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Least Support Orthogonal Matching Pursuit (LS-OMP) Recovery method for Invisible Watermarking Image

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***Abstract*— In this paper a watermark embedding and recovery technique based on the compressed sensing theorem is proposed. Both host and watermark images are sparsified using DWT. In recovery process, a new method called Least Support Matching Pursuit (LS-OMP) is used to recover the watermark and the host images in clean conditions.**

LS-OMP algorithm adaptively chooses optimum L (Least Part of support), at each iteration. This new algorithm has some important characteristics: it has a low computational complexity comparing with ordinary OMP method Also, we develop an invisible image watermarking algorithm in the presence of compressive sampling using the LS-OMP. Simulation results show that LS-OMP outperforms many algorithms.

Keywords— ***Keywords: Compressed sensing, Lest Support Orthogonal Matching Pursuit, Orthogonal matching pursuit, restricted isometry property, Watermark.***

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I. Introduction

Digital watermarking is a process in which digital contents such as video, image, audio, and text are protected by hiding any logo or message into the content. These watermarks should be detected only by the copyright holder who has the private key [1].

In the case of image watermark, for security and robustness, digital watermark signals are commonly embedded in the spatial or frequency domain. Most watermarking algorithms, called lossy watermarking, as a result of loss of cover image quality in a watermarking process in some range not effected on the quality of cover image, especially when recover of watermark in process of fingerprint, the security and quality is so important in process of transmission[1-2].

The most challenge for the reversible watermarking lies in the difficulty to obtain the tradeoff between the watermark quality and the watermark robustness for resisting attacks. Higher image watermark qualities mean more data need for watermarking to be embedded, which yield a better watermark robustness. However, with the increasing of the watermarks quality, the quality of host image would be decreased. That means, the watermarking technology would influence the security of the watermarked image. In recent years, compressed sensing (CS) theory provides a feasible method to solve this problem [2].

II. Background

A. *Compressive Sensing*

The major goal of Compressed sensing (CS) is to recover a high dimensional sparse signal from its low dimensional linear measurements. The standard CS theorem is based on a sparse signal model and uses an underdetermined system of linear equations. Obviously, know that if the measurement matrix satisfies the condition so called restricted isometry property (RIP), the sparse signal can be exactly (or approximately) recovered through truly designed recovery algorithms [3].

A variety of CS reconstruction algorithms have been developed based on convex relaxation, non-convex and iterative greedy search strategies.

In practice, convex based methods have heavy computation, while, the iterative greedy methods have lower complexity and hence their usage may be practically applicable in solving large dimensional CS problems [3-4].

The main principle of the iterative greedy search methods is an estimation of the underlying support set of a sparse vector.

The support set contains indices that are non-zero elements of a sparse vector. To evaluate the support set, iterative greedy search methods use linear algebraic tools such as the matched filter and least square solution iteratively [5].

Orthogonal matching pursuit (OMP) greedy algorithm constructs an approximation by using an iteration process. At each iteration, the locally optimum solution is found. This is done by finding the column vector in A which most closely resembles a residual vector r [5-6].

In this study, we propose Least Support Orthogonal Match-ing Pursuit (LS-OMP) algorithm and CS based digital wa-termarking algorithm using LS-OMP in image reconstruction. The watermark embedding and detection are usually done in DFT, DCT, DWT domain [7-8]. Watermarking of compressive sampled images based on sparse DWT image representation. Further, we analyze the possibility to reconstruct image from such a small set of data, in order to provide successful watermark detection after image reconstruction. The robustness and security of watermarking are enhanced by the usage of Arnold scrambling.

B. OMP Algorithm

Notations: let the signal vector $x = \{x_1, x_2 \ldots\ldots, x_N\}^t$, let the support set $T \subset \{1,2 \ldots., N\}$ denotes the set of indices of the non-zero components of x (i.e $upp(x) = \{i|x_i \neq 0\}$), $A_I \in \mathbb{R}^{Mx|I|}$ consists of the columns of A with indices $i \in I$, A^* denotes the transpose of A, and $A^\dagger$ denotes the pseudo-inverse $\{(A^*A)^{-1}A^*\}$.

Let us state the standard CS problem, which acquires a signal $x \in \mathbb{R}^N$ have a K sparse input, via the linear measurements

$$y=\Phi x \quad (1)$$

Where $\Phi \in \mathbb{R}^{MxN}$ represents a random measurement (sensing) matrix, and $y \in \mathbb{R}^M$ represents the compressed measurement signal. A K sparse signal vector consists of most K nonzero indices ($K < M < N$). The aim of the algorithm is to reconstruct a sparse signal $\hat{x}$ from y using small number of measurements and to achieve good reconstruction quality [9].

We note that the compressed measurement signal y is the linear combination of most K atoms (atom means a column of). One condition for sparse signal recovery is to use the Mutual Incoherence Property (MIP) [10-11]. The MIP requires the correlations among the column vectors Φ to be small.

The coherence parameter μ of sensing matrix is defined as,

$$\mu = \max_{i \neq j} \langle \varphi_i, \varphi_j \rangle \quad (2)$$

where φ_i,φ_j are two columns of Φ with a unit norm and Φ is the concatenation of two square orthogonal matrices. It was first shown by Donoho and Huo [8] in the noiseless case, for the setting where Φ is a concatenation of two square orthogonal matrices .

$$K<1/2(1/(\mu+1)) \quad (3)$$

It is based on the algorithmic structure of OMP [12]. Proposed algorithm, LS-OMP selects one atom in each iteration, according to its future effect on minimizing the residual norm.

III. Least Support OMP

Theorem 3: For any K-sparse vector x, where $x \in \mathbb{R}^N$ and measurement matrix $\Phi \in \mathbb{R}^{mxN}$, and $y \in \mathbb{R}^M$ represents the measurement vector matrix, the LS-OMP algorithm perfectly recovers x from y = Φx, (shown in Figure 1.) if the

$$\left\|y - y_r^\ell\right\|_2 \leq \frac{\delta_{2L}}{1-2\delta_{2L}} \left\|y^{\ell-1}\right\|_2 \quad (4)$$

Assume $\delta_{2L} = 0.4648$.

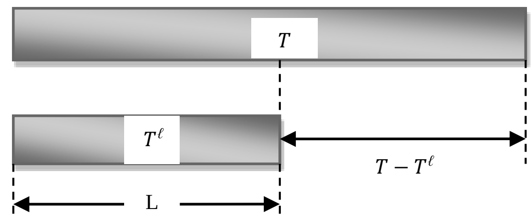


Figure 1. Illustration of support sets for our theorem

A. Least Support OMP (LS-OMP) Algorithm

Inputs: $\Phi_{M\times N}$, $y_{M\times 1}$, K(*number of observations to make*), L(*PoS_* parameter)

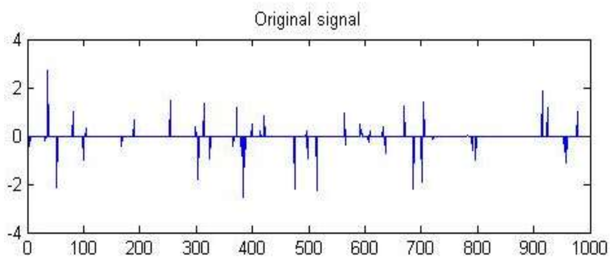
Initilaization : $I_0 = \phi$ (support set for K)
$J_0 = \phi$ (Least Support set)
$\ell = 0$

Procedure:
$J = \Phi' \times y$
Sort the J set descending {find the maximum value of auto correlation between y and Φ }
$res_\ell = y$
Repeat
$\ell = \ell + 1$
$[res_\ell, I_\ell, Aug\_p] = FastResdue(y, \Phi, I_{\ell-1}, J_l)$ {call function FastResdue}
If $\left\|y - y_r^\ell\right\|_2 \leq \frac{\delta_{2L}}{1-2\delta_{2L}} \left\|y^{\ell-1}\right\|_2$ {stopping condition}
Update position set from[1,L] to [1, ℓ]
exit
$res_{\ell-1} = res_\ell$; {upgrade the new value of res }
$I_{\ell-1} = I_\ell$
until i=L {stopping loop}
$\hat{X}_{1\times M}$(index from 1 to L of J) $= Aug\_p_{(1\times L)}$ {Arrange the value of Aug_p in position listed of J}
Output: $\hat{X}_{1\times M}$ {find estimated signal x}

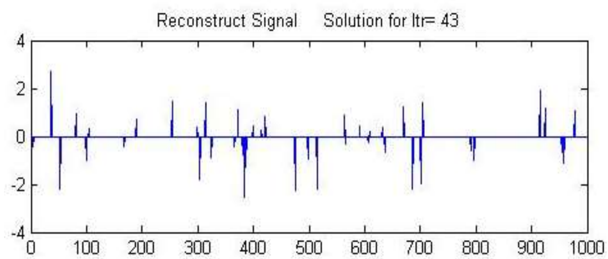
Function: FastResdue algorithm
Inputs:
$\Phi_{M\times N}, y_{M\times 1}, I_{\ell-1}, J_{\ell(1\times 1)}$
Procedure:
$I_\ell = [I_{\ell-1} \cup \Phi_J]$ {union between the set of Φ matrix for column indexed by J, and previous support of size l}
$Aug\_p = I_\ell^\dagger \times y$ {$I_\ell^\dagger$ denote the pseudo-inverse operators of set I_ℓ}
$res_\ell = y - Aug\_p \times I_\ell$ { find residual value}
Output: res_ℓ, I_ℓ, Aug_p

B. Proposed Schemes

Four steps are used for watermarking based CS:



a) Original signal, signal length=1000, No. of sparse=50, max.Itr=200



b) Reconstructed Original signal after 43 iteration using condition $\|y-y_r^l\|_2 \le \frac{\delta_{2K}}{1-2\delta_{2K}}\|y_r^{l-1}\|_2$

Figure 2. Effect of stopping condition on number of iteration needed to reconstruct original signal

First, *watermark embedding and transfer*: Arnold transform is used on watermark image to add some security, to embed the watermark image and DWT is used.

Arnold transform can be found as follows [13]:

$$\begin{pmatrix} i' \\ j' \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} i \\ j \end{pmatrix} \bmod N \qquad (5)$$

Where $i, j \in \{0,1 \ldots N-1\}$

Second, *compression sensing step:* sparsify image by using DWT, add it to the results of first step, built sensing matrix, then find linear measurement vector.

Third, *compressed sensing recovery step:* use proposed LS-OMP to recover the signal, inverse DWT.

Fourth, *Extracting watermark image:* extract watermark image, inverse Arnold transform, show results.

IV. Experimental Results

In this section, we present numerical experiments that explain the effectiveness of the LS-OMP for watermarking algorithms. Reconstructed Signal-to-Noise ratio (R-SNR) is used to measure performance of the reconstructed signal.

$$R - SNR = 10log10 \frac{\|x\|_2{}^2}{\|x-\hat{x}\|_2{}^2} \qquad (6)$$

In the first experiment, we create synthetic sparse signals, setting the length of the signal to N=1000 and sparsity level to K=50. The nonzero coefficients are selected randomly using standard Gaussian distribution. The signals are measured using measurement matrices that have i.i.d. entries drawn from a standard normal distribution with normalized columns. The number of random measurements is set to M=200 and Least Support parameter L =100.

Figure 2 shows the reconstruction result of the LS-OMP algorithm. The original signal can be recovered within 43 iterations.

Figure 3 illustrates the reconstruction time of the ordinary OMP and the LS-OMP. As it is observed LS-OMP is faster than the OMP.

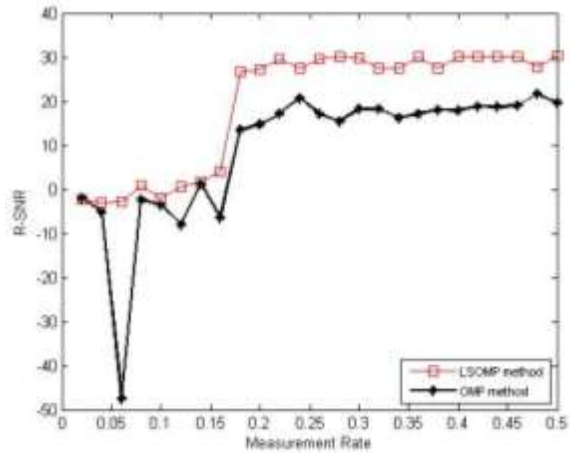


Figure 3. Recontruction time of OMP and LS-OMP.

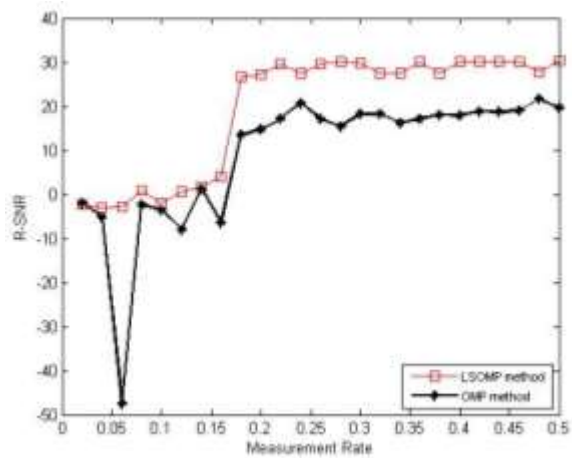


Figure 4. R-SNR values for OMP and LS-OMP.

Figure 4. compares the OMP and OMP-PSK for different number of measurements LS-OMP achieves better R-SNR values than the OMP.

For watermarking verification PSNR are used to evaluate the accuracy of the reconstructed image. The performance of the blind or non-blind watermark extraction result is evaluated in terms of Normalized Correlation Coefficient (NCC), for the extracted watermark W' and the original watermark W:

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j) - \hat{X}(i,j))^2 \quad (7)$$

$$\text{PSNR in db} = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)\ (db) \quad (8)$$

$$NC(W, W') = \frac{\sum_{i=1}^{n} W(i)W'(i)}{\sqrt{\sum_{i=1}^{n} W(i)^2}\sqrt{\sum_{1=1}^{n} W'(i)^2}} \quad (9)$$

Figure 5 gives the visual reconstruction of test image for sampling rate (M/N)=0.5 using the OMP and the LS-OMP and also it shows the effect of changing watermark factor on quality of reconstructed image using both two methods.

a)OMP,wavelet type:Coiflets5; Itr=50,WF=0.1, PSNR=33.0687

b)OMP, wavelet type: Coiflets5, Itr=40;WF=0.08 PSNR = 31.5721

c)LS-OMP, wavelet type:Coiflets5; Itr=50, WF=0.1,PSNR=37.5184

d)LS-OMP, wavelet type:Coiflets5; Itr=40, WF=0.08,PSNR=36.5269

Original watermark image 64x64

e)Original cover image 256x256

Figure 5. **C**omparison of OMP and LS-OMP in watermarking process.

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