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LDPC를 이용한 예측 기반 워터마킹 알고리듬

(Estimation-based Watermarking Algorithm with Low Density Parity Check (LDPC) Codes)

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요 약

본 논문에서는 워터마크 예측과 LDPC 코드를 이용하여 워터마크의 성능을 향상시키는 알고리듬을 제안한다. 워터마크 추출의 경우 삽입된 워터마크의 파워(power)가 원본 영상의 파워에 비해 아주 작기 때문에 워터마크의 추출 성능을 높이기 위해서는 워터마크의 예측이 필수적이다. 본 논문에서는 웨이블릿 영역에서 잡음 제거 필터를 사용하여 워터마크의 예측을 수행하였다. 이렇게 예측된 워터마크에 에러가 발생할 경우 LDPC 코드를 사용하여 수정하였다. 에러 수정 시 삽입된 워터마크의 통계적인 특성을 사용하여 기존의 LDPC 코드의 성능보다 우수한 실험 결과를 도출하였다

Abstract

The goal of this paper is to improve the watermarking performance using the following two methods; watermark estimation and low density parity check (LDPC) codes. For a blind watermark decoding, the power of a host image, which is hundreds times greater than the watermark power, is the main noise source. Therefore, a technique that can reduce the effect of the power of the host image to the detector is required. To this end, we need to estimate watermark from the watermarked image. In this paper, the watermark estimation is done by an adaptive estimation method with the generalized Gaussian distribution modeling of sub-band coefficients in the wavelet domain. Since the watermark capacity as well as the error rate can be improved by adopting optimum decoding principles and error correcting codes (ECC), we employ the LDPC codes for the decoding of the estimated watermark. Also, in LDPC codes, the knowledge about the noise power can improve the error correction capability. Simulation results demonstrate the superior performance of the proposed algorithm comparing to LDPC decoding with other estimation-based watermarking algorithms.

Keywords : Watermark Estimation, LDPC Codes, Wavelet Transform, De-noising Filter.

I. Introduction

With the advent of digital multimedia contents and worldwide distribution channels such as the Internet, new tools, which allow for tracking and copyright protection of contents, are required. One class of tools, which provide these desired functionalities, is digital watermarking. The concept of digital watermarking is to add information, for example an identification number, to the contents. The addition has to be done such that the contents are not visually and aurally altered. Furthermore, the watermark has to be robust, which means that sub-sequent processing of the watermarked contents should not impair the detection of the embedded information.

Digital watermarking is the art of communicating a message by embedding it into multimedia data (host data) and decoding it without access to the original

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non-watermarked host data. In general, these watermarking schemes were built on the principle of spread spectrum. Although many experiments on blind watermark decoding whose performance, in ideal situation, is equivalent to the decoding with a host image have been reported[1], its performance cannot be guaranteed because the blind detection of spread-spectrum watermarks suffers significantly from host data interference[2]. Therefore, a technique which can reduce the effect of the power of the host image to the detector is required. This can be accomplished by a whitening process, which also guarantees reliable communication. That is, to improve the watermark performance we need to estimate the original watermark from the watermarked image as accurate as possible. In this paper, given a watermarked image, we apply an efficient de-noising technique to estimate the watermark. Since the added watermark can be considered as a noise, image de-noising scheme can be used to separate the added watermark from the host signal. It is based on the generalized Gaussian distribution modeling of sub-band coefficients in wavelet domain[3]. This method uses adaptive soft thresholding to estimate the exact watermark. However, when the watermarked data are modified intentionally or unintentionally, the estimated watermark includes a large number of errors. So an error correction code (ECC) such as BCH codes, RS codes or Turbo codes need to be applied in the digital watermarking system to protect the embedded watermark from attacks. Recently, LDPC codes can achieve near Shannon limit error performance and represent a very promising prospect for error control coding[5]. However, to achieve the best performance of LDPC codes, some conditions are required. One of them is that we need to know the exact channel noise power, which is rarely available. Thus, there will be mismatch between the assumed noise power and the true one[5]. In this paper, we exploit the exact knowledge of the embedded watermark power, to calculate the channel noise power from the estimated watermark. So, we can improve the decoding performance of the estimated watermark using the LDPC codes with the exact channel noise power calculated from the estimated watermark.

The rest of this paper is organized as follows. The next section covers the proposed watermark embedding process which consists of message assignment and Human Visual System (HVS). In section III, we explain the watermark estimation in the wavelet domain. Section IV is devoted to message encoding and decoding with LDPC codes. Simulation results are given in section V. Finally, the main contributions of this work are summarized in section VI.

II. Watermark Embedding

Figure 1 shows the overall diagram of the proposed watermarking algorithm, which operates in the spatial domain. Embedding process consists of three steps, namely message assignment with *M-ary* modulation, message encoding with LDPC codes, and watermark embedding with the Human Visual System. Detection process includes watermark estimation, message decoding with LDPC codes, and message extraction with *M-ary* de-modulation.

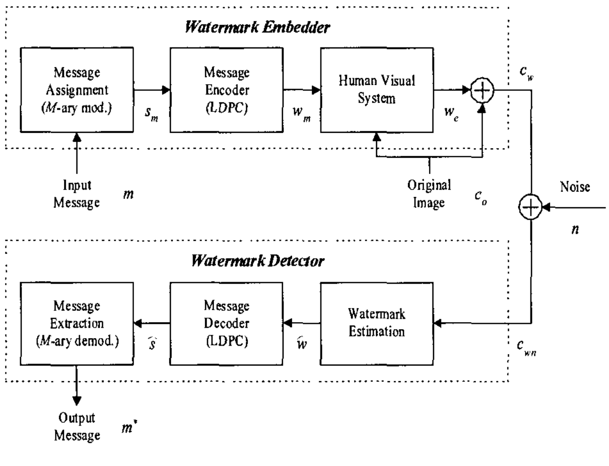


그림 1. 제안된 워터마킹 알고리듬의 블록도
Fig. 1. Diagram of the proposed watermarking algorithm.

1. Message Assignment

From modulation theory we know that increasing the number of symbols may, for certain modulation schemes, result in a decrease of the symbol error probability[6]. Let us investigate the concept of *M-ary* signaling in the context of digital watermarking. The idea is to assign a unique and predefined sequence to each input message[6]. The M bit long messages are mapped to L symbols required for the *M-ary* modulation. This is usually done by grouping $\log_2 L$ bits of the original message and then taking the resulting decimal value as an index to select the appropriate symbol from a set of basis symbols. In the decoding process, the received signal is correlated with all modulation functions representing the different symbols. The index of the largest correlation determines the transmitted symbol. In general, the symbols in a set are either orthogonal or bi-orthogonal. The orthogonal case is the most obvious selection because it inherently results in orthogonal symbols and therefore watermarks are orthogonal to each other.

After assigning the message sequences, a small amount of controlled redundancy is added to produce a code-word w_m, which results in an error correction code. The goal of ECC is to maximize the number of errors that can be corrected while introducing as little redundancy as possible. In this paper, we increase the watermark hosting capacity of images by exploiting the ECC, low density parity check codes[5] in particular. They are known to be best performing to the very near of the Shannon limits[4]. The detail of LDPC is described in section 4.

2. Human Visual System

Let c_o be the luminance value of an original image. Then, the embedding process can be represented as follows;

$$c_w = c_o + \alpha w_m = c_o + w_e, \tag{1}$$

where w_m is the LDPC coded sequence, which is a random variable with a *Bernoulli* (p) distribution such as

$$w_m = \begin{cases} +1 & \text{with probability } p \\ -1 & \text{with probability } 1-p \end{cases} \quad 0 \le p \le 1 \tag{2}$$

and the parameter α is a local weighting factor that depends on the human visual characteristics of the coefficient value in the watermarking space. Although the image is modified without the perceptual degradation of quality, the value α is preserved because the local characteristics of the image do not change very much. The embedded watermark w_e is added to the original image. In general, as shown in Fig. 2, the embedded watermark can be modeled with a Generalized Gaussian distribution. Also, this figure shows that there is little difference of the embedded watermark distribution between the original and the compressed image (compression factor 50 in Jasc Paint Shop Pro™ ver. 7.0) because of the invariance of the local characteristics. This property enables us to calculate the exact power of the embedded watermark in detection process. That is, we can calculate the exact power of the channel noise from the estimated watermark to improve the watermark decoding performance in LDPC codes.

III. Watermark Estimation

During transmission, the watermarked image c_w is corrupted by i.i.d zero-mean Generalized Gaussian noise n with unknown standard deviation σ_n. Thus, at the receiver end, the noisy and watermarked image can be expressed as follows;

$$c_{wn} = c_o + w_e + n = c_o + w_{en} \tag{3}$$

We regard the sum of embedded watermark w_e

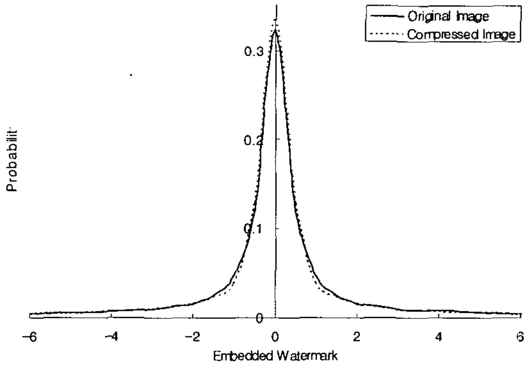


그림 2. 삽입된 워터마크의 확률 분포
Fig. 2. Probability distributions of the embedded watermark.

and channel noise n as the corrupted watermark w_{en}. We can assume that the random variable of w_{en} has zero-mean Gaussian distribution because the embedded watermark and the noise signal have the identical zero-mean Gaussian distribution. Then, our goal is to estimate the embedded watermark with noise $\hat{w}_{en}$ from the noisy and watermarked image such that mean square error is to be minimum.

Let c_{un} be the two-dimensional orthogonal discrete wavelet transform of c_{un}. Then, the wavelet coefficients have four sub-bands such as LL, LH, HL and HH. The sub-bands HH_k, HL_k and LH_k contain the detailed components, where $k \in \{1, 2, \ldots, K\}$ and K represents the scale number. The sub-band LL_k is the low-resolution residue. The wavelet de-signaling method is executed to the coefficients in the detail sub-bands with an adaptive threshold to obtain the estimate of noisy watermark frequency $\hat{W}_{en}$. Then, the de-signaled estimate is inverse-transformed to obtain the estimated noisy watermark $\hat{w}_{en}$. This algorithm, which is very simple to implement and computationally efficient[2], can be summarized with the following steps.

Step 1: Perform multi-scale decomposition of the noisy and watermarked image c_{wn} using the wavelet transform.

Step 2: Estimate the channel noise variance σ_n^2 as follows[2]

$$\sigma_n^2 = \left[\frac{Med\left\{ C_{wn}^{HH_1} \right\}}{0.6745} \right]^2, \tag{4}$$

where $C_{un}^{HH_1}$ is a set of wavelet coefficients in HH_1 band. And the function $Med\{A\}$ is the median filter which selects the median coefficients value form the ordered set of A.

Step 3: For each resolution scale k, compute the scale parameter β_k as follows[2]

$$\beta_k = \sqrt{\log\left(\frac{Q_k}{K} \right)}, \tag{5}$$

where Q_k is the total number of coefficients in each sub-band at k^{th} scale.

Step 4: For the coefficients in the k^{th} sub-band $C_{un}^{Sb_k}$, $Sb_k \in \{HH_k, HL_k, LH_k\}$ (except the low-resolution residue), compute the standard deviation of the sub-band under consideration $\sigma_{C_{un}^{Sb_k}}$. Then, compute threshold $T_{C_{un}^{Sb_k}}$ as follows [2]

$$T_{C_{un}^{Sb_k}} = \frac{\beta_k \sigma_n^2}{\sigma_{C_{un}^{Sb_k}}} \tag{6}$$

For the k^{th} sub-bands, the threshold value is inversely proportional to the standard deviation of the sub-band under consideration where the scale parameter depends only upon the sub-band size. Also, the estimate of channel noise variance is a constant. Thus, more noise means, the higher threshold value. This relationship results in separating noise signal from the noisy image adaptively.

Step 5: Apply threshold in (6) to each coefficient except the low-resolution residue as follows

$$MC_{wn}^{Sb_k}(u,v) = \begin{cases} 0 & \text{if } \left| C_{wn}^{Sb_k}(u,v) \right| > T_{C_{wn}^{Sb_k}} \\ C_{wn}^{Sb_k}(u,v) & \text{otherwise} \end{cases} \tag{7}$$

Step 6: Take the inverse wavelet transform $MC_{wn}^{Sb_k}(u,v)$ to construct the estimate of the noisy watermark $\hat{w}_{en}$. Finally, to improve the watermark decoding performance, we directly use the real value of the estimate from de-noising as the input of the LDPC decoding.

Ⅳ. LDPC Encoding and Decoding

Since watermarking is viewed as a communication system, we adopt LDPC codes as the ECC which definitely helps to achieve more reliable transmission. That is, the encoder takes the message sequence (s_m in this paper) as input, adds controlled redundancy to it, and sends out a longer coded sequence (w_m in this paper). The decoder uses the redundancy introduced by the encoder to detect and correct errors that occurred during transmission.

LDPC coding is a special class of linear parity check coding. It needs a generator matrix G and a parity check matrix H. The matrix H is defined as follows. Each column and row of H consists of small number of 1, and the inner product between any two columns is not greater than 1. The matrix H is constructed at random subject to these constraints. The matrix G is generated from the matrix H by the relationship $GH^T \bmod 2 = 0$. Then, the message sequence vectors s_m is encoded by matrix G such that $w_m = s_m G \bmod 2$ and is BPSK (Binary Phase Shift Keying) modulated such that $\{0,1\} \rightarrow \{-1,1\}$ to make the distance of code-words longer.

The decoding process is to find the most probable vector $\widetilde{w}_{en}$ such that $H\widetilde{w}_{en}^T \bmod 2 = 0$. This starts by calculating the probability that the entry of the estimated noisy watermark $\hat{w}_{en}$ has value 0 or 1 such that [4]

$$f^1(r) = \frac{1}{1+\exp(-2\widehat{w_{en}}(r)/\sigma_n^2)} \qquad f^0(r) = 1 - f^1(r) \tag{8}$$

To calculate the likelihood of $\hat{w}_{en}$, we need the actual noise power of channel σ_n^2. However, in real situation, it is rarely available. So, the best performance of LDPC codes may not be achieved. To alleviate this problem, we estimate the channel noise power $\sigma_{\hat{n}}^2$ from the estimated noisy watermark $\hat{w}_{en}$ with the known watermark power $\sigma_{w_e}^2$. Since the embedded watermark w_e has zero-mean distribution and the invariance of the local weighting factor between original image and noisy watermarked image is preserved, the power of the embedded watermark is given by

$$\begin{aligned}\sigma_{w_e}^2 &= E\left[w_e^2\right] = E\left[\alpha^2 w_m^2\right] \\ &\approx E\left[\hat{\alpha}^2 w_m^2\right] = E\left[\hat{w}_e^2\right] = \sigma_{\hat{w}_e}^2,\end{aligned} \tag{9}$$

where $E|\cdot|$ is expectation operator and the value is $\hat{\alpha}$ a local weighting factor from the noisy watermarked image c_{wn}. Although the watermarked image is corrupted, the parameter $\hat{\alpha}$ is very close to the parameter α because the local characteristics of the image do not change very much. The estimated noisy watermark $\hat{w}_{en}$ with zero-mean Generalized Gaussian distribution can be expressed by the channel noise estimate $\hat{n}$ with zero-mean Generalized Gaussian distribution and the embedded watermark w_e with zero-mean Generalized Gaussian distribution. Then, the power of the estimated noisy watermark $\sigma_{\widehat{w}_{en}}^2$ can be expressed as follows;

$$\begin{aligned}\sigma_{\hat{w}_{en}}^2 &= E[\hat{w}_{en}^2] = E[(\hat{n}+w_e)^2] \\ &= E[\hat{n}^2 + 2\hat{n}w_e + w_e^2] \approx E[\hat{n}^2 + w_e^2] \\ &= \sigma_{\hat{n}}^2 + \sigma_{w_e}^2 \approx \sigma_{\hat{n}}^2 + \sigma_{\hat{w}_e}^2.\end{aligned} \tag{10}$$

Finally, using (10), we can calculate the power of the estimated channel noise as follows;

$$\sigma_{\hat{n}}^2 = \sigma_{\hat{w}_{en}}^2 - \sigma_{\hat{w}_e}^2. \tag{11}$$

To decode LDPC codes with the estimated noise power, we use the sum-product algorithm[9][10], which is sometimes referred to as "Belief Propagation algorithm"[11]. The sum-product algorithm passes message along the edges of a bipartite factor graph[12] that describes the conditional joint probability mass function of the code-word symbols given the received channel output.

To extract the message after LDPC decoding, we apply an *M-ary* de-modulator to LDPC decoded sequence by calculating the normalized correlation as follows;

$$m^* = \underset{m\in\{1,2,\cdots,L\}}{\arg\max} \frac{\hat{s}\cdot s_m}{|\hat{s}||s_m|}, \tag{12}$$

where s_m is a sequence with index m. We choose the optimal index m^* of the maximum correlated sequence as the embedded sequence. This index m^* represents the embedded message.

V. Experimental Results

We tested our algorithm on several natural gray scale test images such as Lena, Babbon, and Fishing Boat of size 512×512. Given an image, we partition it into blocks of size 2048. The sequence used in *M-ary* modulation is the m-sequence of length 1024. We used on orthogonal wavelet transform with three levels of decomposition and Daubechies' length-8 wavelet filter. The dimensions of the matrices used in LDPC codes are as follows.

$$\begin{array}{lll} \text{Message sequences} & : & m_s = 1\times 1024 \\ \text{Code-words} & : & w_m = 1\times 2048 \\ \text{Generator matrix} & : & G = 1024\times 2048 \\ \text{Parity check matrix} & : & H = 1024\times 2048 \\ \text{Code rate} & : & R = 1/2 \end{array} \tag{13}$$

The original and watermarked images are shown in Fig. 3. All watermarked images have the PSNR about 40dB compared to the original ones. Additionally, the subjective quality of the images is higher because we used the local characteristics of the images.

To assess the watermark estimation performance of the proposed algorithm, it is compared with conventional methods such as square prediction filter [14], cross-shaped prediction filter[14], and wiener prediction filter[3]. The squared prediction filter is given by $h_s(m,n)$, where w_s defines the window size and is given by odd number. The filter coefficients are given by;

$$h_s(m,n) = \begin{cases} 1/w_s^2 & |m|,|n| \le (w_s-1)/2 \\ 0 & otherwise \end{cases} \tag{14}$$

where $|\cdot|$ represents the absolute value. The coefficients of the cross-shaped prediction filter $h_c(m,n)$ are given by;

(a) 원영상 및 워터마크가 삽입된 Lena 영상
(a) Original and watermarked Lena image
(PSNR: 39.2859dB)

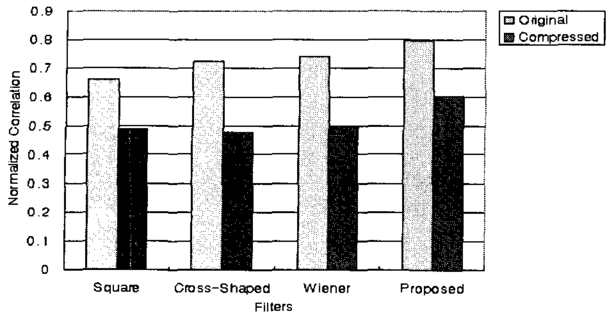
(b) 원영상 및 워터마크가 삽입된 Babbon 영상
(b) Original and watermarked Babbon image
(PSNR: 40.1552dB)

(c) 원영상 및 워터마크가 삽입된 Fishing Boat 영상
(c) Original and watermarked Fishing Boat image
(PSNR: 39.5781dB)

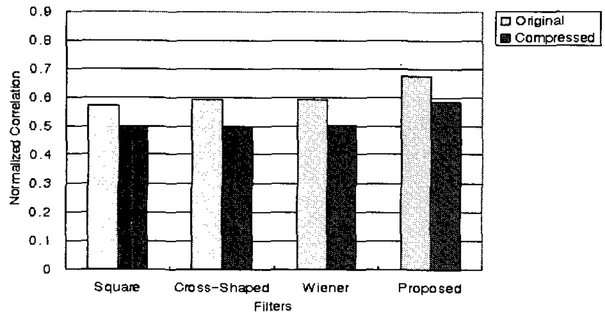
그림 3. 원영상들과 제안된 알고리듬에 의해 워터마크가 삽입된 영상들
Fig. 3. Original image and watermarked image by the proposed algorithm.

$$h_c(m,n) = \begin{cases} 1/(2w_s-1) & m=0, |m| \le (w_s-1)/2 \\ 1/(2w_s-1) & n=0, |n| \le (w_s-1)/2 \\ 0 & otherwise \end{cases} \tag{15}$$

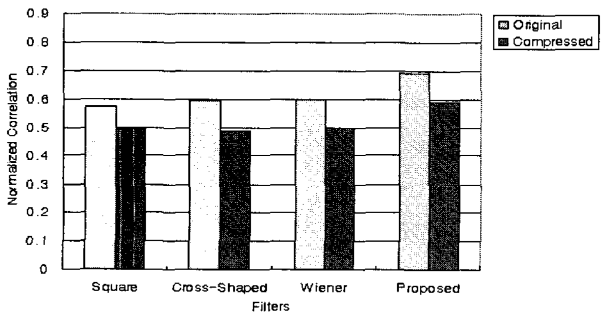
We used MATLAB's image de-noising algorithm wiener2 as wiener prediction filter. The data used for detection after prediction is then given by the difference between the non-filtered data and the filtered data. Fig. 4 shows the normalized correlation (NC) values between the original watermark and the esti



(a) Lena 영상
(a) Lena Image



(b) Baboon 영상
(b) Baboon Image



(c) Fishing Boat 영상
(c) Fishing Boat Image

그림 4. 원영상과 영상압축이 가해진 영상에서의 삽입된 워터마크의 상관관계

Fig. 4. Distribution of added watermark between original and attacked by image compression.

mated ones. The results shows that the NC values of the proposed de-noising filter using the adaptive estimation method are considerably better than others. Now, we need to have a look at a special case when the images are attacked. On the compressed image, the de-noising filter is still better than other filters. From the results of Fig. 4, we conclude that the NC values of the textured images (i.e. Baboon and Fishing Boast) are lower than those of the simple

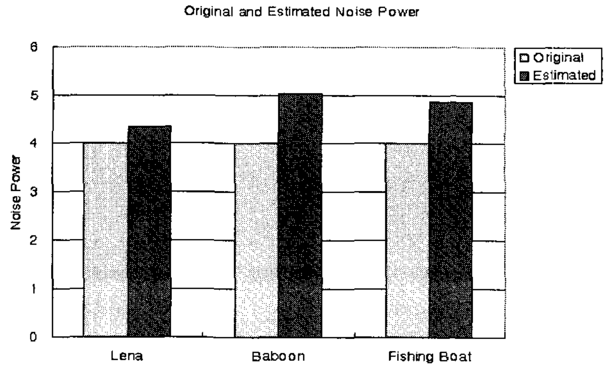


그림 5. 삽입된 워터마크와 예측된 워터마크의 차이

Fig. 5. Difference of the true added watermark and the estimated watermark.

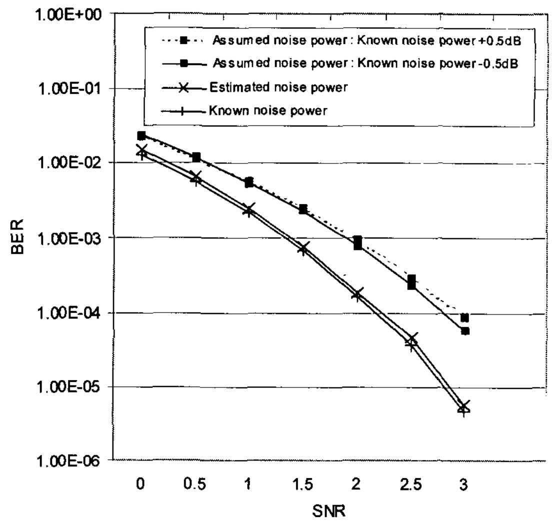


그림 6. 원 잡음, 예측된 잡음, 그리고 가상 잡음과의 BER 곡선 (±0.5dB).

Fig. 6. BER curve between original noise, estimated and assume noise (±0.5dB).

image. This phenomenon is easily explained that the watermark within the textured image is difficult to separate because it can not be easily differentiated from the texture parts.

Fig. 5 depicts the estimated noise power in case where the watermarked image is compressed by compression factor 50 showing no significant difference between them. Finally, Fig. 6 shows the watermark decoding performance in LDPC codes between original, estimated, and assumed channel noise power (0.5dB). As one can see in the graph, the estimated noise power proposed in this paper yields almost similar BER (Bit Error Rate) with those of known noise power.

VI. Conclusions

In this paper, we improved the watermarking performance by estimating the watermark from the attacked image and applying LDPC decoding to the estimated watermark. The watermark estimation can be done by an adaptive estimation method for image de-noising in the wavelet domain based on the generalized Gaussian distribution modeling of sub-band coefficients. When LDPC codes are applied to the estimated watermark, we can solve the mismatch problem between the assumed noise power and the true one by calculating the noise power from the estimated watermark. Simulation results demonstrate the superior performance of the proposed algorithm.

The proposed algorithm can be extended to the geometric attacks such as rotation and scaling etc. To this end, a "self-reference" scheme can be employed by exploiting the periodicity of the repeating block-wise watermarks[13][14].

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