Medical Image Watermarking in Sub-block Three-dimensional Discrete Cosine Transform Domain

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Abstract: *Digital watermarking can be applied to protection of medical images privacy, hiding of patient's diagnosis information and so on. In order to improve the ability of resisting geometric attacks, a new watermarking algorithm for medical volume data in sub-block three-dimensional discrete cosine transform domain is presented. The original watermarking image is scrambled by a Chebyshev chaotic neural network so as to improve watermarking security. Sub-block three-dimensional discrete cosine transform and perceptual hashing are used to construct zero-watermarking. In this way it does not produce medical image distortion and gives the algorithm the ability to resist geometric attacks. Experimental results show that the algorithm has good security, and it has good robustness to various geometric attacks.*

Keywords: *Medical image, Watermarking, Chebyshev chaotic neural network, Sub-block three-dimensional discrete cosine transform domain.*

Introduction

The rapid development of Internet technology brings convenience to people's information exchange, but it also brings more and more attention to the problem of information security and copyright [1, 19]. As an effective means of copyright protection, the digital watermarking technology plays an irreplaceable role in protecting the copyright of the author. Invisibility and robustness are the two most important evaluation indexes of digital watermarking technology. Most of the existing watermarking algorithms can effectively resist conventional attacks such as filtering, noise, JPEG compression, and so on. While the robustness is poor, it is under the geometric attacks such as shearing, scaling, rotation, shifting and so on [9, 16, 23, 24]. The main reason is that the watermarking extraction process generally requires a clear position of the watermarking information. Conventional attack will only cause a slight change of the value of the image pixels. And geometric attacks destroy the synchronization of watermarking information so that watermarking extraction cannot determine the correct position of the watermarking information, thus failing to extract the watermarking. The impact of geometric attacks on the watermarking is devastating.

With the rapid development of network technology, the research of digital watermarking technology has become a hot spot in the field of information security research [2, 9, 13, 18, 20]. The watermarking embedding can bring irreversible changes to the original carrier, which makes the original vector information distortion. However, for some special images, such as medical images, it is not allowed to feature information distortion [3, 6]. Medical image watermarking algorithm has advantages compared to conventional watermarking algorithm. Medical image watermarking algorithm is also required to meet stringent quality requirements of medical image features, which provides a good solution method to the problem [8, 10, 12]. The specific meaning identification information will be embedded in the carrier image. It can realize the electronic medical records of medical image hiding and copyright protection [11, 14, 21]. At present, most of the existing medical images are three-dimensional volume data [15, 17]. So digital watermarking for medical volume data is very important.

In order to improve the ability of resisting geometric attacks, a new watermarking algorithm for medical volume data is presented. The watermarking algorithm combines sub-block three-dimensional discrete cosine transform, perceptual hashing and chaotic neural network. The watermarking extraction key sequence is constructed by perceptual hashing in sub-block three-dimensional discrete cosine transform domain. The watermarking algorithm can resist geometric attacks such as shearing, scaling, rotation and so on, and it also has good robustness.

Chebyshev chaotic neural network

Chaos is a nonlinear deterministic system in similar random process [7]. By bringing two very similar initial values into the same chaotic function for iteration, after a certain stage of the computation, numerical sequence become irrelevant. Chaotic signal has concealment, unpredictable, high complexity and easy to realize characteristics. Therefore, it is especially suitable for secure communication [5, 25].

Because the neural network is a highly nonlinear dynamic system, the chaos has the above characteristics, so the neural network is closely related to the chaos. So the chaotic neural network is considered as one of the intelligent information processing systems, which can realize the real world computing. The research shows that the chaotic neural network has very rich dynamical properties, which are different from the traditional neural network. The scrambling is produced by a novel Chebyshev chaotic neural network in this paper. Its structure is as shown in Fig. 1.

Definition 1

$$Ch_n(x) = \cos(n \arccos x) \tag{1}$$

$$\rho(x) = \frac{1}{\sqrt{1-x^2}}, \ x \in [-1, 1] \tag{2}$$

Eq. (1) is known as the first class Chebyshev polynomials. Eq. (2) is known as the weight function. Eq. (1) is defined as the *n*-orthogonal polynomials of Eq. (2) in space [–1, 1].

Definition 2

$$Ch_n(x) = \frac{\sin[(1+n)\arccos x]}{\sqrt{1-x^2}} \tag{3}$$

$$\rho(x) = \sqrt{1 - x^2}, \quad x \in [-1, 1] \tag{4}$$

Eq. (3) is known as second-class Chebyshev polynomial. Eq. (4) is known as the weight function. Eq. (3) is defined as the n-orthogonal polynomials of Eq. (4) in space [–1, 1].

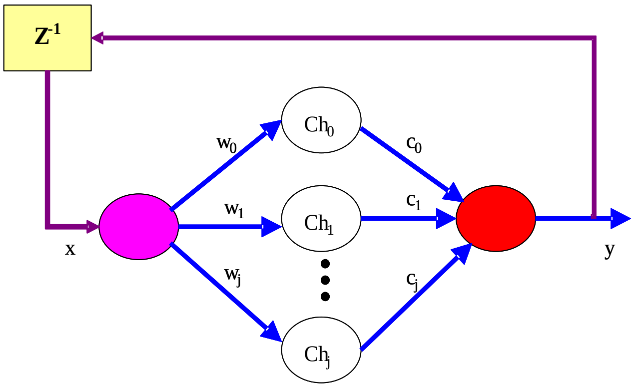


Fig. 1 Network structure

w_j denote the first-layer weights. The excitation function of the hidden layer chooses Chebyshev orthogonal polynomials. The output of hidden layer is

$$O_j = Ch_j(w_j x), \quad j = 0, 1, 2, ..., n. \tag{5}$$

c_j denote the second-layer weights. The output of output layer is

$$y = \sum_{j=0}^{n-1} c_j O_j = \sum_{j=0}^{n-1} c_j Ch_j(w_j x). \tag{6}$$

The weights are obtained by BP learning algorithm training.

Sub-block three-dimensional discrete cosine transform

The three-dimensional discrete cosine transform is basically the two-dimensional discrete cosine transform extension. Its transform formula is as below.

$$\begin{aligned} F(u,v,w) = c(u) \times c(v) \times c(\omega) \times \Bigg[& \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \sum_{z=0}^{P-1} f(x,y,z) \\ & \times \cos\frac{(2x+1)u\pi}{2M} \times \cos\frac{(2y+1)v\pi}{2N} \times \cos\frac{(2z+1)\omega\pi}{2P} \Bigg], \end{aligned} \tag{7}$$

where $f(x, y, z)$ is three-dimensional volume data on the data values in the (x, y, z), $f(x, y, z)$'s three-dimensional discrete cosine transform coefficients are $F(u, v, w)$; $\mu = 1, 2, \ldots, M - 1$; $v = 1, 2, \ldots, N - 1$; $\omega = 1, 2, \ldots, P - 1$.

$$c(\mu) = \begin{cases} \sqrt{1/M} & \mu = 0 \\ \sqrt{2/M} & \mu = 1, 2, ..., M-1 \end{cases}, \tag{8}$$

$$c(\upsilon)=\begin{cases}\sqrt{1/N} & \upsilon=0\\ \sqrt{2/N} & \upsilon=1,\ 2,\ ...,\ N-1\end{cases}, \tag{9}$$

$$c(\omega)=\begin{cases}\sqrt{1/P} & \omega=0\\ \sqrt{2/P} & \omega=1,\ 2,\ ...,\ P-1\end{cases}, \tag{10}$$

where $c(\mu)$, $c(v)$ and $c(\omega)$ are the coefficients in Eq. (7).

Its inverse transform formula is

$$\begin{aligned} f(x,y,z)=\Bigg[&\sum_{\mu=0}^{M-1}\sum_{\upsilon=0}^{N-1}\sum_{\omega=0}^{P-1}c(u)\times c(v)\times c(\omega)\times F(u,v,w)\\ &\times\cos\frac{(2x+1)u\pi}{2M}\times\cos\frac{(2y+1)v\pi}{2N}\times\cos\frac{(2z+1)\omega\pi}{2P}\Bigg]. \end{aligned} \tag{11}$$

In this study, the original medical volume data are divided into 64 sub-volume data. Each sub-volume data is transformed by three-dimensional discrete cosine transform so as to obtain the direct-current components, because of the direct-current components have a strong robust.

Vector standardization

Before data analysis, data standardization is usually required, and then data analysis is conducted with the standard data. Data standardization is statistical data indexation. Vector standardization is that the original vector is scaled, limited to a certain range. There are many vector standardization methods, one of which is used in the study. Based on the original vector of mean and standard deviation, the original vector is standardized.

Perceptual hashing

Perceptual hashing is also called a digital fingerprint or digital signature, which converts the image data for the hundreds or thousands of bits of binary sequence. Perceptual hashing has robustness, abstract, unidirectional, collision resistance, perceptual aspects of advantages, which can be applied to image recognition, image authentication, content monitoring, copyright protection, and many other aspects [22, 26]. The perceptual hashing algorithm follows:

Step 1: The original medical volume data are divided into 64 sub-volume data. Three-dimensional discrete cosine transform conducts for each sub-volume data.

Step 2: Select direct-current components.

Step 3: Standardize the direct-current components.

Step 4: Calculate the average value of the standardization direct-current components.

Step 5: Each pixel gray value is compared to the average value. If the pixel gray value is equal or greater than the average value, its corresponding perceptual hashing value is 1; otherwise, its corresponding perceptual hashing value is 0.

Step 6: Get the perceptual hashing sequence.

The previous step of the perceptual hashing value together constitutes the binary sequence, which is the 64-bit feature vector.

Medical image watermarking algorithm

The robust medical image watermarking includes watermarking construction process and watermarking extraction process. Fig. 2 displays the watermarking construction process. The watermarking extraction process is given in Fig. 3.

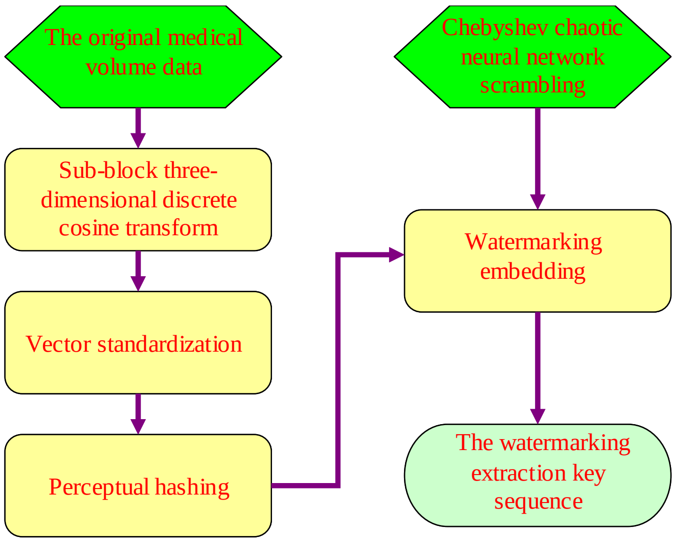


Fig. 2 Construction process

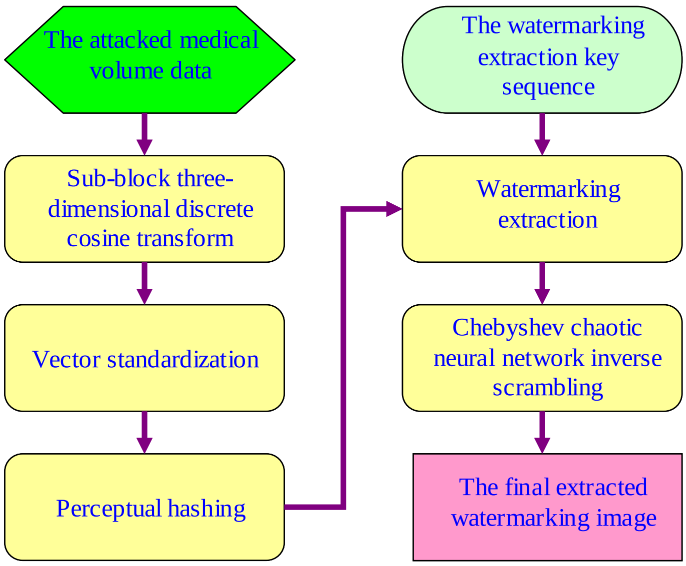


Fig. 3 Extraction process

Experiment

The watermarking algorithm is implemented in Matlab2010a platform. The single hidden layer structure is used in the Chebyshev chaotic neural network. The hidden layer selects 4 neurons. The output layer picks a neuron. The number of training samples is 2000. The maximum training number is 3000 epochs. The expected error is 10^{-6}. Fig. 4 gives the training error curve, which has converged to the expected error in 201 epochs. The initial value of scrambling is 0.77. Fig. 5 illustrates the scrambling chaotic sequence. The original watermarking image and the scrambled watermarking image are given in Fig. 6(a) and (b), respectively.

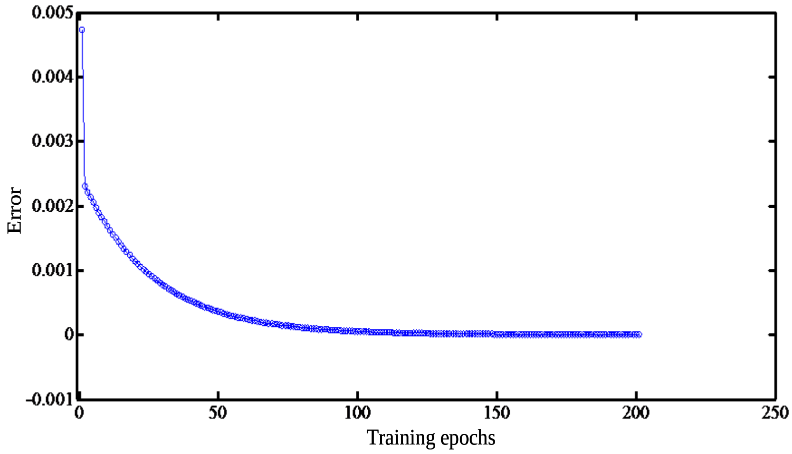


Fig. 4 The training error curve of a chaotic neural network

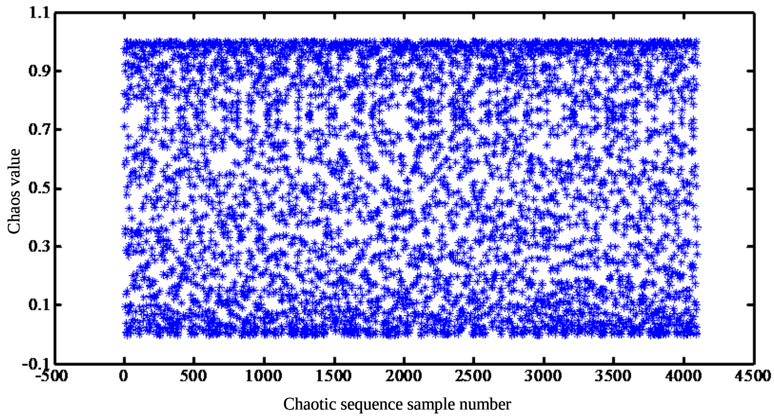


Fig. 5 Chaotic sequence for scrambling

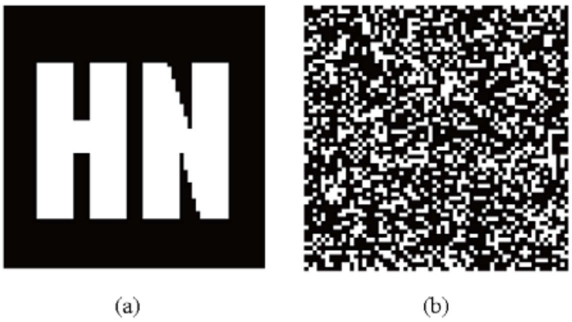


Fig. 6 The watermarking image:
(a) original watermarking image; (b) scrambled watermarking image.

(1) Shearing attack: Medical volume data are sheared from the X-axis direction. The shearing percentage is 32%, the corresponding image processing is shown in Fig. 7(a), (b) and (c). The experimental results show that the extracted watermarking image is easy to distinguish. Fig. 8(a) shows normalized cross correlation coefficient with varying degrees of shearing attack. So it is considered that the algorithm has an excellent robustness to the shearing attack.

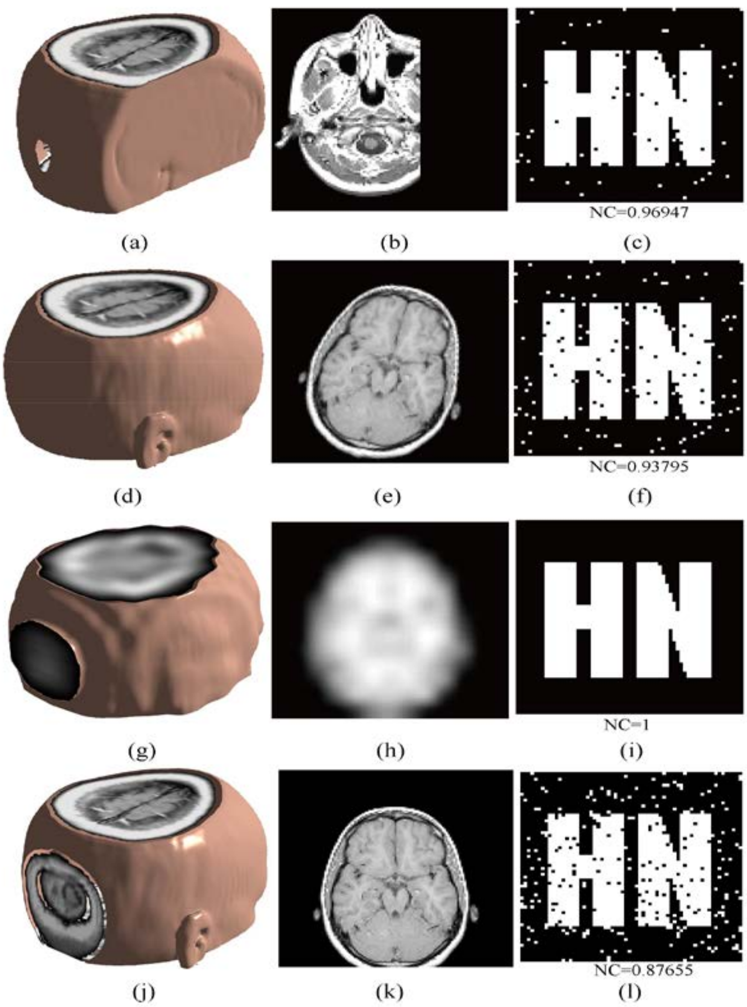
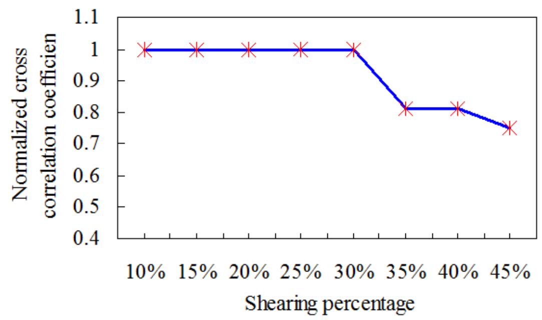


Fig. 7 Experimental results under geometrical attack: (a) Medical volume data under shearing attack; (b) Slice image under shearing attack; (c) Extracted watermarking image under shearing attack; (d) Medical volume data under clockwise rotation attack; (e) Slice image under clockwise rotation attack; (f) Extracted watermarking image under clockwise rotation attack; (g) Medical volume data under scaling attack; (h) Slice image under scaling attack; (i) Extracted watermarking image under scaling attack; (j) Medical volume data under downward shifting attack; (k) Slice image under downward shifting attack; (l) Extracted watermarking image under downward shifting attack.

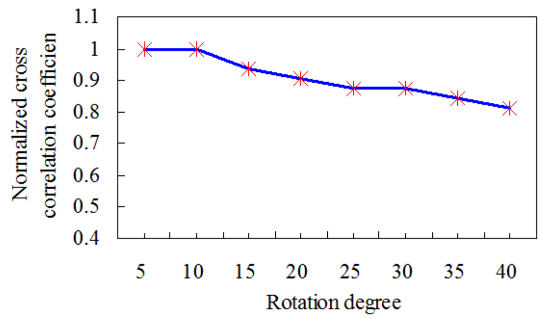
(2) Clockwise rotation attack: Medical volume data are rotated clockwise. When the rotation angle is 15 degrees, the experimental results are shown in Fig. 7(d), (e) and (f). Fig. 8(b) shows that the algorithm can resist clockwise rotation attack.

(3) Scaling attack: Medical volume data are attacked. The scaling factor is 10. Fig. 7(g), (h), (i) and Fig. 8(c) show the experimental results. Hence, the algorithm has a strong robustness to resist scaling attacks.

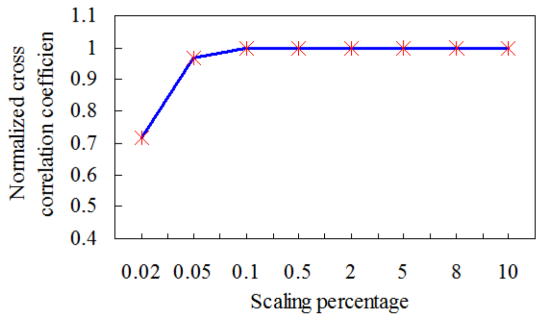
(4) Downward shifting attack: Medical volume data are downward shifted. The downward shifting percentage is 7%. Fig. 7(j), (k), (l) and Fig. 8(d) show the experimental results. So the algorithm has a strong robustness against downward shifting attack.



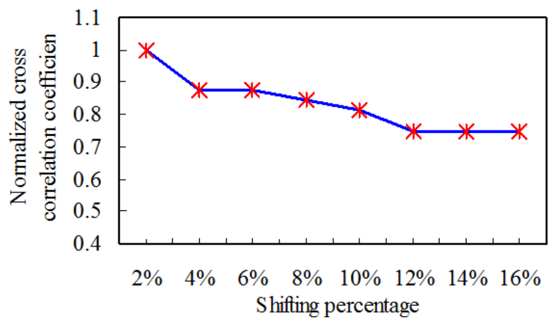
(a)



(b)



(c)



(d)

Fig. 8 Normalized cross correlation coefficient under geometrical attack:
(a) shearing attack; (b) clockwise rotation attack;
(c) scaling attack; (d) downward shifting attack.

Conclusion

In order to improve the ability of resisting geometric attacks, the paper presents a new watermarking algorithm for medical volume data in sub-block three-dimensional discrete cosine transform domain. Sub-block three-dimensional discrete cosine transform is pushed to the three-dimensional medical volume data. The direct-current components are extracted in sub-block three-dimensional discrete cosine transform domain. The zero-watermarking is constructed by the perceptual hashing algorithm. The security of the robust watermarking algorithm depends on a Chebyshev chaotic neural network. The extracted watermarking does not need original medical volume data. It also has a good robustness to geometric attacks, which highlights the advantages of the algorithm.

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