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RESEARCH OF IMAGE RETRIEVAL BASED ON CHAIN CODE HISTOGRAM AND CHAIN CODE SPATIAL DISTRIBUTION ENTROPY

Wei Gao, Yan Song and Jingying Cai

School of Technology
Mudanjiang Normal University
No. 191, Wenhua Street, Aimin District, Mudanjiang 157011, P. R. China
gw2038@tom.com

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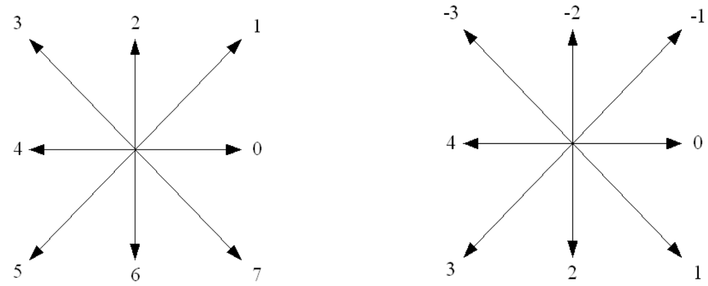
Abstract. *For the problem that the traditional image retrieval methods based on chain code do not consider the spatial distribution feature, a new method that combines the chain code histogram (CCH) and chain code spatial distribution entropy (CCSDE) is proposed. Simultaneously, a kind of similarity calculation way is given to help image retrieval effectively. The simulation results show that the method is able to identify many types of image with high recognition accuracy.*
Keywords: Image retrieval, Chain code, Information entropy, Spatial distribution feature

1. **Introduction.** For the content-based image retrieval (CBIR), the commonly used image feature includes color, shape and texture; the shape feature is normally associated with the target, so it can be seen as a higher class feature compared with the color and texture [1]. Currently, there are a lot of methods to describe the shape feature, which can be summarized into two categories: region-based and contour based. Chain code is one of the important shape feature describing methods based on image contour, which is widely used in CBIR. However, the chain code is so sensitive to noise; moreover, the choice of starting point, object scale, rotation and other factors all will affect the chain code [2].

In view of these problems, some improved methods are proposed. [3] introduced the compressed directional difference chain code (DDCC). Two new codes for frequent two-symbol patterns are added, and one of the symbols removed from the formerly introduced DDCC statistical model. However, this method is only effective for two-pattern classification, and its compression way is so complex which needs to be improved. [4] presented a method for representing 2D tree structures, which are described by a chain based on the Slope Chain Code. The unique tree descriptor presented is in variant under translation and rotation. However, the computational complexity of this method is so high. [5] proposed a parameter-free lung segmentation algorithm with the aim of improving lung nodule detection accuracy, focusing on juxtapleural nodules. A bidirectional chain coding method combined with a support vector machine (SVM) classifier is used to selectively smooth the lung border while minimizing the over-segmentation of adjacent regions. However, the bidirectional chain code proposed in this paper is not satisfying the law of rotation invariant. [6] presented a new universal lossless chain code compression method (UCCC). Different binarisation schemes are used for different chain codes, leading to universal input for further compression. However, this method cannot treat the unknown input mode and also does not satisfy the law of rotation invariant.

Although the above researches get some effects, they all do not consider the spatial distribution feature of chain code, which is an important factor to reflect the image shape. Therefore, a novel image retrieval method based on CCH and CCSDE is proposed in this paper. First, the concept of chain code spatial distribution is given, and then the calculation method of CCSDE is also supplied. Moreover, this paper gives an effective way to calculate image similarity, which can help improving recognition accuracy. Finally, some simulations are done to verify the correctness and validity of the proposed method.

2. **Problem Descriptions.** Directional chain code is an effective encoding method to describe the image edges. The Freeman chain code [7] and Bribiesca chain code [8] are two most commonly used chain codes, as shown in Figure 1.

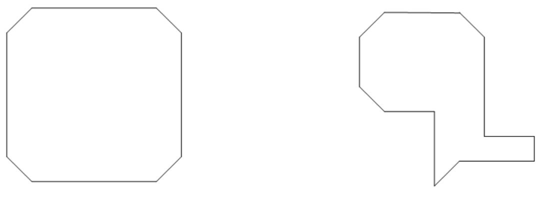


(a) Freeman chain code (b) Bribiesca chain code

Figure 1. Two kinds of chain codes

It can be seen from Figure 1 that, in an image, when the starting point of chain code is changed, it will generate many groups of chain code string with different orders, unable to form an effective one to one mapping between the chain code string and the image. For this problem, some references consider using CCH to describe the feature of chain code [9]. Because the CCH is a statistical description of the chain code, reflecting the probability of a different direction chain code appears in the chain code string, so it can effectively avoid the impact of chain code starting point changes and image scaling [10].

Nevertheless, these methods do not take into account the spatial distribution of different chain code in the chain code string, and therefore cannot effectively solve the problem of the image with different shapes but the same CCH. As shown in Figure 2, these two images with completely different shapes, the chain code strings of them are $\{000007666665444443222221\}$ and $\{666654443221002227000644\}$. By definition, the CCH of them are both $[5/24, 1/24, 5/24, 1/24, 5/24, 1/24, 5/24, 1/24]$. Thus, although their shape is different, it cannot distinguish them by the CCH.



(a) (b)

Figure 2. Example shapes

3. **Chain Code Spatial Distribution Entropy.** The spatial distribution of the chain code is very important, which can reflect the differences between two images from anther way, so some researchers try to use it to solve the problem of image retrieval. For example, [11] introduced two novel shape descriptors, named chain code distribution vector (CCDV) and chain code coherence vector (CCCV), to express the spatial feature of the chain code. However, these two descriptors reflect the spatial distribution feature throughout the

distance, and it is not effective for the local change. While this paper uses the entropy to describe the spatial distribution feature, which is more comprehensive and objective.

The CCSD describes the spatial position changes of the chain code on different directions in the chain code string. If two images are with different shapes, the CCSD of them are certainly different, so the spatial distribution of CCH will also differ.

$$\text{chain code 1}\quad \underbrace{00000}_{0}\,\underbrace{7}_{1}\,\underbrace{66666}_{2}\,\underbrace{5}_{3}\,\underbrace{44444}_{4}\,\underbrace{3}_{5}\,\underbrace{22222}_{6}\,\underbrace{1}_{7}$$

$$\text{chain code 2}\quad \underbrace{6666}_{0}\,\underbrace{5}_{1}\,\underbrace{444}_{2}\,\underbrace{3}_{3}\,\underbrace{22}_{4}\,\underbrace{1}_{5}\,\underbrace{00}_{6}\,\underbrace{222}_{7}\,\underbrace{7}_{8}\,\underbrace{000}_{9}\,\underbrace{6}_{10}\,\underbrace{44}_{11}$$

FIGURE 3. Examples of chain code spatial distribution

As shown in Figure 3, the spatial distribution of CCH for chain code 1 is:

$$\left[h_0^0 = \frac{5}{24}\ h_1^7 = \frac{1}{24}\ h_2^6 = \frac{5}{24}\ h_3^5 = \frac{1}{24}\ h_4^4 = \frac{5}{24}\ h_5^3 = \frac{1}{24}\ h_6^2 = \frac{5}{24}\ h_7^1 = \frac{1}{24}\right] \tag{1}$$

The spatial distribution of CCH for chain code 2 is:

$$\begin{bmatrix} h_0^6 = \frac{2}{24} & h_0^9 = \frac{3}{24} & h_1^5 = \frac{1}{24} \\ h_2^4 = \frac{2}{24} & h_2^7 = \frac{3}{24} & h_3^3 = \frac{1}{24} \\ h_4^2 = \frac{3}{24} & h_4^{11} = \frac{2}{24} & h_5^1 = \frac{1}{24} \\ h_6^0 = \frac{4}{24} & h_6^{10} = \frac{1}{24} & h_7^8 = \frac{1}{24} \end{bmatrix} \tag{2}$$

where h_i^j is the CCH of the chain code on direction i located in position j and can be calculated as follows:

$$h_i^j = \frac{j_L}{C_L} \tag{3}$$

where C_L is the length of the chain code, j_L is the length of the chain code in position j.

Then, we can get the spatial distribution entropy of CCH on direction i:

$$E_i = -\sum_{t=1}^{m} r_t \log(r_t), \quad i = 1, 2, \cdots, n \tag{4}$$

$$r_t = \frac{h_i^j}{\sum\limits_{j=1}^{m} h_i^j} \tag{5}$$

where n is the number of directions, m is the number of sub-strings of the chain code on some direction.

Now, we can define a chain code feature called CCSDE:

$$F_c = \langle (h_1, E_1), (h_2, E_2), \cdots, (h_n, E_n) \rangle \tag{6}$$

This chain code feature combines the CCH and CCSD, so it has the advantages of being invariant to the position and scaling of the image content and has nothing to do with the start point of the chain code. Now, we can calculate the F_c of the two images in Figure 2 being $\langle(0.21, 0), (0.04, 0), (0.21, 0), (0.04, 0), (0.21, 0), (0.04, 0), (0.21, 0), (0.04, 0)\rangle$ and $\langle(0.21, 0.29), (0.04, 0), (0.21, 0.29), (0.04, 0), (0.21, 0.29), (0.04, 0), (0.21, 0.22), (0.04, 0)\rangle$ respectively, which have obvious differences.

Nevertheless, in order to make the feature have the advantage of rotation invariant, according to [12], we perform the rotation normalization for the chain code string before calculating the CCSDE.

4. **Similarity Calculations.**

Currently, the often used similarity calculation methods include Euclidean distance, Mahalanobis distance, and the cosine of the angle and so on, but all of them belong to the hard similarity calculation mode, which are not suitable for the CCSDE proposed in this paper, so we will give a new method to calculate the similarity of the images.

If there are two images X and Y, according to the feature F_c, we define the similarity as:

$$S_{(X,Y)} = \sum_{i=0}^{n} \min(h_{Xi}, h_{Yi}) \times \frac{\min(E_{Xi}, E_{Yi})}{\max(E_{Xi}, E_{Yi})} \tag{7}$$

It can be seen from Formula (7) that the similarity contains two parts: the first part $\min(h_{Xi}, h_{Yi})$ is to guarantee the similarity of the CCH between the two images, and then the second part $\{\min(E_{Xi}, E_{Yi})/\max(E_{Xi}, E_{Yi})\}$ is to guarantee the similarity of the chain code feature on spatial distribution. So it is better for the CCSDE compared with other methods.

Figure 2 is also as an example; based on the calculation of the chain code features, the similarity between the two geometries is calculated separately using Formula (7), the Euclidean distance (ED), Mahalanobis distance (MD) and cosine similarity (CS) approach which are commonly used for similarity calculation. The result is shown in Table 1 that the use of the method in this paper is much better than other methods when calculating the similarity, which proves the proposed similarity calculation method is more suitable for the chain code features of the geometry in this paper.

Table 1. Similarity calculation results

	$S_{(x,y)}$	ED	MD	CS
Similarity	0.0026	0.4110	0.3947	0.3159

5. **Implementation of the Algorithm.**

According to the contents above, the implementation steps of the algorithm for image retrieval based on CCSDE and CCH are:

Step1: Calculate the basic direction chain code of the geometry according to the rule of 8 directions coding;

Step2: Perform rotation normalization for the basic direction chain code string;

Step3: Calculate the CCH of the chain code string according to Formula (3);

Step4: Calculate the CCSDE of the chain code string according to Formula (4);

Step5: Construct graphic chain code features according to Formula (6);

Step6: Calculate the similarity of the chain code features between the graphics to be recognized and the graphics in the database according to Formula (7), and then ultimately for geometry recognition.

6. **Experiments.**

The experimental data are from the SQUID image database which is usually used for CBIR testing. There are total 1100 outline images of different fish in this database, but all of them are irregular shapes, so we use the software Matlab to randomly generate 700 regular shapes, including circular, oval, rectangular, triangular, pentagonal, hexagonal and octagonal. Thus, the total experiment images are 1800.

We will use the CCSDE feature to recognize the shapes in the experiment database, and compare the effort with the classical chain code (CCC) feature, the CCH feature and the method in [8]. In a recognition process, there will be three kinds of recognition results: “right”, “wrong” and “unknown”, so the definition of recognition accuracy is:

$$R_{ACC} = \frac{N_r}{N - N_u} \tag{8}$$

where N_r is the image number of right recognition, N_u is the image number of unknown recognition, and N is the total number of the images.

Under the same conditions, we performed a total of 20 experiments, there are 500 images randomly selected from the database each time, and the recognition result is shown in Figure 4. The results in Figure 4 show that the average recognition accuracy using CCSDE feature is 91.24%, which is much better than other features. [8] method is a little lower than the CCSDE, and the average recognition accuracy is 88.26%. The CCC and CCH methods are only 53.15% and 70.87%, separately, not satisfying the requirement of practical applications.

Next, we will compare the recognition time consuming (RTC) of the algorithms, which is a very important index for identification and plays a major role in the practical applications. It needs to be noted that the RTC here is the average time for a single image. The selection and recognition methods for the image are same as the previous example. Test results are shown in Figure 5. It can be known from the Figure 5 that the time

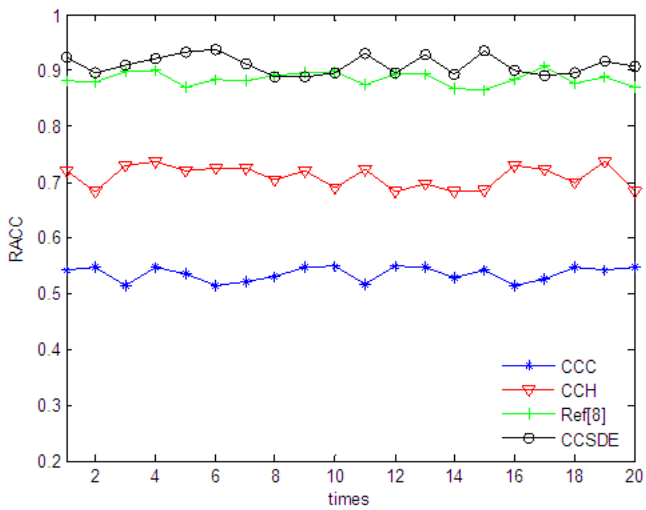


FIGURE 4. Comparison of R_{ACC}

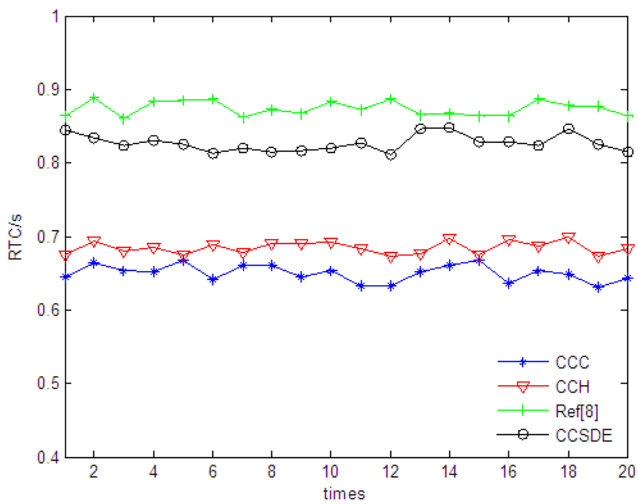


FIGURE 5. Comparison of RTC

consuming of CCC is lowest, and that the average value is 0.6479s. The CCH is a little higher, reached 0.6924s. [8] and the CCSDE are almost the same, about 0.8472s.

Comprehensive comparison of the three indexes of R_{ACC} and RTC, the R_{ACC} of the algorithm in this paper is the highest in these four methods. That shows the feature combined with the CCSDE and CCH is very conducive to identify the geometry, features distinguishment is better and the R_{ACC} for the same graph is not affected by the graphics translation, rotation and scale changes. Moreover, due to calculating the CCSDE, the RTC of the proposed algorithm increases a little. However, from the test results, about 0.85s RTC (average value) fully meets the needs of practical applications. Therefore, the CCSDE feature proposed in this paper is more superior and very suitable for CBIR with high recognition accuracy.

7. **Conclusions.** This paper focuses on the CBIR using the chain code feature. The spatial distribution feature of chain code is studied and analyzed in detail, and then this paper introduces how to calculate the CCSDE and apply it for CBIR. Moreover, a new image similarity calculation method is given, which is in favor of performing CBIR. The simulation results show that the CCSDE feature proposed in this paper has the advantages of being invariant to the position, rotation and scaling of the image content and has nothing to do with the start point of the chain code, so it is very suitable for CBIR. The similarity calculation method given in this paper can reflect the similarity between different images effectively, and it is favorable for the CCSDE feature. However, it is found that when the image contains noise, the recognition result may be impacted partially. In the future studies, we will try to improve the performance CCSDE so that the image recognition accuracy is still high even with the noise.

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