Using Discrete Wavelet Transform for texture classification by using energy

طريقة جديدة لتصنيف صور النسيج باستخدام التحويل المويجي المتقطع (DWT)

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كلية التربية للبنات كلية الآداب

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الملخص:

هـذا البحـث يقـترح طريقـة جديـدة لتصـنيف صـور النسـيج باسـتخدام التحويـل المـويجي المتقطـع(DWT). التصـنيف الجيـد يعتمـد علـى مرحلـة اسـتخلاص المعلومـات. بعـض نمـاذج مـن صـور الانسـجة حللـت باسـتخدام التحويـل المويجي الـذي يعتبر مـن الأدوات الجديـدة والواعـدة في التحليـل.في البحـث الحـالي, لـوحظ إن التحويـل المـويجي كـان مناسـباً في اسـتخلاص المعلومات من صورة النسيج . المحاولات للمعلومات الإحصائية على معاملات التحويل المويجي تمت على عدة تجارب تصنيفية.وقد لوحظ إنه ,عند استعمال الطاقـة و الوسـط الحسـابي سـويتا للمعـاملات التحويـل المـويجي التقريبيـة (LL1,LL2,LL3) كانت مناسبة للحصول على تصنيف نـاجح للصـور بنسـبة خطأ مقبولة

Abstract

In this paper suggests a new image classification scheme of texture images, using the discrete wavelet transformation (DWT). A good classification relies on feature extraction stage. Several samples (texture images) of several classes were analyzed using wavelet transform which is new and promising set of tools. In this work, it was shown that

wavelet transform was appropriate for texture feature extraction. The performances of statistical properties of wavelet detail coefficients were compared in several classification experiments. And it was shown that, when used together (Mean, and energy) the energy and mean absolute of approximation coefficients were appropriate wavelet signatures for achieving a successful image classification with acceptable low error rates.

I. Introduction

Everywhere around us are signals that can be analyzed. For example, there are human speech, medical images, financial data, music and many other types of signals. Wavelet analysis is a new and promising set of tools and techniques for analyzing these signals. Wavelet Transform provides the time-frequency representation of a signal. As a definition, a wavelet is a waveform of effectively limited duration that has an average value of zero [1]. Texture analysis plays an important role in many image processing and pattern recognition tasks such as remote sensing, medical imaging, robot vision and query by content in large image databases. Various methods for texture feature extraction have been proposed during the last decades but the texture analysis problem remains difficult and subject to intensive research. Texture classification is an important subject in pattern recognition and image processing areas. There are several methods developed for this purpose. Three well known methods are local linear transforms, gabor filtering and the cooccurrence approach [2]. In these methods one has to do many difficult mathematical transformations and operations. As an alternative to these and the others, in this paper, the wavelets are used to analyze the textured images. Several texture samples were analyzed and obtained statistical properties of wavelet detail coefficients. Then we classified the texture classes using these

statistical values such as (Mean and energy) of approximation coefficients[3].

2. Discrete wavelet transforms (DWT)

Wavelets are functions generated from one single function W by The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level.

The discrete wavelet transform (DWT) is identical to a hierarchical sub band system where the sub-bands are logarithmically spaced in frequency and represent octave-band decomposition. By applying DWT, the image is actually divided i.e., decomposed into four sub-bands and critically sub-sampled as shown in Fig. 1(a). These four subbands arise from separate applications of vertical and horizontal filters. The sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients i.e., detail images while the sub-band LL1 corresponds to coarse level coefficients i.e., approximation image. To obtain the next coarse level of wavelet coefficients, the sub-band LL1 alone is further decomposed and critically sampled. This results in two level wavelet decomposition as shown in Fig. 1(b). Similarly, to obtain further decomposition, LL2 will be used. This process continues until some final scale is reached. The values or transformed coefficients in approximation and detail images (sub-band images) are the essential features, which are as useful for texture classification and segmentation. Since textures, either micro or macro, have non-uniform gray level variations, they are statistically characterized by the values in the DWT transformed sub band images or the features derived from these sub-band images or their combinations. In other words, the features derived from these approximation and detail sub-band images uniquely

characterize a texture. The features obtained from these DWT transformed images are shown here as useful for texture analysis. [4]

3. Feature extraction:

After the wavelet decomposition for the image we can extract some important features by using the following:

Mean:

The mean implemented by using this equation:

$$Emi = \frac{1}{N}\sum_{j,k}(Dmi(b_j, b_k))^2$$

Energy

The mean implemented by using this equation

$$Emi = \frac{1}{N}\sum_{j,k}(Dmi(b_j, b_k))^2$$

Where N is the total number of wavelet coefficients in D_{ni} which is a sub image.

4. Neural Network classification

A three-layer feed forward back propagation Artificial Neural Network (ANN) was built. Multilayer networks trained by the back propagation algorithm are capable of learning nonlinear decision surfaces and thus make efficient and compact classifiers. The ANN was trained until the sum square error of Sum-Squared Error (SSE) = 2.60265e-012 being reached as the final learning convergence criterion. The input feature vector matrix had a size 2 by 1 elements, so the network had 2 input layer nodes. The hidden layer consisted of four nodes. The output layer had one nodes, which corresponded to the five classes. The logarithmic

sigmoid function was chosen as the threshold unit for all three layers and the learning rate was set to one.[5]

5. Algorithm of the system:

Input: image of size N _ N.
Output: type of image.
Step 1. Read the image.
Step 2. Obtain 128 · 128 sub-image blocks, starting from the top left corner.
Step 3. Decompose sub-image blocks using 2-D DWT (three level).
Step 4. Derive co-occurrence matrices (C) for original image, and detail sub-bands of DWT decomposed sub-image blocks to three level.
Step 5. Calculate features extraction, such as (Mean and energy) from occurrence matrices for three level and save the values in an table (1).
Step 6. Repeating steps from 1 to 5 for all sample images from the same texture class.
Step 7. find the range for each values in each group and save the value in table (2).
Step 8.use the results in final table to represent the input to the ANN in order to known the type of image.
The block diagram of the system was shown in figure (2)

6. Results of image classification system

The steps involved in texture classification are shown in Fig. 4. Here images of size N _ N are considered. We made several classification experiments with various images. Specifically we got Twenty images for five class each class consist of four real world 512x512 images from different natural (brick, fabric, food, tree, flower) 15 images for training and five for test which are presented in Figure 4 . The analysis is carried out by considering sub-images of size 128 · 128. Each 128 · 128 sub-image, taken from top left corner of the original image, is decomposed using one level DWT and co-occurrence matrices (C) (LL1) are derived for sub-image and detail sub-bands (i.e., LH1, HL1 & HH1 sub-bands) of wavelet decomposed sub-image. The (LL1) sub-band is decomposed using tow level DWT and co-occurrence matrices (C) (LL2) are derived for sub-image and detail sub-bands (i.e., LH2, HL2 & HH2 sub-bands) of wavelet decomposed sub-image. The (LL2)sub-band is decomposed using three level DWT and co-occurrence matrices (C) (LL3) are derived for sub-image and detail sub-bands (i.e., LH3, HL3 & HH3 sub-bands) of wavelet decomposed sub-image Then, from these co-occurrence matrices (C)(LL1, LL2, LL3) features extraction, such as (Mean and energy) are computed using formulae given in Eqs. (1)and(2), as image features. In our implementation, the output from the features in table(1) and then find the range for each type to represent the input to the ANN in table (2)The training process taking: 69/250epochs, Sum-Squared Error (SSE) = 2.60265e-012 as illustrated in the figure (3).

7. Conclusions and discussions

We can derive some conclusions from the resulting error rates of the 16 classification experiments:

1. In this paper, the concept of discrete wavelet transform is presented for applying to textured images for decomposing them into detail and approximation regions. Some features, computed out of the wavelet decomposed images, are used for texture classification. The idea behind this proposed method is to exhibit the usage of some features computed from discrete wavelet transformed images for texture classification. The features are approximately the same when the windows or subimages considered are from the same texture and different if they are from different textures.
2. When the number of features used increases, then the classification performance also increases and the mean error rate decreases. Inversely, when the number of features used decreases, then the classification performance also decreases and the mean error rate

increases. This is an acceptable low error rate therefore we can say that, when used together mean and energy of approximation coefficients are suitable features for texture classification.

3. These wavelet features are more suitable for some texture classes while for the others not.

As a result we have found that the selection and the number of features of a given data set were very important for a classification. If selected features are suitable and contain enough information about given samples, then any classifier will classify successfully. And the number of features also plays an important role in classifying tasks.

In this work, we have seen that, when used together, Mean and energy of approximation coefficients yield to an acceptable low error rate in textured image classification.

For future work, the number of features used may be increased or different wavelet families may be used in the analysis for achieving lower error rates in classification.

8. References:

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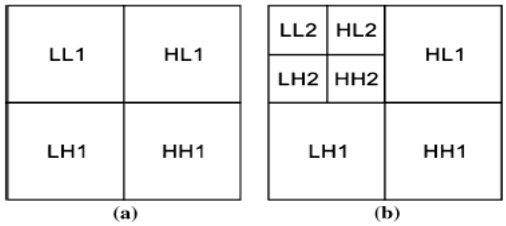

Fig. 1. Image decomposition: (a) one level, (b) two level.

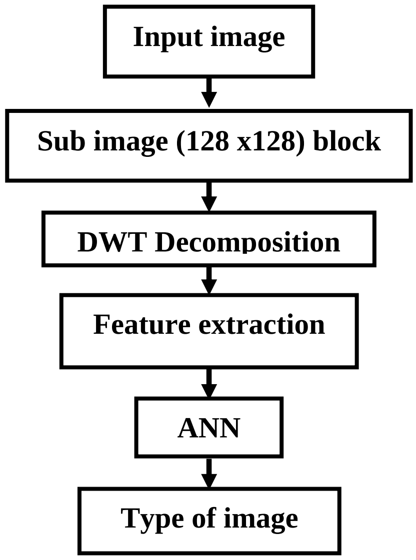

Fig. 2. image classification system.

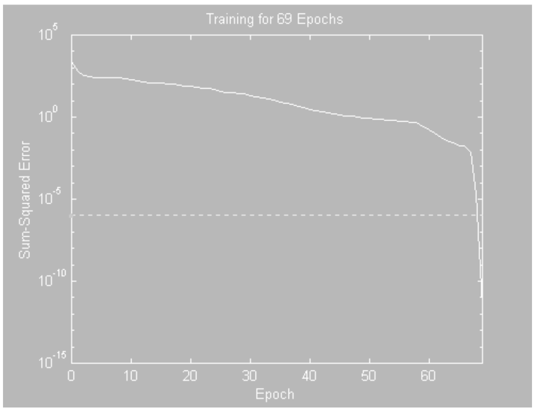

Figure (3) illustrated the training of NN

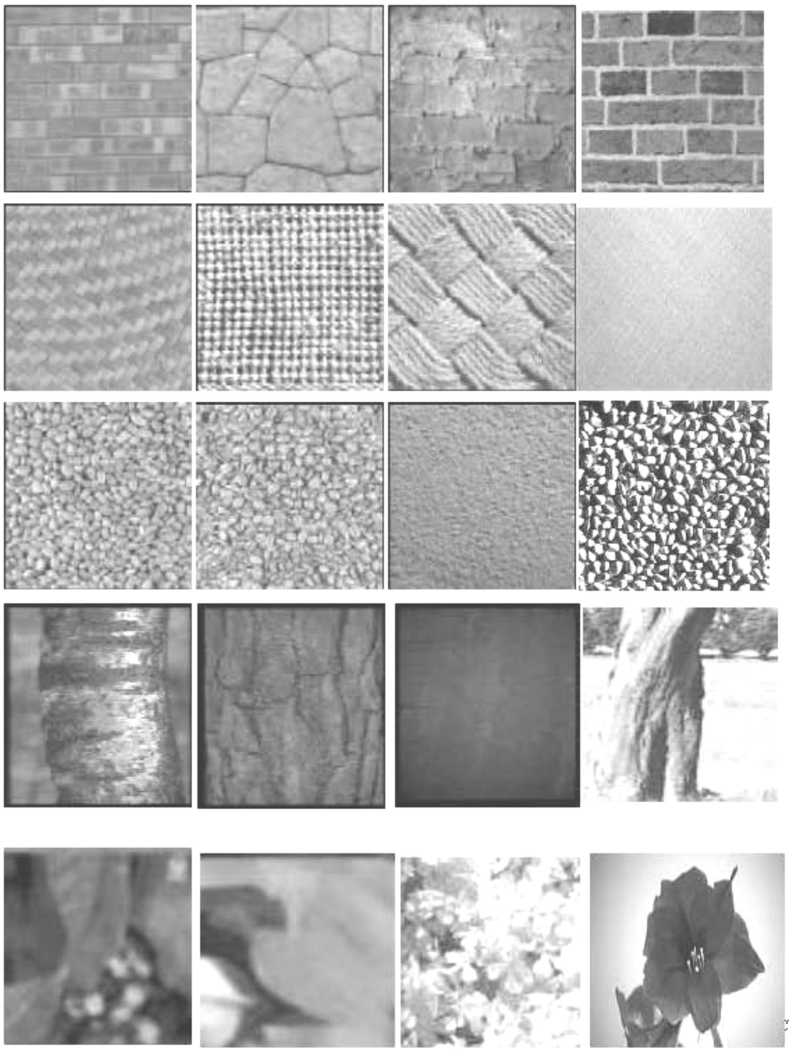

Figure 4
Selected images: from left to right and top to bottom: brick1, brick2, brick3, brick4, Fabric1, Fabric2, Fabric3, fabric4, Food1, Food2, Food3, food4, tree1, tree2, tree3,tree4, flower1, flower2, flower3, flower4.

Name of images	Value of energy	Value of mean
Brick 1	97	764.7472
Brick 2	98	789.4382
Brick 3	95	765.1949
Fabric1	88	370.6381
Fabric2	84	337.2084
Fabric3	80	401.1221
Food1	50	451.2059
Food2	57	475.0093
Food3	59	457.0444
Tree1	61	150.6375
Tree2	69	133.088
Tree3	63	205.1916
Flower1	44	65.1868
Flower2	4 4	71.1162
Flower3	49	90.1868

Table (1) values of mean and energy for images

Group name	Range of energy	Range of Mean
brick	95-98	764-789
fabric	80-88	337-401
food	50-59	451-475
tree	61-69	133-205
flower	44-49	65-90

Table (2) range of values for table 1 for all groups