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Dynamic Background Modeling and Subtraction using Modified Space and time Local Binary Pattern

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Abstract: Conventional background modeling and subtraction techniques have a hypothesis that the views are not of dynamic edifices with restricted disorder. These procedures will perform inadequately in dynamic scenes. In this paper, we present a resolution to this difficulty. We first extend the local binary patterns from the space domain to the spatiotemporal domain and give a distinct dynamic texture extraction operator, named modified spatiotemporal local binary patterns (Modified Space and Time Local Binary Pattern). We present an innovative and practical method for dynamic background modeling and subtraction using Modified Space and Time Local Binary Pattern. In this proposed method, each pixel is represented as a group of Space and Time Local Binary Pattern to dynamic texture histograms which connect spatial texture and temporal motion knowledge together. The histograms collected are processed to get normalized histogram which is the inadequacy of existing Space and time local binary pattern method. Compared with traditional methods, empirical results show that this method accommodates swiftly to the changes in the dynamic background. It gets correct detection of moving objects and succeeds most of the false detections for dynamic changes of natural scenes.

Keywords: Background, Dynamic, Texture, Histogram, Binary pattern

I. INTRODUCTION

In various video monitoring systems, recognising moving objects from a video series captured by a static camera is one of the basic duties. A simple approach for this job is background modeling and subtraction, which first produces an adaptive statistical background model, and then distinct pixels that are unlikely to be produced by this model are marked as foreground. It is always competent to get very big precision in the detection of moving objects with the moderate possible false detection rate. The performance of background subtraction depends essentially on the background modeling technique used. In the method discussed in [1], LBP for the current frame and previous frame is analysed and corresponding histograms are built. But the problem with this method is only histograms are not adequate for texture extraction from the dynamic background. It might detect some false knowledge. Also, only 2 histograms are built one for the current frame and another for the previous frame so it might not get the result we expect from the video. The informal background model reflects that intensity numbers of a pixel can be reduced by a single Gaussian distribution [2]. In [3], the mixture of Gaussians method was analysed to model the background. Although, these models based on Gaussian distributions don't fit in dynamic scenes since they are based on the prediction that the scenes to be modelled are of static behaviour with poor perturbation. When the prophecy is not proper, for e.g., in a dynamic natural scene which consist of duplicate movements like waving trees, window cluttering, flowing water etc, they can't precisely model the background with just a few Gaussians distributions and they may fall short to provide accurate detection [4]. Pixel-based methods mentioned [5] earlier consider that the time series of study is free on each pixel which is a difficult plan and limit their application in the dynamic background. In contrast, region-based techniques have been proposed in. The texture-based technique [6] was used in, and it modelled the background with a group of histograms based on local binary patterns. This method, to a particular extent, can evade labelling some dynamic background pixels as foreground since it extorts region texture characteristics. However, its detection routine will pointedly refuse when scenes have well-built changes. In this paper, we first extend ordinary local binary patterns from the spatial domain to spatiotemporal domain and propose a new dynamic texture extraction operator, named modified spatiotemporal local binary patterns (Space And Time Local Binary Pattern) with processed and normalised histograms. We then present a new method of dynamic background modeling and subtraction using modified Space and Time Local Binary Pattern which combine spatial texture and temporal motion information together of the current frame and then last two frames prior to the current frame. (i.e. frame at time t,t-1,t-2) Experimental results indicate that the proposed method can adapt quickly to changes in the dynamic background. Compared to the work proposed in [3] [7], it achieves more accurate detection of moving objects and suppresses most of the false detections for dynamic changes of nature scenes.

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II. LBP APPROACH

A. Ordinary Local Binary Patterns

Local Binary Pattern (LBP) is very easy yet very well-organized texture operator in which the pixels of an image by thresholding the quarter of every pixel and believes that the result as a binary sequence. Due to its discriminative capability and analytical integrity, the LBP texture operator has to turn out to be a popular approach in diverse applications. It can be seen as a distinguished method to the traditionally divergent statistical and basic models of texture analysis. Reasonably the most vital feature of the LBP operator in real-world applications is its fault tolerance to monotonic grey-scale distortions caused, for e.g., by lighting variations. One more indispensable feature is its mathematical simplicity, which makes it possible to examine images in tricky real-time environments.

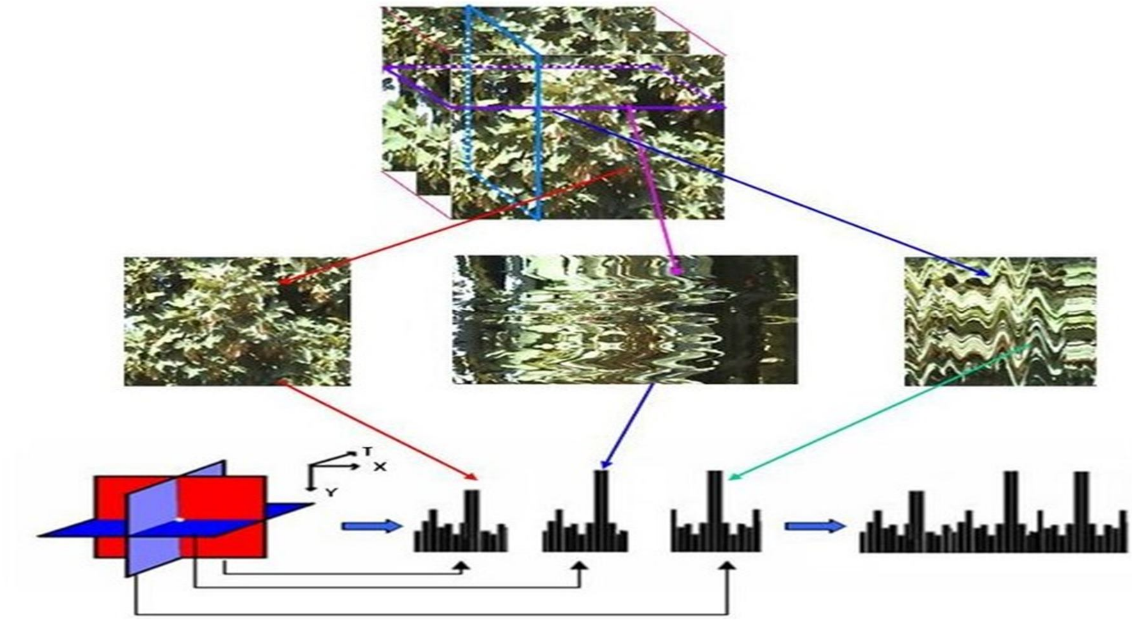

Figure 1 Local Binary Pattern and Histogram Construction

III.MODIFIED SPACE AND TIME LOCAL BINARY PATTERN APPROACH

A. Steps in Modified Space And Time Local Binary Pattern Method [1]

1) Let f_t is the current frame at time t, f_{t-1} be the previous frame at time t – 1 and f_{t-2} is the 2nd previous frame
2) Assume frame ft and central pixel is (x_t,c, y_t,c) with grey value $g_{t,c}$.
3) Consider P evenly spaced neighbouring pixel S($x_{t,0}$, $y_{t,0}$), . . . , ($x_{t,P-1}$ $y_{t,P-1}$) with grey values $g_{t,0}$, . . . , $g_{t,P-1}$ on a circle of radius RLBP in f_t are defined to be the spatial neighbouring pixels of ($x_{t,c}$, $y_{t,c}$).
4) In the f_{t-1}, the equivalent position pixels of P spatial neighbouring pixels is ($x_{t,-1,0}$, $y_{t-1,0}$), . . . , ($x_{t,-1,P-1}$, $y_{t-1,P-1}$) which are defined to be the P temporal neighbouring pixels of ($x_{t,c}$, $y_{t,c}$) with grey values g_t-1,0, . . . , $g_{t-1,P-1}$.
5) In the f_{t-2}, the equivalent position pixels of P spatial neighbouring pixels is ($x_{t,-2,0}$, $y_{t-2,0}$), . . . , ($x_{t,-2,P-1}$, $y_{t-2,P-1}$) which are defined to be the P temporal neighbouring pixels of ($x_{t,c}$, $y_{t,c}$) with grey values g_{t-2},0, . . . , $g_{t-2,P-1}$.
6) The middle pixel and its spatial and temporal neighbouring pixels are presented in Fig. 2. Using these neighbouring grey values, we can find two P-bit LBP codes for central pixel ($x_{t,c}$, $y_{t,c}$) as follows:

B. LBP at Time t[1]

$$LBP^{t}_{P,R}(x_{t,c},y_{t,c}) = \sum_{P=0}^{P-1} S(g_{t,P} - g_{t,c})2^{P}$$ ………. [1]

C. LBP at Time t-1[1]

$$LBP^{t-1}_{P,R}(x_{t,c},y_{t,c}) = \sum_{P=0}^{P-1} S(g_{t-1,P} - g_{t,c})2^{P}$$ …….. [2]

D. LBP at Time t-2

$$LBP^{t-2}_{P,R}(x_{t,c}, y_{t,c}) = \sum_{P=0}^{P-1} S(g_{t-2,P} - g_{t-1,c})2^P$$ …..[3]

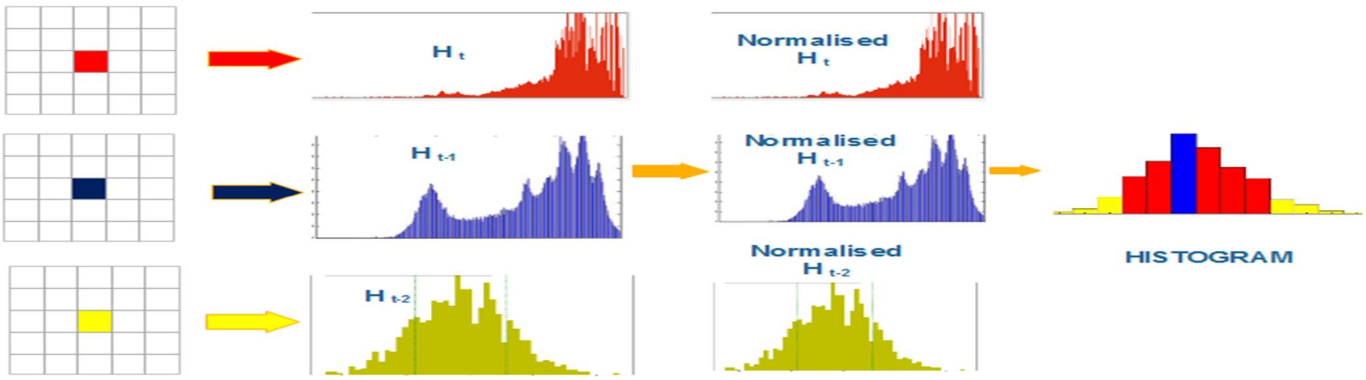

Figure 2 Histogram for LBP at time t, t-1 and t-2

1) LBP(t) and LBP(t-1), LBP(t-2) are called spatial and temporal local binary patterns of the pixel ($x_{t,c}$, $y_{t,c}$), respectively.
2) The first extracts the spatial texture features and the second extract the motion information of neighbouring two frames.
3) Consider R be a circular region of radius R_{region} centred on the pixel (xt,c, yt,c) in the frame ft, we can compute three histograms H_t , H_{t-1} and H_{t-2} over this region as follows

$$H_{t,i} = I\{LBP^{t}_{P,R}(x,y) = i\}\ i = 0,.....,2^{P-1}$$ ……[4]

$$H_{t-1,i} = I\{LBP^{t-1}_{P,R}(x,y) = i\}\ i = 0,.....,2^{P-1}$$ ….. [5]

$$H_{t-2,i} = I\{LBP^{t-2}_{P,R}(x,y) = i\}\ i = 0,.....,2^{P-1}$$ ……[6]

Normalized histograms are constructed for every LBP. These Normalized Histograms are labelled as H_t , $H_{t-1}$and H_{t-2} at i^{th} bin.

$$I(A) = \begin{cases} 1 & \\ 0 & \end{cases} \text{if A is true else}$$ …….[7]

$$H_t = \omega H_{t-2,i} + \omega H_{t-1,i} + (1-\omega) H_{t,i}\ i = 0,1,......2^{P-1}$$ …… [8]

Where Hi is the histogram value at i^{th} bin of H. Parameter 'ω' is the spatiotemporal rate. Figure 2 shows the histograms of the modified Space And Time Local Binary Pattern.

9. Finally modified Space And Time Local Binary Pattern finds H is the dynamic texture explanation of the central pixel of the region R which merges spatial texture and temporal motion information with each other.

Parameter 'ω' gives the importance of temporal motion information in histogram calculations. The computing of modified Space And Time Local Binary Pattern histogram needs the current fame and previous frame

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IV. EXAMPLE OF FINDING LBP BY CONSIDERING 3X3 NEIGHBOURHOOD

1) Consider a neighbourhood of size 3X3 as follows

Figure 3 In each 3x3 block compare central pixel with 8 neighbours

2) Select the central pixel value you want to replace.
a) If the value is greater than equal to centre pixel value then put 0 for it
b) If the value is less than the centre pixel value then put 1 for it

This can be done as follows

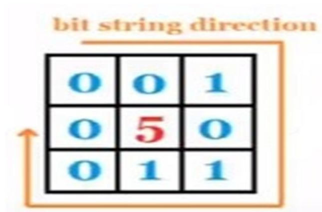

Figure 4 Selection of centre pixel and replacing binary values

3) Obtain the bit string by scanning 3x3 neighbourhoods. Select values as per direction is shown in figure 3. 4. Covert the bit string obtained by scanning 3x3 neighbourhoods to the decimal number. After converting 00101100 to decimal we get 44 decimal value.
4) Replace this number by centre value pixel.

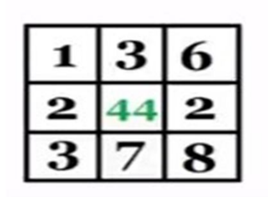

Figure 5 Replacing centre value

5) Construct a histogram for final neighbourhood

V. HISTOGRAM CONSTRUCTION (LBP)

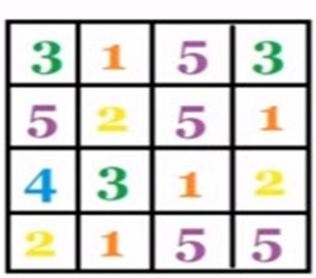

Figure 6 LBP 1

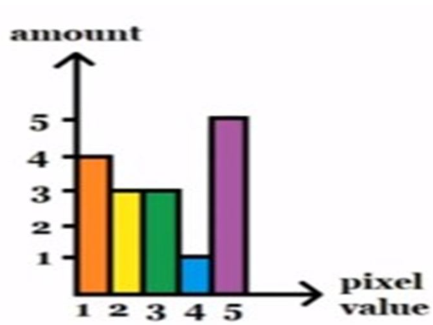

Figure 7 Histogram 1

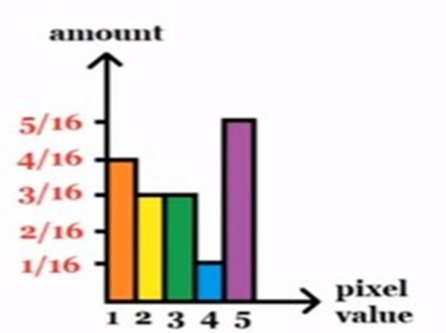

Figure 8 Normalized Computing Histogram

Consider the neighbourhood shown in figure 5 of size 4x4. The values in each block render the pixel depth of every pixel. The histogram of the neighbourhood can be observed in figure 6. Normalized Histogram can also be noticed in figure 7 which was not constructed in [1].

A. Modified Space And Time Local Binary Pattern Features Have Three Benefits

1) It is fault tolerance to monotonic to changes
2) It is efficient and very quick
3) It can obtain spatial texture and temporal motion data of a pixel.

VI. EXPERIMENTAL RESULTS

Figure 10 Comparison results on waving tree sequence, top row is the original frame sequence of 21^{st} ,25^{th} and 45^{th} frame. The first row indicates original frames and the second row indicates ground truth frames using MSTLBP

Method		21^{st}	25^{th}	45^{th}
MSTLBP	False Positive	7	0	13
	False Negative	32	14	21

Table 1 False positive and False Negative rates using MSTLBP

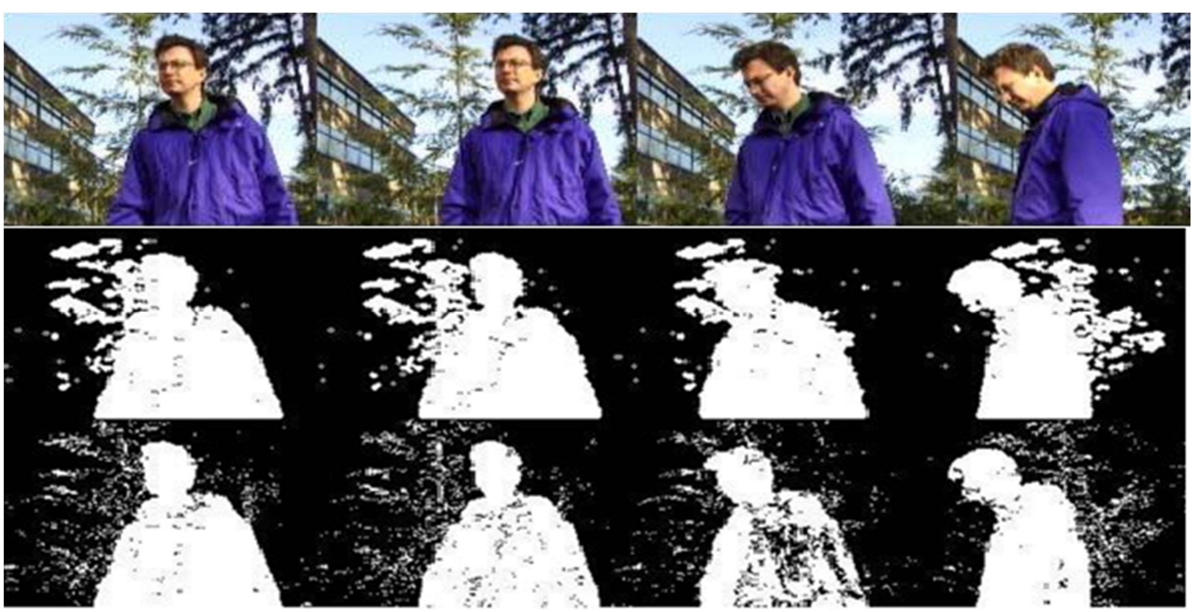

Figure 11[1]- Comparison results on waving tree sequence, top row is the original frame sequence of 152^{nd} ,210^{th}, 235^{th} and 270^{th} frame. The first row indicates original frames and second row indicated ground truth frames using MoG and KDE method

Method		152nd	210th	235th	270th
KDE	False Positive	1635	2012	655	1984
	False Negative	79	128	220	230
MoG	False Positive	872	923	540	1021
	False Negative	182	321	1120	223

Table 2[1] False positive and False Negative rates using KDE and MoG

To check the performance of the proposed method for dynamic scenes, [1] conducted operations using frame series. Two widely-used methods, Mixture of Gaussians (MoG) [2] and Kernel Density Estimation (KDE) [7] are used to control with the recommended method (MSTLBP). Regular pixel based MoG and KDE methods cannot accurately detect moving objects in dynamic scenes. They label large amounts of moving background pixels as foreground and also output an enormous amount of false negatives on the interior areas of the moving object. But, the MSTLBP method can precisely discriminate moving background pixels and actual moving objects. Table [1] shows the result achieved by MSLTBP and Table [2] shows the false positive and negative rates on MoG and KDE[7].

VII. CONCLUSION

In this paper, we have applied the usual local binary originals of the spatial domain to the spatiotemporal field and proposed a new dynamic texture extraction operator, identified modified spatiotemporal local binary patterns (Space And Time Local Binary Pattern) to give normalised histogram for better precision of object detection in dynamic scenes. It is powerful and very fast to estimate. The proposed dynamic modeling and subtraction method is based on space and time local binary pattern. Normalised histograms are very robust to dynamic change in natural scenes such as waving trees and flowing water. It gets detection of moving objects with high precision and reduces most of the false detections by traditional methods. The proposed method can be used in various surveillance applications.

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