Neural Evaluation of Texture Synthesis Results

Kais Rouis, Mounir Sayadi, Farhat Fnaiech

SICISI Unit, Higher School of Sciences and Techniques, University of Tunis

E-mail: kais.rouis@gmail.com, mounirsayadi@yahoo.fr, fnaiech@ieee.org

Abstract—This paper introduces a new idea of using the Self-Organizing Map to compare the similarity between the synthesized textures and the original sample in accordance with human visual system. The approaches of texture synthesis do not provide convincing results for all types of textures, since it is difficult to produce a general definition of this term. So that, we propose to evaluate the quality of results provided by different approaches, based on features of comparison to capture information present in texture image.

I. INTRODUCTION

The study of textures has been the subject of much research devoted to the analysis and synthesis of textured images and it is clear that they did not lead to methods that take into account all the aspects of the notion of texture. The definitions of the term 'texture' are often related to a particular aspect because it is difficult to define a texture as a single mathematical model. Indeed, the large amount of approaches used for texture synthesis demonstrated the absence of a generic definition.

Given a finite sample from some texture, the idea behind a successful texture synthesis algorithm is to generate or synthesize other samples from the same texture [1]. This type of algorithms is often used to make a scene more realistic when a large area is to be covered with a texture visually similar to a small example. Besides, texture synthesis processes can be useful for the interpolation of missing information in the case of picture editing [2]. Another large application of texture synthesis algorithms is generating textures from sample images on different object surfaces to make it as realistic as possible without modeling geometric details [1].

There have been many approaches proposed to solve the texture synthesis problem. However, due to their abilities to capture the local information in a given texture, non parametric methods have achieved the more convincing and pleasing results. Most current techniques of example based synthesis consider the color distribution of the example texture as the realization of a Markov random field. Markov models are able to capture the local and spatial information in an image. However, algorithms use of these models is computationally expensive given that an entire search of the sample image is necessary for each pixel to be synthesized [3].

In order to address the problems of scale and computation cost, Gallagher introduced a novel algorithm using the Dual Tree Complex Wavelet Transform (DTCWT) which presents a very useful tool for spectral and spatial analysis [4]. Firstly, the sample texture is represented under different scales, which allows us to exploit the dominant frequencies present in this sample. Next the synthesis is performed at coarser scales

where the original information is represented by fewer pixels. Then, the advantage of this method is the significant reduction of computational cost.

Generally, a pixel-based synthesis does not provide good results when the sample texture contains patterns with large scale. Then, patch-based approaches overcome this problem by the use of squared blocks of user specified size as synthesis unit. Efros and Freeman propose the Image Quilting algorithm to patch squared blocks together to synthesize a new texture and to hide the boundary line between adjacent blocks [5]. This technique ensures a better preservation of the patterns structure and a considerable reduction of execution time by adding blocks instead of a single pixel.

But the success of texture synthesis methods is still dependent on the type of texture. The visual quality of the generated textures will be influenced primarily by the accuracy of the model, while the efficiency of the sampling procedure will be directly related to the computational expense [1]. Hence, in this paper, we propose to evaluate the quality of results provided by different texture synthesis approaches, based on textural features to capture the information present in a texture image. Then we used the Self-Organizing Map, a type of an artificial neural network which is based on biological observations [6]. This is motivated by how a visual information or other sensory is processed in the human brain. This definition seems useful to determine if the synthesized texture preserves the structure of the original sample.

II. COLOR TEXTURE FEATURES

The textural features can be obtained from a set of parameters that correspond to visual properties such as roughness and directionality or purely mathematical properties. These include features based on second order statistical calculations as the co-occurrence matrices or a multi-resolution representation using wavelet transform according to a tree structure.

A. Color co-occurrence matrix

The concept of color co-occurrence matrices is defined to improve the characterization of color textures [7]. The calculation of these matrices for an image, in which, the color is coded in RGB space, is given as follows:

- C_k et $C_{k'} \in$ (R,G,B) two color components,
- θ is a particular direction,
- d is the distance between the pixel to be analyzed and its neighbors,

- $M^{C_k C_{k'}}[I](d,\theta)$ is the color co-occurrence matrix which measures the spatial interaction between color components C_k et $C_{k'}$ of the pixels of image I located at a distance d and in a direction θ.

The cell $M^{C_k C_{k'}}[I](d,\theta)(i,j)$ of this matrix contains the number of times a pixel p of the image I of which the color component level $C_k = i$, in its neighborhood in a direction θ and at a distance d, situated a pixel p' and which $C_{k'}(p) = j$.

The co-occurrence matrices are sensitive to the spatial resolution. So, they need to be normalized by the total number of co-occurrences.

$$m(x,y) = \frac{M^{C_k C_{k'}}[I]((d,\theta),(x,y))}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} M^{C_k C_{k'}}[I]((d,\theta),(i,j))} \quad (1)$$

$\forall\,(x,y) \in [0,...,(N-1)]$, and N the quantization level of the color components.

TABLE I
HARALICK FEATURES

Feature	Equation
Energy	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} m(i,j)^2$
Contrast	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2\, m(i,j)$
Maximum of probability	$\max_{i,j}\,(m(i,j))$
Homogeneity	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{1}{1+(i-j)^2}\, m(i,j)$
Entropy	$-\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} m(i,j)\,\log\{m(i,j)\}$
Cluster shade	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-M_x+j-M_y)^3\, m(i,j)$
	Where $\quad M_x = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i\, m(i,j)$
Prominence	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-M_x+j-M_y)^4\, m(i,j)$
	and $\quad M_y = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} j\, m(i,j)$

For a given distance d and direction θ, a set of features [8] are extracted from six normalized color co-occurrence matrices (Table I). We take into account both intra and inter-component [11].

B. Multi-resolution analysis

Techniques of multi-resolution analysis can extract features at various scales and considerate fine and coarse information in the texture. Then, we use the wavelet transform with its ability to analyze local spectral properties of a signal. The transform is computed by applying a filter bank in both horizontal and vertical directions with convolutions with rows and columns of the image. The outputs of filters are then sub-sampled by a factor of two in each direction, resulting in one low pass sub band and three detail sub bands. The same process is repeated only on the low pass sub band to generate the next resolution level. Because the texture images have frequencies and orientations, the energy index is a measure of local distribution wavelet coefficients as a function of frequency, orientation and scale. The expression of the energy is given by:

$$E_{B,l}^{C_k} = \frac{1}{NN} \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \{W^{C_k}((B,l),(i,j))\}^2 \quad (2)$$

Where $W^{C_k}((B,l),(i,j))$ is the wavelet coefficient at the location (i,j) at the scale l in the detail sub band B and C_k is the color component ($k = 1,2,3$) [9].

We can characterize a color texture by features that include only intra-component relationships in RGB space [10]. Thus, we apply wavelet transform on each channel to calculate the energy sub-band images of a particular direction.

III. SELF-ORGANIZING MAP

The objective of the self-organizing map (SOM) [6] is to present complex data that belong to a discrete space of large dimensions, according to a topology restricted to one or two dimensions. It is a competitive neural network that learns to categorize data vectors which form the input space.
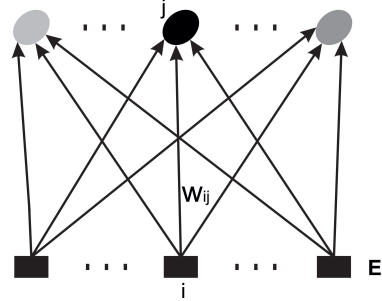

Fig. 1. One-dimensional topology of Self-Organizing Map

It is associated with each neuron of SOM, a weight vector of the same size as the vectors of the input space and a position in the map grid. During the learning process, an input vector is compared using the Euclidean distance, with the weight vector of each neuron. This procedure consists in selecting the most representative neuron of the input data. This last, as well as its neighbors change their weights to respond better to other data, of the same nature as the preceding. Lateral connections between neurons are fixed weights, and they are excitatory in a close neighborhood and inhibitory in a more distant neighborhood. Once the map is constructed, we can determine and study the data distribution in space with low dimension. Each input vector is now assigned to the *winner*

neuron which the weight vector is the closest (by simply using the Euclidean distance).

A one-dimensional topology is shown in figure 1. Each neuron is connected to a number n of inputs, through n connections plastics of respective weights W_{ij} which j is the index of the neuron in the grid and i is the index of the vector in the input space E.
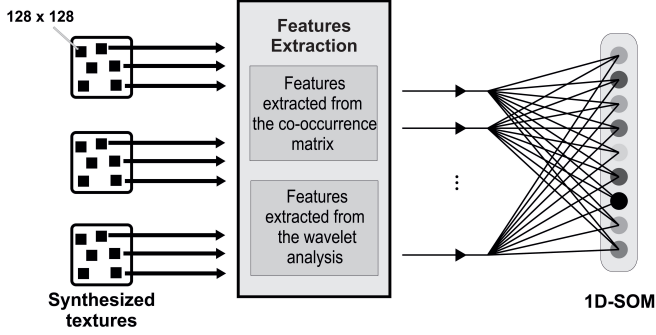
IV. EXPLOITATION OF THE SOM

Fig. 2. Principle of the proposed evaluation technique. The textural features are extracted from the examples taken randomly from each synthesized texture (200 examples are designated for the training process and 100 for the simulation). Next, features vectors are submitted to the SOM to determine the corresponding neuron.

Our goal is to select automatically the best synthesized texture of a given example, from the provided results of different synthesis approaches. Initially, each sample texture is synthesized with three methods (figure 3). Then, examples of the same size as the original sample are selected randomly from each synthesized texture which form the database of the training and simulation process. The next step consists on calculating the textural features from examples designated for training process. The obtained vectors are submitted to the output layer arranged in a one-dimensional array (1D-SOM). A single neuron corresponds to each input vector after a competition between 9 neurons. (figure 2).

Once training is finished, we simulate the 1D-SOM with the desired vector of features that characterizes the orignal sample to determine the corresponding winner neuron. The vectors of features obtained from the examples of simulation are now submitted to the output layer (9 competitive neurons). We want to determine how many vectors are assigned to the neuron most representative of the desired vector (representing the original sample). Thus, the synthesized texture which provided more vectors assigned to this neuron represents the best result.

V. RESULTS AND DISCUSSION

A synthesis method can be efficient only for certain types of textures. For example, the sample *Fabric* has patterns which are organized approximately in a regular manner. So the method of *Image Quilting* is the most appropriate as the addition of blocks preserves the largest structure in the original sample and thus gives good results in the case of structured
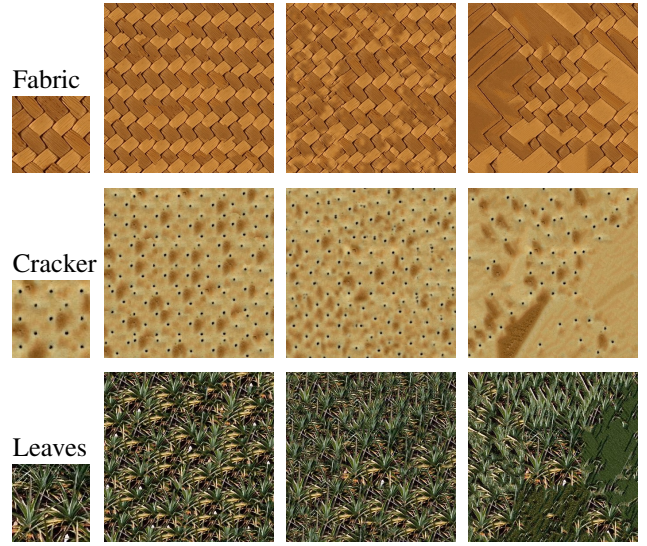

Fig. 3. Results from three texture synthesis algorithms: Image Quilting, DTCWT texture synthesis and Nonparametric Sampling (respectively in column 2, 3 and 4). The original samples have resolutions of 128x128 (first column). All output textures have a resolution of 384x384.
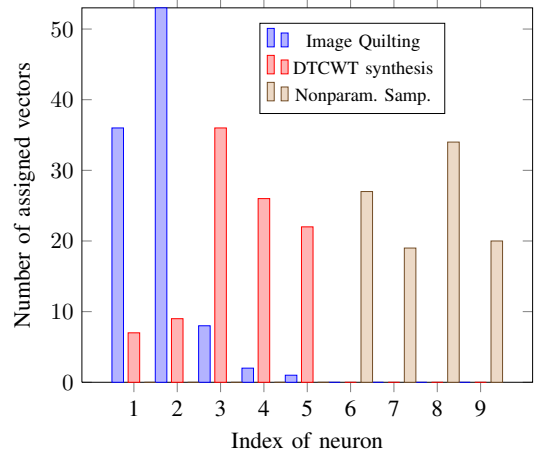

Fig. 4. *Winner neuron index*: **2**. The best synthesized texture is provided by the *Image Quilting* method.

textures (figure 3). The *DTCWT method* did not provide convincing results because it does not take into account the details of higher resolution which generally characterize the regularity and homogeneity that was missing in the synthesized texture of this sample. For the synthesis based on *Nonparametric sampling*, it is clear that the synthesis unit (one pixel) is not sufficient to capture and preserve the structure of patterns and their spatial distribution. This was confirmed by the results of the neuronal evaluation technique shown in figure 4.

But if we consider the texture samples *Cracker* and *Leaves*, the *DTCWT* method provided the best results. The sample *Cracker* has black spots that are distributed regularly in space and brown areas which the intensity and shape will differ from one region to another. These two primitives are not well reproduced in the result obtained by the *Image Quilting* method.
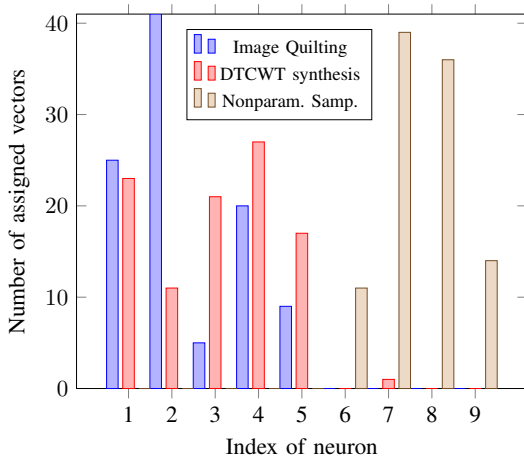
Fig. 5. *Winner neuron index*: **5**. The best synthesized texture is provided by the *DTCWT synthesis* method.

This one presents an excessive repetition of dark brown areas which directly attracts the attention of the observer (figure 3). By cons, the synthesized texture of the wavelet method seems natural although it is not perfectly identical to the original sample in its regular distribution of black spots. According to figure 5, this result corresponds to the higher number of feature vectors assigned to the neuron of index 5, the most representative of the desired vector obtained from the sample *Cracker*.
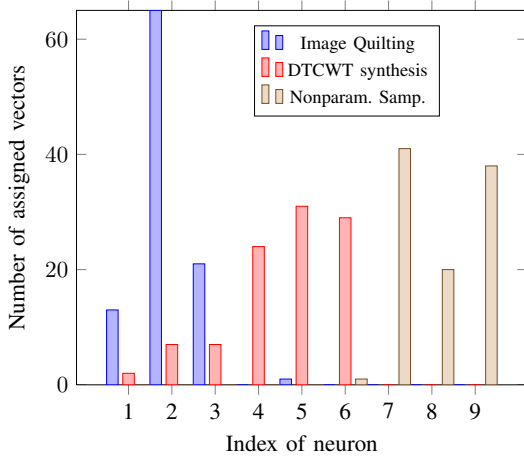

Fig. 6. *Winner neuron index*: **6**. The best synthesized texture is provided by the *DTCWT synthesis* method.

Again, the *Nonparametric sampling* method failed to provide convincing result because of limitations against the preservation of the scale patterns and the overall structure of the texture. We can also clearly identify the slipping into a wrong part of the search space from the related result (figure 3). Similarly, based on figure 6, the representation of the texture *Leaves* in multi-resolution domain gives the advantage to capture some details and maintain their visual appearance. The result of the *DTCWT* method is then more compelling.

VI. CONCLUSION

Textures have no generic definition and a convincing synthesis result depends to the texture sample and its appropriate method. In this paper a new evaluation technique of texture synthesis results was introduced. This technique allows us to determine the best synthesized texture in presence of different approaches. So we used the Self-Organized Map due to its capacity to detect similarities and regularities in the data vectors and determine their distribution in a low dimensional discrete space. The results shown previously have been confirmed by the visual interpretation. Because of limitation of a synthesis method against some type of textures, the proposed technique is suitable for using a wide variety of textures to be synthesized.

REFERENCES

[1] L.Y. Wei and M. Levoy: Texture Synthesis over Arbitrary Manifold Surfaces. ACM SIGGRAPH, 2001.
[2] Simon Robinson Bill Collis and PaulWhite, Wire removal, in The IEE 1st European Conference on Visual Media Production (CVMP), March 15-16, London, UK, 2004, pp. 133–138.
[3] A. A. Efros and T. K: Leung. Texture synthesis by non-parametric sampling. International Conference on Computer Vision, pages 1033–1038, Corfu, Greece, September 1999.
[4] C. Gallagher and A.C. Kokaram: Nonparametric wavelet based texture synthesis. IEEE International Conference on Image Processing (ICIP), Gnes, Italie, September 2005.
[5] A.A. Efros and W.T. Freeman. Image quilting for texture synthesis and transfer. ACM SIGGRAPH, pages 341–346, August 2001.
[6] T. Kohonen: Self-Organized Formation of Topologically Correct Feature Maps. Biological Cybernetics. vol. 46 (1982) 59–69.
[7] C. Palm: Color texture classification by integrative co-occurrence matrices. Pattern Recognition. 37(5) (2004) 965–976.
[8] R. Haralick, K. Shanmugan, and I. Dinstein: Textural features for image classification. IEEE Transactions on Systems, Man and Cybernetics. 3(6) 610–621 (1973).
[9] R. R. Coifman and M. V. Wickerhauser: Entropy-Based Algorithms for Best Basis Selection. IEEE Transactions on Information Theory. (1992) 713–718.
[10] M.A. Akhloufi, X. Maldague, and W.B. Larbi: A new color-texture approach for industrial products inspection. Journal of Multimedia 3(3) (2008) 44–50.
[11] X. Xie and M. Mirmehdi. Texems: Texture exemplars for defect detection on random textured surfaces. IEEE Transactions on Pattern Analysis and Machine Intelligence 29(8) (2007) 1454–1464.