Human Motion Detection in Video Surveillance Using Computer Vision Technique

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Abstract - *Object detection is one of the fundamental steps for automated video analysis in many vision applications. Object detection in video is usually performed by background subtraction techniques. In the existing method they proposed object detection by pixel variation of the image from one frame to another and the background subtracted by the training process in the recorded videos. In the proposed method the object is detected in the live video that is used for the security purpose. This method can be applicable in bank, jewellery shops, military etc., in an efficient way. Camera is fixed at the required place and if there is any human object is detected, it is processed and make the system to realize and produces the alerting sound. Advantages over the existing system are cost and power consumption is reduced as it does not require any sensors. Based on the Camera's range the monitoring area may be increased. In live video 18 frame is processed at a unit time and it takes again 18 frames to process output. In existing system they took 5secs to process 1 frame.*

Key Words: nuclear magnetic resonance, SVD, frame, DECOLOR

1. INTRODUCTION

The term digital image processing generally refers to processing of a two dimensional picture by a digital computer. In context, it implies digital processing of any two-dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency and slide. Photograph or chart is first digitized and stored as a matrix of binary digits in computer memory. For display, the image is stored in a rapid-access buffer memory which refreshes the monitor at 30 frames/s to produce a visibly continuous display. Mini- or microcomputers are used to communicate and control all the digitization, storage, processing, and display operations via a computer network. Program inputs to the computer are made through a terminal and the outputs are available on a terminal television monitor, or a printer/plotter. Digital image processing has a broad spectrum of applications ,such as remote sensing via satellites and other spacecrafts, image transmission and storage for business applications, medical processing, radar, sonar, and acoustic image processing ,robotics and automated inspection of industrial parts. Images acquired by satellites are useful in tracking of earth resources; geographical mapping; prediction of agricultural crops, urban growth, and weather; flood and fire control; and many other environmental applications. Space image applications include recognition and analysis of objects contained in images object obtained from deep space probe missions. Image transmission and storage applications occur in broadcast television .teleconferencing, transmission of facsimile images for office automation, communication over computer networks, closed circuit television based security monitoring systems and In military communications. In medical applications one is concerned with processing of chest X rays, cineangiograms, projection images of transaxial tomography and other in radiology, nuclear magnetic resonance (NMR) and ultrasonic scanning. In automated video analysis object is detected by using many techniques such as active contour based, dimensional based etc., In real time security system there are many advanced systems available. Those systems are mostly embedded systems and many hardware specifications have to meet the efficient security system. Many surveillance cameras are installed in security sensitive areas such as banks, train stations, highways, and borders. The massive amount of data involved makes it infeasible to guarantee vigilant monitoring by human operators for long periods of time due to monotony and fatigue.

In proposed system this paper the human object is captured, a data base about the pixel values are trained to the system. Video Camera is fitted at the bank where security is needed. Whenever human movement is captured by the camera it is immediately detected and processed to make the alarm to produce sound. Investigation methods for moving object detection, tracking, and event analysis. Consider robustness and computational cost as the major design goals of our work. Our proposed method detects moving objects in required environments under changing illumination conditions and in the presence of background dynamics. Also present a fast implementation of the method using an extension of integral images. DECOLOR performs object detection and background estimation simultaneously with a training sequences. In addition, we propose a fast method to construct an appearance model for object tracking using a particle filtering framework. Segmenting out mobile objects present in frames of a recorded video sequence is a fundamental step for many video based surveillance applications but here live video is analyzed.

2. PROBLEM DEFINITION

Object detection is usually achieved by object detectors or background subtraction. An object detector is often a classifier that scans the image by a sliding window and labels each sub image defined by the window as either object or background. Generally, the classifier is built by offline learning on separate datasets or by online learning initialized with a manually labeled frame at the start of a video. Alternatively, background subtraction compares images with a background model and detects the changes as objects. It usually assumes that no object appears in images when building the background model. Such requirements of training examples for object or background modeling actually limit the applicability of above-mentioned methods in automated video analysis Another category of object detection methods that can avoid training phases are motion-based methods which only use motion information to separate objects from the background. Given a sequence of images in which foreground objects are present and moving differently from the background, can we separate the objects from the background automatically. The goal is to take the image sequence as input and directly output a mask sequence. The most natural way for motion-based object detection is to classify pixels according to motion patterns, which is usually named motion segmentation. These approaches achieve both segmentation and optical flow computation accurately and they can work in the presence of large camera motion. However, they assume rigid motion or smooth motion in respective regions, which is not generally true in practice. In practice, the foreground motion can be very complicated with nonrigid shape changes. Also, the background may be complex, including illumination changes and varying textures such as waving trees and sea waves. The video includes an operating escalator, but it should be regarded as background for human tracking purpose. An alternative motion-based approach is background estimation. Different from background subtraction, it estimates a background model directly from the testing sequence. Generally, it tries to seek temporal intervals inside which the pixel intensity is unchanged and uses image data from such intervals for background estimation. However, this approach also relies on the assumption of static background. Hence, it is difficult to handle the scenarios with complex background or moving cameras.

A novel algorithm is proposed for moving object detection which falls into the category of motion based methods. It solves the challenges mentioned above in a unified framework named Detecting Contiguous Outliers in the LOw-rank Representation (DECOLOR). We assume that the underlying background images are linearly correlated. Thus, the matrix composed of vectorized video frames can be approximated by a low-rank matrix, and the moving objects can be detected as outliers in this low-rank representation. Formulating the problem as outlier detection allows us to get rid of many assumptions on the behavior of foreground. The low-rank representation of background makes it flexible to accommodate the global variations in the background. Moreover, DECOLOR performs object detection and background estimation simultaneously without training sequences. The main contributions can be summarized as follows

A new formulation is proposed in which outlier detection in the low-rank representation in which the outlier support and the low-rank matrix are estimated simultaneously. We establish the link between our model and other relevant models in the framework of Robust Principal Component Analysis (RPCA). Differently from other formulations of RPCA, we model the outlier support explicitly. We demonstrate that, although the energy is nonconvex, DECOLOR achieves better accuracy in terms of both object detection and background estimation compared against the state-of-the-art algorithm of RPCA .

In other models of RPCA, no prior knowledge on the spatial distribution of outliers has been considered. In real videos, the foreground objects usually are small clusters. Thus, contiguous regions should be preferred to be detected. Since the outlier support is modeled explicitly in our formulation, we can naturally incorporate such contiguity prior using Markov Random Fields (MRFs). Use a parametric motion model to compensate for camera motion. The compensation of camera motion is integrated into our unified framework and computed in a batch manner for all frames during segmentation and background estimation. Background subtraction is a widely used for detecting moving objects. The ultimate goal is to"subtract" the background pixels in a scene leaving only the foreground objects of interest. If one has a model of how the background pixels behave the "subtraction" process is very simple Background subtraction usually consists of three attributes besides the basic structure of the background model, background initialization background maintenance (updating the background model to account) and foreground/background pixel classification.

3. SYSTEM IMPLEMENTATION

In the area of moving object detection a technique robust to background dynamics using background subtraction with adaptive pixel-wise background model update is described. A foreground-background pixel classification method using adaptive thresholding is presented. Another technique that is robust to sudden illumination changes using an illumination model and a statistical test is presented. We also propose a fast implementation of the method using an extension of integral images. a novel and simple method for moving object detection. The method is based on background subtraction. The first step, referred to as background model initialization, is to construct a background model using the initial frames. The step is based on temporal frame differencing because the background model is not available at the start of a sequence. A typical example is when a sequence starts with a moving foreground object, part of the background model will be covered and hence the background model will not be available. Once the initial background model is constructed, with each subsequent frame, we detect if there is any sudden illumination change. If there is no illumination change, simple background subtraction can be used to find the foreground pixels. The threshold used for this process is determined adaptively according to the current frame. After thresholding the difference of the pixel intensities between the background model and the current frame, a foreground object mask is generated. In the presence of sudden illumination change, we use the illumination effect, which is expressed as a ratio of pixel intensities. We determine if the pixel is a foreground or background pixel by the statistics of the illumination effect of its neighboring pixels. A foreground object mask is generated according to this statistic. The process of obtaining the foreground mask is referred to as foreground-background pixel classification. After obtaining the foreground object mask, the background model should be updated because the scene dynamics are always evolving. We propose a technique that updates the background model according to two factors: how long a pixel has been a background pixel, and how large the value of the pixel is in the difference frame. The first challenge is that it is not a convex problem, because of the no convexity of the low rank constraint and the group sparsity constraint. Furthermore, we also need to simultaneously recover matrix B and F, which is generally a Chicken-and-Egg problem. In our framework, alternating optimization and greedy methods are employed to solve this problem.

The first focus on the fixed rank problem (i.e., rank equals to 3), and then will discuss how to deal with the more general constraint of rank ≤ 3. 4 is divided into two sub problems with unknown B or F, and solved by using two steps iteratively: To initialize this optimization framework, we simply choose Binit = φ, and Finit = 0. Greedy methods are used to solve both sub problems. Then the αk rows with largest values are preserved, while the rest rows are set to zero. This is the estimated F in the first step. In the second step, φ is computed as per newly-updated F.. Singular value decomposition (SVD) is applied on φ. Then three eigenvectors with largest eigenvalues are used to reconstruct B. Two steps are alternatively employed until a stable solution of ˆB is found. The greedy method of solving Eq. 5 discovers exact αk number of foreground trajectories, which may not be the real foreground number. On the contrary, B can be always well estimated, since a subset of unknown number of background trajectories is able to have a good estimation of background subspace. Since the whole framework is based on greedy algorithms, it does not guarantee a global minimum. In our experiments, however, it is able to generate reliable and stable results. The above-mentioned method solves the fixed rank problem, but the rank value in the background problem usually cannot be pre-determined. To handle this undetermined rank issue, we propose a multiple rank iteration method. Then the fixed rank optimization procedure is performed on each specific rank starting from 1 to 3. The output of the current fixed rank procedure is fed to the next rank as its initialization. We obtain the final result B(3) and F(3) in the rank-3 iteration. Given a data matrix of K × 2L with K trajectories over L frames, the major calculation is O(KL2) for SVD on each iteration. Convergence of each fixed rank problem is achieved iterations on average. The overall time complexity is O(KL2). To explain why our framework works for the general rank problem, we discuss two examples. First, if the rank of B is 3 (i.e., moving cameras), then this framework discovers an optimal solution in the third iteration, i.e., using rank-3 model. The reason is that the first two iterations, i.e. the rank-1 and rank-2 models, cannot find the correct solution as they are using the wrong rank constraints. Second, if the rank of the matrix is 2 (i.e., stationary cameras), then this framework obtains stable solution in the second iteration. This solution will not be affected in the rank-3 iteration. The reason is that the greedy method is used. When selecting the eigenvectors with three largest eigenvalues, one of them is simply flat zero. Thus B does not change, and the solution is the same in this iteration. Note that low rank problems can also be solved using convex relaxation on the constraint problem [2]. However, our greedy method on unconstrained problem is better than convex relaxation in this application. Convex relaxation is not able to make use of the specific rank value constraint (≤ 3 in our case). The convex relaxation uses λ to implicitly constrain the rank level, which is hard to constrain a matrix to be lower than a specific rank value. First demonstrate that our approach handles both stationary cameras and moving cameras automatically in a unified framework, by using the General Rank constraint (GR) instead of the Fixed Rank constraint (FR). Here use two videos to show the difference. One is “VHand” from a moving camera (rank(B) = 3), and the other is “truck” captured by stationary camera (rank(B) = 2). The use distribution of L2 norms of estimated foreground trajectories to show how well background and foreground is separated in our model. For a good separation result, F should be well estimated. Thus large for foreground trajectories and small for background ones. In other words, it distribution has an obvious difference between the foreground region and the background region. The FR model also finds a good solution, since rank-3 perfectly fits the FR model. However, the FR constraint fails when the rank of B is 2, where the distribution of between B and F are mixed together. On the other hand, GR−2 can handle this well, since the data perfectly fits the constraint. On GR−3 stage, it uses the result from GR−2 as the initialization, thus the result on GR−3 still holds. The figure shows that the distribution of _ ˆ Fi_2 from the two parts has been clearly separated in the third column of the bottom row. This experiment demonstrates that the GR model can handle more situations than the FR model. Since in real applications it is hard to know the specific rank value in advance, the GR model provides a more flexible way to find the right solution. The algorithm is implemented in MATLAB. All experiments are run on a desktop PC with a 3.4 GHz Intel i7 CPU and 3 GB RAM. Since the graph cut is operated for each frame separately, as discussed in Section 3.3.2, the dominant cost comes from the computation of SVD in each iteration. The CPU times of DECOLOR for sequences in Figs are 26.2,13.3, 14.1, 11.4, and 14.4 seconds, while those of PCP are26.8, 38.0, 15.7, 39.1, and 21.9 seconds, respectively. All results are obtained with a convergence precision of 10_4.The memory costs of DECOLOR and PCP are almost the same since both of them need to compute SVD. The peak values of memory used in DECOLOR for sequences in Figures are around 65 MB and 210 MB, respectively.

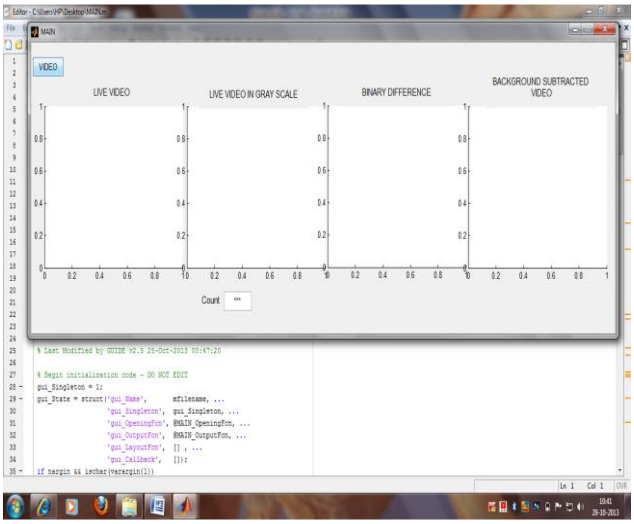

Fig -1: Input

The output window will be generated when we run the program the output will be as shown below. Here we have to click upon the VIDEO button. This is shown in the Figure 1. When we click the video button the image is captured and the count value starts to generate, that is number of person inside. This is shown in the Figure 2. Whenever the human object is appeared it is detected and counted by using the algorithm. The result can be viewed as shown in the Figure 3.

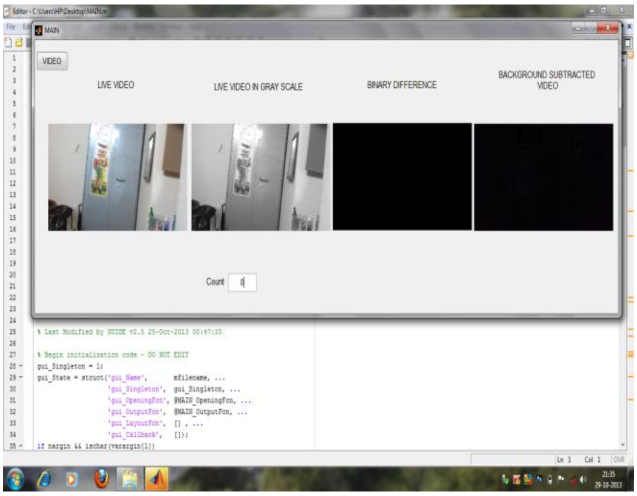

Fig -2: The output no human detected

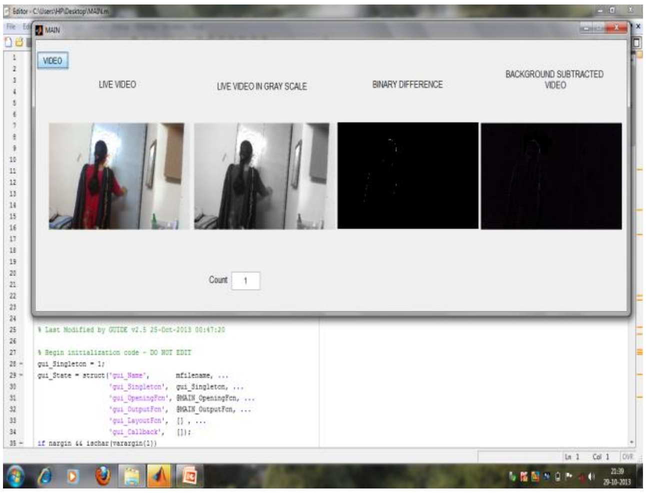

Fig -3: The output human is detected

4. CONCLUSIONS

The proposed method improves the efficiency and reduces cost and time consumption in the security system. Specially to implement in the banks , jewellery shops etc., with the use of DECOLOR technique, background subtraction technique, here object is detected in an efficient manner and comparing to the existing system the number of frames processed per second is improved.

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