Similarity Measurement Between Images

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Abstract

Experimental results of applying two similarity measurements, Euclidean distance and chord distance, to test a set of six Brodatz's textures are reported. Experiments show that in addition to feature extraction, A similarity measurement between images should be simultaneously considered, We also review some other similarity measurements.

1 Introduction

In a digital multimedia era, the research of content-based image retrieval (CBIR) used to establish a database composed of images, each is represented as a vector of features derived from color, shape, and/or texture information. When the query is requested, a similarity measurement between a user-provided image and those prestored in the database is computed and compared to report a few of most similar images. In the process, texture features from Gabor, Daub4, and Haar [3, 5] were commonly extracted as representative vectors for CBIR although no universally best set of texture features ever exists. Most of the existing works highlight a high matched retrieval rate in author-specified databases by using conventional classifiers such as 1-nn classifier, Bayesian classifier, or a Fisher's discriminant [2, 4]. We have realized that the recognition rate in a pattern recognition system should simultaneously consider feature extraction and classifier design [2]. However, a similarity measurement between two images was seldom investigated. This paper studies the effect of similarity measurement between texture features derived from Gabor and wavelet transforms Daub4 and Haar. We report experimental results on a database of Brodatz's textures [1].

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2 Similarity Measurement

A similarity measurement must be selected to decide how close a vector is to another vector. The problem can be converted to computing the discrepancy between two vectors $\mathbf{x}, \mathbf{y} \in R^d$. This paper examines the three distance measurements: Euclidean, Mahalanobis, and chord distances which are reviewed as follows.

2.1 Euclidean Distance

The Euclidean distance between $\mathbf{x}, \mathbf{y} \in R^d$ is computed by

$$\delta_1(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|_2 = \sqrt{\sum_{j=1}^{d} (x_j - y_j)^2} \tag{1}$$

A similar measurement called the cityblock distance, which takes fewer operations, is computed by

$$\tau_1(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|_1 = \sum_{j=1}^{d} |x_j - y_j| \tag{2}$$

Another distance measurement called the supreme norm, is computed by

$$\tau_2(\mathbf{x}, \mathbf{y}) = \max_{1 \le j \le d} |x_j - y_j| \tag{3}$$

2.2 Mahalanobis Distance

The Mahalanobis distance between two vectors $\mathbf{x}$ and $\mathbf{y}$ with respect to the training patterns $\{\mathbf{x}_i\}$ is computed by

$$\delta_2(\mathbf{x}, \mathbf{y}) = \sqrt{(\mathbf{x} - \mathbf{y})^t S^{-1} (\mathbf{x} - \mathbf{y})}, \tag{4}$$

where the mean vector $\mathbf{u}$ and the sample covariance matrix S from the sample $\{\mathbf{x}_i | \ 1 \le i \le n\}$ of size n are computed by $S = \frac{1}{n} \sum_{i=1}^{n} (\mathbf{x}_i - \mathbf{u})(\mathbf{x}_i - \mathbf{u})^t$ with $\mathbf{u} = \frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i$.

2.3 Chord Distance

The chord distance between two vectors $\mathbf{x}$ and $\mathbf{y}$ is to measure the distance between the projected vectors of $\mathbf{x}$ and $\mathbf{y}$ onto the unit sphere, which can be computed by

$$\delta_3(\mathbf{x},\mathbf{y}) = \|\frac{\mathbf{x}}{r} - \frac{\mathbf{y}}{s}\|_2, \tag{5}$$

where $r = \|\mathbf{x}\|_2$, $s = \|\mathbf{y}\|_2$. A simple computation leads to $\delta_3(\mathbf{x},\mathbf{y}) = 2sin(\alpha/2)$ with α being the angle between vectors $\mathbf{x}$ and $\mathbf{y}$. The smaller the angle α, the closer the two vectors $\mathbf{x}$ and $\mathbf{y}$.

A similar measurement based on the angle between vectors $\mathbf{x}$ and $\mathbf{y}$ is defined as

$$\tau_3(\mathbf{x},\mathbf{y}) = 1 - |\cos(\alpha)|, \quad \cos(\alpha) = \frac{\mathbf{x}\cdot\mathbf{y}}{\|\mathbf{x}\|_2\|\mathbf{y}\|_\mathbf{2}} \tag{6}$$

2.4 Pearson's Correlation Coefficient

A measurement derived from Pearson correlation coefficient $\rho(\mathbf{x},\mathbf{y})$ is defined as

$$\delta_4(\mathbf{x},\mathbf{y}) = 1-|\rho|, \;\; \rho = \frac{\sum_{i=1}^{d}(x_i-u)(y_i-v)}{(\sqrt{[\sum_{i=1}^{d}(x_i-u)^2]}\sqrt{[\sum_{i=1}^{d}(y_i-v)^2]}} \tag{7}$$

The larger $|\rho|$ is, the closer the vectors $\mathbf{x}$ and $\mathbf{y}$ are.

2.5 Spearman Rank Coefficient

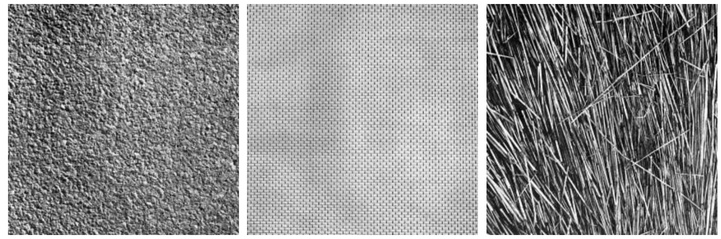
A measurement derived from Spearman rank coefficient $\gamma(\mathbf{x},\mathbf{y})$ is defined as

$$\delta_5(\mathbf{x},\mathbf{y}) = 1 - \frac{6\sum_{j=1}^{d} r_j^2}{d(d^2-1)} \tag{8}$$

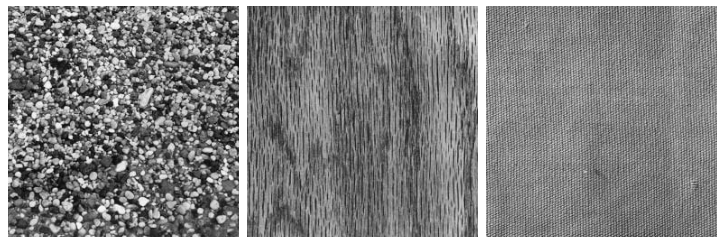
where $r_j = x_{(j)} - y_{(j)}$ is the rank difference between the components of vectors $\mathbf{x}$ and $\mathbf{y}$. Note that $-1 \le \delta_5 \le 1$. the larger δ_5 is, the closer the vectors $\mathbf{x}$ and $\mathbf{y}$ are.

3 Experimental Results

Texture features computed from Gabor, Daubechies' four (Daub4) and Haar transforms [3] tested on 96 textures with 6 categories are given in Table 1. The texture images are shown in Figure 1.



(a) pressed cork (b) aluminum wire (c) straw



(d) beach pebbles (e) wood grain (f) cotton canvas

Figure 1: Six Brodatz's Textures: (a) D04, (b) D06, (c) D15, (d) D54, (e) D68, (f) D77.

Table 2: Leave-one-out Errors on Six Brodatz's Textures.

δ_j	Gabor	Daub4	Haar
Euclidean	4/96	0/96	0/96
Chord	8/96	0/96	3/96

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