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Video Survillence using Multifeature Background Subtraction Algorithm: A Self adaptive Security Mechanism

Neethu Kunjappan, K.Lakshmanan

Abstract*—*This is a security system based on background subtraction algorithm. Currently existing surveillance systems normally use Closed Circuit TVs. Background modeling and subtraction is a natural technique for object detection in videos captured by a static cameras. The proposed paper uses multi feature background subtraction technique. Here it uses a pixel wise background modeling and subtraction using multiple features. Here generative and discriminative techniques are combined for classification. In this algorithm, gradient, color, and Haar-like features are closely integrated so that they can handle variations in space and time for each and every pixel. A e background model that is pixel wise generative is obtained for each feature by Kernel Density Approximation (KDA). Background subtraction is performed using a Support Vector Machine (SVM). The proposed algorithm is resistant to shadow, illumination changes in light and spatial variations of background. It monitors an already captured environment and if an intruder comes, then it will send message alert to the administrator and it will send current streaming video to the admin system. All these actions are performed so fast that it will be easy to catch the intruder and needs no human interaction which makes the system efficient.

Keywords-Background Subtraction Algorithm,Kernel Density Approximation ,Support Vector Machine, Haar-like features

I. INTRODUCTION

Normally all working environments need security. Security can be implemented in many ways, sometimes audio, video or by any other means. Video surveillance systems are most common today. Intelligent video surveillance systems deal with the real-time monitoring of persistent and transient objects within a specific environment. This type of video surveillances can be applied not only to various security systems, but also for environmental surveillance. This surveillance can be used for many other purposes like event detection, visual surveillance and robotics. A normal object detection algorithm can be applied for this purpose, but it may be difficult to detect unknown objects with significant changes in color, shape and texture. So most surveillance systems use static cameras which make the object detection much more easy .In such cases 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 method is normally used in all static cameras.

Different types of background modeling and subtraction algorithms have been proposed by different people which are mostly focused on modeling methodologies, but potential visual features of the object have received little importance. This new algorithm may overcome or reduce this limitation and the combination of several heterogeneous features can improve performance, even when they are complementary and not correlated

Many studies are done for using texture for background modeling to handle space variations on scenes. For this they employ filters, which make it very costly. Instead of this filters, here it uses Haar-like features and gradient features which eliminates potential errors in background subtraction due to shadows of images, illumination changes in light, and spatial and structural variations. In this Algorithm we employ Kernel Density Approximation, where a density function is represented with a compact weighted sum of Gaussians.

When the background is modeled with probability density functions, background probabilities between features may be inconsistent due to illumination changes in light, foreground objects similar in features to the background and shadows of images. For this purpose we use a Support Vector Machine (SVM) which mitigates the inconsistency and the correlation problem among different features. This algorithm works as three different phases, in first phase multiple features are integrated. In the second phase one dimensional density estimation by KDA is done efficiently and finally SVM classifies foreground/background. These phases are strongly coordinated to improve background subtraction performance.

II. LITERATURE SURVEY

The following are the papers which helped get an idea of different modeling schemes employed. Most of the currently existing schemes have their own drawbacks. Our proposed multifeature based algorithm will eliminate most of these drawbacks by incorporating multiple features of objects for background subtraction.

In the paper Non-Parametric Model for Background Subtraction, kernel density estimation techniques which are nonparametric are presented as a tool for constructing statistical representations for the scene background and foreground regions in video surveillance. Since the background or the foreground does not follow a known parametric form, necessarily, kernel estimation methods are a more suitable approach to use in these applications.

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***Correspondence Author(s)**
Neethu Kunjappan, Department of Computer Science and Engg., Annai Mathammal Sheela Engineering College, Namakkal Dist., Tamil Nadu, India.
Prof. K Lakshmanan , Department of Computer Science and Engg., Annai Mathammal Sheela Engineering College, Namakkal Dist., Tamil Nadu,India.

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A background model and background subtraction technique was introduced. The model achieves sensitive detection of moving targets against clustered backgrounds. The model can handle conditions where the scene background is not purely static and contains tiny motions like moving tree branches and bushes. The model can also resist changes in the scene illumination. The model is can suppress false detections which will arise due to small displacements of the camera. Kernel estimation techniques are used for modeling the appearance of foreground regions.

In the paper Motion-Based Background Subtraction using Adaptive Kernel Density Estimation, a technique for the modeling of dynamic scenes for the purpose of background-foreground differentiation and change detection is proposed. The method relies on the utilization of optical flow as a feature for change detection. A novel kernel based multivariate density estimation technique that adapts the bandwidth according the uncertainties in the test and sample measurements are also proposed.

In the paper Real-Time Object Tracking and Classification Using a Static Camera, a vision based system for tracking and classifying dynamic objects in an outdoor environment. The system can handle occlusions and has demonstrated good results over multiple objects in varying weather conditions. In this multiple objects are reliably tracked, even presence of occlusions, and the combination of using recurrent motion and Motion History Images improves classification and tracking performance. The system is a preliminary step towards improving the situational awareness of either human-operated or autonomous vehicles working in joint workspaces.

In the paper Background subtraction in video using recursive mixture models, which uses spatio-temporal filtering and shadow removal, there is an improvement to an existing adaptive Gaussian mixture model, using a multi-dimensional spatiotemporal Gaussian kernel smoothing transform for background modeling in moving object segmentation applications. The model can deal with blurred images, slow light changes and camera vibration in very strong wind, and other difficult environmental conditions like rain and snow. The system can be efficiently used to segment objects when the scenes are both indoor and outdoor, with strong shadows, highlight reflections and light shadows.

In the paper An Improved Adaptive Background Mixture Model for Real time Tracking with Shadow Detection, a new update algorithm for learning adaptive mixture models of background scene for the real-time tracking of moving objects is presented. A method to detect moving shadows using our existing mixture model is proposed. This significantly reduces additional computational burdens. Shadow detection need only be performed upon pixels labeled as foreground and therefore with negligible computational overheads the moving shadows can be detected successfully. The shadow detection will also eliminate the effect of small repetitive motions in the background scene.

In the paper Background subtraction techniques: a review, a review of the most relevant background subtraction methods is presented. This original review allows the readers to compare the methods' complexity with respect to its speed, accuracy and memory requirements. It can also effectively guide them to select the best method for a specific application in a disciplined way.

III. EXISTING SYSTEM

The goal of background subtraction is to obtain an efficient background model from which we can easily detect the foreground objects. At first simple techniques such as frame differences and median filtering were used to detect foreground objects. Some other techniques utilized a combination of local statistics or vector quantization which uses intensity or color at each pixel.

Then came more advanced background modeling methods which uses density factor and which uses density factor, here the background model for each and every pixel is defined by a probability density function of the visual features observed during a training period. The main drawback of this method is that it cannot handle multimodal density functions. As a result, this method is not used in dynamic environments.

A mixture of Gaussians is another popular density-based method which is designed for dealing with multiple backgrounds. Then an adaptive Gaussian mixture model is proposed, where a maximum of K Gaussian components for each pixel are allowed but the number of Gaussians is determined dynamically. After that, variants of incremental EM algorithms have been employed to deal with real-time adaptation constraints of background modeling. Presently more elaborate and recursive update techniques are used.

Most real-time applications rely on models with a fixed number of components. Kernel density estimation is a nonparametric density estimation technique that has been successfully applied to background subtraction. Although it is a powerful representation for general density functions, it requires many samples to estimate the underlying density functions more accurately and this process is computationally very expensive. As a result it is not appropriate for real-time applications such as high-dimensional features are involved.

Most background subtraction algorithms are based on pixel wise processing. Different multilayer approaches are also introduced, where background models are constructed at the pixel, region, and frame levels. Here the informations from each layer is combined for discriminating foreground and background. The co-occurrence of visual features within neighborhood pixels is used for robust background subtraction in dynamic scenes. Different types of visual features may be used to model a background, which includes intensity, gradient, color, texture, motion etc. Color and intensity are probably the most popular and mostly used features which are used in background modeling. But to overcome their limitations several attempts have been made to integrate other features. Recently, a feature selection technique was proposed for background subtraction.

3.1 Limitations of Existing System

The existing system uses different modeling schemes for getting a perfect background from the scene for detecting the moving foreground object. Most of these have their own limitations and drawbacks. Our proposed system will eliminate many of these limitations. An important limitation of the existing system is its high hardware cost. Different hard wares likes color filters are costly and they have to be used in the existing system. This makes the system not so cost effective.

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The system will become less secure also. Another drawback is that it needs human interaction for implementing security. It also lacks computational capability while monitoring. It doesn't keep track of the previous surveillance operations. So we lack a backup of the system in case of necessity.

IV. PROPOSED SYSTEM

The proposed system uses a background modeling and subtraction method based on the 1D KDA using multiple features. KDA can be defined as a flexible and compact density estimation technique. We employ the SVM, which takes a vector of probabilities obtained from multiple density functions as an input.

4.1 Multiple Feature Combination

The mostly used features for background modeling and subtraction are pixel wise color since they are directly available from images and it is more discriminative. It is natural to monitor color variations at each pixel used for background modeling. Its drawbacks are that they are not invariant to illumination changes and shadows and multidimensional color features are typically correlated, so that joint probability modeling may not be advantageous. Another limitation is that they rely on local information only and cannot handle structural variations in neighborhoods. Color, gradient, and Haar-like features are integrated together to alleviate the disadvantages of pixel wise color modeling. The gradient features are more adaptive to illumination variations than color or intensity features and are able to model local statistics effectively. That is why gradient features are occasionally used in background modeling problems. The strength of Haar-like features lies in their simplicity and the ability to capture neighborhood information. By itself the Haar-like features are weak, but the collection of weak features has significant classification power. The integration of these features is expected to improve the accuracy of background subtraction.

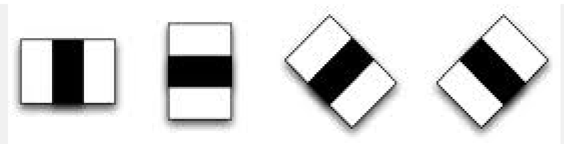

Fig. no:1 Haar like features for background modeling

4.2 Background Modeling by KDA

For each feature of each pixel a background probability is modeled with a Gaussian mixture density function. For this purpose there are various methods. We propose KDA, where the density function for each pixel is represented with a compact and flexible mixture of Gaussians. The KDA is a technique used for density approximation and it is based on mixture models. In KDA mode locations are detected by itself. The curvature fitting around the associated mode will compute covariance for each Gaussian.

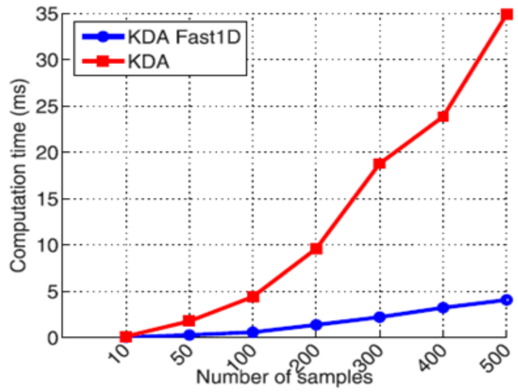

Fig. no: 2 Comparison between original KDA and 1D KDA

For each feature, we first construct a 1D density function at each pixel by kernel density estimation based on Gaussian kernel. One remaining issue is bandwidth selection. Although KDA handles multimodal density functions for each feature, it is cannot handle long-term background variations. Thus the background models must be updated periodically or incrementally.

4.3 Optimization in One Dimension

All the samples located between a sample and its associated mode converges to the same mode location. As a result every convergence location in the underlying density function can be found without running the actual mode-finding procedure for all the sample points. This is the most expensive part in the computation of KDA. The proposed algorithm employs a simple method to find all the convergence points by a single linear scan of samples using the above properties, efficiently. Perform the mean-shift mode finding from the smallest sample by scanning the samples in the ascending order. Then the current sample moves in the gradient ascent direction by the mean-shift algorithm in the underlying density function and passes another sample's location during the iterative procedure. During the mean-shift iterations, if a mode is found then its location is stored and after that the next sample is considered. After the scan of all samples is finished, each sample is associated with a mode and thus the mode-finding procedure is complete.

4.4 Foreground and Background Classification

After background modeling, each pixel is associated with k 1D Gaussian mixtures, where k is the number of features integrated. Background and foreground classification for a new frame is performed using these distributions. In most of the density-based background subtraction algorithms, the probabilities of each pixel are combined in a linear way. But such simple methods may not work well under many real-world situations due to feature dependency and nonlinearity. Inconsistency among features is aggravated when many features are integrated and data are high dimensional, soa classifier is trained over the background probability vectors for the feature. Another advantage to integrating the classifier for foreground and background segmentation is to select discriminative features and there by reducing the feature dependency problem. Here an SVM is employed for the classification of background and foreground.

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4.5 *Advantages of Proposed system*

Although there exists a lot of systems, they have their own limitations. The proposed algorithm will eliminate most of these disadvantages. The background subtraction algorithm using multiple features has good qualitative performance compared with others.The performance of feature combinations is evaluated qualitatively. The combination of gradient, color and Haar-like features outperforms other feature sets in segmentation. This algorithm based system has a number advantages compared to the existing environments. The important advantage of using our algorithm is its Low maintenance cost. It occupies less storage and so it requires only less memory. Due to high speed processing, the performance will be better than the existing one.

V. CONCLUSION

This paper introduced a multiple feature integration algorithm for background modeling and subtraction, where the background is classified with a generative method and background and foreground are classified by a discriminative technique. The characteristics of individual features are considered and perform of multiple feature integration. RGB colors and three Harr-like features are correlated, and the fourth and fifth Haar-like features have nontrivial correlation with vertical and horizontal gradient features. The histograms of background probabilities for foreground and background pixels are presented for three different features—a representative feature for color, gradient, and Haar-like feature. The combination of heterogeneous features improves back- ground/foreground classification performance. The inclusion of the feature does not help much because background probabilities of pixels in these two feature bands are highly correlated. This problem is alleviated when gradient or Haar-like feature are integrated; foreground and background pixels are now more separable so that classification is more straightforward.

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