A STUDY OF DIGITAL WATERMARKING RECOGNITION USING ORTHOGONAL CODE SEQUENCES WITH A BACK-PROPAGATION NEURAL NETWORK

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ABSTRACT

Digital watermarking is an encryption technology commonly used to protect intellectual property and copyright. In this study, we restored watermarks that had already been affected by noise interference, used the Walsh–Hadamard codes as the watermark identification codes, and applied salt-and-pepper noise and Gaussian noise to destroy watermarks. First method, we used a low-pass filter and median filter to remove noise interferences. The second one, we used a back-propagation neural network algorithm to suppress noises. We removed nearly all noise and recovered the originally embedded watermarks of Walsh–Hadmard codes.

Keywords: digital watermark; Walsh–Hadamard code; salt-and-pepper noise; Gaussian noise; back-propagation neural network.

RECONNAISSANCE OPTIQUE DE FILIGRANE NUMÉRIQUE À L'AIDE DE CODE DE SÉQUENCES ORTHOGONAUX AVEC RÉSEAU DE NEURONS DE RÉTRO-PROPAGATION

RÉSUMÉ

Le cryptage numérique est une technologie utilisée couramment pour protéger la propriété intellectuelle et le droit d'auteur. Pour cette étude, nous avons restauré des filigranes qui avaient déjà été affectés par des interférences de code Walsh–Hadamard comme code d'identification, et l'application de l'effet poivre et sel, et bruits gaussiens dans le but de détruire les filigranes. Pour la première méthode, nous avons utilisé un filtre passe-bas et un filtre médian pour enlever les interférences de bruit. La seconde méthode consistait en l'utilisation d'un système d'algorithme de réseau de neurons de rétro-propagation pour supprimer les bruits. Nous avons enlevé presque tous les bruits et retrouvé les filigranes originaux insérés de code Walsh–Hadamard.

Mots-clés : filigrane numérique ; code Walsh–Hadamard ; effet poivre et sel ; bruit gaussien ; réseau de neurons de rétro-propagation.

1. INTRODUCTION

With the evolution of Internet technology, information sharing has made multimedia become common and accessible. This has attracted people's attention to intellectual property and copyright issues. Digital watermarking is a commonly employed method to protect intellectual property and copyrights and can be used to certify the authenticity of ownership. Among the numerous available methods [1], coding method is one of the candidates which used ordinal or random sequence embedded into the documents and photos in digital watermarking. To certify ownership, calculations such as correlation calculations are required.

Recently, logo images have been used as watermarks and embedded in digital media images because this offers the advantage of allowing people to easily see the embedded logo image. To enable the detection of watermarks even after common attacks, watermarks must satisfy certain requirements. Secrecy means differences between the images before and after the watermark is embedded cannot be perceived. Robustness means watermarks should be irremovable, detectable, and extractable. However, although watermarks possess these two characteristics, attacks that exceed the watermarks' tolerance may destroy the watermark or render the watermark inextricable.

Watermarks should possess secrecy and robustness [2, 3]. In the research, signature casting is performed in the spatial domain by slightly modifying the intensity level of randomly selected image pixels. Signature detection is done by comparing the mean intensity value of the marked pixels against that of the not marked pixels. Statistical hypothesis testing is used for this purpose. The signature can be designed in such a way that it is resistant to JPEG compression and low-pass filtering. The method needs filtering process comparing with the proposed method can only use the optimal method to recover the original watermark.

Traditional digital watermarking primarily embeds watermarks in high-frequency or unperceivable areas [4]. By the method operates in the frequency domain embedding a pseudo-random sequence of real numbers in a selected set of DCT coefficients. Watermark casting is performed by exploiting the masking characteristics of the Human Visual System, to ensure watermark invisibility. The embedded sequence is extracted without resorting to the original image, so that the proposed technique represents a major improvement to methods relying on the comparison between the watermarked and original images. The difference between the research and proposed method is that the codes only coded in spatial domain without DCT transformation. Although this method increases secrecy, the watermark can be easily destroyed or eliminated by image processing.

In this study, we embedded an orthogonal sequence code Walsh–Hadamard (WH) code sequences [5, 6], into the image. The orthogonal coding method can easy identify different user with each own code. It makes the watermark become more robust and secure of protected document. In the research, a real logo is embedded into media with a set of Walsh Code Sequences (WCSs) and interleaving techniques. The corrupted image with logo will be extracted without the help of original uncorrupted image. The extracted logo is then corrected by Intra-Pixel Prediction (IPP) method. In the study, we used commonly observed image noise, such as salt-and-pepper and Gaussian noise to interfere with the watermarks. Subsequently, we used filters, such as low-pass filters and median filters, to filter the noise. Finally, we used back-propagation neural (BPN) networks [7–11] to filter the noise and recover the embedded watermark. The optimal method of BPN networks is strongly removed the noise from interfered document, and the results show that the higher peak signal-to-noise ratio (PSNR) can be obtained after the proposed method.

2. METHODOLOGY OF DIGITAL WATERMARKING RECOGNITION

Digital watermarking technology is established and analysized into the following three parts: (1) the establishment of watermarks; (2) interference with the image; and (3) obtaining watermarks by removing interference using filters and BPN network.

First, we established watermarks using a quasi-orthogonal sequence code of WH codes because of its

(a) (b)

Fig. 1. (a) The original image; and (b) the watermarked image.

beneficial auto-correlation and extremely poor cross-correlation. Through the orthogonal characteristic of each row, the maximum auto-correlation value of WH code was reached after the correlation calculation was conducted. Cross-correlation values with other sequences were rendered at the minimum. The WH code is then embedded into the image pixel by pixel. After correlation calculation, we can identify which code is embedded in the image. Below we present the specifications introduction, the formulae, and graphs.

WH code is obtained by selecting the row of the WH matrix ($N \times N$, where $N = 2n$) except the first row of the matrix with all ones. It is well known that each row except the first row contain $N/2$ negative ones and $N/2$ positive ones. An $N \times N$ WH matrix can be generated by the recursion as following

$$\mathbf{H}_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}, \quad \bar{\mathbf{H}}_2 = \begin{bmatrix} -1 & -1 \\ -1 & 1 \end{bmatrix}, \quad \text{and} \quad \mathbf{H}_N = \begin{bmatrix} H_{N/2} & H_{N/2} \\ H_{N/2} & \bar{H}_{N/2} \end{bmatrix}, \tag{1}$$

where N is a power of 2.

For an $N \times N$ WH matrix, there are $N-1$ WH code sequences, and the auto-correlation value is equal $N/2$ and cross-correlation value between different twos is zero.

After the WH codes were generated, we transformed a color image into a gray-scale image and embedded the WH code into the gray-scale image. These WH code covered the entire gray-scale image. Figure 1 shows the original gray-scale image and the watermarked image.

After embedding the watermarks, we interfered with the watermarked image using general two image noises. The two types of noise used in this study were salt-and-pepper noise and Gaussian noise. First, salt-and-pepper noise, it is also known as bipolar impulse noise. The noise distribution is as follows: If $B > A$, gray-scale B appears as a bright spot in the image; otherwise, it is a dark spot. Considering that P_a or P_b is zero, the impulse noise is unipolar. If the impulse noise is bipolar, it is called salt-and-pepper noise.

$$p(z) = \left\{ \begin{array}{ll} P_a, & \text{for } z = a \\ P_b, & \text{for } z = b \\ 0, & \text{otherwise} \end{array} \right\}. \tag{2}$$

The other noise is Gaussian noise and this type of noise is also called normal distribution noise. The mathematical model is as follows:

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\mu)^2/2\sigma^2}, \tag{3}$$

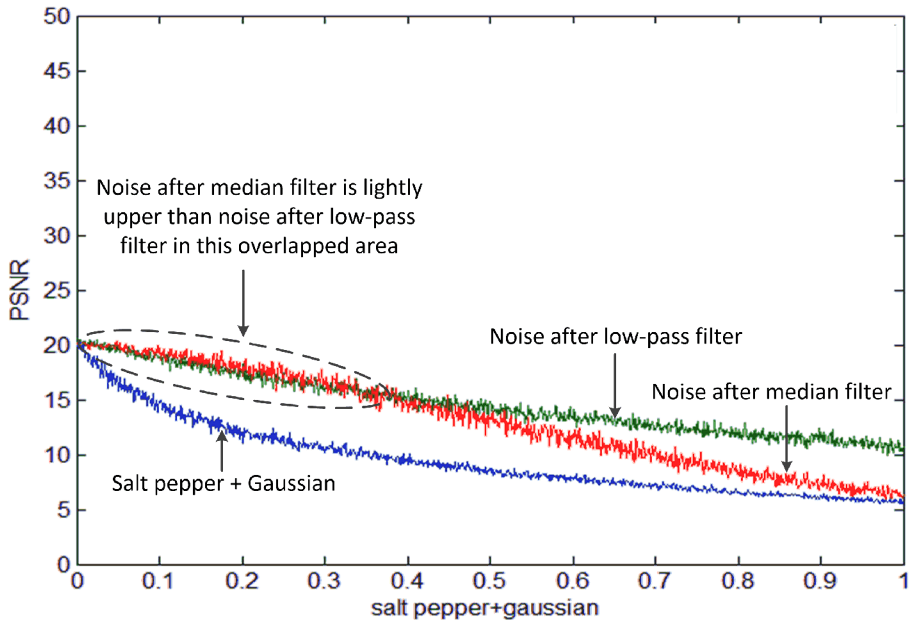

Fig. 2. PSNR performance before and after filters.

where z is the noise gray-scale value; μ is the mean of z; and σ is the standard deviation.

After completing image interference, we calculated the peak PSNR value of each noise strength and plotted a distribution map. As shown in Fig. 2, by adding salt-and-pepper and Gaussian noise to the image, we found that the stronger the noise, the more substantially the PSNR value declines.

Subsequently, we used two types of filters (low-pass filters and median filters) to filter the watermarked images with added noise. A low-pass filter is equivalent to conducting smooth filtering in the spatial domain. We can infer that it reduces the gradient of pixels in proximity. Thus, low-pass filter waves have the effect of blurring images. The second filter is median filters with nonlinear filter effect. They use a size-fixed window W to scan each pixel on the entire image and sequentially arrange each pixel value in the window, replacing the original pixel value with the median of the sequentially arranged pixel values as the resulting output.

After processing using filters, we created another PSNR value distribution map for the image and found that the PSNR values tended to increase; however, the level of increase was not significant. The watermarked image still exhibited interference from noise, hindering the identification of watermarks. Finally, regarding the employed BPN network algorithm, we selected a conjugate gradient training method because they are suitable for classification and identification.

3. SIMULATION RESULTS

The noise image PSNR distribution trained using BPN networks is shown in Fig. 3. We separated noise and WH code from the image and input noise and WH code into BPN networks for training. In the input and output ends, we set 1000 neurons, respectively. The number of training iterations was 2,000.

The image shows that PSNR values increased significantly, approaching the PSNR value 48.1308 dB of images embedded with watermarks only. However, many PSNR values exhibited a vibration phenomenon when we only using BPN network method.

Subsequently, we processed the images with noise interference using filters before training with BPN networks. After training was completed, we plotted the PSNR distribution map, as shown in Figs. 4 and 5.

Figures 4 and 5 show that the PSNR vibrations decreased substantially. Nevertheless, the vibrations did

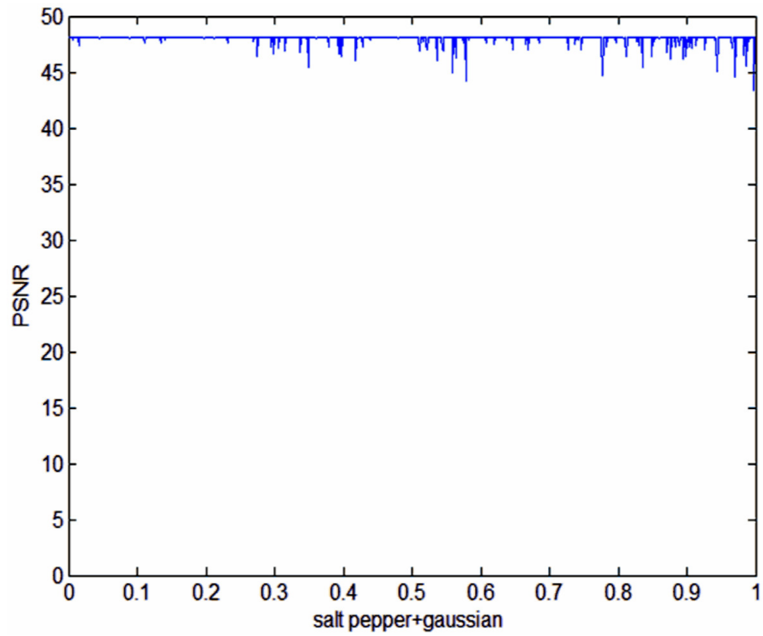

Fig. 3. PSNR performance of the salt-and-pepper and Gaussian noise condition after BPNN.

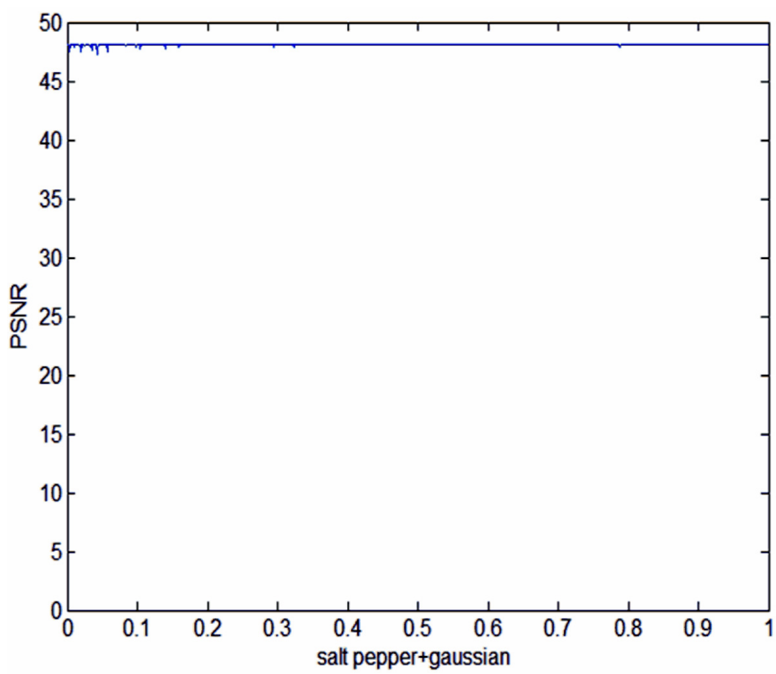

Fig. 4. PSNR after low-pass filtering with BPNN.

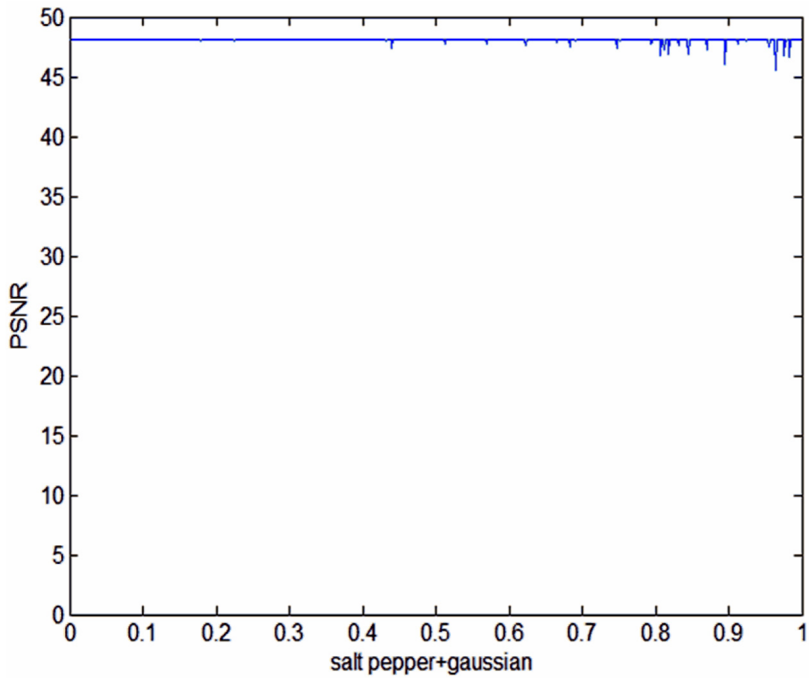

Fig. 5. PSNR after median filtering with BPNN.

not disappear. The image processed using a low-pass filter showed that more vibrations existed at low noise strengths, whereas nearly no vibrations existed at higher noise strengths. The effect of using median filters was the exact reverse of the effects of using low-pass filters. Based on this observation, we determined that using median filters at the low noise strengths can achieve superior PSNR values for BPN network training. However, using low-pass filters at high noise strengths can also obtain superior PSNR for during BPN network training. When the noise is high, low-pass filters can be selected to filter the noise before using BPN technology to obtain superior PSNR performance. In summary, using BPN network training can remove noise from destroyed watermarked images and recover the original embedded watermarks.

4. CONCLUSIONS

The majority of watermarking technologies have focused on embedding sequences into high-frequency areas or unperceivable areas. By contrast, the watermarking method presented in this study embedded WH codes into each pixel of the image and then interferes with the image using image noise and filters. Finally, we used BPN network algorithms to remove the noise and recover the original embedded watermarks. Thus, using BPN network scheme with filters can successfully improve the PSNR value and retrieve watermarks.

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