Watermark Detection in Impulsive Noise Environment Based on the Compressive Sensing Reconstruction

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Abstract. *The watermark detection procedure for images corrupted by impulsive noise is proposed. The procedure is based on the compressive sensing (CS) method for the reconstruction of corrupted pixels. It is shown that the proposed procedure can extract watermark with a moderate impulsive noise level. It is well known that most of the images are approximately sparse in the 2D DCT domain. Moreover, we can force sparsity in the watermarking procedure and obtain almost strictly sparse image as a desirable input to the CS based reconstruction algorithms. Compared to the state-of-the-art methods for impulse noise removal, the proposed solution provides much better performance in watermark extraction.*

Keywords

Image Watermarking, Impulsive noise, Compressive sensing, Sparse reconstruction, Gradient algorithm

1. Introduction

Digital watermarking techniques are introduced to protect digital multimedia content mostly in the sense of authorship protection, authentication or integrity protection [1, 2, 3]. Generally, watermarking is implemented by inserting a certain sequence (watermark) to the existing digital content.

The sequence is embedded in spatial or some transformation domain like the discrete cosine transform (DCT) [1, 3], the discrete wavelet transform (DWT) [1, 4], time-frequency or space/spatial-frequency transformation [1, 2, 5]. When considering invisible and robust watermarking scenario, it has been shown that the transform domain based approaches overcome the performance of time or spatial domain techniques. Embedding another image (logo image) into the original one is a special case of the watermarking.

If the watermarked image is corrupted by the impulsive noise the watermark detection is deteriorated. For instance, using median filtering as a common method for removing impulse noise will completely degrade (or remove) the water-

mark. Some recently developed denoising techniques [6, 7] restore high-quality images even with a high noise level.

An efficient two stage adaptive method for restoration of images corrupted by impulse noise is proposed in [6]. Therein, the restoration is based on the mean value of the neighboring uncorrupted pixels, showing improved performance comparing with the other state-of-the-art techniques. Another interesting approch presented in [7] is based on adaptive median filtering and block matching and 3D filtering (BM3D) scheme. All of these methods provide high structural similarity index (SSIM) and good peak signal-to-noise ratio (PSNR), between the non-noisy and reconstructed image, but still the embedded watermark cannot be recovered from the resulting image even when the low noise intensity is applied at the input.

In this paper, we propose a procedure for watermark detection from the corrupted images. The procedure is based on the compressive sensing (CS) [8, 9] reconstruction algorithms. Namely, by exploiting the image sparsity property and the advantages of CS reconstruction approach, it is possible to achieve high watermark detectability beside the high quality of restored image. Unlike the classical restoration techniques that are mainly based on a certain kind of interpolation (filtering) thus dealing with small interpolation errors, the CS-based algorithms are able to restore the exact values of corrupted pixels under some conditions. Here, we employ the recently proposed gradient descent reconstruction algorithm [10, 11], while the sparsity is enforced in the 2D DCT domain.

We will assume that the corrupted pixels positions are known. In the case of impulsive noise, the corrupted pixels can be detected by using statistical tools. Moreover, recent research shows that corrupted pixels can be accurately detected by examining sparsity measure [13].

The presented approach could be extended to other sparsity domains like the discrete Fourier domain or wavelet domain. Generally speaking, any linear transform of an image that satisfies the sparsity property can be applied following the same principles as in the case of the DCT. However, the watermark insertion, image reconstruction, and water-

mark detection procedures should be adapted to the specific transform domain, since different domains have their own properties. The 2D DCT is considered here as the most commonly used domain in image analysis and definitely one of the widely explored in watermarking applications.

The main contribution of the paper is the improvement of watermark detection in the case of heavy impulse noise. The robustness to other common attacks has not been changed with the proposed detection procedure compared to the standard 2D DCT watermarking. Particularly, the DCT based watermarking is generally robust to JPEG compression, especially if the watermark is inserted in lower bit planes. In the case of rotation attack, the DCT-based approaches cannot retrieve the watermark without additional patterns used for the inverse transform. Finally, instead of filtering (e.g. median filtering procedure), here we propose to use a total reconstruction approach providing the improvement of results.

The paper is structured as follows. In Section 2 a brief theoretical introduction to the CS reconstruction is given. The proposed method is introduced in Section 3. The examples and statistical analysis are presented in Section 4.

2. CS theory and reconstruction

The signal is sparse if the number of its non-zero values K in a certain representation domain is much smaller than a total number of signal values N. Sparse signal vector will be denoted by $\mathbf{X}$. The signal is measured and M observed measurements are expressed as a linear combination of coefficients in $\mathbf{X}$. Measurements are stored in vector $\mathbf{y}$. Relation between measurements and sparse coefficients is

$$\mathbf{y} = \mathbf{AX} \tag{1}$$

where $\mathbf{A}$ is an $M \times N$ measurement matrix.

It is shown that, under some conditions [8, 9], sparse signal $\mathbf{X}$ can be uniquely reconstructed from the available measurements. This is classical CS reconstruction problem that can be formulated as a following minimization problem

$$\min \|\mathbf{X}\|_0 \quad \text{subject to } \mathbf{y} = \mathbf{AX} \tag{2}$$

where $\|\mathbf{X}\|_0$ denotes the number of non-zero coefficients in $\mathbf{X}$, and it is called ℓ_0 pseudo-norm (or ℓ_0 norm) although it does not satisfy basic norm properties.

Minimization procedure can be performed by using a direct search procedure assuming that at most K coefficients in $\mathbf{X}$ are nonzero and analyzing all possible positions of these coefficients. If there is only one combination satisfying the constraint, then the reconstruction problem is solved and a solution is unique. This approach is not computationally feasible since the total number of combinations $\binom{N}{K}$ is too large.

Another approach is to formulate minimization problem

in a convex form. The ℓ_1 norm is a closest convex approximation of the ℓ_0 pseudo-norm. The problem formulation becomes

$$\min \|\mathbf{X}\|_1 \quad \text{subject to } \mathbf{y} = \mathbf{AX}. \tag{3}$$

It is shown that, under some conditions, problem (3) have the same solution as (2) [8, 9]. There are several reconstruction techniques that have been developed for different scenarios [14, 15, 10, 11]. Without loss of generality, we will use recently proposed gradient-based reconstruction method [10, 11]. This method does not change values of the available samples (pixels) and use finite approximation of the sparsity measure gradient for correction of the corrupted samples. The gradient approximation is obtained by varying current value of each corrupted sample by adding and subtracting some finite value Δ. The algorithm performance is fast, provides accurate solution and does not assume the strict sparsity constraint, which is highly important in practical applications.

It is known that most real-word images are sparse (or approximately sparse) in the 2D DCT domain [2, 13]. The image pixels can be considered as measurements of the 2D DCT of the image. In this case complete (full) set of measurements is well defined (all image pixels form a full set of measurements). If some pixels are missing or corrupted, we are dealing with the reduced set of measurements and CS reconstruction techniques could be applied in order to reconstruct missing (corrupted) pixels.

Since the image, and the corresponding 2D DCT, are two-dimensional signals they should be rearranged in a vector form in order to reduce pixel reconstruction to formulation (3). The measurement vector $\mathbf{X}$ is obtained by stacking 2D DCT columns, and measurement matrix $\mathbf{A}$ is obtained from the corresponding 2D DCT weighting coefficients. The measurements vector $\mathbf{y}$ contains values of all available (uncorrupted) image pixels.

3. Proposed watermarking method

3.1 Watermarking procedure

The original image is divided into $B \times B$ blocks, where B is block size. The 2D DCT is calculated for each block. A set of coefficients suitable for watermark embedding is selected. The watermark sequence is then embedded into a given bit-plane of the selected 2D DCT coefficients.

For coefficients selection we define a binary matrix $\mathbf{R}$ of order $B \times B$, with the coefficients given by

$$R_{i,j} = \begin{cases} 1 & \text{for } d_1 \le i + j - 1 \le d_2 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

for $i, j = 1, 2, \ldots, B$, where d_1 and d_2 are starting and ending anti-diagonal filled with ones in matrix $\mathbf{R}$. The coefficient selection matrix aims to avoid low and high frequency parts

of the 2D DCT block. Therefore the number of selected coefficients N_{sel} is

$$N_{sel} = \sum_{k=d_1}^{d_2} \min\{k, 2B - k\} \qquad (5)$$

where the number of elements on the k-th anti-diagonal of matrix $\mathbf{R}$ is $\min\{k, 2B - k\}$ for $k = 1, 2, \ldots, 2B - 1$. As a illustration, for the block size 4×4, $d_1 = 3$ and $d_2 = 4$ the selection matrix is

$$\mathbf{R} = \begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \qquad (6)$$

with 7 selected coefficients out of 16 coefficients in total.

The coefficients selection procedure is repeated for each block resulting in a set of the coefficients that will be used for watermarking.

The watermark is inserted in the bit-plane b of the selected coefficients by replacing b-th bit of each coefficient with corresponding watermark bit [2, pp.205–210]. Namely, the watermark is a binary sequence and could also represent a logo image. The total length of watermark should not exceed a total number of the selected coefficients in all blocks. If the total number of selected coefficients is higher than the watermark length, the watermark is repeated to cover all selected coefficients.

The strict sparsity property is preferable for the exact CS reconstruction of corrupted pixels. Prior to the watermark embedding, we can sparsify 2D DCT of each block by setting coefficients below some predefined threshold T to 0. This is a small but important modification of the classical watermark insertion scheme [2]. The threshold T should be set in a way to avoid significant image degradation. Also, the sparsity can be enhanced by applying image compression to neglect certain 2D DCT values, as in the case of JPEG compression algorithm.

Watermarked image is obtained by applying inverse 2D DCT on each block. The watermark insertion procedure is described in Algorithm 1.

3.2 Watermark detection

It is possible that some pixels of the watermarked image are corrupted. The corrupted pixels can significantly degrade watermark detection, especially when the watermarking is performed in the transformation domain. Two common noise types are Gaussian and impulse noise. Impulse noise can appear in the watermarked image as a consequence of channel transmission errors via noisy communication channels or due to memory cell faults in digital image storage [2, pp. 174–175], [12, pp. 435–439]. One of the frequently analyzed cases of impulse noise is salt & pepper noise. In this case, some randomly positioned pixels are changed to black (value 0) or white (value 255 for 8-bit gray-scale image). The

corrupted pixels can be easily detected in this case. Recent research [13] propose CS based technique for corrupted pixels detection within a full range of pixel values (from 0 to 255 for 8-bit images).

Algorithm 1 Watermark insertion procedure

Input:
- Original image $\mathbf{s}$
- Block size B, threshold T, selection matrix $\mathbf{R}$
- Bit-plane b for watermark insertion
- Watermarking sequence $\mathbf{w}$

1: Calculate block 2D DCT of the input image with block size $B \times B$
2: Set all 2D DCT coefficients with amplitude below threshold T to 0.
3: Select coefficients for watermarking by using selection matrix $\mathbf{R}$.
4: Insert watermarking sequence $\mathbf{w}$ into bit-plane b of the selected coefficients (in all blocks) by replacing actual bits with watermark sequence bits
5: Calculate inverse block 2D DCT

Output:
- Watermarked image $\mathbf{s}_w$

Algorithm 2 Watermark detection procedure

Input:
- Corrupted watermarked image $\mathbf{s}_{wc}$
- Block size B, watermark bit-plane b, selection matrix $\mathbf{R}$

1: **for all** $B \times B$ image blocks **do**
2:     Find set of corrupted pixels $\mathbb{N}_c$
3:     Reconstruct corrupted pixels by using CS reconstruction
4: **end for**
5: Calculate block 2D DCT of the reconstructed image with block size $B \times B$
6: Select coefficients where the watermark is inserted by using selection matrix $\mathbf{R}$
7: Extract bit-plane b form the selected coefficients into watermark sequence $\mathbf{w}_d$

Output:
- Extracted watermark sequence $\mathbf{w}_d$
- Reconstructed image $\mathbf{s}_r$

If the watermarked image is corrupted with impulsive noise, image restoration should be applied prior to watermark extraction. Here we will use the CS based procedure for reconstruction of the missing pixels pro-

posed in [10, 11]. The reconstruction code is available at `http://www.tfsa.ac.me/pap/sup-001179.zip`.

In the first stage, for each $B \times B$ block, the set of corrupted pixels within selected block is estimated. Then, the CS reconstruction procedure is applied.

After image restoration, the watermark sequence is extracted as b-th bit-plane of the selected 2D DCT coefficients [2]. If the number of selected coefficients is higher than watermark length, several copies of watermark sequence are obtained.

The image restoration and watermark detection procedure are described in Algorithm 2.

3.3 Performance measures

Since image reconstruction is performed prior to watermark detection we will use peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) as performance measures. For $N \times M$ images $\mathbf{s}_w$ and $\mathbf{s}_r$ the PSNR is defined as

$$\text{PSNR} = 10 \log_{10} \frac{255^2}{\frac{1}{NM} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[s_w(i,j) - s_r(i,j) \right]^2}. \quad (7)$$

The SSIM is proposed in [16] as universal image quality index used to measure the similarity between two images. It is based on means, variances, and covariance of the corresponding images. The SSIM take values from 0 to 1, where 1 means that there is no difference between compared images.

Watermark detection quality is measured using the error-bit-rate (EBR). It is the ratio between the number of wrongly detected bits and the total number of bits in the watermark sequence. For binary watermark sequence $\mathbf{w}$ of length N_w and detected watermark sequence $\mathbf{w}_d$ it is calculated (in percents) as

$$\text{EBR} = 100 \frac{\sum_{i=1}^{N_w} |w(i) - w_d(i)|}{N_w}. \quad (8)$$

4. Examples

The proposed procedure is applied to 512×512 8-bit gray-scale image "Lena". The chosen watermarking image is 1-bit 26×10 image "LOGO". The proposed watermarking procedure is applied with block size $B = 32$, threshold $T = 40$ and third bit-plane ($b = 3$) is used for watermark embedding. The original, watermarked, and logo image are presented in Fig. 1. The PSNR in the watermarked image $\mathbf{s}_w$ is 31.1 dB (with original image $\mathbf{s}$ as reference) and SSIM is 0.815.

The watermarked image is corrupted with salt & pepper noise. Noise intensity is 6% for upper subplots in Fig. 2 and 20% for lower subplots in Fig. 2. Corrupted images are presented in the first column of Fig. 2. The detected watermark image is presented in all cases. We can see that watermark detection from the corrupted images is not possible.

Next, we apply restoration method presented in [6]. For 6% noise level, the PSNR in the reconstructed image $\mathbf{s}_r$ is 48.4 dB (with uncorrupted watermarked image $\mathbf{s}_w$ as reference). Corresponding SSIM is 0.9976. For 20% noise level, the PSNR of 42.5 dB and SSIM 0.9914 are obtained. This method achieves high PSNR and SSIM, so the reconstructed images (second column in Fig. 2) quality is good. However, when we try do detect the watermark, for 6% corrupted pixels we obtain "LOGO" image with some wrong pixels. In the case of 20% corruption, the watermark detection is not possible.
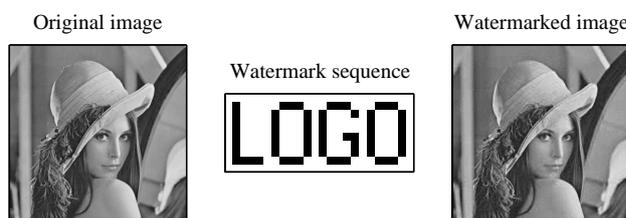

Figure 1. Watermark detection example. Original image (512 × 512), enlarged logo image (26 × 10) and watermarked image are presented.
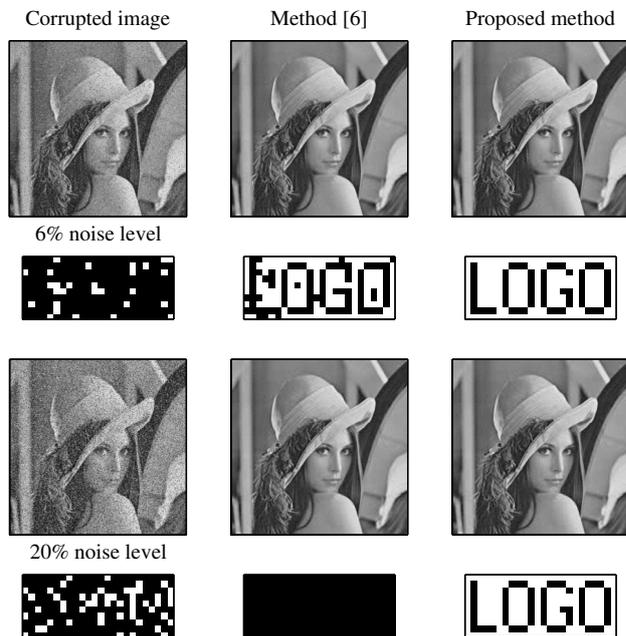

Figure 2. Watermark detection from the image corrupted by salt & pepper noise with 6% and 20% of corrupted pixels. The detection results for noisy image are presented in the first column, the results with restoration proposed in [6] are in the second column and the results obtained by the proposed method are in the third column. The detected LOGO sequences are given below images.

The method proposed in this paper include CS based reconstruction of the corrupted pixels. The reconstructed images are presented in Fig. 2, the third column. The achieved

PSNR is 65.0 dB ans SSIM 0.9998 for 6% corrupted pixels. For 20% corrupted pixels the PSNR is 59.3 dB and SSIM is 0.9994. That is significantly better than reconstruction method [6]. We can see that in both cases we detect the watermark with no errors.

In the next experiment, we vary noise intensity from 1% to 50%. Image "Lena" is used here and the watermarking sequence was randomly generated 26×10 1-bit image. The PSNR and SSIM are used as a measure of the reconstruction quality. The EBR in the detected watermark is used as a measure of detection quality. The results are presented in Table 1 and Fig. 3. The mean value of EBR, PSNR, and SSIM over 20 random realizations of watermark sequence and noise are presented in Table 1. The mean value and standard deviation of the EBR are plotted in Fig. 3. We can see that the proposed technique achieves better EBR, PSNR, and SSIM compared to [6]. The watermark can be successfully detected for noise level up to 25% while, the restoration method proposed in [6] fails to detect watermark for noise level above 9%.

Table 1. Watermark detection and image reconstruction results. Error bit rate in the detected watermark, PSNR, and SSIM for reconstructed images is given for various noise levels.
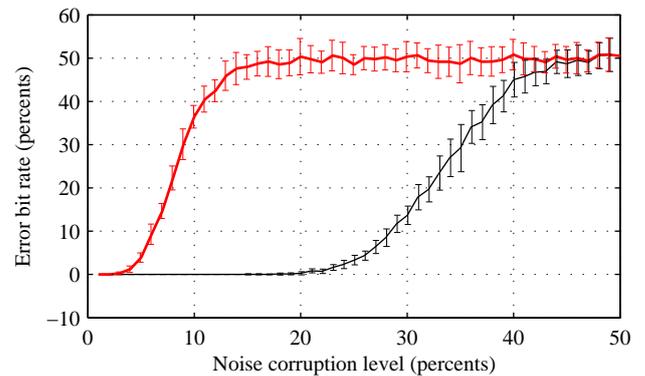
Noise level	Proposed method			Method in [6]		
	EBR	PSNR	SSIM	EBR	PSNR	SSIM
1%	0.00	73.03	1.0000	0.00	56.41	0.9996
2%	0.00	70.05	0.9999	0.00	53.28	0.9993
3%	0.00	68.32	0.9999	0.27	51.50	0.9989
4%	0.00	66.95	0.9999	1.23	50.20	0.9985
5%	0.00	66.01	0.9999	3.92	49.22	0.9981
6%	0.00	65.22	0.9998	9.31	48.32	0.9978
7%	0.00	64.56	0.9998	14.69	47.65	0.9974
8%	0.00	63.94	0.9998	22.31	47.04	0.9970
9%	0.00	63.39	0.9998	30.10	46.46	0.9966
10%	0.00	62.93	0.9997	36.46	45.92	0.9961
15%	0.04	61.10	0.9996	47.96	44.03	0.9941
20%	0.29	59.69	0.9995	50.35	42.55	0.9917
25%	3.31	58.60	0.9993	48.48	41.29	0.9890
30%	13.67	57.57	0.9991	50.33	39.89	0.9853
35%	29.21	56.57	0.9989	48.71	38.39	0.9802
40%	45.02	55.56	0.9987	50.79	36.25	0.9695
45%	48.69	54.64	0.9984	49.63	34.09	0.9510
50%	50.48	53.17	0.9979	50.48	33.76	0.9434

The proposed procedure is statistically tested on 49 standard test images (available online at `http://descai.ugr.es/cvg/CG/base.htm`). The results obtained with test images 1–25 are given in Table 2. Noise intensity was 20%. We can see that the proposed technique provide EBR below 10% in all presented cases, while for most images the EBR is 0.

5. Conclusion

Watermark detection form the images corrupted by impulsive noise is analyzed. It is shown that state-of-the-art reconstruction methods could not be applied when the noise level is high. Although the reconstructed images visual quality is high, the watermark is significantly degraded by filtering. The proposed technique is based on the CS reconstruction of the corrupted pixels. It is demonstrated on examples and tested on standard test images database. It is shown that the proposed technique is able to extract watermark even from heavily corrupted images (with up to 25% of corrupted pixels).

Figure 3. Error bit rate for varying noise corruption level. Proposed method – thin black line, method [6] – thick red line. The results are obtained by averaging over 20 realizations. Standard deviation is calculated and presented with vertical bars.

Table 2. Results obtained for 20% corrupted pixels for standard gray-scale test images database

Test image	Proposed method			Method in [6]		
	EBR	PSNR	SSIM	EBR	PSNR	SSIM
#1	0.00	59.29	0.9996	46.25	31.95	0.9682
#2	0.00	59.48	0.9995	52.50	41.13	0.9864
#3	0.00	56.98	0.9994	47.08	36.58	0.9755
#4	0.00	59.29	0.9995	54.17	42.75	0.9882
#5	0.00	59.48	0.9995	42.50	44.66	0.9924
#6	0.00	56.61	0.9994	50.00	36.10	0.9739
#7	0.00	48.51	0.9994	50.00	28.10	0.9585
#8	1.67	60.03	0.9995	47.92	42.61	0.9905
#9	0.00	55.94	0.9994	60.00	33.45	0.9757
#10	0.83	59.87	0.9995	47.08	38.65	0.9898
#11	0.00	45.15	0.9985	52.08	25.94	0.9299
#12	0.00	54.74	0.9992	55.00	35.16	0.9674
#13	0.00	59.10	0.9996	45.83	36.49	0.9846
#14	0.00	52.68	0.9997	45.42	30.12	0.9539
#15	0.00	56.55	0.9996	52.92	34.15	0.9717
#16	0.00	54.27	0.9995	50.42	32.62	0.9579
#17	0.00	55.17	0.9994	45.00	31.10	0.9533
#18	0.00	45.99	0.9989	44.17	28.09	0.9417
#19	0.00	56.81	0.9994	42.92	37.02	0.9783
#20	0.00	58.85	0.9996	42.50	37.37	0.9795
#21	2.92	60.00	0.9995	50.83	39.38	0.9842
#22	0.83	53.84	0.9995	49.17	33.55	0.9742
#23	5.00	60.25	0.9994	50.42	44.46	0.9925
#24	2.50	60.03	0.9995	43.75	42.24	0.9890
#25	9.17	59.42	0.9993	48.33	43.59	0.9878

Acknowledgments

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