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Moving Object Detection under Various Illumination Conditions for PTZ Cameras

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Abstract

Video surveillance has become an increasing research field now a day. The fundamental step in video surveillance is the Moving object detection. Most of the works focused on background modeling in PTZ camera but still lacking under different positions and various illumination conditions. While the camera is on pan and sudden zoom, the pixel intensity of each position may vary and it cannot adapt the motions when the target is faraway or closer. This issues cause major problem in Background Modeling (BM). **Objectives:** To solve this problem a texture based method adapted to handle grey-scale variation, rotation variation and various illumination conditions of the moving objects. **Methodology/Analysis:** Modified version of LBP, that combines the advantages of LBP and SIFT descriptor known as eXtended Centre Symmetric Local Binary Patterns XCS-LBP. Finally GMM (Gaussian Mixture Model) is used for segmenting the foreground Extraction by the XCS-LBP descriptor with similarity measure. **Findings:** Experimental result shows that the proposed method is robust to obtain foreground extraction with outstanding performance under various lighting conditions. **Applications/Improvements:** In this paper, proposed method can be used in variety of applications such as detection of objects under some climatic conditions like fog, smoke, dew, snow falling areas. Further improvements are made to remove shadows.

Keywords: Background Modeling, PTZ Camera, Segmentation

1. Introduction

Recently, Pan/Tilt/Zoom (PTZ) camera-based system has great attention due to its flexible changes to point the target over the Field Of View (FOV) and offers more information even at long distance. Nevertheless, most proposed work related to fixed cameras. But those algorithms will not work out in PTZ camera environment due to scene change.

Background Subtraction (BS) is a fundamental task in video surveillance applications.

Enormous numbers of background subtraction method deal with fixed cameras have been presented[1,5-12]. However, there is very less work for PTZ camera-based background modeling. The following difficulties are addressed for PTZ cameras, camera movement to point out the target even in rotation, wide field have various lighting changes. In addition, when a PTZ camera zooms in/out, it has parallax effects.

PTZ background modeling has been made with certain advancement[13–16]. Still, there are difficult issues in the literature addressed in detail. Most of the literature focused on background modeling in PTZ camera but still lacking under different position and various illumination conditions. These issues motivate us to give a solution to overcome the various illumination conditions in the moving objects.

In this paper, Modified version of LBP, that combines the advantages of LBP and SIFT descriptor known as eXtended Centre Symmetric Local Binary Patterns XCS-LBP. Finally GMM (Gaussian Mixture Model) is used for segmenting the foreground Extraction by the XCS-LBP descriptor with similarity measure. By this combination, an effective background modeling algorithm can be developed over fixed cameras.

The majority of the review illustrates BS that needs to face several challenging situations such as illumination

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changes, dynamic backgrounds, bad weather, camera jitter, noise and shadows. Several feature extraction methods have been developed to cope with these situations. Color based features are the mostly used, but there are numerous limitations when illumination changes, shadows and camouflage occurrences are present. A mixture of local texture descriptors recently have attracted great attention especially the Local Binary Pattern for background modeling, because of its simple and fast to compute.

1.1 The Literature Survey for PTZ Camera Surveillance is Listed From (2005-2015)

- Frame to Frame correspondence methods [13-17]: To create frame registration. This method can obtain aligned warp frames by the correspondence matched frames. But the registration may be corrupted by moving objects. Furthermore, lack of global scene information leads the segmentation intractable. This method cannot hold the variation of PTZ movements.
- Frame-to-global methods [18-19]: Make use of stitched panorama to give the global spatial foreground detection information. This method has issues like, e.g., serious frame distortion. For constructing the panoramic frame, method has an assumption that there is no major motion parallax. But it is difficult to hold this assumption in some dynamic scenario. With the small number of corresponding matched features, it is complex to build the registration frames. In addition, steps involved are very challenging and expensive for a panoramic frame.

  Recently[2], PTZ based Hierarchical Background Modeling involves with frame registration, thus it can able to handle the above issues and to detect moving foreground objects through the partition of the broad scene at every layer, when camera rotates into a small number of limited scenes by few overlaps. But, it does not work on the dynamic conditions and under sudden illumination.
- The optical flow clustering[20-22]: Computes dense or sparse optical flows as well as gather them to categorize moving object. Still, the method fails for real time scenarios.
- Neural-based background subtraction[23]: This method able to segment moving objects from the background modeling automatically by adapting the background scene changes in a self-organizing method. Background disparities mostly arise because of slow illumination variation, waving trees, otherwise shadows cast by moving objects.

Most of the extensive survey describes the BM techniques for PTZ camera as well as to segment moving objects via PGMM, Automatic self organizing BS, etc. Even though it can segment the moving objects with different position and location but lacks under dynamic variation of sudden illumination. Color features are the extensively employed but have several restrictions when illumination changes, shadows and camouflage occurrences are present.

A key idea to solve these issues is a variety of local texture descriptors for background modeling, especially the Local Binary Pattern (LBP) because of its simple and fast computation. Texture is a significant prompt permit person to differentiate objects. Since the brain capable to translate vital disparity information at scales slighter than that of the perspective object and it can able to gives complete descriptions of approaches to analyze binary and grey texture frames. Though, the original LBP descriptor in[24] is not able to design BM due to its sensitive noise, a small change in the middle value will lead false detection rate. A large number of local texture descriptors based on LBP[25] have been proposed a robust background modeling under illumination conditions. Most of them are regrettably either very time-consuming or produce a long feature histogram[26,27]. The variant by introducing a new neighboring pixels comparison strategy that allows the descriptor to be less sensitive to noisy pixels and to give a short histogram, while maintaining robustness to illumination changes and slightly gaining in time consumption when compared to its direct competitors.

Key idea came from this[28] and[5,29] is to solve the issue in the control of illumination changes as well as shadows associated with the moving objects.

In this paper, Modified version of LBP, that combines the advantages of LBP and SIFT descriptor known as eXtended Centre Symmetric Local Binary Patterns XCS-LBP. Finally GMM (Gaussian Mixture Model) is used for segmenting the foreground Extraction by the XCS-LBP descriptor with similarity measure. By this combination, an effective background modeling algorithm can be developed over fixed cameras. An experimental result shows that the proposed method can segment moving objects with efficient performance under a variety of illumination change scenario.

2. Methodology

This paper, aims to propose a background modeling in PTZ cameras under various illumination conditions that performs background modeling followed by segmentation. Figure 1 gives the flow of the methodology.

Here, a PTZ video can be taken as an input. This input video can be converted into a sequence of frames. The interested regions from these frames are detected. The features of the interested region are extracted using XCS-LBP. Then these features are weighted, normalized and fed for the detection of foreground/background using GMM.

2.1 Interest Region Detection

The fundamental step in video surveillance is Moving object detection. There are many detectors that are used for detecting the interested regions like bob, corners and scale invariant like structures. Here the Hessian-Affine is used to detect the interest regions. As a preprocessing step, hessian affine detector is used that depends on particular, feature interest key points. A multiple scale iterative algorithm is also used by hessian affine to spatially localize as well as to choose scale and affine invariant key points. Though, at every individual level, the interest points are selected by Hessian detector derived from the Hessian matrix.

$$H(x)=\begin{bmatrix} L_{xx}(X) & L_{xy}(X) \\ L_{xy}(X) & L_{yy}(X) \end{bmatrix} \quad (1)$$

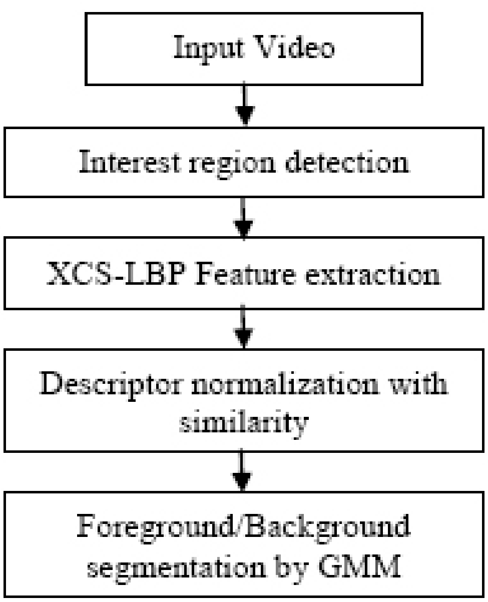


Figure 1. Overall flow diagram.

Where the partial derivates in their directions

$L_x(X)$ be the x direction,

$L_y(X)$ be the y direction,

$L_y(X)$ be the x and y direction.

2.2 XCS-LBP Feature Extraction

Usually the process of feature extraction is carried out using Local Binary Pattern descriptor introduced[22] which is simple and fast to compute. Here it compares the differentiation between the ranges of middle pixel as well as its adjacent pixels. Also it produces longer histograms. To address the problem, the modified LBP is introduced by Heikila et al.[26] for feature extraction called as CS-LBP. It compares difference between the pair of center symmetric pixels. But still there remains long histogram. So this paper introduces an extended version of CS-LBP called as eXtended Center Symmetric Local Binary Patterns. Here it compares the pairs of center symmetric pixels and considers the center pixel too. This method gives shorter histograms and more robust under various illuminations.

The XCS-LBP (eXtended CS-LBP) is denoted by[27]:

$$XCS-LBP_{P:R(C)}=\sum_{i=0}^{\frac{p}{2}-1} s\left(g_1(i,c)+g_2(i,c)\right)2^i \quad (2)$$

where the threshold function s, is used to determine the types of local pattern transition and is defined as a characteristic function:

$$s(x_1+x_2)=\begin{cases} 1 & f\ (x_1+x_2)\geq 0 \\ 0 & otherwise \end{cases} \quad (3)$$

and where $g_1(i,c)$ and $g_2(i,c)$ are defined by:

$$\begin{cases} g_1(i,c)=\left(g_i-g_{i+\left(\frac{p}{2}\right)}\right)+g_c \\ g_2(i,c)=(g_i-g_c)\left(g_{i+\left(\frac{p}{2}\right)}-g_c\right) \end{cases} \quad (4)$$

Extracted features for the given input using the XCS-LBP operator. The 3 parameters in this operator: radius as R, N-Number of adjacent pixels, in addition to Threshold on the gray level dissimilarity as T. Our experimental results have illustrated that outstanding values for these parameters for R is {1, 2}, for N is {6, 8}, and for T is {0, ..., 0.05}.

2.3 Descriptor Normalization with Similarity Measure

To build a descriptor, the input area should be separated into cells within the location grid. There are many grids like Cartesian, log polar, etc. Of these Cartesian grid gives the better performance[26]. In this paper 3x3(9 cells) otherwise 4x4 (16 cells) Cartesian grids. For every cell an XCS-LBP is constructed. Therefore, the resulting descriptor is a 3-D histogram of XCS-LBP feature locations and its values. Suddenly variations causes the feature to move as one cell to another, in order to refuse boundary effects in the descriptor, bilinear interpolation of x and y magnitudes, and their weight of the feature among the 4 adjacent cells are assigned. Thus the allocation of every cell is determined by the bilinear interpolation weights.

Finally, the descriptor is constructed by the histograms of the feature calculated for the every cell to form an $M \times M \times 2^{N/2}$ dimensional vector, where the sizes of the grid are M and N and CS-LBP area. For (M = 3, N = 6), (M = 3, N = 8), (M = 4, N = 6), and (M = 4, N = 8) the lengths of the XCS-LBP descriptors like 72, 144, 128, and 256. Then the descriptor is normalizing to unit length. The manipulation of very huge descriptors is reduce by T (thresholding) every element. Sharing of features has better importance than single large values. After setting/testing the threshold to 0.5 to 1 which is precisely the same value as used in the SIFT algorithm. At last, the descriptor is re-regularizes to unit length.

Then the similarity measures are taken for that descriptor to detect the target accurately. Amongst the variety of similarity measure, the Euclidean distance/Sum-of-Squared-Differences (SSD) as well as the Sum-of-Absolute Differences (SAD) are more helpfu[1]. The finest results connected to the quality of motion predicted frame have been attaining using the SSD as well as SAD.

This helps to get more exact target motion segmentation and to create background modeling without false positives. And also can able to hope up with sudden illumination conditions.

2.4 Foreground/Background Extraction using GMM

The constructed background model is fed to the segmentation. Stauffer and Grimson[5] suggest modeling the values of a pixel in a frame as a Mixture of Gaussians (MoG) for segmentation. Assuming a pixel to be context, and MoG contains its pixel value with adequate and reliable proof. The probability of detecting a moving pixel value I_p^t at scale change of t given below for pixel p.

$$P\left(I_p^t\right) = \sum_{k=1}^{K} w_t^k \eta\left(I_p^t, \mu_k^t, \Sigma_k^t\right) \tag{5}$$

where the number of distributions is K.

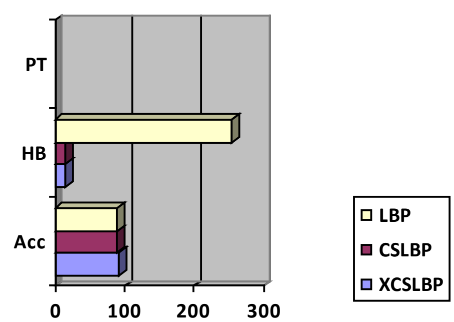
$$\eta\left(I_p^t, \mu_k^t, \Sigma_k^t\right) = \frac{1}{(2\Pi)^{\frac{n}{2}} \left|\Sigma_k^t\right|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}\left(I_p^t - \mu_k^t\right)^T \left(I_p^t - \mu_k^t\right)\right) \tag{6}$$

The mean as well as covariance matrix of the k^{th} Mixture of Gaussian at time t, correspondingly. Each pixel has its sum of K different Gaussian distributions. Handling illumination variations, recent pixel values from the succeeding frames are familiar to adjust the mixture model, to provide a major component of the model. First B distribution is taken as background otherwise its foreground.

3. Results and Discussion

The proposed method is simulated using MATLAB 2013b software on Windows 8.1. Various standard databases captured from PTZ cameras are collected using various websites, papers[21,29]. The proposed segmentation is done efficiently by XCS-LBP of texture features for BM with similarity measure and foreground/background extraction by GMM in videos.

In this paper, proposed method designed for every pixel an unchanging circular region area and calculates a N number of binary length pattern, where every ordered pattern value is 1 if the difference among the



	Acc	HB	PT
LBP	90	255	0.5ms
CSLBP	89	16	0.08ms
XCSLBP	92	16	0.05ms

Figure 2. Performance analysis.

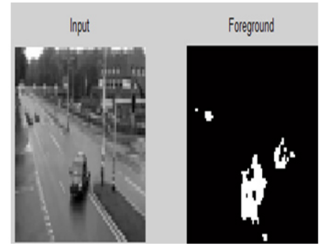
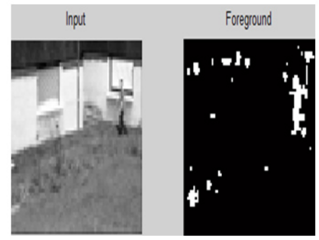
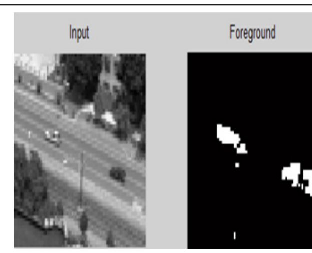
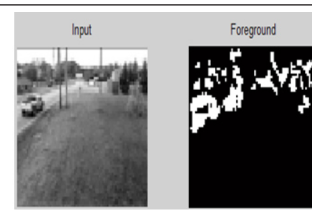
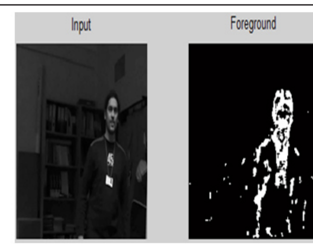
Datasets	Input image	Segmented output
Two position PTZ camera (Frame 19)		
Zoom in Zoom out (Frame 06)		
Intermittent Pan (Frame 08)		
Continuous Pan (Frame 14)		
Sudden illumination (Frame 18)		
Sudden illumination (Frame 57)		

Figure 3. Background modeling of different scenes under different conditions using XCS-LBP and segmented using GMM.

central point and a specific pixel in the circle is larger than a T. These patterns are calculated for every adjacent pixel lying in the circular region. Then the histogram of binary patterns is estimated. Hence the process consequently done for each and every frame and then to similarity measure among the histograms is estimated for every pixel. Finally, GMM is used to segment the foreground.

First, the results of moving object detection on frames of 6 different scenes from different video sequences are presented and shown in Figure 3. The background modeling is achieved using XCSLBP. The proposed descriptors are experimented on real outdoor video scenes. Each video sequence offers different challenging situation of real world like moving trees, casted shadows, and presence of the nonstop car flow close to the surveillance region, climatic circumstances (sunny, rainy, snowy conditions), quick light variation and the occurrence of large size objects. The proposed descriptor overcomes these situations and gives best result. From these results the descriptor obviously appears to be less sensitive to the background subtraction method. The segmentation process is carried out using GMM as shown in Figure 3. Figure 2 Illustrates the XCS LBP performed well compared to other algorithms. Enhanced Segmentation output of sudden illuminations has proved by its Accuracy (Acc) and less no. of Histogram Bins (HB). By its estimation the Performance Time (PT) is reduced for the PTZ camera.

4. Conclusion

In this Paper, proposed an method for the various illumination circumstances with the moving objects in PTZ camera environment, So far, few researches have been done on the issue of sudden illumination, but if the camera is continuously panned or excessively zoomed in or zoomed out, the problem is not handled in those researches in PTZ environment. This paper overcomes such problems by the proposed method of XCS-LBP of texture features with similarity measure obtained with less histograms bins under the sudden illuminations in both indoor as well as outdoor situations. Finally the better accurate results are obtained for segmentation through the GMM. Further, shadow in complex scenes have to be considered.

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