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# A Novel Integrated Model for Anomaly Detection Using Machine Learning

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## ABSTRACT

Abnormal behavior detection refers to the problem of finding patterns in data that do not conform to expected behavior. Detection of abnormal behavior is an important area of research in computer vision and is also driven by a wide of application domains, such as smart video surveillance. In this paper, we present a novel based-energy approach for abnormal behavior detection using deep learning techniques. Use an adaptive optical flow model to operate on moving particles instead of objects and fuses features with the shape and trajectory information. We introduce an integrated multiple behavior model for accurate abnormal behavior detection in a complex crowd scene. We use not only the personal behavior model, but also multiple social behavior models. The experimental results show that our proposed method efficiently detects the abnormal behavior in a crowded scene. To detect the abnormal behavior, experimental results on the Institute of Automation, Chinese Academy of Science multi-view behavior database and self-photo videos demonstrate the robustness and effectiveness of our method.

Keywords: Pattern Recognition, Abnormal Crowd Tracking, GMM, Machine Learning, Deep Learning.

# INTRODUCTION

The analysis of human activities in crowded scene is one of the most challenging tasks in computer vision. Since the analysis of human actions performed by individuals is not a fully solved problem, crowd scene analysis is a very important task in computer vision. Recently, crowd behavior analysis has received a lot of attention since it is applicable to new domains such as automatic detection of riots or chaotic acts used in intelligent surveillance system. Nowadays, abnormal behavior detection system plays a very important role in various areas, such as prison, firefighting, public security, bank etc. With the popularization of the monitor and all kinds of abnormal events occurring, the shortcoming of traditional surveillance system is becoming more and more obvious. In fact, the traditional surveillance system can't early warn us when abnormal behavior is happening. It is a very time-consuming work when we find some useful video clips later. And it can't meet the needs of some department.

The problem such as complexity and abstract of detecting and identifying abnormal behavior in acrowd scene attract many researchers. Handling a situation that relates with the abnormal in a crowd is not easy. The most important problem in this scenario includes the density of the crowded scenes and the state of being abnormal or normal. Nonetheless, there are some difficulties in analyzing behavior of human in crowd scene, and the one of the most common approach is conducted by using video surveillance. With the Closed-Circuit Television (CCTV) technology, video surveillance has become apparent in this field to observe some parts of a process from control environment which is required in each and every intelligent crowded scene. One of those topics in video surveillance is about crowd analysis. Crowd analysis is being used in video surveillance application for automatic detection of anomalies and alarms. There are mainly four components are in Crowd analysis, typically the application involves crowd management strategies, virtual environments, public space design, visual surveillance and intelligent environment. However, here we are focusing on the visual surveillance crowd analysis application. During last decade, research on detecting abnormal behavior has actively evolved taking the advantage of recent developments in some related fields such as Pattern Recognition (PR), Biomedical Information (BI), Soft Computing (PR), Computer Vision (CV), Mathematical Modeling (MM), Image Signal Processing (ISP), Data Mining (DM), Computational Intelligent (CI), Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL). Here is a review of the recent advances in the area of detecting abnormal behavior for detecting human in crowded scene is presented since 2000; unless that are some material facts that is necessary to state a research prior than that.

# LITERATURE SURVEY

Analysis and modeling of motion patterns have been studied in the fields where simulation plays an important role, such as graphics, and civil engineering as well as intelligence surveillance and robotics. Buxton provided a detailed review of the models that have been used for learning scene activities. Presented a vector quantization-based approach for learning typical trajectories of pedestrians in the scene. Present a motion-based technique to detect high-level semantic events in video sequence. Use object-tracking to detect unusual events in image sequences.

Human and traffic monitoring is applications of abnormal crowd behavior. Techniques fordetecting crowd sense are crowd density estimation, crowd motion detection, crowd tracking and crowd behavior recognition. Crowd density estimation used for measuring a crowd status. For describing the

characteristic of crowd and identifying behavior pattern in crowd used crowd motion detection. Crowd tracking is used for acquiring trajectories of the movements thatdetermines abnormalities is occurs or not. Crowd behavior recognition is used for analyzing behaviors of crowd.

We propose a new method to detect abnormal behavior in the crowd scene using multiple behavior models. We introduce an integrated multiple behavior model to detect abnormality in a complex crowd scene. Our model consists of a personal behavior model and social behavior models. Each behavior model is based on the information of motion instead of actions or events. Personal behavior is modeled by the motion information of each pedestrian and social behavior is modeled after each pedestrian's surrounding neighbor. Our behavior model is based on an energy function that expresses the desirability of motion in each location. The energy function combines personal behavior factors and social behavior factors that influence the pedestrian's motion. Personal and social behavior energy components are emulated by the abnormal crowd dynamics with a high degree of accuracy.

#### Learning object motion patterns for anomaly detection and improved object detection Authors: Arslan Basharat ; Alexei Gritai ; Mubarak Shah Published in: 2008

We present a novel framework for learning patterns of motion and sizes of objects in static camera surveillance. The proposed method provides a new higher-level layer to the traditional surveillance pipeline for anomalous event detection and scene model feedback. Pixel level probability density functions (pdfs) of appearance have been used for background modelling in the past but modelling pixel level pdfs of object speed and size from the tracks is novel. Each pdfis modelled as a multivariate Gaussian mixture model (GMM) of the motion (destination location & transition time) and the size (width & height) parameters of the objects at that location. Output of the tracking module is used to perform unsupervised EM-based learning of every GMM. We have successfully used the proposed scene model to detect local as well as global anomalies in object tracks. We also show the use of this scene model to improve object detection through pixel-level parameter feedback of the minimum object size and background learning rate. Most object path modelling approaches first cluster the tracks into major paths in the scene, which can be a source of error. We avoid this by building local pdfs that capture a variety of tracks which are passing through them. Qualitative and quantitative analysis of actual surveillance videos proved the effectiveness of the proposed approach.

#### A Review on Crowd Behavior Analysis Methods for Video Surveillance Authors: Saurabh Maheshwari, Surbhi Heda Published in : 2011

Abnormal Crowd Detection has become the most viral and active research topic in computer vision. There is need of automated tracking of the abnormalities in surveillance video sequence for the detection of abnormal events. These systems are mainly used for supervising and security purpose. This automated system can alarm for abnormality in fairs, temples. It can also be used for the traffic monitoring etc. Crowd is a group of individuals belonging to a community or society. In the crowd, there exist many behavior abnormalities. Crowd density estimation, crowd motion detection, crowd tracking and crowd behavior recognition are multiple techniques for detecting abnormalities. Computer based crowd analysis algorithm can be divided into three groups; people counting, people tracking and crowd behavior analysis. In this paper, we will discuss multiple techniques of abnormal crowd detection background subtraction, optical flow, 3D Convolutional neural network, hydrodynamics lens. Once detected, a moving object could be classified as a human being using shape-based, texture-based or motion-based features. Comparison of available techniques for detecting abnormal crowd in surveillance videos has alsobeen done in this paper.

#### Detection of abnormal behaviors in crowd scene: A review Authors: Nilam Nur Amir Sjarif, Siti Mariyam Shamsuddin, Siti Z Mohd Hashim Published in : 2016

Crowd analysis becomes the most active-oriented research and trendy topic in computer vision nowadays. Typically, crowd is a unique group of individual or something involves community orsociety where the phenomena of the crowd are very familiar in a variety of research discipline such as sociology, civil and physics [1]. Within the crowd, there exist many behavior anomalies or abnormality. There are many ways of detecting these abnormalities such as crowd density estimation, crowd motion detection, crowd tracking and crowd behavior recognition. All of these protocols normally involve three steps: pre-processing, object detection and event/behavior recognition. In this paper, we provide state-of-the-art of crowd analysis from 2000 until now. Based on our analysis from these substantial reviews, we propose a general framework and pattern taxonomy of detecting abnormal behavior in a crowded environment accordingly.

#### Crowd Abnormal Behavior Detection Based on Label Distribution LearningAuthors: Min Sun; Dongping Zhang ; Leyi Qian ; Ye Shen Published in : 2018

In general, some abnormal crowd behaviors are associated, for example, fight causes tumble or panic and tumble causes stampede. And those abnormal behaviors often happened at the same time. However, most researchers consider those mixed abnormal behaviors as only one behavior and ignore the other behaviors appearing in the video. To analyze those behaviors better, this paper proposes a method using label distribution learning to detect the crowd abnormal behavior such as stampede, fight, panic and tumble. We consider that every behavior sequence associated with some behavior labels, and the behavior label distribution covers a series of behavior labels, representing the describe degree that each behavior labels describe the behavior sequence. Then alabel distribution learning algorithm named BFGS can be used to learn the behavior label distribution. Through this way, we not only can obtain which behavior happened, but also all behaviors are taken into account for each behavior sequence. The experimental results show that our approach achieves better performance for crowd abnormal behaviors detection.

#### Abnormal Crowd Tracking and motion analysis

Automated analysis of crowd activities using surveillance videos is an important issue forcommunal security, as it allows detection of dangerous crowds and where they are headed. Public places such as shopping centers and airports are monitored using closed circuit television (CCTV) in order to ensure normal operating conditions. Computer vision-based crowd analysis algorithm can be divided into three groups; people counting, people tracking and crowd behavior analysis. In this paper the behavior understanding will be used for crowd behavior analysis. The purpose of these methods could lead to a better understanding of crowd activities, improved design of the built environment and increased pedestrian safety.

By reviewing all papers we conclude that the support vector machines (SVM) are universal binary classifiers based on statistical and optimizing theories. The SVM is particularly attractive to biological analysis due to its ability to handle noise, large dataset and large input spaces and mapping of non-linear input data into a high dimensional feature space with minimum error on training set. During this binary classification process, it constructs a hyper plane in the feature space that separates optimally two different classes of feature vectors. These feature vectors are mapped into a feature space by using the kernel function

We found that we need one algorithm for calculate the distance between two persons so we pick the KNN algorithm to find distance of person for easily identifying. We used Python language for our project.

#### **PROPOSED SYSTEM**

Use Case Diagram

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use Cases. Use Case diagrams are formally included in two modeling languages defined by the OMG: The Unified Modeling Language (UML) and the Systems Modeling Language (SysML).

#### Class Diagram

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, and the relationships between the classes. The class diagram is the main building block in object-oriented modeling. They are being used both for general conceptual modeling of the systematic of the application, and for detailed modeling translating the models into programming code. The classes in a class diagram represent both the main objects and or interactions in the application and the objects to be programmed. In the class diagram these classes are represented with boxes which contain three parts: A class with three sections.

- The upper part holds the name of the class
- The middle part contains the attributes of the class
- The bottom part gives the methods or operations the class can take or undertake

In the system design of a system, a number of classes are identified and grouped together in a class diagram which helps to determine the static relations between those objects. With detailed modeling, the classes of the conceptual design are often split in a number of subclasses.

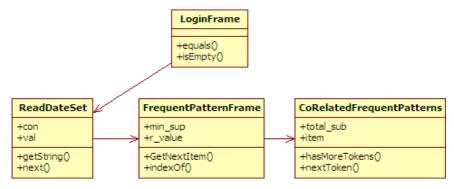


Figure 3.1: Class diagram

• Activity Diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. [1] In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control. Activity diagrams are constructed from a limited repertoire of shapes, connected with arrows. The most important shape types:

- Rounded rectangles represent activities;
- Diamonds represent decisions;
- Bars represent the start (split) or end (join) of concurrent activities;
- A black circle represents the start (initial state) of the workflow;
- An encircled black circle represents the end (final state).

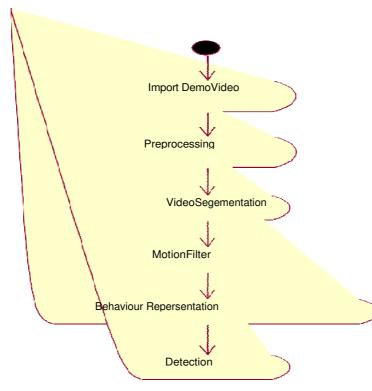


Figure 3.2: Activity Diagram

Arrows run from the start towards the end and represent the order in which activities happen. Hence, they can be regarded as a form of flowchart. Typical flowchart techniques lack constructs for expressing concurrency. However, the join and split symbols in activity diagrams onlyresolve this for simple cases; the meaning of the model is not clear when they are arbitrarily combined with decisions or loops. While in UML 1.x, activity diagrams were a specialized form of state diagrams, in UML 2.x, the activity diagrams were renormalized to be based on Petri net-like semantics, increasing the scope of situations that can be modeled using activity diagrams. These changes cause many UML 1.x activity diagrams to be interpreted differently in UML 2.x

#### Sequence Diagram

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams. A sequence diagram shows, as parallel vertical lines (lifelines), different processes or objects that live simultaneously, and, as horizontal arrows, the messages exchanged between them, in the order in which they occur. This allows the specification of simple runtime scenarios in a graphical manner. For instance, the UML 1.x diagram on the right describes the sequences of messages of a (simple) restaurant system. This diagram represents a Patron ordering food and wine, drinking wine then eating the food, and finally paying for the food. The dotted lines extending downwards indicate the timeline. Time flows from top to bottom. The arrows represent messages (stimuli) from an actor or object to other objects. For example, the Patron sends message 'pay' to the Cashier. Half arrows indicate asynchronous method calls. The UML 2.0 Sequence Diagram supports similar notation to the UML 1.x Sequence Diagram with added support for modeling variations to the standard flow of events.

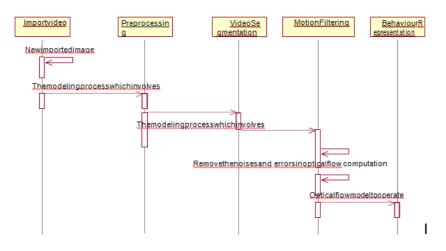


Figure 3.3: Sequence Diagram

#### **Collaboration Diagram**

A Collaboration diagram is very similar to a Sequence diagram in the purpose it achieves; in other words, it shows the dynamic interaction of the objects in a system. A distinguishing feature of a Collaboration diagram is that it shows the objects and their association with other objects in the system apart from how they interact with each other. The association between objects is not represented in a Sequence diagram. A Collaboration diagram is easily represented by modeling objects in a system and representing the associations between the objects as links. The interaction between the objects is denoted by arrows. To identify the sequence of invocation of these objects, a number is placed next to each of these

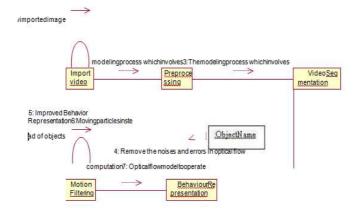


Figure 3.4: Collaboration diagram

#### Elements of a Collaboration diagram

- A Collaboration diagram consists of the following elements:
- Object:
- The objects interacting with each other in the system.
- Depicted by a rectangle with the name of the object in it, preceded by a colon and underlined.

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- A Collaboration diagram consists of the following elements:
- Object:
- The objects interacting with each other in the system. Depicted by a rectangle with the name of the object in it, preceded by a colon and underlined.
- Relation/Association:
- A link connecting the associated objects. Qualifiers can be placed on either end of the associationto depict cardinality.

#### Messages:

An arrow pointing from the commencing object to the destination object shows the interaction between the objects. The number represents the order/sequence of this interaction.

# IMPLEMENTATION AND RESULTS

#### 4.1 Data Sets

In my project there is no data set. In place of data set we used live video. By placing the video it will takes photos by reading the video on the base of photos it will give output.

#### 4.2 System Architecture

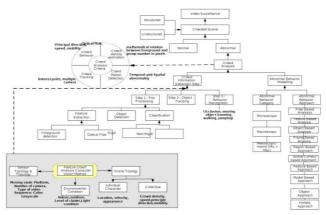


Figure 4.1 System Architecture

Software Requirements Specification (SRS) document specifies a complete description of the behavior of the system, which is to be developed. The SRS document includes a set of use cases that describe user's interactions with the software. Use cases are also referred as functional requirements. The SRS document also contains non-functional or supplementary requirements inaddition to the use cases. Non-functional requirements are the requirements, which imposeconstraints on the design or implementation (For example performance engineering requirements, Load balance, quality standards, or design constraints, general requirements).

- Video Surveillance: To Transmit a signal to a specific place
- Crowed Scene: crowed places
- Crowed Analysis: Analysis the crowed video
- Import video
- Preprocessing the video by removing background noise
- Video segmentation is collection of frames
- Motion filter are special effects used to modify the appearance of image and videoclips
- Behavior Recognition: Recognition the behaviors of persons in the video

#### Results

4.2.1 Execution Steps (screens)

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Figure 4.2: Executing Classifier.py (starting point)

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Figure 4.3: Video classification using logistic

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Figure 4.4: Video classification using SVM

Analysis is to detect movement of crowd. It characterizes by the shape of each person and the portions of image that containing moving present in the crowd scene is well managed usingframe by frame examination to be getting more accurately abnormal crowd behavior detection.

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Figure 4.5: Core.py execution

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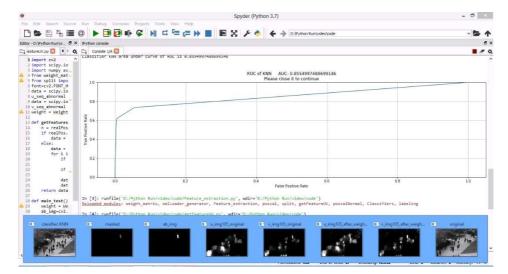
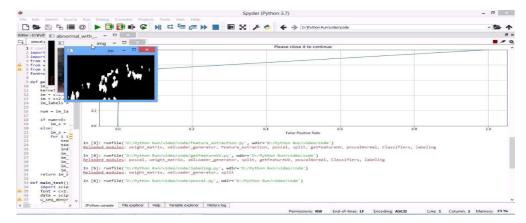


Figure 4.6: FeatureUV.py file execution

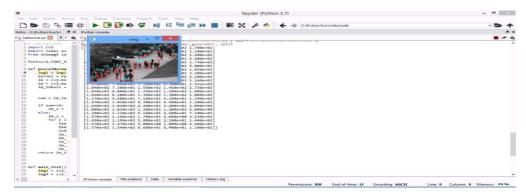
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Figure 4.7: Labeling.py file execution

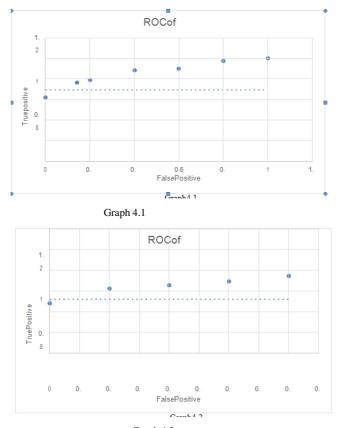


#### Figure 4.8: Poscal.py file Execution



#### Figure 4.9: Behavior detection

In this output the machine calculated height of the persons and distance of every person ACCURACY GRAPHS



Graph 4.2

#### **CONCLUSION AND FUTURE SCOPE**

In this paper, we introduced a method to detect abnormal behaviors in a crowd scene using an integrated multiple behavior model. We showed how our method captured the dynamics of crowd behavior based on the multiple behavior models which consisted of the personal andsocial model of individuals without individual object tracking or segmentation. The result of our proposed method showed that our method was effective in the detection of abnormal behaviors in a crowd scene. It would be interesting to extend our behavior model by using an explicit model of pedestrian behavior that considers more personal and social property. Furthermore, in our future work, we will take into consideration not only pedestrian behavior but also static sceneobjects such as benches.

Most of the previous methods are used on personal property such as individual trajectory for detecting abnormal behavior. However, this approach is not desirable in a crowd environment since it is difficult to extract personal properties in a crowd scene and the person's behavior is affected by social factors such as a pedestrian group. Recently, these social factors have been studied to understand the behavior of person. On the other hand, social factorbased method hasits own drawback; it has difficulties to detect the personal property such as a person's abnormal movement. In feature we are going to implement this project with more accuracy

# REFERENCES

- 1. Mumford, C.L., et al., The Analysis of Crowd Dynamics: From Observations toModelling, in Computational Intelligence, Springer Berlin Heidelberg. (2009), pp. 441-472.
- 2. Husni, M. and N. Suryana, "Crowd event detection in computer vision". Signal Processing Systems (ICSPS), 2nd International Conference, (2010), pp. 444-447.
- 3. Yufeng, C., et al., "Abnormal Behavior Detection by Multi-SVM-Based Bayesian Network", International Conference on Information Acquisition (ICIA), (2007), pp. 298-303.
- Blanc-Talon, J., et al., Crowd Behavior Recognition for Video Surveillance, in Advanced Concepts for Intelligent Vision Systems. Springer Berlin / Heidelberg, (2008), pp. 970-981.
- Jacques Junior, J.C.S., S.R. Mussef, and C.R. Jung, "Crowd Analysis Using Computer Vision Techniques", Signal Processing Magazine, IEEE, Vol 27, No.5 (2010), pp. 66-77.
- 6. Zhan, B., et al., "Crowd analysis: a survey", Machine Vision and Applications, Vol 19, No. 5, (2008), pp. 345-357.
- Garate, C., P. Bilinsky, and F. Bremond, "Crowd event recognition using HOG tracker". Performance Evaluation of Tracking and Surveillance (PETS-Winter), Twelfth IEEE International Workshop, (2009).
- 8. Zhi, Z., et al., "Energy Methods for Crowd Surveillance", International Conference on Information Acquisition (ICIA), (2007), pp.504-510.
- 9. Weiming, H., et al., "A survey on visual surveillance of object motion and behaviors." Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions, Vol. 34, No. 3, (2004), pp. 334-352.
- Haering, N., P. Venetianer, and A. Lipton, "The evolution of video surveillance: an overview", Machine Vision and Applications, Vol. 19, No. 5,(2008), pp. 279-290.
- 11. Ko, T, "A survey on behavior analysis in video surveillance for homeland security applications", Applied Imagery Pattern Recognition Workshop (AIPR),37th IEEE, (2008).
- 12. Meyer, M., et al., "Video surveillance applications using multiple views of a scene", Aerospace and Electronic Systems Magazine, IEEE, Vol. 14, No. 3, pp. 13-18.
- 13. Lee, J., A. Bovik, and B. Al, "Video Surveillance, in The Essential Guide to Video Processing (Second Edition)", Academic Press: Boston, (20010), pp. 619-651.
- 14. Mehran, R., A. Oyama, and M. Shah, "Abnormal crowd behavior detection using social force model", IEEE Conference on Computer Vision and Pattern Recognition (CVPR), (2012), pp. 935-942.
- 15. Ermis, E.B., et al., "Abnormal behavior detection and behavior matching for networked cameras", International Conference on in Distributed Smart Cameras (ICDSC), Second ACM/IEEE, (2019).