Self Organised Mapping Approach for unsupervised Texture Segmentation using Wavelet Packet Transform

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Abstract-
The texture is most important attribute in many image analysis or computer vision applications. In this Paper it is described a new unsupervised approach based on wavelet packet transform for texture image segmentation using LabVIEW. This transform is able to decompose an image not only from low frequency parts, but also from middle high frequency parts, in which there is certain amount of texture information. After the extraction of the features, a clustering is carried out by using SOM (Self Organised Mapping) algorithm, which is capable of preserving density information of the data and determining how many different textures (clusters) are present in the image. Experimental results are shown and are compared with conventional methods.

Keywords- texture segmentation; wavelet packet; SOM; LabVIEW

I. INTRODUCTION

Textures contain important information for humans and are much used in the interpretation and analysis of various types of surfaces and objects. Besides, they can be defined as a set of spatial relations and arrangements of elements in a neighbourhood. Textural analysis is a difficult task in image processing. However, this is a fundamental step in many applications such as remote sensing, medical diagnosis, pattern recognition and surface inspections. According to Livens [1] we can divide texture analysis methods into 4 segments:

- Statistics: In general, these methods achieve higher rates of discrimination than the structural methods and transforms. Examples of such methods are histogram analysis [2], co-occurrence matrix [3] and texture spectrum;
- Structural: In these methods, the texture is defined as a composition of primitive patterns organized according to some rules. They have the advantage of producing a good description of the image, but are more useful to synthesis. An example of a tool for structural analysis is mathematical morphology [4];
- Models: Perform the analysis using mathematical models (stochastic and fractal). Some image parameters are extracted from the model and used as features to analyze the image. Its disadvantage is the computational complexity in the estimation of parameters [5];
- Transforms: In this case, the image is represented in a new space, for example the frequency/scale space, where the textural characteristics become more accessible. The main examples are the transform images: Fourier, Gabor [6] and Wavelets [7].
A large number of research works used to analyze texture image were proposed in the past [8], [9], [10]. But the traditional statistical approaches to texture analysis are restricted to the texture on a single scale.

Recent studies of human vision system suggest that the spatial/frequency representation, preserving global and local information, is adequate for quasi-periodic signals [11]. This has motivated new developments in multiresolution texture models. Currently, methods based on wavelet transform have received a lot of attention by providing analysis and characterization of the signal in different scales [7], [11], [12].

Coifman and Wickerhause [13] generalized the wavelet basis function including a library of modulated waveform orthonormal bases called wavelet packets. This can decompose an image from the middle-high frequency parts. The wavelet packet decomposition is a generalization of the classical wavelet decomposition.

In this research, an algorithm called SOM (Self Organised Mapping) was chosen to perform the clustering of the features of the textures. SOM is capable of preserving the density information of the data and of automatically determining the number of clusters, which is fundamental for an unsupervised method. The block diagram of the proposed method can be seen in below.

II. WAVELET PACKET TRANSFORM

The main objective of the wavelet transform is to represent a signal as a superposition of basic orthogonal functions, called wavelets. These are obtained through dilation and translation of a single function called the mother wavelet, represented in 1

\[
\psi(m, n) = 2^{-m/2} \psi(2^{-m} x - n) \quad (1)
\]

Where \( m \) and \( n \) are integers [11].

The resulting wavelet decomposition coefficients of a signal can be obtained by 2

\[
C(m, n) = \int f(x) \psi(m, n)(x) \, dx \quad (2)
\]
and, the original signal can be obtained by 
\[ f(x) = \sum C(m, n) \psi(m, n)(x). \]  
(3) 

The mother wavelet \( \psi(x) \) is constructed from a scaling function \( \phi(x) \) according to 4 and 5
\[ \psi(x) = \sqrt{2} \sum g(k) \phi(2x-k) \]  
(4) 
\[ \phi(x) = \sqrt{2} \sum h(k) \phi(2x-k) \]  
(5)

where
\[ g(k) = (-1)^k h(1-k) \]

\( h(k) \) are the coefficients of Daubechies wavelet transform[15]

The wavelet packet decomposition is capable of decomposing the signal in the middle-high frequency, not only in low and high frequency parts. This property is of fundamental importance for the characterization of texture, so that there is many textural information present in the intermediate frequency range [11].

Since the most significant information of a texture often appears in middle frequency channels, further decomposition just in the lower frequency region, such as the traditional wavelet transform, may not be sufficient to carry out the segmentation. The key difference between this algorithm and the traditional wavelet transform is that decomposition is no longer simply applied to the low frequency sub signals recursively. Instead, it is applied to the output of any filter. Thus, more detailed information can be obtained.

### III. OVERVIEW OF LabVIEW

The software technique use here is LabVIEW It is a graphical programming language for data acquisition and control, data analysis, data presentation. It is Laboratory Virtual Instrument Engineering workbench. It uses icons instead of lines of text to create applications.

LabVIEW offers hundred of built in analysis functions that cover different areas and methods of extracting information from acquired data. These functions can be used in many areas of image processing such as colour pattern matching, filters, image analysis, image and pixel manipulation, image processing.

LabVIEW provides an extensive library of virtual instruments and functions to help in programming. Sub VIs are used to build a more complex main program in a conventional programming language.

### IV. TEXTURE SEGMENTATION

Texture segmentation is a fundamental problem in image analysis. Here we partition an image into set of regions which are uniform and homogeneous. For example, in industrial inspection, the goal of segmentation is often to separate objects from the background. In
remote sensing applications we may wish to segment a satellite image into different regions like sea, land, clouds etc.

Clustering is an unsupervised classification technique which is widely used in pattern recognition and in image segmentation. In image segmentation a set of features, a feature vectors is extracted for each image pixel. The extracted feature vectors are partitioned into clusters in feature space. Each cluster can be identified to represent a specific class of image features.

The most popular clustering method used here is self organised mapping (SOM) algorithm. SOM is an unsupervised technique. It makes a topology-preserving mapping from a high dimensional feature space onto a two dimensional lattice. The mapping is nonlinear. This SOM is a practical tool for clustering and visualisation of high dimensional data.

The SOM system is known as a Kohonen Network. This has a feed-forward structure with a single computational layer of neurons arranged in rows and columns. Each neuron is fully connected to all the source units in the input layer. A one dimensional map will just have a single row or column in the computational layer.

The aim is to learn a feature map from the spatially continuous input space, in which our input vectors live, to the low dimensional spatially discrete output space, which is formed by arranging the computational neurons into a grid.

The stages of the SOM algorithm that achieves this can be summarised as follows:

1. **Initialization** – Choose random values for the initial weight vectors $w_j$.
2. **Sampling** – Draw a sample training input vector $x$ from the input space.
3. **Matching** – Find the winning neuron $I(x)$ that has weight vector closest to the input vector, i.e. the minimum value of
   \[
   D_I(x) = \sum_{i=1}^{D} (x_i - w_{ji})^2
   \]
4. **Updating** – Apply the weight update equation
   \[
   \Delta w_{ji} = \eta(t) T_{j,I(x)}(t) (x_i - w_{ji})
   \]
   where $T_{j,I(x)}$ is a Gaussian neighbourhood and $\eta(t)$ is the learning rate.
5. **Continuation** – keep returning to step 2 until the feature map stops changing.

This process is done using LabVIEW tool and the results are obtained successfully.

V. **EXPERIMENT RESULTS**

This section presents the performance of the proposed methodology. Initially, the texture image was decomposed using the wavelet packet transform. The features were obtained by the power of 2 of the decomposition components. After the features extraction, the principal component analysis was used, aiming to reduce the characteristics. The clustering was performed by SOM algorithm.

Figure (a) shows image size of 371x2740.96x32 bit RGB image. Figure (b) & (c) presents the segmentation carried out by the methodology of unsupervised SOM approach.

It is observed that the result obtained by the proposed method are better than those presented by supervised method.
VI. CONCLUSIONS

In this work, a new methodology for unsupervised segmentation of texture images was presented. The process can be divided in three principal steps: wavelet packet transform, features extraction and clustering.

The wavelet packet transform was chosen because it is capable of obtaining details of middle-high frequency, where the most significant information of a texture often appears. To perform the clustering the SOM algorithm was used. This algorithm has the advantage of determining automatically the number of clusters, so the user might not have prior knowledge of the image. The experiments presented in this work showed that this is an important point in the segmentation result.
Experimental results presented prove the efficiency of our method. Several comparisons with other existing methods in literature were made. In some comparisons, the result obtained by our method was better, in others, the result was similar, but our method does not require the interference of the user.

REFERENCES


