Self-Eigenroughness Selection for Texture Recognition Using Genetic Algorithms

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Abstract. To test the effectiveness of Self-Eigenroughness, which is derived from performing principal component analysis (PCA) on each texture roughness individually, in texture recognition with respect to Eigenroughness, which is derived from performing PCA on all texture roughness; we present a novel fitness function with adaptive threshold to evaluate the performance of each subset of genetically selected eigenvectors. Comparatively studies suggest that the former is superior to the latter in terms of recognition accuracy and computation efficiency.

1 Introduction

PCA-based method has been successfully used for supervised image classification [1]. While any image in the sample space can be approximated by a linear combination of the significant eigenvectors, this approach does not attempt to minimize the within-class variation since it is an unsupervised technique. Thus, the projection vectors chosen for optimal representation in the sense of mean square error may obscure the existence of the separate classes. In this paper, instead of using the common properties of classes in the training set, we use a given class's own scatter matrix to obtain its discriminative vectors, called the Self-Eigenvectors. We also give a Self-Eigenvector selection algorithm to test the effectiveness with respect to the Eigenroughness, where both an enrolled dataset and an invader dataset are used for experiments.

This paper is organized as follows. An extraction of texture roughness is presented in Section 2. The Eigenrouhness and Self-Eigenroughness techniques are introduced in Section 3, respectively, and the genetic eigenvector selection algorithm is proposed in Section 4. Experimental results are discussed in Section 5.

2 Texture Roughness

To describe texture, one obvious feature is energy [2]. The image of a real object surface is not uniform usually but contains variations of intensities which form certain

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repeated patterns. The patterns can be the result of physical surface properties such as roughness, which often has a tactile quality and therefore exhibits various energy variations over texture region. It is proper in reality to quantify the texture content by the roughness descriptor which provides measures of properties such as smoothness, coarseness, and regularity, being very useful as a distinctive preprocessing of texture characterization. In order to extract out texture roughness from its background, a smoothing filter is used to move the center from pixel to pixel in an image to guarantee the desired local edge enhancement. This continues until all pixel locations have been covered and a new image is to be created for storing the response of the linear mask. The local standard average μ and energy ε of the pixels in the 3 × 3 neighborhood defined by the mask are given by the expressions

$$\mu(x,y)=\frac{1}{\rho}\sum_{i=-1}^{1}\sum_{j=-1}^{1}f(x+i,y+j), \tag{1}$$

$$\varepsilon(x,y)=\frac{1}{\rho}\sum_{i=-1}^{1}\sum_{j=-1}^{1}(f(x+i,y+j)-\mu(x,y))^2 , \tag{2}$$

where ρ = 9 is a normalizing constant, $f(x, y)$ is the input image, and $\varepsilon(x, y)$ is corresponding to the roughness image formed with energy enrichment.

3 Self-Eigenroughness

PCA can be used to find the best set of projection directions in the sample space composed with roughness features that will maximize the total scatter across all texture images. Projection directions are called the Eigenroughness, namely,

$$\text{Eigenroughness:}\, T = \{\boldsymbol{m}, \boldsymbol{W}_K\}, \tag{3}$$

where $\boldsymbol{m}$ denotes the mean vector of the N-dimensional observation vector obtained from all two-dimensional roughness images, $\boldsymbol{W}_K = (\boldsymbol{w}_1,\ldots,\boldsymbol{w}_K)$, and $K << N$. The vector $\boldsymbol{w}_K$ is the Eigenroughness corresponding to the K-th largest eigenvalue of the sample covariance matrix. The K principal components in $\boldsymbol{W}$ are the orthonormal axes onto which the retained energy under projection is maximal. Although PCA is as optimal representation criterion in the sense of mean square error, yet it does not consider the classification aspect. Based on our observation that the variations between images of different textures reflecting the changes in texture identity are almost always larger than the variations between images of the same texture, the single Eigenroughness set is not efficient to be used for analyzing a nonlinear structure such as complicated textures with large variations of roughness. To overcome this drawback, a variant of the PCA technique proposed by Torres and Vilá [3] is adopted in this work. In what follows, independent PCA is performed for each texture using its available images for recognition purpose. Like the traditional PCA, the independent PCA decorrelates the components and arranges them in order of decreasing significance but with a different amplitude distribution. The analysis results in a set of Eigenroughness for each texture, called Self-Eigenroughness,