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Implementation of Textile Image Segmentation Using RotationalGabor Filter and Echo State Neural Network

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Abstract- This paper presents the segmentation analysis on Textile images. In this work, a systematic approach has been developed to extract the Textile textures from the given texture images. The features of the textile images are extracted and it is used for segmenting those images using Wavelet Gabor Filter and Echo State Neural Network. The proposed methods combine to improve the segmentation accuracies and to analyze the effects of parameters of the proposed algorithms in segmentation of textures.

Index Terms - Segmentation, Textile Textures, Supervised method, Wavelet Gabor Filter and Echo State Neural Network

1 Introduction

IN textile industries, texture adds richness to fabric design. The fabric design can be analyzed for flaws and other quality related to concepts in manufactured textiles using image processing. Computer programming can be used for automated computational methods for retrieving visual information and understanding the image content based on textural properties in images. Difficulty exists in texture analysis is to obtain appropriate quantitative texture descriptions.

Many texture analysis methods have been proposed in the past. The available methods can be categorized into model-based, geometrical, statistical and signal processing methods. A descriptive approach describes a texture by a set of selected features, which provides particular. A texture is represented by a specific signature that is distinguished from the signatures extracted from other textures.

Examples of more recent approaches are methods based on local linear transforms and multiresolution feature extraction, Unser et al., 1989, feature smoothing and probabilistic relaxation, Hsiaoetal, 1989, Voorhees and Poggio 1987 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. Boundary based segmentation of textured images have been used by Eom and Kashyap 1987. In all cases, the edges (or texture boundaries) are detected by taking two adjacent windows and deciding whether the textures in the two windows belong to the same texture or to different textures. If it is decided that the two textures are different, the point is marked as a boundary pixel.

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Blostein and Ahuja 1989 perform similar processing in order to extract texture tokens in images by examining the response of the LoG filter at multiple scales. They integrate their multi-scale blob detection with surface shape computation in order to improve the results of both processes. Super and Bovik 1991 have proposed using Gabor filters and signal processing methods to estimate the fractal dimension in textured images. The fractal dimension is not sufficient to capture all textural properties. It has been shown by Keller et al., 1989 that there may be perceptually very different textures that have very similar fractal dimensions. Therefore, another measure, called lacunarity, has been suggested in order to capture the textural property that will let one distinguish between such textures. Ohanian and Dubes 1988 have studied the performance of various texture features. They compared four fractal features, sixteen co-occurrence features, four Markov random field features, and Gabor features. They used Whitney's forward selection method for feature selection. The evaluation was done on four classes of images: Gauss Markov random field images, fractal images, leather images, and painted surfaces. The co-occurrence features generally outperformed other features (88% correct classification) followed by fractal features (84% classification). Using both fractal and co-occurrence features improved the classification rate to 91%. Their study did not compare the texture features in segmentation tasks. It also used the energy from the raw Gabor filtered images instead of using the empirical nonlinear transformation needed to obtain the texture features as suggested by Jain et al., 1991.

2 Gabor and Wavelet Models

The proposal to use the Gabor filters in texture analysis was made by Turner 1986. Later Jain and Farrokhnia 1991 used it successfully in segmentation and classification of textured images. Gabor filters have some desirable optimality properties. They used a version of the Gabor transform in which window sizes for computing the Gabor filters are selected according to the central frequencies of the filters.

Chellappa et al., 1985, model texture by assuming each pixel depends on a specific set of neighbours together with an added random signal. The parameters of this model are estimated for a given texture and used to represent it.

Unser et al., 1989, proposed unsupervised segmentation of textured images. Local texture properties are extracted using local linear transforms that have been optimized for maximal texture discrimination. Charles et al., 1991 proposed multiple resolution algorithm for segmenting images into regions with differing statistical behavior. In addition, an algorithm is developed for determining the number of statistically distinct regions in an image and estimating the parameters of those regions. Both algorithms use a causal Gaussian autoregressive model to describe the mean, variance, and spatial correlation of the image textures. The algorithms can be used to perform unsupervised texture segmentation.

Cohen et al., 1991 described textile fabric inspection using the visual textural properties of the fabric. The problem is to detect and locate the various kinds of defects that might be present in a given fabric sample based on an image of the fabric. Stochastic models are used to model the visual fabric texture. The authors use the Gaussian Markov random field to model the texture image of non defective fabric.

Jain et al., 1991 described Gabor filters can be interpreted as oriented band-pass filters, Authors used a dyadic even-symmetric Gabor filter bank to generate energy features for texture segmentation, and reported successful results.

Pichler et al., 1996 compared the pyramidal and tree structured wavelet transform with the Gabor filtering in segmenting textured images. Thomas et al., 1996 developed a method for the design of multiple Gabor filters for segmenting multi-textured images. Although design methods for a single Gabor filter have been developed, the development of general multi-filter multi-texture design methods largely remains an open problem. Previous multi-filter design approaches required one filter per texture or were constrained to pairs of textures.

Kruizinga et al., 1999 describe the performance of a number of texture feature operators. The features are all based on the local spectrum which is obtained by a bank of Gabor filters. The comparison is made using a quantitative method which is based on Fisher's criterion.

Paragios et al., 1999 states that the textured feature space is generated by filtering the input and the preferable pattern image using Gabor filters. Wavelet-based techniques gain more and more attention in texture segmentation because of their multi-resolution property, which leads to multi-resolution segmentation.

Ian R Fasel et al., 2002 presented a systematic analysis of Gabor filter banks for detection of facial landmarks.

Simona et al., 2002 describes texture features that are based on the local power spectrum obtained by a bank of Gabor filters. The features differ in the type of nonlinear post-processing which is applied to the local power spectrum. The following features are considered: Gabor energy, complex moments, and grating cell operator features.

Arivazhagan et al., 2003 proposed texture classification using (i) wavelet statistical features, (ii) wavelet co-occurrence features and (iii) a combination of wavelet statistical features and co-occurrence features of one level wavelet transformed images with different feature databases. It is found that, the results of later method are promising.

Liu and Zhou 2004 use wavelet transform together with block-based segmentation to produce automatic texture segmentation.

Rong Lu et al., 2005 proposed image segmentation algorithm based on random neural network and Gabor filtering technique. This uses Gabor functions of different frequencies and orientations for feature extraction. To overcome time consuming problem of feature extraction, a quartered segmentation strategy is introduced using Gabor filters. This method can segment images successfully.

Mak et al., 2007 developed an automated inspection system for textile fabrics based on Gabor filters. The Gabor filters are designed on the basis of the texture features extracted optimally from a non-defective fabric image by using a Gabor wavelet network (GWN).

Gholam et al., 2008 explained that passing initial image through each filter will result a new filtered image that has significant properties of the original image. Small values of parameters of Gabor filters will cause a faster computation of each filtered image. Because of the nature of the Gabor filters there is no need to equalize and quantize the original image.

Wong et al., 2009 proposed a stitching detection and classification technique which combines the improved thresholding method based on the wavelet transform with the back propagation (BP) neural network.

3 Rotational Wavelet Gabor Filter

The Gabor wavelet is used as the discrete wavelet transform with either continuous or discrete input signal, while there is an intrinsic disadvantage of the Gabor wavelets which makes this discrete case beyond the discrete wavelet constraints: the 1-D and 2-D Gabor wavelets do not have orthonormal bases. If a set of wavelets has orthonormal bases, the inverse transform could be easily reconstructed by a linear superposition, and this wavelet transform provides a complete representation. The non orthonormal wavelets could provide a complete representation only when they form a frame. The non orthonormal properties are not much required, if the Gabor wavelets are used for feature extractions. The transformed coefficients are used for distance and hence the orthogonal constraint could be omitted.

Texture segmentation plays an important role in identifying and recognizing a material, characteristic for particular type of image. Wavelets are used for the computation of single and multi-scale roughness features because of their ability to extract information at different resolutions. Extracted Features are in multiple directions using directional wavelet obtained from partial derivative of Gaussian distribution function. The derivatives of first and second wavelets are used to obtain the features of the textured image at different orientations like

$0°$,$45°$, $90°$ and $135°$.

The implementation of texture segmentation steps are as follows:

Step 1: Read a texture image.
Step 2: Calculate the first partial derivative w0, w90.
Step3: Calculate second partial derivative w(0,90),w(0,0), w(90,90).
Step 4: Find directional roughness feature by using arithmetic averaging.
Step 5: Calculate total energy.
Step 6: Calculate percentage of energy.
Step 7: Done for three orientation ?
Step 8: If No, then goto step 1.
Step 9: If Yes, Apply k-means algorithm.
Step 10: Initialize no. of clusters, no. of iterations, energy value.
Step 11: Assign class label based on intensity values.
Step 12: Find center for each class.
Step 13: Find distance between class centers.
Step 14: Is the distance between classes $d_{previous} > d_{present}$?
Step 15: If No, goto step 11.
Step 16: If Yes, Texture image is segmented and classification is done.

4 Algorithm Proposed for Image Texture Segmentation

4.1 Echo State Neural Network

An Artificial Neural Network (ANN) is an abstract stimulation of a real nervous system that contains the neuron Units collection. Axon Connections are used to communicating with each other. Artificial neural networks are computing elements which are based on the function of the biological and structure of neurons. These networks have neurons or nodes which are described by difference or differential equations.

The ESNN with a concept new topology has been found by ESNN possesses a highly interconnected and recurrent topology of nonlinear PEs that constitutes a reservoir of rich dynamics and contains information about the history of input and output patterns. The outputs of this internal PEs (echo states) are fed to a memory less but adaptive readout network (generally linear) that produces the network output. The important property of ESNN are recurrent topology has fixed connection weights is that only the memory less readout is trained. Recurrent Neural Network Training is reduces the complexity and to make simple linear regression while preserving a recurrent topology, but obviously in overall architecture some important constraints are not yet been fully studied.

The echo state condition is defined in terms of the spectral radius (the largest among the absolute values of the eigen values of a matrix, denoted by (|| ||) of the reservoir's weight matrix (|| W || < 1). This condition states that the dynamics of the ESNN is uniquely controlled by the input, and vanishes the effect of the initial states. The current design of ESNN parameters relies on the spectral radius selection. There are many possible weight matrices with the same spectral radius, but unfortunately they do not perform at the same level of mean square error (MSE) for functional approximation.

The recurrent neural network is a reservoirs of highly interconnected modelling of non linear dynamical components, the reservoir states of which are called echo states. The memory less linear regression readout is trained to produce the output. Consider the discrete-time recurrent neural network with M input units, N internal PEs, and L output units. The input unit value at time n is $u(n) = [u_1(n), u_2(n), . . ., u_M(n)]^T$,
The internal units are $x(n) = [x_1(n), x_2(n), . . ., x_N(n)]^T$, and
Output units are $y(n) = [y_1(n), y_2(n), . . ., y_L (n)]^T$.

The ESNN algorithm for training is as follows:
Step 1: Read a Pattern (I) (texture image feature) and its Target (T) value.
Step 2: Decide the number of reservoirs.
Step 3: Decide the number of sides in the input layer = length of pattern.
Step 4: Decide the number of sides in the output layer = number of target values.
Step 5: Initialize random weights between input and hidden layer (Ih) hidden and output .
Step 6: Calculate F=Ih*I.
Step 7: Calculate TH = Ho * T.
Step 8: Calculate TT = R*S.
Step 9: Calculate S = tan h(F+TT+TH).
Step 10: Calculate a = Pseudo inverse (S).
Step 11: Calculate Wout = a * T and store Wout for testing.

The ESNN algorithm for testing is as follows:
Step 1: Read a Pattern (I) (texture image feature).
Step 2: Calculate F=Ih*I.
Step 3: TH = Ho * T.
Step 4: TT = R*S.
Step 5: S = tan h(F+TT+TH).
Step 6: a = Pseudo inverse (S).
Step 7: estimated = a * Wout
Step 8: Classify it.

5 Results and Discussions

This paper presents the results of segmentation for 20 textile images. These images fall under the category of artificial regular, natural and stochastic textures. The Table1 presents the methods and the parameters used for segmenting the textures.

Table 1 Parameters used

Serial No.	Proposed methods	Parameters used
1	Rotational Wavelet Gabor filter	Block of pixels and rotation angles

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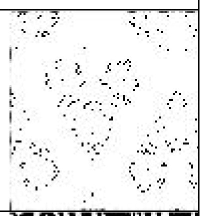
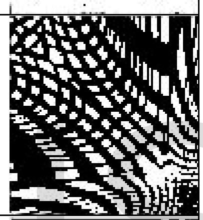
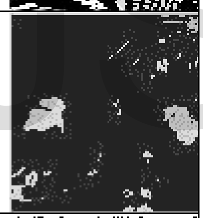
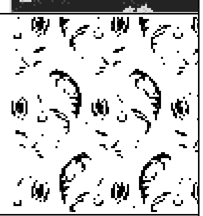
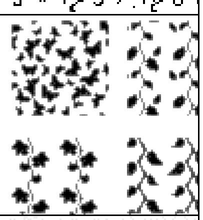
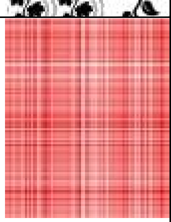
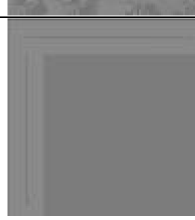
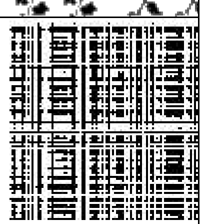
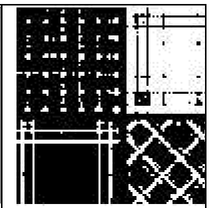
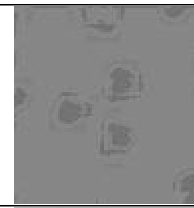
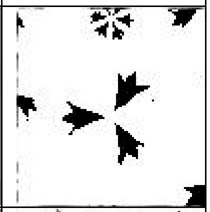
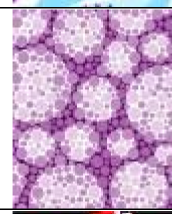
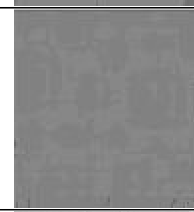
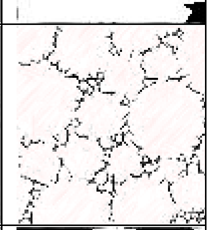
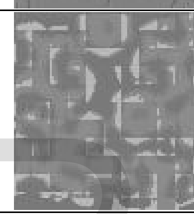
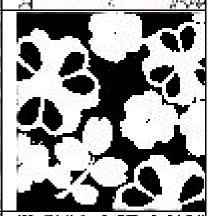
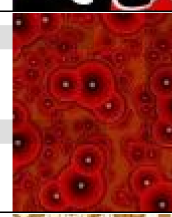
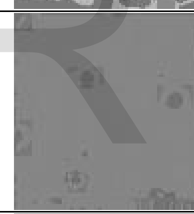
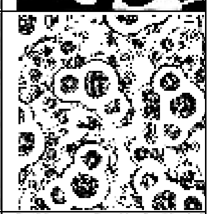
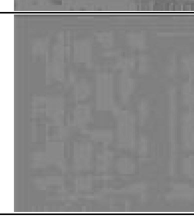
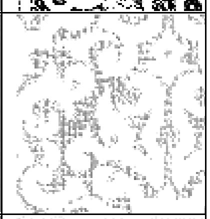
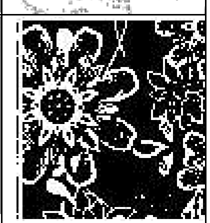
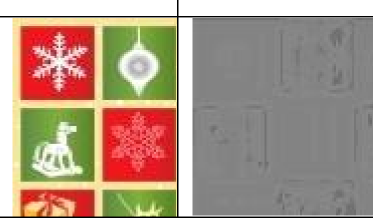
2	ESNN	Number of reservoirs and initial weights

Table 2 presents 20 textile images. Column 2 shows the original true color image. Column 3 shows the segmented images with labelling. The labelled portions appear segmented. The image contains 0 (black) and 255(white). Similarly, ESNN segmented outputs (Column 4) are presented.

TABLE 2

S. no	ORIGINAL IMAGE	ROTATIONAL WAVELET GABOR FILTER	ECHO STATE NEURAL NETWORK
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			No Segmentation

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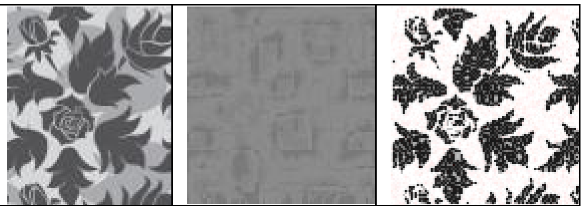
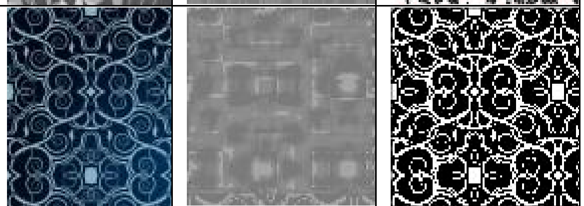
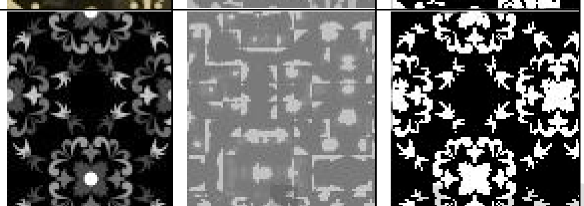
15	
16	
17	
18	
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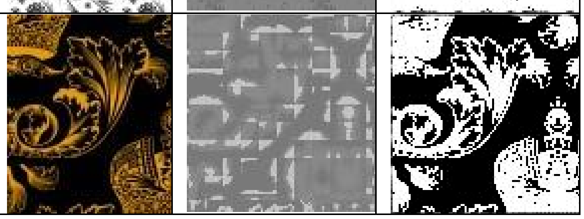
20	

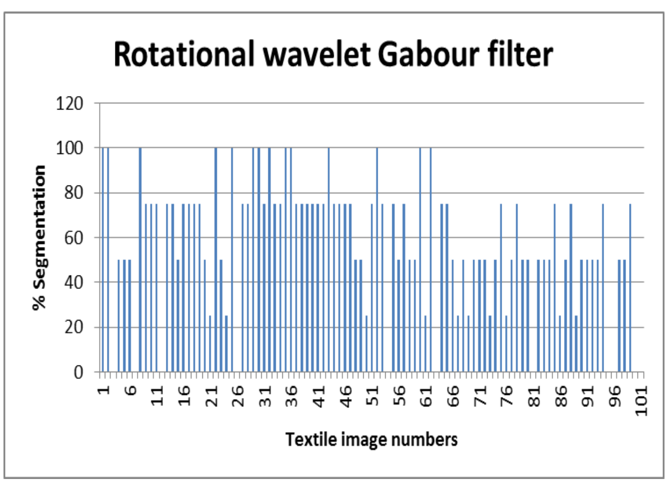


Fig.1 Segmentation by rotational wavelet Gabor filter

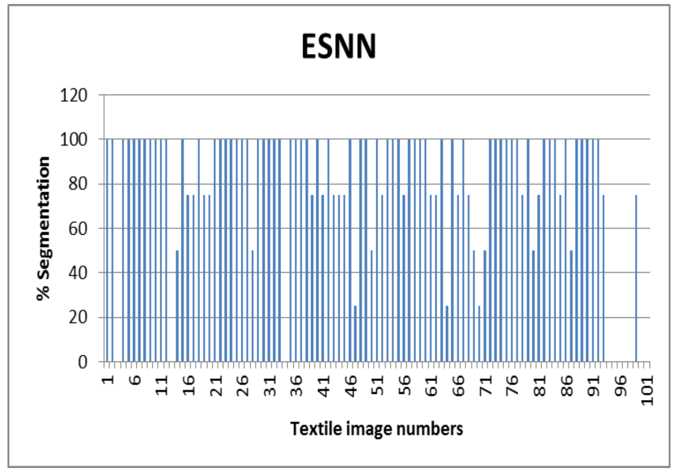


Fig.2 Segmentation by ESNN

Figure 2 presents image segmented by ESNN. The x-axis shows the textile image numbers given in Table 2. The y-axis shows the percentage of the respective image segmented.

6 Conclusions

This paper has considered texture segmentation for textile textures. The conclusions of this research work are as follows:

1. The recurrent echo state neural network is a promising method for segmenting a given texture. The quality of texture depends upon the number of reservoirs.

This work has focuses in texture segmentation of textile images. These images are considered as they have lots of objects in the images. Textile images have been downloaded from the internet resources. Randomly, 100 textile images have been considered for the research work. Rotational wavelet gabor filter and Echo state neural network have been used for segmenting the images. Features are generated from rotational wavelet gabor filter and segmentation of the images are done. Similarly Echo State Neural Network is used for segmenting the features generated by the ESSN algorithm are used for training and testing the ESNN methods. During testing the final weights are obtained and are used along with the features of existing images to achieve segmentation. The ESNN segmentation performance is based on threshold, number of reservoirs and range of initial weights assigned. In general, when the number of reservoirs is 18 to 21, then the segmentation of the images are good. However, the segmentation performance of ESNN is much better than that of wavelet gabor filter.

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