ABSTRACT

Performance of texture classification for a given set of texture patterns depends on the choice of feature extraction technique. Integration of features from various feature extraction methods not only eliminates risk of method selection but also brings benefits from the participating methods which play complimentary role among themselves to represent underlying texture pattern. However, it comes at the cost of a large feature vector which may contain redundant features. The presence of such redundant features leads to high computation time, memory requirement and may deteriorate the performance of the classifier. In this research work, a pool of texture features is constructed by integrating features from seven well-known feature extraction methods. In the second phase, a few popular feature subset selection techniques are investigated to determine a minimal subset of relevant features from this pool of features. In order to check the efficacy of the proposed approach, performance is evaluated on publically available Brodatz dataset, in terms of classification error. Experimental results demonstrate substantial improvement in classification performance over existing feature extraction techniques. Furthermore, ranking and statistical test also strengthen the results.

Keywords: Classification, Ensemble Approach, Feature Extraction, Feature Selection, Texture

DOI: 10.4018/IJCVIP.2015010103
1. INTRODUCTION

Texture classification is a process of determining the class of texture, from a set of known texture classes, to which a given image or sub-image belongs. Texture is an inherent property of an image and plays a vital role in distinguishing images. In the last few decades, remarkable progress has been made in texture classification but it is still considered as a challenging problem. Wide range of real-time applications of texture classification such as automated detection of defects and quality control of texture images, medical diagnosis, microscope images, postal address recognition and interpretation of maps, remote sensing and geological images has motivated the research community to develop robust and efficient techniques.

The performance of texture classification mainly depends on the choice of: (i) features to represent an image and (ii) classifier to learn a decision model. In literature, numerous feature extraction techniques have been proposed, which can be classified into four categories (Tuceryan & Jain, 1998; Materka & Strzelecki, 1998; Zhang & Tan, 2002): structural, statistical, model based and signal processing based techniques.

Structural techniques represent textures as being composed of simple primitive structures called “texels” (or textons or texture elements) and placement rules that govern their spatial arrangement. They provide a good symbolic description of an image and are most effective for representing regular textures. But extraction of texels is a complex process (Zhang & Tan, 2002). On the other hand, statistical techniques characterize the texture in terms of statistical properties that measures correlation among the grey levels of an image (Materka & Strzelecki, 1998). However, they do not explicitly consider the hierarchical structure of the texture. Moreover, the complexity of computing higher order statistical features increases with the increase in number of grey levels. Model-based techniques, construct a model of an image that can be used to describe as well as synthesize the texture (Zhang & Tan, 2002). The parameters of the model describe the basic texture properties. However, parameter estimation and the choice of suitable model are two basic problems in these techniques. In signal processing based techniques, features are constructed by convolving images with spatial or (and) frequency domain filters. These techniques perform well with both random and regular textures. But a key problem of these techniques is to choose or design appropriate filters.

Each feature extraction technique is capable of classifying textures to a large extent. However, as discussed above, each technique has its own advantages and disadvantages. According to Puig and Garcia (Puig & Garcia, 2002), no single feature extraction technique is good enough to distinguish different texture patterns found in nature or real time applications data. In particular, some technique (such as Local binary pattern) may be superior for a given texture but may not perform well for some other types of textures where some other technique like Gabor filter or wavelet transform may be more suitable. It is pointed out (Puig & Garcia, 2002) that for a wide variety of textures, the complementary information obtained by integrating features from different families of feature extraction techniques may lead to better classification than individual techniques. However, the integration of textural features from different techniques will result into a high dimensional feature vector. The decision model developed in presence of large number of features may take high computation time and require more memory, which deteriorate the performance of the classifier. In literature, to reduce the dimensionality of feature vector, feature selection is suggested (John, Kohavi, & Pfleger, 1994). Feature selection is mainly categorized into two groups (John, Kohavi, & Pfleger, 1994): wrapper approach and filter approach. Wrapper approach is computationally intensive as it uses a classifier to determine a relevant subset of features. On the other hand, filter approach is simple and less computationally intensive as it does not use any classifier. Filter approach is further categorized as univariate and
An Integrated Approach to Design Patterns Formalization
www.igi-global.com/chapter/integrated-approach-design-patterns-formalization/8149?camid=4v1a

A Modular Framework for Vision-Based Human Computer Interaction
www.igi-global.com/chapter/modular-framework-vision-based-human/48312?camid=4v1a