Texture Classification Using Energy Features and Wavelet Transform

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Abstract

Texture plays an important role in pattern recognition and image processing. In this paper a new algorithm for texture image classification based on energy features and discrete wavelet transform (DWT) is presented. Laws' energy texture features are well known for texture analysis and have been used for various pattern recognition applications. But one of the main tasks in texture analysis is to search out solution for different scales. DWT has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where scalability is important. This paper examines the texture classification using texture features (Laws' features) in two level wavelet transform images. The main idea is to investigate fusion of texture features extracted from DWT decomposed images to improve classification results.

1 Introduction

In image processing a decision is made about which image points or regions of the image are relevant for further processing. Sometimes the widespread practice of pixel processing isn't a good solution. It is necessary to analyses region characteristics. Therefore texture analysis is an important and useful area of study in machine vision. Texture classification and image processing is the technique by which different regions of an image are identified on the base of texture properties.

There is no single method of texture representation for a variety of existing textures. Generally, texture is a regular repetition of an element or pattern on a surface of an image. Image texture can be defined as spatial variation of pixel intensity (gray values). Texture regions can be defined in any kind of image (satellite image, medical image, etc.) which doesn't contain clearly marked objects. Such image involves extended objects (figures) with different orientation, shape and intensity.

There are a lot of routine algorithms and methods in texture analysis. In the last few decades, many approaches have been used to compute the texture features, including statistical methods, geometrical methods, model based methods and signal processing methods (Xiangua Xie, 2008; Petrou, 2006; Zhang, 2002; Tuceryan, 1998; etc.).

1.1 Statistical methods

Spatial distribution of gray values is one of the defining characteristics of texture. Within the bounds of statistical approach a large number of texture features have been proposed. The most well-known and widely used features are gray level co-occurrence matrix-based texture features (GLCM) which was presented by Haralick (1979). An important property of many textures is the repetitive nature of the placement of texture elements in the image. The autocorrelation function of an image can be used to assess the amount of regularity.

1.2 Geometrical methods

The geometrical method of analysis takes into account geometrical properties of these texture elements. Voronoi tessellation has been proposed by Tucerayan and Jain. It allows extracting of texture features (1990). The structural models of texture suppose that textures are composed of texture primitives. Voorhees and Poggio (1987) have proposed a method based on filtering the image with Laplacian of Gaussian (LoG) masks at different scales and combining this information to extract the blobs in the image. A method of computing texture tokens by doing a medial axis transform has been suggested by Tomita and Tsuji (1990).

1.3 Model based methods

Model based texture analysis methods are based on the construction of an image model that can be used not only to describe texture, but also to synthesize it. Markov random fields (MRFs) have been popular for modeling images (Tuceryan, 1998). Mandelbrot (1983) proposed fractal geometry which is very useful and popular in modeling.

1.4 Signal processing methods

There are a lot of algorithms to compute features from filtered images which are then used in classification or segmentation tasks. Spatial domain filters are the most direct way to capture image texture properties (the Roberts operator, the Laplacian operator, spatial filters which are based on spatial moments, etc.) (Tuceryan, 1998) Another way is frequency analysis which best done in the Fourier domain (Tuceryan, 1998). Turner (1986) and Bovik (1987) have proposed the Gabor filters in texture analysis.

Enumerated above methods have initiated wide spread occurrence and usage of texture analysis. They have become the foundations for another researchers, methods and algorithms.

2 Extraction of texture features by Laws' masks

Within the bounds of signal processing methods texture energy approach was developed by K. I. Laws (1980). It's a successful methodology for image segmentation using texture analysis. The approach has been used for various texture analysis applications. Up till now it is a subject of investigation for many research people.

Laws identified the following properties as playing an important role in describing texture: uniformity, density, coarseness, roughness, regularity, linearity, directionality, direction, frequency and phase. Laws' texture features determine texture properties by assessing Average Gray Level, Edges, Spots, Ripples and Waves in texture. The approach uses basic convolution kernels for image filtering. The following set is a number of one dimensional (1-D) kernels of a length of five:

$L5 = [1 \quad 4 \quad 6 \quad 4 \quad 1]$	Level detection
$E5 = [-1 \quad -2 \quad 0 \quad 2 \quad 1]$	Edge detection
$S5 = [-1 \quad 0 \quad 2 \quad 0 \quad -1]$	Spot detection
$R5 = [1 \quad -4 \quad 6 \quad -4 \quad 1]$	Ripple detection
$W5 = [-1 \quad 2 \quad 0 \quad -2 \quad 1]$	Wave detection

Each mask is generated by convolving a vertical one-dimensional operator with a horizontal one-dimensional operator. According to this approach, textural features are extracted from image that had previously been filtered by each of the 25 Laws' masks (2-D).

Finally, 25 different windows could be generated as follows:

$$
\begin{array}{lllll}
L_5L_5 & E_5L_5 & S_5L_5 & W_5L_5 & R_5L_5 \\
L_5E_5 & E_5E_5 & S_5E_5 & W_5E_5 & R_5E_5 \\
L_5S_5 & E_5S_5 & S_5S_5 & W_5S_5 & R_5S_5 \\
L_5W_5 & E_5W_5 & S_5W_5 & W_5W_5 & R_5W_5 \\
L_5R_5 & E_5R_5 & S_5R_5 & W_5R_5 & R_5R_5
\end{array}
$$

If we used *mask* to filter the image $I_{(i,j)}$, the result was a "texture image" (TI_{mask}).

All the two-dimensional masks, except *L5L5*, have zero mean. According to Laws, texture image TI_{L5L5} is used to normalise the contrast of all the texture images $TI_{(i,j)}$. This step makes these descriptors contrast-independent.

$$Normalize(TI_{mask}) = \frac{TI_{mask}}{TI_{L_5L_5}} \tag{1}$$

The outputs from Laws' masks are put to "texture energy measurement" (*TEM*) filters. The average of absolute value is computed over a moving window.

$$TEM_{i,j} = \sum_{u=-7}^{7}\sum_{v=-7}^{7}[Normalized\,(TI_{i+u,j+v})] \tag{2}$$

This stage is performed on a smoothed version of the original image. Each feature is normalised so that it is invariant to the effects of variable illumination and contrast.

We use 15×15 descriptor windows. By combining the 25 *TEM* descriptors, we obtain 14 rotation invariant texture energy measurements (*TR*). For example TR_{W5R5} is obtained as follows:

$$TR_{W5R5} = TEM_{W5R5} + TEM_{R5W5} \tag{3}$$

For TR_{W5W5} is obtained as follows:

$$TR_{W5W5} = TEM_{W5W5} * 2 \tag{4}$$

Usually, these texture features are used for image segmentation or classification on the basis of textural similarity. In the last few decades, many algorithms have been proposed within the bounds of this approach (Rachidi, 2008; Motofumi, 2007; Hafiz Adnan Habib, 2004; etc.).

3 Wavelet transform

The grand problem is that in the real world we have no features that should be invariant due to changes in orientation, scale or other visual appearance. There is a fair quantity of textural analysis methods. The majority of them suppose that a class of texture images doesn't contain textures with different rotation, scale and illumination. However this statement is not true for the working models.

The main task for this research is an algorithm design for calculation of texture features which will be invariant with respect to scale. Wavelet-based image processing is very useful for research of invariant texture features which can be received for each level of wavelet analysis. It is prospective study in texture analysis. Wavelet transformation is a good alternative for Fourier transform. It has fitness for work with nonstationary signal. The nonstationary signal is analysed by decomposition on the basic functions witch are received from some prototype by compression, stretching and shift.

Many studies have shown that use of wavelet transforms for texture description can achieve good classification performance (Xiangua Xie, 2008; Petrou, 2006; Zhang, 2002; Tuceryan, 1998; etc.).

As well-known, the orthogonal wavelet decomposition of a given image possesses a pyramidal structure. In fig. 1 the data structure of two levels wavelet decomposition was shown. On the each level, one approximation image and three details images can be got. Those details images are horizontal, vertical and diagonal details respectively.

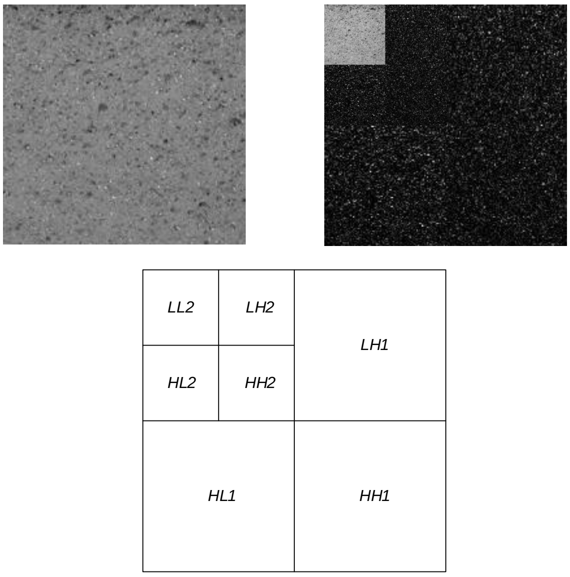

Fig. 1. Image decomposition. Two levels.

4 Proposed algorithm

We have proposed algorithm of texture image classification with usage of technology of wavelet transformation. The main stages of it are presented on fig. 2.

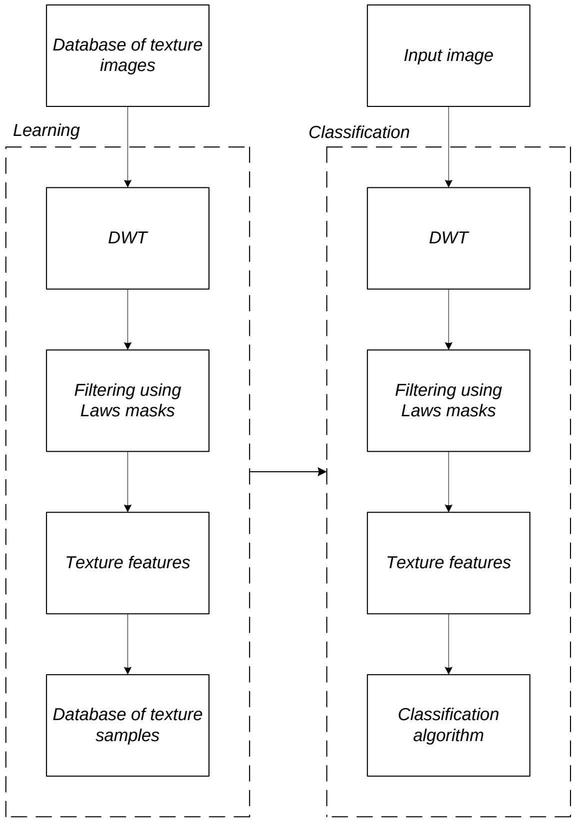

Figure 2: Proposed algorithm.

<u>Learning.</u> The first stage of proposed algorithm is an implementation of two level discrete wavelet transform. Convolution of the approximating and detailing information to Laws masks is performed at each level of decomposition. The Daubechies wavelet DB4 is used for decomposition. 14 energy texture maps are the result of the given procedure. For each of these maps the average energy value is calculated (Lukashevich, 2008). Thus, the database of texture features samples is formed.

<u>Texture classification</u>. Procedure of textural classification is similar to learning stages. Classification is performed by using the minimum value of Euclidian distance between vectors of texture features.

Testing of the offered algorithm was executed on the basis of KTH-TIPS image database. The KTH-TIPS (Textures under varying Illumination, Pose and Scale) image database was created to extend the CUReT database in two directions, by providing variations in scale as well as pose and illumination, and by imaging other samples of a subset of its materials in different settings (KTH-TIPS image database home page). Each of 10 classes of image database is presented by 9 subclasses. Samples of textures are presented on fig. 3.

Figure 3: Test images used in the experiments.

The given database has been selected for experiments because textures in 9 scales are presented (table 1) in it. Texture image with unit scale is image with scale number 5.

A number of scale	Relative scale	Camera distance
1	$2^{-1.00} = 0.500$	14.00
2	$2^{-0.75} = 0.595$	16.65
3	$2^{-0.50} = 0.707$	19.80
4	$2^{-0.25} = 0.841$	23.55
5	$2^{-1.00} = 1$	28.00
6	$2^{+0.25} = 1.189$	33.30
7	$2^{+0.50} = 1.414$	39.60
8	$2^{+0.75} = 1.682$	47.09
9	$2^{+1.00} = 2.000$	56.00

Conclusion and future work

Preliminary test data of the proposed algorithm have shown high performance for texture classification. Within the bounds of one class of textures with 9 subclasses accuracy of texture recognition with scales 4, 6, 7 reaches 70,4 %. It should be noted that KTH-TIPS image database which was used in experiments is very difficult. Therefore accuracy of the proposed algorithm it will be either considerably higher on practical examples.

As future works we are planning to examine different wavelet function (Daubechies, Haar, etc.) for achievement better classification results. The another direction of our research is to find the optimal number of level of wavelet decomposition.

Acknowledgment

This work was supported by grant for PhD. Students of Ministry of Education of Republic of Belarus.

Reference

Clark, M. and A.C. Bovik (1987). “Texture segmentation using Gabor modulation/demodulation” // Pattern Recognition Letters, 6. pp. 261-267.

Hafiz Adnan Habib, Mohammad Haroon Yoursaf, M. Mohibullah (2004). “Modified Laws Energy Descriptor for Inspection of Ceramic Tiles”. In proceedings of National Conference on Emerging Technologies. pp. 137-140.

Haralick, R.M. (1979). “Statistical and Structural Approaches to Texture,” In proceedings of the IEEE, 67. pp. 786-804.

Jianguo Zhang, Tieniu Tan (2002). “Brief review of invariant texture analysis method” // Pattern Recognition, 35, pp. 735-747.

http://www.nada.kth.se/cvap/databases/kth-tips/

Kociołek, M. Materka, A. Strzelecki M. Szczypiński P. (2001) “Discrete wavelet transform – derived features for digital image texture analysis”. In proceedings of International Conference on Signals and Electronic Systems, 18-21 September 2001, Lodz, Poland, pp. 163-168.

Laws, K.I. (1980). Textured Image Segmentation. Ph.D. thesis. University of Southern California. Los Angeles, California, 1980.

Lukashevich, M.M. and R. Kh. Sadykhov (2008). “Algorithm for texture segmentation using energy features”. (In Russian) // Doklady BGUIR, 6(36). pp. 109-116.

Mandelbrot, B. B. (1983). *The Fractal Geometry of Nature*, Freeman, San Francisco.

Motofumi T. Suzuki, Yoshitomo Yaginuma (2007). “A Solid Texture Analysis Based on Three Dimensional Convolution Kernels”. In proceedings of SPIE-IS&T Electronic Imaging, SPIE Vol. 6491, 64910W pp.1-8 San Jose, USA, 01/2007.

Petrou, M. and P.G. Sevilla (2006). *Image Processing: Dealing with Texture*. Wiley, Chichester, UK.

Tomita, Fumiaki and S. Tsuji (1990). *Computer Analysis of Visual Textures*, Kluwer Academic Publishers, Boston.

Tuceryan, M. and A. K. Jain (1990). “Texture Segmentation Using Voronoi Polygons,” IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-12. pp. 211-216.

Tuceryan, M., Jain, A.K. (1998). *Texture Analysis. The handbook of Pattern Recognition and Computer Vision. 2nd Edition* – World Scientific Publishing Co. Singapore. P. 207–248.

Turner, M.R. (1986). “Texture Discrimination by Gabor Functions,” Biological Cybernetics, 55. pp. 71-82.

Xiangua Xie (2008). “A Review of Recent Advances in Surface Defect Detection using Texture analysis Techniques”. Electronic Letters on Computer Vision and Image Analysis. –Vol. 7, №3. – P. 1-22.

Rachidi, M., etc. (2008). “Laws’ masks descriptors applied to bone texture analysis: an innovative and discriminant tool in osteoporosis”. Skeletal Radiology. – Vol. 37, № 6. P. 541-548.

Voorhees, H. and T. Poggio (1987). “Detecting textons and texture boundaries in natural images,” In Proceedings of the First International Conference on Computer Vision, pp. 250-258, London.