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Watermarking for Compressive Sampling Applications

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***Abstract*—Compressive sampling is a newly developed topic in the field of data compression. For current researches, compressive sampling techniques focus on compression performances. There are very few papers aiming at the integration of watermarking into compressive sampling systems. In this paper, we propose an innovative scheme that considers the copyright protection of data with compressive sampling. By carefully utilizing the relationships between coefficients, very few amounts of transmitted coefficients are capable of reconstructing the image to some extent. Moreover, secret information embedded beforehand can be recovered with acceptable rate in correctly extracted bits even experiencing through the lossy channels for data delivery. Simulation results with our algorithm have demonstrated the effectiveness for integrating watermarking into compressive sampling systems.**

Keywords-compressive sampling; watermarking; copyright protection; image quality; robustness

I. INTRODUCTION

Compressive sampling is a newly developed topic in data compression researches. Conventional approaches for sampling the signals follow the Nyquist-Shannon sampling theorem, which requires the sampling rate of more than twice the bandwidth of the signal. Therefore, it comes out an idea about how to select a sampling rate, which is smaller than the Nyquist rate, with the capability of reconstructing the original signal to some extent. By use of compressive sampling, such a goal of choosing a sampling rate less than the Nyquist rate may be achieved, and signals or images can be recovered. Two principles in compressive sampling are the *sparsity*, which pertains to the signals of interest, and the *incoherence*, which relates to the sensing modality [1][2]. They will be addressed in more detail in Sec. II.

Because the topic of compressive sampling has emerged in the last couple of years [3][4][5], researches focused on the reconstruction capability of signals, with the amount of data far less than that of Shannon's theorem expected. Therefore, few papers aiming at compressive sampling with the application to watermarking applications can be looked for in literature [6][7][8][9]. In this paper, we are trying to integrate the watermarking scheme into the compressive sampling system. With the scenario in this paper for transmitting signals after compressive sampling over lossy channels, which is inspired by [10] and [11], the watermark embedded beforehand can be extracted to some degree at the receiver, meaning that the robustness can be retained, hence the copyright of original multimedia content can be protected. Besides, the watermarked image quality, or imperceptibility, with compressive sampling should be acceptable in comparison with relating standard such as JPEG 2000 [12].

This paper is organized as follows. In Sec. II, we present fundamental descriptions of compressive sampling, and relating works that aim at watermarking for compressive sampling application are also addressed. Then, in Sec. III, we present the proposed algorithm that is capable of protecting the copyright of data after compressive sampling and transmitting over lossy channels. Simulation results are demonstrated in Sec. IV, which point out the potential of integrating watermarking into the structure of compressive sampling with the proposed algorithm. Finally, we make the conclusion of this paper in Sec. V.

II. BACKGROUND DESCRIPTIONS OF COMPRESSIVE SAMPLING AND RELATING TOPICS

In this section, we first address the background descriptions of compressive sampling in brief. Then, relating works in literature and their correlation to this paper are also discussed in short. Conventional scheme and corresponding observations can be described as follows.

A. Background Descriptions

Compressive sampling, also named compressed sensing, abbreviated as CS, aims at looking for new sampling scheme that goes against the widely acquainted Nyquist-Shannon theorem. It is composed of the *sparsity* principle, and the *incoherence* principle [1][2].

- For the *sparsity* principle, it relates to the information rate in data compression. In

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compressive sampling, it is expected to be much less than the bandwidth required, and can be represented by the proper basis φ. For the signal $f(t)$, with the orthonormal basis φ, it can be represented by

$$f(t)=\sum_{i=1}^{n} x_i\, \varphi_i(t) \cdot \tag{1}$$

Here, $x_i = \langle f(t), \varphi_i(t)\rangle$ denotes the coefficients of $f(t)$.

From practical applications, taking discrete cosine transform (DCT) or discrete wavelet transform (DWT) for example; very few coefficients of x_i in the frequency domain are able to reconstruct the image in the spatial domain because of sparsity. That is, most coefficients in the frequency domain are small, and remaining ones that are relatively large capture most of the information. If we take the S largest coefficients in absolute value for reconstruction, we obtain the reconstructed image $f_S(t)$ by

$$f_S(t)=\sum_{i=1}^{S} x_i\, \varphi_i(t) \cdot \tag{2}$$

The difference between $f(t)$ and $f_S(t)$ should be small.

- For the *incoherence* principle, it extends the duality between time and frequency. The basis $\boldsymbol{\varphi}$, which acts like noiselet, is employed for sensing the signal $f(t)$. Correlation between φ and $\boldsymbol{\varphi}$ should lie between 1 and $\sqrt{n}$, where n is the number of basis in Eq. (1).

Here, we will utilize the fundamental descriptions of compressive sampling for making the integration of watermarking possible.

B. *Relating Topics in Literature*

There are only a few papers aiming at the combination of compressive sampling and watermarking researches. We are going to make brief discussions here, and make differentiations between our proposed algorithm and those in literature.

In [6], authors proposed an algorithm for image tampering identification and localization with compressive sampling. In [7], authors followed the concept of compressive sampling to conquer the intentional processing of output image with different compression ratios. In [8], authors combined the data encryption method with compressive sampling. Finally, in [9], authors apply compressive sampling to the classification of watermarked and original images. Even though the goals for these and our papers tend to provide copyright protection with compressive sampling, methods in these papers are totally different.

Unlike relating topics in literature above, in this paper, we follow the concepts in [10] and [11] for developing our watermarking algorithm. Data after compressive sampling and watermarking are expected to deliver over lossy channels. At the receiver, embedded secret should be extracted to retain the copyright protection capability. Both robustness and imperceptibility, presented by bit-correct rate (BCR) and peak SNR (PSNR), are taken care of.

III. WATERMARKING FOR COMPRESSIVE SAMPLING

Based on the structure of compressive sampling Fig. 1, with some necessary modifications, watermarking can be integrated into the structure of compressive sampling with the following steps as the preliminary.

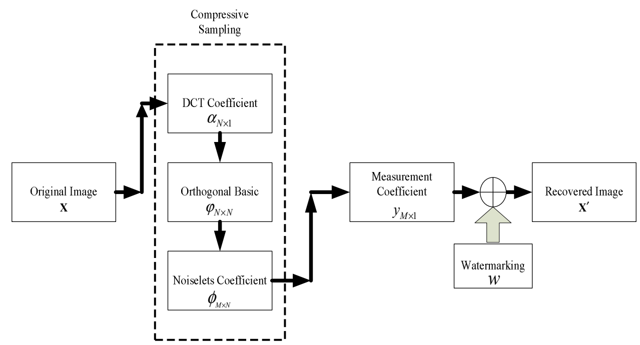

Figure 1. Watermark embedding with compressive sampling.

Step 1. We apply DCT to the original image $\mathbf{X}$, and get the transform coefficient matrix $\boldsymbol{\alpha}$. Both have the size of *N*. For instance, we may turn the 2-D image with the size of 512×512 into the 1-D array with the size of 262144×1.

Step 2. With compressive sampling, relationship between original image and coefficient matrix can be shown with the representation matrix φ in Eq. (3),

$$\mathbf{X}_{N\times 1} = \varphi_{N\times N}\, \boldsymbol{\alpha}_{N\times 1} \cdot \tag{3}$$

Also, the M measurement coefficients, y_i, $1 \le i \le M$, can be gathered together into a vector, which can be represented by Eq. (4) and Eq. (5),

$$y_i = \langle \mathbf{X}, \phi_i \rangle, \quad i = 1, \cdots, M. \tag{4}$$

$$\mathbf{Y}_{M\times 1} = \boldsymbol{\varphi}_{M\times N}\, \mathbf{X}_{N\times 1} \cdot \tag{5}$$

Here, $\boldsymbol{\varphi}$ denotes the sensing matrix. Combining Eq. (3) and Eq. (5), we can obtain

$$\mathbf{Y}_{M\times 1} = \boldsymbol{\varphi}_{M\times N}\, \varphi_{N\times N}\, \boldsymbol{\alpha}_{N\times 1} \cdot \tag{6}$$

Because M implies the number of measurement coefficients, it should be much less than the image size *N*. That is, $M \ll N$. We choose K_1 coefficients in $\boldsymbol{\alpha}$, and K_2 coefficients in φ, with the condition that $K_1 + K_2 = M$. We are going to perform watermark embedding with the diagram in Fig. 1.

A. *Watermark Embedding*

In data embedding, we group the elements in $\mathbf{Y}$ into non-overlapping pairs. For simplicity, we suppose that K_1 is an even number. The even-numbered coefficients may be changed due to data embedding,

$$y'_{2m} = \begin{cases} y_{2m-1} + w, & \text{if } |y_{2m} - y_{2m-1}| < T_E; \\ y_{2m}, & \text{otherwise.} \end{cases} \tag{7}$$

Here, $m = 1, 2, \cdots, \frac{1}{2}K_1$, w denotes the secret bit with the value of 0 or 1, and T_E is the threshold value for data embedding. If T_E is too small, fewer secret bits can be embedded and they might be extracted in error due to lossy transmission. On the contrary, if T_E is too large, the error induced due to embedding may also increase accordingly, which would deteriorate the output image quality. Therefore, the value of T_E should be carefully chosen. After data embedding, the watermarked image $\mathbf{X}'$ can be produced.

B. Data Transmission

The watermarked image $\mathbf{X}'$ at the output of Fig. 1 is expected to transmit over lossy channels. In our simulations, coefficients are randomly dropped, which is similar to the schemes in [10] and [11], and received image at the decoder is denoted by $\mathbf{X}''$ in Fig. 2.

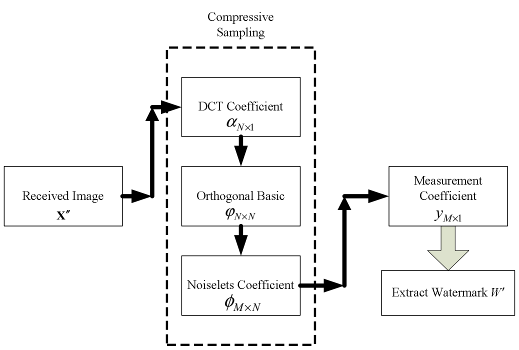

Figure 2. Watermark embedding with compressive sampling.

C. Watermark Extraction

For the extraction of embedded watermark, let the extracted watermark be w', and the one of the following conditions can be met in Eq. (8).

$$w' = \begin{cases} 0, & \text{if } \left|y'_{2m} - y'_{2m-1}\right| < T_{D1}; \\ 1, & \text{if } T_{D1} \le \left|y'_{2m} - y'_{2m-1}\right| < T_{D2}; \\ \text{undefined}, & \text{otherwise.} \end{cases} \tag{8}$$

Here, corresponding to the embedding procedure, in the received image, after performing compressive sampling, two neighboring coefficients are grouped as a pair. We first set the two thresholds for decoding, T_{D1} and T_{D2}, with the condition that $0 < T_{D1} < T_{D2}$. If the difference between the pair of coefficients is small, the extracted watermark bit is set to '0'. Then, when the difference grows larger, the watermark bit is set to '1'. Finally, if the difference is too large, no watermark bit should be extracted because such a pair might not be used for embedding, or the coefficient values might be influenced by the lossy channel.

IV. SIMULATION RESULTS

In our simulations, we fix two sets of number of coefficients with $(K_1, K_2) = (2000, 40000)$ and $(1000, 20000)$, and change the embedding threshold T_E. Here, the K_1 coefficients correspond to the candidates of data embedding.

(a) Recovered Lena with 2000 compressive sampling coefficients, PSNR = 32.81 dB. Image size is 512x512.

(b) Recovered Lena with compressive sampling and, 571 bits embedded, PSNR = 29.47 dB.

(c) JPEG2000-compressed image with the same compression ratio of 131 times. PSNR = 28.16 dB.

Figure 3. Watermarking with compressive sampling for the test image `Lena`. 2000 coeffieicnts are selected for reconstruction of image.

TABLE I. COMPARISONS OF EMBEDDING CAPACITY AND OUTPUT IMAGE QUALITY BY VARYING EMBEDDING THRESHOLD. K_1 AND K_2 ARE 2000 AND 40000, RESPECTIVELY.

T_E	Capacity (bit)	Selection rate (%)	PSNR (dB)
0	0	0.00	32.81
200	571	57.10	29.47
250	652	65.20	28.23
350	747	74.70	26.47

TABLE II. COMPARISONS OF ROBUSTNESS BY VARYING LOSSY RATES. CORRESPONDING TO TABLE I.

(T_{D1}, T_{D2})	Lossy rate	BCR (%)
$(1, 3)$	0%	74.43
	20%	66.48
	25%	64.16
	30%	61.52

TABLE III. COMPARISONS OF EMBEDDING CAPACITY AND OUTPUT IMAGE QUALITY BY VARYING EMBEDDING THRESHOLD. K_1 AND K_2 ARE 1000 AND 20000, RESPECTIVELY.

T_E	Capacity (bit)	Selection rate (%)	PSNR (dB)
0	0	0.00	30.04
200	218	43.60	28.97
250	252	50.40	28.48
350	305	61.00	27.39

TABLE IV. COMPARISONS OF ROBUSTNESS BY VARYING LOSSY RATES CORRESPONDING TO TABLE III.

(T_{D1}, T_{D2})	Lossy rate	BCR (%)
$(1, 3)$	0%	70.64
	20%	61.69
	25%	62.86
	30%	65.32

Output image qualities can be observed from Figs. 3(a) and 3(b) for subjective evaluations, and Tables I for objective assessments. For the better evaluation, we use JPEG 2000 with the same compression ratio of 131 (or 262144 : 2000) in Fig. 3(c) for comparisons. Also, the selection rate denotes the ratio between the numbers of secret bits to the number of pairs for embedding in Eq. (7). By increasing T_E, more capacity can be embedded, with degraded output image quality. Similar results can be observed in Table III. However, fewer selection rate and inferior image quality for $K_1 = 1000$ in Table III is presented due to the less coefficients for selection.

We can also check robustness of extracted watermarks in Tables II and IV. We can observe from Eq. (7) that the even-numbered coefficients y'_{2m} after data embedding should be close to the odd-numbered reference y_{2m-1}. Thus, we set $T_{D1} = 1$ and $T_{D2} = 3$ for watermark extraction in Eq. (8). With the increase in lossy rates, the bit-correct rates (BCR) decrease accordingly. BCR values are the average over twenty simulations. Comparing between the results in Table II and Table IV, we observe the better performance with those in Table II. It might be because the more selection of coefficients for embedding, and the fewer possibility for erroneous extraction of output secret bits. Coefficients from noiselets, or K_2, may hardly be helpful for data extraction.

V. CONCLUSIONS

In this paper, we proposed the new application for compressive sampling with watermarking. Very few coefficients at the encoder are delivered to the decoder, and data loss may be expected during transmission. We incorporate the concept of compressive sampling and the implementation of watermarking, and propose an effective means for retaining the ownership of data after compressive sampling. Simulation results reveal that the reconstructed image at the decoder is reasonable even very few coefficients are received. Furthermore, embedded watermark can be recognizable even when the coefficients experience the data loss through the delivery channels. We point out this new, possible application for watermarking with compressive sampling, and further extensions and open issues may be explored in the future.

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