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Abnormal Activity Detection from Video using SVM Algorithm

Kshitija Deshmukh[1], Aishwarya Kokane[2], Shweta Konde[3], Guide-Gauri Virkar[4]

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ABSTRACT: Real-time activity recognition using body sensor networks is an important and challenging task and it has many probable advantages. To capture human activity and analyze that data, these both activities are very essential in abnormal activity detection. To analyze data is crucial part for finding out actual facts behind human activity. Since it uses state transition table methodology for effectively discovering abnormal activity, recognize it and track it for old age people or kids from remote location. Here paper introduces an automated approach to activity tracking that identifies common activities that naturally occur in an individual's routine. Here it uses conventional SVM (Support Vector Machine). It is a binary classifier which is used to classify two classes of data. So by considering these capabilities it can track the occurrence of regular actions to supervise functional health and to detect changes in human being's routine and everyday life. In this paper it describe our activity of data mining and tracking it in the field of image processing approach and validate our algorithms on data collected from remote sensors.

KEYWORDS: Human Activity, Classification, Multi-class SVM, Tele-health Care, State Transition, Smart Home Monitoring System, abnormal pattern recognition.

I. INTRODUCTION:

The understanding of context and human activities is a core component that supports and enables all kinds of context-aware. Proposed work developed a fully supervised learning methodology which recognition abnormal activity accurately with a minimal number of requests for ground-truth labels. To recognize human activity even when there are no training data for a particular activity class. This methodology can generalize previously learned knowledge and extend its capability to recognize new activity classes. Like old aged people want to live an independent lifestyle, but at old age people become prone to different accidents, so living unaccompanied has high threat and is repeated. Learning and recognizing human activities of daily living is very useful and essential to build smart home monitoring system [1] describe a fuzzy logic system for recognizing activities in home environment using a set of sensors: physiological sensors, microphones, infrared sensors, debit sensors and state-change sensors. Hence, real –time processing of data is must for recognizing activity behavior and predicting abnormal situations of the elderly. To deal with issues such as monitoring the daily activities, performance tracking of normal behavior and wellbeing of elderly living alone a system which is non invasive, flexible, low cost and safe to use is designed and developed. For recognizing the normal activities multi-class SVM is used here. As the data has many attributes SVM uses a kernel function for training, selected from all the various reputed kernel functions. Abnormal activities are detected by finding out all possible activities that can be performed from the current activity. To find out all possible activities, the data has to be classified using all classes, which requires high computational time. To reduce the computational time SVM uses transition table which help in avoiding unreachable states for classification. The proposed approach is inspired by the following observations: Many human activities and perspective types share the same basic semantic parameters: For example, the

- Parameters Sit, Run, Walk, Fall, Stand etc. these are common activity and can be observed in different scenes like having lunch, working at desk, talking on mobile etc activities. Therefore, the statistical model of parameters can potentially be transferred from one activity to another. The limits of supervised learning can be overcome by incorporating human knowledge: Rather than collecting

- Sensor data and labels for every context, using nameable parameters allows humans to describe a context type without the process of sensor data collection. For example, one can easily associate the activity "office working" with the motion-related attributes such as "Sitting," "HandsOnTable," and sound-related attributes such as "Printer Sound," "Keyboard Sound," and "Conversations."

Abnormal activities:

An abnormal activity is defined as any out-of-ordinary and non-usual activity that may expose a person or group of people to danger in a particular context [1]. The authors of [2] define "abnormal activities" as "activities that occur rarely and have not been expected in advance". This definition can vary depending on the field or context being studied, as for the analysis of crowd activities in the street where any behavior of fraud or theft can constitute abnormal activities. Similar to normal activities, abnormal activities are of different types: gestures, elementary actions, events, interactions, behaviors or group actions [3]. The authors of [4] classify abnormal activities into: group activities that could encompass evacuation (rapid dispersion resulting from panic), single-direction herding, crowd formation, local dispersion and splitting at different time instances as in [5], as well as the activities of one person such as a fall as in [6], immobility as in [7], unusual speed as in [8] and walking in the wrong direction.

Figure 01: Abnormal activities in ATM

Motivations to abnormal activities detection:

The analysis and recognition of human activities is considered the most important area of future research in video surveillance [9]. This is justified by the need to monitor and assist elderly or disabled people in carrying out their daily activities [10]. This need, accompanied with its relative costs and the technological progress made in terms of cameras and sensors [10], have motivated the researchers to propose a wide range of approaches and methods for the recognition of various types of human activities, in different contexts or environments for monitoring purposes. One of the recent axes in this field is the detection of abnormal activities in order to ensure immediate intervention, by human or machine, in case of danger or necessity [11]. This axis is not yet rich neither in specific methods nor in dedicated databases; however, it avails of the used techniques in human activities recognition by adapting them to the case of unusual activities. The advent in this axis is also motivated by the level of adopted supervision for the learning of the various human activities (supervised, unsupervised or semi-supervised), the used techniques to eliminate the noise, and thus ensure the robustness of the characteristics of interest, as well as the appropriate measures for the comparison of descriptors and classifiers, as in [4]. Moreover, other questions related to the abstraction and representation of the behaviors of individuals in a given scene as well as to the significant features allowing the choice of the characteristics to be extracted were asked as in [4]. In general, we have studied and analyzed some recent works of recognition of abnormal activities such as [11, 12, 13, 14]; in particular, surveys such as [15] which presents an extensive study of anomalies detection in various fields of application and [16] which provides a general study on the detection of abnormal behaviors in different contexts of human activity. Fig. 2 summarizes the motivations cited above.

Figure 02: CCTV control room

II. RELATED WORK

1. Supervised Learning: In the field of mobile, wearable, and pervasive computing, extensive research has been done to recognize human activities (e.g. sitting, walking, running) [2, 3].In terms of the learning method, the majority of the research in this field used supervised learning approaches, including discriminative classifiers (e.g. Decision Trees, SVM) and generative models (e.g. Naive Bayes, Hidden Markov Model), where a classifier is trained on a large set of labeled examples of every target activity. There has also been prior study of representing high-level activities as a composite of simple actions, using a supervised layered dynamic Bayesian network. A widely acknowledged problem is that labeled examples are often time consuming and expensive to obtain [4, 5, 6].

2. Semi-Supervised and Transfer Learning To lessen the reliance on labelled training data and to exploit the benefits of abundant unlabeled data, previous work has incorporated semi-supervised learning into activity or context recognition systems [7]. Semi-supervised learning approaches can improve the recognition accuracy by refining the decision boundary based on the distribution of the unlabeled data, or by assigning highly-confident estimated labels to the unlabeled data.

3. Active Learning The idea of active learning algorithms is that a machine learning algorithm can perform better with less training data if it is allowed to choose the data from which it learns [8].Active learning has been used to improve the accuracy of human activity recognition. It extends the previous work by integrating active learning in

the framework for activity recognition, so that the system is able to recognize undefined activities.

4. Unsupervised Learning Another related research direction is unsupervised learning. Unsupervised learning focuses on clustering or pattern discovery rather than classification [9]. In human activity understanding is divided into activity recognition and activity pattern discovery. The first category focuses on accurate detection of human activities based on a pre-defined or pre-trained activity model, while the second category focuses on finding unknown patterns directly from low-level sensor data. The output of these approaches is a set of unnamed clusters which cannot be used for classification or recognition purposes. To perform recognition, labels are still needed to connect the discovered patterns to the actual classes.

5. Rule-Based Approach There is also some rule-based approaches to activity recognition. In [11], Storf et al. proposed a multi-agent based framework using rules and manual configurations written in the Extensible Markup Language (XML) format. The authors also used fuzzy reasoning ex. Detection of activity “preparing meal” involves a set of cases and rules, including the combination of usage stove, usage fridge, stay at kitchen counter, etc. with different weights for each case. Rule-based approaches may be hard to apply without much domain knowledge, or when the rules are not straightforward and thus have to be learned from data.

6. Zero-Shot Learning The idea of zero-shot learning has recently been explored and has been shown to be useful for recognizing unseen new classes [12]. It presented one early study on the problem of zero-shot learning, where the goal is to learn a classifier that can predict new classes that were omitted from the training dataset. Inspired by their work, our work extends the zero-shot learning framework to handle sequential data by modeling the sequence and structure of the attributes.

III. PROPOSED SYSTEM

The proposed system focuses on identifying abnormal activities with less computational time. The abnormal activities are stated using state transition table, which holds all possible states. The system is trained to classify the activities performed by the individuals and report the abnormalities.

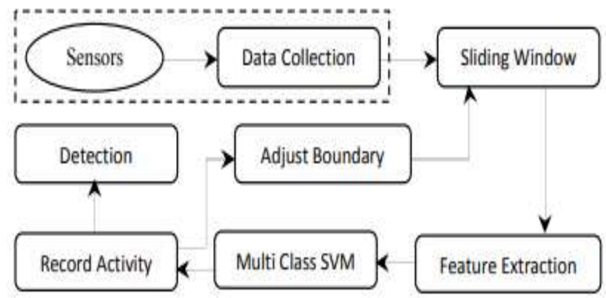

Figure 03: Proposed work

The system recognizes 9 different activities of an individual using multi-class SVM. The general architecture of the system is shown in Figure 1. The raw data received from sensors of an individual performing various activities is large in size, where all the data cannot be used as such, where the data has to be split into chunks and processed. The sliding window is used to split data into window of size N data for the system to recognize the activity. The sliding window reduces the flow rate and sends less data to the system to recognize the activity performed by the individual. As the sliding window splits the data into window size N, there is huge possibility that the system may not have sufficient data for recognizing the activity. In such cases, window boundary has to be adjusted [14] and the process has to be repeated with the new data.

Here it presents how abnormal activity detection takes place in the concept of smart home effectively on given input which is generated by remote sensors. The first step, it must consider is how to identify the everyday and repeatable activity which would be detectable by sensors or cameras that comprise our smart home concept. Once it discover and categorize the activity and associate specific occurrences of the activity, we are keeping its appropriate entries in database. So it can build a model to recognize the activity and begin to analyze the occurrences of the existing as well as new activity. But how then it discovers new or run time activity which is not present in database? For that it uses Active directory concept which will detect Non-Distinguished learning concept at run time. Here it is performing number of functionality on given input data such as filtering, normalization, multi class SVM, K-means and Random forest algorithm. Following Systems block diagram Fig 3 shows functionality of our system.

a. Input Data: The sensed data is captured and collected, then continuously transmitted to the application which is present at hospital or any remote place for helping if any abnormal activity takes places know as a receiver. Captured data are continuously monitored and compared with different parameters, attributes and patterns.

b. Data collection (Data tracking and discovering): The Tracking, learning and recognition framework is not dependent of sensor data types or device types, so the source of sensor data is any kind of data. Selecting the right set of parameters or attribute is important for improving the recognition accuracy. Suppose persons intention to perform exercise activities, which may include warm up in which it include different sub activities are performed like lifting hands, sleeping, pitching, walking, and running. Each sub-activity can then be further broken down into fine-grained motions of limbs, joints, and muscles and on that basis it has been discovered appropriately. The abnormal activities are stated using state transition table, which holds all possible states. The system is trained to classify the activities performed by the individuals and report the abnormalities. The system recognizes 9 different activities of an individual using multi-class SVM. The general architecture of the system is shown in Fig 1. The sliding window is used to split data into window of size N data for the system to recognize the activity. The sliding window reduces the flow rate and sends less data to the system to recognize the activity performed by the individual. The proposed system uses seven features mean of each axis, standard deviation of each axis and velocity. These features help in reducing the noise in the dataset and influence in classifying the data with higher accuracy.

c. Multi Class SVM In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. SVM helps in categorization since it is used for classification of images and its data. It gives significant search accuracy [12].

d. Abnormality Activity Detection Abnormality Activity can be detected by categorizing the defined activities, Active directory activity which is not defined but it is normal activity and the undefined which is not normal that traces can be tagged as abnormal activity. The transition table used for multi class SVM selection the same can be used for defining the normal activities. The transition table defines all possible states that can be performed by an individual. If any events occur out of the range of the transition table, the event is marked as abnormal.

IV. RESULTS AND DISCUSSIONS:

The proposed system is implemented in python and the system is trained using SVM tool. The experimental setup uses the dataset collected from online.. The dataset contains four five min video of activities performed by each individual. From the sensor data received seven features are extracted, that help classifying the activities. With the feature extracted dataset, training samples are selected and the classifier for each activity is trained. To design the classifier, a suitable kernel function has to be chosen. To identify the suitable kernel function for the problem a study was conducted. SVM classifier is built using various well known kernel functions and their performance is studied. The study results are shown following figure. After designing the novel multi-class SVM, the system has to be tested. The feature dataset is given to the system for classification.

Figure 4: Abnormal activity detection using proposed method

The comparison chart of computational time is shown in Figure 5 . The system is tested by varying number of samples and computational time is evaluated. It clears shows that the proposed scheme consumes less computational power than the conventional approach.

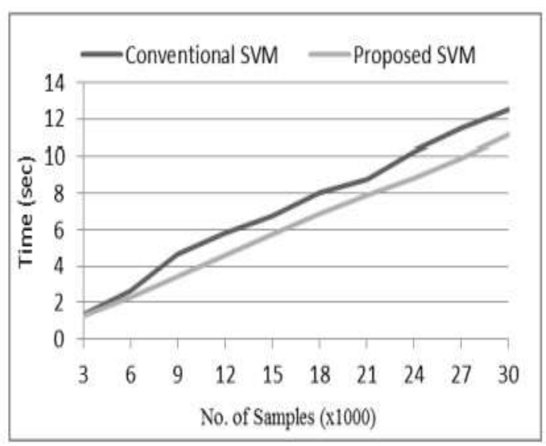

Figure 5: Comparison of computational time

Other than the computational time, the performance metrics of the classifier are also compared in Table 21 After classification, the results are analyzed and performance is evaluated. From Table 1, it is clear that conventional SVM classifier has better performance. In order to have high performance, it takes more computational power.

TABLE 01: PERFORMANCE COMPARISON

	Conventional SVM	Proposed SVM
Accuracy	95.8 %	96.4 %
Precision	96.1 %	96.7 %

The Proposed classifier has achieved high performance at the rate of high computational time. The proposed system consumes less computational power yet reaches performance closer to the conventional classifier.

V. CONCLUSION AND FUTURE WORK

Abnormal activity recognition system proposed in this paper works efficiently in real time. The proposed system classifies the activities and detects abnormality with high degree of accuracy. A new approach is introduced for multi-class SVM classification, which checks for the states that are unreachable from the current state and avoids them. The transition table is used to select the classifiers by which the data has to be classified into any of the activities. It reduces the computational time without loss of accuracy. The performance measures such as accuracy, precision and sensitivity of the proposed system are better, making it reliable for real world applications. The future work can focus on using data from environmental and physiological sensors. More sensors can be used to understand the context information and the health condition of the patient to provide better assistance.

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