A TEXTURE CLASSIFICATION TECHNIQUE USING LOCAL COMBINATION ADAPTIVE TERNARY PATTERN DESCRIPTOR

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Abstract

Image Retrieval, Object Recognition and Robotic manipulation are several applications of Material Recognition. It is frequently treated as a Texture Classification problem. The two essential features required for material organization more suitable for real-world applications, are i) Robustness to scale and ii) to pose variations, with respect to various challenges in processing the real-world images, which bring out many problems such as scale changes, poses and illumination changes, low quality etc. Scale changes, because material appearance varies drastically whether the image presents zoom in or zoom out. Poses and Illumination changes, depends on the point of view and illumination used to capture the material image. In Proposed method, it is aimed to develop a powerful approach for Texture Classification based on new descriptor Local Combination Adaptive Ternary Pattern (LCATP), used to encode both colour and local structure information. This descriptor overcomes the low quality of an image by introducing a accepting range, which makes it more robust and less sensitive to noise. LCATP descriptor is developed by using a combination of three different adaptive thresholding techniques which leads to overcome the grey-scale changes present in the image, because of low quality, non-uniform regions, bad illumination and shadows etc. In addition, Mean Histogram (MH) used jointly with LCATP so as to integrate color information into the descriptor. This method is then extended to four different colour spaces. The Final descriptor, LCATP fusion is formed by fusing the basic histogram (H) and Mean Histogram (MH) obtained from the different colour spaces.

As a result, the Final descriptor properties such as robustness to scale and pose changes are evaluated using the challenging KTH-textures under varying illumination, pose and scale (TIPS2b) dataset along with the least squares support vector machines classifier. Usage of Final descriptor exhibits a significant improvement related to the state-of-art results.

1. INTRODUCTION

In [1], Ojala et al. proposed the Local Binary Pattern (LBP) to address rotation invariant texture classification. LBP is efficient to represent local texture and invariant to monotonic gray scale transformations. Heikkila et al. [2] presented center-symmetric LBP (CS-LBP) by comparing center-symmetric pairs of pixels. Liao et al. [3] proposed Dominant LBP (DLBP) for texture classification. Tan and Triggs [4] presented Local Ternary Pattern (LTP), extending the conventional LBP to 3-valued codes. However LTP is no longer strictly invariant to gray-level transformations due to the simple strategy on the selection of the threshold. Zhang et al. [5] proposed Local Derivative Pattern (LDP) to capture more detailed information by introducing high order derivatives. However, if the order is greater than three, LDP is more sensitive to noise than LBP.

Guo et al. [6] proposed Completed LBP (CLBP) by combining the original LBP with the measures of local intensity difference and central pixel gray level. Zhao et al. [7] proposed the Local Binary Count (LBC), to address rotation invariant texture classification by totally discarding the micro-structure which is not absolutely invariant to rotation under the huge illumination changes. Zhao et al. [8] presented Completed Robust Local Binary Pattern (CRLBP) by modifying the center pixel gray level to improve the LBP, but a more parameter has to be tuned.

Material recognition has several applications, for instance, image retrieval, object recognition and robotic manipulation. It is often treated as a texture classification problem. To make the material classification more suitable for real-world applications, it is fundamental to verify the performance of the proposed approach towards different challenges in processing the real-world images, which bring out many difficulties.

2 Traditional LBP an d its variants

2.1 Local binary pattern

LBPs, initially proposed by Ojala et al. [9] for texture analysis, are non-parametric descriptors that speak to the nearby structure of a picture effectively by contrasting every pixel and its neighbors [10]. It has ended up being a straightforward yet capable administrator to depict the neighborhood structures as a result of its different gainful properties: robustness to illumination, computational simplicity and ability to encode texture details.

Every pixel of the picture is named with a decimal number, purported 'LBP code ': the central pixel (P_c) is contrasted and its neighboring pixels (P_n) lying at a separation R from P_c, if the estimation of P_n is $\geq P_c$ it will be coded with the worth 1 else it is set to 0. The binary numbers got are then multiplied by the relating estimations of a weight mask. The last decimal label of the pixel P_c is deducted by summing the different values computed, as given by (1) [10, 11]. Fig. 1 demonstrates a case of a LBP code calculation.

$$LBP(P_c, R) = \sum_{1=0}^{P_n-1} S(g_n - g_c)2^i \qquad (1)$$

Where S indicates sign function, g_n, g_c are grey values of P_n , P_c respectively.

A rotation invariant LBP is acquired by picking the smallest value from the P − 1 bitwise shift operations connected on the binary pattern. This last is likewise considered as uniform (U(LBPP, R)) if the number of transitions from 0 to 1, or on the other hand, in the binary number is ≤2 (see [12] for more points of interest). The LBP descriptor is then characterized as

$$LBP_{P,R}^{riu_2} = \begin{Bmatrix} \sum_{n=0}^{P-1} S(g_n - g_c), & if U(LBP_{P,R}) \\ P+1, & otherwise \end{Bmatrix} \quad (2)$$

2.2 Local ternary pattern

Tan and Triggs [13] recommend that the traditional LBP has a tendency to be sensitive to noise, for the most part in quasi-uniform picture regions as the utilized limit is ascertained in view of the accurate estimation of the centre pixel P_c. To conquer this issue, they proposed to utilize another methodology: LTPs [13]: the contrast amongst g_n, g_c is then coded by three qualities, as opposed to two, utilizing an edge t, so that the sign capacity S(x) of (1) is replaced by (3)

$$S = \begin{Bmatrix} 1, & if\, g_n \geq g_c + \tau \\ 0, & if\, g_c - \tau < g_n < g_c + \tau \\ -1, & if\, g_n \leq g_c - \tau \end{Bmatrix} \quad (3)$$

The resulting LTP is then split into two binary patterns: lower LTP (c = −1) and upper LTP (c = 1). Finally, the histograms computed from the two binary codes are concatenated to form the features vector

$$b_c(x) = \begin{cases} 1, & if\ x = c \\ 0, & otherwise \end{cases} \ with\ c \in \{-1,1\} \quad (4)$$

2.3 Local adaptive ternary pattern

Regardless of the way that LTP permits to overcome some limitations of LBP, it displays a few disadvantages itself [14]. Truth be told, the execution of this descriptor depends on upon the threshold of the limit value t. Akhloufi and Bendada [14] proposed then the LATP where the estimation of the edge t is figured in light of the local statistics. The S capacity is then replaced by (5)

$$S = \begin{Bmatrix} 1, & if\, g_n \geq (\mu_1 + k\sigma_1) \\ 0, & if\, g_n < (\mu_1 + k\sigma_1) and\ g_n > (\mu_1 - k\sigma_1) \\ -1, & if\, g_n \leq (\mu_1 - k\sigma_1) \end{Bmatrix} \quad (5)$$

where μ_1 is the neighborhood mean, σ_1 is the nearby standard deviation and k is a steady [14]. Akhloufi and Bendada utilize Niblack's strategy [15] to figure the threshold value t. The local adaptive thresholding gives more strength to illumination variations and less sensibility to noise. There are different adaptive thresholding methods. In the following area, four of the locally adaptive thresholding strategies are discussed.

3 Local adaptive thresholding approaches

Unlike global thresholding techniques, which select a single threshold value to be applied for the entire image, the local adaptive thresholding methods allow the selection of different thresholds values specific to each pixel based on its neighborhood statistics. Therefore they are more suitable for image thresholding.

3.1 Niblack's method

The threshold provided by Niblack's method [15] is calculated pixel-wise using the local mean (μ_1) and standard deviation (σ_1) computed over a w × w window around the central pixel. The local threshold for a given pixel is defined by (6)

$$T(i,j) = \mu_1(i,j) + K_N \sigma_1(i,j) \quad (6)$$

The parameter k_N is used to control the impact of the standard deviation on the threshold value. It can be set to a negative or a positive value depending on the quality of the image [15]. The value of k_N is fixed to −0.2 by Niblack.

3.2 Modified Niblack's method

Unlike Niblack's method, this approach incorporates both local and global characteristics of the image to deduce the threshold value. In addition, the parameter k_N is no more a fixed value, but an adaptive one specific to each pixel depending on its local characteristics (k_{MN}). The weight k_{MN} is computed using (7)

$$k_{MN} = k' * \frac{\mu_g \cdot \sigma_g - \mu_1 \cdot \sigma_1}{\max(\mu_g \cdot \sigma_g, \mu_1 \cdot \sigma_1)} \quad (7)$$

Where μ_g and σ_g are, respectively, the global mean and standard deviation of the whole image. μ_1 and σ_1 are, respectively, the local mean and standard deviation computed over a w × w window and $K' = -0.3$.

3.3 Wolf's method

Wolf and Jolion [18] propose an adaptive thresholding algorithm designed to enhance the local contrast by normalising the various elements used to compute the threshold value for Niblack's algorithm . The binarisation decision is then based on the contrast instead of the grey values of the different pixels. The threshold expression is given by

$$T = (1 - K_w) \times \mu_1 + K_w . M + \frac{\sigma_1}{R}(\mu_1 - M_W) \quad (8)$$

Where R is the maximum of the local standard deviations of the whole image. We denote by M_W the minimum value of the grey level of the entire image. The parameter k_W is used in order to control the uncertainty around the mean value. k_W is fixed to 0.5

3.4 Yung's method

Chiu et al. [20] make use of the local information by incorporating the local mean and the standard deviation computed from the gradient magnitude G [20] into the threshold formula given by

$$T = \mu_1 \cdot \left(1 - k_y e^{-\mu_{1G}/M_y}\right) \quad (9)$$

Where $M_y = max_1(\mu_{1G})$, μ_1 denotes the local mean of the grey-level image and μ_{1G} is the local mean of the gradient magnitude. The parameter k_y is used to minimise the influence of the information deduced from the gradient for computing the thresholding value.

4 Proposed approach

We start this section by reviewing the four colour spaces in which we will define the new descriptor. Then, the LCATP is introduced.

4.1 Colour spaces

The colour images to be handled are normally represented in the red, green and blue (RGB) color space. In any case, this colour representation has a few disadvantages: the colour components are exceptionally related absence of human interpretation and so forth [21]. In this way diverse colour spaces were checked.

The transformation to the LSH_{uv} colour space from the (L*u*v*) is defined by

$$\begin{cases} L_{UV} = L^* \\ S_{uv} = C_{uv}/L^* \\ H_{uv} = \arctan(v^*/u^*) \end{cases} \quad (10)$$

Where $C_{uv} = \sqrt{u^{*2} + v^{*2}}$

And L*u*v* is defined by

$$L^* = \begin{cases} \left(\frac{29}{3}\right)^3 \frac{Y}{Y_n}, & if \frac{Y}{Y_n} > \left(\frac{6}{29}\right)^3 \\ 116\left(\frac{Y}{Y_n}\right)^{1/3} - 16, & otherwise \end{cases} \quad (11)$$

$$u^* = 13L^*.(u' - u'_n)$$

$$v^* = 13L^*.(v' - v'_n)$$

$$u' = \frac{4X}{X+15Y+3Z} \quad \text{and} \quad u'_n = \frac{4X}{X_n+15Y_n+3Z_n}$$

$$v' = \frac{4Y}{X+15Y+3Z} \quad\quad v'_n = \frac{4Y_n}{X_n+15Y_n+3Z_n}$$

X_n , Y_n and Z_n are tristimulus values for a specified reference white point and X, Y and Z are defined by the linear transformation given by

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4306 & 0.3415 & 0.1784 \\ 0.222 & 0.7067 & 0.0713 \\ 0.0202 & 0.1295 & 0.9394 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (12)$$

The $I_1I_2I_3$ colour space provides a stabilisation of the RGB one, achieved by a decorrelation of the RGB components by applying the linear transformation of

$$\begin{cases} I_1 = \frac{1}{3}(R + G + B) \\ I_2 = \frac{1}{2}(R - G) \\ I_3 = \frac{1}{2}(2G - R - B) \end{cases} \quad (13)$$

The transformation from the RGB colour space to LC_1C_2 is given by

$$\begin{bmatrix} L \\ C_1 \\ C_2 \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.5 & 0.5 & -1 \\ 0.866 & -0.866 & 0 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (14)$$

Equations (15) define the RGB to $O_1O_2O_3$ transformation

$$\begin{cases} O_1 = (R - G)/\sqrt{2} \\ O_2 = ((R + G) - 2B)/\sqrt{6} \\ O_3 = (R + G + B)/\sqrt{3} \end{cases} \quad (15)$$

4.2 LCATP descriptor

Our approach incorporates the LTP with three different methods of local adaptive thresholding: modified Niblack(T_N), Wolf (T_W) and Yung (T_Y) [20] to create the LCATP descriptor. The S function, given by (3), is then replaced by (16)

$$S = \begin{cases} 1, if\ g_n \geq T_{N1} and\ g_n \geq T_{w1}\ and\ g_n \geq T_{Y1} \\ -1, if\ g_n \leq T_{N2} and\ g_n \leq T_{W2} and g_n \leq T_{y2} \\ 0, otherwise \end{cases} \quad (16)$$

To calculate LCATP: a circle of radius R and the number of neighbours P_n

$$T_{N_1} = \mu_1 + k_{MN} \cdot \sigma_1 \quad T_{N_2} = \mu_1 - k_{MN} \cdot \sigma_1 \quad (17)$$

$$T_{w_1} = \mu_1 + \left|K_w\left(1 - \frac{\sigma_1}{R}\right)(\mu_1 - K_w)\right| \quad , T_{w_2} = \mu_1 - \left|K_w\left(1 - \frac{\sigma_1}{R}\right)(\mu_1 - K_w)\right| \quad (18)$$

$$T_{Y_1} = \mu_1 \cdot \left(1 + k_y e^{-\mu_{1G}/M_y}\right) \quad , T_{Y_2} = \mu_1 \cdot \left(1 - k_y e^{-\mu_{1G}/M_y}\right) \quad (19)$$

We then extract two histograms (basic histogram (H) and MH) from the ULCATP and LLCATP. A new operator (MH) is then implemented to incorporate the colour information into the final descriptor: the local means of the grey-level values over the image are computed and then accumulated into the histogram bins. Finally, H and MH are concatenated to create the final descriptor

$$MH(h) = \sum_{i=1}^{N}\sum_{j=1}^{M} L(LCATP(i,j),h), h \in [0,k] \quad (20)$$

4.3 Final fused descriptor LCATP_F

In the last step, we use the resulted descriptors along with the LS-SVM classifier [28, 29] in order to evaluate the performance of the resulted method for texture recognition.

$$LCATP_F = [LC_1C_2\_LCATPI_1I_2I_3\_LCATPLSH_{uv}\_LCATPO_1O_2O_3\_LCATP] \quad 21$$

5. RESULTS

Fig.1. Input Test Image

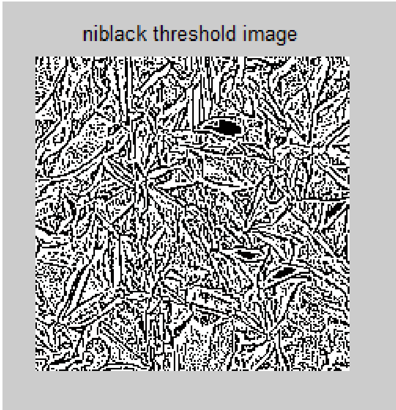

Fig.2. Niblack Threshold Image

Fig.3. Wolf Threshold Image

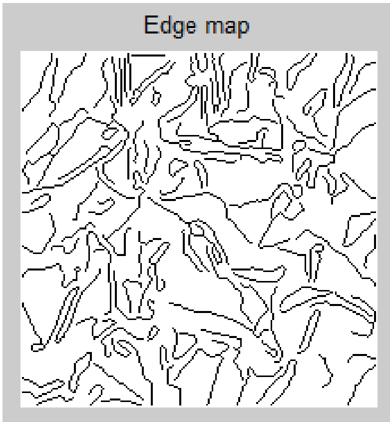

Fig.4. Edge Mapping

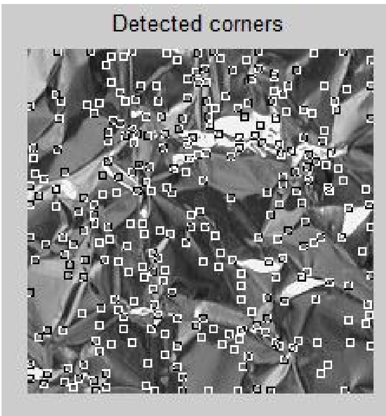

Fig. 5.Detected Corners of an image

6. CONCLUSION

In this paper, A new texture descriptor (LCATP_F) is fused with three different local adaptive thresholding techniques: modified Niblack's method, Wolf's method and Yung's method to make the texture classification more efficient. Here, another descriptor, MH is also used in order to improve the performance of the proposed method by incorporating the contrast information.

The obtained results of the first set of trials show a significant improvement of the classification rate (99. 81%) over the previous researches results. The recognition rates achieved on the second test (82. 30%) prove the scale invariant property of the LCATP_F descriptor, with an improvement of more than 6% over the previous state-of-the-art results. Finally, the classification results of the last experiment (97.66%) prove the robustness of the proposed method to pose changes.

On the basis of the obtained results, we believe that the proposed approach could be applicable in different computer vision tasks involving scale and pose variation, such as object recognition in complex scene etc.

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