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Texture analysis and classification methods

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ABSTRACT

In many types of images including aerial images, biomedical images, satellite images etc., textures play an important role in object and surface identification. It also plays an important role in the fields of pattern recognition and computer vision applications such as image/video retrieval and industrial inspection. It also helps in robot navigation and other applications. Many papers have been published in the field of texture analysis and classification. Traditional methods have assumed that the training and testing inputs are of the same alignment and gray scales. But in practice we come across rotations and gray scale changes, which required new methods. This paper presents a limited and interesting survey of the different texture analysis and classification methods mentioned in the literature.

KEY WORDS: Texture classification, Texture analysis, Rotation invariant, Wavelets, LBP.

1. INTRODUCTION

In the beginning of research on textures second order statistics was used in the analysis. In the next few years, Gaussian Markov Random Field (GMRF) (Chellapa, 1985) and Gibbs distribution methods (Derin, 1986) which used stochastic relationships for the analysis were used. These methods had the disadvantage of being based on the coupling between image pixels on a single scale (Chang, 1993). In the scheme proposed by K L Laws (1980), local linear transformations and energy computations were used to extract features (Chang, 1993). The introduction of multiresolution analysis tools like wavelets has helped greatly in the effective characterization of different scales of the texture. The above mentioned and other earlier methods like co-occurrence matrix method, gabor filtering, wavelet transforms and wavelet frames assumed that the training and testing samples were of the same or similar orientations (Zhenhua Guo, 2010). Any rotations in the testing samples, which often occurred in real life samples, affected the performance of the classification method. This lead to the need for and introduction of rotation invariant methods for texture classification. The circular autoregressive model (Kashyap, 1986) proposed by Kashyap and Khotanzad was the first among the many such methods proposed for rotation invariant texture classification. More methods like multiresolution auto regressive model (Mao, 1992), LBP histogram and MR8 methods have been proposed in the literature.

Genetic Programming and Texture Classification: In the conventional approaches first a feature vector is computed based on human derived theories and models. Then a classifier is used to assign a class to the feature vector. Most methods vary on the feature vector computation stage. The conventional methods had the drawbacks of the identification of correct features, identification of the combination of features to be used and the computation complexity. Vic Ciesielski, Andy Song and Brian Lam (Vic Ciesielski, 2007) have proposed the use of genetic algorithms in texture classification. In the GP classifier approach proposed by them they have used a genetic programming classifier in the second step. In another approach Vic Ciesielski (2007) have used a single step classification wherein the images are given directly to the genetic programming system. The classifiers are evolved directly from the image pixels without the need for a separate feature extraction stage.

Texture Classification with minimal training images: Targhi (2008), have proposed a new approach for texture classification with minimum number of training images. Their approach is based on using Lambertian photometric stereo to generate additional training examples from a limited set of input training images. The resulting classification performance obtained has been better than that obtained using the large set of original images. By this method they have overcome the tedious and time consuming work of producing a large set of training images for example say under different illuminating conditions.

Texture Classification using Wavelets and SVM: Wavelets have the advantage of representing features at different scales. Kim (2002) have used Support Vector Machine (SVM) as a single step for texture classification wherein the gray level values of the raw pixels were directly fed to the SVM. They have adopted one-against-others decomposition along with a neural network for multitexture classification problem. Li (2003) have employed the Discrete Wavelet Frame Transform (DWFT) for single texture classification problems and not for multi-texture classification problem. Rajpoot and Rajpoot have in (Rajpoot, 2004) proposed the combination of 2D Discrete Wavelet Transform for feature extraction step and SVM for classification stage. DWT subband filtering based local energy function has been used for feature extraction and manual parameter selection has been applied in the SVM. Rajpoot and Rajpoot (2004) have made their method applicable to both single and multi-texture classification problems.

Rotation and Gray Scale Invariant Texture Classification: Many rotation invariant classification methods like multiresolution autoregressive model [108], Gaussian Markov Random Field (GMRF) (Deng, 2004), autocorrelation model (Campisi, 2004) have been proposed in the literature. The method proposed by Ojala (2002), used LBP

histogram for rotation invariant texture classification. The MR8 algorithm proposed by Varma and Zisserman (2005), uses a texton library built from a training set and classifies an unknown image according to its texton distribution (Zhenhua Guo, 2010). In the method proposed by Ojala (2002), they have used the joint histogram of the two complementary features, namely LBP/VAR. Since the value of VAR is continuous a quantization step is needed. In (Zhenhua Guo, 2010), Zhenhua Guo, Lei Zhang, David Zhang have proposed a scheme that builds a rotation variant LBP histogram and then applies a global matching procedure. To overcome the quantization problem of Ojal (2002), they have proposed a new operator called the Local Binary Pattern Variance (LBPV) which computes the VAR from a local region and accumulates it into the LBP bin. The LBPV operator along with the global matching scheme has greatly reduced number of training samples required (Zhenhua Guo, 2010). The Adaptive LBP scheme proposed by Zhenhua Guo in (Zhenhua Guo, 2010) uses directional statisitical features like the mean and standard deviation to improve the efficiency of the LBP classification. Ojala in (Pietietikainen, 2000) have proposed the use of distribution based classification approach that highly improved the efficiency of the rotation invariant classification. T Ojala (2002) have proposed a very simple and efficient multiresolution approach to gray-scale and rotation invariant texture classification. Their method is based on detecting certain LBPs for any angular space quantization and for any spatial resolution. The method is robust in terms of gray scale variations and is computationally simple.

2. METHODS & MATERIALS

The methods available in the literature include Gaussian Markov Random Field (GMRF) and Gibbs distribution methods, co-occurrence matrix method, gabor filtering, wavelet transforms, wavelet frames, circular autoregressive model, multiresolution auto regressive model, LBP histogram, MR8 methods, Local Binary Pattern Variance (LBPV) and adaptive LBP schemes have been proposed in the literature. The choice of methods depends on the application and the computing power available.

3. RESULTS

The methods that are available in the literature and mentioned above have its own advantages and drawbacks. The Support Vector Machine (SVM) method proposed by Kim, 2002, has been used as a single step for texture classification wherein the gray level values of the raw pixels were directly fed to the SVM. They have adopted one-against-others decomposition along with a neural network for multitexture classification problem. Rajpoot et al have in proposed the combination of 2D Discrete Wavelet Transform for feature extraction step and SVM for classification stage. DWT subband filtering based local energy function has been used for feature extraction and manual parameter selection has been applied in the SVM. The method is applicable to both single and multi-texture classification problems. Ojala, 2000, has proposed a very simple and efficient multiresolution approach to gray-scale and rotation invariant texture classification. Their method is based on detecting certain LBPs for any angular space quantization and for any spatial resolution. The method is robust in terms of gray scale variations and is computationally simple.

4. CONCLUSION

Texture analysis and classification has been in the center of many applications like product quality checking, biomedical image analysis, analysis of satellite and aerial images etc. We have presented a selected study of the texture classification algorithms available in the literature.

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