Scale Space Texture Classification Using Combined Classifiers with Application to Ultrasound Tissue Characterization

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Abstract—**Texture is often considered as a repetitive pattern and the constructing structure is known as texel. The granularity of a texture, i.e. the size of a texel, is different from one texture to another and hence inspiring us applying scale space techniques to texture classification. In this paper Gaussian kernels with different variances (σ^2) are convolved with the textures from Brodatz album to generate the textures in different scales. After some preprocessing and feature extraction using principal component analysis (PCA), the features are fed to a combined classifier for classification. The learning curves are used to evaluate the performance of the texture classifier system designed. The results of classification show that the scale space texture classification approach used can significantly improve the performance of the classification especially for small training set size. This is very important in applications where the training set data is limited. The application of this method to ultrasound liver tissue characterization for discrimination of normal liver from cirrhosis yields promising results.**

Keywords— **Scale space, texture classification, combined classifiers, tissue characterization, liver**

I. Introduction

Liver disease is one of the most prevalent diseases in the world and an early diagnosis helps to prevent changing the state of the disease to a developed stage. Liver diseases are of two types: focal and diffused. In the former, only part of the liver is affected by a tumor while in the latter, the whole liver or at least one lobe is completely affected. In diffused liver diseases like cirrhosis, the texture of liver in ultrasound B-scan images is affected by the kind of pathology that makes it distinguishable from normal liver. However, the accuracy of the diagnosis by the sonologist based on qualitative criteria, i.e. visual inspection of the ultrasound images is low. Thus, computer aided texture classification systems can help to improve the diagnosis. In this paper we develop one algorithm for texture classification, which is proved to be efficient especially when just a small number of data samples is available for training and testing.

There is a vast literature on texture analysis, as can be judged from the innumerable applications the texture analysis has in various fields [1, 2].

Texture analysis techniques are classified basically into four types of approaches: statistical [3], structural, transform-based [4, 5] and model-based [1, 6, 7].

In recent years, scale space theory has been recognized as the vital tool for texture analysis [8]. This is because texture displays a multi-scale property. Whatever may be the representation, it is applicable in different scales.

In this paper scale space theory is used to produce multi-scale texture images. The patches are extracted from these textures and after feature extraction using principal component analysis (PCA), the features are applied to some basic classifiers. The outputs of these basic classifiers are then combined using a fixed combination rule to classify the textures. The performance of the whole system is evaluated using learning curves for different learning set sizes. Finally the application of the method and its effectiveness to liver ultrasound tissue characterization is shown.

II. Scale space texture classification

A texture classification system is typically consisting of several stages including preprocessing, feature extraction and classification [9]. Each stage is explained below in the context of scale space texture classification.

A. Scale space analysis

Texture is usually considered as a repetitive pattern and this constructing repetitive structure is of varying size in different textures. This inspires us to apply multi-scale techniques in texture analysis. Here, scale space theory, which is biologically motivated based on the model of front end vision, is used for multi-scale texture classification. In scale space image analysis, 2-D Gaussian kernels as given in (1), with different variances (σ^2) are convolved with the image to generate the image in different scales. This generates multi-scale images and each image emphasizes on details in

the corresponding scale. The larger the Gaussian kernel variance (σ^2), the more emphasis on coarser structures.

$$G_{2D}(x, y; \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

This is shown in Fig. 1 where a texture from Brodatz album is convolved with Gaussian kernel of varying variance.

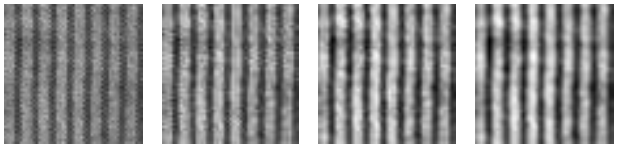

Fig. 1- Texture D11 of Brodatz album in 4 different scales.

To discriminate two or more textures, we use the additional information provided in different scales to achieve a better performance (comparing to single scale). To this end, the patches are extracted from the textures in the original and other scale space. The size of the patch is an important factor that depends on the sizes of the texel and the applied Gaussian kernel. It also affects the dimensionality of the feature space as larger patches generate more features. This may impose problems with respect to the computation speed as well as to the necessary training set size. This is further explained in relation to feature extraction and classification.

B. Feature extraction

Working in high dimensional feature space usually imposes problems as we need more data samples for training. This phenomenon is called the curse of dimensionality. It may cause the peaking phenomena in classifier design [2]. There are two solutions to this problem. First, to increase the training set size and second to reduce the feature space dimension using feature selection/extraction techniques. Many feature selection/extraction techniques are addressed in the literature among which Principal Component Analysis (PCA) is one of the most prevalent ones.

In PCA, we consider a population of random vectors of the form:

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}^T \quad (2)$$

The mean vector and covariance matrix of this random population can be calculated as follows:

$$\mathbf{m}_\mathbf{x} = E\{\mathbf{x}\} \quad (3)$$

$$\mathbf{C}_\mathbf{x} = E\{(\mathbf{x} - \mathbf{m}_\mathbf{x})(\mathbf{x} - \mathbf{m}_\mathbf{x})^T\} \quad (4)$$

In PCA, the eigenvectors of the covariance matrix C_x are used to define a transform matrix A, the rows of which are made up of the eigenvectors weighted by decreasing magnitude of corresponding eigenvalue. Rotation of the input vectors to the eigenvectors yields an uncorrelated data set, i.e., its covariance matrix is a diagonal matrix.

Feature extraction for the purpose of dimension reduction using PCA can be achieved by selection of only first few components (eigenvectors) corresponding to the largest eigenvalues. This preserves up to specified fraction of the variance in the original data set [9]. The main question is how many components are needed to guarantee that thereby sufficient information of the original data set is preserved in the transformed (uncorrelated) space. We answer this question here in our multi-scale context of texture classification. By going to higher scales, i.e. convolving the image with the Gaussian kernel of larger variances, we lose the details and therefore we expect that fewer components are needed to preserve the information in the original random vector. This is shown in Fig. 2 by drawing the cumulative fraction of the eigenvalues, which also represent the fraction of the variance of the original data, in two scales for texture D11 from Brodatz album. It is clear that as we go to higher scales, fewer components are required to preserve the same amount of variance of the original data.

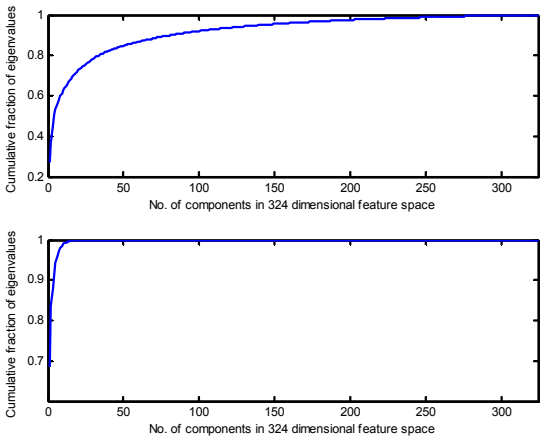

Fig. 2- Cumulative fraction of eigenvalues (i.e., preserved variance) for texture D11 in the original space (top graph) and after convolving the texture with a Gaussian kernel of variance 9 (bottom graph).

C. Classifier

The next issue to address in this texture classification system is the classifier. We have so far produced the data in different scales and reduced the dimensionality of the feature space using PCA. As explained in the previous section, the feature space dimension will be different after applying PCA when we go from one scale to another.

Based on this, parallel combined classifiers seem natural as they can be used for combining different feature spaces.

Combined classifiers are used in multiple classifier source applications like different feature spaces, different training sets, different classifiers applied for example to the same feature space, and different parameter values for the classifiers for example k in k nearest neighbor (k-NN) classifier. The block diagram of the parallel combined classifier used in this paper is shown in Fig. 3. There are two parameters to be selected in this combined classifier, i.e. the type of the basic classifier and the combination rule. The selection of these two options is discussed in section IV.

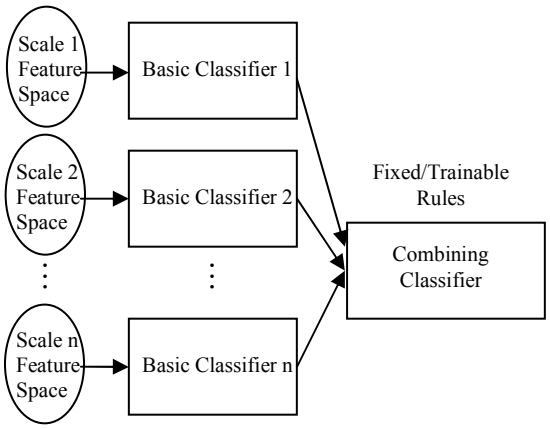

Fig. 3- Block diagram of the combined classifier used in this paper.

III. Experiments

To verify the effectiveness of the proposed method, experiments were performed on a supervised classification of some test images. The test images are from Brodatz album and some normal and cirrhosis B-scan ultrasound liver images shown in Fig. 4 and Fig. 5 respectively. The experiments performed are explained separately for textures from Brodatz album and liver images.

A. Experiments on textures from Brodatz Album

Preprocessing: The textures are convolved with 2D Gaussian kernels in 5 different scales. The scales ($\sigma^2/2$) of the Gaussian kernels used in the convolution are 1.5, 3, 4.5, 6 and 7.5. We add the original texture to this scale space to get a scale space texture of 6 scales.

To make sure that for all textures the full dynamic range of the gray level is used contrast stretching is performed on all textures in different scales. Also, to make the textures indiscriminable to mean or variance of the gray level, DC cancellation and variance normalization are performed.

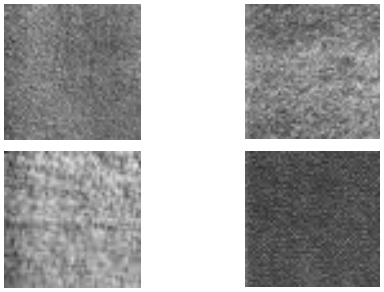

Fig. 4- Textures D4, D9, D19 and D57 from Brodatz album used in the experiments.

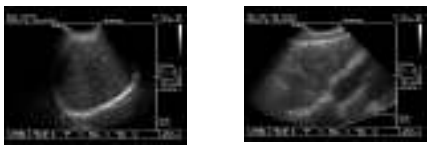

Fig. 5- A typical normal liver (left) and cirrhosis (right) B-scan image used in the experiments.

Feature extraction: 1800 patches with size 18×18 are extracted from the textures in different scales. Then, PCA is used for the purpose of feature extraction. The number of components used for dimension reduction is chosen to preserve 90% of the original variance in the transformed (reduced) space. This is between about 3 and 50 components in the highest and lowest scales.

Combined classifier: A variety of basic classifiers and combining rules are tested to find the best one. Among the basic classifiers tested are some normal-based density classifiers like quadratic discriminant classifier (qdc), linear discriminant classifier (ldc), and nearest mean classifier (nmc). The Parzen classifier was also tested as a representative of non-parametric based density classifier. Six basic classifiers one for each scale are used. The mean, product and voting fixed combination rules as well as the nearest mean trainable combination rule are tested for comparison.

Evaluation: The performance of the texture classification system is evaluated by drawing the learning curve for a variety of training set sizes. For each training set size, the remaining of the patches are used to test the system and hence the training and testing data are separate. The error is measured 10 times for each training set size and the results are averaged.

B. Experiments on B-scan ultrasound liver images

Normal liver and liver affected by cirrhosis are used in the experiments. The region of interest (ROI) is taken from the center of the image where the image is the most focused. The size of the ROI is 32×32. Here, only three different scales in addition to the original image are used and since

the granularity of the texture is lower, lower scale values are used for the Gaussian kernel, i.e. 1, 2 and 3. The patches have the size of 6×6. 1000 patches are extracted from the liver images in different scales. Based on the results of texture classification on Brodatz album, the quadratic classifier (qdc)is used as base classifier and the mean fixed combination rule as combined. Evaluation is performed in the same way as for the experiments on Brodatz album.

IV. Results

A variety of tests are performed using different parameters as explained in the previous section. Among tested basic classifiers explained in the previous section, qdc performed the best. This can be justified based on the feature extraction method used as PCA is a linear dimension reduction that performs integration in the feature space. Consequently, the features tend to be normally distributed based on the central limit theorem. On the other hand, among tested combination rules, mean fixed rule performs the best.

Fig. 6 displays the learning curves in single and multiple scales for the textures from Brodatz album. The peak of the curve is a result of peaking phenomena as explained in Subsection II-B. It is important to notice that multi-scale texture classification improves the performance of the classification significantly especially in low training set sizes which is very important in applications where training data set is limited like ultrasound liver tissue characterization.

Fig. 7 displays the learning curves in single and multiple scales for liver images. Although the size of the training set is quite limited here, the performance is still remarkable that shows the effectiveness of the approach.

V. Discussion and conclusion

Scale space theory, PCA and combined classifiers are integrated into a texture classification system. The system is very efficient especially in low training set size that the system can significantly improve the performance of the system comparing to single scale based on the information provided in multiple scales.

Since in liver tissue characterization one major problem is limitation in image acquisition as the images should be standardized, this method can be very effective in this application. Promising results obtained from applying the method to discriminate normal liver from cirrhosis.

In this paper we only used intensity scale space for texture classification. As future work, we will also consider gradient scale space, i.e. derivatives of Gaussian kernel in different scales for generation of multi-scale texture.

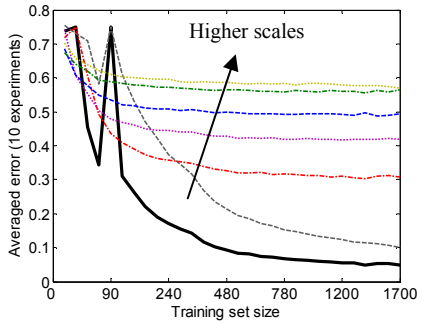

Fig. 6- Learning curves for the classification of 4 textures from Brodatz album in single (thin curves) and multiple (thick curve) scales.

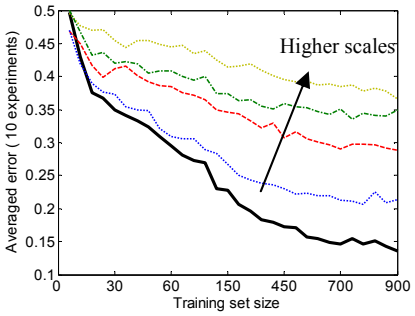

Fig. 7- Learning curves for the classification of normal liver and cirrhosis in single (thin curves) and multiple (thick curve) scales.

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