done by support vector machine (SVM) classifier algorithm. After long decades, the abnormal activities are determined from the public places and crowd for detecting the anomaly events and road safety.

In [4] proposed a novel framework for global anomaly detection via block-level feature extraction using context location

(CL) and motion-rich STVs (MRSTVs). The histogram of optical flow orientation and motion magnitude features from spatio-temporal volumes (STVs) are used as global feature descriptor to capture motion characteristics of normal and abnormal events. Simple and cost-effective one-class SVM classifier is employed to learn normal behaviour from MRSTVs during training and detect abnormal STVs from test data. Thereafter, a spatio-temporal post-processing technique detects frame-level abnormal behaviour and reduces false alarm rate. The past researches mainly focused on investigating motion patterns in crowds, while the emotional aspects of crowd behaviors are left unexplored.

However, in [5] analyzing the emotion of crowd behaviors is indeed extremely important, as it uncovers the social moods that are beneficial for video surveillance. They proposed novel crowd representation termed Crowd Mood. Crowd Mood is established based upon the discovery that the social emotional hypothesis of crowd behaviors can be revealed by investigating the spacing interactions and the structural levels of motion patterns in crowds. To that end, they first learned the structured trajectories of crowds by particle advection using low rank approximation with group sparsity constraint, which implicitly characterizes the coherent motion patterns.

Second, rich emotional motion features are explicitly extracted and fused by Support Vector Regression (SVR) to reflect social characteristics [5]. Pedestrian injuries and fatalities are one of the most significant problems related to travel and road safety. This problem is solved by vision based intelligent system that can detect low speeds and directions of pedestrians and can help him/her by (a) increasing the time associated to a green light for pedestrians, (b) using audible signals to help the pedestrians understanding that there are cars approaching the crossing. Gait measures are shown to be affected by the complexity of the task (e.g., talking and texting) performed during walking. Their study focused on the effect of distraction states, distraction types (visual such as texting/ reading and auditory such as talking/listening), and pedestrian-vehicle interactions on the gait parameters of pedestrians at crosswalks [6] [7]. In this work, a new suspicious behavior detection method that can be used for crime detection. The main contributions of this works are:

- The video surveillance data helps to monitoring the pedestrians for measures the suspicious behaviour.
- Track the pedestrians using MM track algorithm
- Extract the gait parameter based on two types of module: spatial coordinate module and fixed coordinate system module.
- Finally, measures the suspicious behaviours using speed profiles such as walk ratio and Acceleration Auto Correlation (AAC).

This paper is organized as follows. In section 2, related works are presented. In section 3, proposed work determined the suspicious behaviours with the fixed coordinate system module and spatial coordinate module. In section 4, calculated the result and discussion. Finally, in section 5, drawn the conclusion. The Fig.1 shows the proposed work flow.

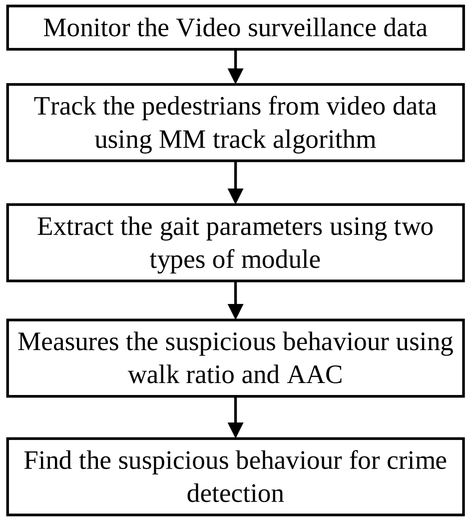

Fig.1. Workflow of Proposed Model

2. RELATED WORKS

In [8], the authors proposed a deep learning technique for automatic pedestrian recognition based on image normalization and CNN architecture. Their proposed architecture learns pedestrian representation adaptively to achieve efficient recognition with higher accuracy and lower pre-processing time. their work earns unique pedestrian features quickly and accurately. Images from data set are resized into fixed scale, normalized by zero-centered mean with unity standard deviation and feed into the proposed DCNN to identify pedestrian from non-pedestrian.

In [9], the authors presented a computer vision and queuing theory-based technique to detect pedestrians and compute key macroscopic statistics of a pedestrian traffic. They performed the task of pedestrian detection in a specified region of interest in a traffic video using an Aggregated Channel Feature based detector. Their novel technique proposed further implemented in-situ at the traffic monitoring camera sites to realise a distributed traffic management system.

In [10], the authors introduced a revertive connection into the pedestrian re-recognition detector, making it more similar to the human cognitive process by converting a single image into an image sequence; then, the memory image sequence pattern re-identifies the pedestrian image. Their approach endows deep learning-based pedestrian re-recognition algorithms with the ability to memorize image sequence patterns and allows them to re-identify pedestrians in images. At the same time, their work proposed a selective dropout method for shallow learning.

In [11], the authors proposed a fast method for detecting pedestrians in surveillance systems having limited memory and processing units. Their proposed method applies a model compression technique based on a teacher student framework to a random forest (RF) classifier instead of a wide and deep network because a compressed deep network still demands a large memory for a large number of parameters and processing resources for multiplication.

In [12], the authors suggested that processing in device situations is carried out for detecting crowd anomaly. A system of abnormality analysis focused on enhanced k-means is being suggested in this article. This system integrates mean shift with the classification process for k-means to ensure fast and precise identification of crowd abnormality.

In [13], the authors addressed three elements of this problem. Firstly, the moving crowd is defined by a novel global element. This function may well define the point-of-interest details regarding spatial and temporal motion. Then, a technique is followed that first clusters the feature point and then measures the collectivity which allows the computing of individual groups collectively more coherent and efficient.

In [14], the study used the optical flow as the supplementary information for anomaly detection. They build a deep WCAE-LSTM network, which captures spatial variances with CAE and temporal variances with three convolutional LSTM (ConvLSTM) units, and proposed a weighted Euclidean loss that focuses on the moving foregrounds, thus restraining the influences of complex backgrounds and also global-local analysis is proposed to jointly achieve anomaly detection and localization.

In [15], the authors presented the contributions on three aspects: (1) a new structural context descriptor is designed to characterize the structural properties of individuals in crowd scenes; (2) a self-weighted multiview clustering method is proposed to cluster feature points by incorporating their orientation and context similarities; (3) a novel framework is introduced for group detection.

In [16], the authors proposed a crowd anomaly detection framework that satisfied continuous feed in of spatio-temporal information from live CCTVs. Firstly, an extraction algorithm for the spatial-temporal texture is built. Their method will efficiently strip textures from the video with ample information about crowd motion. It is by the adoption of Gabor-filtered textures with the maximum entropy values of knowledge.

In [17], the authors introduced a new system for global abnormality identification while using context location (CL) as well as motion-rich STVs (MRSTVs) through block-level function extraction. In order to record motion properties of regular and irregular cases, the histogram of optical movement direction as well as motion magnitude features in spatio-temporal volumes (STVs) is being used as a regional object descriptor.

In [18], the authors focused on the methodology of deep learning. Specific deep learning approaches are measured according to its algorithms and models. The key goal of this experiment is to implement deep learning strategies to identify the exact list, the people involved and the behavior that has arisen in a broad crowd in all climatic conditions.

3. METHODOLOGY

This work determined the suspicious behaviour from video data for detecting the crime events. This work divides the process in three types which are tracking the pedestrians, Extract the gait parameter which considered based on modules C) find the suspicious behaviours among pedestrians with the help of speed profiles. The data set used in this work was taken from UMN classification dataset [1]. The Fig.2 shows the outline of the pedestrians' suspicious behaviour methodology.

3.1 PEDESTRAINT TRACKING

One of the online tracking approach algorithms is MM track which is cluster-based appearance modelling for detecting the pedestrians [2]. MMTrack algorithm is a hybrid single pedestrian tracking algorithm and it provides the benefits of discriminative and descriptive approaches for tracking which is companion by a rule for mapping from world coordinates to image coordinates using a homography matrix i.e. a camera calibration process. The role of this calibration is generating a transformation that allow the recovery of real-world coordinates (e.g., metric coordinates) from the pixel-based coordinates of the video images. Such mapping between the real world and the image space lead to the correct collection of the tracked trajectory information such as gravity, dynamic, horizontal, vertical components of pedestrians as well average walk speed, acceleration profile. Pedestrian walking trajectories are extracted, along the frames. Given the video sequence, there are n number of pedestrians are obtained over the frames. The collection of n pedestrian can be represented by the matrix formation along with the speed profile and component of the pedestrian.

$$\text{SB} = \begin{bmatrix} p_0 \\ \\ p_n \end{bmatrix} \begin{bmatrix} x & f & wk \\ y & v & AAC \\ z & s & 0 \end{bmatrix}$$

where SB denotes the suspicious behaviour, in this work determined the suspicious behaviour of pedestrians with the help of speed profiles and axes for detecting the crime events. Analysing the pedestrian's using video data [1].

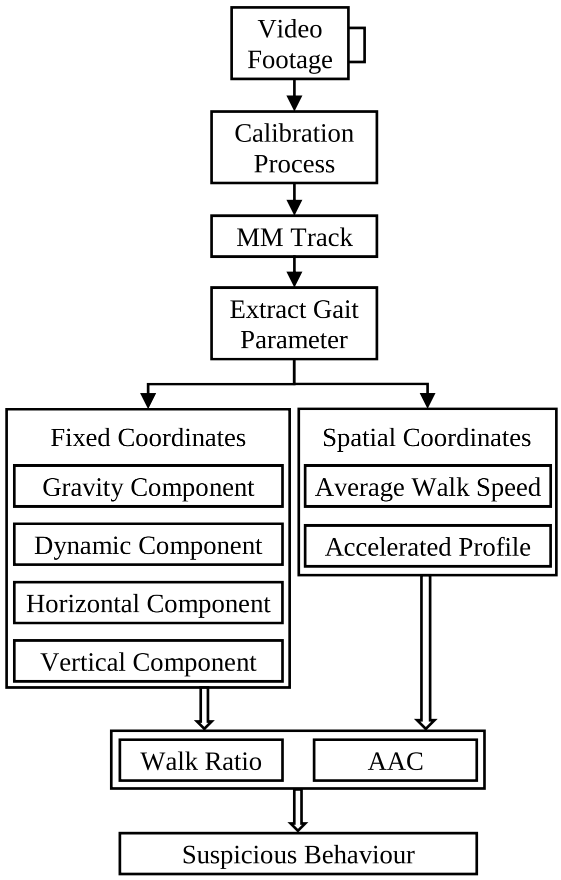

Fig.2. Outline of the suspicious behaviour methodology

3.2 EXTRACT THE GAIT PARAMETERS

The benefits of extract the gait ability to capture the natural movement of pedestrians and minimizing the risk of crime events. In this phase the gait parameters are extracted based on two modules, they are

- Spatial coordinate module
- Fixed coordinate system module

3.2.1 Spatial Coordinate Module:

This module observed each pedestrian step to introduce a cyclic fluctuation in the speed profile which means that each cycle in the speed profile corresponds to a new step taken by pedestrian. The speed profile of each pedestrian is utilized to evaluate the average step frequency for that pedestrian. The spatial coordinate of each pedestrian across time is used to evaluate the average walking speed. Evaluate the average step length based on the following fundamental linear computation. In section 3.1.1, discuss the speed rules with walk ratio.

$$\textit{Walking Speed} = \textit{Step Frequency} * \textit{Step Length} \quad (1)$$

This module also evaluated the acceleration profile using speed profile. In the following derivation, where A denotes the acceleration profile and it is a time series of length n-δ and i= {δ +1, …., n} a discrete poral index.

$$A = \frac{\Delta(s)}{\Delta t} = \frac{S_i - S_i - \delta}{\delta} \quad (2)$$

3.2.2 Fixed Coordinate System Module:

Started the fixed coordinate system module is started by computing the gravity component on each axis such as (f, v, s) of the pedestrians. With the expected gravity component, the magnitude of vertical and horizontal components of pedestrians which are calculated from video data [1].

More explicitly let a vector c = $\{c_f, c_v, c_s\}$ of each pedestrian which is a one-point acceleration measurements or acceleration measurements on respective axes. Considered, N number of acceleration vectors are collected during sample interval. There are various components used in section 3.1.2 for identify the suspicious behaviour.

In Fig.3 shows analysing the pedestrian using different axes. This module used the video data on fixed coordinate system. in Fig.3 denotes three axes which considered to displays the fixed coordinate system for monitoring the gait behaviour i.e. are f is the direction of walking movement, v is the vertical to the ground, s is the orthogonal to the other two axes.

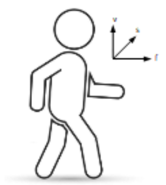

Fig.3. Analysing the pedestrian using axes

3.3 MEASURES THE SUSPICIOUS BEHAVIOUR

This section measures the suspicious behaviour using modules in real-time using video surveillance. This system is designed to detect instantaneous big changes in crime events. In videos, the suspicious behavior is the sudden movement of people or sudden slow movement of people. When people walk in multiple directions at the same time, the direction of movement appears very irregular, length and speed of the movement is also dramatically increased or decreased. The proposed module is guide to analysing the gait speed of the pedestrians.

3.3.1 Using First Module:

Walk Ratio (WR): The WR is a speed independent indicator of walking pattern that describes the temporal and spatial coordination. WR is resulting from the frequency and amplitude of the rhythmic leg movements when walking. The deviation from the normal WR reveals some degree of abnormal walking patterns. The WR is calculated as the average step length (L_{step}) divided by the step frequency (F_{step}).

$$\mathrm{WR} = L_{step} / F_{step} \quad (3)$$

Table.1. Speed Rules

Status	Ranges	Description
Valid	$\theta > WR$	The pedestrian walk speed is high than reference value
Invalid	$\theta < WR$	The pedestrian walk speed is less than reference value

In this process, set the threshold value which is validate with walk ratio (WR) value. The threshold value is based on the reference range of pedestrian walk. The average length is decreased when the person walks with a little step. The value change depends on the step length or stride length in walk ratio.in Table.1, contains the ranges of walk speed

3.4 ACCELERATION AUTO CORRELATION (AAC)

The AAC is a measure of the pedestrian step similarity and regularity are measured by AAC which are derived by investigating the similarity in the acceleration profile shape or waveform. Pearson’s correlation coefficient is used to measure the AAC with lag time defined as a function of an arbitrary number of steps. A greater degree of gait measure is associated with a higher ACC value.

3.5 USING SECOND MODULE

Gravity Component: The gravity component denoted by a vector $g = \{g_f, g_v, g_s\}$ is derived by taking averages of all measurements on each axis collected during sample interval i.e.

$$g_f = \frac{\sum_{i=1}^{N} c_f(i)}{N}; g_v = \frac{\sum_{i=1}^{N} c_v(i)}{N}; g_s = \frac{\sum_{i=1}^{N} c_s(i)}{N} \quad (4)$$

Dynamic Component: Dynamic component d that represents walking motion excluding the gravity component is

$$\{c_f - g_f, c_v - g_v, c_s - g_s\} \quad (5)$$

Vertical Component: The vertical component p is calculated using projection of d onto the vertical axis v as follows

$$p = \frac{d * v}{v * v} v \tag{6}$$

Horizontal Component: Horizontal component h can be easily evaluated as

$$h = d - p \tag{7}$$

The proposed method determined the suspicious behavior for crime event detection by using simple modules. Generally, as pedestrians, their walk speed based on their personal variations or any surroundings issues. In crime detection, one of the major monitoring is suspicious behaviour which helps to identify the behaviors of each pedestrians beside the number of pedestrians. In this work, compute the automatic suspicious behavior detection in terms of speed profiles and components features.

4. RESULT AND DISCUSSION

In order to compare the different pedestrian gait speed detection techniques, number of images is taken [1] to perform the experiment. For comparison, two pedestrian techniques such as Deformable Part Model (DPM), RealBoost method are taken. For conducting the experiment in terms of true positive rate, pedestrian gait speed detection time.

4.1 GAIT SPEED DETECTION TIME (PDT)

Gait speed detection time is defined as the amount of time taken for detecting the pedestrian walk speed. It is the product of number of images and time consumed for detecting pedestrian walk speed from one image. The mathematical formula for pedestrian gait speed detection time is given as follows. In formula, n denotes the number of images

$GSDT = n$ * gait speed detection from one image

Table 2. Detect the gait speed

Number of Images	Gait Speed Detection Time (ms)		
	DPM	**Real Boost Method**	**Proposed Module**
10	36	31	24
20	39	33	27
30	43	36	31
40	47	40	35
50	49	42	39
60	52	44	41

The Table.2 contains the comparison of gait speed detection time between different pedestrian gait speed detection techniques. This comparison takes the number of images ranging from 10 to 60 and the speed is measured by milliseconds (ms).

The result shows the pedestrian gait speed detection time comparison of three techniques, namely DPM, RealBoost method and proposed module. Pedestrian gait speed detection time of proposed module is comparatively lesser than that of deformable part model (DPM) and RealBoost method. Because of time complexity is increased while detecting the pedestrian gait speed.

4.2 TRUE POSITIVE RATE

True positive rate measures the proportion of gait pedestrian that are correctly detected. TPR is defined as the ratio of number of pedestrians that are correctly identified from images to the total number of images. It is measured in terms of percentage (%). True positive rate is mathematically formulated as,

Table.3. Analysing the true positive rate

Number of Images	True Positive Rate (%)		
	DPM	**Real Boost Method**	**Proposed Module**
10	71	64	78
20	72	66	80
30	74	69	83
40	76	71	85
50	78	73	87
60	80	74	88

The Table.3 contains the comparison of true positive rate between different pedestrian detection techniques. This comparison takes the number of images ranging from 10 to 60 which is measured by percentages (%).

The result shows the true positive rate comparison of existing techniques namely Deformable Part Model (DPM), RealBoost method. True positive rate of proposed module is comparatively higher than that of RealBoost method and DPM. Because proposed technique correctly identified gait pedestrian input image from the video surveillance.

5. CONCLUSION

This work is developed to detecting the crime events from measuring the suspicious behaviour. This work proposed the two types of modules, each module contains the speed computation profile which helps to measure the suspicious pedestrian for real time detection (crime). In first module, θ performs the validation role. This work monitoring the pedestrian gait speed using proposed computations which shows the dissimilarity from the n number of pedestrians. With the help of video surveillance, pedestrian gait monitoring is complex task and hard to explore in real time. But this proposed work executed the gait speed through the walk ratio, AAC, and gravity, dynamic, horizontal, vertical components of pedestrian and detect the crime event from the suspicious pedestrian behaviour. The efficiency comparison of proposed work to other pedestrian detection method i.e. DPM and RealBoost. The proposed work has achieved higher true positive rate and less gait speed detection time than DPM and Real Boost method. In future, the research goal will be focused on stationary crowd analysis.

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