Efficient Motion Detection to Background Subtraction Support Security

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Abstract— Detection of moving objects in video streams is the first significant step of information extraction in many computer vision applications. Even there is usefulness to segment video streams into moving and background components, moving objects detection concentrates on recognition, classification, and activity analysis by making the latter steps efficient. We propose a technique through artificial neural networks which is applied in image processing of human and more commonly in cognitive science. The technique which is proposed can handle scenes containing moving backgrounds, steady illumination variations, has no bootstrapping restrictions, can include into the background model shadows cast by moving objects, and achieves strong detection for different types of videos taken with stationary cameras. We compare our method with other modelling techniques and report results, in terms of processing speed and accuracy for the color video sequences that represent typical situations critical for video surveillance systems. Facial features are segregated at different resolutions to provide noise information, edge, smoothness, and blurriness present in a face. WLD descriptor represents an image as a histogram of differential excitations and gradient orientations and also it has various interesting properties like robustness to noise and smart detection of edges, illumination changes and powerful image representation in feature extraction stage. The Gabor filter bank is used to extract the features from face regions to discriminate the illumination changes. These collective features are useful to distinguish the maximum number of samples accurately and it is matched with already stored original face samples for identification. The simulated results will be shown that used granulation and hybrid spatial features descriptors has better discriminatory power and recognition accuracy in the process of recognizing different facial appearance.

Keywords: Moving Objects, WLD, Orientations

I. INTRODUCTION

Intelligent video surveillance systems deal with the real-time monitoring of persistent and transient objects within a specific environment. An automated video surveillance and alarming system provides surveillance and alerts the security guard of any undesired activity via his cell phone. It would be a promising replacement of traditional human video surveillance system. It provides a high degree of security. The project presents robust face recognition based on granular computation and hybrid spatial features extraction.

II. RELATED WORKS

In several video surveillance applications, such as the detection of abandoned/stolen objects or parked vehicles, the detection of stationary foreground objects is a critical task. In the literature, many algorithms have been proposed that deal with the detection of stationary foreground objects, the majority of them based on background subtraction techniques. In this paper we discuss various stationary object detection approaches comparing them in typical surveillance scenarios (extracted from standard datasets). Firstly, the existing approaches based on background-subtraction are organized into categories. Then, a representative technique of moving object detection and motion segmentation is described. Finally, a comparative evaluation using objective and subjective criteria and also human face detection is performed on video surveillance sequences selected from the PETS 2006 and I-LIDS for AVSS 2007 datasets, analysing the advantages and drawbacks of each selected approach.

A. Motion Segmentation

A common approach for motion segmentation is to partition the dense optical-flow field .This is usually achieved by decomposing the image into different motion layer. The assumption is that the optical-flow field should be smooth in each motion layer, and sharp motion changes only occur at layer boundaries. Dense optical flow and motion boundaries are computed in an alternating manner named motion competition, which is usually implemented in a level set framework.

B. Background Subtraction

In background subtraction, the general assumption is that a background model can be obtained from a training sequence that does not contain foreground objects [2]. Moreover, it usually assumes that the video is captured by a static camera.

III. DOMAIN DESCRIPTIONS

Detection of moving objects in video streams is the first relevant step of information extraction in many computer vision applications. Aside from the intrinsic usefulness of being able to segment video streams into moving and background components, detecting moving objects provides a focus of attention for recognition, classification, and activity analysis, making these later steps more efficient. We propose an approach based on self-organization through artificial neural networks, widely applied in human image processing systems and more generally in cognitive science. The proposed approach can handle scenes containing moving backgrounds, gradual illumination variations and camouflage, has no bootstrapping limitations, can include into the background model shadows cast by moving objects, and achieves robust detection for different types of videos taken with stationary cameras. We compare our method with other modelling techniques and report experimental results, both in terms of detection accuracy and in terms of processing speed, for colour video sequences that represent typical situations critical for video surveillance systems.

A. Frames Segmentation

Segmentation is an important step in many image processing applications. The idea is to partition an image into a set of regions corresponding to objects in the image based on some feature such as motion or texture. The features used for segmentation may vary continuously between video frames at two different regions [4]. This makes it difficult to draw the line between two regions. It may even be possible that they are in fact so similar that they should be only one region. We have proposed segmentation algorithms based solely on estimations of the motion in image sequences.

B. Noise Removal

Shadows occur when objects occlude light from a light source. On one hand, shadows provide rich information about object shapes and light orientations. They provide strong clues about the shapes, relative positions, and surface characteristics of the objects. They can indicate the approximate location, intensity, shape, and size of the light source(s).

In fact, in some circumstances the shadows constitute the only components of the scene, as in shadow-puppet Theatre and in pin screen animation. On the other hand, shadows may cause embarrassments for visual applications. For example, objects together with their shadows form distorted figures and adjacent objects may be connected through shadows. Both can confuse object recognition systems. Segmenting objects from shadows can be a nontrivial task; shadows can be broadly divided as cast and self-shadows. As revealed in that figure, the self-shadow is a part of the object, which is not illuminated by the light source. The cast shadow lying beside the object belongs to the background. For object recognition and many other applications, cast shadows are undesired and need to be eliminated; if self-shadows are not part of objects they should be eliminated. If objects have intensities similar to those of shadows, shadow removal could become extremely difficult. Even though objects and shadows can be separated, object shapes are often incomplete.

C. Image Compression

Common among all video compression techniques is the reduction of “invisible” details to achieve compression and reduce hard disk consumption and bandwidth demands. The video image details that are visible post-compression demonstrate the trade-offs involved between different methods of compression.

In our project, MPEG (Moving Picture Experts Group) is used for monitoring applications where a stream of high-quality video and audio are needed, while limiting the amount of bandwidth used, relative to the quality level. Applications include surveillance requiring constant high frame rate, high quality, and the possibility to guarantee bandwidth. Examples are banks, airports, casinos and shopping malls.

D. Hardware Communication

A static camera observing a scene is a common case of a surveillance system. Detecting intruding objects is an essential step in analysing the scene. Even though there exist a myriad of segmentation algorithms in the literature. Most of them follow a simple one or two frame differencing except and nearly everyone assume that the background does not vary and hence can be captured a priori. This limits their usefulness in most practical applications.

E. Security Alert

If anything motions deducted in our application mean, it’s automatically sends an alert message to a particular person.

F. Log Maintenance

In this module, we store each and every information into a database for a future use. It’s like a history file for future verification.

IV. ALGORITHM

– *WEBER'S LAW*

Ernst Weber, an experimental psychologist in the 19th century, observed that the ratio of the increment threshold to the background intensity is a constant. This relationship, known since as Weber's Law, can be expressed as:

$$\Delta I / I = k,$$

Where ΔI represents the increment threshold (just noticeable difference for discrimination); I represents the initial stimulus intensity and k signifies that the proportion on the left side of the equation remains constant despite variations in the I term. The fraction $\Delta I/I$ is known as the Weber fraction. Weber's Law, more simply stated, says that the size of a just noticeable difference (i.e.,ΔI) is a constant proportion of the original stimulus value. So, for example, in a noisy environment one must shout to be heard while a whisper works in a quiet room.

A. Differential Excitation

We use the intensity differences between its neighbours and a current pixel as the changes of the current pixel. By this means, we hope to find the salient variations within an image to simulate the pattern perception of human beings. Specifically, a differential excitation ξ(xc) of a current pixel xc is computed as illustrated in Fig. 1. We first calculate the differences between its neighbours and the centre point using the filter.

$$\varepsilon(x_e) - \arctan\left[\frac{v_s^{00}}{v_s^{01}}\right] - \arctan\left|\Sigma_{i=0}^{p-1}\left(\frac{x_i - x_c}{x_c}\right)\right|$$

B. Orientation

For the orientation component of WLD, it is computed as: where Ii (i=0,1,…p/2-1) are the neighbors of a current pixel; R(x) is to perform the modulus operation, i.e., R(x) = mod(x, p) , (10) where p is the number of neighbors as mentioned. we are only needed to compute half of these angles because there exists symmetry for I q s when i takes its values in the two intervals [0, p/2-1] and [p/2, p-1].

For simplicity, I’s value is quantized into T dominant orientations. Before the quantization, the value of _ is mapped into the interval [0, 2_] according to its value computed using Eq. (9) and the sign of the denominator and numerator of the right side of Eq. (9). Thus, the quantization function is as follows:

$$\phi_i = f_u(\Theta') = \frac{2t}{T}\pi, \text{ and } t - \mathrm{mod}\left(\left|\frac{\Theta'}{2\pi/_T} + \frac{1}{2}\right|, T\right)$$

V. PROPOSED SYSTEM

To address this problem, in this paper, we propose a novel highly decentralized information accountability framework to keep track of the actual usage of the users' data in the cloud. In particular, we propose an object-cantered approach that enables enclosing our logging mechanism together with users' data and policies. We leverage the XML programmable capabilities to both create a dynamic and travelling object, and to ensure that any access to users' data will trigger authentication and automated logging local to the XMLs. To strengthen user's control, we also provide distributed auditing mechanisms. We provide extensive experimental studies that demonstrate the efficiency and effectiveness of the proposed approaches. One of the important concerns that need to be addressed is to assure the customer of the integrity i.e. correctness of his data in the cloud.

As the data is physically not accessible to the user the cloud should provide a way for the user to check if the integrity of his data is maintained or is compromised. In this paper we provide a scheme which gives a proof of data integrity in the cloud which the customer can employ to check the correctness of his data in the cloud. This proof can be agreed upon by both the cloud and the customer and can be incorporated in the Service level agreement (SLA). It is important to note that our proof of data integrity protocol just checks the integrity of data i.e. if the data has been illegally modified or deleted.

VI. IMPLEMENTATION VALUATIONS

A. Post Processing

Background modelling uses the observed video frame to calculate and update the background model that is representative of the scene without any objects of interest [1]. Foreground detection is where the pixels that show a significant difference to those in the background model are flagged as foreground. Data validation is used to examine the found objects of interest and to eliminate any false matches. A foreground mask can then be output in which pixels are assigned as foreground or background. The foreground detection stage can be described as a binary classification problem whereby each pixel in an image is assigned a label to the class of foreground or background. Formally, for every pixel p in image I, a label pl is assigned where I € {0, 1} where 0 = background and 1 = foreground .

After this mask is obtained, background pixels are usually set to white or black to allow focus on the foreground object. Many simple decision rules to classify each pixel have been suggested, each of which can be carried out in any one of a number of colour spaces. Many background subtraction algorithms reduce down to the simple subtraction of the pixel in the expected background image from the pixel in the observed image and any significant change indicates that an object of interest has been identified.

One of the most popular decision rules is to threshold this simple subtraction Simple Decision Rules The foreground detection stage can be described as a binary classification problem where by each pixel in an image is assigned a label to the class of foreground or background. Formally, for every pixel p in image I, a label pl is assigned where I € {0, 1}where 0 = background and 1 = foreground After this mask is obtained, background pixels are usually set to white or black to allow focus on the foreground object.

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B. Feature Recognition

The utterance-length feature statistics include mean, variance, range, quantile maximum, quantile minimum, and quantile range. The quantile features were used instead of the maximum, minimum, and range because they tend to be less noisy.

The pitch features were extracted only over the voiced regions of the signal. The video motion-capture derived features were occasionally missing values due to camera error or obstructions[14]. To combat this missing data problem, the features were extracted only over the recorded data for each utterance. These audio-visual features have been used in previous emotion classification problems. In this section we give an overview of basic WLD descriptor and its extension.

This descriptor represents an image as a histogram of differential excitations and gradient orientations, and has several interesting properties like robustness to noise and illumination changes, elegant detection of edges and powerful image representation. WLD descriptor is based on Weber's Law. According to this law the ratio of the increment threshold to the background intensity is constant. The computation of WLD descriptor involves three steps i.e. finding differential excitations, gradient orientations and building the histogram.

VII. CONCLUSION

By this application, initially the moving object is detected and which in turn is used to find presence of Human by using Background Subtraction, Noise Removal and WLD algorithms. And send an immediate message alert to user in case there is a presence of it, which in turn helps the user to find the presence of the intruder and alert the security. We have used all these techniques in order to improve the performance of the system by reducing the time and space complexity of the process. The proposed approach can handle scenes containing moving backgrounds, gradual illumination variations and camouflage, has no bootstrapping limitations, can include into the background model shadows cast by moving objects, and achieves robust detection for different types of videos taken with stationary cameras.

VIII. FUTURE WORKS

In the future, we will propose and evaluate the video files in all formats which we take as inputs and also for classifying each objects based on its appearance and the shape with the use of Web Local Descriptor.

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