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Detection of Unusual Activites at ATM Using Machine Learning

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***Abstract*—**The idea of designing and implementation of security against ATM theft is born with the observation of our real life incidents happening around us. This project deals with prevention of ATM crimes and hence overcome the drawback found in existing technology in our society. This paper uses machine learning to enhance the security in ATM. When any suspicious activities such as a man holding a gun in his hand is detected using ORB algorithm, a person attempting to close the camera at ATM, more than two persons entering into ATM, fighting scenes happening at ATM will be detected as an unusual activity and alarm is raised at ATM and a message is passed to nearest police station. Parallelly an email consisting a snap of unusual activity will be sent to the registered police official e-mail id, this helps the police officers to analyze the situation and overcome the fake alarms.

***Keywords*—** Unusual Activity, Machine Learning, ATM security

I. Introduction

We belong to the age of digitized and smart world. people are getting smarter day by day with the help of new technology and new innovations. The main reason behind new innovations is overcoming through existing problem. A small step towards economy is introduction of Automated Teller Machine (ATM) which allows customers to compute the basic transactions at any time without the need of human teller. Group of people do mal-practices over this ATM system which puts people, organization or banks into million rupees of losses.

This paper is a proactive measure that ensures the safety of the people and it also prevents the physical attacks by predicting the vulnerability of the ATM. For safety issues cameras can monitor the real time occurrences, collect the data and cannot come out with analyzing the behavior of people. Here machine learning helps us to analyze the behavior by monitoring which is performed through consecutive frames which are extracted from video.

Unusual event detection in a video is a challenging task in a computer vision, as the definition of what an unusual event looks like depends very much on the context. For instance, a car driving on the street is regarded as a normal event, but if the car enters a pedestrian area, this is regarded as an abnormal event. Similarly, a person who entered the ATM and completes his basic transactions is considered to be normal event. But, if the person who enters the ATM with some weapons such as knife, pistol is considered to abnormal event.As it is generally impossible to find a sufficiently representative set of unusual activities, the use of the traditional supervised learning methods is usually ruled out. Hence, most abnormal event detection approaches learn a model of familiarity from a given training video and label the events as abnormal if they deviate from the model.[1]

Feature-based image matching is an important aspect in many computer-based applications, such as object recognition, images stitching, structure-from-motion and 3D stereo reconstruction [2]. These applications require often real-time performance. Feature-based algorithms are well-suited for such operations. Different algorithms are used for image processing like Scale-invariant feature transform (SIFT), Speeded Up Robust Features (SURF), Oriented FAST and Rotated BRIEF (ORB). ORB is a very fast binary descriptor based on BRIEF, which is rotation invariant and resistant to noise. It can be demonstrated through experiments how ORB is at two orders of magnitude faster than SIFT, while performing as well in many situations. The efficiency is tested on several real-world applications, including object detection and patch-tracking on a smart phone. ORB builds on the well-known FAST keypoint detector and the recently-developed BRIEF descriptor; for this reason, we call it ORB (Oriented FAST and Rotated BRIEF). Both these techniques are attractive because of their good performance and low cost. ORB includes the addition of a fast and accurate orientation component, the efficient computation of oriented BRIEF and analysis of variance and correlation of oriented BRIEF features.

II. Related Work

In this section, the author describes the research works in which they related and correspondingly used in the present paper and they implemented with the following

Object recognition with ORB and its Implementation *on* FPGA[2]This paper organizes as follows, gives an overview of a general methods of object recognition and significance of ORB over SIFT and SURF in different cases. This paper also provides an idea to implement ORB algorithm on FPGA to increase the execution speed by utilizing the reconfigurable nature and pipelining of the FPGA.

Deep Appearance Features for Abnormal Behavior Detection in Video[1]. —The present paper considers the usage of deep learning and transfers learning techniques in fall detection by means of surveillance camera data processing. As a dataset, an open dataset gathered by the Laboratory of Electronics.

III. METHODOLOGY

VIDEO SURVEILLANCE SYSTEMS
ATM security has turned into an industry in and of itself. ATM transactions are quick and convenient, but the machines and the areas surrounding them can be susceptible to criminal activity if not properly protected. The use of video surveillance, especially new IP-based security cameras can help to ensure that ATM transactions are safe. Hence Video – Surveillance Systems have become a major interest in our daily life. It can monitor a specific location for specific targets and mainly to achieve security.

The system include:
Moving object detection, Segmentation Process, Event recognition and Object identification.

Moving object detection:
Moving objects often contain almost important information for surveillance videos, traffic monitoring, human motion capture etc. There are several schemes available to detect such changes. They are Temporal differencing and Background modeling and subtraction.

a. Temporal differencing: First method is the simplest one and has low computational cost but performance is quite poor in the real life surveillance applications.
b. Background modelling and subtraction: Background subtraction methods are widely exploited for moving object detection in videos in many applications.

Figure 1, shows an overview of the background modeling and subtraction system as in

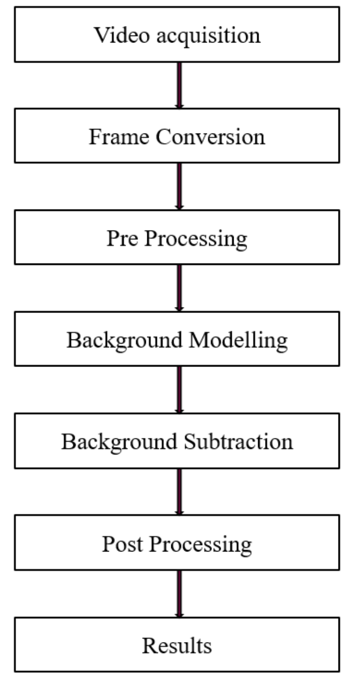

Figure 1. Overview of background subtraction system

1) Video Acquisition: This step deals with acquiring the video by any one of the video capturing device such as Handycam, Mobile camera, USB camera, CCTV camera etc.

2) Frame conversion: After capturing the video, it is converted into frames of suitable type so that further processing could be done conveniently.

3) Preprocessing: Some pre-processing is applied on the frames of the video to reduce noise. There are some common methods of preprocessingas : Smooth, Dilate, Erode, Median, Open, Close etc.

4) Background Modeling: After preprocessing background modeling is used to create an ideal background (static or dynamic) according to environmental changes. This is an important step of the system that sometime may include image subtraction operations. It is the defining characteristics of any background subtraction system. According to the literature there are several background modeling techniques which are categorized as recursive or nonrecursive techniques.

5) Background Subtraction: Conventionally, assuming that the background is stationary, then the moving object can be determined by taking the difference between the background image and the input image. Background subtraction finds moving objects information by subtracting background model.

6) Post processing: A data set collected is not directly suitable for induction (knowledge acquisition); it comprises in most cases noise, missing values, the data are not consistent, the data set is too large, and so on. Therefore, we need to minimize the noise in data, choose a strategy for handling missing (unknown) attribute values ,use any suitable method for selecting and ordering attributes (features) according to their informativity (so-called attribute mining).These techniques have an objective to improve foreground mask.

7) Results: This is the final step in the process which extracts the moving object from the frame. The result of this step helps in the judgment of the efficiency of the background subtraction system.

B) Segmentation process:
Segmentation is the most important part in image processing. Image segmentation is the division of an image into regions or categories, which correspond to different objects or parts of objects. The image segmentation is based on two steps. In the beginning, the image is converted into grayscale image and then thresholding is applied to segment objects. Every pixel in an image is allocated to one of a number of these categories. A good segmentation is typically one in which:

(a) Pixels in the same category have similar grey scale of multivariate values and form a connected region.

(b) Neighboring pixels which are in different categories have dissimilar values.
Segmentation is often the critical step in image analysis: the point at which we move from considering each pixel as a unit of observation to working with objects (or parts of objects) in the image, composed of many pixels. If segmentation is done well then all other stages in image analysis are made simpler. In thresholding, after computing the absolute difference between the current frame and the first frame, pixels are allocated to categories according to the range of values in which a pixel lies. The boundaries between adjacent pixels in different categories have been superimposed in white on the original image. We then dilate the thresholdimage to fill in holes, then find contours on threshold image.[5]

C) Event Recognition:
Event recognition is the ultimate purpose of a fully automated surveillance system. It is not easy to define the type of motion that is meaningful in surveillance context. There are many studies that address different type of events as in. In event recognition objects are detected by using background subtraction and then their boundaries are extracted to produce a skeleton. This skeleton provides important motion cues, such as body posture etc. Motion activities of segmented skeletons/blobs can be utilized in event detection and recognition, such as walking or running, fight or theft, overcrowding etc.

Fast (Features from Accelerated and Segments Test) :FAST features do not have an orientation component and multiscale features. So orb algorithm uses a multiscale image pyramid. An image pyramid is a multiscale representation of a single image, that consist of sequences of images all of which are versions of the image at different resolutions. Each level in the pyramid contains the downsampled version of the image than the previous level. Once orb has created a pyramid it uses the fast algorithm to detect keypoints in the image. By detecting keypoints at each level orb is effectively locating key points at a different scale. In this way, ORB is partial scale invariant.After locating keypoints orb now assign an orientation to each keypoint like left or right facing depending on how the levels of intensity change around that keypoint. For detecting intensity change orb uses intensity centroid. The intensity centroid assumes that a corner's intensity is offset from its center, and this vector may be used to impute an orientation.
First, the moments of a patch are defined as:

$$m_{pq} = \sum_{x,y} x^p y^q I(x, y)$$

ORB descriptor-Patch's moment's definition

With these moments we can find the centroid, the "center of mass" of the patch as:

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right)$$

ORB descriptor—Center of the mass of the patch

We can construct a vector from the corner's center O to the centroid -OC. The orientation of the patch is then given by:

$$\theta = \text{atan2}(m_{01}, m_{10})$$

ORB descriptor—Orientation of the patch

IV. RESULTS AND DISCUSSION

An efficient method is implemented to detect abnormal activities which occurs at ATM.In this system, as soon as it detects the unusual activity held in the ATMs it generates the alarm and sends a alert message to the nearest police station for the safety of the customers.

V. CONCLUSION AND FUTURE SCOPE

It is clear that the proposed new framework will be able to detect an unusual events such as overcrowding situation and fight within ATMs. The need of developing such security system is the increasing number of suspicious actions at the ATM. The results show that above algorithm is efficiently applicable without any computational schemes.

This scheme could be further moderated for that situation where one ATM room consists of two or more ATM machines. The proposed algorithm is the basic scheme for detecting unusual event that may be further modified to deal with the challenges such as camouflage and sleeping person problems by using more efficient background subtraction techniques.

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