A New Texture Feature Based on GLCM and Its Application on Edge-detection

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Abstract. In visual interpretation and recognition, the distinction and discrimination of objects in an image depend not only on the complexity of the texture of the image, but also the intensity of the contrast of the image texture. In the commonly used texture features, entropy can better reflect the complexity of the texture, but it can not reflect the difference between the gray values. The contrast can reflect the contrast of the image texture, but since only the difference is taken into consideration, the difference in the size of the pixel value itself is not considered. In view of the above phenomenon, in order to make the texture features satisfy the higher recognition and recognition of image differentiation, this paper proposes a new texture feature based on the gray level co-occurrence matrix. The new texture feature not only reflects the sharpness of the texture, but also reflects the complexity of the texture and applies the texture feature to edge detection. The results show that the edge detection based on the new texture features proposed in this paper can effectively detect various edges and has a good inhibitory effect on noise. At the same time, the edge detection results can effectively distinguish the edges of different degrees of change.

1. Introduction

The texture describes the irregular and macroscopic regularity of the image, including the relationship between the surface structure of the object and its spatial space [1-2]. Textures can generally be divided into natural textures, artificial textures, and mixed textures. In order to quantitatively describe the texture of images, many texture analysis methods have been proposed. Texture analysis refers to the process of extracting texture features for certain image processing techniques and obtaining texture qualitative or quantitative description. Image texture analysis has been extensively used in target recognition and analysis, texture synthesis, image retrieval and motion analysis [3]. The commonly used texture analysis methods include statistical analysis, structural analysis, model analysis and spectral analysis [3]. The statistical analysis method has a real good description of the detail and randomness of the texture and is highly adaptable, and it is dominant in texture analysis [4]. The texture extracted by the gray level co-occurrence matrix (GLCM) method has strong discriminating ability, and has strong vitality in statistical methods [5-6]. There is a wide range of applications for textures from GLCM of image retrieval, target recognition, image classification, and change monitoring in the fields of medicine, transportation, and remote sensing. In this paper, a different
texture feature is proposed based on the gray level co-occurrence matrix, which not only reflects the definition of the texture, but also reflects the complexity of the texture.

2. Methodology

2.1. Spatial gray level co-occurrence matrix

In order to better reflect the gray scale spatial correlation between image pixels, Haralick et al. [7] proposed spatial gray level co-occurrence matrix that represents the statistical probability of joint distribution of two pixels. Spatial gray level co-occurrence matrix reflects the comprehensive information of the image gray-scale with respect to direction, adjacent interval and variation amplitude, which can be used as information for analysing image primitives and arrangement structure. GLCM is the probability \( P(i, j, \delta, \theta) \) that a pixel \((x, y)\) with a gray scale of \(i\) appears simultaneously with a pixel \((x+\Delta x, y+\Delta y)\) with a distance of \(\delta\) and a gray scale of \(j\). That is

\[
P(i, j, \delta, \theta) = \left\{ \begin{array}{ll}
(f(x, y) = i, f(x + \Delta x, y + \Delta y) = j; \\
x = 0, 1 \ldots N_x - 1; y = 0, 1 \ldots N_y - 1
\end{array} \right.
\]

(1)

Among them, \(i, j = 0, 1 \ldots G - 1\); \((x, y)\) is the pixel coordinate of the image; \(G\) is the gray level of the image; \(N_x, N_y\) are the number of rows and columns of the image respectively.

The spatial gray level co-occurrence matrix in this paper adopts four directions including \(0^\circ\), \(45^\circ\), \(90^\circ\) and \(145^\circ\), and \(\delta = 1\).

2.2. Texture features based on GLCM

Based on the gray level co-occurrence matrix, Haralick et al. [7] has defined 14 gray level co-occurrence matrix feature parameters for texture analysis. Ulaby et al. [8] found that among the 14 texture features based on the gray level co-occurrence matrix, only 4 features are unrelated. The four most common and unrelated features, such as Angular Second Moment (ASM), Contrast (CON), Correlation (COR), Entropy (ENT2), are used to extract the texture features of the image [5, 9].

\[
\text{ASM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P^2(i, j, \delta, \theta)
\]

(2)

\[
\text{CON} = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P^2(i, j, \delta, \theta) \right\}, \quad (n = |i - j|)
\]

(3)

\[
\text{COR} = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} ij \cdot P(i, j, \delta, \theta) - u_1 u_2}{\delta_1^2 \delta_2^2}
\]

(4)

\[
\text{ENT}_2 = -\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j, \delta, \theta) \log_2 P(i, j, \delta, \theta)
\]

(5)

Among them, \(u_2 = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j, \delta, \theta)\), \(u_1 = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j, \delta, \theta)\), \(\delta_1^2 = \sum_{i=0}^{G-1} (i - u_1)^2 \sum_{j=0}^{G-1} P(i, j, \delta, \theta)\), \(\delta_2^2 = \sum_{j=0}^{G-1} (j - u_2)^2 \sum_{i=0}^{G-1} P(i, j, \delta, \theta)\). Among the four commonly used textures, ASM reflects the uniformity of image gray distribution and the thickness of the texture; CON reflects the intensity of the contrast in the image, mainly monitoring the contrast edge of the image and its edge effect [10]; COR reflects the degree of similarity between row or column elements in a gray level co-occurrence matrix, and is a measure of the linear relationship of gray scales; ENT2 reflects the degree of confusion and complexity of texture in image images.
In visual interpretation and recognition, the distinction and discrimination of objects in an image depend not only on the complexity of the texture of the image, but also on the intensity of the contrast of the image texture. In the commonly used texture features, entropy can better reflect the complexity of the texture, but it cannot reflect the difference between the gray values. For example, when two adjacent elements are 0 and 1, it is equivalent to 0 and 100 in the texture entropy statistics. The contrast can reflect the contrast of the image texture, but since only the difference is taken into account, the difference in the size of the pixel value itself is not considered. If two adjacent elements are 0 and 5, 250 and 255 are equivalent in the statistics of contrast and will be added together. In view of the above phenomenon, in order to make the texture features satisfy the higher recognition and recognition degree in image discrimination, a different texture feature is proposed in this paper, as in

\[
\text{New Texture Feature} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (|i-j| \cdot P(i, j, \delta, \theta) \log_2 P(i, j, \delta, \theta))
\]

3. Edge detection strategy based on texture features

Image edges are one of the important local features in image changes. Local texture features are needed when applying texture features to edge detection. The local texture feature is a texture feature of the partial image within the selected cell window. For local texture feature calculation, the pixel window size is generally 3*3 or 5*5. In literature [11], when applying local second-order texture entropy and edge detection, the edge effect is better when the window size is 3*3 than when 5*5. Therefore, this paper will calculate the local second-order texture entropy in 3*3 windows respectively and use it for edge detection.

![Flowchart for edge detection using texture features](image-url)
Literature [11] used the local second-order texture entropy to represent the nature of the gray-scale variation of local regions, and proposed an edge detection method based on local texture entropy, and obtains better detection results. The new texture features proposed in this paper are not only can reflect the gray level variation of the local area and also can reflect the gray level complexity. Therefore, this feature of the new texture feature can be used for edge detection. In this paper, the mean of the texture eigenvalues calculated by the spatially dependent gray level co-occurrence matrix in four directions is taken as the texture feature value of the central pixel, and the larger the texture feature value is judged as the edge, and the smaller one will be judged as Non-edge. The flow chart is shown in Figure 1.

4. Results and discussion
In order to verify the feasibility of the above edge detection strategy, three images including the image Lena with human body, the pentagon with building body and the comprehensive image with residential land and land body participated in the edge detection. Three texture features, such as the new texture features proposed in this paper, contrast and entropy, are involved in edge detection based on texture features. At the same time, the edge detection results of the Sobel operator and the second-order Laplace operator with the best performance in first-order edge detection are taken as the control group. The edge detection results are presented in Figure 2, Figure 3 and Figure 4 respectively.

Figure 2 shows Lena and its edge detection results. Among them, Figure 2(a) is the original gray-scale image; Figure 2(b) is the edge detection result by Sobel; Figure 2(c) is the edge detection result by Laplace; Figure 2(d) is edge detection results based on ENT; Figure 2(e) is the result of edge detection based on CON; Figure 2(f) is edge detection result based on the new texture feature proposed in this paper. And there is a same distribution order of the edge detection results in Figure 3 and Figure 4.
Figure 3. The pentagon and its edge detection results.

Figure 4. Comprehensive image and its edge detection results.

From Figure 2 to Figure 4, it can be found that Sobel edge detection can effectively detect various edges. However, Sobel operator is sensitive to gray-scale changes and cannot suppress the influence of noise. For example, there are more flocculent textures in the detection results of Lena's face. Laplace edge detection is effective in detecting thin lines and isolated points, such as the edges of buildings. However, in the Laplace edge detection result, the information of the edge direction is lost, resulting in a double-pixel edge, such as two edges detected by Lena's shoulder. The edge detection effect based on ENT2 is not ideal, mainly because entropy can better reflect the complexity of texture, but cannot
reflect the difference between gray values. The edge detection effect based on CON is not ideal, and only the edges with great gray variation can be detected. The main reason is that contrast can reflect the contrast degree of image texture, but it only takes into consideration the difference, not the difference of pixel value itself. The edge detection based on the new texture features proposed in this paper can effectively detect all kinds of edges and has a beneficial effect on noise suppression. At the same time, the edge detection results can effectively distinguish the edge with a different degree of variation. The reason is that the new texture features not only reflect the clarity of the texture, but also reflect the complexity of the texture.

5. Conclusions
A new texture feature based on the gray level co-occurrence matrix has been proposed in this paper. The new texture feature not only reflects the sharpness of the texture, but also reflects the complexity of the texture and applies the texture feature to edge detection. The results show that the edge detection based on the new texture features proposed in this paper can effectively detect various edges and has a good inhibitory effect on noise, and the edge detection results can effectively distinguish the edges of different degrees of change. In addition, the regional value of the texture feature can effectively reflect the complexity and clarity of the texture, and may have a good application prospect in image classification, which needs further study.

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