In this paper we present oblivious schemes of ghost-based watermarking for DCT coefficients and examine the fundamental resistance to some attacks. First we introduce a bipolar ghost model, which consists of a composite signal and its complementary signal, and formulate the power cepstrum for the model. Next we define the cepstral difference between the composite and complementary signals to improve the cepstral performance, and examine some properties of the cepstral difference. After that, we explain two types of oblivious algorithms for the ghost-based watermarking in DCT domain taking the above properties into account. The experimental results for some test images show that the watermark information in each image can be detected sensitively by our schemes even when the watermarked images are subjected to processing technique such as clipping.

1. INTRODUCTION

The technique of cepstral signal processing has been applied to the analysis of speech and image signals [1] [2] with success. By exploiting the peculiarity of cepstral technique, we proposed some schemes of ghost-based watermarking [3] [4]. However the fundamental performance of these schemes was not examined sufficiently from the viewpoint of attacks.

In this paper we present oblivious schemes of ghost-based watermarking for DCT coefficients and examine the fundamental resistance to some attacks. First we introduce a bipolar ghost model, which consists of a composite signal and its complementary signal, and then we formulate the power cepstrum for the model. Next we define the cepstral difference between the composite signal and the complementary signal to improve the cepstral performance, and examine some properties of the cepstral difference. After that, we explain two types of oblivious algorithms for the ghost-based watermarking in DCT domain taking the above properties into account. Finally from the experimental results for M-sequence-watermarked images, we show that the watermark information in each image can be detected sensitively by our schemes even when the watermarked images are subjected to processing technique such as clipping.

2. BIPOLAR GHOST MODEL AND ITS CEPSTRUM

Now let us consider a composite signal:

\[ g(n) = (1 - \alpha) x(n) + \alpha x(n - M) \]  

(1)

where \( x(n), \alpha \) and \( M \) denote an original signal, mixture ratio \( |\alpha| \leq 0.5 \) and time lag, respectively. Then the power cepstrum \( \tilde{g}_{pc}(q) \) of \( g(n) \) can be given by

\[ \tilde{g}_{pc}(q) = a_{pc}(q) + f_{pc}(q) + x_{pc}(q) \]  

(2)

where \( a_{pc}(q) = Z^{-1}[\log|A|^2] \) \((Z^{-1}[\cdot] : \text{the inverse of z-transform} Z[\cdot]) \), and then \( f_{pc}(q) \) and \( x_{pc}(q) \) denote the cepstrums of \( f(n) = \delta(n) + B \delta(n - M) \) and \( x(n) \), respectively. Here we note that if \( x(n) \) is a random-walk signal (i.e. the spectrum of \( x(n) - x(n - 1) \) is white), then

\[ x_{pc}(q) = \log|\eta|^2 \cdot \delta(q) + \frac{1}{\eta^2}(q - 1), \]  

where \( \eta^2 \) is constant and \( u(n) = 1(n \geq 0), 0 \) (otherwise). [5]

Next we consider a complementary composite signal:

\[ \tilde{g}(n) = (1 - \tilde{\alpha}) x(n) + \tilde{\alpha} x(n - M), \tilde{\alpha} = -\alpha. \]  

(3)

Then the power cepstrum \( \tilde{g}_{pc}(q) \) of \( \tilde{g}(n) \) can be given by

\[ \tilde{g}_{pc}(q) = a'_{pc}(q) + f'_{pc}(q) + x_{pc}(q) \]  

(4)

where \( a'_{pc}(q) = Z^{-1}[[\log|A'|^2], f'_{pc}(q) \) denotes the cepstrum of \( f'(n) = \delta(n) + B' \delta(n - M) \).

In this paper we refer to a pair of \((g(n), \tilde{g}(n))\) as a bipolar ghost model, while we refer to a pair of \((g(n), \tilde{g}(n)|_{\alpha=0} = x(n))\) as a unipolar ghost model.

3. CEPSTRAL DIFFERENCE FOR BIPOLAR GHOST MODEL

The cepstral difference \( d_{pc}(q) \) between \( g(n) \) and \( \tilde{g}(n) \) is defined as \( d_{pc}(q) = g_{pc}(q) - \tilde{g}_{pc}(q) \). Then we have

\[ d_{pc}(q) = \{ \begin{array}{ll} \sum_{k=1}^{\infty} (-1)^{k-1} \frac{B^k + B'^k}{k!} \delta(|q| - kM) & (|q| \geq 1) \\ \frac{1}{2 \log(|A|/|A'|)} & (q = 0) \end{array} \]  

(5)
where $A = 1 - a$, $B = \frac{a}{1+a}$, $A' = 1 + a$, and $B' = \frac{a}{1+a}$.

Evaluating the above Eq. (5) at short frequencies ($q = 0, M$) yields $d_{pc}(0) = 2\log \left(\frac{1+a}{1-a}\right)$ and $d_{pc}(M) = 2\log \left(\frac{1-a}{1+a}\right)$. Plots of $d_{pc}(q) (q = 0, M)$, $d' = d_{pc}(M) - d_{pc}(0)$ and $d_0 = e_{pc}(M) - e_{pc}(0)$ are shown in Fig. 1, where $d_0 = e_{pc}(M) - e_{pc}(0)$; $d_{pc}(q) = g_{pc}(q) - x_{pc}(q)$ denotes the result of unipolar ghost model in the literature [3]. From Fig. 1, the following properties can be obtained.

(1) $d > 0$ when $a > 0$, and $d < 0$ when $a < 0$ (sign),
(2) $|d| \approx 3d_{pc}(M)$ (amplitude),
(3) $d$ (bipolar ghost) $> |d_0|$ (unipolar ghost),

where $0 < |d_0| \leq 0.25$.

Therefore, this paper, the above property (1) for the bipolar ghost model is exploited to detect watermarks from watermarked images, and instead of a pair of composite signals $(g(n), g(n))$ in time domain, a pair of composite signals $(g(m), g(m))$ in DCT domain is used to embed watermarks with more energy in an image.

**4. OBLIVIOUS WATERMARKING ALGORITHMS**

### 4.1. Basic Algorithm

♦ Generation of Bipolar Ghost in DCT Domain

\(\begin{align*}
\text{(S1)} & \quad \text{Set } i = 0. \\
\text{(S2)} & \quad \text{Obtain two sequences of DCT coefficients } (\tilde{x}_i(m); x_i(m)) (0 \leq m < N' = \frac{N}{2}) \text{ from a set of original signals in the } i\text{-th subblock of an image by using either Method I or Method II of 4.2.} \\
\text{(S3)} & \quad \text{Next, calculate two types of composite signals } g_1(m) = h(\tilde{x}_i(m), a, M, N'); \quad g_2(m) = h(\tilde{x}_i(m), a, M, N'),
\end{align*}\)

where $\tilde{a} = -a$ and $a = \frac{1}{1+a}$ and

$$h(x(m), a', M, N') = \begin{cases} x(m) & (0 \leq m < M), \\
(1 - a')x(m) + a'x(m - M) & (M \leq m < N').\end{cases}$$

\(\begin{align*}
\text{(S4)} & \quad \text{If } i \geq last\_lock \text{ then quit, else go to (S2) after } i = i + 1. \\
\end{align*}\)

♦ Calculation of Cepstral Difference

\(\begin{align*}
\text{(S5)} & \quad \text{Set } i = 0. \\
\text{(S6)} & \quad \text{Calculate the cepstral difference: } d_{pc}^{(i)}(q) = FFT[10 \log_{10} |FFT[x_i(m)]|^2 - FFT[10 \log_{10} |FFT[y_i(m)]|^2|],
\end{align*}\)

where $IFFT[\cdot]$ denotes the $N'$-point inverse FFT, and then $s_1(m)$ and $y_1(m)$ are the weighted versions of $g_1(m)$ and $g_2(m)$, respectively.

(S7) Calculate the extracted sequence: $d(i) = d_{pc}^{(i)}(M) - d_{pc}^{(i)}(0)$, which is used to detect watermarks by means of cross-correlation.

(S8) If $i \geq last\_lock$ then quit, else go to (S6) after $i = i + 1$.

### 4.2. Methods for Obtaining Two Types of Sequences

**Method I**

1) Extract a sequence $x_i(n)(0 \leq n < N_2 = N)$ from a set of original signals in the $i$-th subblock of an image (see Fig. 2).
2) Calculate the $N_2$-point DCT of $x_i(n) : X_i(k) = DCT[x_i(n)] (0 \leq k < N_2)$, and then extract the mid-sequence components: $X_i^{\prime}(k') = X_i(k' + 64)(0 \leq k' < \frac{N_2}{2})$.
3) Divide the above components into two types of sequences: $x_i^{\prime}(m) = X_i^{\prime}(2m); x_i(m) = X_i^{\prime}(2m + 1)(0 \leq m < N' = \frac{N}{2})$.

**Method II**

1) Divide a set of original signals into two types of sequences $(x_0(n'); x_1(n')) (0 \leq n' < N_2 = \frac{N}{2})$ in the $i$-th subblock of an image (see Fig. 3).
2) Calculate the $N_2$-point DCT's of two sequences: $X_0(k') = DCT[x_0(n')]; X_1(k') = DCT[x_1(n')] (0 \leq k' < \frac{N_2}{2})$.
3) Extract the mid-sequence components: $x_i(m) = X_0(m + 32); x_i(m) = X_1(m + 32)(0 \leq m < N' = \frac{N}{2})$.
5. EXPERIMENTAL CONDITIONS

The standard images SIDBA’/’GIRL’ and ’MOON’ ($N \times N = 256 \times 256$ pels, 256 gray levels) are used for our simulation, of which the conditions are summarized as follows.

(1) Ghost-based modulation of M-sequence : In this study, we use M-sequence as watermark information and generate watermarked images by means of the following procedure.

$\{ A_0, A_1, \ldots, A_{N_0-1}, \text{”0’} \}$ (period $N_0 = 256$).

$\{ A_1, \ldots, A_{N_0-1}, \text{”1’} \}$ (period $N_0 = 256$).

(2) The above extended M-sequence is embedded into an original image by using the ghost parameters ($a$, $M$), and then the conversion rule that $a = +a_0$ (binary symbol = “1”), $a = -a_0$ (otherwise), where $0 < a_0 \leq 0.5$, is used sub-block by sub-block at the step (S3) of 4.1.

(3) Cross-correlation function (CCF) : The standard images SIDBA’/’GIRL’ and ’MOON’ ($N \times N = 256 \times 256$ pels, 256 gray levels).

$\text{SNR} = 10 \log_{10}(255^2/\text{MSE dB})$ (7)

where $\text{MSE}$ is the mean square error between the gray levels of original and watermarked images.

(1) AWGN (Additive White Gaussian Noise) test

(2) Clipping test

6. EXPERIMENTAL RESULTS

6.1. Basic Results

(1) Number of errors vs. mixture ratio

Figures 4(a) and (b) show the error properties of watermarked images for “GIRL” and “MOON”, respectively, where Methods I and II denote the processing methods described in 4.2. From Fig. 4(a), it is found that the performance of Method II is superior to that of Method I. From Fig. 4(b), it is found that the performance of Method II is relatively superior to that of Method I when $|\alpha| \geq 0.09$.

Next we examined the lower bound ($\alpha_{th}$) of mixture rate $\alpha$ such that the M-sequence pattern can be detected from the sharp peak of CCF, and it has been confirmed that $\alpha_{th} = 0.05$ (Methods I and II) in Fig. 4. Here we note that the patterns of embedded M-sequence (watermarks) can be estimated by CCF when the number of errors is less than 110 errors (i.e. BER < 43%) [3].

(2) SNR vs. mixture ratio

Figures 5(a) and (b) show the SNR properties of watermarked images for “GIRL” and “MOON”, respectively. From Fig. 5, it is found that the value of SNR in each method decreases as the value of $|\alpha|$ increases.

(3) Watermarked images and their CCFs

Figures 6 and 7 show examples of watermarked images for “GIRL” by means of Methods I and II, respectively, and the corresponding error images are shown in Figs. 8 and 9, respectively. From Figs. 6 and 7, it is found that the degradations in watermarked images are quite invisible since $\text{SNR} > 40 \text{dB}$. From error images (Figs. 8 and 9), we can observe that most image degradations introduced by watermarks are located around edges and in textured areas. Here we note that in the spatial masking areas [8] such as edges and textured areas, the human visual system (HVS) is less sensitive to image degradations than in smooth areas.

Next Figs. 10 and 11 show the CCFs for Figs. 6 and 7, respectively, and it is found that we can sensitively detect the sharp peaks† of Figs. 10 and 11 at the delay $\tau = 0 \text{ or } 256$.

As another example, we also produced the watermarked images (Figs. 12 and 13) for “MOON”. Then it is found that the image degradations in Figs. 12 and 13 are quite invisible, and that we can sensitively detect the peaks of Figs. 16 and 17 at the delay $\tau = 0 \text{ or } 256$.

6.2. Results of Resistance Tests

(1) AWGN (Additive White Gaussian Noise) test

(2) Clipping test

6.2.1. Watermarked images and their CCFs

† By comparing with the previous result [3] in time domain, it is confirmed that the peak value of CCF in Fig. 11 is about two times as much as that of CCF in the previous result, where $M = 2$, $|\alpha| = 0.1$, $\text{SNR} = 40.8 \text{dB}$, because the mixture ratio that $|\alpha| = 0.2$ is used in Fig. 7.
(3) Lossy coding test
Figures 25(a) and (b) show the error properties of compressed images for “GIRL” and “MOON”, respectively, where original watermarked images via Methods I and II are compressed between 0.25[bpp] and 2.0[bpp] by using the JPEG2000 coding. From Fig. 25, it is found that the performance of Method II is relatively superior to that of Method I.

Next Fig. 26 shows an example of JPEG2000-compressed image of Fig. 7, where compression ratio is 1/8, and its error image is shown in Fig. 27. Figure 28 shows the CCF for Fig. 26, and from this figure, it is found that we can still detect the peak of CCF at the delay $\tau = 0$ ($\alpha = 256$).

From the results of previous experiments [4], it has been confirmed that our methods have the resistance to JPEG coding.

7. CONCLUSION
In this paper we have presented oblivious schemes of ghost-based watermarking for DCT coefficients, and then we have examined the fundamental resistance to some attacks. Experimental results for some test images show that the watermark information in each image can be detected sensitively by our schemes even when the watermarked images are subjected to AWGN, clipping and lossy coding. In this paper M-sequences are used as PN sequences, but we can also use Gold sequences [9] to increase the number of sequences. Hereafter we will introduce the Gold sequences in our schemes.

8. REFERENCES
Fig. 6 Watermarked image I \((M = 2, |a| = 0.2, 43.2[dB])\).
Fig. 7 Watermarked image II \((M = 2, |a| = 0.2, 41.4[dB])\).

Fig. 8 Error image \((\times 5)\) for Fig. 6.
Fig. 9 Error image \((\times 5)\) for Fig. 7.

Fig. 10 CCF for Fig. 6.

Fig. 12 Watermarked image I \((M = 2, |a| = 0.2, 42.0[dB])\).
Fig. 13 Watermarked image II \((M = 2, |a| = 0.2, 43.0[dB])\).

Fig. 14 Error image \((\times 5)\) for Fig. 12.
Fig. 15 Error image \((\times 5)\) for Fig. 13.

Fig. 16 CCF for Fig. 12.

Fig. 11 CCF for Fig. 7.

Fig. 17 CCF for Fig. 13.
(a) "GIRL".

(b) "MOON".

Fig. 18 The number of errors vs. mixture ratio $a$ after AWGN-addition ($M = 2, \sigma = 16$).

Fig. 19 AWGN-added version of Fig. 7 ($Method II, \sigma = 16, SNR = 24.1[\mathrm{dB}]$).

Fig. 20 Error image ($\times 5$) for Fig. 19.

Fig. 21 CCF for Fig. 19.
Fig. 22 The number of errors vs. mixture ratio $\alpha$ after clipping ($M = 2, \kappa = 50\%$).

Fig. 23 Clipped version of Fig. 7.

(a) $\kappa = 50\%$, $SNR = 14.1\, dB$.

(b) $\kappa = 75\%$, $SNR = 12.5\, dB$.

Fig. 24 CCFs for clipped images.

(a) CCF for Fig. 23(a).

(b) CCF for Fig. 23(b).
Fig. 25 The number of errors vs. bit rate
\( (M = 2, |a| = 0.2, \text{JPEG2000}) \).

(a) "GIRL".

(b) "MOON".

Fig. 26 Compressed version of Fig. 7
\( (\text{Method II, 1.00 [bpp], 35.9[dB], JPEG2000}) \).

Fig. 27 Error image \((\times 5)\) for Fig. 26.

Fig. 28 CCF for Fig. 26.