Logo Watermarking for Image Protection in the Compressive sensing Scenario

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***Abstract* — The analysis of logo embedding based watermarking procedure in the presence of compressive sensing scenario is examined in this paper. The compressive sensed image is represented by a set of available coefficients, which are used for logo embedding using the image bit-planes modification. After the logo embedding and detection procedure are defined for the available CS measurements, the new type of watermarking attack is introduced. The watermarking attack also uses the CS concept to regenerate reconstructed image, with the aim to deteriorate logo during the image reconstruction process. The achieved results shown that the logo can be still detectable under the CS attack although it is significantly affected.**

***Keywords* — compressive sensing, measurements, watermarking, logo embedding,**

I. Introduction

Digital watermarking has been widely used for the protection of digital data [1]-[4]. Various methods for protection of different types of signal have been developed in recent years. Watermarking is shown to be efficient in image and audio protection, video applications, etc. [5]-[12]. Watermarking procedure consists of watermark embedding and watermark detection. Embedding could be done in time, frequency or time-frequency domain [9]-[11]. The watermark detection procedure is based on measuring responses of various watermarking detectors, or, by perceptually observing the extracted signal.

Watermark could be created as pseudo random sequence, or it can be formed as an image, such as logo image. In order to prove the ownership, owner of the digital material should be able to extract watermark form the signal. Extraction is successful, i.e., the ownership is proved, if the detector response is large enough or extracted image is of satisfactory quality if the watermark is embedded in the logo form. Important properties that watermark should satisfy are imperceptibility and robustness to various attacks.

In the recent years, a widely studied field within the signal processing is the Compressive Sensing (CS) theory [13]-[18]. CS allows signal to be sampled at the rate far lower than traditional, Nyquist-based sampling. Having just small set of signal samples, original signal can be reconstructed by using powerful mathematical algorithms for optimization. CS requires signal to satisfy a priori defined conditions in order to be applied. Also, acquisition procedure should be defined in a way that provides successful signal reconstruction from small set of available signal samples.

In this paper we consider the logo based image watermarking procedure as well as the CS as attack on the watermarked image. Namely, the logo is embedded into DCT image coefficients that correspond to the available CS measurements. Then the logo extraction procedure is defined in a reverse manner. The binary logo is embedded and extracted form several specific bit-planes of the image. Bit planes are chosen such that avoids watermark to be visible in the image. Also, the influence of the new type of attack based on the CS scenario (so called CS attack) is analyzed, showing that it may severely degrade the embedded logo but it remains still readable.

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II. Compressive Sensing Reconstruction of Images Using TV-Minimization Approach

The Shannon-Nyquist sampling theorem states that the signal can be exactly reconstructed from its samples, when the sampling rate is at least twice the maximal signal frequency. This may result in a large number of samples, and consequently, different compression algorithms have been used to efficiently store or transmit the data. Compressive sensing has been introduced in signal processing application as a new sampling approach providing exact signal reconstruction using much fewer samples than that required by the standard sampling theory [13]-[18]. It deals with the signals which are sparse in a certain transform domain, which means that the signals can be represented by a small number of important coefficients when expressed in appropriate basis. For a signal that can be represented using K nonzero coefficients in the transform domain, we may say that it is K-sparse. Such signal can be reconstructed using small set of M measurements out of N, as long as $M>K$ holds. The measurements are randomly acquired resulting in a certain measurement vector:

$$y = \Phi x, \tag{1}$$

where matrix Φ is used to model the random measurement process. Since the original signal x can be expressed in certain basis Ψ (where the signal is sparse), then we can write:

$$y = \Phi x = \Phi\Psi X \, , \tag{2}$$

where X is a full length transform domain vector. The previous relation represents the system of M equations with N unknowns. Since $M<<N$ the system in undetermined and has infinite number of solutions. The solution of this problem could be to exploit the sparsity property and thus to search for the sparsest solution [15]:

$$\widehat{X} = \min \|X\|_{\ell_0} \;\; subject\ to \;\; y = \Phi\Psi X, \tag{3}$$

where $\widehat{X}$ is a solution of the minimization problem. However, solving the ℓ_0 minimization programme is an NP-complete problem which is not suitable in practical applications. Thus instead of ℓ_0 norm, in practice we might use the ℓ_1 norm:

$$\widehat{X} = \min \|X\|_{\ell_1} \;\; subject\ to \;\; y = \Phi\Psi X \, . \tag{4}$$

A. TV minimization algorithm

For two-dimensional signals such as images, which are not strictly sparse in any domain, we may use an alternative recovery method based on fact that the image gradient is sparse. A commonly used approach is based on the total-variation (TV) of an image, which has been used in image in denoising applications, image restoration, etc. [19].

Consider a linear observation model in the form:

$$y = \theta s + w \, , \tag{5}$$

where y denote observations, θ is observation matrix, s denotes signal values and w is additive noise. Signal s can be recovered using relation:

$$\hat{s} = \arg\min_{s} \gamma(s) \, , \tag{6}$$

where:

$$\gamma(s) = \|y - \theta s\|^2 + \varepsilon TV(s) \, , \tag{7}$$

holds and ε is regularization term. TV of the signal s is sum of the gradient magnitudes at each point and can be written as:

$$TV(s) = \sum_{i,j} \|\nabla_{i,j} s\|_{\ell_2} \, , \tag{8}$$

where ∇ denotes differentiation operator. At the pixel position (i,j) we can write:

$$\nabla_{i,j} s = \begin{bmatrix} s(i+1,j) - s(i,j) \\ s(i,j+1) - s(i,j) \end{bmatrix} . \tag{9}$$

In the discrete form, TV can be defined as follows:

$$TV(s) = \sum_{i,j} \sqrt{(\nabla_s^h)^2 + (\nabla_s^v)^2} \, , \tag{10}$$

where:

$$\nabla_s^h = s_{i+1,j} - s_{i,j} \, ,$$
$$\nabla_s^v = s_{i,j+1} - s_{i,j} \, , \tag{11}$$

denote row and column differences, respectively. The equality constrained TV minimization problem for a measurements vector y and a sparse vector of transform domain coefficients s can be defined as follows:

$$\min_{s} \; TV(s) \;\; s.t. \;\; y = \theta s \tag{12}$$

It can be recast as the second-order cone problem:

$$\min_{t,s} \sum_{i,j} t_{ij} \quad s.t. \;\; \|\nabla_{ij} s\|_{l_2} \le t_{ij}$$
$$y = \theta s, \tag{13}$$

which can be solved using the second-order cone programming based on the log-barrier method.

III. WATERMARKING BASED ON LOGO EMBEDDING PROCEDURE

A. The procedure for logo embedding

In this section we present the procedure for logo embedding in the DCT domain. Note that only a certain set of CS measurements is available as imposed by the CS scenario. The available DCT image coefficients in both scenarios will be denoted as C. In order to provide robustness of the proposed method, logo is created as a binary image that will be spread in several bit planes of the image coefficients. Since the logo is a 2D signal, we will observe it as a square matrix of size $P \times P$ with binary coefficients. Similarly, we need to select from C a random subset C_P of length P^2 that will be used for logo embedding. The coefficients from the subset C_P selected for logo embedding are further rearranged into the square matrix of the same size as logo, while each coefficient is represented using constant number of B bits.

A few bit planes form P (from B available bit-planes) are considered for logo embedding. It is recommendable to use middle level bit-planes to avoid the influence on the signal quality, but on the other side to provide certain robustness since it is known that watermark from the least significant bit-planes could be easily removed.

An important issue in logo watermarking applications is security, which is here provided on several levels. Firstly, the logo is divided by using a unique security key. Namely, a unique random matrix is used to divide logo into b layers, which will be embedded in the b image bit-planes, similarly as it was done in [6]. Each layer contains unique positions, such that the composition of all layers provides the complete logo. An illustration is shown in Fig. 1.

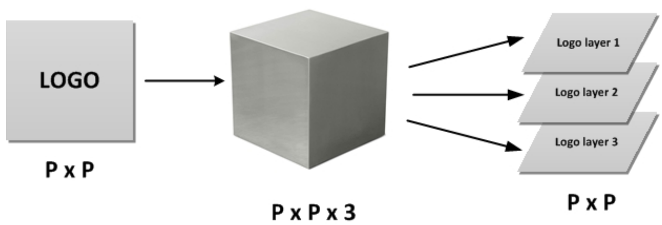


Fig. 1. Logo decomposition process

The logo is divided into layers according to:

$$L_k(i,j) = L(i,j) \;\; for \;\; \omega_{k-1} < \Re(i,j) < \omega_k$$
$$k = 1,2\ldots,b \;;\; i = 1,2\ldots P \;;\; j = 1,2\ldots P \qquad (14)$$

where L_k is k-th layer, b is the number of selected bit planes, $\Re$ is random matrix $P \times P$, while the thresholds ω_k are obtained as:

$$\omega_k = k\frac{\max(\Re)-\min(\Re)}{b}.$$

By using the threshold values and a secret seed to create matrix $\Re$, the security key for watermarking procedure is obtained.

The matrix of selected coefficients C_p is observed through the biplanes: C_p(k bit)=$C_{pk.}$. The logo layers L_k are embedded into bit planes of DCT coefficients C_p by altering C_{pk} as:

$$C_{pk}(i,j) = \begin{cases} L_k(i,j) & if \quad L_k(i,j) = 1 \\ C_{pk}(i,j) & otherwise \end{cases}. \qquad (15)$$

Note that only the bits $C_{pk}(i,j)$="0" will be changed from to "1" in case when the value of $L_k(i,j)$= "1". Therefore, the logo embedding process does not change the entire bit-planes and consequently does not introduce any visible image degradation.

B. *The procedure for logo extraction*

The steps of logo extraction procedure follow from the logo embedding process. In the extraction procedure, the same subset of measurement C_p are selected and rearranged into square matrix. Also, the same bit planes k=1,…,b should be selected:

$$F_k(i,j) = \begin{cases} C_{pk}(i,j) & for \quad L_k(i,j) = 1 \\ 0 & otherwise \end{cases} \qquad (16)$$

where again: $L_k(i,j) = L(i,j) \;\; for \;\; \omega_{k-1} < \Re(i,j) < \omega_k$.

All parameters have the same meaning as described in logo embedding procedure. Additional security key is set on the CS measurements used for logo embedding. Namely, if one would know the rule to choose random coefficients for logo embedding/extraction then the logo can be retrieved completely from the bit-planes of selected measurements:

$$F_k(i,j) \equiv L_k(i,j) \;\; if \; C_{pk}(i,j) \in V_Q \,,$$

where V_Q denotate measurements vector defined by random function Q, while ($\equiv$) denotes identical operator. An illustration of logo extraction is shown in Fig 2.

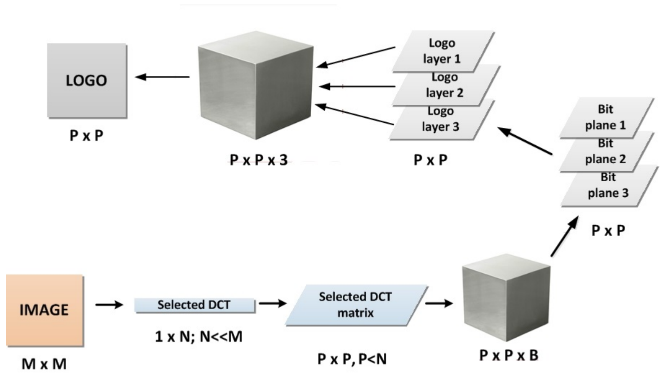


Fig. 2. Scheme of logo extraction procedure

C. *Compressive sensing as attack*

Assume that the logo is embedded in the several bit-planes of selected coefficients C_p, and can be efficiently reconstructed. In the light of compressive sensing, we now observe the influence of simulating another CS scenario which will act as the attack on watermarking procedure.

Therefore, a set of Q coefficients are selected from the original image to act as a set of CS measurements. Then the image is reconstructed following the algorithm presented in Section II. After the reconstruction, image coefficients are modified, and logo extraction procedure might be affected depending on the number Q of available samples used in the attack implementation. The experimental results are obtained in the next section.

IV. Experimental Evaluation

*Example 1***:** The logo is divided into three layers, using random matrix as previously explained (Fig. 3)

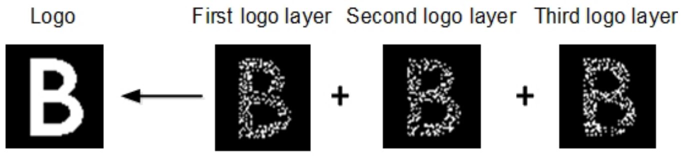
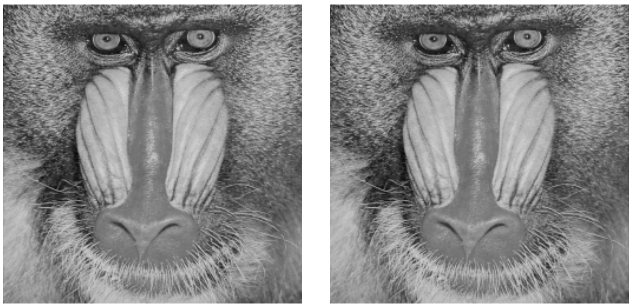


Fig. 3 Watermark - Logo divided into three layers

The CS measurements are taken randomly form the entire image (having at least 4000 low pass coefficients while the rest is taken randomly from other parts). The total number of measurements is close to 50%. The logo is embedded in first 3600 (about 10% of measurements). Logo of size 60x60 is embedded into the bit-planes b=4, 5, and 6 out of the total number of bit-planes B=10 (the middle level bit-planes assures that the resulting image quality is not degraded). After CS procedure (proposed in Section 2) is completed, logo is extracted from the reconstructed image (the achieved PSNR is 35dB). In the logo extraction procedure, the same random measurements are taken and reconstructed logo is identical to the original (Fig. 5a).

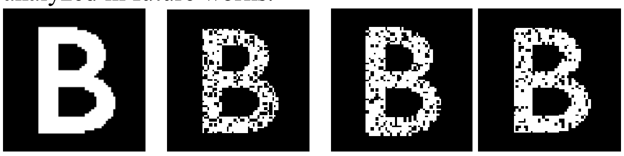


a) b)

Fig. 4. Original and watermarked images

Furthermore, the original image is exposed to the Compressive sensing scenario (as watermarking attack). Namely, even if we already reconstructed the image, the new CS procedure is performed as an attack. We again assume that only certain of measurements are available (50%, 60% or 70%), and we discard other coefficients. Then the TV min reconstruction algorithm is performed in order to reconstruct the image again (Fig. 5b,c and d). Finally, logo extraction is performed on CS reconstructed image version and the achieved logo extraction results are shown in Fig. 5. Note that the attacked reconstructed image contains far less information about logo (the images was twice exposed to CS with random measurements) and logo reconstruction is not remarkable, but we may say that it is still visible.

We can conclude that the CS based watermarking attack may severely influence logo reconstruction process, and the alternative logo embedding scenarios should be analyzed in future works.



a) b) c) d)

Fig. 5. Results of logo reconstruction: a) no CS attack, b) after CS attack with 50% of measurements, c) after CS attack with 60% of measurements, d) after CS attack with 70% of measurements

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