TEXTURE CLASSIFICATION BY USING STRUCTURAL TEXTURE SIMILARITY MATRICES

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ABSTRACT

We are creating new metrics for texture similarity that describe for human visual perception and the random nature of textures. The metrics depend entirely on local image statistics and allow essential point-by-point deviations between textures that based on human evaluation are basically identical. These metrics offer the ideas of structural similarity and to lead research in texture analysis-synthesis. They are working by using a steerable filter decomposition and incorporate a brief set of sub band statistics, calculate globally or in sliding windows. We will do systematic tests to examine metric performance in the context of "known-item search," the retrieval of textures that are "identical" to the query texture. This eliminates the need for not easily managed subjective tests, thus to make comparisons with human performance on a large database. This indicate that the proposed metrics outperform peak signal-to-noise ratio (PSNR), structural similarity metric (SSIM) and its variations, as well as state-of- the-art texture classification metrics, using standard statistical measures.

Keywords - Image retrieval, perceptual quality, statistical models, Similarity Matching

I.INTRODUCTION

Digital images play an important role in our everyday life. In many areas of science, commerce and government images are daily acquired and used. During the past decades we have been observing a permanent increase of image data, leading to huge storage. The national geographic imagery collection of the United States currently has a size in the range of Petabytes (PB) and daily grows by several Terabytes (TB).The rapid evolution indicates the demand of qualitative and quantitative image retrieval systems. To date, various commercial systems and Internet search engines feature keyword-based image retrieval. Usually, the results are not satisfactory due to the high complexity of images that can not easily be described by words. Therefore, content-based image retrieval achieved in importance during the past decade.

The development of objective metrics for texture similarity differs from that of traditional image similarity metrics, which are often referred to as quality metrics, because essentialy visible point-by-point deviations are possible for textures that according to human judgment are essentially identical. Employing metrics that are insensitive to such deviations is particularly important for natural textures, the stochastic nature of which requires statistical models that gives an understanding of human perception. we are presenting new structural texture similarity (STSIM) metrics for image analysis and content-based retrieval (CBR) applications.

We have developed a method that represents the global structure of an image, as well as the local structure of perceptual groups and their connectivity. The relations between perceptual groups are evaluate under the usage of Euclidean distance matrices. The features are invariant against similarity transformations and robust against changes in illumination. The method can be applied to a broad range of applications.
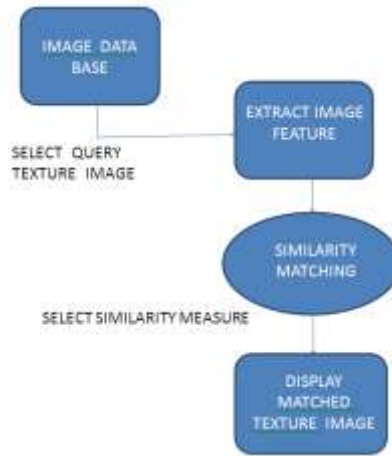

FIG 1. PROPOSED BLOCK DIAGRAM

II.RELATED WORK

In this section we are giving a idea of related structure-based feature extraction methods in the area of image classification and content-based image retrieval. The most used features are the Structure-based features which are frequently used for image representation, classification and content-based image retrieval tasks [2]. Further the authors in [3] have successfully included texture with structure and colour features. The review of the literature shows that,to extract observable and important features for CBIR applications an image's structure can be used.

III.STRUCTURAL SIMILARITY

The **structural similarity** (SSIM) is a method for measuring the similarity between two images. The SSIM index is a full reference metric,In other words, distortion-free image or uncompressed image is used as reference for measuring the image quality between two images. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be unpredictable with human eye perception.

The SSIM metric is calculated on various windows of an image. The measure between two windows x and y of common size $N{\times}N$ is:

$$SSIM(x,y) = \frac{(2\mu x\mu y+c1)(2\sigma xy+c2)}{(\mu x^2+\mu y^2+c1)(\sigma x^2+\sigma y^2+c2)}$$

with

- μ_x the average of x;
- μ_y the average of y;
- σ_x^2 the variance of x;
- σ_y^2 the variance of y;
- σ_{xy} the covariance of x and y two variables to stabilize the division with weak denominator;
- l the dynamicrange of the pixel-values (typically this is$2^{\text{# per pixe}}$ -1);
- k1=0.01 and k2=0.03 by default.

SSIM TEST RESULT

- If two texture images are different the output is SSIM OUTPUT=0.2023
- If two texture images are same the output is SSIM output=1

IV.EUCLIDEAN DISTANCE MATRIX

 An Euclidean Distance Matrix (EDM) is a two-dimensional array.EDM consist of distances taken from a set of coordinates or points from a feature space. Thus,an EDM includes knowledge about distance between points.

Euclidean space is a set of points which consistof coordinates.Specifically,an Euclidean Distance Matrix is a real valued n × n matrix E containing the squared distances of pairs of points from a table of n points (Xk, Yk), with {k = 1, 2, . . . n}. An EDM is defined as

$$E = \begin{bmatrix} e11 \; e12 \; \cdots e1n \\ e21 \; e22 \; \cdots e2n \\ en1 \; en2 \; \cdots enn \end{bmatrix}$$

where

$e_{ij} = \sqrt{(Xi\text{-}Xj)^2 + (Yi\text{-}Yj)^2}$

withi,j ={1,2,. . .,n},

(Xi − Xj)2 + (Yi − Yj)2, with i,j ={1,2,. . .,n}, (4.1)

describes the Euclidean distance between the feature points i and j.

An EDM E inherits the following properties from the norm k · k2:

1. eij≥ 0, i 6= j non-negativity

2. eij = 0, i = 0 self-distance

3. eij = eji symmetry

4. eij≤ eik + ekj , i 6= k 6= j triangle inequality.

V.DATABASE CONSTRUCTION
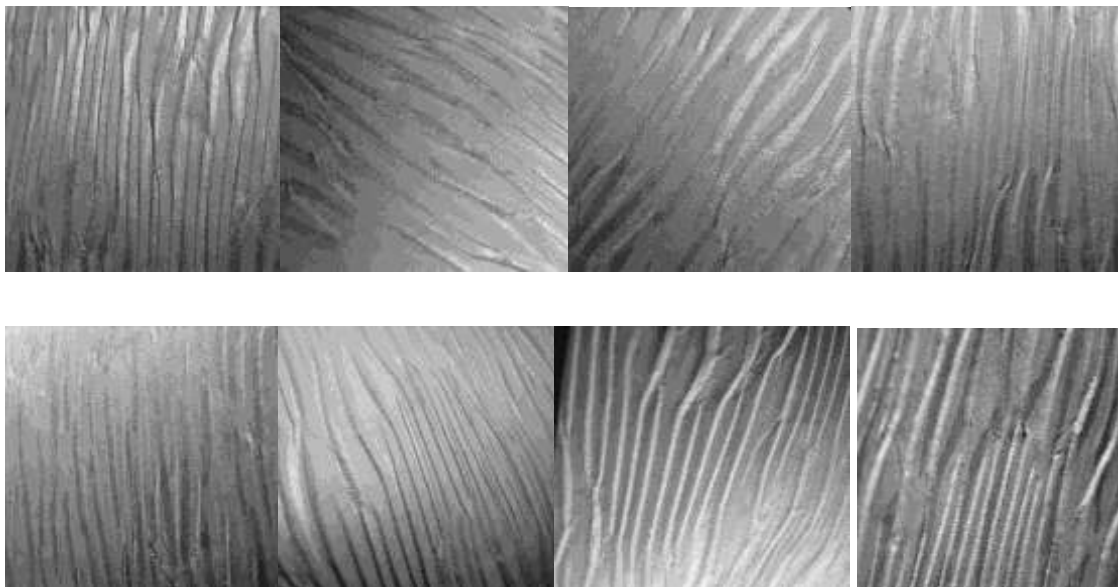
Fig 2.Texture images from broadatz database

Table 1. Experimental Results

SSIM	MSE	PSNR
0.2504	0	INF
0.1639	544.147	19.8015
0.1472	3968.07	11.3613
0.1354	697.08	14.1536
0.2302	934.82	17.8316

VI. CONCLUSION

We have developed a structure-based feature extraction method which is capable of representing the global structure of an image, as well as the local structure of perceptual groups and their connectivity. The metrics allow substantial point-by-point deviations between textures that according to human judgment are essentially identical. This eliminates the need for subjective tests, thus enabling comparisons with human performance on a large database.

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