International Journal of Innovation and Scientific Research
ISSN 2351-8014 Vol. 4 No. 2 Jul. 2014, pp. 70-76

http://www.ijisr.issr-journals.org/

Background Modelling and Subtraction in High Level Computer Vision Application with Security

D.Balasubramanian and V.Saranraj

Assistant professors,
Department of Information Technology,
VRS college of Engineering and Technology,
Villupuram, Tamilnadu, India

ABSTRACT: Intelligent video surveillance system deal's with the real-time monitoring of persistent and transient objects within a specific environment. In existing video surveillance using CCTV (close circuit television) works with binary segmentation algorithm and it had critical pre processing steps in various high level computer vision application. This can be applied not only in security systems, but also uses in environmental surveillance. The basic principle of moving object detecting is given by the Background Subtraction algorithm. Then, a self-adaptive background model that can update automatically and timely to adapt to the slow and slight changes of natural environment is detailed. When the subtraction of the current captured image and the background reaches a certain threshold, a moving object is considered to be in the current view, and the mobile phone will automatically notify the central control unit and automatic alerting system alert the authorized user through SMS and user can view the detected image by GPRS enabled mobile devices.

KEYWORDS: Background Modelling and Subtraction, GPRS, SMS, surveillance.

1 INTRODUCTION

The identification of regions of interest is typically the first step in many computer vision applications, including event detection, visual surveillance, and robotics. A general object detection algorithm may be desirable, but it is extremely difficult to properly handle unknown objects or objects with significant variations in color, shape, and texture. Therefore, many practical computer vision systems assume a fixed camera environment, which makes the object detection process much more straightforward; a background model is trained with data obtained from empty scenes and foreground regions are identified using the dissimilarity between the trained model and new observations. This procedure is called background subtraction.

Various background modelling and subtraction algorithms have been proposed [1], [2], [3], [4], [5] which are mostly focused on modelling methodologies, but potential visual features for effective modelling have received relatively little attention. The study of new features for background modelling may overcome or reduce the limitations of typically used features, and the combination of several heterogeneous features can improve performance, especially when they are complementary and uncorrelated. There have been several studies for using texture for background modelling to handle spatial variations in the scenes; they employ filter responses, whose computation is typically very costly. Instead of complex filters, we select efficient Haar-like features [6] and gradient features to alleviate potential errors in background subtraction caused by shadow, illumination changes, and spatial and structural variations.

Model-based approaches involving probability density function are common in background modelling and subtraction, and we employ Kernel Density Approximation (KDA) [3], [7], where a density function is represented with a compact weighted sum of Gaussians whose number, weights, means, and covariances are determined automatically based on mean-shift mode-finding algorithm. In our framework, each visual feature is modelled by KDA independently and every density

Corresponding Author: D. Balasubramnian (balaauc@gmail.com)

function is 1D. By utilizing the properties of the 1D mean-shift mode-finding procedure, the KDA can be implemented efficiently because we need to compute the convergence locations for only a small subset of data. When the background is modelled with probability density functions, the probabilities of foreground and background pixels should be discriminative, but it is not always true. Specifically, the background probabilities between features may be inconsistent due to illumination changes, shadow, and foreground objects similar in features to the background. Also, some features are highly correlated, i.e., RGB color features. So, we employ a Support Vector Machine (SVM) for nonlinear classification, which mitigates the inconsistency and the correlation problem among features. The final classification between foreground and background is based on the outputs of the SVM.

There are three important aspects of our algorithm integration of multiple features, efficient 1D density estimation by KDA, and foreground/background classification by SVM. These are coordinated tightly to improve background subtraction performance. An earlier version of this research appeared in [8]; the current paper includes more comprehensive analysis of the feature sets and additional experiments.

2 RELATED WORKS

Video surveillance takes place normally by using CCTV cameras (Closed Circuit Television) for monitoring or surveillance for intruder detection in case of emergencies in hospitals, shopping mall, banking sectors, and personal purpose automation and so on.

Later Video fusion approach also used for monitoring such systems. These systems are designed in such a way that monitoring images are stored and there is a need for human to interact for knowing about the changes in the current surveillance systems and than they will intimate to the concerned organization. Hence this is not a fast secured monitored due to the time delay taken for human interaction.

Due to time delay, we cannot get the update information for every minute or second and so it is not possible to detect the intruder in an appropriate time. This system uses the moving average algorithm to store the monitored images. Also this system lack the computation capability for surveillance meant for security

3 PROPOSED FRAMEWORK FOR BACKGROUND MODELING AND SUBTRACTION ALGORITHM

This section describes our background modelling and subtraction method based on the 1D KDA using multiple features. KDA is a flexible and compact density estimation technique, and we present a faster method to implement KDA for 1D data. For background subtraction, we employ the SVM, which takes a vector of probabilities obtained from multiple density functions as an input.

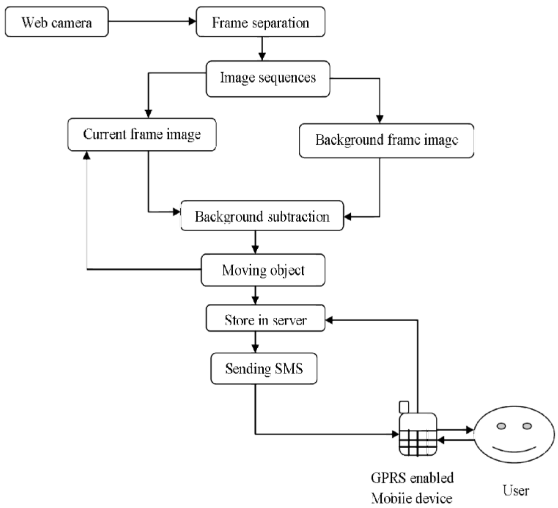

Fig. 1.Overall structure of high level computer vision application

3.1 MULTIPLE FEATURE COMBINATION

The most popular features for background modelling and subtraction are probably pixel wise color (or intensity) since they are directly available from images and reasonably discriminative. Although it is natural to monitor color variations at each pixel for background modelling, they have several significant limitations as follows:

1. They are not invariant to illumination changes and shadows.
2. Multidimensional color features are typically correlated and joint probability modelling may not be advantageous in practice.
3. They rely on local information only and cannot handle structural variations in neighbourhoods.

We integrate color, gradient, and Haar-like features together to alleviate the disadvantages of pixel wise color modelling. The gradient features are more robust to illumination variations than color or intensity features and are able to model local statistics effectively. The strength of Haar-like features lies in their simplicity and the ability to capture neighbourhood information. Each Haar-like feature is weak by itself, but the collection of weak features has significant classification power. The integration of these features is expected to improve the accuracy of background subtraction. We have 11 features altogether, RGB color, two gradient features (horizontal and vertical), and six Haar-like features. The Haar-like features are extracted from rectangular regions at each location in the image, while the gradient features are extracted with 3 _ 3 Sobel operators. The fourth and fifth Haar-like features are similar to the gradient features, but differ in filter design, especially scale.

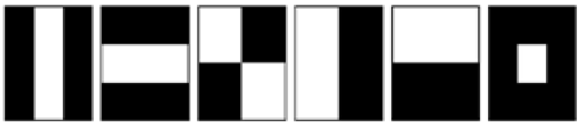

Fig. 2.Haar-like features for our background modelling

3.2 FOREGROUND AND BACKGROUND CLASSIFICATION

After background modelling, each pixel is associated with k 1D Gaussian mixtures, where k is the number of features integrated.

Background/foreground classification for a new frame is performed using these distributions. The background probability of a feature value is computed by (2), and k probability values are obtained from each pixel, which are represented by a k-dimensional vector. Such k-dimensional vectors are collected from annotated foreground and background pixels, and we denote them by yj (j = 1, . . ., N), where N is the number of data points.

In most density-based background subtraction algorithms, the probabilities associated with each pixel are combined in a straight forward way, either by computing the average probability or by voting for the classification. However, such simple methods may not work well under many real-world situations due to feature dependency and nonlinearity. For example, pixels in shadow may have a low-background probability in color modelling unless shadows are explicitly modelled as transformations of color variables, but high-background probability in texture modelling.

Also, the foreground color of a pixel can look similar to the corresponding background model, which makes the background probability high although the texture probability is probably low. Such inconsistency among features is aggravated when many features are integrated and data are high dimensional, so we train a classifier over the background probability vectors for the feature set,{Yj}1:N.Another advantage to integrating the classifier for foreground/background segmentation is to select discriminative features and reduce the feature dependency problem; otherwise, highly correlated non discriminative features may dominate the classification process regardless of the states of other features.

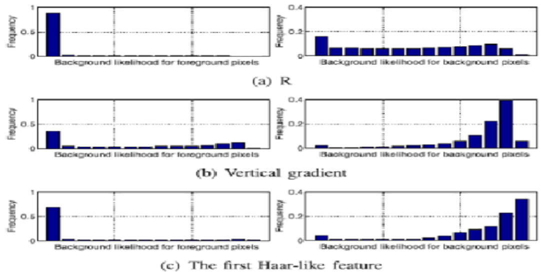

Fig. 3. *Feature performance for classification. The histograms of background probability for foreground and background pixels are presented for each feature.*

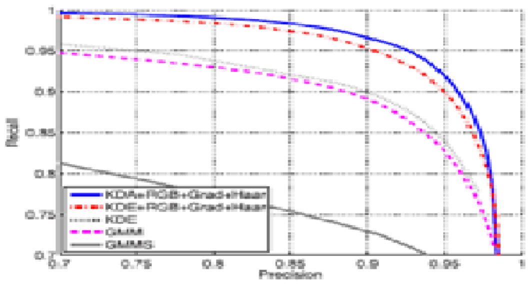

Fig. 4. *PR curves for different density estimations*

4 EXPERIMENTS

We present the performance of our background modeling and subtraction algorithm using real videos. Each sequence involves challenges such as significant pixelwise noises (subway), dynamic background of a water fountain (fountain), and reflections and shadow in wide area.

4.1 IMAGE CAPTURING USING WEBCAM

In this module we are capturing the video from webcam using Java Media Framework (JMF) API. JMF is a framework for handling streaming media in Java programs. JMF is an optional package of Java 2 standard platform. JMF provides a unified architecture and messaging protocol for managing the acquisition, processing and delivery of time-based media. JMF enables Java programs to get the video image from web camera

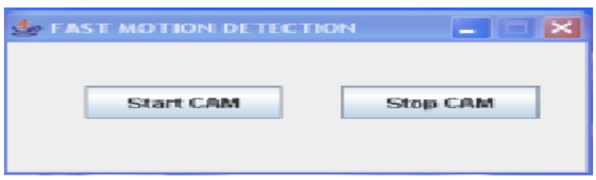

Fig 5 camera control for fast motion detection

4.2 BACKGROUND DETECTION

K-means clustering is a method of cluster analysis which aims to partition observations into k clusters in which each observation belongs to the cluster with the nearest mean. The problem is computationally difficult; however there are efficient heuristic algorithms that are commonly employed that converge fast to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centres to model the data, however k-means clustering tends to find clusters of comparable spatial extend, while the expectation-maximization mechanism allows clusters to have different shapes.

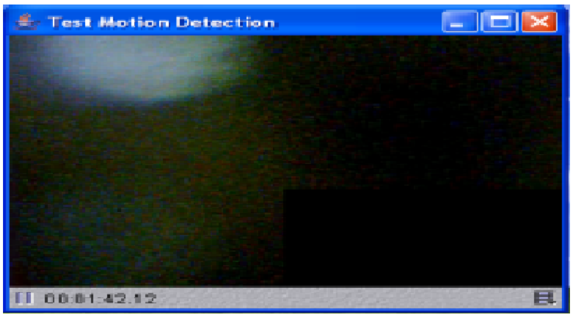

Fig 6 capturing frames for test motion detection

4.3 IMAGES STORES IN SERVER

After the background template has been constructed, the background image can be subtracted from the observed image. The result is foreground (moving objects). Actually, the background is timely updated. To classify a new pixel value with respect to its immediate neighborhood in the chosen color space, so as to avoid the effect of any outliers. This motivates us to model each background pixel with a set of samples instead of with an explicit pixel model. and so the current value of the pixel is compared to its closest samples within the collection of samples.

In case of some random disturbances, each pixel will fluctuate in a small range even there is no expected moving objects in the scene. So there must be a strategy to judge it. A threshold is defined in the system. If the difference of one pixel between real time frame and template is more than 10, then add 1 to the threshold. When differences of all pixels in the frame are all calculated, moving objects is thought to appear if the threshold is more then 3 percent of the total number of pixels in the frame.

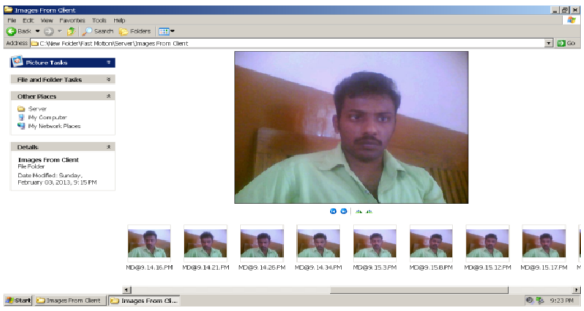

Fig 7 motion detected images stores in server

4.4 ALERTING SYSTEM

After detecting the changes in video frames, we are alerting the central control unit or the user through SMS using the GSM Modem. A GSM modem is a wireless modem that works with a GSM wireless network. A wireless modem behaves like a dial-up modem. The main difference between them is that a dial-up modem sends and receives data through a fixed telephone line while a wireless modem sends and receives data through radio waves. Typically, an external GSM modem is connected to a computer through a serial cable or a USB cable. Like a GSM mobile phone, a GSM modem requires a SIM card from a wireless carrier in order to operate.

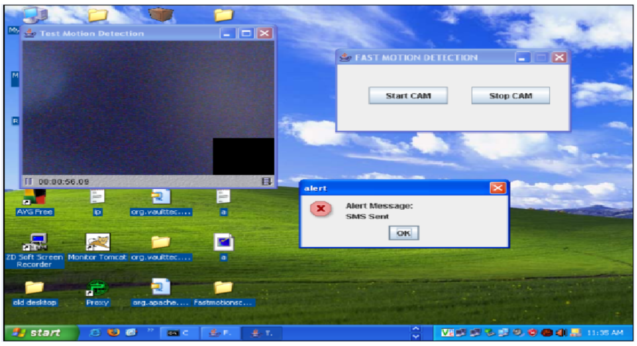

Fig 8 alerting system

After the receiving of SMS by an authorized user, they can view the detected image by GPRS enabled mobile devices.

4.5 Comparison between High Level Computer Vision Application With Security and CCTV Video surveillance system

Features	CCTV Video surveillance system	Background Modelling And Subtraction In High Level Computer Vision Application With Security
Memory	Store's continuously	When object detect in current frame
Human interaction	Needed	Not needed
Alerting features	Not applicable	Applicable by sending SMS
Remote monitoring	Not applicable	Applicable by using GPRS enabled mobile devices

Fig 9 Comparison between High Level Computer Vision Application With Security and CCTV Video surveillance system

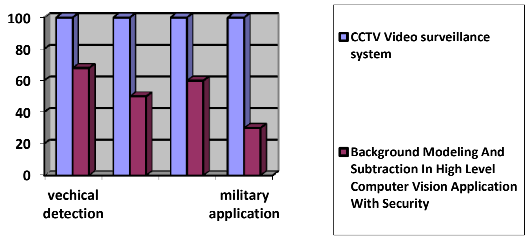

Fig 10 memory consumption between High Level Computer Vision Application With Security and CCTV Video surveillance system in many applications

5 Conclusion

We have introduced a multiple feature integration algorithm for background modelling and subtraction, where the background is modelled with a generative method and background and foreground are classified by a discriminative technique. Here we can use background subtraction in many high level computer vision applications, some of the security features enclosed, like SMS generation and remote monitoring using a GPRS enabled mobile phone devices. Our algorithm demonstrates better performance and less storage space than CCTV video surveillance system and the performance is tested quantitatively and qualitatively using a variety of indoor and outdoor video applications.

References

[1] A. Elgammal, D. Harwood, and L. Davis, “Non-Parametric Model for Background Subtraction,” Proc. European Conf. Computer Vision, pp. 751-767, June 2000.

[2] C. Stauffer and W.E.L. Grimson, “Learning Patterns of Activity Using Real-Time Tracking,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 8, pp. 747-757, Aug. 2000.

[3] B. Han, D. Comaniciu, and L. Davis, "Sequential Kernel Density Approximation through Mode Propagation: Applications to Background Modeling," Proc. Asian Conf. Computer Vision, 2004.

[4] D.S. Lee, "Effective Gaussian Mixture Learning for Video Background Subtraction," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 27, no. 5, pp. 827-832, May 2005.

[5] Z. Zivkovic and F. van der Heijden, "Efficient Adaptive Density Estimation Per Image Pixel for Task of Background Subtraction," Pattern Recognition Letters, vol. 27, no. 7, pp. 773-780, 2006.

[6] P. Viola and M. Jones, "Rapid Object Detection Using a Boosted Cascade of Simple Features," Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 511-518, 2001.

[7] B. Han, D. Comaniciu, Y. Zhu, and L.S. Davis, "Sequential Kernel Density Approximation and Its Application to Real-Time Visual Tracking," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 30, no. 7, pp. 1186-1197, July 2008.

[8] B. Han and L.S. Davis, "Adaptive Background Modeling and Subtraction: A Density-Based Approach with Multiple Features" Intelligent Video Surveillance Systems and Technology, Y. Ma and G. Qian eds., ch. 4, pp. 79-103, CRC Press, 2010.