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Texture Analysis using Wavelet Transform

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KEYWORD

Content based Image retrieval (CBIR); Markov Random Field (MRF); Gray Level co-occurrence Matrix(GLCM);

ABSTRACT

In this research application of wavelet based multiscale image analysis methods for texture analysis has been highlighted. These methods are based on multiresolution properties of the two-dimensional wavelet transform, which is used to extract the features needed to discriminate and differentiate various textures more accurately then existing methods, we also took into account the texture model, the noise distribution, and the inter-dependence of the texture features which further help in discriminating factor. Multiresolution approach is nothing but a modified wavelet transform called the tree-structured wavelet transform or wavelet packets for texture analysis and classification. This approach is motivated by the observation that a large class of natural textures can be modeled as quasi-periodic signals whose dominant frequencies are located in the middle frequency channels. With the transform, we are able to zoom into any desired frequency channels for further decomposition and thus we could extract more texture features as compared to other methods.

1. Introduction

The term texture is used to point to intrinsic and intuitive properties of surfaces, especially those that don't have a smoothly varying intensity like roughness, granulation and regularity. Since Texture provides essential information for many image classification tasks like object identification from aerial or satellite photographs, biomedical images and many other types of images so it motivated me go with the analysis part as much of the research is required in extracting image properties (data) to work on, for getting accurate and relevant output related to those properties in accordance with the research field involved. This report emphasizes on wavelet based texture analysis methods operated on images from Brodatz album using MATLAB with the help of filters created to extract low frequency contents.

More formally texture could be defined as the set of local neighborhood properties of the gray levels of an image region. Texture analysis is fundamental to many applications such as automated visual inspection, biomedical image processing, CBIR and remote sensing (Vetterli, 1991).

The topic of texture analysis can be broadly classified in to two main problems:

1. Texture Classification: - It provides the effective discrimination between different textures.

2. Texture Segmentation: - It divides a given image in to distinct region based on textural information.

2. Existing system

Much research has been done in the area of texture classification from the last few years. Some of the traditional approaches for texture analysis and classification are:

2.1. Structural approaches

These approaches define texture by some well-known primitives and spatial arrangements of those primitives. This method provides a good symbolic description of the image however, this feature is more useful for synthesis than analysis tasks. This approach is suited for highly regular texture.

2.2. Statistical approaches

These approaches represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. This approach is computationally efficient then structural approaches. Statistical descriptors like sub band histogram, co-occurrence matrices, autocorrelation, n-th order moments, MRFs are used in these approaches (Unser, 1986).

2.2.1. Methods for texture analysis based on statistical approaches

1. GLCM :-

GLCM is a tabulation of how often different combinations of gray levels (pixel brightness value) occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest (Mohanaiah, 2013).

2. Auto correlation and Fourier method :-

This method calculates the variance of intensity over the whole region of a texture. It also shows repeatability of the texture. This method is use full for distinguishing short range and long range order in the texture (J. Behar, 1992) (Zeevi, 1989).

2.3. Problems in existing work

Measuring the relative performance of different texture analysis technique is a difficult task as almost infinite range of possible texture exist thus it is almost impossible to provide a global measurement of the performance of various exsisting techniques , but a comparative study has been done and few major shortcomings of the existing technique are found :-

1. These methods give only the spectral details of the image without considering the temporal properties hence these methods are not suitable for analyzing images with time varying spectra (Mallat, 1989) (P. Vautrot, 1996).
2. These methods provide only the frequency information , time information cannot be obtained through these methods (N. Fatemi-Ghomi, 1996).

3. Proposed work (multiscale approaches)

This is an approach in which statistical and structural approaches are combined together so that we can perform multiresolution analysis for the given texture. Thus, in the proposed work we will combine existing methods and wavelet transform to enhance texture analysis.

3.1. Solution for proposed work

Wavelet transform is a tremendous new theory and a very powerful model for texture analysis. It is a multiresolution analysis tool commonly applied to texture analysis and classification and also Wavelet based pre-processing is a very successful method providing proper Image Enhancement and remove noise without considerable change in overall intensity level. It is also useful for contrast enhancement in noisy environment (Herley).

This transform is most appropriate for non-stationary signals and is designed in such a way that we get good frequency resolution for low frequency components and high temporal resolution for low frequency components and thus it follows with Heisenberg uncertainty principle (Kuo).

3.1.1. Types of wavelet transform

1. Discrete Wavelet Transform: - it transforms a discrete time signal to a discrete wavelet representation. This transform is useful for applications where scalability and tolerable degradation are important (M. Antonini, Image coding using wavelet transform, 1992).

   In DWT the most prominent information in the signal appears in high amplitude and less useful information appears in low amplitude, thus by using the low pass and high pass filters also known as analysis filters we could easily expand a digital signal and extract essential features from it (Fan A. L., 1992).
2. Continuous wavelet transform: - This transform uses fully scalable modulated window which is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions (Reddy & Kumar Vijyaya, 2014).

3.2. Experimental dataset

Based on previous experimental studies “real time recognition with Texture Database” (R. W. Richard, 1993).The dataset used in the experiments on the developed texture analysis system consist of 2 types of texture images, which are retrieved from Brodatz album, and other sources.

Figure 1: Images from Brodatz album (Door image and Puppy Image)

3.3. Proposed methodology

1. Calculate entropy value
2. Convert RGB to Grayscale Image
3. Perform modulation to extract bitplanes of image
4. Reduce the contrast of bright regions using logaritmic operator.
5. Enhance the contrast of bright regions using exponential raise operator.
6. Draw histogram and perform histogram equalization.
7. Perform low pass filtering to capture low frequency contents.
8. Remove noise from the image.
9. Compare average and median filter by adding salt and pepper noise.
10. Apply high pass filter for edge detection.
11. Finally analyze image using wavelet transform to get horizontal vertical and diagonal details.

4. Experimental evaluation

Sr. No	**Method Applied**	**Result Obtained**

1	i = imread ('C:\Users\Vinay\Downloads\door.jpg');
	imshow(i);
	e = entropy(i)
		This gives an entropy value of the image.

2	b= rgb2gray(i); imshow(b)	This gives the grayscale image

Sr. No	Method Applied	Result Obtained

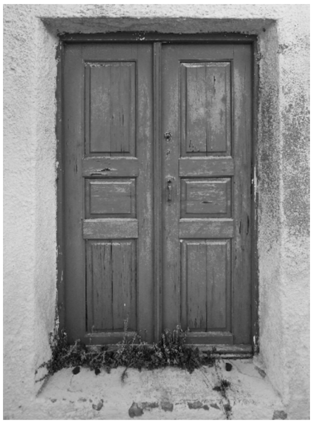
3	c = double(b)
	d = mod(c,2);
	imshow(d);
	d1 = mod(floor(c/2),2);
	d2 = mod(floor(c/4),2);
	d3 = mod(floor(c/8),2);
		This gives bit planes for higher evaluation of image (Bovik, 1990).

4	S = C*log(1+r) (r is the image on which we perform logarithmic operation, C is constant, S is the output image)	This logarithmic operator reduces the contrast of bright regions in an image.
5	$S = C*r^{y}$ (r is the image on which we perform exponential operation, C is constant, S is the output image).	This exponential raise operator enhance the contrast of Bright Regions.
6	Create a filter f = ones(3,3)/9 ; g = filter2(f,b,'same'); filter2 is inbuilt filter command	Perform low pass filtering to capture the low frequency contents of the image (Simoncelli, 2000).

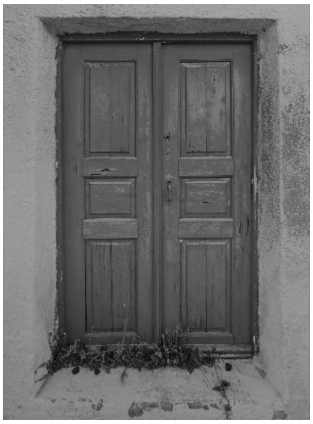
7	d = imnoise(b,'gaussian',0.01);
	sigma = 3;
	cutoff = ceil(3*sigma);
	h = fspecial('gaussian',2*cutoff +1,sigma);
	k = conv2 (b, h,'same');
	imshow(k/256)
		After adding gaussian noise of variance '0.01', standard deviation and cut -off is defined.
		When the image is passed through the created gaussian filter, noise is removed.

8	L = imnoise (b , 'salt&pepper',0.); M = fspecial('average'); N= filter2(M,L); Imshow(uint8(N)) O = medfilt2(L); Imshow(uint8(O))	This gives the comparison of average and median filter by adding salt and pepper noise
9	P = edge(b,'prewitt');	Low frequency contents are blocked and image is analyzed using high pass filter for edge detection.
10	i=imread('C:\Users\Vinay\Downloads\door.jpg'); [iar,ihr,ivr,idr] = dwt2(i(:,:,1),'db2'); [iag,ihg,ivg,idg] = dwt2(i(:,:,2),'db2'); [iab,ihb,ivb,idb] = dwt2(i(:,:,3),'db2'); >> ia(:,:,1)=iar ; ia(:,:,2)= iag ;ia(:,:,3) = iab; >> ih(:,:,1)=ihr ; ih(:,:,2)= ihg ;ih(:,:,3) = ihb; >> iv(:,:,1)=ivr ; iv(:,:,2)= ivg ;iv(:,:,3) = ivb; >> id(:,:,1)=idr ; id(:,:,2)= idg ;id(:,:,3) = idb; >> figure, imshow(ia/255);	Finally, image is analyzed using wavelet transform to get horizontal, vertical and also diagonal details of the image by downsampling it by 2. We can further down sample the image by 2 to get more detailed extraction of the features.

Table 1 : Described Methods used and corresponding Results obtained



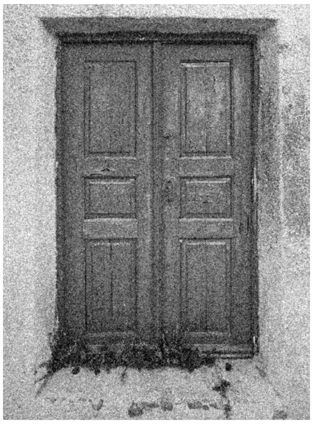
Step 2



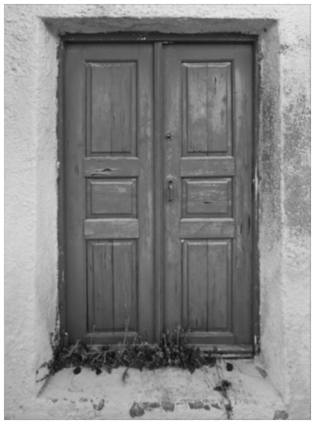
Step 4

Step 5

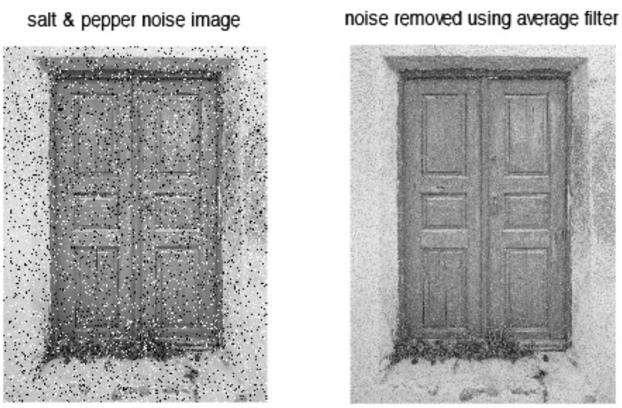
Step 6



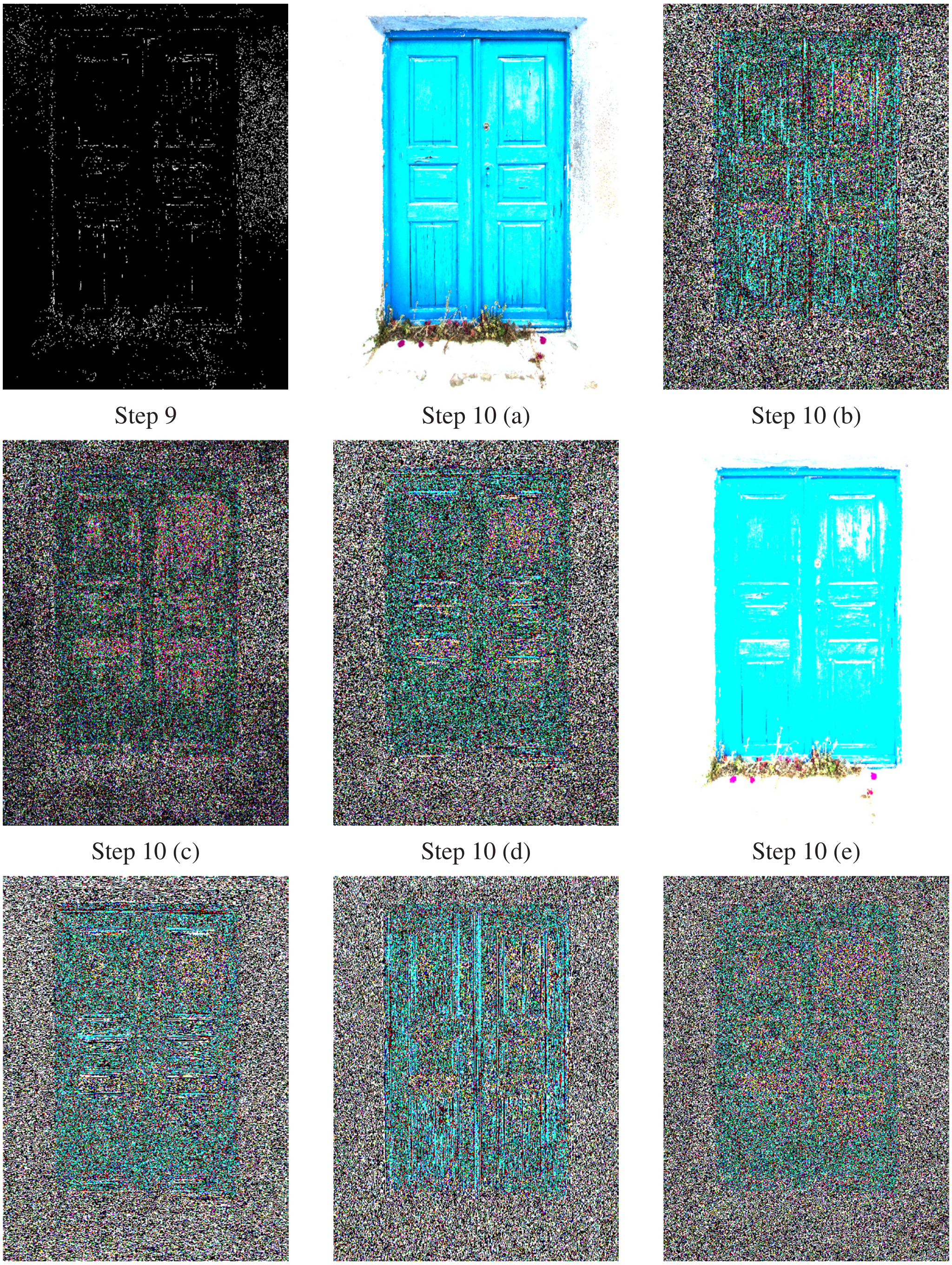
Step 7 (Gaussian noise)



Step 7b (noise removed)



Step 8



Step 9 | Step 10 (a) | Step 10 (b)

Step 10 (c) | Step 10 (d) | Step 10 (e)

Step 10 (f) | Step 10 (g) | Step 10 (h)

Figure 2 : Images corresponding to various methods applied in Table 1 validating the result obtained.

5. Result & conclusion

After performing various existing texture analysis approaches and designed wavelet transform approach we came to know that in case of fourier transform individual bit plane analysis is done and result is obtained by combining the analyzed image, while in case of wavelet transform horizontal, vertical and diagonal details of the image are obtained at once with respect to both frequency and time.

The final experimental results have proved that such texture analysis approach is worth to be implemented in real life applications.

6. Future scope

Results show that the selection on different mother wavelet functions can cause a significant impact in terms of accuracy and time during a texture analysis process. Therefore, cautions have to be taken in picking correct wavelet function in order to enhance the performance of a analyzer.

It is possible to create an own customized wavelet basis to suit the requirements in texture analysis. However, this is definitely not an easy task as it requires a strong base of knowledge in many areas, such as mathematics and physics. Since the current wavelets are still not able to analyze well on all types of textures, a new wavelet basis may be required.

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