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Rapid and Brief communication

Scale-orientation histogram for texture image retrieval

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Abstract

In this paper, a *Scale-orientation histogram* is defined for analyzing the "directionality" and "periodicity", which are two of the most important deterministic dimensions in human texture perception. This histogram is applied to texture retrieval in a case study, and the experimental results illustrate its effectiveness.

Keywords: Texture analysis; Scale-orientation histogram (SOH); Image retrieval

1. Introduction

As an important aspect of computer vision and pattern recognition, texture analysis has broad applications. For example, it can be used for texture-rich image retrieval so as to save the time and effort of browsing an entire database [[1,2]].

The most important dimensions of human texture perception can be described as "directionality", "periodicity", and "randomness" [[1]]. In this paper, we will define a so-called *Scale-orientation histogram* (SOH) that transforms the original texture image into another two-dimensional space, which mainly concerns the two deterministic properties of the texture, that is, "directionality" and "periodicity". The application of SOH to texture retrieval is also illustrated in a case study.

2. Scale-orientation histogram

For an intensity pattern that is strongly oriented along one direction, its power spectrum is clustered along a line through the origin in the Fourier transformation domain, and the direction of the line is perpendicular to the dominant spatial orientation. Instead of performing the actual computation in the Fourier transformation domain, the orientation map, θ, and the anisotropic strength map, g, can be calculated directly from an intensity image, I, respectively [[3,4]] as follows:

$$\theta(x,y|\Omega) = \frac{1}{2}\tan^{-1}\frac{\iint_\Omega 2I_xI_y\,\mathrm{d}x\,\mathrm{d}y}{\iint_\Omega (I_x^2 - I_y^2)\,\mathrm{d}x\,\mathrm{d}y} + \frac{\pi}{2}, \tag{1}$$

$$g(x,y|\Omega) = \frac{\left(\iint_\Omega (I_x^2 - I_y^2)\,\mathrm{d}x\,\mathrm{d}y\right)^2 + \left(\iint_\Omega 2I_xI_y\,\mathrm{d}x\,\mathrm{d}y\right)^2}{\left(\iint_\Omega (I_x^2 + I_y^2)\,\mathrm{d}x\,\mathrm{d}y\right)^2}, \tag{2}$$

where $\tan^{-1}$ is a four-quadrant arctangent function, and I_x and I_y are partial derivatives of $I(x,y)$. Note that Ω is a neighborhood around a pixel, (x,y), and its size is related to the scale on which we analyze an image. The value of the anisotropic strength, g, is close to 1 for a strongly oriented pattern, and close to 0 for isotropic regions. Due to the integration in the equations, the above measures are insensitive to noise.

Based on the above definition, we can transform the original intensity image into a new two-dimensional space by using the following equation:

$$H(r,a) = \sum_{x,y}\{g(x,y|2^r\Omega):\ \theta(x,y|2^r\Omega) = a\},$$
$$-\infty < r < +\infty,\ a \in [0,\pi), \tag{3}$$

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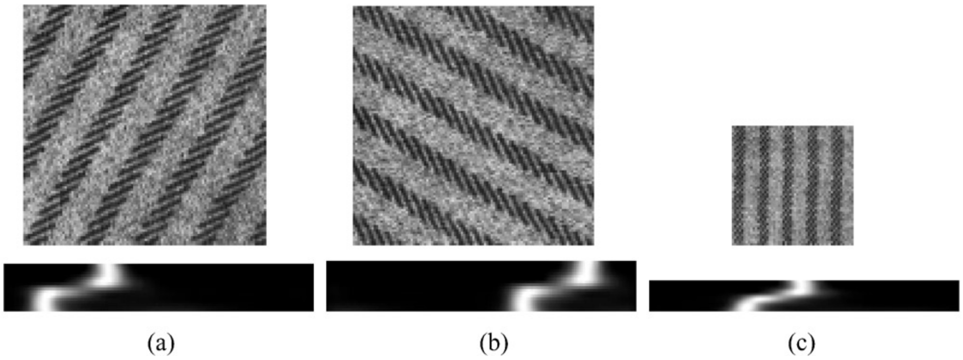

Fig. 1. The SOHs of three texture images: (a) original D11 texture, (b) rotated D11, and (c) zoomed D11. The texture images are listed in the first row and below them are their corresponding histograms, in which the vertical and horizontal axes represent the scale factor and orientation angle, respectively.

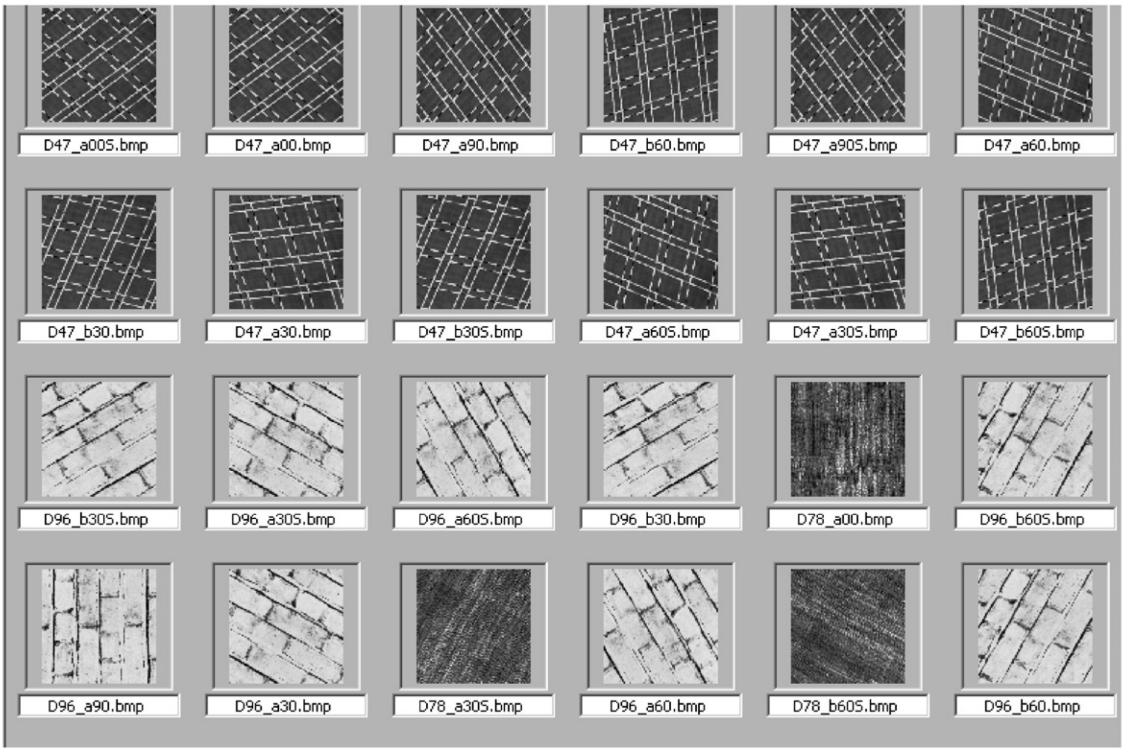

Fig. 2. An example for texture image retrieval based on SOH, which are displayed in a browser window. The test image is on the upper-left position and the retrieved images are listed in raster-scan order by descending similarity. The first 11 retrieved images are of the same subject with the test texture.

where $2^r\Omega$ is also a neighborhood around the pixel, (x, y), and it is produced by zooming-in or zooming-out on Ω until it is shown at 2^r size. Obviously, Eq. (3) is the sum of the anisotropic strength along an orientation, a, on a scale, r, so it can be used to investigate the orientation's distribution for a texture image on different scales. That means we can easily tell the directionality of a texture image from the transformed map, H (for example, we can simply do it by finding the position of a_0 where $H(r, a_0)$ is large enough). The periodicity of the texture along the orientation, a_0, can also be studied by just analyzing the distribution of $H(r, a_0)$. For a digitalized image, the transformed map can be regarded as a novel kind of histogram, which we call an SOH.

We can prove that the above transform has the following properties: (1) $H(r,a)$ is π-periodic with respect to a. (2) Zooming on the image causes a translation of $H(r,a)$ along the r-axis. (3) Rotation within the plane of the image causes a translation of $H(r,a)$ along the a-axis. (4) $H(r,a)$ is continuous in the parameters r and a, and this will guarantee that Properties 2 and 3 still hold after digitization. (5) The SOH is insensitive to noise.

3. Texture image retrieval using an SOH

As stated above, SOH is a good tool for analyzing the periodicity and directionality of the texture. Moreover, the rotation and zooming of the texture only causes the shift of its SOH. As a result, it is suitable to apply SOH for rotation-and-scale invariant texture image retrieval.

First, the SOHs of the reference images in the database need to be produced. Given a test texture image, we also compute its SOH. All of these SOHs have to be normalized according to the size of the original images. Next, we compare the SOH of the test image with that of each reference image and their similarities can be computed. Then the reference images are then listed according to a ranking of their similarities.

For a comparison of the normalized SOHs of two texture images, $H_1(r,a)$ and $H_2(r,a)$, a similarity measurement can be defined as

$$P(H_1,H_2) = \min_{t,\theta} \int_{-\infty}^{+\infty} \int_0^{\pi} |H_1(r+t,a+\theta) - H_2(r,a)| \, \mathrm{d}r \, \mathrm{d}a. \quad (4)$$

This means that we can slide the image window to find the best match between two SOHs, and the minimal difference is regarded as their similarity. When the difference reaches the minimum value, the values of t and θ can be regarded as the zoom factor and rotation angle, respectively, between these two images.

4. Experimental results

Fifty typical texture images are selected from the Brodatz album and each of them is rotated and zoomed 11 times using different angles and factors. Therefore, a total of $50 \times 12 = 600$ texture images are used for our experiments. First, all of their SOHs are computed. In Fig. 1, the SOHs of three texture images generated from the same original texture are provided, in which the vertical and horizontal axes represent the scale factor and orientation angle, respectively. It can be seen that their SOHs are quite similar regardless of the shift differences between their images.

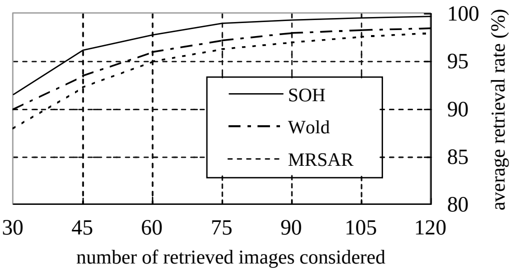

Fig. 3. The average retrieval rates between our algorithm, Wold decomposition and MRSAR over the database by considering from 30 to 120 top retrieved images.

We also test the retrieval ability of our SOH algorithm on the image database by using 'leaving-one-out' strategy. One example is given in Fig. 2, in which the test image is shown in the upper-left position, and the retrieved images are listed in raster-scan order by descending similarity. All the 11 texture images from the same subject as the test texture are ranked foremost. In Fig. 3, the average retrieval rate of our algorithm is plotted against those of two state-of-the-art algorithms, the Wold model and MRSAR model [[1]]. The results show that the SOH algorithm is much better at dealing with any rotation and zooming that has been applied to the texture images.

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