International Conference on Control, Engineering & Information Technology (CEIT'13)
Proceedings Engineering & Technology - Vol.2, pp. 181-185, 2013

Texture classification using fuzzy fusion between variance map and entropy of LBP distribution, and mathematical morphology

Moussa Mzoughi, Hassen Seddik, and Anissa Selmani

Department of Electrical Engineering, CEREP , ESSTT
5,Av. Taha Hussein,1008Tunis,Tunisia

moussa.mzoughi.1988@gmail.com
hassene.seddik@estt.rnu.tn
anissaselmani02@gmail.com

***Abstract*— Texture classification, is a subject widely used in different image processing fields. Local invariant features, e.g. local binary pattern (LBP), has the drawback of losing global spatial information, while global features preserve little local texture information. In this paper, a new approach for superposed texture classification and region of interest extraction is presented. Based on combining mixed statistical and non-deterministic discriminative attributes for efficient texture classification. The global approach supervised by fuzzy logic block allowing through its membership functions to weight the appropriate characterising feature. The proposed approach is found to be reliable when dealing with image composed by texture of quasi-similar models. The accuracy of the output classified texture is estimated by different criteria.**

***Keywords*— Variance map, LBP, entropy, fuzzy fusion, mathematical morphology.**

I. Introduction

Image segmentation is the process of the image partition into regions with similar characteristics. Most natural image zones exhibit textures, for this reason the segmentation of the textured images is a major field of research in computer vision [1]. An effective texture algorithm is of importance in diverse areas, including robotics, remote sensing, medical imaging, etc. Texture classification is difficult to be achieved because the textured regions are usually characterized by non linear intensity variations [1].

Ahenhua Guo et al. [2] proposed the texture descriptor, LBP variance (LBPV). They used the LBP distribution to estimate the principal orientation of the texture and then use them to align the respective histograms. The LBPV proposed to characterize the local contrast information into the one dimensional LBP histogram. To accelerate the matching scheme, Ahenhua Guo et al. propose a method to reduce feature dimension using distance measurement. Their experimental results in that the LBPV operator and global matching schemes can achieve significant improvement.

In [3], Alaoui et al. proposed an unsupervised method for texture image classification, which is based on Kohnen maps and mathematical morphology. This map is represented by the underlying probability density function (PDF) estimated by non-parametric technique in the n-dimensional space, from the weight vectors resulting of the learning process. So each modal region of the underlying PDF corresponds to one homogenous region in the texture image. A fuzzy logic based texture descriptor [4] Fuzzy Local Texture Pattern (FLTP) has been proposed by E.M. Srivasan et al. After texture classification, the results have shown that the FLTP method is robust against rotation variation. Vijayalakshmi et al. [5] proposed an approach for texture classification by combining statistical texture feature of LBP and texture spectrum then they used the Euclidean distance for similarity measurement. The experimental results show that 97.77% classification accuracy is obtained by their method. Xiuwen Liu et al. [6] employed a spectral histogram as a feature static for texture classification and measured the distance between two spectral histogram using X^2-statistic.their classification experiments show that the spectral histogram representation provides a robust feature statistic texture and generalizes well.

In our paper we proposed a new approach based fuzzy logic presenting a fusion between the variance map of an image and the entropy of the LBP distribution to separate and classify with high accuracy superposed textures. The fuzzy classifier is fed by two inputs (variance and entropy of the LBP distribution). The output generates two different classes. This primary classification is then processed by mathematical morphologies.

II. Proposed Approach

The proposed approach exploits several attributes (variance map, LBP, entropy, fuzzy logic and combined with morphological operators). The different steps are detailed in the following section.

A. *Variance map of the image*

The measures of local variance are very important in image processing for texture characterisation and studies of spatial image structure to gain insight information of image local scale [7]. The distribution of local variance provides some structural information of image. Regions having the smallest variance; are those areas containing many edges such as textured zones. Those having a higher variance are homogenous regions [7]. Local variance of an image can give a distinction between a homogenous area and a textured area. We pretend that combining it with other discriminate features it can gives an accurate distinction between two superposed textures.

The local variance of an image is defined by:

$$VAR(I_{i,j}) = \frac{1}{m \times n} \sum_{i=1}^{n} \sum_{j=1}^{m} (p_{(i,j)} - \bar{I}_{i,j})^2 \qquad (1)$$

$$\bar{I}_{i,j} = \frac{1}{m \times n} \sum_{i=1}^{n} \sum_{j=1}^{m} p_{(i,j)} \qquad (2)$$

Where p is the pixel in the image, $m \times n$ is the total number of pixels in Ii,j.

Variance map of an image is calculated the variance value of a window S(i,j) with size s×s, in every iteration. The computed outputs are thresholded to obtain a binary matrix that is able to characterize the processed texture as presented by the following equation. A variance map is finally generated for each texture class.

$$S\ i,j = \begin{cases} 0 & \text{if} \quad var(S\ i,j) > V \\ 1 & \text{if} \quad var(S\ i,j) < V \end{cases} \qquad (3)$$

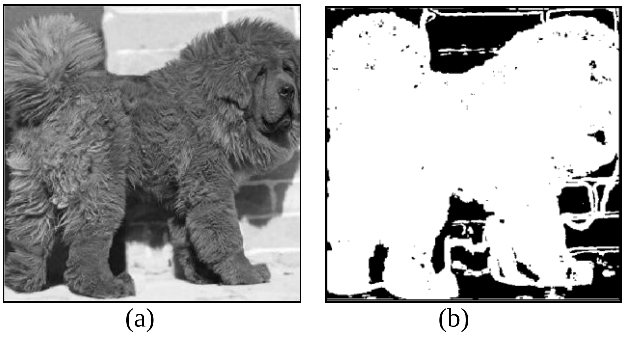


Fig. 1 variance map of image “dog “ of size (403×403) pixels; (a) original image, (b) variance map of image

As shown in Fig. 1 we can see that the map variance can provide a specific class for each texture. But it seems that some unwanted regions, corresponding to the edges of wall and of the shadow with low intensity interfere.

B. Local Binary Pattern distribution

The local binary pattern (LBP) approach [8] proposed by Ojala et al. provides highly discriminative texture attributes. The LBP operator uses a binary representation of texture units localized in image neighbourhoods. Considering a window X(i,j) whose size 3x3 pixels. The LBP value for such a neighbourhood is estimated as follows:

- Threshold of all pixels of original neighbourhood (Fig. 2 (a)) reaches two levels (0 and1) (Fig. 2 (b)) by comparing the intensity value of the centre pixel (gc) with intensity value of each pixel of X i,j (gp), based on the following rules:

$$X = \begin{cases} 1 & \text{if} \quad gp > gc \\ 0 & \text{if} \quad gp < gc \end{cases} \qquad (4)$$

- Multiply the values of the pixels in the threshold neighbourhood by the binomial weights (Fig. 2 (c)) assigned to the corresponding pixel
- We add the values of the eight pixels (Fig. 2 (d)) and affect the sum of the central pixel as shown in the following rule :

$$LBP = \sum_{i=1} E_i 2^{i-1} \qquad (5)$$

Where the set of E_i is the values of the eight pixels corresponding to (Fig. 2 (d))

6	5	2
7	6	1
9	3	7

(a)

1	0	0
1		0
1	0	1

(b)

1	2	4
8		16
32	64	128

(c)

1	0	0
8		0
32	0	128

(d)

Fig. 2 An example of LBP value estimation

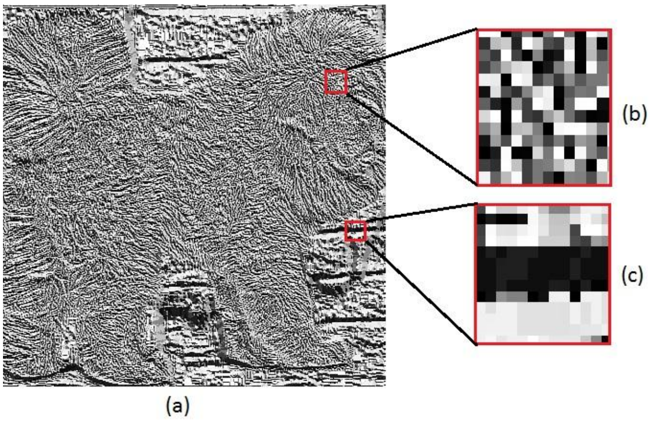


Fig. 3 (a) LBP representation of the image, (b) and (c) zoom of two different regions from the LBP distribution

The main goal using LBP pattern is to provide a specific pattern for each different class of the image. But some disadvantages appear when edges; shadow and borders in a specific class remain preserved. For this reason we aim to develop attribute mixtures able to classify the image regions without preserving proper characteristics belonging to the image zones.

C. Entropy

Entropy is a statistical measure of randomness that can be used to characterize the textured image [9].

Calculating iteratively the entropy of a selected window with varied size (s×s) allows obtaining an optimal entropy value relative for each region of the LBP distribution. Changing the window size iteratively in each time generates an optimal value of the entropy that gives a specific characteristic of each region (desired body to classify (dog) and unwanted regions to classify (edges)).

The entropy is defined as:

$$H = \sum_{i=1}^{n} P_i \log_2 P_i \qquad (6)$$

$$P_i = \sum_{k=1}^{255} \frac{n \times k}{k} \qquad (7)$$

$$n = \sum_{i=1}^{n} \sum_{j=1}^{m} LBP_{(i,j)} \qquad (8)$$

Where P_i contain the histogram counts of the window as shown in Fig . 3.

(a) (b) (c)

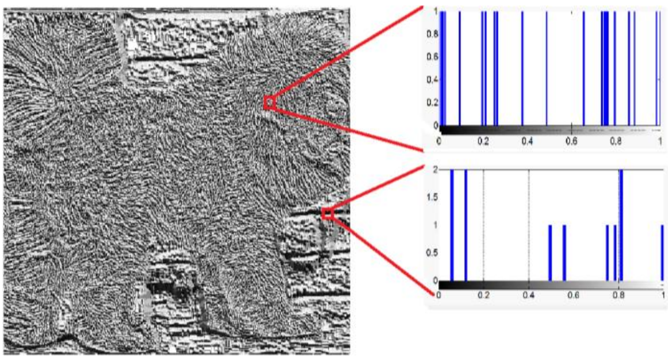


Fig. 4 (a) LBP representation of the image, (b) and (c) histogram of two different regions from the LBP distribution

D. Fuzzy fusion between variance map of the image and entropy of LBP distribution

Fuzzy image processing has three main steps: image fuzzification, membership adjusting and overlaps, and image defuzzification. The main power of fuzzy image processing is in the middle step (membership modification) [10].

In our case we have two inputs (entropy value and variance map of the image) so our fuzzy fusion is shown in Fig. 4:

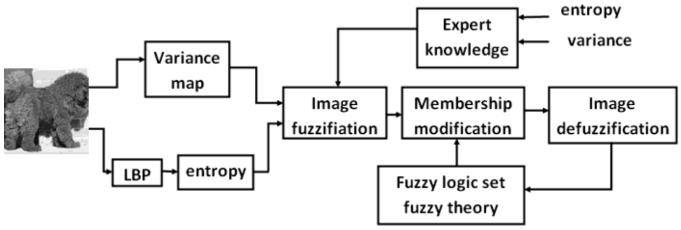
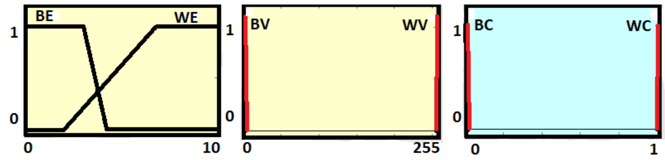


Fig. 5 fuzzy fusion

After the image data is transformed from gray-level plane to the membership plane (fuzzyfication), appropriate fuzzy techniques modify the membership values. In fuzzy set, the membership is a matter of degree, i.e, degree of membership of an object in a fuzzy set expresses the degree of compatibility of the object with the concept represented by the fuzzy set [11].



(a) (b) (c)

Fig. 6 membership function of fuzzy fusion; (a) input (1) correspondent to entropy value, (b) input (2) correspondent to variance map, (c) output correspondent to output classes

The fusion between variance map of image and entropy value of LBP distribution is given by the rules of the fuzzy fusion:

If input (1) is BE, and input (2) is WV, then output is BC

If input (1) is WE, and input (2) is BV, then output is WC

After image defuzzification we get a primary classification as is evident from Fig. 6:

Fig. 7 image defuzzification

According to Fig. 6 we see that the fuzzy fusion succeeds to remove many undesirable areas to classify. However, there are some spots that can be corrected by mathematical morphology.

E. Mathematical morphology

Mathematical morphology is applied in many applications in image processing such as edge detection, object segmentation, noise suppression, and so on, because it provides a systematic approach to analyse the geometric characteristics of image [12].

It is based on two operations; a window that scans the image and that transforms the pixels with respect window contents:

- Dilatation of an image A by structure element B is defined as:

$$A \oplus B = \{a + b / \ for\, a \in A\, and\ \ b \in B\} \qquad (9)$$

- An image erosion by a structure element B is defined as:

$$A \ominus B = \{P / P + b \in A \forall b \in B\} \qquad (10)$$

The size and shape of structuring element can be changed according to the image content and forms; it can be (square, cross, disk, line...) [12].

In this work; opening and closing operation are even important to adjust with accuracy the classified outputs; they are presented by the following equations [13]:

- An opening of an image A by structure element B is defined as:

$$A \circ B = (A \ominus B) \oplus B \qquad (11)$$

- A closing of an image A by structure element B is defined as:

$$A \bullet B = (A \oplus B) \ominus B \qquad (12)$$

After the application of mathematical morphology on the defuzzification image we obtain final texture classification.

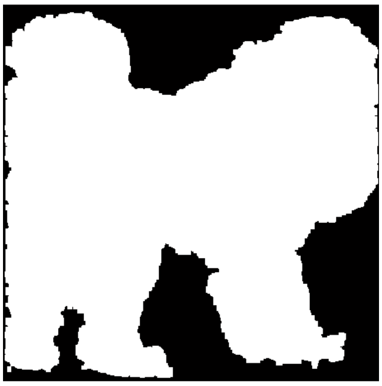


Fig. 8 output classified image after applying mathematical morphology

As shown in Fig. 7, mathematical morphology improved the classification results by adding more homogeneity to the different classes.

F. Evaluation methods of classificationresults

The error rate of classification image [1] is given by:

$$E = \frac{M_p}{T_p} \qquad (13)$$

Where M_p is the number of misclassified image pixels, it results from a substruction of classified image and optimal segmentation, T_p is the total number of image pixels. So the percentage of correct classification is given by the following equation:

$$CC\% = (1 - E) \times 100 \qquad (14)$$

To obtain not only the classification rate for all the textures in the image we add a second evaluation method that provides a mismatch ratio of each class, this coefficient E_i (Ew for white class and E_b for black class) [14] is given by:

$$E_i = \frac{M_i}{C_i} \qquad (15)$$

With M_i is the number of misclassified class pixels (Mw for white class and M_b for black class) and C_i is the total number of desired class pixels. (Cw for white class and C_b for black class). The percentage of correct classification for each class is given by:

$$CC_i\,\% = (1 - E_i) \times 100 \qquad (16)$$

We have also another evaluation method named Vinet distance [15] is defined as:

$$VD\% = (1 - \sum_{i=1}^{n} E_i) \times 100 \qquad (17)$$

G. Proposed algorithm for texture classification

The proposed approach for texture classification mixes many techniques such as variance, LBP, entropy, fuzzy fusion and mathematical morphology. It is also efficient for the separation of the superposed textures.

To achieve these targets, the following steps are followed:

- Step1: classification using variance map algorithm as mentioned in equation (3)
- Step2: calculate the CC_i % (equation 14) of body desired to classify. In this step we specify a threshold CCt% and:

If $CC_i\% > CCt\%$ then pass to step5 else pass to step 3

- Step3: applying the LBP distribution on the original image and determine the optimal window size able to characterize the texture. From it , we calculate the entropy of each textured region as mentioned in equation (6).

- Step4: application of the fuzzy fusion between variance map of the image and entropy of LBP distribution as that shown in Fig. 4 and Fig. 5.
- Step5: applied a mathematical morphology on the output of the fuzzy fusion or the variance map to improve the primary classification.

III. EXPERIMENTAL RESULTS

Our classification method is validated by classification accuracy estimators. The following figure presents the classification results of different composed textures.

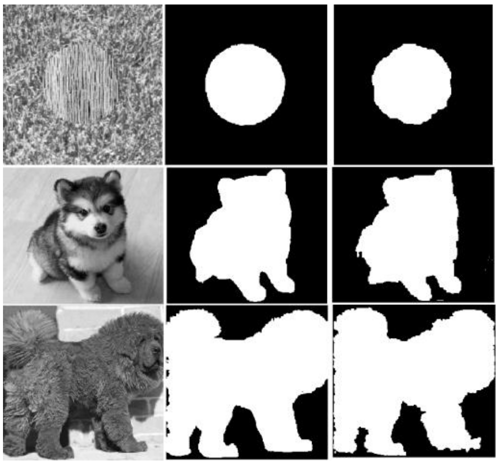


Fig. 9 texture classification results; (a) original images respectively (Pic1, Pic2, Pic3, Pic4, Pic5), (b) desired classification, (c) texture classification with the proposed method

TABLE I
CLASSIFICATION METHODS VALUES FOR EACH CLASSIFIED IMAGE

Evaluation methods / images	$CC\%$	$CCw\%$	$CC_b\%$	$VD\%$
Pic1	98.97	97.82	99.47	97.29
Pic2	97.20	99.18	99.38	98.56
Pic3	96.75	99.71	99.24	98.95
average	98.37	98.30	99.75	97.88

High rates of classification results are shown in the table above. These rates prove the efficiency of the proposed method to discriminate and determine different composed textures even if they have similar pattern.

IV. CONCLUSION

We have demonstrated that the fusion between variance map and entropy of LBP distribution using fuzzy logic provides a feature to separate the superposed textures in order to obtain a primary classification.

The mathematical morphology is used as a second technique to improve the fuzzy fusion output. The experimental results and the classification accuracy measurements prove that the proposed method supply a reliable and efficient texture classification.

REFERENCES

[1] Lotfi Tlig, Mounir Sayadi, Farhat Fnaiech, "A new fuzzy segmentation approach based on S-FCM type 2 using LBP-GCO features", *Signal Processing: Image Communication 27 (2012) 694–708,* 2012

[2] Zhenhua Guo, Lei Zhang, David Zhang, "Rotation invariant texture classification using LBP variance (LBPV) with global matching", *Pattern Recognition 43 (2010) 706–719,* 2010

[3] Mohammed Talibi-Alaoui, Abderrahmane Sbihi,"Fractal Features Classification for Texture Image Using Neural Network and Mathematical Morphology", *Proceedings of the World Congress on Engineering 2012,* Vol I WCE 2012, July 4 - 6, 2012, London, U.K.

[4] E. M. Srinivasan, Dr. K. Ramar, Dr. A. Suruliandi, "Rotation Invariant Texture Classification using Fuzzy Local Texture Patterns", *International Journal of Computer Sci ence And Technology,* IJCST Vol. 3, Iss ue 1, Jan. - March 2012.

[5] B. Vijayalakshmi, V. Subbiah Bharathi, "A Novel Approach to Texture Classification using Statistical Feature*", International Journal of Information Technology Convergence and Services (IJITCS)*, Vol.1, No.5, October 2011

[6] Xiuwen Liu, DeLiang Wang, "Texture Classification Using Spectral Histograms", *IEEE Transactions On Image Processing,* VOL. 12, NO. 6, JUNE 2003

[7] Yunyu Shi, Youdong Ding, "On the role of local variance in image fidelity assessment", *2nd International Conference on Signal Processing Systems (ICSPS),* 2010

[8] T. Ojala, M. Pietikainen, D. Harwood, "A Comparative Study of Texture Measures with Classification based on Feature Distributions", *Pattern Recognition*, vol. 29, 1996, pp. 51-59.

[9] C.-P. Tan, J.-Y. Koay, K.-S. Lim, H.-T. Ewe, H.- T. Chuah, "Classification Of Multi-Temporal Sar Images For Rice Crops Using Combinedentropy Decomposition And Supportvector Machine Technique" Progress In Electromagnetics Research, PIER 71, 19–39, 2007

[10] Tizhoosh, *Fuzzy Image Processing,* Springer,(1997), Berlin.

[11] P. Burillo, N. Frago, R.Fuentes, "Fuzzy Morphological Operators in Image Processing," *Mathware and Soft Computing*,(2003),10.

[12] Yee Yee Htun, Dr. Khaing Khaing Aye, "Fuzzy Mathematical Morphology approach in Image Processing", *World Academy of Science*, Engineering and Technology 18 2008

[13] Wayne, Lin Wei-Cheng, "Mathematical Morphology and Its Applications on Image Segmentation" Dept. of Computer Science and Information Engineering, National Taiwan University, June 7, 2000

[14] J. Moreira, L.Da fontoura costa, "Neural-based color image segmentation and classification using self-organizing maps", *Anais do IX SIBGRAPI,* (1996): 47-54

[15] N.Martin, "segmentation d'image couleur, du prétraitement a l'évaluation", université de Rouen