Texture Image Segmentation Based on Wavelet Signatures

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Abstract

In this paper, we formulate the segmentation problem based on textured images as an optimization problem, and adapt evolutionary algorithms for the selection in a wavelet feature space. The purpose here is to demonstrate the efficiency of GHM multiwavelets in texture discrimination with respect to D4 scalar wavelets. Comparative studies suggest that the former transform features may contain more texture information for discrimination than the latter.

Keywords: texture segmentation, GHM multiwavelet, D4 scalar wavelet.

1. Introduction

Texture is the visual cue due to the repetition of image patterns. It is used in several tasks such as classification of materials, scene segmentation and extraction of surface shapes from the texture variations. A prototypical study in a wavelet theory provides a good framework for a multichannel texture analysis [1]. Chang and Kuo [2] developed a tree-structured wavelet transform algorithm for texture classification, which is similar to the wavelet-packet best-basis-selection algorithm of Coifman and Wickerhauser [3]. Unser et al. [4] studied texture classification and segmentation problems using wavelet frames in which the output of the filter banks is not subsampled. It results in a texture description invariant with respect to translation of the input signal, and improves robustness of texture classification. Chitre and Dhawan [5] presented an M-band wavelet technique for the classification of natural textures. Compared with the standard 2-band wavelets, M-band wavelets are more suitable for the analysis of high-frequency signals with relatively narrow bandwidths [6]. Zhang and Tan [7] reviewed numerous filtering approaches to textural feature extraction. The most major filtering approaches included for comparison are Law mask, ring/wedge filters, eigenfilters, Gabor filter banks, discrete cosine transform, quadrature mirror filters, wavelet transforms, wavelet packets, wavelet frames, etc. The textural features are computed as the local energy of the filter response. They found no single filtering approach that performs best for all test images.

Multiwavelets have increasingly attracted a lot of theoretical attention and provide a good indication of a potential impact on signal processing [8]. In this paper, a novel texture segmentation scheme is proposed both to extend the experimentation made in [8] and to test the effectiveness of the Geronimo-Hardin-Massopust (GHM) discrete multiwavelet transform (DMWT) with respect to the D4 scalar wavelet [9]. On the other hand, a problem in genetic wavelet texture analysis 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. We further present an

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evolutionary framework for feature selection in which successive generations adaptively develop behavior in accordance with their natural needs. The rest of this study is organized as follows. Section 2 discusses wavelet extrema density feature.s Section 3 presents coevolutionary selection algorithms for classified wavelet discriminators, and Section 4 draws conclusions based on experimental results and discussions.

2. Extraction of Feature

Recently, Wang [10] introduced the extrema number as a particular feature of coarseness, being very useful as a distinctive measure for the works of texture classification. Features that perform better in a classification environment should have a stronger potential to perform better in an image segmentation role. This interpretation prompts us to use the extrema density of wavelet coefficients as a measure of coarseness of the texture. Coarseness at a pixel is considered as the extrema density in a square window N^2 ($N \in$ Z) around the corresponding wavelet coefficients. Thus, the wavelet extrema density (*WED*) measure, the number of extrema per unit area in row and column scans for the wavelet coefficients of 2-D signal *f* (*Wf*) of the pixel *p* are defined by

$$WED_p = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} W_e\, f(i, j), \tag{1}$$
$$W_e\, f = \{\, Max_r Wf \cap Max_c Wf,\ Max_r Wf \cap Min_c Wf,\ Min_r Wf \cap Max_c Wf,\ Min_r Wf \cap Min_c Wf \,\}.$$

Where the operators Max_r and Min_r denote the coordinates of local row maximum and row minimum, respectively. Local column maximum Max_c and column minimum Min_c are defined similarly. A pixel is a local extremum if it is both a local row extremum (maximum or minimum) and a local column extremum. Coarseness of an image is not an absolute measure, but it depends on the level at which the image processed. The low resolution subbands make a textured surface seem smoother, while the subbands bring forward the rough structure of the surface at high resolution. Moreover, the larger the size of the window the more reliable the texture features found; but the less accurate the boundaries between feature clusters become. This leads to a trade-off between choosing good region segmentation or good boundaries between regions.

3. Evolutionary Feature Extraction

In the proposed method inspired from a natural evolution processes [11] , individuals are grouped in populations and thereafter referred as *inter* population P_b and *intra* population P_w randomly created. The two populations have interdependent evolutions (coevolution). The term *inter* reflects the reluctance, which is quantified by the mean square distance between pattern points that belong to different classes of this individual for the opposite class. An individual of the population P_b , I_x , will compete with each individual of the population kernel K_b which is the collection of individuals with best inter distances. The term *Inter* is formulated as follows:

$$[Inter]_{I_x \in P_b} = \sum_m (I_x \Leftrightarrow I_m) \quad \text{with} \quad I_m \in K_b,\ m = 1,\ldots, M, \tag{2}$$
$$(I_x \Leftrightarrow I_m) = \begin{cases} D_b^x - D_b^m & \text{if } D_b^x > D_b^m, \\ p & \text{if } D_b^x \le D_b^m, \end{cases}$$

where D_b is the Euclidean distance between classes and p is a penalty. Conversely, the term *Intra* reflects the attraction of this individual for its own class. An individual of the population P_w , I_x , will compete with each individual of the population kernel K_w which is the collection of individuals with best intra distances. A best individual of the population kernel K_b will compete with each of the best individuals of the opposite population kernel K_w. The combined results of these competitions directly provide the fitness function, and then the fitness function Θ is defined as a number composed of two terms:

$$\Theta = [Inter] - [Intra], \tag{3}$$

The evaluation process of Θ is randomly combined with the *Inter* individual of the population kernel K_b and the *Intra* individual of the population kernel K_w. A feature selection step is activated for choosing all the combination of the two kernel individuals allowed reproducing at the next generation. The strategy of feature selection involves selecting the best subset Γ_q,

$$\Gamma_q = \{\alpha_u \mid u = 1, ..., q;\ \alpha_u \in \Omega\}, \tag{4}$$

An original feature set Ω is defined :

$$\Omega = \{\beta_v \mid v = 1, ..., Q\},\ Q > q. \tag{5}$$

In other words, the combination of *q* features from Γ_q will maximize Equation (3) with respect to any other combination of *q* features taken from *Q*, respectively. The new feature β_v is chosen as the (κ+1)st feature if it yields

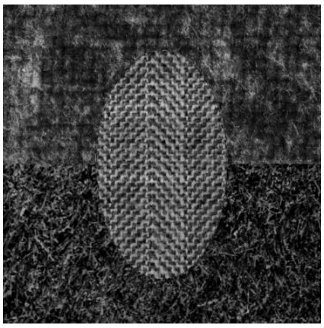
$$\underset{\forall \beta_v}{\text{Max}}\ \underset{\forall \alpha_u}{\text{Max}}\ \Delta[Inter]\ (\alpha_u, \beta_v), \tag{6}$$

where $\alpha_u \in \mathrm{A}_\kappa$, $\beta_v \in \Omega - \Gamma_\kappa$, and $\Delta[Inter](\alpha_u, \beta_v)$ = $[Inter](\alpha_u, \beta_v) - [Inter](\alpha_u)$. For the evaluation value of Equation (2), $[Inter](\alpha_u)$ is the feature selected with α_u, $[Inter](\alpha_u, \beta_v)$ is the candidate, and β_v is added to the already selected feature α_u. In a similar way, the feature selection mechanism minimizes *intra* measure and helps to facilitate pixel-by-pixel classification by removing redundant features that may impede recognition. The proposed schemes consider both the accuracy of clustering and the cost of performing segmentation.

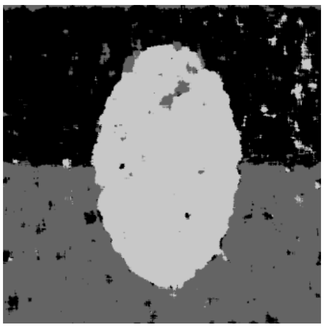
To speed up such a selection process, we present a packet-tree selection scheme based on fitness value of Equation (3) to locate dominant wavelet subbands. Following this innovative idea, the decomposed subbands at the current level, which can be viewed as the parent and children nodes in a tree, will be selected only if the predecessor at the previous level is selected. Otherwise, the scheme skips the successors and considers the next subbands. With a direct encoding scheme, the genetic representation is used to evolve potential solutions using standard 512 × 512 Brodatz textures [12] with 256 gray levels. According to the roulette wheel selection strategy [11], the combination of populations P_b and P_w is individuals with a higher fitness value in Equation (3) that will survive more at the next generation. The combinative individuals selected in the previous step are used to as the parent individuals. Their chromosomes are combined by the proposed combinative crossover criterion, which means the i-th gene of the offspring individual is set as either parent individual at random so as to toward the chromosomes of two offspring individuals. The size of each of the population remains constant during evolution. The mutation operation randomly changes a bit of the chromosome. The reported results have the following parameter settings: population size = 20, number of generation = 1000, and the probability of crossover = 0.5. A mutation probability value starts with a value of 0.9 and then varies as a step function of the number of iterations until it reaches a value of 0.01.

4. Results and Conclusions

Considering both the feature space dimension and the computation complexity of wavelet transforms, levels 0-3 are generated for the D4 wavelet, and levels 0-1 are generated for the GHM multiwavelet. At first, the four-category raw textured image (see Figs. 1(a) and 2(a)) is decomposed into frequency selective subbands based on wavelet packet decomposition. Then the features about a pixel are obtained with a window convolving with each subband, and they form a feature vector for coevolutionary selection and K-means clustering. The window size has been experimented with several values, and a typical choice turns out to be 31 31. Since the textured image may contain inhomogeneous texture regions, the feature of a pixel is further replaced by the average of a smoothing window 31 31 of features centered at the pixel.



(a)



(b)

(c)

Figure 1: Segmentation of the three-category textured image: (a) Raw image. (b) Feature selection using D4 wavelet. (c) Feature selection using GHM multiwavelet.

As illustrated in Tables 1 and 2, Figs. 1(b) and 1(c), and Figs. 2(b) and 2(c), the WED measure has shown suitable for the characterization of texture properties. Moreover, the performances with feature selections improve significantly over those without feature selections. This improvement is due to the fact that the number of features in a high dimensional space is reduced, so the curse of dimensionality phenomenon is alleviated. In the meanwhile, we also notice that the multiwavelet outperforms the scalar wavelet a little with the packet-tree feature selection. This is seemingly supported by the fact that the number of features used in the latter is not many ; and, hence, with feature selection the former is more adaptive and beneficial for texture discrimination.

Table 1: Segmentation performance without and with feature selection using D4 wavelet and GHM multiwavelet for the three-category textured image, respectively.

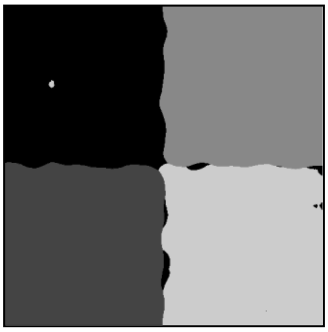
Error rate (%)	Without feature selection	With feature selection
D4 scalar wavelet	5.19	3.78
GHM multiwavelet	6.25	2.62

Table 2: Segmentation performance without and with feature selection using D4 wavelet and GHM multiwavelet for the four-category textured image, respectively.

Error rate (%)	Without feature selection	With feature selection
D4 scalar wavelet	5.73	4.10
GHM multiwavelet	8.66	3.18

(a)

(b)



(c)

Figure 2: Segmentation of the four-category textured image: (a) Raw image. (b) Feature selection using D4 wavelet. (c) Feature selection using GHM multiwavelet.

Acknowledgments

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References

[1]. J. C. Goswami and A. K. Chan, Fundamentals of Wavelets: Theory, Algorithms, and Applications, 2nd Edition, John Wiley & Sons, 2011.

[2]. T. Chang and C. C. Kuo, “Texture Analysis and Classification with Tree-structured Wavelet Transform,” IEEE Trans. Image Process., vol. 2, pp. 429-441, 1993.

[3]. R. R. Coifman and M. V. Wickerhauser, “Entropy-based Algorithms for Best Basis Selection,” IEEE Trans. Information Theory, vol. 38, pp.713-719, 1992.

[4]. M. Unser, N. Chenouard, and D. Van De Ville, “Steerable Pyramids and Tight Wavelet Frames in L2(ℝd),” IEEE Trans. Image Process., vol. 20, pp. 2705-2721, 2011.

[5]. J. Yuan, D. Wang, and A. M. Cheriyadat, “Factorized Based Texture Segmentation,” IEEE Trans. Image Process., vol. 24, pp. 3488-3497, 2015.

[6]. P. Steffen, P. N. Heller, R. A. Gopinath, and C. S. Burrus, "Theory of Regular M-band Wavelet Bases," IEEE Trans. Signal Process., vol. 41, pp. 3497-3510 , 1993.
[7]. J. Zhang, and T. Tan, "Brief Review of Invariant Texture Analysis Methods," Pattern Recognition, vol. 35, pp. 735-747, 2002.
[8]. F. Keinert, Wavelets and Multiwavelets, CRC Press, 2004.
[9]. I. Daubechies, Ten Lectures on Wavelets, SIAM, 2004.
[10]. J. W. Wang, "Face Localization Based on Wavelet Extrema," IEICE Electron. Express, vol. 5, pp. 516-522, 2008.
[11]. D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, 1989.
[12]. P. Brodatz, Textures: A Photographic Album for Artists and Designers, 1966.

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