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A Survey: Background Modelling and Object Detection Using Local Texture Features

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Abstract: Object detection is the most important stage due to it has great impact on next stages. Moving objects detection in dynamic environment has several challenges such as illumination changes (gradual, sudden), noise, dynamic background, etc. Color, texture, edge, motion, transform domain and stereo feature, each of these features has a source of strength to solve a particular problem and at same time has weaknesses to face the other problems. In this research, we will review the local pattern methods which are also called local texture descriptors which are used in background modelling and the detection of moving objects. For each method the mechanism is explained to solve the problems that facing background subtraction. Then, comparison is achieved between benchmark methods in terms of the use of spectral, spatial and temporal information. In addition, determining which type of problems will be resolved by each method separately.

Key words: Background modelling, object detection, local pattern, local texture, video surveillance, background subtraction

INTRODUCTION

The texture is a significant feature of several kinds of images. It is possible to appear in many images range from a microscope to remote sensing images. The texture area in the image can be categorized by varying or non-uniform spatial distribution of color or intensity. The structure of texture depends of illumination of surface, surface topology and reflection coefficient (Manjunath and Ma, 1996).

The texture analysis can play a vital role in a large number of computer vision applications such as biomedical images, aerial or satellite images and texture generation for computer graphic animation. Texture analysis has been a topic to large number of researches for several decades ago, wide range of methods have been proposed for discriminating texture. Most of traditional methods do not have the ability to reach well enough of real world texture and too complex in term of computationally to meet the real time requirements (Randen and Husoy, 1999).

In the last years very computationally efficient and discriminative local texture features have been presented, Local Binary Pattern (LBP) has important progress to achieve texture analysis for large number of computer vision applications. Local texture descriptor (such as LBP) is used in modern fields such as motion analysis, content based retrieval from video database, action recognition, biometric analysis and most traditional applications of computer vision. Local texture descriptor is an effective and simple tool which classifies the pixels by thresholding the neighboring pixels with center pixel, so, it is effective and gives good results in the background modelling and moving object detection (Varma and Zisserman, 2002).

With the great progress of capture and storage devices in recent years ago, video surveillance has become an important subject related to city security, home, traffic analysis, etc. The amount of video data has increased dramatically and automatic video analysis has become necessary (Hadi and Sabah, 2015). Background modelling and foreground detection is essential step for video processing applications such as optical motion capture, content based video retrieval, intelligent video surveillance, human machine interaction, activity recognition and many other applications (Bouwmans *et al*., 2014).

Methods of traditional background modelling focus on the temporal changes between consecutive frames to detect moving objects. Average, median and standard deviation represent traditional methods that depend on thresholding the difference between reference model and current frame, these methods fail to deal with challenging situations such as dynamic background, illumination changes and noise due to it do not have the ability to construct multi-modal background. Background model must be robust to overcome a number of challenges by building a multi-model and be adapting with challenging situations (Bouwmans *et al*., 2014).

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The methods of background model are classified into pixel based methods and region (block) based methods, the classification depends on the method is used to construct background model. In pixel based methods each pixel remains independent when building the model. This case is the most common but does not take into account temporal and spatial features. These methods are not effective for environments that have rapid changes in the background (Maddalena and Petrosino, 2008).

In region (block) based methods, the frames is divided into non-overlapped or overlapped blocks, the features associated with the block are calculated such as correlation, covariance and histogram to model the block. The block based methods provide high effectiveness against dynamic background. In non-overlapping methods the moving object is segmented and produced coarser shape than the overlapping methods. In overlapping methods each pixel is modeled based on features of block, the detection of moving object is done at pixel level, so, the object's shape is better than non-overlapping methods (Moeslund *et al*., 2006; Xue *et al*., 2011). Features can be categorized by their essential properties into the following types (Li *et al*., 2004):

Spectral features: It can be obtained directly from the images such as intensity, color or by converting to another color space such as HSV, HIS, C1C2C3, YUV and normalized RGB. Spectral features are possible to identify changes easily if the difference in color value between the background and foreground is large so, the spectral features lead to detect FP (False Positive) due to illumination variations and to detect FN (False Negative) when the object has same color with background, this is called camouflage problem. Spectral features ignore the relationships between the adjacent pixels to the target pixel.

Spatial features (texture and edge features): It help to extract the moving object that has camouflage problem with background in addition, these features have the ability to handle shadow problem. They are not applicable with dynamic background for pixel level as long as the spatial features are variable over time.

Temporal feature: Represents the relationship between consecutive frames. In this study, the most important ways of local texture descriptor will be reviewed. The strengths and weaknesses of each method are explained and a comparison between these methods will be showed.

LOCAL TEXTURE DESCRIPTOR

The texture is fundamental characteristic of the surfaces, it is possible to see anywhere such as images of outdoor and indoor scene, sky, grass, trees, bushes, roads, lakes, buildings, etc. which show different types of texture. The well-known methods of texture analysis can be classified into four classes: geometrical, statistical, model based and signal processing (Manduchi and Fox, 2001).

Most of traditional proposed methods are very complex computationally to satisfy the real time requirements of several computer vision applications. The modern proposed methods of local texture descriptors have efficient in term of time complexity and discriminative power (Cula and Dana, 2001).

In this study, the focus of the methods range from 2D and 3D and spatio-temporal texture and how are applied to model background and object detection. The background subtraction one of application areas which uses texture analysis effectively and efficiently, local binary pattern method and its variants consider as example for texture analysis due to their discriminative power and computational simplicity.

Local Binary Pattern (LBP) (Heikkila *et al*., 2004): The LBP is a powerful means of texture description, each pixel of image block is labeled by comparing it with the central value of image block and representing the result as binary manner (code of LBP):

$$\mathrm{LBP}(i_c, j_c) = \sum_{p=0}^{p-1} s(v_p - v_c)2^p \tag{1}$$

Where:

v_c = Value of the center pixel (i_c, j_c)

v_p = Value of the neighborhood pixels

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x<0 \end{cases} \tag{2}$$

The original LBP method works with 3*3 block size of pixels which works with square neighbors as shows in Fig. 1. The LBP operator can use set of circularly neighbors as illustrate in Fig. 2, the bilinear interpolation is used when the value of neighbors do not fall exactly on pixel locations. When circularly neighbors are used then the pixels spaced with Radius R equally.

Each block is modeled as set of LBP histograms. Due to the method work on block level, therefore, the shape of object is not accurate. Heikkila and Pietikainen (2006),

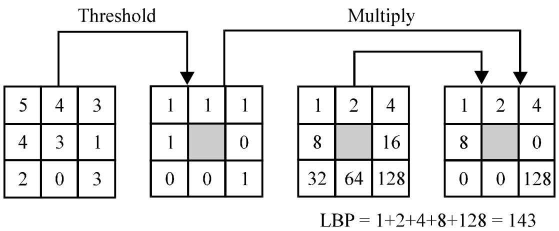

Fig. 1: An example for calculating the original LBP code

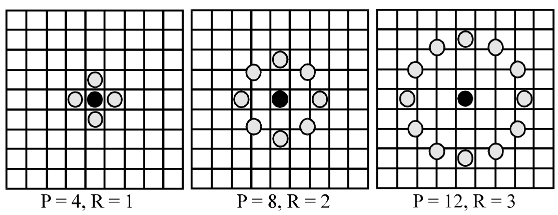

Fig. 2: Circularly neighbor of P and R

each pixel is modeled as set of LBP histograms that are computed for a region with a specific radius around each pixel.

Spatio-Temporal Local Binary Pattern (STLBP) (Shimada and Taniguchi, 2009; Zhang *et al*., 2008): Local binary pattern is extended from spatial domain to spatio-temporal domain then an effective method is presented for dynamic background modelling and moving object detection using STLBP operator. In this method each pixel is modelled as set of dynamic histograms of STLBP operator which merge temporal motion with spatial texture information together as illustrates in Fig. 3. The STLBP operator is computed as following:

$$\mathrm{STLBP}_{P,R}(i_c,j_c) = \sum_{p=0}^{P-1} s(\nu_p-\nu_c)2^p + \sum_{p=0}^{P-1} u(\nu_p-z_p)2^{P+p} \quad (3)$$

$$u(x) = \begin{cases} 1 & |x| \geq T_z \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where, T_z is a threshold which faces illumination changes gradually.

Epsilon Local Binary Pattern (ε-LBP) (Maddalena and Petrosino, 2008): The LBP has ability to adapt with illumination change and simplicity in term of time complexity, therefore, LBP operator has two major disadvantages as following:

- The neighborhood pixels are conditional independent with center pixel which lead to the neighborhood pixels will give local texture description for center pixel
- The distance between center pixel and neighborhood pixels only take into account the differences signs which lead to some wrong results

The ε-LBP operator is designed to overcome of two disadvantages related with original LBP operator. The ε-LBP formula is illustrated in Eq. 5:

$$\varepsilon\text{-}\mathrm{LBP}_{P,R}(i_c,j_c) = \sum_{p=0}^{P-1}\left(\frac{\nu^{\wedge}_p - \nu^{\vee}_p}{\nu_c} - \varepsilon\right)2^p \quad (5)$$

Where:

$\nu^{\vee}_p$ and $\nu^{\wedge}_p$ = The gray value of counter-clockwise and clockwise neighborhood of ν_p

ε = Indicates to noise parameter to make ε-LBP operator able to cope with noise

Figure 4 illustrates ε-LBP operator. The ε-LBP operator implements to obtain local texture feature for each pixel, then background subtraction is achieved based on two basic stages, the background modelling stage and moving object detection stage. In first stage, the probability that pixel represent foreground is computed based on the difference between adaptive mean ε-LBP and current ε-LBP. In the second stage, the probability is checked by applying thresholding operator to classify the pixels into foreground or background, then updating the adaptive mean ε-LBP by user depending on learning rate.

Center Symmetric Local Binary Pattern (CS-LBP): The CS-LBP operator produces more compact binary patterns compared with original LBP descriptor as shown in Fig. 5, the CS-LBP operator produces 2^4 binary patterns whereas LBP descriptor produces 2^8 binary patterns.

CS-LBP descriptor is more powerful on the flat area in the image by applying small threshold T for gray level differences, equation of CS-LBP descriptor shows in Eq. 6 (Heikkila *et al*., 2006):

$$\mathrm{CS\text{-}LBP}_{R,P,T}(i,j) = \sum_{i=0}^{(p/2)-1} s\left(p_i - p_i + (p/2)\right)^{2^i} \quad (6)$$

$$s(x) = \begin{cases} 1 & x>T \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where, p_i and $p_{i+(p/2)}$ are center symmetric pairs of pixels which spaced on circle of Radius R equally. Jiansheng

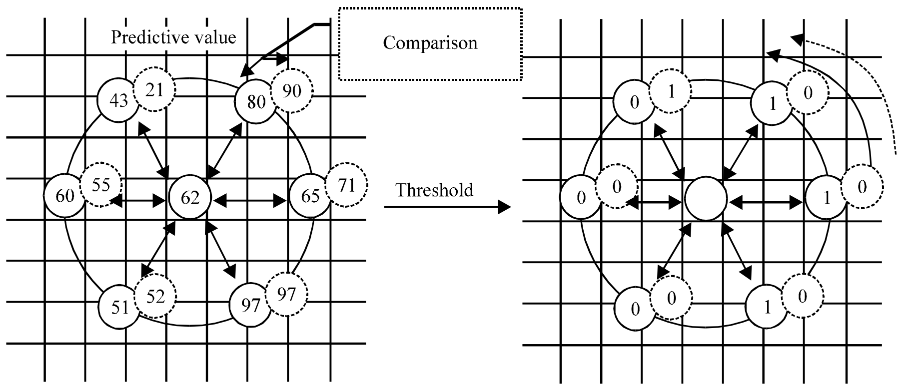

Fig. 3: STLBP example

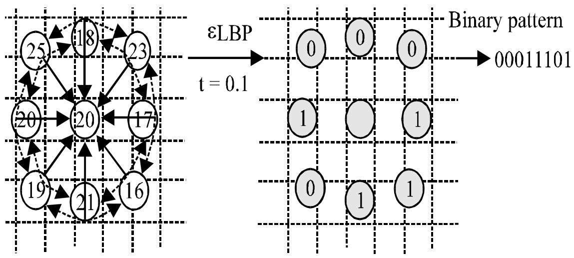

Fig. 4: Example of ε-LBP operator with 8 neighboring pixels

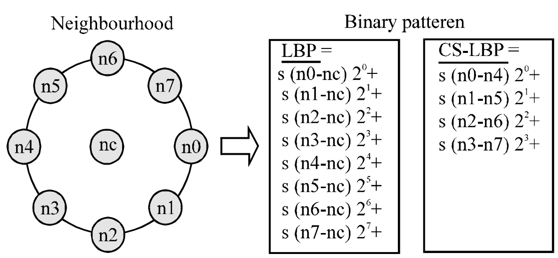

Fig. 5: Example of CS-LBP operator with 8 neighboring pixels

and Xuliang (2013) present method based on CS-LBP descriptor, it involves of two main stages. In the first one, the CS-LBP histogram is constructed for each pixel in the image, the aim of this stage is to initial the model of background. In the second one, distance measure is calculated to obtain the similarity value between the histograms of two pixels belonging to background model and current frame, respectively. The similarity value is used to classify the pixel into background or foreground.

Spatial-Color Binary Pattern (SCBP) (Zhou *et al*., 2011): LBP and CS-LBP operators are calculated based on gray values, only texture information is obtained in real video surveillance, the foreground objects have color information is different from the color information of background. Therefore, in addition to intensity information, color information is important feature to discriminate between moving objects and background. Based on this fact, SCBP descriptor is proposed to improve the LBP operator and to obtain best result in term of background modelling. The formula of SCBP operator:

$$\begin{aligned} SCBP_{2,N,R} &= (i_c,j_c) = LBP_{N,R}(i_c,j_c)+2^{N+1} \\ & s(R_c,G_c|\gamma)+2^{N+2}s(R_c,B_c|\gamma)+2^{N+3}s(B_c,R_c\gamma) \end{aligned} \tag{8}$$

$$s(a,b|\gamma) = \begin{cases} 1 & \text{when } a > b\gamma \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where, B_c, G_c and R_c are color channels of the center pixel (i_c, j_c), γ>1 is a factor remove noise. Zhou *et al*. (2011), the features of color and texture information are extracted. Additionally, refine model is constructed to enhance the boundary of moving objects. For each pixel, multi SCBP histograms are calculated for a region with radius around the target pixel, then the pixel in new frame is labeled into foreground or background according to similarity degree between background and model SCBP histogram, then the label is refined and the model is updated.

Uniform Local Binary Pattern (ULBP) (Yuan *et al*., 2011): Uniform Local Binary Pattern (ULBP) operator is extension of basic LBP operator (Fig. 6). P-bits binary code (fixed) is produced by LBP operator. The occurrence of jumping (0-1, 1-0) in LBP code is defined as transition, the transition process is defined as follows:

$$\begin{aligned} U_{P,R}(i_c,j_c) &= \sum_{p=0}^{p=2}\big(s(\nu_i-\nu_c)\oplus s(\nu_{i+1}-\nu_c)\big)+ \\ & \big(s(\nu_{p-1}-\nu_c)\oplus s(\nu_0-\nu_c)\big) \end{aligned} \tag{10}$$

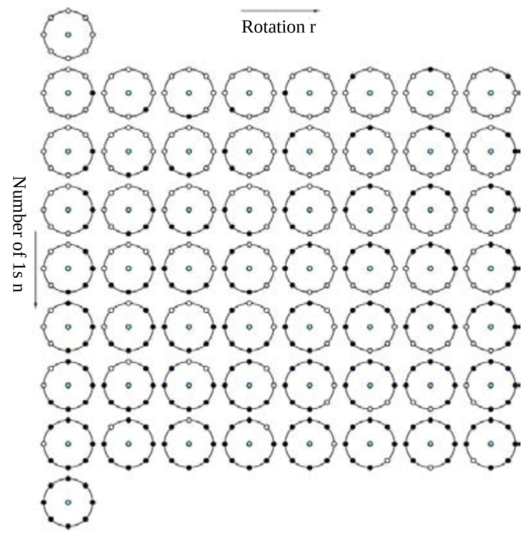

Fig. 6: Different uniform binary patterns (p = 8)

where, ⊕ is a XOR logical operator. Binary pattern code is known as uniform, if it has at most 2 transitions. An instance, the patterns (11111111, 00000000) have 0 transitions, 11110011 and 10011111 are uniform binary pattern due to they have 2 transitions and 10101100 is non-uniform due to it has 6 transitions. It's clearly U has even number lies between 0-P. The number of uniform patterns can be calculated as follows:

$$N_u = P\,(P\text{-}1)+3 \tag{11}$$

An example, when P = 8 (number of neighboring pixels) then $N_u = 59$, Fig. 6 illustrates uniform pattern when P = 8.

Yuan *et al*. (2011), the Uniform Local Binary Pattern (ULBP) is used with new method for thresholding to deal with noise interfere adaptively. The background model is built by combine enhanced LBP with color information by adopting a Mixture of Gaussian (MOG) method that uses several models to represent the background. Finally, LBP features vector is simplified to reduce time complexity.

Local Ternary Pattern (LTP) (Tan and Triggs, 2010; Wu *et al*., 2015): The LBP operator is sensitive to noise, due to the threshold is central pixel i_c, especially when the image has near-uniform regions or smooth regions. In order to overcome the previous problem the LBP operator is extended to new operator with three value code, this operator is called Local Ternary Pattern (LTP), Fig. 7 shows LTP operator. LTP operator is defined as follows:

$$LTP_{P,R,T}(i_c, j_c) = \sum_{p0}^{p-1} s(v_i - v_c)3^i \tag{12}$$

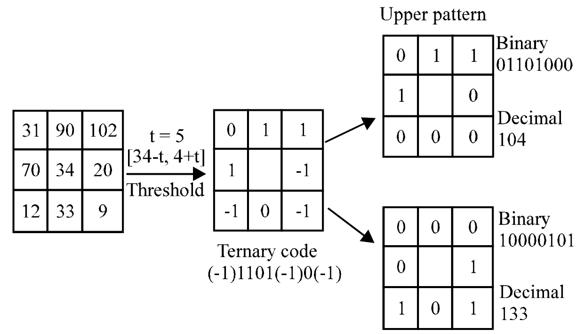

Fig. 7: Example of LTP operator with 8 neighboring pixels

$$s(x) = \begin{cases} 1 & x \geq T \\ 0 & |x| < T \\ -1 & x \leq T \end{cases} \tag{13}$$

where T is threshold that defined by user. In order to decrease the dimension of features, the ternary pattern is split into positive and negative part. Background subtraction technique uses LTP operator in a similar way to LBP operator.

SCALE INVARIANT LOCAL TERNARY PATTERN (SILTP)

LTP descriptor has robustness against the noise due to using a small acceptance range but it is not invariant to scale of intensity values (Zhang *et al*., 2012). The property of intensity scale invariant is very important because illumination changes either local or global. From previous reason, the SILTP descriptor is proposed to handle illumination change and noise, the descriptor illustrates in Fig. 8. Ternary pattern is computed as follows:

$$SILTP_{P,R,T}(i_c, j_c) = \oplus_{p=0}^{p-1} s_T(v_c, v_p) \tag{14}$$

Where:

v_c = The gray level of center pixel
v_p = The gray level of neighboring pixels equally spaced on circle of Radius R
⊕ = The concatenation operator
T = A scale factor of comparing range
s_T = A piecewise function which is defined as follows:

$$s(v_c, v_p) = \begin{cases} 01 & v_p > (T+1)v_c \\ 10 & v_p < (T+1)v_c \\ 00 & \text{otherwise} \end{cases} \tag{15}$$

Zhang *et al*. (2012), the SILTP operator is efficient to handle illumination changes, particularly for moving

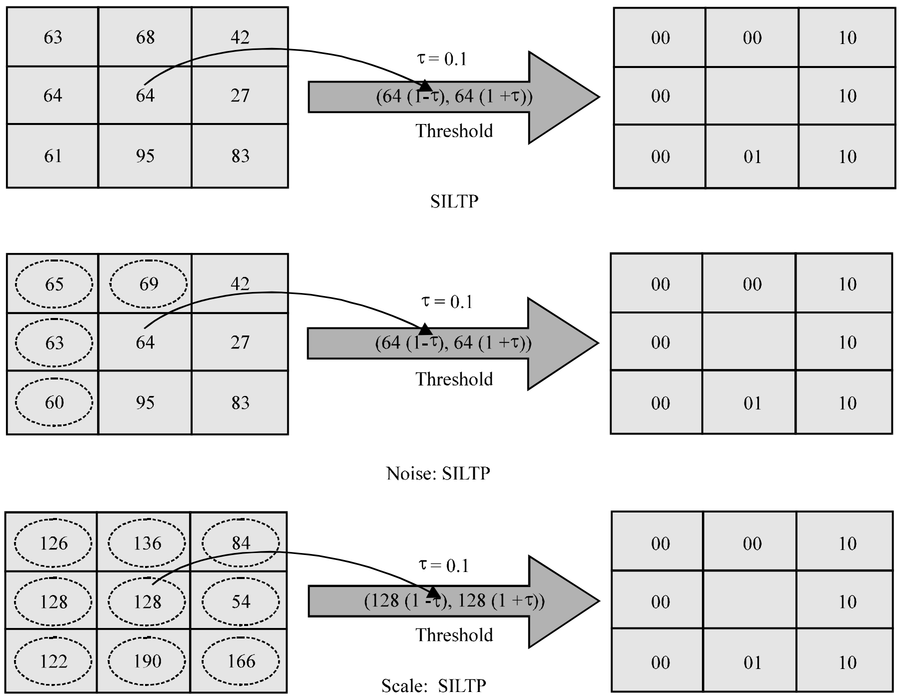

Fig. 8: Example of SILTP descriptor with 8 neighboring pixels; First row: original coding; Second row: coding with noise; Third row: coding with scale transform; The red pixels are changed with scale transform or by noise

soft shadow. Technique of pattern, Kernel Density Estimation (KDE) is used to model the probability distribution of local pattern. In addition to multimodal background model and multi-scale fusion technique are used which are worked based on SILTP operator.

Intensity Local Binary Pattern (iLBP) (Vishnyakov *et al.*, 2014): When binary pattern codes of LBP are compared the intensity information is ignored completely. Because of this, contradictory state is happened due to the result of comparison pixels is wrong, especially when the pixels intensity values is significantly different but their LBP codes is identical.

Intensity local binary pattern descriptor is proposed to overcome main drawbacks which were existed in previous ways of local pattern. The definition of iLBP (i, j) descriptor is a collection of intensity (i, j) and LBP (i, j) descriptor:

$$\text{iLBP}(i, j) = \{\text{LBP}(i, j), I(i, j)\} \tag{16}$$

Based on iLBP descriptor, the Distance D_{iLBP} between two iLBP descriptors in image location i, j is calculated as follows:

$$D_{iLBP}(i, j) = K|I(i)\text{-}I(j)|+H(\text{LBP}(i), \text{LBP}(J)) \tag{17}$$

where, H(.) refers to hamming distance between tow descriptors. K represents a proportionally factor that is used to satisfy the possible value of hamming distance, K sets from 2^{-8} to 2^{-4}.

Background Local Binary Pattern (BGLBP) (Davarpanah *et al.*, 2016): Background local binary pattern descriptor is introduced in order to face several challenges (illumination variations and noise) which other methods of local texture unable to cope with these challenges. BGLBP operator is computed according to the equations:

$$\text{BGLBP}_{P,R} = \begin{cases} \sum_{i=0}^{\left(\frac{p}{2}\right)-1} s\left(v_i, m, v_{\left(\frac{p}{2}\right)+i}\right)^{2^i} & U\left(LB\left(\frac{P}{2}\right)\right) \leq 2 \\ 2\left(\frac{p}{2}\right) & \text{otherwise} \end{cases} \tag{18}$$

$$s(v_i, m, v_{((P/2)+1)} = \{(1 \text{ if } (((v_i \geq m \geq v_{((P/2)+i)} \| (v_i < m < v_{((P/2)+i))} \text{ and } ((\text{abs}(v_{(i\text{-}m)})+ \text{abs}(v_{((P/2)}\text{-}m)) \geq \beta \,\&@0 \tag{19}$$

$$m = \frac{1}{p}\left(v_c + \sum_{i=o}^{p-1} v_i\right) \tag{20}$$

Where:

$v_i(i = 0, ..., i = p-1)$ = The gray level of p equally spaced on circle of radius R that constitutes a set of circular symmetric neighbor

v_c = Gray level of the central pixel

U = The Uniform patterns

From Eq. 20, the average of local intensity values is computed, the result is used as threshold value to detect variations in the neighboring pixels, the aim is to reduce the noise. From Eq. 19, the illumination variations in the image is ignored by comparing the intensity value of particular pixel with intensity value of corresponding diagonal pixel. From Eq. 18, half the changes are accounted for uniform neighboring pixels which lead to reduce time complexity.

Perception based Local Binary Pattern (PLBP) (Chan, 2016): Perception based local binary pattern operator is proposed in order to satisfy the color variations. The confidence interval of a sample has a value of color component c is defined as follows (c-d, c-d), d variable depends on the perceptual properties of variable c and d variable must be large for brighter color and small for darker color. The linear perception relationships are defined as follows:

$$d = 0.11*c \tag{21}$$

The neighboring pixels are compared with the center pixel if the color value is outside the confidence interval of central pixel then the feature value f is defined as follows:

$$f = b_{half}-d_{city}+1 \tag{22}$$

Where:

d_{city} = The distance between particular pixel of the block and the central pixel

b_{half} = The half size of the block. If the color value of given pixel is within confidence interval of central pixel then the feature value is 0 else the feature value is 1

Finally, all feature values of neighboring pixels are summed to generate binary pattern for central pixel. Figure 9 illustrates the perceptual based LBP.

The first two rows have confidence interval in the range 56.9, 70 while the third row has confidence interval in the range 113.9, 142.

Accordingly, the perceptual LBP operator has two main advantages, the first one is strength against the noise and the second one is robust to cope with scale transform (Table 1).

63	68	42	→	0	0	1
64	64	27		0		1
61	95	83		0	1	1

65	69	42	→	0	0	1
63	64	27		0		1
60	95	83		0	1	1

130	138	84	→	0	0	1
126	128	54		0		1
120	190	166		0	1	1

Fig. 9: An example of perceptual based LBP

Table 1: Comparison between local texture methods

Operators	Robust to: Illumination variations	Robust to: Noise	Using of: Spectral information	Using of: Spatial information	Using of: Temporal information
LBP pixel level	✓	-	-	✓	-
LBP block level	✓	✓	-	✓	-
STLBP	✓	-	-	✓	✓
ε-LBP	✓	-	-	✓	-
CS-LBP	✓	-	-	✓	-
SCBP	-	-	✓	✓	-
ULBP	-	✓	-	✓	-
LTP	✓		-	✓	-
SILTP	✓	✓	-	✓	-
iLBP	✓		✓	✓	-
BGLBP	✓	✓	✓	✓	-
PLBP	✓	✓	✓	✓	-

CONCLUSION

In video surveillance system, the background modelling and moving objects detection stage suffer from several problems. There are many feature types can be computed in spectral, spatial, temporal domain which can be used in this stage. Each one of these features can address specific type of problems. Texture features are suitable to address range of problems such as illumination changes in local level (linear and monotonic), global level, noise, dynamic background and shadow. Common methods of texture features extraction are usually used with the spatial domain consist of local binary pattern operator and variants. Different strategies are used to fuse more than one feature within the operator to enhance the ability of method to cope with problems. The main properties will be explained in of all studied LBP variants which are reviewed above.

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