

Texture Modeling and Segmentation towards content based image retrieval system

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المستخلص :

يقوم هذا البحث بتصنيف الصور النسيجية وذلك بتقطيع الصور الأصلية إلى صور صغيرة ذات أطوال ثابتة (8*8)، وذلك باستعمال طريقة التحويل المويجي لمعالجة الصور ذات الأبعاد (128*128) بالمستوى الرمادي. حيث يقوم البحث بعد عملية تقطيع الصورة الأصلية بمرحلتين رئيسيتين هي التصنيف والاسترجاع. في مرحلة التصنيف الأجراء المتبع يتطلب تقطيع للصورة النسيجية للصورة المختبرة. في مرحلة الاسترجاع الصور المصنفة سوف تعنون متبوعة بقرار منطقي معطى. بعد اختبار أكثر من 25 صورة معدل الاسترجاع 65% أنجزت بنجاح.

Abstract:

There are many techniques to extract features. Some use direct and other use transformation such as Fourier Transform, Discrete cosine transform and Wavelet Transform. Such Transforms convert the signal from time domain to frequency domain and vice versa. The Wavelet Transform conducts the change a frequency and reflects that in time. This research uses the Wavelet Transformation method to process images with (128*128) pixels, knowing that these images are in grayscale. An algorithm is proposed for texture classification using Wavelet Transform. The texture classification of an image means dividing it into sub images of fixed or variable length. Hence, this algorithm first takes the image and then it divides it into block of (8*8) dimension. There are two phases mainly in the proposed algorithm, classification and retrieval phases.

In the classification phase, the procedure that followed requires the texture segmentation and wavelet transform computation of the test image. In the retrieval phase, the classified texture will be labeled following a given logical decision.

1 Introduction

Natural images are well characterized as a linear combination of energy concentrated in both frequency and space [1] [2]. Most of the energy of typical image is concentrated in low-frequency information, and some of it on the high-frequency part for the remaining components of the image. Particularly, most of the energy is spatially concentrated around edges. The efficient transform coding models calls for a transform that compact's energy into few low-frequency coefficients, while the high-frequency energy is represented in a few spatially clustered high-frequency coefficients [3] [4].

One of such transform is the Wavelet Transform, which is used here in signal representation due to its capability of decomposition using basis functions [5]. As a result the aim of this transformation is to find a texture modeling system.

2. The Database

A database of 25 pictures are collected that consist of a wide spread of different textures of size (128*128). These pictures are labeled as Im0 till Im24 and are shown in Appendix A. These images are divided into (8*8) frame textures. As a result a total of 6400 textures are formed. These will be used for generation of the texture models and as well as testing the proposed algorithm.

This size is preferred here since the (8*8) size has been used in several standard applications like image compression JPEG and in image transmission.

3. A proposed texture modeling system

The main block diagram of the proposed texture modeling system structure is given in Fig (1). After taking an input image a partition of equal size will be carried out on it. As a result it will be divided into 8*8 textures.

Next the discrete wavelet transform will be applied to each texture and the computation of the energy of each decomposed matrix will be performed. Now, comparison of each texture with other textures will be started until the different texture for all images under consideration will be found. Finally a labeling process will be achieved.

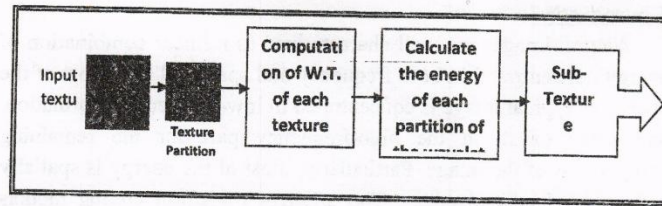


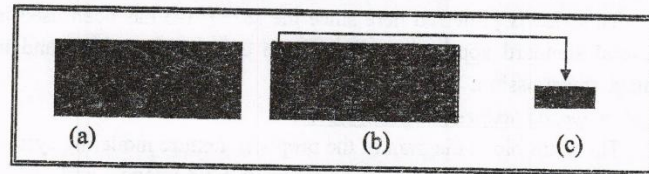
Fig (1) Main structure of the proposed system

Thus the main aim of this structure is to form a model of texture from that will be labeled to be the reference sets.

3.1 Texture Segmentation

For this partition process the frame size of the image is not important. Because the aim here is to divide the given image into segments of equal length of size (8*8) pixels.

For example if the given image is of (128*128) pixels, then the partition process results in 256 textures of the mentioned (8*8) size. Fig (2) shows this partition process. Table (1) gives the values of the pixel elements of one of these textures.



Original image (128*128) Grid of partition into 256 textures

Zooming of one texture

Fig ((2) a,b,c) Partition of a given image

The matrix presented below shows the real values of first sub image from image one.

Table (1) The detail values of the texture in Fig (2),(c).

Pixels Values (8*8)							
105	106	103	104	110	121	129	127
95	108	116	120	120	122	119	101
101	116	129	126	114	89	70	67
122	127	121	101	77	41	30	44
133	119	89	56	46	37	29	40
128	90	48	26	40	47	48	44
111	72	37	25	35	53	58	47
101	70	50	35	37	49	51	45

3.2 The Feature Extraction process:-

The success of any algorithm depends firstly on the selection of features. The better in this selection is the higher performance of the rebuild algorithm. It was found by several researchers that sometimes leaving the spatial domain and replace it with its transformation mostly give a better result when dealing with image signals. Hence in this feature extraction process the Discrete Wavelet Transform (DWT) was selected. The reason for this selection was the ability of the (DWT) in converting the image into the frequency domain in addition keeping the spatial domain information.

Hence after image Partitioned, It was subjected to (DWT) determination. The aim here is to reduce the huge data that is not included in classification process to be done on it. The resulting textures of interest are known as the references to be stored for future analysis.

The *Discrete Wavelet Transform* (DWT) is a popular transform in the field of digital image processing. An algorithm that was used here for its computation will be given here with a demonstrated example.

Note that, it is first necessary to choose the type of basis function that is useful for the application under consideration. Several of these basic functions are considered. Among these is the Haar basis function. The Haar wavelet is probably the simplest wavelet to understand. There are a wide variety of popular wavelet algorithms: Mexican Hat wavelets and Morlet wavelets. These wavelet algorithms have the advantage of better resolution for smoothly changing time series. But they have the disadvantage of being more expensive to

calculate than the Haar wavelets. The higher resolution provided by these wavelets is not worth the cost for financial time series, which are characterized by transitions.

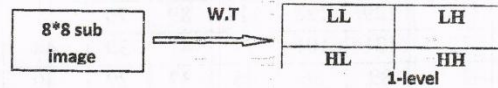


Fig (3) Calculation of Wavelet Transforms

After extensive experimental test the Haar gave the best feature representation for the current process. Hence the computation method that followed here will be given in detail for Haar wavelet.

- Step-1- Take a given texture which is here of size (8*8) pixels.
- Step-2- Apply the (DWT) of Haar on it using Equations (1), (2).

$$F_L(n) = \frac{x(2n) + x(2n+1)}{\sqrt{2}}, \dots\dots\dots(1)$$

$$F_H(n) = \frac{x(2n) - x(2n+1)}{\sqrt{2}}, \dots\dots\dots(2)$$

Each step in the forward Haar transform calculates a set of wavelet coefficients and a set of averages. If a data set s_0, \dots, s_{N-1} contains N elements; there will be N/2 averages and N/2 coefficient values. The averages are stored in the upper half of the N element array and coefficients are stored in the lower half. The averages become the input for the next step in the wavelet calculation.

Where for iteration $i+1$, $N_{i+1} = N/2$. The recursive iteration continues until a single average and a single coefficient are calculated. This replaces the original data set of N elements with an average, followed by a set of coefficient whose size is an increasing power of two (e.g., $2^0, 2^1, 2^2 \dots N/2$). The above operations will be conducted on the columns after transforming the rows. As a demonstrated example on the previous steps consider the image shown in Fig (2). Now, after applying Haar wavelet transform on this texture the resultant coefficients are given in Fig (3). The resultant of this step will be a matrix of four sub segments. These usually known are [Low-low

(LL), Low- High (LH), High-Low (HL) and High-High (HH)] as given Fig (4).

Step-3- Calculate the energy for each sub band images namely the (LL) the (LH) the (HL) and finally the (HH).

154.5	185.5	237.5	279.5
232	272.5	287	293
267.5	260	265.5	245.5
228.5	250.5	256.5	201.5

(a) The (LL) data

-25.5	-15.5	-7.5	-15.5
-25	-17.5	3	24
21.5	14	-5.5	-1.5
-16.5	-10.5	9.5	22.5

(b) The (LH) its image representation

-5.5	-9.5	-15.5	-3.5
-10	-8.5	-1	-30
3.5	-1	1.5	5.5
-1.5	-8.5	9.5	12.5

(c) The (HL) its image representation

-1.5	-2.5	-0.5	5.5
-1	-2.5	-7	-2
-2.5	7	2.5	-3.5
1.5	-3.5	-5.5	-2.5

(d) The (HH) its image representation

Fig (4) Image Representation of WT

Thus, for each sub images the normalized energy value will be computed using the conventional equation given here:

$$P_{nom} = \frac{\sum_{y=0} \sum_{x=0} S_{xy}^2}{n} \dots\dots\dots (3)$$

This result in a vector with 4 energy values of the form E = (e1, e2, e3, e4)

For the current example these energy values are this E can be written as

$$E = [(LL), (LH), (HL), (HH)] = [40.029, 0.081016, 0.12789, 0.0079531].$$

The normalized energy values will be stored for this texture of the given image.

4. Generation of References Textures

After computing the DWT of each block of the given image the classification step will be started. The aim here is to select the different textures from each image. These selected textures are considered as reference textures. The selection process or the generation of the reference texture was achieved using the following steps:

Step-1- The first texture will be considered as the first selected reference texture.

Step-2- This first reference texture will be compared with the rest of the textures of the given image. The aim here is to find or remove any texture that is similar to it.

Step-3- The similarity measure has been achieved using distance measure. Thus the absolute difference between the energy vectors of the textures is used. This can be expressed by the following equation:

$$D_t(t_1, t_2) = \sum E | (e_{t1i} - e_{t2i}) | \quad \text{where } t_1 \text{ for texture 1 and } t_2 \text{ for the texture 2, } e_{t1i} \text{ the } (i) \text{ the energy of texture one.}$$

Step-4- The number of generated reference textures depends on the selection of threshold value. To demonstrate this process numerical values will be used to simply it understands. For example an image of size (128*128) is considered which gives 256 textures of (8*8) pixels. Now, using a threshold value of 0.2 for the absolute distance measure, it will rise to generating 215 different textures. If this threshold value is changed to 2.5 then the selection process generate 31 different textures see table (2). Increasing this threshold value to 4.5 this results in the generation of only 19 different textures shown table (3).

Step -5- The final step of the generation process implies the comparison of the selected texture references of all images. It is regarded as the final step of the generation of the reference textures. As a demonstration form the first 6 images are shown in Appendix A, a total of 33 texture references are generated. These 33 textures are shown in Fig (5)

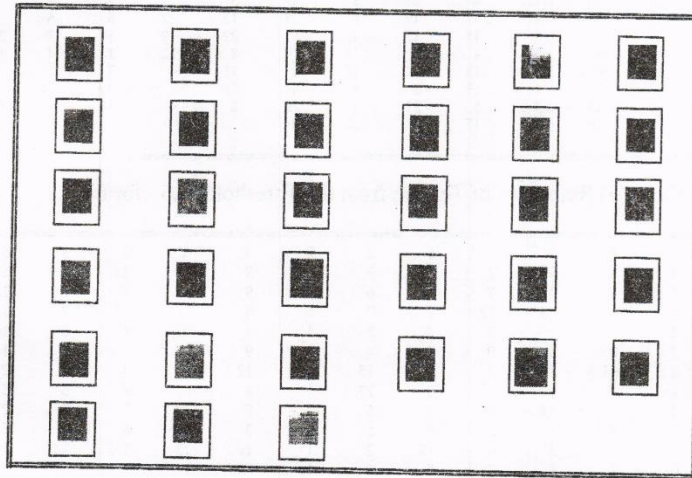


Fig (5) Total of Segment Reference

5. Image Retrieval using Labeling Technique

After generating the 33 reference textures for the 10 training images, a labeling process is conducted for the test images using these textures. The aim here is to retrieve images using these labels. The reference textures are numbered from 1 up to 33 and those textures that are similar to these take their corresponding numbers. The retrieving process was achieved through the following procedure.

Step-1- Give a test image it is first required to divide it into textures of (8*8) pixels.

Step-2- Compute the DWT of each (8*8) texture using Haar basis function. Then the energy of each texture as mentioned before.

Step-3- Start classifies each block of the test image into one of the 30 reference textures. The same absolute distance measure was used.

The result of this step is labeled version of the test image. For example a test image of dimension (128*128) pixels is considered here. After passing it through this retrieval processes the labeled form of the image is given in Table (4) for different value of the threshold.

6. Evaluation Test of the Algorithm

As a demonstrated example take the image given in Fig (6). Image size 256 textures each of 8 * 8 pixels. After labeling the image only consists of 20 different textures as given in Table (5).

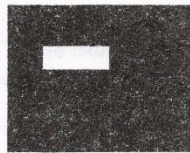


Fig (6) the Test Image

7. Evaluation Test of the Result

Several experimental tests have been carried out to evaluate the performance of the proposed algorithms. The data based mentioned before were used and here only the results of 10 images are given here. In Table (5), given the result of computing energy of the texture of a given image (im1). The values in this table can be demonstrated as follows. Consider the row started with texture 7, the next four values in its front are corresponded the energy values of this texture in the image. These are corresponded the four levels of the resultant Wavelet Transform of the texture. Using the proposed algorithm of generation of reference texture and using them in the labeling of these textures result in Table (6). From this table it is clear that the 256 texture are classified into only sixty different types. The numbers in these tables are corresponding to the texture sequence in the reference set. The sequences of the textures of the given image are remaining the same, which is not given in the table. It is easy to follow such sequence knowing that the first texture is placed in the left corner of the table and the first thirteen textures are given in the first row of the table, which is [1 1 2 2 2 2 3 3 3 2 2 2 2]. The second row corresponds to the latest twelve textures starting from texture 14 up to texture 25 and so on.

Table (6) Reference of Original Image

1	1	2	2	2	2	3	3	3	2	2	2	2
	2	1	1	1	2	2	2	2	1	1	3	3
	1	2	2	2	2	2	1	2	2	2	2	1
	3	3	1	1	3	3	1	2	2	2	2	4
	2	2	1	1	1	1	3	3	1	1	1	1
	2	2	4	4	4	1	1	1	1	1	3	3
	1	1	1	1	5	4	4	4	2	1	1	1
	2	2	3	1	2	2	1	1	1	2	4	2
	1	1	1	2	2	2	2	2	2	2	2	1
	1	1	2	1	1	2	2	2	2	2	5	2
	2	2	4	1	1	1	3	1	1	2	1	2
	2	2	2	2	2	2	4	1	1	1	1	4
	1	3	1	2	2	2	1	2	2	2	1	1
	1	1	4	4	4	1	1	1	2	1	3	3
	2	1	1	1	1	4	4	4	2	2	3	1
	1	1	3	3	1	1	1	1	2	2	4	2
	2	2	1	1	1	3	1	1	1	1	1	2
	2	2	4	2	2	2	2	2	3	1	3	1
	3	1	2	2	2	2	1	1	2	2	2	2
	2	3	3	3	1	2	2	2	2	1	1	1
	1	2	2	2	2	1	3	3	2	2	2	2
	1	1	1									

To examine the power of this algorithm a part of the test image is removed and entered a retrieval test. Table (7) gives the result of the labeling test and it was successfully classified although a part of the image is removed. It was found that removing up to 35% of the image the classification work without any error. However, it was failed up this level of removing.

The first column is the sequence of the test image, as given in appendix A. The second column corresponds to the number of different textures in the test image. For example, image number im7 has a total of (36) different texture out of the total of 256 textures.

The results for 10 images are tabulated in table (8). The third column corresponds to the test result. If the symbol is (Ok) this means it is a successful test and (Not) corresponds to a fail classification therefore, only two out of these 10 images are failed in this test. Thus the classification score is 80%.

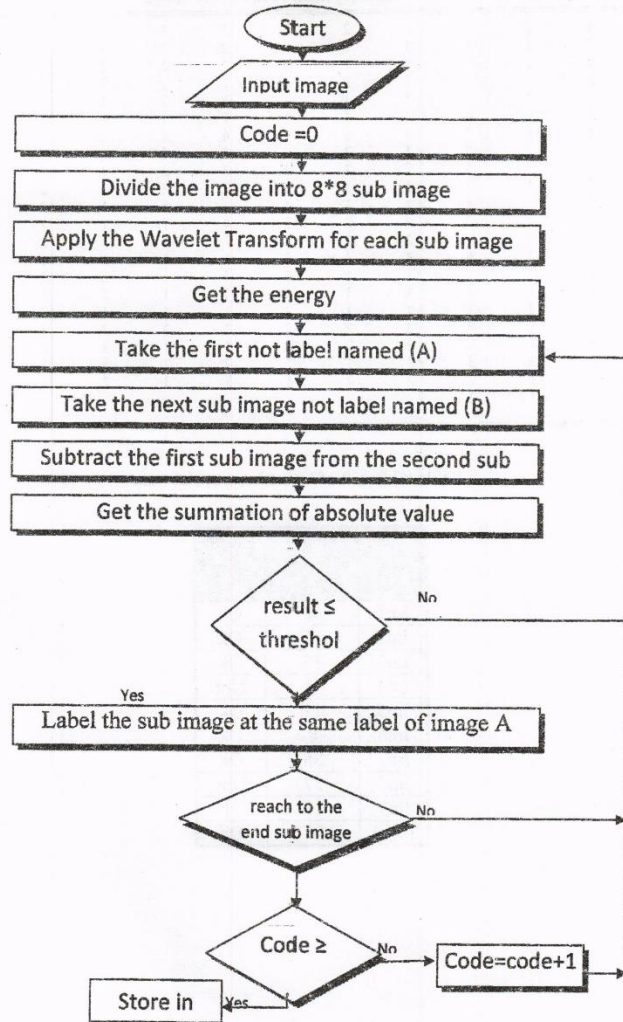
Table (7) Reference of Test Image

1	1	2	2	2	2	3	3	3	2	2	2	2
2	1	1	1	1	2	2	2	2	1	1	1	3
1	2	2	2	2	2	2	1	2	2	2	2	1
3	3	1	1	1	3	3	1	2	2	2	2	4
2	2	1	1	1	1	1	3	3	1	1	1	1
2	2	4	4	4	4	1	1	1	1	1	3	3
1	1	1	1	1	5	4	4	4	2	1	1	1
2	2	3	1	2	2	2	1	1	1	2	4	2
1	1	1	1	2	2	2	2	2	2	2	2	1
1	1	2	1	1	1	2	2	2	2	2	5	2
2	2	4	1	1	1	1	3	1	1	1	2	1
2	2	2	2	2	2	2	4	1	1	1	1	4
1	3	1	2	2	2	2	1	2	2	2	2	1
1	1	4	4	4	1	1	1	1	2	1	3	3
2	1	1	1	1	1	4	4	4	2	2	1	1
1	1	3	3	1	1	1	1	1	2	2	4	2
2	2	1	1	1	1	3	1	1	1	1	1	2
2	2	4	2	2	2	2	2	2	3	1	3	1
3	1	2	2	2	2	1	1	2	2	2	2	2
2	3	3	3	1	2	2	2	2	2	1	1	1
1	2	2	2	2	2	1	3	3	2	2	2	2
1	1	1	1	1	1	1	1	1	1	1	1	1

Table (8) Result of Algorithm wavelet Haar

No. Of image	No. of different texture	Result
Im1	4	Ok
Im2	7	Ok
Im3	13	Ok
Im4	6	Not
Im5	11	Ok
Im6	8	Ok
Im7	36	Ok
Im8	57	Not
Im9	18	Ok
Im10	25	Ok

Fig. (7) Flowchart of the Proposed Algorithm



8. Conclusions

In this work the wavelet transform has used to establish texture image retrieval. The proposed algorithm of texture classification and retrieval based on wavelet transform in the selection of different textures from a sufficient texture database. These are used later in the retrieval and the classification process. A summary of some conclusions could be the following: -

- 1-Selection of (8*8) size for the texture was an excellent choice, which resulted in the improvement of the classifier performance.
- 2-It has been seen that it's of high speed in the decoding process.
- 3-The reference textures selected by the proposed techniques are of an excellent representation to the corresponding images such that their energy achieved a retrieval score of 95%.
- 4-The proposed method needs only those different textures of the test image with even a better result than those conventional methods that need all the texture.

9. future work

They needs for further studies to be conducted in the following points. These points associate with different applications of the Wavelet Transform in texture image.

1. Applied the system on remote sensing image.
2. Using the Probabilistic Neural Network.
3. The use of the Wavelet in the color texture analysis.
4. Using new features such as entropy.
5. Using Multi-wavelet to extract features from an image may develop the performance of the system.

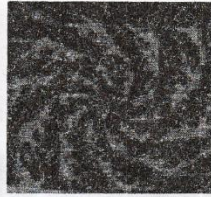
10. References

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- [2] Afary A.R., Emamy H., "Satellite Image Fusion Using Wavelets Transform," Ali Reza Afary; National Cartographic Center, Hasan Emamy; K. N. Toosi University of Technology, Internet explorer
- [3] Poggio, F., "Regularization Theory, Radial Basis Functions and Networks," From Statistics to Neural Nets: Theory and Pattern Recognition Applications, NATO ASI Series, (136), 83-104, (1994).
- [4] Misiti, M., Misiti, Y., Oppenheim, G. and Poggi, J.M. "Wavelet toolbox user's Guide", ver.1, copyright by the math works, Inc., 1997.
- [5] Mahomoud, W.A., Amamra, "Identification of digital modulation techniques using the discrete wavelet transform", conf. on computational Aspects, 2002.

Appendix A



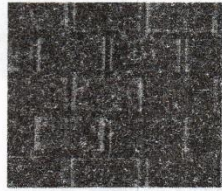
im1



im2



im3



im4



im5



im6



im7



im8



im9



im10



im11



im12



im13



im14



im15



im16



im17



im18



im19



im20



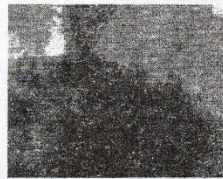
im21



im22



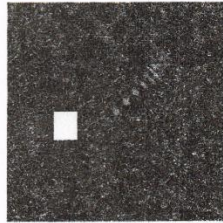
im23



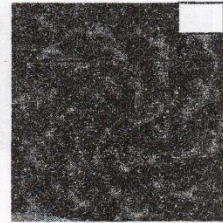
im24



im25



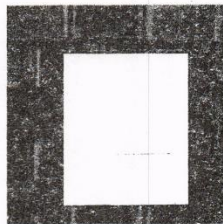
img1



img2



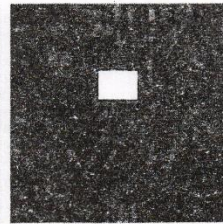
img3



img4



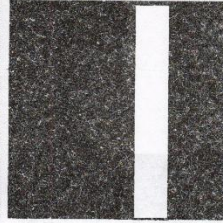
img5



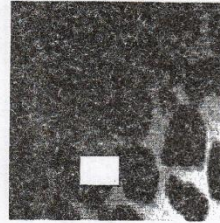
img6



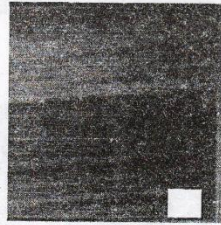
img7



img8



img9



img10