Integrated Intelligent Research (IIR)
International Journal of Web Technology
Volume: 05 Issue: 01, June 2016, Pages: 65-68
ISSN: 2278-2389

Change Detection using Spatio-Temporal Features and Feedback Loops

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Abstract - Change detection is one of the most commonly used tasks in video processing. Background subtraction based change detection is the first step in many video applications to detect the foreground objects. Most of the background subtraction methods such as Local Binary patterns (LBP) and Local Ternary Patterns (LTP) are implemented using pixel by pixel representation. These can be viewed as improvements in many cases but they suffer in complexity, processing speed and illumination variations. In this paper, Local Binary Similarity Patterns (LBSP) makes pixel level decisions with automatic adjustment of tuning parameters for locally adapting to the changing input. It assigns the binary codes based on the similarity. For dynamic texture analysis, each pixel is modelled as a group of Spatiotemporal LBP (STLBP) histograms which combine spatial texture and temporal motion information together. The feedback loops are used to adjust the internal parameters and these adjustments are based on the continuous monitoring of model fidelity and segmentation noise which is observed under the form of blinking pixels. Adaptive background subtraction methods address all types of real time challenges including sudden illumination variations, background movements, shadows and ghost artifacts (falsely classified background regions).

Keywords – Change detection, Background subtraction, Spatio-Temporal features, Feedback parameters, Foreground segmentation.

I. INTRODUCTION

Change detection is a fundamental task in video processing applications. It includes visual surveillance such as crowd monitoring, forensic retrieval, small environments and content retrieval such as event detection, object tracking. It attributes a changed label to a pixel whose photometric properties deviate from those of background scene. Change detection algorithms are generally split into three major steps: First, a background model of the scene is created and it is updated by analysing the frames from the video sequence. FG/BG segmentation labels are assigned to all pixels in every new frame. Finally, regularization is used to combine information from neighbouring pixels. Among many types of change detection algorithm, there is no single algorithm that addresses all the real time challenges including sudden illumination variations, background movements, camouflage (hidden objects) and ghost artifacts(falsely classified background regions). Background subtraction techniques are used for detecting moving objects in an image sequence. If the difference between the current frame and reference frame is less than the threshold value, then no foreground object is detected otherwise foreground object is detected. The popularity of background subtraction algorithms such as Gaussian Mixture Model (GMM) [14], Scale Invariant Local Ternary Patterns (SILTP) [6], Local Binary Patterns (LBP) [5], and Kernel Density Estimation (KDE) [9] largely comes from its computational efficiency, which allows applications such as human computer interaction, video surveillance and traffic monitoring to meet their real-time goals. Background modelling allows high speed implementation which relies on independent pixel models that are arranged into a larger background model. Parameters that control model sensitivity and adaptation rate are usually defined by the user but it is very difficult to adjust the parameters when illumination variations, dynamic background elements and hidden objects are present in a scene at the same time. Most of the methods use global thresholds and it is possible to adjust such parameters based on the comparisons between observations and predicted values. But this approach cannot be used continuously due to the disparities caused by the foreground objects. Bad parameterization causes segmentation noise which is observed in the form of blinking pixels.

In this work, Change detection based on BG subtraction using spatiotemporal features such as LBSP and STLBP is proposed. The feature vector is computed by its corresponding histogram patterns. This feature vector helps to find the difference between current image and the reference image. This approach allows the process of detecting the local changes caused by hidden foreground objects which are not visible at the pixel level. STLBP detects even small changes because of taking the spatial texture and temporal or motion information together. Feedback scheme based on background monitoring approach updates two dynamic parameters such as maximum sample distance threshold (R) and model update rates (T) which are used to monitor the background dynamics and segmentation noise. It avoids illumination variations and over adaptation. Pre-processing and color conversion/normalization are avoided to make the method's complexity minimal and for simple implementation. Regularization step is limited to morphological processing or median blurring which are able to eliminate the segmentation noise in the form of blinking of pixels.

II. CHANGE DETECTION

Change detection algorithm separates the foreground object from the background objects to detect the change in video sequence. Background subtraction is based on the adaptation and integration of spatio-temporal features (STLBP and LBSP) in a non-parametric model that is then automatically tuned using pixel level feedback loops.

III. SPATIO-TEMPORAL FEATURES

The individual pixels are characterised using spatio-temporal features based on RGB values and LBSP features. LBSP

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features can be categorised as Local Binary patterns (LBP) and Local Ternary Patterns (LTP).

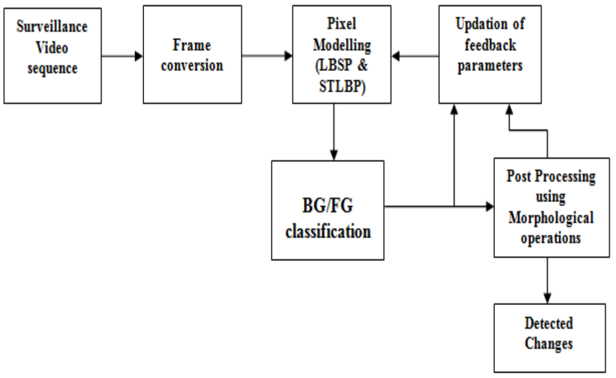

Fig 1. Illustration of Change detection

A. **Local Binary Similarity Patterns**

The principle of LBSP is to compare a center pixel with neighbouring pixels and check for similarity. It assigns the binary codes based on the similarity. LBSP is computed on an n x n region R, and the neighbouring pixels are to be compared with the center pixel that may be all the pixels or a subset of P pixels in R. LBSP is defined as

$$LBSP_R(x_c,y_c)= \sum_{p=0}^{p-1} d(i_p-i_x)2^P \quad (1)$$

with

$$d(i_p,i_x)=\begin{cases} 1 & \text{if } |i_p-i_x|\leq T_d \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where i_p - Intensity of p^{th} neighbour of (x_c, y_c).

i_x - Central reference which corresponds to the pixel intensity at (x_c, y_c) of R.

T_d- Internal similarity threshold.

LBSP is related to the internal threshold. Due to the nature of inter-LBSP (selecting the center pixel to be in another region), the modification ($T_d= T_r.i_x$) has to be applied to make it effective against shadows. To apply this modification, equation (3) becomes

$$d(i_p,i_x)=\begin{cases} 1 & \text{if } |i_p-i_x|\leq T_r.i_x \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where

T_r - Relative internal threshold which bounds to the interval of (0, 1) which is scaled over the time based on texture content of analysed frames. Labelling decision (foreground: FG, background: BG) are taken using

$$L_f(x,y)=\begin{cases} bg & H(LBSP_f(x,y),LBSP_M(x,y))\leq T_h \\ fg & H(LBSP_f(x,y),LBSP_M(x,y))>T_h \end{cases} \quad (4)$$

Where

H(x) -Hamming distance between two descriptors.

T_h - Similarity threshold.

LBSP gives better performance than color because it is more robust to noise as it considers neighbouring pixels in labelling decisions.

B. **Spatiotemporal Lbp (STLBP)**

In order to model the dynamic scenes using both spatial texture and temporal motion information together, the ordinary local binary patterns are extended from spatial domain to spatiotemporal domain. For this, STLBP integrates spatial texture and temporal information together which is very important to accurately label moving background pixels.

In the current frame f_t, the central pixel is denoted as $(x_{t,c}, y_{t,c})$ with gray value $g_{t,c}$. P equally spaced neighbouring pixels $(x_{t,0}, y_{t,0}),\ldots, (x_{t,P-1}, y_{t,P-1})$ with gray values $g_{t,0},\ldots,g_{t,P-1}$ on a circle of radius R_{LBP} in f_t are defined to be the spatial neighbouring pixels of $(x_{t,c}, y_{t,c})$. Using these neighbouring gray values, LBP codes are computed for central pixel $(x_{t,c}, y_{t,c})$ which are given as

$$LBP_{P,R}^{t}(x_{t,c},y_{t,c}) = \sum_{p=0}^{P-1} s(g_{t,p} - g_{t,c})2^P \quad (5)$$

$$LBP_{P,R}^{t-1}(x_{t,c},y_{t,c}) = \sum_{p=0}^{P-1} s(g_{t-1,p} - g_{t,c})2^P \quad (6)$$

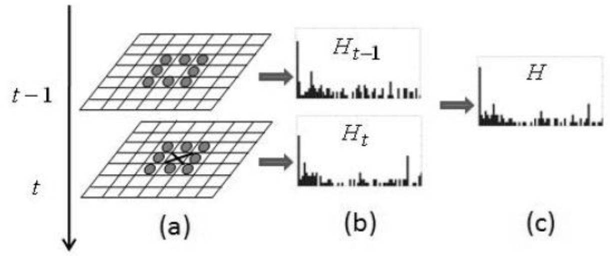

Fig.2. The computing procedure of STLBP histogram on center pixel (marked with X). (a) The spatial neighborhood and temporal neighborhood (marked with circles) of the center pixel. (b) Histograms computed in current and previous frames. (c) The STLBP histogram.

$LBP_{P,R}^{t}(x_{t,c}, y_{t,c})$ and $LBP_{P,R}^{t-1}(x_{t,c}, y_{t,c})$ are called spatial and temporal LBP of pixel location $(x_{t,c}, y_{t,c})$ respectively. Let R be a circular region of radius R_{region} centered on the pixel $(x_{t,c}, y_{t,c})$ in the frame f_t, two histograms H_t and H_{t-1} are computed over this region as in fig (2),

$$H_{t,i}=\sum_{x,y\in R} I(\,LBP_{P,R}^{t}(x,y)=i) \qquad i=0,\ldots,2^P-1 \quad (7)$$

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$$H_{t-1,i} = \sum_{x,y \in R} I(LBP^{t-1}_{P,R}(x,y) = i) \qquad i = 0,..,2^P-1 \tag{8}$$

where

$H_{t,i}$ and $H_{t-1,i}$ are the histogram values at i^{th} bin of H_t and H_{t-1}, respectively.

Then these two histograms can be summed to form a spatiotemporal local binary pattern (STLBP) histogram H as follows:

$$H_t = \omega H_{t-1,i} + (1-\omega) H_{t,i} \qquad i = 0,..,2^P-1 \tag{9}$$

where

H_i – Histogram value at i^{th} bin of H.

ω - Spatio-temporal rate which reflects the temporal information in histogram statistics. STLBP statistics H is used as the dynamic texture description of the center pixel of the region which combines spatial texture and temporal motion information together.

IV. FEEDBACK SCHEME

Feedback scheme based background monitoring approach measure background dynamics based on the comparison between pixel models and local observation as well as measure local segmentation noise levels. BG dynamics are analysed to measure motion entropy of single pixel location over temporal information. Two dynamic controllers for R and T rely on local indicators which are observed from monitoring the background dynamics and segmentation noise. To obtain an indicator, the recursive moving average is defined as

$$D_{min}(x) = D_{min}(x).(1-\alpha) + \alpha d_t(x) \tag{10}$$

where α - Learning rate ranges from 25 to 100.

$d_t(x)$ -Minimal normalized distance between all samples.

For every new segmented frame (S_t), the binary map of all blinking pixels (X_t) is computed by using an XOR operation with previous segmentation results (S_{t-1}). Segmentation noise indicator v is given by,

$$v(x) = \begin{cases} v(x) + v_{incr} & \text{if } X_t(x) = 1 \\ v(x) - v_{decr} & \text{Otherwise} \end{cases} \tag{11}$$

Where v_{incr} and v_{decr} are taking the values of 1 and 0.1 respectively.

Local distance thresholds (R) can be recursively adjusted for each new frame using the equation (12),

$$R(x) = \begin{cases} R(x) + v(x) & \text{if } R(x) < (1 + 2D_{min}(x))^2 \\ R(x) - (1/v(x)) & \text{Otherwise} \end{cases} \tag{12}$$

The relation between the R(x) and $D_{min}(x)$ are chosen as linear relation since it favours sensitive behavior in static regions. Another parameter T is recursively adjusted using the equation (13),

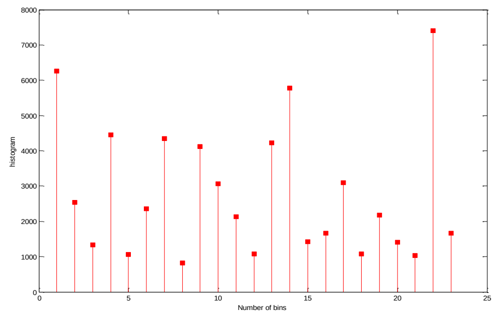
$$T(x) = \begin{cases} T(x) + (1/(v(x) D_{min}(x))) & \text{if } S_t(x) = 1 \\ T(x) - (v(x)/D_{min}(x)) & \text{if } S_t(x) = 0 \end{cases} \tag{13}$$

V. RESULTS AND DISCUSSION

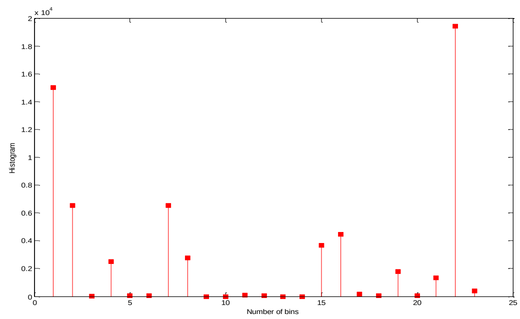
a)Reference frame

b) Current frame

Fig 2. (a) Reference frame and (b) current/testing frame is taken from the copy machine sequence of CDnet.



a) LBP histograms



b) STLBP histograms

Fig 4. (a) LBP histograms and (b) STLBP histograms are computed for the “copy machine” input sequence.

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a)Background subtracted image

b) Gray changed object

c) Gray changed object

Fig 5. a) Background subtracted image b) Gray changed foreground object c) Binary changed object.

Table I

Input Video	Recall (Re)	Precision (Pr)	F-measure(%)	Specificity (Sp)	PWC
Copy machine	0.99	0.97	97.92%	0.98	0.15

VI. CONCLUSION

In this work, background subtraction based spatio-temporal features are used to characterize the local representations in pixel level models and detect the foreground objects. Feedback scheme is used to update the parameters such as distance threshold (R) and update rate (T) for monitoring the segmentation noise in the form of blinking of pixels. This allows for fast responses to dynamic background motion.

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