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# A LITERATURE REVIEW ON TEXTURE CLASSIFICATION USING WAVELET TRANSFORM

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**ABSTRACT**
Classification of image textures is an important task in image processing and pattern recognition. Over the years, extensive researches have been done for the classification of the texture images. The wavelet transform is an important multi-resolution analysis tool has been commonly applied to image analysis and various classification systems. The texture is characterized by a set of channel variances estimated at the output of the corresponding filter bank.

**KEYWORDS:** Texture classification, wavelet transform, accuracy, Brodatz database.

## I.INTRODUCTION

Classification of texture pattern is one of the most important problems in pattern recognition[1]. Classification method based on the Discrete Cosine Transform (DCT) coefficients of texture image[3]. This analysis used has an over complete wavelet decomposition, which yields a description that is translation invariant. Classification experiments with $l_2$ Brodatz textures indicate that the discrete wavelet frame (DWF) approach is superior to a standard (critically sampled) wavelet transform feature extraction. The soft computing models were trained using 80% of the texture data and remaining 20% used for testing and validation purposes. The performance comparison was made among the soft computing models for the texture classification problem.

## II.TEXTURE CLASSIFICATION

### A. Filtering Techniques

This paper shows, the most major filtering approaches to texture feature extraction and perform a comparative study. Filtering approaches includes, Laws masks, ring/wedge filters, dyadic Gabor filter banks, wavelet transforms, wavelet packets and wavelet frames, quadrature mirror filters, discrete cosine transform, eigen filters, optimized Gabor filters, linear predictors, and optimized finite impulse response filters. These filtering keeps the local energy function and the classification algorithm identical for most of the approaches[2]. For reference, comparisons with two classical non-filtering approaches, co-occurrence (statistical) and autoregressive (model based) features, are given. This paper is an attempt to present a ranking of the tested approaches based on extensive experiments.

 

**Pros:**
The filter *optimization* approaches is a low feature count, thus many of the optimization schemes yields to computational characteristics.

**Cons:**
The development of powerful texture measures that can be extracted and classified with a low computational complexity.

### B. SVD Based Modeling

This paper introduces a new model for image texture classification based on wavelet transformation and singular value decomposition. The probability density function of the singular values of wavelet transformation coefficients of image textures is modeled as an exponential function. The model parameter of the exponential function is estimated using maximum likelihood estimation technique. Truncation of lower singular values is employed to classify textures in the presence of noise. Kullback-Leibler distance (KLD) between estimated model parameters of image textures are used to perform the classification using minimum distance classifier. The exponential function permits us to have closed-form expression for the estimate of the model parameter and computation of the KLD[4]. These closed-form of expression reduce the computational complexity of the proposed approach. This Experiment shows, the proposed approach improves recognition rates using a lower number of parameters on large databases. The proposed approach achieves higher recognition rates compared to that of the other approaches like traditional sub-band energy-based approach, the hybrid IMM/SVM approach, and the GGD-based approach.

**Pros:**
It significantly reduces memory space required for storing the features of training texture images. Main aim of employing SVD is to achieve higher recognition rates on larger databases, requiring less computation.

**Cons:**
Statistical and Model-based approaches are more apt only for highly regular deterministic textures.

### C. Linear Regression Model

The wavelet transform is an important multi resolution analysis tool which has already been commonly applied to texture analysis and classification . In this paper, a new approach to texture analysis and classification with The simple linear regression model based on the wavelet transform is presented and its good performance on the classification accuracy is demonstrated in the experiment[5]. The current work focus on the simple linear regression model which is used to employ the linear correlation using the theoretical analysis in the future.

**Pros:**
Texture analysis and classification with the simple linear regression model based on the wavelet transform presented good performance on the classification accuracy. This model is natural and effective for more textures.

**Cons:**
The classification rate is extremely affected by the noise. The energy of Gaussian noise spreading over the entire spectrum, affect the frequency channels with small energy, which leads to the sensitivity of the features

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to the noise. Further ,the threshold rule in the classification phase is affected by the noise.

**D. Gaussian Mixtures**

Texture classification generally requires the analysis of patterns in local pixel neighborhood. Statistically, the underlying processes are comprehensively described by their joint probability density functions (jPDFs).Framework is applicable to a wide variety of classification problems, such as industrial inspection, making the possible number of classes the more challenging problem[6]. In industrial inspection, where illumination and image acquisition can be controlled. Whereas making classes which leads to the more challenging problem. Achieving the representational-level invariance in the framework. Other plans include to replace the k-NN by its fuzzy counterpart , which has shown to perform well in industrial inspection tasks. Moreover, the investigation of other density estimators within this framework seems worthy. Finally, using unsupervised classification method, can be applied to extend the framework.

**Pros:**
Using the oriented difference filters, this framework avoids the quantization errors and its classification performance is applicable. The primary goal of this contribution is to circumvent the curse of dimensionality using GMM-based density estimation, extensions toward such non-linear steps are beyond the scope of this paper.

**Cons:**
Using too low numbers of the decomposition levels may result in the loss of critical texture characteristics.

**E.Wavelet Based Image Texture**

Yongsheng Dong and Jinwen Ma proposed an efficient one-nearest neighbor classifier of texture via the contrast of local energy histograms of all the wavelet sub bands between an input texture patch and each sample texture patch in a Given training set. They have investigated the supervised texture classification problem by contrasting the local energy histograms of all the wavelet sub-bands between an input texture patch and each sample texture patch in a Given training set. The contrast is conducted with a discrepancy measure defined as a sum of the symmetrized Kullback–Leibler divergences between the input and sample local energy histograms on all the wavelet sub-bands, and then the one-nearest-neighbor classifier is built[7].

**Pros:**
The method proposed by Yongsheng Dong and Jinwen Ma are satisfactory in classification performance.

**Cons:**
Weak in Classification accuracy.

**F . Dominant Neighborhood Structure**

This paper introduce new global texture descriptor that is based on the texture DNS[8]. Texture features are obtained by generating an estimated global map representing the measured intensity. similarity of any given image pixel and its surrounding neighbors within a certain window. This research, to enhance the classification performance of the proposed method. By increasing the classification accuracy can be explored through using other robust classifiers such as SVM.

 

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**Pros:**
The DNS features are robust to noise and rotation-invariant. The proposed method produces higher classification rates than the method in the case of the Outex database. The obtained classification rate when the method is applied to texture set with large number of classes (CUReT) is excellent and highly comparable to the fused CLBP approach that employs three times in the proposed method's of feature size.

**Cons:**
To enhance the classification performance of the proposed method, increase the classification accuracy can be explored through using other robust classifiers.

## G. Discrete Cosine Transforms

Texture can be considered as a repeating pattern of local variation of pixel intensities. In this texture classification, the goal is to assign an unknown sample image to a set of known texture classes. This paper attempted to classify 3 different types of textures using artificial neural networks and Evolving Fuzzy Neural Network (EFuNN).Compared to ANN, an important advantage of Neuro-fuzzy models is their reasoning ability (if-then rules) of any particular state[9].

**Pros:**
Soft computing model are easy to implement and produce desirable mapping functions by training on the given data set. Choosing suitable parameters for the soft computing models is more or less a trial and error approach.

**Cons:**
Optimal results will depend on the selection parameters.

## CONCLUSION

The above survey clearly demonstrates a wide coverage of texture classification. It clearly illustrate the problem in texture classification because of the contrast between the local energy histograms and all the wavelet sub-bands of an input texture patch. Each sample texture patch in a given training set. The various analysis shows that the proposed method is not applicable to the present state of the art approaches [7]. The plan is to enhance the classification performance of the proposed method which lead to increase in the classification accuracy by using robust classifier such as SVM. The reason for using SVM classifier is more feasible than the DNS features which is noisy and make variation in rotation [8]. This paper is an attempt to show that the wavelet transform, it is an important multi-resolution tool has been commonly applied to image analysis and various classification systems.

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