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Research Article

REAL TIME SECURITY USING DECOLOR METHOD FOR MOVING OBJECT DETECTION

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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. Proposed method going to achieve 10 frames/sec. For this process the Digital Image Processing tool in MATLAB 7.12(R2011A) software is used.

Keywords: DECOLOR Detecting contiguous Outliers in the Low Rank Representation, RPCA Robust Principal Component Analysis.

INTRODUCTION

The background subtraction is performed on an image sequence taken with a static camera. Since there is no significant camera motion between consecutive frames in an image sequence, it is reasonable to assume that the same small area of the scene is always observed by the same sensor in the camera. Therefore each pixel in a video sequence consistently represents the same part of the scene. Once a moving object passes through the scene the values of pixels that correspond to the parts of the scene occluded by the moving object will change. Indeed the simplest way to detect changes in the scene described in is to compare pixel values of two adjacent frames in the video sequence and mark the pixels whose difference is greater than some predefined threshold as foreground. Although simple and fast, this approach does not retain any history about the scene and only edges of moving objects are detected as objects rarely move fast enough to cover entirely new area of the scene in the next frame[3] DECOLOR performs object detection and background estimation simultaneously without training sequences. We propose a new formulation of 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)[4]. Differently from other formulations of RPCA, we model the outlier support explicitly. DECOLOR can be interpreted as '0-penalty regularized RPCA, which is a more faithful model for the problem of moving object segmentation. Following the novel formulation, an effective and efficient algorithm is developed to solve the problem. 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[1,4]

Background Subtraction

Background subtraction must be rbust against illumination. It should avoid non stationary background objects. Background adaptation techniques could also be categorized as: 1) Non-recursive and 2) Recursive. A non-recursive technique estimates the background based on a sliding-window approach. The L observed video frames are stored in a buffer, considering the existing pixel variations in the buffer the background image will be estimated. Since in practice the buffer size is fixed as time passes and more video frames come along the initial frames of the buffer are discarded which makes these techniques adaptive to scene changes depending on their buffer size. However, in the case of adapting to slow moving objects or coping with transient stops of certain objects in the scene the non-recursive techniques require large amount of memory for storing the appropriate buffer. With a fixed buffer size this problem can partially be solved by reducing the frame rate as they are stored.[5]

The recursive techniques instead of maintaining a buffer to estimate the background they try to update the background model recursively using either a single or multiple model(s) as each input frame is observed. Therefore, even the very first input frames are capable to leave an effect on new input video frames which makes the algorithm adapt with periodical motions such as flickering, shaking leaves, etc. Recursive methods need less storage in comparison with non-recursive methods but possible errors stay visible for longer time in the background model. The majority of schemes use exponential weighting or forgetting factors to determine the proportion of contribution of past observations.[6,5]

Computation

Computational cost is one of the most notable shortcomings. Also, it has serious challenges when the training sequences are disturbed by the presence of foreground objects and takes quite long for algorithm to estimate the real background[7].Background model updating process can be performed in two different ways; either by selective updating or blind updating. In the former technique, the observed sample from the input frame is added to the model if and only if it belongs to the estimated background. However, in the latter one, simply every new sample is added regardlessof its assigned category[8]. Both of these approaches have their advantages and disadvantages[6].

The selective updating method raises the ability of algorithm in detecting the foreground objects more accurately, due to the fact that object related pixels are excluded from the updating procedure. However in the case of any wrong decisions, it will lead to persistent errors in future decisions. This undesired situation in the literature is referred to as the deadlock situation.The blind updating approach is not affected by such a problem because it does not differentiate between samples as it updates the background model however this will result in poor detection of the targets (more false negatives). This problem can partially be solved by including less proportion of foreground-object related pixels through increasing the time window of sampling process. When the time window is made wider, the adaptation process will be slowed down and therefore more false positives will be visible in foreground representation.

Formulation

Given a sequence D, our objective is to estimate the foreground support S as well as the underlying background images B. To make the problem well posed, we have the following models to describe the foreground, the background, and the formation of observed signal. Background model. The background intensity should be unchanged over the sequence except for variations arising from illumination change or periodical motion of dynamic textures. Thus, background images are linearly correlated with each other, forming a low-rank matrix B. Besides the low-rank property, we don’t make any additional assumption on the background scene. Thus, we only impose the following constraint on B:

$$\mathrm{rank}(B) \leq K$$

where K is a constant to be predefined. Intrinsically, K constrains the complexity of the background model. Foreground model. The foreground is defined as any object that moves differently from the background. Foreground motion gives intensity changes that cannot be fitted into the low-rank model of background. Thus, they can be detected as outliers in the low-rank representation. Generally, we have a prior that foreground objects should be contiguous pieces with relatively small size[1].

Foreground segmentation

The detection of body parts in images inevitably leads to many false positives. Applying the kinematic constraints between body parts effectively handles parts of this problem but we still want to allow rather arbitrary poses that occur in real-life video and which are often important poses when recognizing the actions of people; this could for example be a person falling to the ground or jumping back to avoid a passing car. To increase the precision of the pose estimation we therefore apply a foreground segmentation to reduce the search space for body parts. In[4] the search space is reduced in two steps by applying a HOG-based upper-body detector and next doing a soft segmentation of body parts within the upper-body detections. However, doing detection of individual persons is prone to errors when people are interacting closely, e.g., when hugging. We therefore take a different approach and reduce the search space by background subtraction. In this way we reduce the search space to foreground regions and the overall scale of a person at the same time. Including all foreground regions in the search space also allows us to search for body parts that are occluded by other foreground object.

Background subtraction requires a static camera and is therefore not applicable in all scenarios, but the majority of cameras that are observing people are static cameras (typically surveillance cameras). This means that the use of efficient background subtraction is not a limiting factor for a great number of real-life application. To be robust in handling both foreground camouage and shadows. This is achieved by separating intensity and chromaticity in the background model. Moreover, the background model is multi-modal and multi-layered which allows it to model moving backgrounds such as tree branches and objects that become part of the background after staying stationary for a period of time. To maintain good background subtraction quality over time it is essential to update the background model and describes two different update mechanisms to handle rapid and gradual changes respectively. By using this robust background subtraction method we achieve good segmentation results in real-life outdoor scenes.

Block diagram

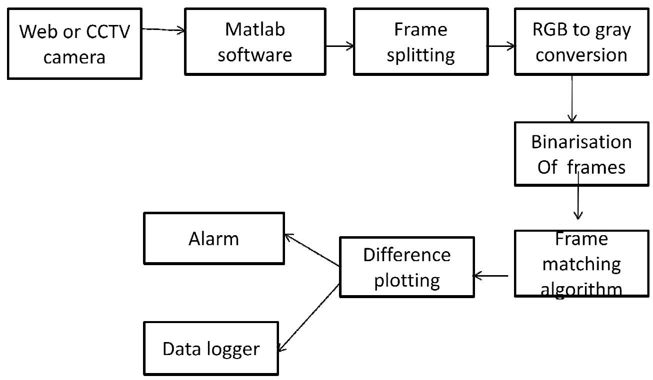

Figure 1: Block diagram of the proposed method

The proposed method block diagram is shown in the above fig 1.It consists of 8 differential blocks. First it captures the video from the camera, the video that is processed using MATLAB software. After that frame splitting, background subtraction, RGB to gray conversion, binarisation of frames, frame matching, difference plotting are done. When the difference is detected alarm made to be alerted and the data are entered to the data logger.

The ouput will be like Fig.2 with alert sound,

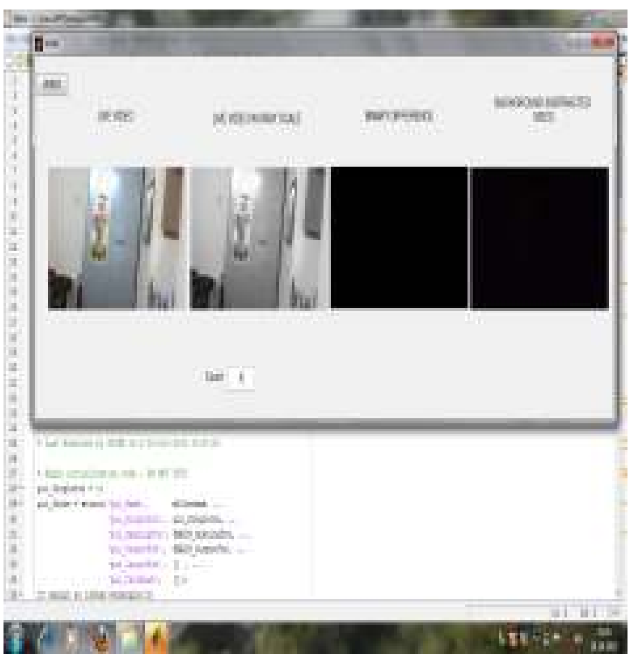

Figure 2: Output Window

DECOLOR

DECOLOR on several real sequences selected from public datasets of background subtraction is tested by[1]. Since we aim to evaluate the ability of algorithms in detecting moving objects at the start of videos, we focus on short clips composed of beginning frames of videos. All examples in Fig. 6 have only 24 or 48 frames, corresponding to 1 or 2 seconds for a frame rate of 24 fps. We compare DECOLOR with three methods that are simple in implementation but effective in practice. The first one is PCP, which is the state-of-the-art algorithm for RPCA. The second method is median filtration, a baseline method for unimodal background modeling. The median intensity value around each pixel is computed, forming a background image. Then, each frame is subtracted by the background image and the difference is thresholded to generate a foreground mask[10]

The advantage of using median rather than mean is that it is a more robust estimator to avoid blending pixel values, which is more proper for background estimation[11] .The third method is mixture of Gaussians[12].It is popularly used for multimodal background modeling and has proven to be very competitive compared with other more sophisticated techniques for background subtraction [13,14].The objects are large and always presented in all frames, DECOLOR recovers the background and outputs a foreground mask accurately. Notice that the results are direct outputs of Algorithm 1 without any postprocessing. The results of PCP are relatively unsatisfactory. Ghosts of the foregroud remain in the recovered background. This is because the ‘1-penalty used in PCP is not robust enough to remove the influence of contiguous occlusion. Such corruption of extracted background will result in false detection.. Moreover, without the smoothness constraint, occasional light changes (e.g., near the boundary of fluorescent lamps) or video noises give rise to small pieces of falsely detected regions. The results of median filtration depend on how long each pixel is taken by foreground.

Our 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. The dominant cost comes from the computation of SVD in each iteration. The CPU times of DECOLOR for sequences 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 Figs are around 65 MB and 210 MB, respectively1.

CONCLUSION

This method can be effectively implemented in banks and jewellery shops, where there should be needed high protection during night time and snapshots of moving object detection can be mailed. Now alert sound can be implemented, in future call to respective authorities and police station can be analysed and implemented.

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