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DELIVERING QUALITY SCIENCE TO THE WORLD

An overview of image retrieval algorithms based on texture features

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Abstract: With the development of computer science and technology and the rapid growth of global information, how to extract useful visual information quickly has been paid more and more attention. However, the main technology is content-based image retrieval. The commonly used image visual features include active color, texture and shape, in which texture is one of the main visual features of image, and is widely used. In this paper, the image retrieval algorithm based on texture features is studied, and the effectiveness of the retrieval algorithm is verified by experimental simulation, in which the texture feature extraction algorithm based on gray level co-occurrence matrix is used. Firstly, it describes the basic principles of image retrieval and the realization method of the texture feature extraction algorithm of gray-level co-occurrence matrix, and introduces and analyzes the image similarity measurement required for image retrieval.
Keywords: Image retrieval; gray-scale co-occurrence matrix; texture characteristics.

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1. INTRODUCTION

We are in an era of information globalization. The rapid development of science and technology has made various information technologies continue to be improved. However, among various types of information resources, images have the characteristics of giving people a more intuitive image, and thus become an important part of the collection of resources in our daily lives. Among them, the collection and retrieval of image information is one of the important ways of collecting information in our lives. However, in the process of image retrieval, problems such as a large number of databases and intricate arrangement of pictures are encountered. Therefore, content-based image retrieval has increasingly become the focus of research. This article mainly introduces the algorithm of texture feature extraction and image similarity measurement in content-based image retrieval and analyzes its running results.

2. ALGORITHM INTRODUCTION

2.1 Overview of texture analysis

The original definition of texture comes from human touch on the surface of an object. However, there is no accurate texture definition so far. Used to reflect the roughness, smoothness, randomness and regularity of the object. People's perception of textures is combined with their psychological effects, so it is difficult to express them in words. A distinctive feature of texture is that it is regional. In pattern recognition, texture is used to distinguish areas of an image. There are many ways to describe the texture area, such as the number of distinguishable gray-scale elements, the size of a specific area, and the relationship between gray-scale elements to describe the texture.

The so-called texture analysis is the process of obtaining a quantitative or qualitative description of the target image texture, where the qualitative description of the extraction method is to use some predefined image processing techniques to extract texture features.

There are three main methods for analyzing texture features: structural analysis, statistical analysis, and spectrum analysis. Among them, the structural analysis method may be relatively suitable for micro-texture analysis (the target image is irregularly distributed in a certain area). Relatively speaking, the macro-texture analysis (analysis method with multi-scale and multi-resolution texture) is relatively more complicated. A combination of statistics and structure will be used to analyze the texture of the target image. The spectrum analysis method is unique and needs to use the frequency characteristics of the Fourier spectrum to describe the period of the image or the two-dimensional image mode.

(1) The definition of texture in the structural analysis method is a combination of many regularly distributed small texture units. Structural analysis is an analysis method based on the spatial domain. In essence, it can be understood that complex textures are also composed of smaller, regular and simple textures. The analysis process of the structure analysis method is divided into three steps. The first is image enhancement, then the texture primitives in the target image are extracted, and finally some specific parameters of the texture are calculated.

(2) Statistical analysis method is one of the earliest application methods in texture analysis, and it is also a relatively important method. Statistical analysis methods use gray-scale histograms to describe textures, but if only the gray-scale histograms describe textures, spatial information cannot be expressed. In order to make full use of all kinds of information, people thought of the method of establishing gray-level co-occurrence matrix.

(3) In the frequency spectrum analysis, the high frequency components in the image are closely related to the texture. The spectrum analysis method uses a transform domain method. Spectrum analysis methods are often used in image retrieval systems, including: pixel field method, co-occurrence matrix method, visual texture feature expression method, fractal coding method and wavelet transform method [7].

This article mainly introduces the use of gray-level co-occurrence matrix method to extract texture features of target images, and discusses image retrieval based on texture features.

2.2 Texture feature extraction technology

Based on the detailed description of the above texture analysis method, the following will continue to discuss the image retrieval texture feature extraction method.

2.2.1 Grayscale histogram

The grayscale histogram is a description of the proportions of different gray levels that appear in the image [1]. The abscissa represents the gray level of the image, and the ordinate represents the number of occurrences of these gray levels. Combine these gray levels and their frequency of occurrence and draw them on the same coordinate system to get a gray histogram. It is a representation of the gray distribution of an image, and it is a very important feature of the image.

2.2.2 Based on the texture feature of the gray-level co-occurrence matrix.

All the surface of the object in the image can be regarded as a certain surface in the three-dimensional space. The central moment method and gray-level difference statistical method used in the histogram can only be further studied in three-dimensional The gray distribution of a specific pixel in an image in space. It cannot represent the spatial correlation of gray levels between pixels. Two pixels in a three-dimensional space at a distance can have the same or different gray levels. The ability to find the distribution between them is of great significance to the development of image texture analysis. In the early 1970s, a model method of spatial gray-level co-occurrence matrix was proposed [1]. It assumes the spatial distribution of all pixels in the image. Texture information and use it as a prerequisite for widely used texture analysis methods. Assuming that an image has Nx pixels in the horizontal direction and Ny pixels in the vertical direction, the maximum gray scale NR of all pixels in the image is defined as follows:

$$L_x = \{1,2,\ldots,N_x\} \tag{2-1}$$

$$L_y = \{1,2,\ldots,N_y\} \tag{2-2}$$

$$G = \{1,2,\ldots,N_g\} \tag{2-3}$$

Therefore, we can regard the image f to be subjected to texture analysis as a transformation from $L_x \times L_y$ to G, that is, all points in $L_x \times L_y$ corresponds to a grayscale contained in f, and can also be expressed as $f: L_x \times L_y \to$G. The spatial gray-level co-occurrence matrix is the relationship function established between the direction θ and the separation distance d, which can be recorded as:

$$\left[P_{\theta,d}(i,j)\right] \tag{2-4}$$

Element in row i and column j of matrix $\lfloor P_{\theta,d}(i,j)\rfloor$, Among them $(i,j) \in G \times G$, θ =0 °,49 °,90 °,135 °the definition of different θ matrix elements is as follows:

$$\left\lfloor P_{0^0,d}(i,j)\right\rfloor = \left|\{[(k,l),(m,n)] \in D : k-m=0, |l-n|=d, f(k,l)=i, f(m,n)=j\}\right| \tag{2-5}$$

$$\left[P_{45^0,d}(i,j)\right] = \left|\left\{\begin{matrix}[(k,l),(m,n)] \in D : (k-m=d, l-n=-d) \text{ or} \\ (k-m=-d, l-n=d), f(k,l)=i, f(m,n)=j\end{matrix}\right\}\right| \tag{2-6}$$

$$\left\lfloor P_{90^0,d}(i,j)\right\rfloor = \left|\{[(k,l),(m,n)] \in D : |k-m|=d, l-n=0, f(k,l)=i, f(m,n)=j\}\right| \tag{2-7}$$

$$\left[P_{135^0,d}(i,j)\right] = \left|\left\{\begin{matrix}[(k,l),(m,n)] \in D : (k-m=d, l-n=d) \text{ or} \\ (k-m=-d, l-n=-d), f(k,l)=i, f(m,n)=j\end{matrix}\right\}\right| \tag{2-8}$$

In the formula | {…} | , refers to the cardinality of the set, D=(Lx, Ly) × (Lx, Ly). [Pθ, d (i, j)] is the entire θ direction of the element in the i-th row and j-th column of the matrix, and one of the pixels with a distance of d has the value i , and the other value is the number of corresponding points j where d can take 1, 2, 3, 4, 8, etc. value.

The gray-level co-occurrence matrix is obtained by combining all the directions of the gray level of the image, the distance between two adjacent pixels, and the magnitude of change. When we analyze the arrangement rules and layout of the elements in the image, it is based on gray Above the degree of symbiosis matrix. We usually do not directly use the feature vector in texture analysis to calculate the gray level co-occurrence matrix of the image, but extract the feature vector of the texture on the basis of it, which is the secondary statistic. Haralick et al. extracted the following 14 features from the gray-level co-occurrence matrix (set gray level as L) [2]:

Angle second pitch

$$f_1 = \sum_{i=1}^{L}\sum_{j=1}^{L}\{p(i,j)\}^2 \tag{2-9}$$

Contrast

$$f_2 = \sum_{n=0}^{L-1} n^2 \left\{ \begin{matrix} \sum_{i=1}^{L}\sum_{j=1}^{L} p(i,j)2 \\ |i,j| = n \end{matrix} \right\} \tag{2-10}$$

Related

$$f_3 = \frac{1}{\sigma_x \sigma_y}\left\{ \sum_{i=1}^{L}\sum_{j=1}^{L} ijp(i,j) - \mu_x \mu_y \right\} \tag{2-11}$$

Where μ_x, σ_x are the mean and variance of $\{p_x(i); i = 1,2,..., N_g\}$ respectively, and μ_y, σ_y are the mean and variance of $p_y(j); j = 1,2,..., N_g$ respectively.

Variance

$$f_4 = \sum_{i=1}^{L}\sum_{j=1}^{L}(i-\mu)^2 p(i,j) = \sum (i,\mu)^2 p_x(i) \tag{2-12}$$

Where μ is the mean of $p(i,j)$.

Inverse variance

$$f_5 = \sum_{i=1}^{L}\sum_{j=1}^{L}\frac{1}{1+(i-j)^2} p(i,j) \tag{2-13}$$

Sum average

$$f_6 = \sum_{i=2}^{2L} ip_{x+y}(i) \tag{2-14}$$

Sum variance

$$f_7 = \sum_{l=2}^{2L}(i - f_6)^2 p_{x+y}(i) \tag{2-15}$$

Sum entropy

$$f_8 = \sum_{j=2}^{2L} p_{x+y}(i) \log\left[p(i,j)\right] \tag{2-16}$$

Entropy

$$f_9 = -\sum_{i=1}^{L}\sum_{j=1}^{L} p(i,j) \log\left[p(i,j)\right] \tag{2-17}$$

Sum variance

$$f_{10} = p_{x-y} \tag{2-18}$$

Difference entropy

$$f_{11} = -\sum_{i=2}^{L} p_{x-y}(i) \log\left[p_{x-y}(i)\right] \tag{2-19}$$

Related information measurement

$$f_{12} = \frac{HXY - HXY1}{\max(H_X - H_Y)} \tag{2-20}$$

$$f_{13} = \left\{1 - \exp\left[-2.0(HXY2 - HXY)\right]\right\}^{\frac{1}{2}} \tag{2-21}$$

Where H_x is the entropy of P_x, H_y is the entropy of P_y,

$$\text{HXY} = -\sum_{i=1}^{L}\sum_{j=1}^{L} p(i,j) \log\left[p(i,j)\right] \tag{2-22}$$

$$\text{HXY1} - \sum_{i=1}^{L}\sum_{j=1}^{L} p(i,j) \log\left[p_x(i) p_y(j)\right] \tag{2-23}$$

$$\text{HXY2} = -\sum_{i=1}^{L}\sum_{j=1}^{L} p_x(i) p_y(j) \log\left[p_x(i) p_y(j)\right] \tag{2-24}$$

Maximum correlation coefficient

$$f_{14} = \text{The second largest eigenvalue of matrix Q} \tag{2-25}$$

In the formula, the element of the i-th row and j-th column of matrix Q is

$$Q(i,j) = \sum_{k=1}^{L} \frac{p(i,k)\, p(j-k)}{p_x(i)\, p_y(j)} \tag{2-26}$$

The amount of calculation of the gray-level co-occurrence matrix is extremely large. In order to achieve the goal of convenient calculation, the following common features are usually used to extract the texture features of the image [3]:

Angle second moment (energy)

$$\text{ASM} = \sum_i \sum_j p(i,j)^2 \tag{2-27}$$

The second moment of angle is to calculate the sum of all the elements in the gray-level co-occurrence matrix and the sum of squares. It is a measure of the average gray level of image texture, and describes the average gray level distribution and texture roughness of the image. Based on the value of the second moment of the angle, the average value and regularity of the texture pattern can be roughly inferred.

Contrast (moment of inertia)

$$\text{CON} = \sum_i \sum_j (i-j)^2\, p(i,j) \tag{2-28}$$

Contrast is the moment of inertia adjacent to the main diagonal of the gray-level co-occurrence matrix. It is used to measure the distribution of matrix values and the degree of change of some local information in the image, the depth of texture grooves and the clarity of the image react.

Entropy

$$\text{ENT}=-\sum_i\sum_j p(i,j)\log(i,j) \tag{2-29}$$

Entropy is the randomness of the texture distribution. When the entropy takes the maximum value, it means that the image distribution at this time is very random.

Inverse moment of difference (local stationarity)

$$\text{IDM}=\sum_i\sum_j \frac{1}{1+(i-j)^2}p(i,j) \tag{2-30}$$

The inverse gap is a measure of the size of the local area change of the image texture. The larger its value, it means that the texture change of this part is not very uniform.

2.2.3 Gray-level co-occurrence matrix feature extraction

In the process of texture feature extraction, the image brightness is divided into 256 gray levels, and 4 gray-level co-occurrence matrices $p_{(1,0)}, p_{(0,1)}, p_{(1,1)}, p_{(1,-1)}$ in different directions are selected, and the amount of calculation is related to the gray distribution of the image. It is related to the number of pixels in the image. If the image G contains a total of L gray levels, and each gray level is a matrix with R rows and C columns, then we can estimate that its calculation amount is $L^2 * R * C$. Then calculate the second moment, entropy, contrast, inverse moment and variance of the gray-level co-occurrence matrix in four different directions. Finally, these five feature combinations are used as texture feature vectors [4].

2.3 Image similarity measurement

After the above processing, the texture feature of the image is extracted, and a feature vector is formed based on the extracted texture feature. Therefore, we can use the feature vector formed above to represent similar images. The comparison of image similarity in image retrieval is essentially the comparison of different image feature vectors. Therefore, we can know that the size of the image feature vector will have an important impact on the performance of the image retrieval system.

If in the image database, feature vectors can be used to represent any image feature in the image, where X and Y are the minimum values of any two feature vectors that satisfy the image similarity measure, symmetry, self The measurement axioms for similarity and triangle inequality measurement. Distance similarity can be judged by using distance metrics or statistical methods. Common distance metrics include Euclidean distance, Manhattan distance, Minkowsky distance, Mahalanobis distance, etc. [5].

Euclidean distance

The application of Euclidean distance [6] is widely used to measure distance. The calculation is very simple and is related to the rotation invariance of the system. It is defined as follows:

$$D(X,Y)=\sqrt{\sum_{i=1}^{d}(X[i]-Y[i])^2} \tag{2-31}$$

When the data is missing or the weights of all feature vectors of the image are different, the Euclidean distance cannot be used to measure the similarity of the image. Therefore, in order to avoid this

situation, people normalize the Euclidean distance in the actual application process. The normalized Euclidean distance is defined as follows:

$$D(X,Y)=\frac{\sqrt{\sum_{i=1}^{d}(X[i]-Y[i])^2}}{\sqrt{n}} \tag{2-32}$$

Manhattan distance

Manhattan distance is also called block distance. The calculation complexity is the same as Euclidean distance. It is defined as follows:

$$D(X,Y)=\sum_{i=1}^{d}\left|X[i]-Y[i]\right| \tag{2-33}$$

Minkowsky distance

Minkowsky distance is defined as follows:

$$D(X,Y)=\sqrt{\sum_{i=1}^{d}\left|X[i]-Y[i]\right|^{P}} \tag{2-34}$$

Minkowsky distance belongs to the distance function [7], and its parameter is P. In a certain image dimension, different weights can be used to calculate the non-negative weight ω1, which is defined as follows:

$$D_{\omega}=\sqrt{\sum_{i=1}^{d}\omega_1\left|X[i]-Y[i]\right|^{P}} \tag{2-35}$$

Mahalanobis distance

Mahalanobis distance is a computationally complex weighted Euclidean distance, defined by a covariance matrix C, and its definition is as follows:

$$D(X,Y)=\sqrt{(X[i]-Y[i])^T C^{-1}(X[i]-Y[i])} \tag{2-36}$$

C-1 is the inverse covariance matrix of C, and C is the identity matrix. Mahalanobis distance[8] becomes Euclidean distance. When there is no relationship between the shared amount of feature vectors, Mahalanobis distance can be simplified.

Correlation coefficient ρ

Correlation coefficient ρ is defined as follows:

$$\rho(X,Y)=\frac{\sum_{i=1}^{d}(X[i]-\overline{X}[i])(Y[i]-\overline{X}[i])}{\sqrt{\sum_{i=1}^{d}(X[i]-\overline{X}[i])^2\sum_{i=1}^{d}(Y[i]-\overline{X}[i])^2}} \tag{2-37}$$

Where $\overline{X}=[\overline{X}[1],\overline{X}[2],\cdots,\overline{X}[d]]=$ is the average of all vectors in the database. When we map the points X and Y to the unit sphere, 2-2p (X, Y) is the Euclidean distance of the projection interval.

In the above projection interval, the value of the correlation coefficient corresponds to the search space scale and the rotation invariant one-to-one. The correlation coefficient can be used to perform parameter statistics on the nature of the coupling behavior of various variables.

Relative entropy

Relative entropy can only be applied to random distributions, and its definition is as follows:

$$D(X,Y)=\sum_{i=1}^{d}X[i]\log\frac{X[i]}{Y[i]} \tag{2-38}$$

It has practical meaning only when the elements X and Y are positive numbers and $\sum_{i=1}^{d} X[i] = \sum_{i=1}^{d} Y[i] = 1$. Because there is no symmetry for relative entropy, and it does not conform to the triangle inequality, I know from the above that it is not a distance measure. In the process of running the image retrieval system, it regards the first independent variable as a query vector and the second independent variable as a database vector.

χ^2 Distance

χ^2 Distance can only be applied to random distribution, and its definition is as follows:

$$D_{x^w}(X,Y) = \sum_{i=1}^{d} \frac{X^2[i] - Y^2[i]}{Y[i]} \tag{2-39}$$

If $\sum_{i=1}^{d} X[i] = \sum_{i=1}^{d} Y[i] = 1$ and only if the elements X and Y are both positive, they have actual meaning. Its calculation and splitting process are very time-consuming.

3. SUMMARY

This chapter starts from some basic concepts of texture features, respectively introduces texture features based on gray level co-occurrence matrix and the extraction of problem features. Compared with other similar articles, this article chooses the most representative feature extraction method based on gray level co-occurrence matrix in the field of texture feature extraction, and introduces the calculation formula and steps of this algorithm in a more concise language. At the same time, the distance formulas commonly used in image similarity measures commonly used in subsequent image retrieval are listed one by one.

The development of image retrieval is a process from simple to complex, from low-level to high-level, from the initial text information query to content-based image retrieval. At the same time, as people's research on image understanding and image recognition continues to deepen, a retrieval based on image semantics is proposed, which makes full use of the semantic information of the image and improves the capability of the image retrieval system. With the rapid development of multimedia data compression technology and the Internet, there are various forms of information. Visual information data includes not only single image data but also video data. According to the characteristics of video data, high-speed and reliable retrieval is also a need for research. The subject [9]. Pushing information retrieval technology to practicality is also the main goal of information technology development.

REFERENCES

[1] Wang Huiming, Shi Ping. Image texture feature extraction method[J]. Journal of Communication University of China (Natural Science Edition), 2006(01): 49-52.

[2] Hong Jiguang. Gray-gradient co-occurrence matrix texture analysis method[J]. Acta Automatica Sinica, 1984(01): 22-25.

[3]Faugeras O D,Pratt W K. Decorrelation methods of texture feature extraction.[J]. IEEE transactions on pattern analysis and machine intelligence,1980,2(4).

[4] Guo Dejun, Song Zhecun. Research on texture image classification based on gray-level co-occurrence matrix [J]. Forestry Machinery and Woodworking Equipment, 2005(07): 21-23.

[5]Van Heel Marin. Similarity measures between images[J]. Van Heel Marin,1987,21(1).

[6]David M. J. Tax; Robert Duin; Dick De Ridder (2004). Classification, Parameter Estimation and State Estimation: An Engineering Approach Using MATLAB. John Wiley and Sons. ISBN 0-470-09013-8.
[7] Zhou Zhihua. Machine learning. Beijing: Tsinghua University Press, 2016: 200
[8] Li Yurong, Xiang Guobo. A linear discriminant analysis classification algorithm based on Mahalanobis distance[J]. Computer Simulation, 2006, 23(008):86-88.
[9] Xiang Youjun, Xie Shengli. Overview of Image Retrieval Technology [J]. Journal of Chongqing University of Posts and Telecommunications (Natural Science Edition), 2006, (03): 348-354.