Image Watermarking Based On Wavelet Packet Transform With Best Tree

P. Kumhom\textsuperscript{1}, Member, S. On-rit\textsuperscript{1}, Non-member, and K. Chammongthai\textsuperscript{1}, Member

\textsuperscript{1}Department of Electronics and Telecommunication Engineering, Faculty of Engineering, King Mongkut’s University of Technology Thonburi, Bangkok 10140, Thailand
E-mail : ipinnhom@kmutt.ac.th

ABSTRACT

This paper proposes a watermarking embedding and extracting methods in the frequency domain based on a selection of a high frequency range containing large amount of information. The selected high-frequency range contributes to the imperceptibility of the watermark while the robustness against compression is achieved because the selected frequency range contains large amount of information. The entropy-based algorithm is adopted to find the best tree of the wavelet packet transform (WPT). Such best tree represents the best basis of the WPT whose corresponding frequency subband contains high information energy. In addition, for security aspect of the watermarking process, the bits of the watermark image is randomly permuted before embedding them to the selected subband. The key of the pseudo-random generator provides the security for the watermark. Each bit of the permuted watermark image are embedded to the original image by adjusting the WPT coefficients of the selected subband, which also allows us to vary the level of watermarking. The proposed methods are tested with various benchmark images of various sizes and with various watermarking levels. The JPEG compression, Gaussian noise and filtering were applied as the attacks. The results showed that the average peak signal-to-noise ratio (PSNR) was varied from around 50 dB to 24 dB under various compression ratios while the average normalized correlation (NC) was closed to unity for image quality of greater than or equal to 60 \%. Also, the results showed improvement over previous method when both the perceptibility and readability are considered.

Keywords: digital watermark, image watermarking, Wavelet Packet Transform (WPT), best-basis algorithm, entropy-based algorithm, best tree WPT, image compression

1. INTRODUCTION

As we turn toward the information-oriented society, there are needs for protecting the information, which can be in various forms of media such as sounds, images, and videos. Regardless of its media forms, most information is distributed as digital signals, especially via networks such as the Internet. This raises crucial problems regarding authenticity and copyright of the information. One of the solutions to the problems is by embedding an authenticity signature called “digital watermark” into the information so that only the authorized users can use the information.

However, the watermarking process involves various problems which depend on several factors including the types of the information, changes of the information, etc. There are several researches and studies of watermarking in various forms of media. For example, in form of sound, Boney, Tewfik and Hamdy\cite{1} proposed a method of spectrum distribution and pseudo random, and embedding in the parts related to human audible system (HAS). Bender, Gruhl and Morimoto\cite{2} proposed a method of watermarking in sound data by spectrum distribution coding, signal phase coding and repeating coding. In form of digital documents, the watermarks are embedded into sentences by mainly using property of characters. For instance, Brassil et al.\cite{3} proposed three ways of digital watermark embedding, line shift coding, word shift coding and feature coding. These methods are robust against noises, but not protected from watermark deleting. The third form of information is digital video. Since a video signal can be viewed as continuous images, the relation among several images in the sequence is advantageously utilized. For example, Hsu et al.\cite{4} proposed a watermark embedding method by the relation of two frames, and Langelaar et al.\cite{5} presented the use of data difference for video signal compression, and watermark was embedded by MPEG-1 coding.

In this paper, we focus on the information in digital image (or image) form in which we want the watermarking to possess the following properties:

- **Imperceptibility**: Human Visual System (HVS) should not be able to detect the difference of the original image and the watermarked image. That is the watermark must be hidden inside the image.
- **Robustness**: A watermarked image should be robust against intentional or unintentional changes of
image such as compression, filtering, rotating.

- **Security:** A good watermarking must prevent unauthorized persons to be able to extract the watermark.

- **Readability:** The extracted watermark should be similar to the original watermark in order to verify that it is the signature.

There are various researches trying to achieve these goals, and we may divide them into two approaches: spatial domain and frequency domain. In spatial domain approach, basically, intensity of the least significant bits (LSB) in an image is adjusted to embed the watermark image. For instance, Van Schyn德尔 et al. [6] presented a method to adjust at least two least significant bits. Walton [7] used pseudo-random codes to distribute the watermark in entire image, then check sum of seven-bit data. Wolfgang et al. [8] developed the method proposed by Van Schyn德尔 to add bipolar m-sequence of 1 and -1 in 8 x 8 pixel-blocks. Bender et al. [2] utilized statistic way called Patchwork to select values that are pairs of intensity levels, and adjusted the selected values at low intensity level. This method is effective in the case of constant intensity distribution. Normally, the techniques in the spatial domain approach are simple and robust against geometric changes such as image cutting, and rotation. However, the watermarks embedded in this approach may not be robust against high compression ratio.

In the frequency domain approach, various transforms such as Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), and Wavelet Transform (WT) are applied to transform an image to the frequency domain. Then, in order to embed a watermark into the image, the obtained coefficients of the selected transform are adjusted accordingly to the watermark. Hsu et al. [9] has shown that the median frequency range is a good choice for embedding the watermark because the influence of the watermark to the original image is considered to be small. Koch et al. [10] distributed an watermark over DCT coefficients of the frequency range randomly selected. Cox et al. [11] applied the Gaussian Sequence as the watermark for adjusting 1000 DCT coefficients of low frequency range with highest visibility. Bors and Pitas[12] proposed to adjust the DCT coefficients in the middle frequency range of selected 8 x 8 blocks. In stead of frequency, Ruanaidh et al. [13] proposed a method of adjusting phases based on Discrete Fourier Transform (DFT). Also using the DCT, Ryu and Lee [14] proposed a robust watermarking based on minimal DCT quantization errors. The method gives a high robustness of the watermark against compression.

In the following researches, the wavelet transformation is applied to digital watermarking. Kunder and Hatzinakos [15] presented the method to embed watermark by using Gaussian random number as embedded key. They fused the embedded key with the coefficients in the appropriate frequency range and counted this range as watermark. With this method, the watermark can be easily embedded but may be distorted in extraction process. Z.H. Wei [16] tried to solve the problem by using “Joint Notification Difference” (JND) method to generate the embedded key, which is the value of the difference between the neighborhood coefficients. The resulting watermarks are more robust to the high compression ratio than those of Kunder. In 1999, Kim and Moon [17] improved the watermark embedding algorithm by setting the threshold number to filter the coefficients. The threshold is pre-specified by the image owner. The coefficients in the altered frequency range are compared with the threshold. The coefficient that higher than the threshold is multiplied to all the coefficients in the appropriate frequency ranges and then defined this area as watermark.

Although the methods in [15] [16] [17] can be efficiently applied to embed the digital watermarks, they can be easily detected by an intruder. Because these watermarks are generated from random numbers, the peak in distinctly location generated from the correlation between original image and watermark embedded image is easily investigated. Therefore, the intruder can know the watermark location and then remove it. One way to solve the problem is by predening an image as watermark and then embed it into the selected frequency range. Min-Jen Tsai et. al. [18] used wavelet transformation to convert the original image into several groups of coefficients. Concurrently, the image predefined as watermark is transformed using chaotic transformation that enlarges the size of watermark image to the size of altered frequency range. The coefficients of original and watermark images are combined and then define as watermark area. With this method, the watermarks are robust to the higher compression ratio than those in [15] and [16] but they are in the same level as those in [17]. In addition, the location of watermark can be safe from removal by the intruder. However, the method in [18] has some drawbacks because it uses the chaotic transformation which causes the watermark to occupy large portions of image and spread over the whole frequency range. As a result, the clarity of the watermark might be lost in high compression ratios. Barni et. al. [19] proposed an improved wavelet-based watermarking via pixel-wise masking. Similar to [11], the method took the advantage of the human visibility system. Based on the practical requirements of watermarking systems, Wang et. al. [20] proposed a watermarking algorithm for ownership verification of digital images by embedding the watermark into a selected middle frequency. For security proposes, not only does an owner can select the middle frequency to which the watermark is embedded, he can random the filter banks for implementing
the wavelet transform as well. Also, the binary image watermark is converted into an image of real numbers. From experiments, Wang’s method gives a very high imperceptibility measured in term of peak signal to noise ratio (PSNR) and high readability measured in term of normalized correlation (NC).

Based on the fact that embedding watermark into the middle frequency gives the robustness of the watermark against the attacks especially the compression, this paper proposes a method of how the middle frequency range should be selected. The proposed method is based on the wavelet packet transformation with the best basis resulting from an entropy-based algorithm [21] and [22]. In addition, to achieve the security aspect of the watermark, the bits of the watermark image are randomly permuted so that only those who have the key can reconstruct the watermark back. The remainders of the paper are organized as follows. We introduce the background and basic concept of the proposed method in Section 2. Then, Section 3 provides the details of the embedding and extracting watermark methods. Section 4 provides the experimental results. We, then, discuss the results in Section 5 and gives the conclusions in Section 6.

2. BACKGROUND AND BASIC CONCEPT

Embedding a watermark into an image can be considered as adding noises, albeit controlled ones, to the image. As a result, it causes the watermarked image to vary from the original one. However, we want the watermarked image to look the same by human eyes; i.e. we do not want these noises to be seen. But, at the same time, we want the added noises to stick with the image no matter how the image is changed intentionally or unintentionally. One of the intentional changes is the compression of the image in order to reduce the storage space and/or fasten the transfer of the image over networks. These two properties are usually against each other. Particularly, the watermark can be hidden effectively in high frequency range. However, the tradeoff is that high-frequency signal is not robust against compression such as JPEG in the sense that the extracted watermark is significantly different from the original watermark. On the other hand, putting the watermark in the low frequency range may be noticeable by human eyes. Our proposed methods are based on the fact that there must be a frequency range in which both properties are optimized. The problem becomes how we can select such an optimal frequency range. We proposes to use the WPT as the transformation tool because it can provides many possible frequency subbands depending on the levels of the transformation and a chosen tree. An appropriate subband is selected from the entropy-based best tree of the WPT reviewed in the next section.

2.1 Wavelet Packet Transform With Best Tree

Let \( x \in l^2(\mathbb{Z}^2) \) be an image of size \( M_1 \times M_2 \). We can decompose \( x \) into subbands of different frequency localization by repeated applications of a pair of quadrature mirror filters (QMF), denoted by \((H,G)\), where \( H \) and \( G \) are the lowpass and highpass QMF, respectively. By means of tensor product, denoted by \( \otimes \), we can define a quadruple \( F \) of 2-dimensional separable filters as

\[
F = (F_0, F_1, F_2, F_3)
= (H \otimes H, H \otimes G, G \otimes H, G \otimes G)
\]  

(Fig.1: The octave-band tree of the standard wavelet transform at 2 levels

(Fig.2: The full quadtree of 2-level WPT)

(Fig.3: The best tree of 2-level WPT for the Lena image)

By this construction, each step of decomposition yields four subbands which are the images of \( l^2(\mathbb{Z}^2) \) under the projection operator related to \( F_0, F_1, F_2, \)}
and $F_3$. For example, the first step of the transformation decomposes a given image $x$ into four subbands denoted by $W_{1,0}$, $W_{1,1}$, $W_{1,2}$, and $W_{1,3}$. Repeatedly applying the filter $F$ to $x$ gives a quadtree structured decomposition of $x$. The collection of all subband decompositions of $x$ with a maximum number of $L$ levels form a balanced quadtree of depth $L$. For example, Figure 2 shows the full quadtree of the WPT at 2 levels. In general, at each node $(l,k)$ of a quadtree, where $0 \leq l \leq L$ is a level of the tree and $0 \leq k < 4^l$ identify subbands in the level, the original image $x$ is represented by a component in the subband $W_{l,k}$ consisting of $4^l \times M_1 \times M_2$ coefficients.

Note that each subband decomposition corresponds to a basis $V$ in the Hilbert space $l^2(\mathbb{Z}^2)$ called wavelet packet (WP) basis. For example, the standard wavelet basis which is related to an octave-band tree shown in Figure 1 is such a WP basis. Figure 2 and 3 are other examples of such WP bases. Also, each subband decomposition is related to a particular partition of the frequency axis. Hence, under a cost function, one can find the best basis for the WPT, and the corresponding tree is called the best tree.

Coifman and Wickerhauser [21] proposed an algorithm for finding the best basis based on the so-called pseudo-entropy information cost given by

$$M_H(u) = - \sum_j |u_j|^2 \log |u_j|^2,$$  \hspace{1cm} (2)

which is an additive analogue to the Shannon-Weaver entropy in the sense that minimizing the former implies minimizing the latter. This cost function has proved to be successful in image-compression schemes. Since the best basis based on such cost function gives subbands with high entropy, embedding a watermark in such a subband should be robust against changes such as compression.

2.2 Basic Concepts

Our basic ideas are based on the following facts and observations:

- A watermark image should be embedded into only a small frequency range, in which case we can avoid a frequency range that is greatly effected by changes such as compression.
- Normally, information exists in the low frequency ranges. Hence, they are safe from changes such as cropping by some compression processes. However, since low frequency ranges consist of large amount of information, embedding a watermark in this range will cause the visibility of the watermark. At the same time, most of the compression methods would cut signals in high frequency range because they usually are noises. However, if we divide the frequency range to small enough range, there exists frequency ranges, in here referred to as the “subbands of interest,” whose information energy is high, and at the same time, is imperceptible by the human eyes. As a result, they will not be eliminated by the compression methods despite being in high frequency ranges.

- The wavelet packet transform [23,24] can divide an image into as small subbands as we want depending on the level of transformation. For example, Figure 2 shows the full quadtree describing the wavelet packet transform in 2 levels. In such quadtree, a node at a level $l$ of the tree corresponds to a subband consisting of $4^{-l} \times M_1 \times M_2$ coefficients, where $0 \leq l \leq L$, $L$ is the maximum level of the WPT, and $M_1 \times M_2$ is the size of the original image. For example, if the original image is of size $256 \times 256$ pixels, a subband at level 2 of the transformation is of size $64 \times 64$. By choosing a watermark image of size $64 \times 64$ pixels, we can distribute the watermark bits over a selected subband at level 2. In general, let the sizes of the original image and the watermark image be $M_1 \times M_2$ pixels and $N_1 \times N_2$, respectively. Then, taking WPT to the $l$th level, where

$$l = \frac{1}{2} \log \frac{M_1 \times M_2}{N_1 \times N_2},$$  \hspace{1cm} (3)

results in a subband at level $l$ into which the watermark image can be embedded by adjusting the $N_1 \times N_2$ coefficients of a selected subband.

- The entropy-based algorithm [21] can be applied to find the best basis based on the information cost in Equation 2. As a result, we can locate subbands at high enough frequency range with an appropriate size and with large enough amount of information. For example, Figure 3 shows the best tree of WPT for the Lena image of size $256 \times 256$ pixels at level 2 generated by the entropy-based algorithm. Note that the best tree varies accordingly to the original image and the level of transformation.

3. PROPOSED METHODS

In this section, we explain the proposed watermark embedding and extracting methods based on the basic idea described in the previous section.

3.1 Watermark Embedding Method

The proposed embedding process comprises of 6 steps as shown in Figure 4.

1. The Wavelet Packet Transform (WPT) is applied to the original image. The level of transformation is dictated by the size of the transformation following Equation 3 and the best tree of the transformation is chosen by an entropy-based algorithm [21]. Fig. 5 shows an example of the result from this step. In this example, the original image is of size $256 \times 256$ pixels and the watermark image is of size $64 \times 64$ pixels. Hence, the appropriate level of the WPT is two, and the best tree for this image is shown in Figure 3.

2. One of the blocks from the branches of the best tree (the highest level of transformation) is randomly selected for embedding the watermark.
3. The bits of the watermark image is randomly permuted in major-row order. This step is carried out as follows. Let the watermark image is a binary image of size $N_1 \times N_2$. Then, the bits of image at coordinates $(0,0), (0,1), \ldots, (0,N_2-1), (1,0), \ldots, (N_1-1,N_2-1)$ are permuted by a Linear Feedback Shift Register (LFSR) with a specific key. As a result, the bits of the watermark are randomly permuted as shown in Figure 6.

4. The level of watermarking referred to as $B$ level is multiplied to all the permuted watermark bits before combining the watermark to the original image.

5. The permuted watermark bits after the modification are added to the coefficients of the WPT in the selected block. Note that the number of bits of the watermark is equal to the number of coefficients in the block. The coefficients in other blocks stay the same. Let the watermark image and the selected block are of size $N_1 \times N_2$. Equation 4 illustrates the modification of the coefficients by the watermark.

$$C_w(i,j) = C_o(i,j) + B \times W(i,j),$$

where $C_o(i,j)$ and $C_w(i,j)$, $0 \leq i < N_1$ and $0 \leq j < N_2$, are the $(i,j)^{th}$ coefficients in the selected block of the original image and the watermarked image, respectively. $W(i,j)$ is the bit value of the watermark after permutation, and $B$ is the level of watermarking.

6. The watermarked image is the result of the Inverse Wavelet Packet Transform (IWPT) of the output from step 5. Figure 7 shows an example of the watermarked image of the Lena image shown in Figure 5.

### 3.2 Watermark Extracting Method

Figure 8 illustrates the extracting of the watermark provided that we know (1) the original image, (2) the level of the WPT and the block whose coefficients are changed, and (3) the pseudo-random seed. The following steps describe the extracting algorithm.

1. Both the watermarked image and the original image are transformed by the WPT with the known level of transformation.

2. The entropy-based algorithm is used to find the best tree of the transformation, and the known block is selected from both images.

3. Subtracting the selected coefficients of the original image from the corresponding coefficients of the watermarked image. Let the size of watermark be $N_1 \times N_2$, and $C_w(i,j)$ and $C_o(i,j)$, $0 \leq i < N_1$ and $0 \leq j < N_2$, be the $(i,j)^{th}$ coefficients in the selected block of the watermarked image and the original image, respectively. Then,

$$\tilde{W}(i,j) = C_w(i,j) - C_o(i,j),$$

where $C_o(i,j)$ and $C_w(i,j)$, $0 \leq i < N_1$ and $0 \leq j < N_2$, are the $(i,j)^{th}$ coefficients in the selected block of the original image and the watermarked image, respectively.
where $\tilde{W}$ implies the embedded watermark.

4. The watermark bits are obtained by thresholding the $\tilde{W}$. Since the values of the watermark were multiplied by a positive number $B$ before embedding, we simply take zero as the threshold value. Let $\tilde{W}_b$ be the values of the watermark bits. Then,

$$\tilde{W}_b(i, j) = \begin{cases} 1 & \text{if } \tilde{W}(i, j) < 0 \\ 0 & \text{if otherwise} \end{cases}$$

5. The watermark bits in step 4 are still in permuted form as shown in Figure 9 (a). The actual watermark image is obtained by inverse pseudo-random permutation of the watermark bits as shown in Figure 9 (b).

![Fig.8: The purposed watermarking extracting method](image)

![Fig.9: (a) The extracted watermark image before the inverse pseudo-random permutation (b) the extracted watermark image](image)

4. EXPERIMENTS AND RESULTS

4.1 The Experiments

To test the proposed methods, a set of experiments is performed under the following conditions.

- The goal is to measure the imperceptibility of the watermarked images and the readability of the extracted watermarks against JPEG compression and other signal processing methods such as Gaussian, median pass, and low pass filters. The Peak Signal to Noise Ratio (PSNR) and the Normal Correlation (NC) shown in Equation 7 are used to measure the imperceptibility and the readability, respectively.

$$NC = \frac{\sum_{i=0}^{N_1-1} \sum_{j=0}^{N_2-1} W(i, j)\tilde{W}(i, j)}{[W(i, j)]^2}$$

- We chose a collection of 24 standard images as the tested images. The first 12 images of size $256 \times 256$ pixels are Airplane, Baboon, Barbara, Bird, Boat, Bridge, Camera, Goldhill, Lamp, Lena, Montage, and Zelda, and the remaining images of size $512 \times 512$ pixels are Airplane, Baboon, Barbara, Boat, Couple, Fruit, Girls, Goldhill, Lena, Pepper-1, Pepper-2, and Zelda.
- The watermark image, which is a binary image displaying “VISION LAB KMUTT” shown in Figure 6 (a), is of size $64 \times 64$ pixels. Hence, the levels of WPT for images of size $256 \times 256$ pixels and of size $512 \times 512$ pixels are 2 and 3, respectively.
- For each image, the level of watermarking (B level) is varied from 10dB to 30dB (at 10dB, 20dB, and 30dB).
- For the test against the JPEG compression, the image quality is varied from 0 % to 100 % with a step of 10 %. The relation between the image quality and JPEG compression ratios is provided.
- For the test against Gaussian noise, we fixed Gaussian mean at zero and varied the variance from 0.01 to 0.09.

4.2 The Results

4.2.1 JPEG Compression Results

Table 1 collects the results in terms of the average PSNR, NC, and JPEG compression ratios of the tested images after embedding the watermark with 3 different levels of watermark (B levels.) Note that the JPEG compression ratios are computed for each image quality at different watermarking levels. Figure 10 and 11 show the JPEG compression ratios for each B level at different image qualities.

Table 2 provides the standard deviation of the PSNR and the NC to show the variation of results with respect to various images.

The effects of the JPEG compression to the imperceptibility and the readability are plotted in Fig. 12 to Fig. 15; Fig. 12 and Fig. 13 shows the effect to imperceptibility, and Fig. 14 and Fig.15 illustrates the effect to the readability, respectively.

The JPEG compression effect in relation to the WPT level is shown in Fig. 16 and Fig. 17.

To illustrate the effect of the JPEG compression to an individual tested image, the PSNR and the NC for the Lena image of both sizes are shown in Fig. 18 to Fig. 21.

4.2.2 Gaussian Filter Results

Table 3 collects the results in term of the average PSNR of the tested images under the zero-mean Gaussian noise at various variances after embedding the watermark with 3 different levels of watermark (B levels). The readability measured in term of the NC of the extracted watermark and the original watermark is also provided.
Table 1: Average JPEG compression ratios, PSNR and NC of 12 images of size 256 × 256 pixels (denoted by S1) and 12 images of size 512×512 pixels (denoted by S2) at 10 different image qualities and 3 watermarking levels (B levels)

<table>
<thead>
<tr>
<th>Image Quality</th>
<th>Level</th>
<th>B=10dB</th>
<th>B=20dB</th>
<th>B=30dB</th>
<th>S1</th>
<th>S2</th>
<th>S1</th>
<th>S2</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>90%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>80%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>70%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>60%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>50%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>40%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>30%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>20%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>10%</td>
<td>10dB</td>
<td>1.49</td>
<td>1.55</td>
<td>1.58</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 2: The standard deviations of JPEG compression ratios, PSNR and NC of 12 images of size 256 × 256 pixels (S1) and 12 images of size 512×512 pixels (S2) at 10 different image qualities and 3 watermarking levels (B levels)

The effects of the Gaussian noise to the imperceptibility and the readability are plotted in Fig. 22 to Fig. 25; Fig. 22 and Fig. 23 shows the effect to imperceptibility, and Fig. 24 and Fig. 25 illustrates the effect to the readability, respectively.

To illustrate the effect of the Gaussian filter to an individual tested image, Fig. 26 shows the watermarked images of Lena under zero-mean Gaussian at 0.05 variance and Fig. 27 shows the corresponding extracted watermarks.

4.2.3 Median Pass Filter Results

Table 4 and Table 5 collect the results in terms of the PSNR of the 6 tested images under the median pass filter after embedding the watermark with 3 different levels of watermark (B levels) and the NC of the extracted watermark.

4.2.4 Low Pass Filter Results

Table 6 and Table 7 collect the results in terms of the PSNR of the 6 tested images under the low pass filter after embedding the watermark with 3 different levels of watermark (B levels) and the NC of the extracted watermark.
Table 3: Average PSNR and NC of tested images of size $256 \times 256$ pixels (S1) and tested images of size $512 \times 512$ pixels (S2) under the zero-mean Gaussian noise at 10 different variances and 3 watermarking levels (B levels)

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR (dB)</th>
<th>NC</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
<th>0.06</th>
<th>0.07</th>
<th>0.08</th>
<th>0.09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baboon</td>
<td>29.71</td>
<td>29.84</td>
<td>29.97</td>
<td>30.11</td>
<td>29.95</td>
<td>29.85</td>
<td>29.75</td>
<td>29.67</td>
<td>29.59</td>
<td>29.51</td>
<td>29.44</td>
</tr>
<tr>
<td>Lena</td>
<td>27.15</td>
<td>27.23</td>
<td>27.27</td>
<td>27.31</td>
<td>27.25</td>
<td>27.19</td>
<td>27.13</td>
<td>27.07</td>
<td>26.99</td>
<td>26.93</td>
<td>26.87</td>
</tr>
</tbody>
</table>

Table 4: The PSNR and NC of tested images of size $256 \times 256$ pixels under the middle pass filter at 3 watermarking levels (B levels)

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR (dB)</th>
<th>NC</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
<th>0.06</th>
<th>0.07</th>
<th>0.08</th>
<th>0.09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baboon</td>
<td>27.28</td>
<td>27.32</td>
<td>27.36</td>
<td>27.40</td>
<td>27.34</td>
<td>27.28</td>
<td>27.22</td>
<td>27.16</td>
<td>27.10</td>
<td>27.04</td>
<td>26.98</td>
</tr>
<tr>
<td>Lena</td>
<td>24.88</td>
<td>25.01</td>
<td>25.05</td>
<td>25.09</td>
<td>25.03</td>
<td>24.97</td>
<td>24.91</td>
<td>24.85</td>
<td>24.79</td>
<td>24.73</td>
<td>24.67</td>
</tr>
</tbody>
</table>

Table 5: The PSNR and NC of tested images of size $512 \times 512$ pixels under the middle pass filter at 3 watermarking levels (B levels)

Table 6: The PSNR and NC of tested images of size $256 \times 256$ pixels under the low pass filter at 3 watermarking levels (B levels)

Table 7: The PSNR and NC of tested images of size $512 \times 512$ pixels under the low pass filter at 3 watermarking levels (B levels)

5. DISCUSSIONS

In the next section, we discuss the results in various aspects.

5.1 On Imperceptibility

The PSNR is used to objectively measure the capability of hiding the watermark, where the higher PSNR, the more transparency of the watermark.

Effects of the Watermarking Level (B Level) on the PSNR: Given a fixed level of the transformation, we found that the effects of the level of watermark on PSNR at the high compression ratios (low image quality) are very small comparing to those at the low compression ratios as shown in Figure 12 and 13 for the case of average values and Figure 18 and 19 for the case of the Lena image. Moreover, the higher level of WPT, the less effect the B level has on the PSNR.

Under the Gaussian noise and the filtering attacks, the effect of the watermark level is similar to the JPEG compression effect but with less effect as shown in Fig. 22, Fig. 23, and Table 4-Table 7.

Effects of the WPT Level on the PSNR: Expectedly, given fixed level of watermarking (B level) and image quality, the effect of the WPT level is that the deeper WPT level, the higher PSNR as shown in Figure 16. Obviously, it takes longer processing time for the case of deeper WPT level.

Under the Gaussian noise and the filtering attacks, the effect of the WPT level to the PSNR is very small.

5.2 On Robustness

Table 8: The PSNR before the attacks of the proposed method at B=10dB comparing with Ryu's method [14] and Wang's method [20]

Comparison with Other methods: Table 8 shows the comparison of the PSNR before the attacks with other methods such as Ryu’s method [14] and Wang’s method [20]. It shows that proposed method gives the highest PSNR before the attacks. However, after

extracted watermark.

In the next section, we discuss the results in various aspects.

5. DISCUSSIONS

In this section, we discuss many aspects of our proposed methods from the experimental results in Section 4.
Fig. 12: The average PSNR of the 12 images of size $256 \times 256$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 13: The average PSNR of the 12 images of size $512 \times 512$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 14: The average NC of the 12 images of size $256 \times 256$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 15: The average NC of the 12 images of size $512 \times 512$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 16: Comparing the average PSNR in terms of WPT levels, whereas the 12 images of size $256 \times 256$ pixels and $512 \times 512$ pixels represent the WPT level 2 and 3, respectively. The watermarking levels is at 10 dB.

Fig. 17: Comparing the average NC in terms of WPT levels, whereas the 12 images of size $256 \times 256$ pixels and $512 \times 512$ pixels represent the WPT level 2 and 3, respectively. The watermarking levels is at 10 dB.
Fig. 18: The PSNR of the Lena image of size $256 \times 256$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 19: The PSNR of the Lena image of size $512 \times 512$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 20: The NC of the extracted watermark from the Lena image of size $256 \times 256$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 21: The NC of the extracted watermark from the Lena image of size $512 \times 512$ pixels at different compression ratios after the embedding of the watermark with 3 different $B$ levels.

Fig. 22: Average PSNR of watermarked images of size $256 \times 256$ pixels under the zero-mean Gaussian noise at 10 different variances and 3 watermarking levels ($B$ levels).

Fig. 23: Average PSNR of watermarked images of size $512 \times 512$ pixels under the zero-mean Gaussian noise at 10 different variances and 3 watermarking levels ($B$ levels).
the attack such as JPEG compression, the proposed method yields lower but comparable PSNR comparing with Wang’s method [20]; for example, the proposed method gives 36.56 at 5.51 compression ratio (80% quality) while Wang’s method gives 41.7 at 4.76 compression ratio.

5.2 On Readability

The NC computed by Equation 7 is used to objectively measure the readability of the extracted watermark comparing to the original watermark, where the closer to unity of the NC, the more similarity of the two watermarks.

Effects of the Level of Watermarking (B Level) on the NC: Figure 14 and 15 shows the average NC for different B levels at 10 image quality for the cases of WPT level at 3 and 2, respectively. As expected, the higher watermarking level, the better NC for both cases. Comparing to the case of PSNR, the watermarking level has more effects to the NC.

Effects of the WPT Level on the NC: Figure 17 shows the effects of WPT level to the NC at fixed B level at 10 dB. Notice that the WPT level has more effects to the NC than does the PSNR. While deeper WPT level yields a better PSNR, it causes a lower NC.

Comparison with Other methods: As shown in Table 9 the proposed method gives a better NC than Wang’s when the watermarked images are under the Gaussian noise and median filter.

It is important to emphasize two important points regarding the proposed methods. Firstly, the proposed methods allow us to vary two parameters, the watermarking level (B level) and the WPT level, that effect the imperceptibility (the PSNR) and the readability (the NC). From the experiments, we conclude that the effects of both parameters to the NC are greater than those to the PSNR, which confirms our
Table 9: The NC of the proposed method at B=20dB comparing with Wang’s method [20] under the Gaussian noise and median filter

<table>
<thead>
<tr>
<th>Images</th>
<th>Gaussian Noise</th>
<th>Median Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Proposed</td>
<td>Wang’s</td>
</tr>
<tr>
<td>Baboon</td>
<td>0.995</td>
<td>0.972</td>
</tr>
<tr>
<td>Babara</td>
<td>0.992</td>
<td>0.971</td>
</tr>
<tr>
<td>Lena</td>
<td>0.992</td>
<td>0.971</td>
</tr>
</tbody>
</table>

The basic idea that by selecting a high frequency subband with high entropy, we should be able to effectively hide the watermark even at a relative high level of watermarking. This allows us to boost the readability of the watermark up while keeping the imperceptibility within an acceptable level. Finally, the proposed methods work well with all kinds of images as shown by small deviations shown in Table 2.

Comparing with other methods, the proposed method gives just comparable results in terms of the PSNR. However, when considering both the PSNR and NC, the proposed method is better. One drawback of the proposed method is that it requires the original image for the watermark extracting process while the blind extracting is preferable.

6. CONCLUSIONS

We proposed to embed a watermark image into a subband of the wavelet packet transform whose basis is the best one in the sense that the information in the subband is relatively high even at the high frequency range. As a result, a high imperceptibility of a watermarked image and the high readability of the extracted watermark against the image changes particularly the compression are achievable simultaneously. The security of the watermark is added by the pseudorandom permutation of the bits of the watermark image before embedding. The experiments show promising results in a sense that the method work well when considering both perceptibility and readability, and that it worked well with various kinds of the benchmark images. Finally, by selecting appropriate WPT level and the watermarking level, we can individually optimize the watermarking for each image.

References

[18] M. Tsai, Y. Yu, and Y. Chen, “Joint wavelet and spatial transformation for digital watermark-
Kosin Chamnongthai received the B.Eng. degree in Electrical Engineering (2nd honors) from King Mongkut’s University of Technology Thonburi (KMUTT), Bangkok, Thailand in 1988 and the Ph.D. degree in Electrical and Computer Engineering from Drexel University, Philadelphia, PA, USA, in 2001. He had been with the department of Electrical Engineering before joining the department of Electronic and Telecommunication Engineering Department of King Mongkut’s University of Technology Thonburi(KMUTT), Bangkok, Thailand, as lecturer in 1991, assistant professor in 1993 and associate professor in 1996 until now. His current research interests include image processing, computer vision, robot vision, and natural language processing. He is a member of the Institute of Electronics Information and Communication Engineers, Information Processing Society, Thai Robotics Society and the ECTI.

Surajate On-rit was born in 1973. He received the B.S.I.Ed in Telecommunication Engineering (Second Honors) from the King Mongkut’s Institute of Technology Ladkrabang, Bangkok Thailand in 1997 and M.Eng in Electrical Engineering from King Mongkut’s University of Technology Thonburi, Bangkok Thailand in 2000. He has worked at faculty of Industrial Technology, Rajabhat Institute of Ubonratchathani, Ubonratchathani, Thailand, as lecturer since 1997. His research interests include digital watermarking, computer networking, microprocessor and microcontroller applications and digital hardware design.

Pinit Kumhom received the B.Eng. degree in Electrical Engineering (2nd honors) from King Mongkut’s University of Technology Thonburi (KMUTT), Bangkok, Thailand in 1988 and the Ph.D. degree in Electrical and Computer Engineering from Drexel University, Philadelphia, PA, USA, in 2001. He had been with the department of Electrical Engineering before joining the department of Electronic and Telecommunication Engineering, KMUTT, where he is currently an Assistant Professor. His research interests include applications of image processing and DSP algorithms, hardware implementation of algorithms, and ASIC/FPGA/SoC design. He is a member of the ECTI.