Density-Based Multi feature Background Detraction using K-Means

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***Abstract*-- Intelligent video stakeout systems deal with the real-time monitoring of persistent and transient objects within a specific environs. This can be applied not only to various security systems, but also to environs stakeout. Firstly, the basic principle of moving object detecting is given by the Background Detraction algorithm. Then, a self-adaptive background model that can update automatically and timely to adapt to the slow and slight changes of natural environs is detailed. When the detraction of the current captured photocopy and the background reaches a certain verge, a moving object is considered to be in the current view, and the cellular device will automatically notify the central control unit or the user through cellular call, Message System or other means.**

The proposed algorithm can be implemented in an substantial system with little memory consumption and storage space, so it's feasible for cellular device and other substantial platforms, and the proposed solution can be used in constructing cellular security monitoring system with low-cost hardware and equipments

***Index Terms*—Stakeout, monitoring, background, magnitude , Detraction.** *(key words)*

I. Introduction

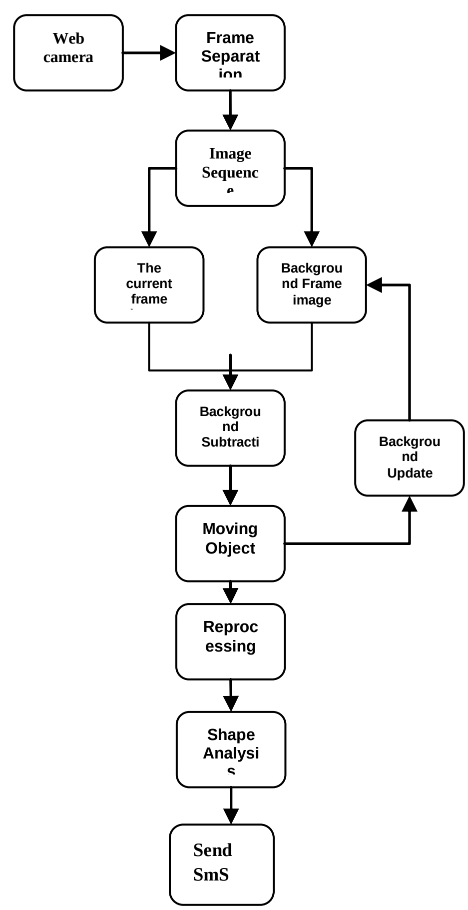
Video stakeout takes place normally by using CCTV cameras (Closed Circuit Television) for monitoring or stakeout for intruder detection in case of emergencies in hospitals, banking areas, personal purpose machine control and so on. Later Video fusion approach also used for monitoring such systems. These systems are designed in such a way that monitoring photocopy's are stored and there is a need for human to interact for knowing about the changes in the current stakeout 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. These systems use the moving average algorithm to store the monitored photocopy's. Also this system lack the computation capability for stakeout meant for security.

II. Background Detraction Techniques

Background detraction is a widely used approach for detecting moving objects @on stabile cameras. Many distinct methods have been proposed over the recent years and both the novice and the export can be confused about their benefits and restraint. In order to overcome this problem, this popper provides a review of ice main methods and an original categorization based on speed, memory requisite and accuracy, Such a review can effectively guide ice designer to select the most suitable method for a given application in a principled way. Methods analyzed include parametric and

non-parametric background density estimates and spatial correlation approaches.

BLOCK DIAGRAM FOR PROPOSED SYSTEM:



Modules:

1. **Quality Analysis**

We describe the characteristics of individual quality's and the performance of multiple quality integration. The correlation between every pair of quality's. RGB colors like quality's are significantly correlated; We propose a pixel wise background modeling and detraction technique using k-mean clustering algorithm. Where generative and discriminative techniques are combined for classification .The quality's improves background/foreground classification performance.

2. Classification

After background modeling, each pixel is associated with k 1DGaussian mixtures, where k is the number of qualitys integrated. Background/foreground classification for a new frame is performed using these distributions. The background probability of a quality 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 ¼ 1; . . .;N), where N is the number of data points. In most density-based background detraction algorithms, the probabilities associated

3. Background Detection

K-means clustering is a method of cluster analysis which aims to partition n examinations into k clusters in which each examination belongs to the cluster with the nearest mean. The complication is figuring difficult; however there are efficient heuristic algorithms that are commonly employed that converge fast to a local optimum. These are usually collateral to the probability-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. plus, they both use cluster centers to perfect the data, however k-means clustering tends to find clusters of comparable spatial extend, while the probability-maximization mechanism allows clusters to have different shapes.

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 grid. A wireless modem behaves like a dial-up modem. The main variance 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 peripheral GSM modem is connected to a computer through a serial cable or a USB cable. Like a GSM cellular system, a GSM modem requires a SIM card from a wireless carrier in order to operate.

Some specifications:

K-Means Algorithm: *k*-means clustering

Overview

- A clustering algorithm
- An resemblance to an NP-hard combined optimization problem
- It is unsupervised
- "*K*" stands for number of clusters, it is a user injunction to the algorithm
- From a set of data points or examinations , *K*-means attempts to assort them into *K* clusters
- The algorithm is iterative in nature

Explanation:

- $X_1,\ldots, X_N$ are data points or vectors or examinations
- Each examination will be impute to one and only one cluster
- $C(i)$ denotes cluster number for the i^{th} examination
- Variance measure: Euclidean distance metric
- *K*-means reduces within-cluster point scatter:

$$W(C)=\frac{1}{2}\sum_{k=1}^{K}\sum_{C(i)=k}\sum_{C(j)=k}\left\|x_i-x_j\right\|^2=\sum_{k=1}^{K}N_k\sum_{C(i)=k}\left\|x_i-m_k\right\|^2$$

where

- m_k is the mean vector of the k^{th} cluster
- N_k is the number of examinations in k^{th} cluster

Example:

k-means clustering result for the Iris flower data set and actual species visualized using ELKI. Cluster means are noted using larger, translucent symbols.

k-means clustering and EM clustering on an artificial data set ("mouse"). The tendency of *k*-means to produce equi-sized clusters leads to bad results, while EM profits from the Gaussian distribution present in the data set

Mean switch clustering:

Basic switch clustering algorithms maintain a set of data points the same size as the injunction data set. Initially, this set is copied from the injunction set. Then this set is iteratively replaced by the difference of those points in the set that are within a given distance of that point. By contrast, *k*-means limits this updated set to *k* points usually much less than the number of points in the injunction data set, and replaces each point in this set by the mean of all points in the *injunction set* that are closer to that point than any other (e.g. within the Voronoi partition of each updating point). A mean switch algorithm that is similar then to *k*-means, called *likelihood mean switch*, replaces the set of points undergoing replacement by the mean of all points in the injunction set that are within a given distance of the changing set. One of the advantages of mean switch over *k*-means is that there is no need to choose the number of clusters, because mean switch is likely to find only a few clusters if indeed only a small number exist. However, mean switch can be much slower than *k*-means. Mean switch has soft variants much as *k*-means does.

Canny Brim Detection Algorithm:

Canny's aim was to discover the optimal brim detection algorithm. In this situation, an "optimal" brim detector means:

good detection – the algorithm should mark as many real brims in the photocopy as possible.

good localization – brims marked should be as close as possible to the brim in the real photocopy.

minimal response – a given brim in the photocopy should only be marked once, and where possible, photocopy noise should not create false brims.

To satisfy these requirements Canny used the calculus of variations – a technique which finds the function which optimizes a given utile. The optimal function in Canny's detector is described by the sum of four exponential terms, but it can be reached by the first derivative of a Gaussian.

Proposed System

- Here K-means and Canny Brim Detection combined.
- An IVS system provides a low-cost intelligent cellular system-based video stakeout solution using moving object recognition technology.
- The basic principle of moving object detecting is given by the Background Detraction 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 detraction of the current captured photocopy and the background reaches a certain starting point.
- A moving object is considered to be in the current view and the cellular system will automatically notify the central control unit or the user through SMS.

CONCLUSION

We have introduced a multiple quality integration algorithm for background modeling and detraction, where the background is modeled with a generative method and background and foreground are classified by a discriminative technique. KDA is used to represent a probability density function of the background for RGB, gradient, and Haar-like quality's in each pixel, where 1Dindependent density functions are used for simplicity. For classification, an SVM based on the probability vectors for the given quality set is employed. Our algorithm demonstrates better performance than other density-based techniques such as GMM and KDE, and the performance is tested quantitatively and qualitatively using a variety of indoor and outdoor videos.

REFRENCE

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