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Evolutionary Feature Selection for Texture Classification Using Multiwavelets

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Abstract

In this paper, we use multiwavelet transforms to perform texture classification on twelve Brodatz textures. To increase the correct classification rate, feature selection is considered. Here we use the coevolutionary algorithm rather than the genetic algorithm (GA) which is widely used in many researches to accomplish the training phase of feature selection. In the classification phase, the mean and variance of the selected features are calculated with the leave-one-out algorithm to obtain the results. From the results of our experiment, we can see that classification using our method is very efficient.

1 Introduction

Texture analysis plays an important role in computer vision and pattern recognition. In earlier approaches, it was focused on analysis of the first-order or second-order statistics of texture [1]. Recently, multichannel and multiresolution methods have been widely studied, [2]. Many research works such as Gabor [2] used separable and non-separable wavelet transforms with single-mother wavelet functions [3][4] have been done on texture classification and segmentation for last decade. However, it is known that there is a limitation for the time-frequency localization of a single wavelet function. On the other hand, multiwavelets that have several advantages in comparison to single

wavelets can simultaneously possess orthogonality, linear phase symmetry, and a shorter support for a given number of vanishing moments [5].

Although decompositions for computing coefficients can map the useful information content into a lower dimensional feature space, yet they achieve no dimensionality reduction of the original features. Coifman and Wickerhauser [6] used an entropy criterion to decide if a subimage needs to be further decomposed, which is known as adaptive wavelet transforms. Based on genetic algorithms (GA) [7], Wang *et al.* [4] proposed the Max-Max method to evaluate the classification performance of each subset of selected features. A feature of GA is that the chromosomes interact only with the fitness function, but not with each other. This method precludes the evolution of collective solutions to problems, which can be very powerful.

2 Feature Selection

We propose a new method that is derived from the principles of the natural species evolution theory [8] for the classification of texture images. Two populations with interdependent evolutions (coevolution) referred to as P_A and P_B are created. A character string called the chromosome, as done in genetic algorithms represents an individual of the population. A chromosome is composed of a set of genes. In our case, each gene corresponds to the description of a multiwavelet subband. A direct encoding scheme is used to construct binary strings whose length is equal to the number of features. It is usually unnecessary and expensive to decompose all subbands in each

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level to achieve a full decomposition. To avoid such a full decomposition, we consider a top-down criterion (see Fig. 1) that is based on fitness value to locate dominant multiwavelet subbands.

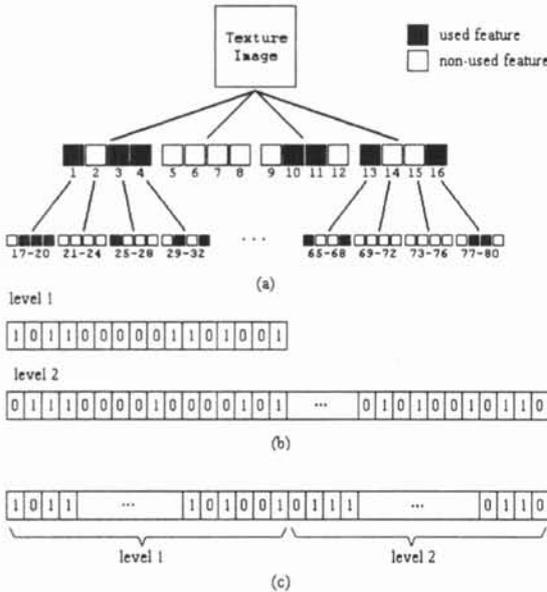


Fig. 1 (a) Top-down feature selection path, (b) the string of each decomposition level, (c) the string of all decomposition levels.

The environment in which individuals evolve is a set of twelve Brodatz texture images (see Fig.2). An individual placed on the texture images produces a fitness value that depends on the importance in the underlying images of the genes coded in the individual chromosome. The fitness function of an individual is a number composed of two terms: *Inter* and *Intra* [9]. *Inter* reflects the reluctance of this individual for the opposite class. This reluctance is quantified by the mean square distance between pattern points that belong to different classes. Conversely, the term *Intra* reflects the attraction of this individual for its own class. And then we combine the inter individuals which have better inter scores from P_A and the individuals which have better intra scores form P_B to generate new individuals by this criterion: if the i -th gene of the inter and the i -th gene of the intra are the same, then the i -th gene of the new individual is set as either individual. If it is not, the i -th gene of the new individual will be set as either individual randomly. Where i is the order of a gene in an individual. An example of combining 2 individuals is shown in Fig. 3.

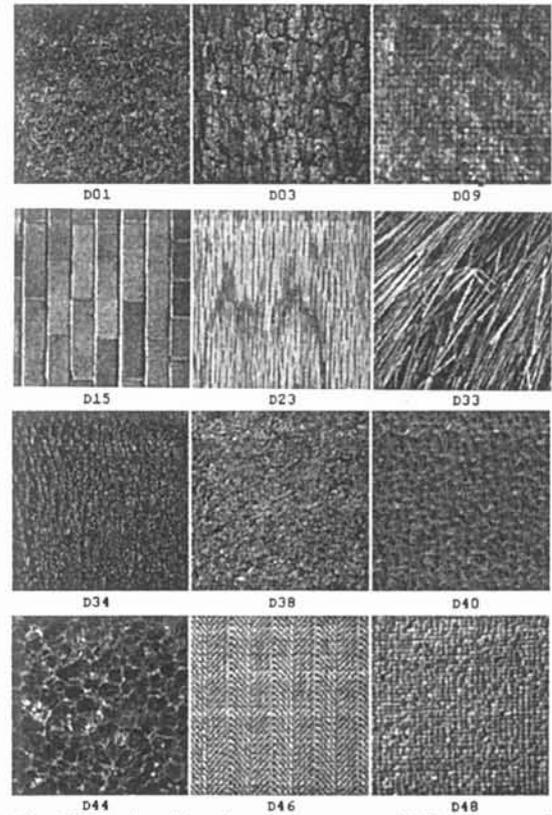


Fig.2 Twelve Brodatz textures which are used in our experiment.



Fig. 3 An example of combining two individuals into a new one.

After generating the new chromosomes, we calculate the fitness scores for each one by using the following equation:

$$Fitness = (1 - \xi \cdot \delta / \chi) \cdot (Inter - Intra) \dots (1)$$

Where ξ is the weighting constant greater or equal to one, δ is the number of subbands selected, χ is the number of training samples, and *Inter* and *Intra* are the inter score and intra score respectively of a new individual. This arrangement is respond to the fact that the number of features should be reduced more to alleviate the serious Hughes phenomenon [10] when χ is limited. An individual of a population P_A (corresponding to *Inter* population) will compete with each of

the best individuals (kernels) of the opposite population P_B (corresponding to *Intra* population). The combined results of these competitions directly provide the fitness function.

The training phase composed of the evaluation, selection, and reproduction steps correspond to a generation is repeated until the fitness functions of both population kernels do not progress. In practice, for each of the populations, the sum of the kernel fitness functions is computed. The kernels of the two populations at the last generation are preserved for further use in the classification phase.

3 Experimental results

Classification experiments were conducted using twelve standard 512×512 Brodatz textures with 256 gray levels obtained from a public archive. The collection of the textures consists of textures of both statistical and structures natures. One thousand 256×256 overlapping subimages are randomly chosen from the original image and used in the training and the classification phases. The features of extrema number [4] were first extracted using GHM multiwavelet transforms [5] (see Fig. 4) and then texture classifications with feature selection were performed with the simplified Mahalanobis classifier [9] to optimize classification by searching for near-optimal feature subsets. The mean and variance of the decomposed subbands are calculated with the leave-one-out algorithm [9] in classification. During the classification phase, the unknown texture is matched against the database and the best match is taken as the classification result. The reported results for each classification task have the following parameter settings: population size = 20, number of generation = 1000, and the maximum decomposition level = 2. Table 1 shows the performances of the proposed method with three independent runs, each of them using a distinct seed of the random generator.

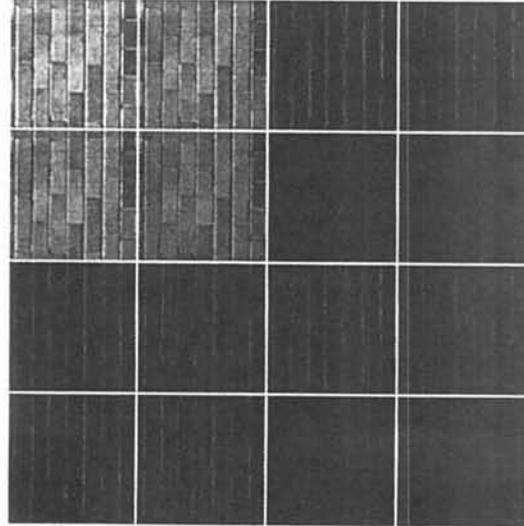


Fig. 4 One level of multiwavelet transforms for one Brodatz texture.

No. of Run	$\xi=1$	$\xi=2$	$\xi=3$	$\xi=4$	$\xi=5$
1	98.83	98.80	98.54	98.82	98.58
2	98.85	98.72	98.80	98.71	98.66
3	98.96	98.73	98.90	98.79	98.73
Avg	98.88	98.75	98.75	98.77	98.79

Table 1 Classification results of the top-down decomposition using multiwavelet transforms with coevolutionary feature selection, correct rate in %.

No. of Run	$\xi=1$	$\xi=2$	$\xi=3$	$\xi=4$	$\xi=5$
1	98.47	98.48	98.29	98.49	98.43
2	98.41	98.38	98.62	98.29	98.49
3	98.41	98.43	98.38	98.51	98.49
Avg	98.43	98.43	98.43	98.43	98.47

Table 2 Classification results of the top-down decomposition using wavelet transforms with coevolutionary feature selection, correct rate in %.

4 Discussion

Different weighting constants will effect the amount of used subbands for the classification phase, and will effect the correct rate and testing time of experimental results. Thus, we can select a large ξ (such as 5) to decrease the amount of used subbands to decrease the classification time, or select a suitable ξ to improve the classification correct rate.

Table 2 shows the results of using wavelet transforms with the same parameter settings.

Compare these two Tables, we can see that although both transforms are efficient, multiwavelets are better than wavelets.

5 Conclusion

It is proved that the feature selection using coevolutionary algorithms is very efficient. Further discussions about classification rate versus sample size, wavelets versus multiwavelets, without versus with feature selection, coevolutionary versus genetic algorithms, and performance on noisy image will be done.

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