A DIFFERENCE PERCEPTUAL HASHING ALGORITHM FOR MEDICAL VOLUME DATA AGAINST LOCAL NONLINEAR GEOMETRIC ATTACKS

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I. INTRODUCTION

With the progress of communication technology, particularly the wide application of Internet, more and more medical images are transmitted in the public network [1-2]. How to protect the patient's personal information, medical image retrieval, identification and authentication, become more and more urgent [3-4]. The research of perceptual hashing is based on image watermarking technology, and also refers to the basic theory of traditional cryptography hashing and multimedia authentication [5-6]. It has become a hot spot in the related research fields of multimedia processing and security [7]. Perceptual hashing can transform multimedia data into shorter bit sequences. Perceptual hashing provides a reliable technical guarantee for the protection, identification and authentication of multimedia digital content. Perceptual hashing can be applied to medical images [8]. As the medical imaging equipment advance, most medical images used in hospitals are three-dimensional medical volume data, so it is of great significance to study the perceptual hashing of medical volume data. However, in practical applications, there is usually a type of geometric attacks, which belong to local nonlinear geometric attacks. At present, there are few perceptual algorithms that can resist local nonlinear geometric attacks, so it is of great significance to study perceptual hashing algorithms against local nonlinear geometric attacks. In order to solve this problem, a new difference hashing algorithm is proposed to resist local nonlinear geometric attacks. Experimental results prove that the difference hashing algorithm has strong ability to resist local nonlinear geometric attacks.

II. IMAGE PERCEPTUAL HASHING

Image perceptual hashing is usually called image digital fingerprint or image digital digest, which can map images into a group of hash sequences, which greatly reduces the storage of digital images and brings great convenience to the management and maintenance of images. It has become a research hotspot in the field of multimedia signal processing and security [9-10]. Perceptual feature extraction is the core of perceptual hashing algorithm. The effectiveness and reliability of perceptual feature extraction will directly affect the robustness of image perceptual hashing sequence. Its robustness means that the same image will produce the same perceptual hashing value after processing by the perceptual hashing function. After various image processing or attacks, we can judge whether it is the original image or whether the image with the same or similar content has the same or similar perceptual hashing value.
III. DISCRETE COSINE TRANSFORM

Discrete cosine transform is widely used in the field of information processing. It is the core of lossy image compression. It has faster calculation speed, high accuracy, and has a very important position in image processing. Because discrete cosine transform can convert signals in the space domain to the frequency domain, it has good decorrelation performance. The discrete cosine transform transformation itself is lossless and symmetrical. The original image undergoes discrete cosine transform. After the transform, the energy of the discrete cosine transform coefficients is mainly concentrated in the upper left corner, and most of the remaining coefficients are close to zero. Perform threshold operations on the transformed discrete cosine transform coefficients, and reset coefficients less than a certain value to zero. This is the quantization process in image compression, and then the inverse discrete cosine transform operation can get the compressed image.

A. One-dimensional discrete cosine transform

\[ f(x), x = 0, 1, \ldots, N - 1 \text{ is a one-dimensional discrete signal, and its one-dimensional discrete cosine transform is} \]

\[ F(u) = c(u) \sum_{n=0}^{N-1} f(n) \cos \left( \frac{\pi (2n + 1)u}{2N} \right) \]

as follows.

\[ c(u) = \begin{cases} \sqrt{1/N} & u = 0 \\ \sqrt{2/N} & u = 1, 2, \ldots, N - 1 \end{cases} \]

Where,

The inverse one-dimensional discrete cosine transform is

\[ f(x) = \sum_{n=0}^{N-1} c(u)F(u) \cos \left( \frac{\pi (2x + 1)u}{2N} \right) \]

\[ x, u = 0, 1, \ldots, N - 1 \]

B. Two-dimensional discrete cosine transform

For the image \( f(x, y) \), its size is \( M \times N \). So its two-dimensional discrete cosine transform is:

\[ F(u, v) = c(u) c(v) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \cos \left( \frac{\pi (2x + 1)u}{2M} \cos \left( \frac{\pi (2y + 1)v}{2N} \right) \right) \]

\[ u = 0, 1, \ldots, M - 1; v = 0, 1, \ldots, N - 1 \]

\[ c(u) = \begin{cases} \sqrt{1/M} & u = 0 \\ \sqrt{2/M} & u = 1, 2, \ldots, M - 1 \end{cases} \]

\[ c(v) = \begin{cases} \sqrt{1/N} & v = 0 \\ \sqrt{2/N} & v = 1, 2, \ldots, N - 1 \end{cases} \]

The two-dimensional inverse discrete cosine transform is

\[ f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} c(u) c(v)F(u, v) \cos \left( \frac{\pi (2x + 1)u}{2M} \cos \left( \frac{\pi (2y + 1)v}{2N} \right) \right) \]

\[ x = 0, 1, \ldots, M - 1; y = 0, 1, \ldots, N - 1 \]

C. Three-dimensional discrete cosine transform

For the image \( f(x, y, z) \), its size is \( M \times N \times P \). So three-dimensional discrete cosine transform formula is as

\[ F(u, v, w) = c(u) c(v) c(\omega) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \sum_{z=0}^{P-1} f(x, y, z) \cos \left( \frac{\pi (2x + 1)u}{2M} \cos \left( \frac{\pi (2y + 1)v}{2N} \right) \cos \left( \frac{\pi (2z + 1)\omega}{2P} \right) \right) \]

\[ u = 0, 1, \ldots, M - 1; v = 0, 1, \ldots, N - 1; w = 0, 1, \ldots, P - 1 \]

In the formula,

\[ c(u) = \begin{cases} \sqrt{1/M} & u = 0 \\ \sqrt{2/M} & u = 1, 2, \ldots, M - 1 \end{cases} \]

\[ c(v) = \begin{cases} \sqrt{1/N} & v = 0 \\ \sqrt{2/N} & v = 1, 2, \ldots, N - 1 \end{cases} \]

\[ c(\omega) = \begin{cases} \sqrt{1/P} & \omega = 0 \\ \sqrt{2/P} & \omega = 1, 2, \ldots, P - 1 \end{cases} \]

Its inverse transform formula is as

\[ f(x, y, z) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} \sum_{w=0}^{P-1} c(u) c(v) c(\omega)F(u, v, w) \cos \left( \frac{\pi (2x + 1)u}{2M} \cos \left( \frac{\pi (2y + 1)v}{2N} \right) \cos \left( \frac{\pi (2z + 1)\omega}{2P} \right) \right) \]

\[ x = 0, 1, \ldots, M - 1; y = 0, 1, \ldots, N - 1; z = 0, 1, \ldots, P - 1 \]

Here, the value at the volume data \( f(x, y, z) \) is \( f(x, y, z) \). \( F(u, v, w) \) is the coefficient of the three-dimensional discrete cosine transform.
IV. DIFFERENCE PERCEPTUAL HASHING ALGORITHM

A new difference perceptual hashing algorithm based on three-dimensional discrete cosine transform is proposed in this paper. The difference hashing algorithm uses the difference between adjacent elements in each column of the volume data feature matrix to generate a hashing sequence. The construction of the feature matrix of volume data is realized by performing three-dimensional discrete cosine transform and three-dimensional inverse discrete cosine transform on volume data. Fig. 1 describes the flow of the difference perceptual hashing algorithm.

It can be seen from the flowchart that the medical volume data is first subjected to three-dimensional discrete cosine transform, and the transformed low-frequency coefficients (4*5*5) are selected for inverse three-dimensional discrete cosine transform, and the coefficient characteristics of the volume data are extracted to construct a feature matrix (16*5), so that the three-dimensional medical volume data is mapped into a two-dimensional feature matrix. Secondly, calculate the difference value between adjacent elements in each column of the feature matrix (16*5), then according to whether each difference value is negative, a 64-bit binary hashing sequence is generated, and the two-dimensional feature matrix is mapped to a one-dimensional hashing sequence. The one-dimensional hashing sequence represents the characteristics of the three-dimensional medical volume data, and is also called the feature vector of the volume data.

V. EXPERIMENT

The difference perceptual hashing algorithm is tested against local nonlinear geometric attacks. The original medical volume data is selected as the medical volume data shown in Fig. 2 (a), and its slice image is shown in Fig. 2 (b). Firstly, the local nonlinear geometric attack experiment is carried out on the medical volume data. The medical volume data and corresponding slice images under the local nonlinear geometric attack are shown in Fig. 3. Secondly, the original medical volume data and the medical volume data after local nonlinear geometric attack are generated 64 bit binary hashing sequences respectively through the difference hashing algorithm.
Then, the matching values between the hash sequence of medical volume data attacked by local nonlinear geometry and the hashing sequence of original medical volume data are calculated by using formula 7. In order to facilitate comparison, formula 7 is also used to calculate the matching value between the hash sequence of the medical data and the hashing sequence of the original medical data without attack. The matching value calculation formula is shown in formula 7, which is equal to the length of the hashing sequence minus the Hamming distance between the hashing sequences.

$$P_{value} = N - disp(m, m) = N - \sum_{k=1}^{N} |h(k) - h_r(k)|$$  \hspace{1cm} (7)

In the formula, $N$ represents the length of the two matching hashing sequences and, and the hash sequences extracted from the two objects are represented by $h$ and $h_r$ respectively. In the formula 7, the smaller the matching value, the more different or similar the two matched hashing sequences; the larger the matching value, the more identical or similar the two matched hashing sequences.
The calculated matching value is shown in Fig. 4. The vertical axis in the figure represents the matching value between hashing sequences, and the horizontal axis represents the attack type. The first type is no attack, and the matching value is 64. The second type is the ripple twist attack, the twist amount is 300%, and the match value is 63. The third type is the squeeze twist attack, the twist amount is 10%, and the match value is 63. The fourth type is the sphere twist attack, with a 10% warp and the match value is 60. The fifth category is the rotate twist attack, the twist is 10 degrees, and the match value is 63. The sixth type is water wave twist attack, the amount of water wave distortion is 10%, and the matching value is 63. This shows that the hashing sequence extracted by the difference perceptual hashing algorithm has good resistance to local nonlinear geometric attacks.

![Fig. 4 Anti local nonlinear geometric attacks experiments](image)

**VI. CONCLUSIONS**

In summary, the three-dimensional discrete cosine transform is used to transform the volume data, and then the differential hash algorithm is used to extract the hash sequence as the feature vector of the volume data. The feature vector has good resistance to local nonlinear geometric attacks. It can be used in volume data retrieval, recognition and watermarking embedding.

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