Remote Based Intelligent Video Surveillance System

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ABSTRACT

The surveillance detection related events from video input is a sophisticated technology in real time security related applications. Many current and Existing solutions to this problem are simply slight variations on frame differencing concept. This proves to be difficult to configure and operate effectively. This Proposed sytem presents a new approach to this problem based on extracting and classifying the background contents of each video frame using a CAM equipped with a standard framegrabber. The action of objects classified as people is further categorized into a series of events such as person leaving ,entering ,deposits object, and so forth.A background model is used to obtain candidate surveillance objects from input video.

I. INTRODUCTION

Although a number of surveillance systems use some form of prediction in their implementation, the majority of surveillance systems still passively monitor their environments and only raise alarms when anomalous behaviour is recognized or detected. Such sudden alarms do not give the response team enough time to prepare themselves and by the time they arrive at the scene it may be too late to stop the perpetrator(s). Other surveillance systems do not even raise alarms, but instead they only keep recordings of events which then have to be analysed by human operators. This is a very laborious and error prone task even for the operators that are fully focused on the task at hand[1-4,9].

The IU process involves a combination of image processing and artificial intelligence tasks that are performed on environment data in order to get an understanding of what is happening in that environment. Once the environment has been captured in a sequence of images the basic back-bone of the IU process is shown below[5].

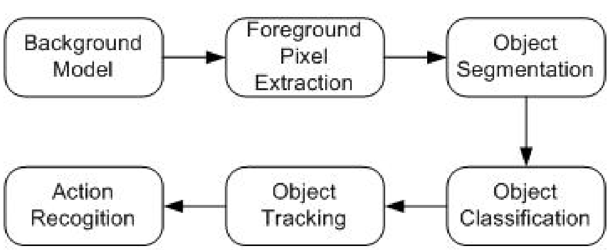


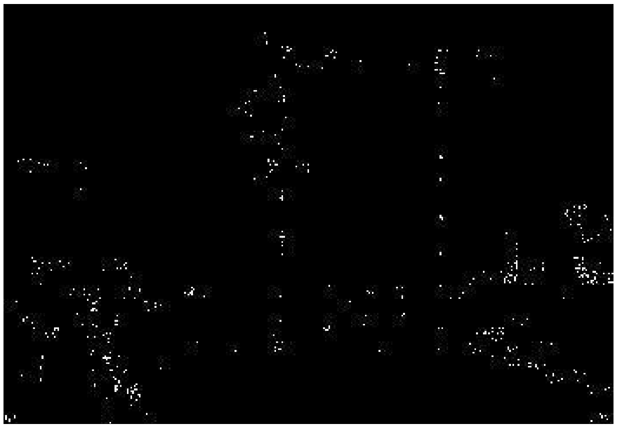
Figure 1: The back-bone of a general IU process

Non-adaptive techniques generally assume that the environment will not change much and thus construct the BM at initialization of the system without any further changes to the BM during run-time. An example of this would be an average of the first 50 frames of an image sequence being used as the BM. Such techniques are easy to implement and are not computationally intensive. Hence, they may be a good starting point for the implementation of an IU component and may also give the developer an idea of how the environment is behaving[6,7].

2. RELATED WORK

Image Noise

Image noise can be considered as an unexpected or erratic change in a pixel's appearance usually presenting itself as either a min (0) or max pixel colour value (255). According to Russ [5], image noise normally originates from the digital input device. Image noise is noticed when consecutive frames are compared or when a BM is used for comparison. In general, image noise is an undesired phenomenon because it can be detected as valid foreground pixels by the FPE part of the IU system which may ultimately lead to false assumptions in the object segmentation part of the IU system. Figure 3 below, demonstrates the appearance of random image noise. Two successive images are shown on the left hand side and the difference between the images is shown on the right hand side. This difference demonstrates the random noise that is present[6].



Hence, image noise needs to be dealt with accordingly in the FPE part of the system.

Shadows

According to Friedman et al. [1], shadows are one of the most serious problems experienced by video surveillance systems resulting in systems under-counting or over-counting the number of foreground objects by as much as 50%. In an experimental setup, a light source can be placed above the environment to minimize the effect of shadows. However, in a real world environment shadows cannot be dealt with in such a simplistic manner.

In an attempt to remove shadows, Friedman et al. [1] model their BM to have 3 classes that a given pixel can be classified as; of which one is a pixel's appearance when a shadow is present. Baba et al. [3] present a shadow removal technique based on the density of the shadow. Finlayson et al. [6] present a shadow removal method based on extracting a 1-D illumination invariant image from the original image, subtracting it from the original image leaving only the shadows and then using an edge detector to remove the shadow edges.

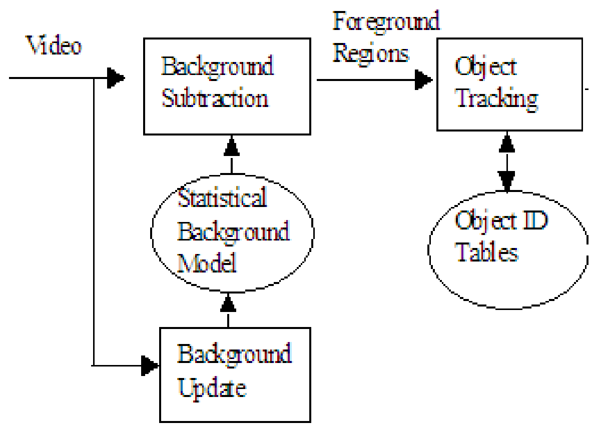
Object Representation The representation of a blob is very important for the classification and tracking steps in IU. The representation of the blob refers to the visual appearance of the blob when displayed by the surveillance system to the end user. Quite often there is no need to display all the pixels that form the blob to the end user; hence a more appropriate representation of the blob is generally used. In addition, the representation of the blob affects the amount of memory that is used to store and display the blob to the end user. The process of compacting the blob representation usually result in less processing needed in the classification and tracking steps of IU.

3. PROPOSED APPROACH

The Video Content Analyzer module has five components (Fig.)[:

- *Background Subtraction:* Detect foreground regions (objects and people) based on a statistical model of the camera view when no objects or people are present.
- *Object tracking:* Track each foreground region despite occlusions or merging and splitting of regions.
- *Event Reasoning:* Determine which regions represent people and which represent stationary objects, and classify the behavior of people into a small set of surveillance related events classes.
- *Graphical User Interface:* Display video input and event diagnosis to the system operator.
- *Indexing and Retrieval:* Index the video stream as it is being stored with the event information, and retrieve video sequences based on event queries.

The first four of these components have been constructed in a preliminary version of the VCA module. The final component, indexing and retrieval, is currently under design and development.



Proposed System

Figure 2: Background Subtraction with moving background

Background Subtraction

The approach taken to identifying foreground regions is to[10]:

1. Construct a model of the background scene by sampling the scene when no people or other relevant objects are present.
2. Compare new images of the scene to this background model and determine any discrepancies; these are considered foreground regions.
3. Update the background model as each new image is collected.

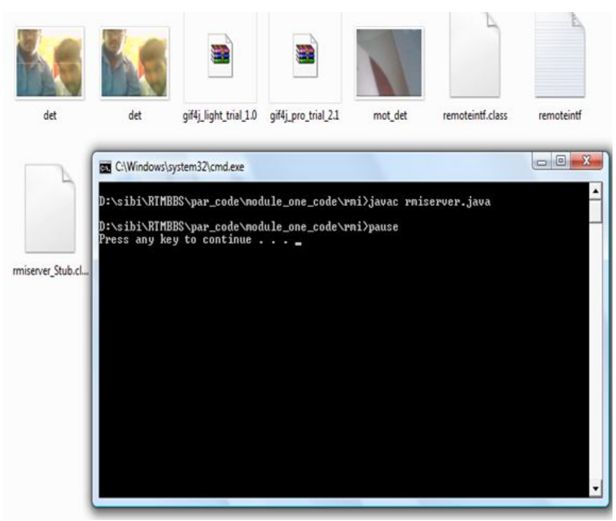
4. For each frame, a neighborhood window considers suburbs of 'n' last and 'n' next frame of current frame.
5. N last frame added together and make a composition frame. In the other hand these frame, place on top of each other. The same action is done for n next frame. In this phase, we have 3 frames: current frame, composition of n last frame and composition of n next frame.

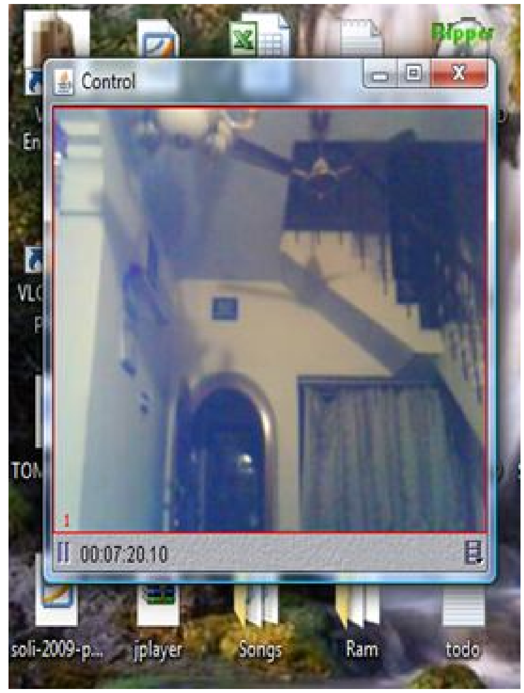
4. EXPERIMENTAL RESULTS

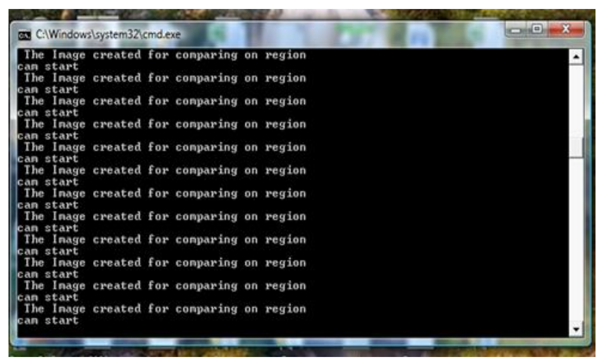
All experiments were performed with the configurations Intel(R) Core(TM)2 CPU 2.13GHz, 2 GB RAM, and the operation system platform is Microsoft Windows XP Professional (SP2)

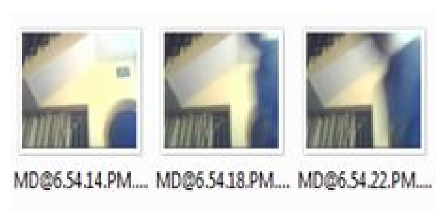
Starting the Remote Monitoring Application:

Results of Background Video Surveillance:









5. CONCLUSION AND FUTURE WORK

The paper briefly reviewed the background and progression of surveillance systems, including a short review of the first and second generation of surveillance systems. The focus of this research was to detect and predict anomalous behaviour of individuals in an environment using a camera as a way to capture the information about the environment. The monitored environment that was chosen was the UCT Agents Research Lab. A prototype video surveillance system was developed in order to demonstrate the research conducted during this dissertation and also to achieve the research goals that were set out.

This system effectively identifies background of the videos using background video surveillance extraction algorithm.

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