NATIONAL UNIVERSITY OF SCIENCE AND TECHNOLOGY POLITEHNICA BUCHAREST

Doctoral School of Electronics, Telecommunications and Information Technology

Decision No. ... from ...

Ph.D. THESIS SUMMARY

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CONTRIBUŢII LA MARCAREA IMAGINILOR OBŢINUTE PRIN EŞANTIONARE COMPRESIVĂ

CONTRIBUTIONS TO THE WATERMARKING OF IMAGES SENSED BY COMPRESSIVE SAMPLING

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Chapter 1

Introduction

Recent developments in technology provide a large variety of devices that empower a continuously growing number of people to acquire, process, distribute and store digital media with accessible costs.

A relevant example is the evolution of the mobile phone. It was first released to the consumer market in the 1980s and billions are currently owned all over the world. The functionalities of mobile phones have also expanded greatly as they now play multiple roles such as of a digital camera, recorder, daily planner or compass.

This context raises concerns on topics such as digital privacy, the authenticity of digital media or communication security, but for the average user most of the best practises designed to protect their privacy remain unknown or perhaps too difficult to follow. Laws have been written so that each person's rights are protected against exploitation.

When it comes to digital images, the concept of watermarking consists in invisibly and robustly embedding information in a host image. One of its main purposes is content protection and authentication, thus playing an important role in assuring digital privacy.

The recent theory of compressive sensing (CS) first emerged in 2006 [6] [4] and proposes an effective manner to acquire images directly in a compressed form. It showed promising results in the field of digital security [29], in algorithms that perform various functions (privacy protection, authentication, tampering detection and others).

This thesis provides a new perspective on how combining digital watermarking and compressive sensing can protect digital privacy in different scenarios.

1.1 Presentation of the field of the doctoral thesis

The theory of compressive sensing comes as an alternative to the traditional approach for acquiring signals, as proposed by the Shannon sampling theorem. It provides a new approach, relying on the fact that multiple signals can be represented in a suitable base so that they can be approximated by a small number of non-zero coefficients.

CS has been researched and integrated in multiple domains such as medical imaging [9], cloud data center monitoring [14], image coding [15], radar imaging [8], 5G system design [28] and so on.

The purpose here is not to replace classical imaging techniques, but to expand them. The CS approach can be used to design systems which benefit from using a low complexity system on the acquisition side.

Digital watermarking represents embedding information into a carrier signal. Each watermarking system is designed to best suit its applications, thus the increased usage of digital media led to the development of watermarking techniques that serve multiple purposes: proof of ownership, copyright control, tamper detection, authentication, transaction tracking and so on [27].

Based on the type of digital signal in which the embedding is done we can mention multiple research directions, some notable examples being: medical images [24], audio watermarking [11], satellite imagery [1] and video watermarking [2].

In relation to CS, digital watermarking can provide multiple promising research directions based on the requirements of each application and domain.

1.2 Scope of the doctoral thesis

The main purpose of the thesis is to develop a novel watermarking schema based on the CS theory and analyze its behavior, characteristics and limitations. The watermark needs to be designed so that it can be used in a CS scenario.

The importance of watermarking in digital signal processing is undeniable, as its possible applications in security, confidentiality and data integrity are considered topics of interest in different fields.

Considering the existing techniques that were examined as part of the bibliography, the intersection of digital watermarking and CS is a promising direction for multiple applications in different research domains. Each of these methods faces its unique challenges and compromises must be made based on the purpose and requirements of the application.

The thesis aims to assess the impact of watermarking on the quality of reconstructed signals from compressed sensed measurements, as well as to evaluate the capacity, transparency and robustness of the proposed watermarking techniques. It will also require the implementation of simulation tools for testing watermarking techniques.

1.3 Content of the doctoral thesis

The thesis is structured in seven chapters that systematically present the research on the topic of watermarking compressed sensed samples. The introductory chapter contains a brief presentation of the research field, research objectives and the thesis structure.

The second chapter presents an overview of the theoretical aspects of digital watermarking and compressive sensing and an extensive literature review of watermarking in the context of compressive sensing scenarios.

The third chapter then describes a scenario in which image compressed samples are watermarked and contains a detailed analysis of how the CS parameters affect the watermarking algorithm in relation to its capacity, robustness and transparency [20].

Chapter four proposes a privacy enabling architecture for a CS scenario in which a reversible watermark is embedded on the fly in the samples acquired by a single pixel camera [18].

The fifth chapter focuses on expanding the watermarking algorithm presented in Chapter 4 with more original contributions such as multi-bit insertion and image distribution to unauthorized users [19].

The sixth chapter presents a joint watermarking and partial encryption algorithm specifically designed for CS samples.

The seventh and final chapter contains the conclusions and ends with a list of original contributions to the field and a list of original publications.

Chapter 2

Theoretical Background

Considering that the scope of this thesis is to develop a novel watermarking technique suitable for CS scenarios, the following chapter presents a theoretical background of both compressive sensing and digital watermarking, as well as an in-depth analysis of the state of the art research in the field.

2.1 Compressive Sensing

The sampling operation allows us to convert the surrounding world from a collection of continuous-time signals to one of discrete-time signals. This is extremely important because we are then able to process these discrete signals by using computers or specialized digital signal processors.

For functions that vary in time, sampling means recording the function's value every T seconds, T being the sampling interval or sampling period. The sampling frequency (f_s) represents the number of samples per second, so $f_s = 1/T$

The sampling theorem specifies the minimum frequency at which a continuous-time signal needs to be uniformly sampled so that the original signal can be completely reconstructed from the samples:

Theorem 1 (Nyquist–Shannon sampling theorem) *If a continuous-time signal x(t) has a limited frequency band, thus having no components higher than f_m, it can be completely determined by uniform sampling with a frequency of $f_s \geq 2f_m$*

The CS theory [7] provides a way to use a total number of samples smaller than the value specified by the Nyquist-Shannon sampling theorem. These samples are acquired directly in a compressed form, and based on them the original image can be recovered with the use of a reconstruction algorithm.

2.1.1 Sparsity and incoherence in CS

In order to successfully apply the CS theory to a signal, two requirements must be met: the sparsity of the original signal (or image in this case) and the incoherence of the sensing basis and original signal basis.

Sparsity refers to the fact that the signal contains a small number of non-zero elements compared to its total size.

Incoherence between the basis used to represent the signal (ψ) and the one used to sample the signal (ϕ) is also a requirement so that the CS reconstruction can be possible.

2.1.2 The CS theory

In the CS theory the samples, called measurements, are obtained by projecting the original signal on a number of sensing vectors ($\varphi_1, ..., \varphi_M$). These represent the rows of the sensing matrix, referred to as ϕ. The size of the sensing matrix $\phi \in \mathbb{R}^{M \times N}$ is given by the length of x (N) and the number of sensing vectors (M), where $M << N$.

The CS sampling equation is:

$$y = \phi x \tag{2.1}$$

Considering the case of 2D images, the discrete signal $x \in \mathbb{R}^{N \times 1}$ we wish to reconstruct is the serialised image. If $s \in \mathbb{R}^{N \times 1}$ is the signal's sparse representation using the orthonormal transform matrix $\psi \in \mathbb{R}^{N \times N}$, x can be written as:

$$x = \psi s \tag{2.2}$$

Combining this equation with 2.2, the relationship between the measurements y and the sparse representation of the signal s is:

$$y = \phi \psi s = \theta s \tag{2.3}$$

In order to successfully reconstruct the signal based on y, the transform matrix ψ must be incoherent with the measuring matrix ϕ.

2.2 Digital Watermarking

Watermarks are patterns added to paper as a way to prove its authenticity. These are used to avoid or at least discourage the forgery of official documents such as identity cards, passports, currency, stamps.

In a similar manner, digital watermarking consists in embedding information to digital media (common examples being images and audio or video media). The embedded data represents the watermark and has multiple purposes, the most common ones being copyright protection, source tracking, tamper detection and the transmission of auxiliary data. [13]

2.3 State of the art

In recent years, multiple studies have been done on the subject of how to combine watermarking techniques with the CS theory. Based on how the two are interlaced, four research directions can be observed:

1. CS seen as an attack on the watermarked signal

   In this case, the watermark is embedded in the original signal in order to obtain the watermarked signal and then CS is performed. It's effects on the watermark are measured in terms of robustness.

2. CS used for the design of the watermark

   The watermark itself can be constructed based on the CS measurements and then embedded.

3. Data encryption (watermark cryptography)

   Considering the random nature of the measurement matrix, applying the CS theory can be considered a light encryption model.

4. CS used as a support for the watermark

   The theory of CS is used directly in the watermark scenario, for example in the embedding stage.

Out of these topics, the latter is the main focus of this thesis.

Chapter 3

On the Watermarking of Image Compressed Samples

After having established the theoretical foundations for our thesis, one of the most important steps is to understand how the parameters employed in the CS theory impact the acquired CS measurements and thus the data compression and reconstruction quality. On top of this, the parameters directly impact the embedding of a digital watermark in the CS samples in relation to its capacity, transparency and robustness.

This chapter studies the parameters that influence the performance of a watermarking scenario in the context of CS, such as the sensing matrix choice, the applied sparsifying transform and the reconstruction algorithm.

We consider three different sensing matrices (Gaussian, Bernoulli and circulant), two orthogonal transforms – Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) – and two greedy CS algorithms i.e., Orthogonal Matching Pursuit (OMP) and Compressive Sampling Matching Pursuit (CoSaMP).

The algorithm proposed by Huang et. al [12] was selected for watermark embedding in the CS samples and will be evaluated by its robustness, transparency and capacity.

We show that the watermark capacity and recovery rate are affected by the sparsifying transform and the measurement matrix used for sampling. The transparency of the watermark is assessed based on Peak Signal to Noise Ratio (PSNR) and tested against the two recovery algorithms.

The original contributions related to the role of CS parameters on a selected watermarking algorithm are:

- Extended the original version of the watermarking scenario for multiple types of CS parameters by using DWT for the image transform, in addition to DCT, two new recovery algorithms (OMP and CoSaMP) and three measurement matrices: Gaussian, Bernoulli and binary circulant.
- Formulate conclusions on how to choose the optimal configuration of CS parameters.

This has been published in the conference paper *On the Watermarking of Image Compressed Samples* [20].

The performed experiments analyzed how the watermark embedding and detection is affected by the sensing method that delivers the compressed samples, as well as how the watermark impacts the CS reconstruction itself.

The number of bits that are embedded at a given threshold depends both on the measuring matrix and the sparsifying transform. The best results were obtained when using the binary circulant matrix and WT. However, this combination fails to provide a good recovery rate for the watermark after data transmission over a noisy channel.

The number of watermark bits that are embedded in the measurement vector directly affects the reconstruction quality since the measurement values are not redundant. A high watermark capacity can be obtained, but it comes with the cost of a lower quality of the reconstructed image.

The channel SNR influences both the watermark recovery and the image reconstruction. If the SNR is high, the recovery rate is also high, with no false positive values detected and the reconstructed image is of good quality.

The CS reconstruction algorithm does not influence either the watermark embedding or the reconstruction. However, our results show that OMP returns better reconstruction results and is less influenced by the embedded watermark than CoSaMP.

The tests show that a trade-off must be made in order to obtain the best watermark capacity while preserving a good quality of the CS reconstruction. Considering this, the association of DCT with a circulant measurement matrix offers the best watermark capacity and recovery rates, while the quality of the CS reconstruction has been better for OMP.

Compromising either the capacity or transparency should be decided at application level based on its specifications or requirements.

Chapter 4

Compressive sensing based watermarking as a security layer for computational imaging applications

When it comes to human visible wavelengths, the use of CCD and CMOS technology to develop new sensors has helped digital cameras become smaller, less expensive and offer higher quality images. However, these technologies cannot be used by applications using different wavelengths (such as far infrared) and although other options exist, the costs are considerably higher when operating outside the visible region of the electromagnetic spectrum.

This limitation triggered the need to research different approaches, one of them being the use of compressive sensing (CS) theory and algorithms to design new imaging system architectures.

This chapter introduces some basic concepts related to single pixel imaging (SPI) and proposes a method to add a watermark in the measurements resulted from CS sampling using a single pixel camera. The added security layer allows only authorized users to access the original image. The novelty factor is that in the case of unauthorized users, a much lower quality image than the original one can still be viewed.

Single-pixel camera

The single-pixel camera (SPC) as proposed by Duarte et. al. [5] replaces the array of pixels traditionally used to capture a scene with an architecture that computes random linear measurements of the scene. Based on the CS theory the sampling and compression steps are merged into one. The reconstruction of the scene is then performed based on the acquired measurements. This method offers a simplified architecture of the camera on the data acquisition side, at the cost of increased computational time for data reconstruction.

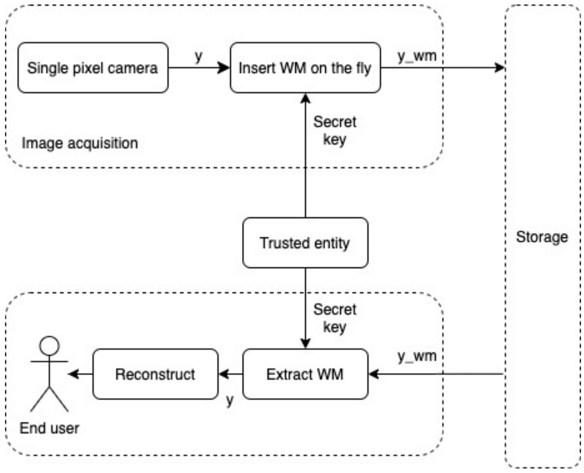

Fig. 4.1 Proposed scenario architecture

Watermarking algorithm for CS scenario

Let us consider a CS scenario in which a watermark is embedded in the CS measurements. The method we propose is to extract a number of values from the CS measurements and insert them as watermark in the resulting truncated measurement sequence.

It is important to use a watermarking algorithm with a moderate transparency: this allows a deteriorated but yet recognisable version of the original image to be reconstructed based on the watermarked measurement sequence. The watermark also needs to be reversible, so that after extraction the image can be reconstructed at the original quality. We analyze the watermark capacity as a possible source of distortion. The watermark robustness is not tested. The selected algorithm is proposed by Sachnev et. al [23] for digital images and it expands the algorithm presented by Thodi et. al in [26].

The simulations are done on Lena and Peppers images of 256x256 pixels. The CS reconstruction is done from a number of measurements representing 50% of the image size (compression ratio of 1.6), with the algorithm described in [3].

The capacity plot from Fig. 4.2 shows that the capacity increases with the value of the thresholds used for insertion until a certain level, after which the value remains approximately the same. The maximum percentage of measurements that are extracted from y and then inserted as a watermark stays below 2% in all simulations.

Another aspect we analyzed is what reconstruction quality an unauthorized user can obtain (watermark transparency). Fig. 4.3 presents the PSNR values obtained when reconstructing the image from the watermarked measurements as a function of the insertion capacity. The PSNR is computed between the reconstructed image and the original one.

Even when inserting a short watermark, the image quality is altered, the PSNR dropping below 30dB. This is mainly caused by the lack of correlation among the measurements.

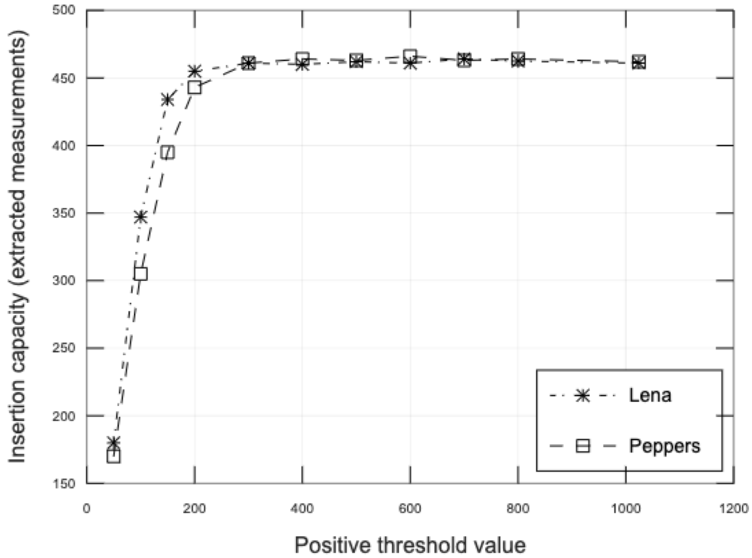

Fig. 4.2 Watermark capacity measured as the number of inserted measurement values plotted agains the T_p threshold for both Lena and Peppers

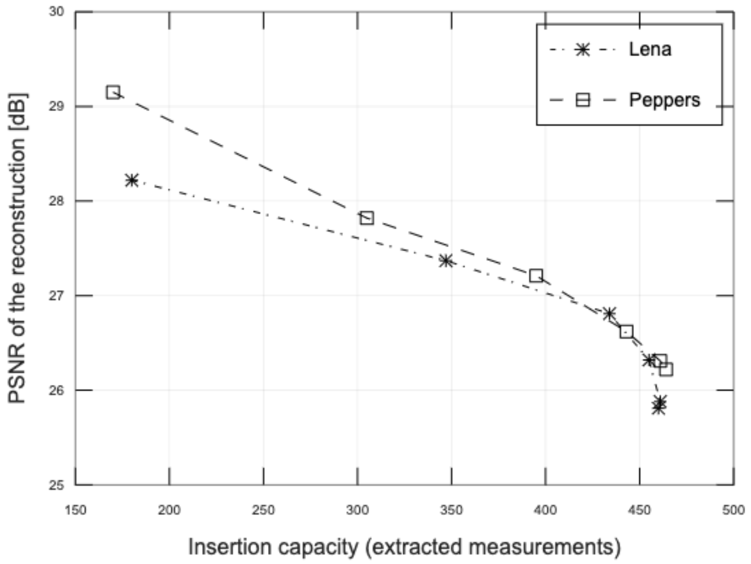

Fig. 4.3 The PSNR [dB] values obtained when reconstructing the image from measurements watermarked at different capacities

Chapter 5

Multi-bit watermark insertion for single pixel camera measurements

In this chapter we analyse a scenario in which a multi-bit reversible watermark is inserted on the fly in the measurement values of a SPC, thus allowing only authorised users to reconstruct the image at its original quality. For other users, a low quality version of the image is still available. The inserted information consists of a set of encrypted measurement values. The results show that both the watermark capacity and quality of the reconstructions are affected by the number of bits used to represent the watermark and the type of matrix used for sampling.

The watermarking algorithm discussed in the previous chapter is updated to allow the insertion of multiple bits (x) at the same time.

We denote by b_x the decimal value of the x bits and $b_{max} = 2^x - 1$ is the maximum possible watermark value, d_i the prediction error and T the threshold used for delimiting which samples are eligible for WM insertion.

The original value y_i is replaced by the new watermarked value y_{wm_i}:

$$y_{wm_i} = \begin{cases} y_i + b_{max} \cdot d_i + b_x & \text{if } d_i \in [-T, T] \\ y_i + b_{max}T + b_{max} & \text{if } d_i > T \text{ and } T \geq 0 \\ y_i - b_{max}T & d_i < -T \text{ and } -T < 0 \end{cases} \tag{5.1}$$

For watermark extraction, the value of the modified prediction error is computed as:

$$D_i = y_{wm_i} - \overline{y} \tag{5.2}$$

The original prediction error d_i is computed as:

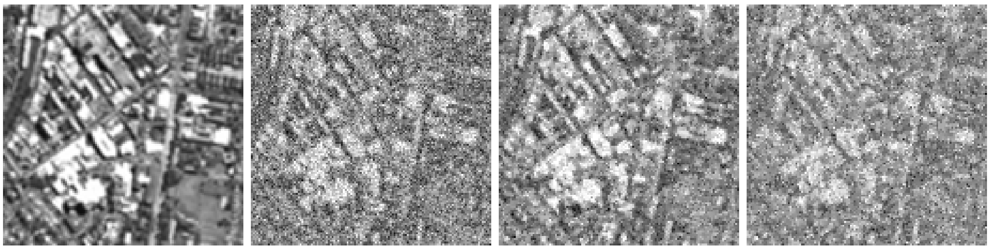

Fig. 5.1 From left to right: Sidney original image and reconstructions from measurements having watermark inserted on 8 bits for matrices S (PSNR 17.12 dB), Hadamard (PSNR 19.00 dB) and BPDB (16.50 dB)

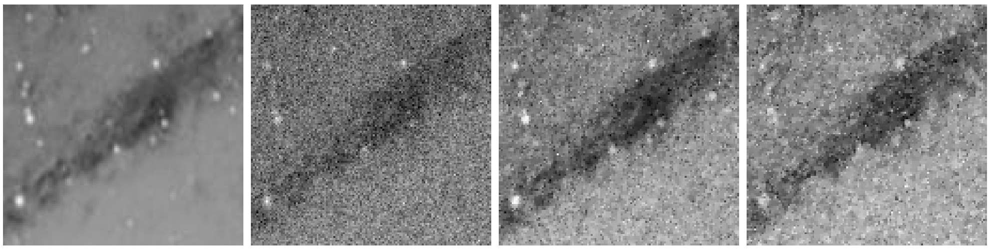

Fig. 5.2 From left to right: Andromeda original image and reconstructions from measurements having watermark inserted on 8 bits for matrices S (PSNR 20.91 dB), Hadamard (PSNR 23.83 dB) and BPDB (PSNR 22.41 dB)

$$d_i = \begin{cases} \lfloor D_i/2^x \rfloor \text{ if } D_i \in [-2^x T, 2^x T + b_{max}] \\ D_i - b_{max}(T-1) \text{ if } D_i > 2^x T + b_{max} \text{ and } T \geq 0 \\ D_i + b_{max} T \text{ if } D_i < -2^x T \text{ and } -T < 0 \end{cases} \tag{5.3}$$

The embedded value is recovered as:

$$b_x = D_i \mod 2^x, D_i \in [-2^x T, 2^x T + b_{max}] \tag{5.4}$$

The original value y_i is also recovered, based on the predicted value and the prediction error:

$$y_i = d_i + \bar{y} \tag{5.5}$$

We performed simulations on two images of size 128x128 pixels that have very different sparsities: Andromeda, a sparse crop from a larger image of the Andromeda galaxy and Sidney, a low sparsity crop from a satellite image of the city Sidney. The CS reconstruction is done from a number of samples equal to 50% of the image pixels in the case of Andromeda and 70% of the image pixels for Sidney.

The three CS measurement matrix types are Hadamard (Sylvester's construction), S-matrix with the first row and column set to zero [25] and BPBD [10].

The first step was to measure the watermark capacity for each image and measurement matrix combination, with the number of bits used to represent the watermark x varying

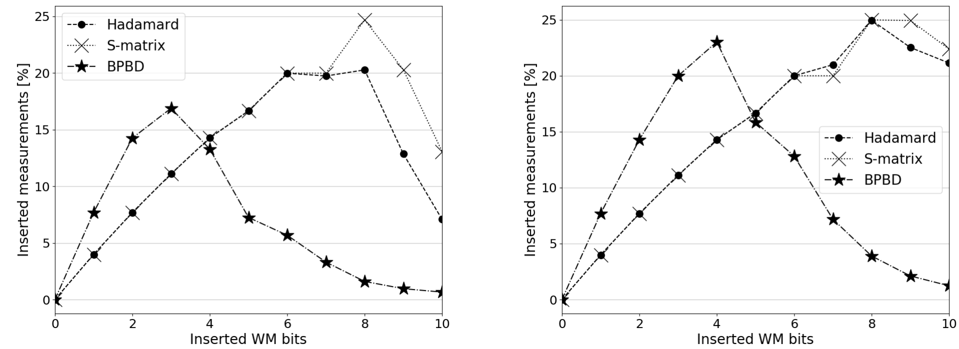

Fig. 5.3 Watermark capacity for Sidney (left) and Andromeda (right) for various number of bits x used to represent the watermark

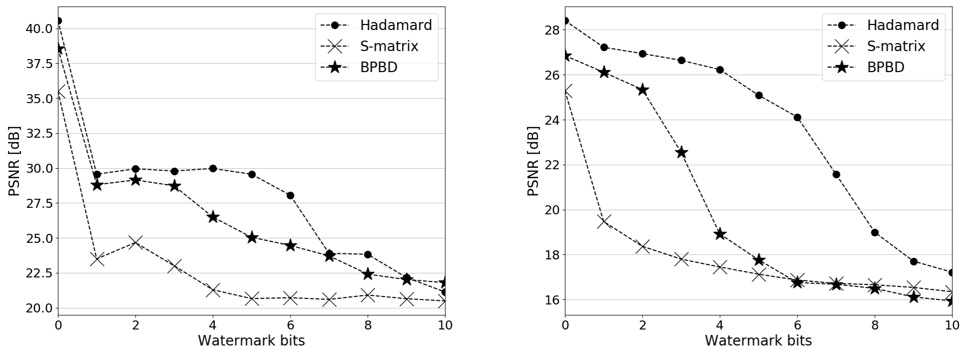

Fig. 5.4 Variation of the reconstruction quality for Andromeda (left) and Sidney (right) for various number of bits x used to represent the watermark

from 1 to 10 (Fig. 5.3). The results confirm that increasing the number of bits also increases the watermark capacity only up to a point.

The reconstructed image's quality is directly affected by two factors: the watermark insertion, which alters the measurement values, and the decreased number of measurements that results from it.

Figure 5.4 contains the PSNR values obtained for the same variation of x. The tests show that the most degraded reconstructions are obtained when using the S measurement matrix. Figures 5.1 and 5.2 show the images obtained from CS reconstruction of watermarked measurements on 8 bits.

The tests showed that insertion capacity for matrices Hadamard and S is very similar, and higher than for BPBD.

Using the S measurement matrix offers the highest insertion capacity with the greatest degradation of reconstructed images when compared to the other two.

For sparse images a good quality CS reconstruction can be obtained from a smaller number of samples.

Chapter 6

Joint Watermarking and Partial Encryption of Compressive Sensed Data

This chapter proposes a method for the joint watermarking and partial encryption of Compressive Sensing measurements. It consists in encrypting a part of measurements and inserting the code into the rest.

The encryption is done by performing the xor operation with a secret key. For insertion, we use a modified version of the prediction error expansion algorithm, adapted to fit the statistics of CS measurements. A particularity of the method is the on-the-fly insertion that makes it appropriate for the sequential acquisition of measurements by a Single Pixel Camera. Without the secret key, an unauthorized user can reconstruct only a low quality image but with recognizable content.

As opposed to the common practice of using transparent watermarks, the embedding is done on a high number of bits such to cause strong visual distortion if an unauthorized user tries to reconstruct the image from the watermarked measurements.

The relative capacity is defined based on the capacity in number of inserted bits C and the total number of measurements L:

$$C_r = \frac{C}{L} \tag{6.1}$$

For loose thresholds (as used in our simulations), C_r can be approximated as:

$$C_r \approx \frac{n}{1+n/16} \tag{6.2}$$

The novelty of the method consist of performing aight encryption of part of CS measurements and use as carrier of the rest and also, the on-the-fly insertion of the encrypted measurements. Another original aspect is the use of a modified version of the prediction error expansion algorithm.

The method is evaluated under the following aspects: the watermark capacity, the distortion introduced by the partial encryption and the impact on data volume. An

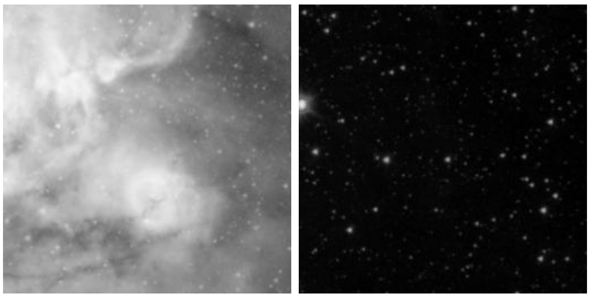

Fig. 6.1 Two examples of patches used for tests: a dense one (left) and a sparse one (right).

equation is derived for the insertion capacity and the experimental rate-distortion curve of the method is given.

Experimental Results

We experimentally test our method under the following aspects: embedding capacity, distortion, and impact on data volume. The results are given for loose thresholds, which means that insertion is performed in all available samples.

The experiments are carried out on both simulated and experimental data.

The simulated data are obtained from an image of the W51 nebula converted to grayscale using the weighted method, normalized to have values between 0 and 1 and split into 359 patches of 256 x 256 pixels each. The idea behind this choice was the potential of SPC in sky exploration, where bands of the electromagnetic spectrum like far infrared are of interest.

Fig. 6.1 shows two patches that have different sparsities, corresponding to a high and low value of the standard deviation.

The real set data was obtained as part of experiments done under white light by using the setup in [17].

We considered a total number of measurements representing 40% of the image size and a loose threshold of $T = 500$, which ensures that all measurements are eligible for insertion.

In Fig. 6.2, the relative capacity C_r is plotted against the number of insertion levels n. The curve has an ascending trend, with capacity values ranging from 0.9 bits/measurement for 1 level to 7.5 bits/measurements for 14 levels.

PSNR values are computed and used to evaluate the distortion compared to the image reconstructed from the original measurements. Figure 6.3 plots the PSNR median computed on all collected values (all 359 patches). A drop in the reconstruction quality can be noticed after 6 levels. Up to 7 insertion levels, the distortion is not visible. For this reason, we restrict our analysis to insertion levels $n \in [7, 14]$.

The distortion and the capacity are closely related (Fig. 6.4), both increasing with the number of insertion levels.

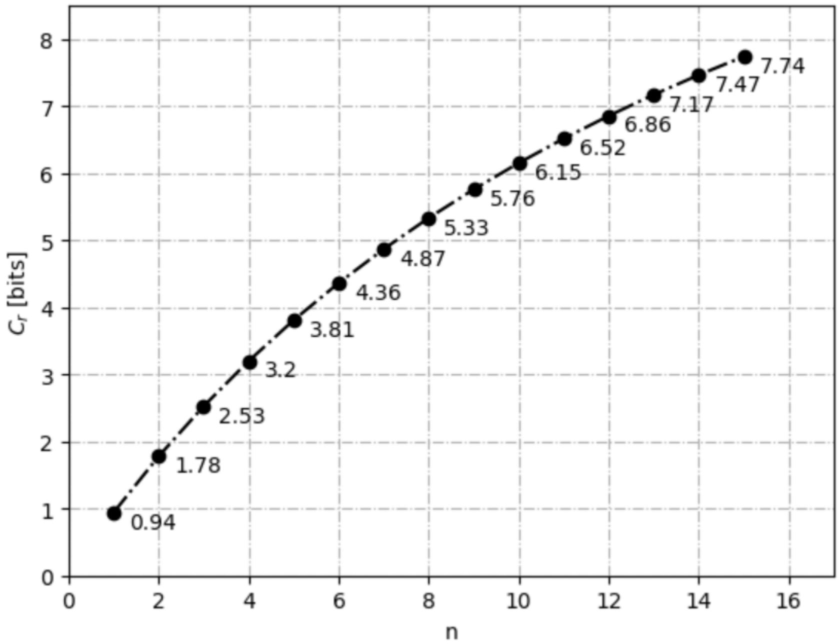

Fig. 6.2 The relative capacity C_r vs. the number of insertion levels n, for loose thresholds ($T = 500$).

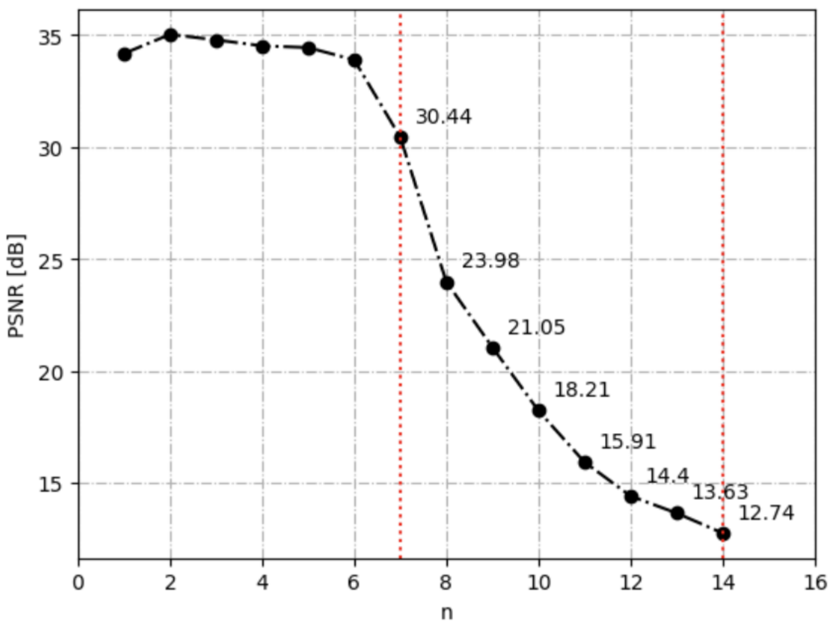

Fig. 6.3 Experimental values of PSNR plotted against the number of insertion levels n. The vertical dotted lines marks the range of interest for the application.

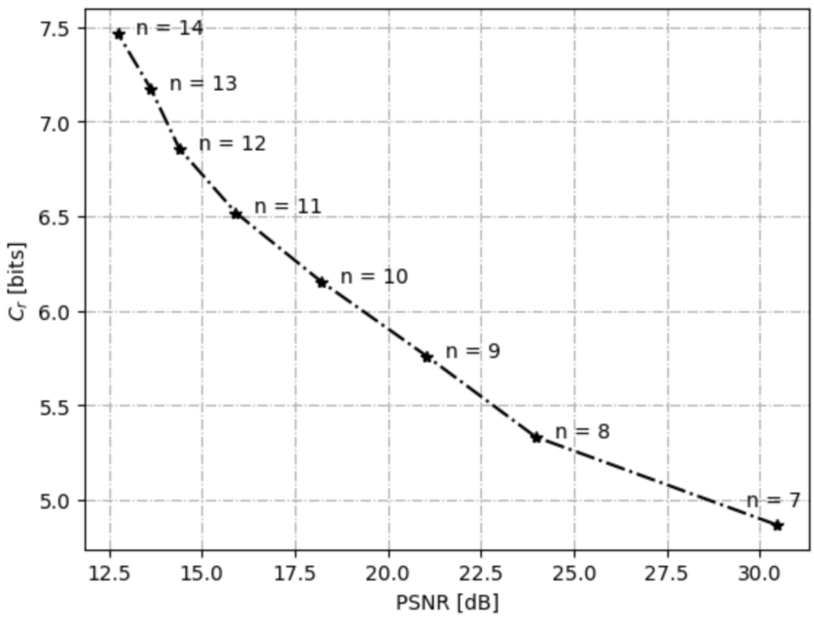

Fig. 6.4 Relative Capacity C_r as a function of PSNRs median.

Due to relying on prediction error expansion, the watermarking algorithm modifies the data volume at insertion time.

The insertion in real data with our method led to lower PSNR values compared to simulated measurements. At 10 insertion levels, the PSNR is 10.48 dB for the real image and about 14 dB for the images reconstructed from simulated measurements.

Chapter 7

Partial Encryption With Data Hiding Performed On-the-fly On Compressed Sensed Measurements

This chapter proposes a method to perform RDH with partial encryption in CS measurements by encrypting part of them using a secret key and then inserting the resulting values on-the-fly in the following eligible measurements. The insertion results in visible distortion, while the images reconstructed based on the marked measurements still have discernible content. The proposed modifications to the prediction error expansion algorithm adapt it for usage in a SPC scenario while limiting the data expansion. This variation is innovative compared to the algorithm proposed in Chapter 6 and allows the user to control if the modified measurements require additional memory compared to the original ones.

The research has been accepted for publishing in the conference paper "Partial Encryption With Data Hiding Performed On-the-fly On Compressed Sensed Measurements".

The proposed method combines the partial encryption with the reversible data hiding offering a way to control the visible distortion inserted in the encrypted image. The partial encryption consists in XORing selected CS measurements with a single-use secret key generated via a cryptographically secure pseudo-random number generator (CSPRNG). The key must be longer than the encrypted plaintext and must be transmitted using a secure communication protocol. The prediction error expansion algorithm, modified to match the statistics of CS measurements, is used to embed the encrypted measurements into the non-encrypted ones. One strength of the method is on-the-fly embedding, a feature that makes it appropriate to use in a SPC scenario.

7.1 Method description

The main innovation of the proposed method when compared to the one discussed in the previous chapter is the fact that it does not expand the data volume of individual CS measurements. In the data embedding step of the prediction error expansion algorithm [23], values that are not eligible for insertion are not expanded anymore, but instead a position map is used to keep track of the marked positions. This approach allows us to limit the data expansion caused by the insertion algorithm, the final purpose being not to exceed the original data representation beyond 16 bits. Since part of the measurements are embedded in the insertion step, the final number of transmitted measurements is reduced. In addition to this, transmitting the position map also introduces an overhead.

The SPC performs a sequential acquisition of CS measurements, allowing the proposed method to insert data on-the-fly. In order to do this, some changes were made to the prediction error expansion algorithm:

- CS measurements are statistically independent, so instead of computing the predicted value based on a measurement's neighbors, we use an estimate of the CS measurement mean as the predicted value.
- Since the predicted value is now a constant and does not need to be computed based on measurement values, all positions are evaluated for data embedding.
- Prediction error expansion is no longer performed when data is not embedded. Instead, a position map is used to keep track in which positions data is inserted thus ensuring the data hiding remains reversible. This allows the data volume to be conserved.
- Data insertion is done on n multiple levels [19].

Considering this, the prediction error is only expanded for eligible positions in order to insert bn_i. Considering n to be the number of inserted bits and bn_i their decimal representation, the threshold $T > 0$ is used to assess eligibility when expressing the expanded prediction error:

$$D_i = \begin{cases} 2^n \cdot d_i + bn_i & \text{if } d_i \in [-T, T] \\ d_i & \text{if } d_i \notin [-T, T] \end{cases} \tag{7.1}$$

7.2 Experimental Results

The conducted experiments aim to evaluate the embedding capacity and introduced distortion of the proposed method, while measuring the impact of the insertion on the final data volume.

The results are generated and analyzed for both simulated and real data. The image of the W51 nebula was obtained by NASA's Spitzer Space Telescope [16] and is used to generate the simulated data: it is first converted to grayscale using the luminosity method, then the obtained values are normalized to fall into the range $[0,1]$ and finally, it is cut into 359 patches of size 256×256 pixels.

The experiments proved the modified data hiding algorithm can be successfully deployed on CS measurements and indeed limits the data expansion. Being a reversible algorithm, it allows authorized users to use the original measurements for reconstruction.

The method focuses on limiting data expansion by modifying the deployed RDH algorithm to use a position map instead of prediction error expansion for the measurements that are not eligible for insertion. The measurement data volume expands with about $2-3\%$ when using $T = 20$.

The experiments show that even embedding 1 bit of information leads to a visible image distortion for both real and simulated input data. The image content directly impacts both insertion capacity and reconstruction quality because tight thresholds are used. Using the threshold T is also a way to control the image distortion while adding an extra security level against ECA attacks.

Chapter 8

Conclusions

The thesis contains contributions to the field of digital watermarking in the context of compressive sensing. It is focused on the development and evaluation of a novel on the fly watermarking schema designed for embedding in CS measurements, specifically in single pixel camera samples. The results presented in this thesis are focused on researching a novel watermarking algorithm suited for compressive sensing applications.

8.1 Original contributions

The original contributions presented in this thesis are as follows:

- An extensive study on the influence of CS parameters on the watermarking of CS acquired samples, based on experimental tests and simulations [20].
- A watermark embedding and extracting method designed specifically to allow on the fly insertion in CS samples, the watermark being embedded while the input signal is being acquired [18].
- An updated version of the error expansion algorithm, modified to allow multi-bit watermark insertion and maximize capacity based on the properties of the CS samples [19]
- A watermark design for on the fly insertion in SPI measurements, taking into consideration all the limitations and requirements of this scenario [19]
- An image acquisition and distribution architecture that allows unauthorized users to also access a low quality version of the original image [18, 19, 22]
- A mathematical model and correlated experimental data for the capacity of the proposed watermarking schema [22]
- An updated version of the prediction error expansion algorithm that limits the data expansion in a SPC scenario [21]

8.2 List of original publications

8.2.1 Journal papers

1. C. Popa, C. Damian and D. Coltuc, "Joint Data Hiding and Partial Encryption of Compressive Sensed Streams", accepted for publication at *Information* Journal, MDPI. Impact Factor 2.4, Q2

8.2.2 Conference papers

1. C. Popa, D. Coltuc and C. Damian, "On the Watermarking of Image Compressed Samples," 2019 International Symposium on Signals, Circuits and Systems (ISSCS), Iasi, Romania, 2019, pp. 1-4, doi: 10.1109/ISSCS.2019.8801773.

2. C. Popa and D. Coltuc, "Compressive sensing based watermarking as a security layer for computational imaging applications," 2020 International Symposium on Electronics and Telecommunications (ISETC), Timisoara, Romania, 2020, pp. 1-4, doi: 10.1109/ISETC50328.2020.9301129.

3. C. Popa and D. Coltuc, "Multi-bit watermark insertion for single pixel camera measurements," 2021 International Symposium on Signals, Circuits and Systems (ISSCS), Iasi, Romania, 2021, pp. 1-4, doi: 10.1109/ISSCS52333.2021.9497437.

4. C. Popa, C. Damian and D. Coltuc and C. Damian, "Partial Encryption with Data Hiding Performed On-the-fly on Compressed Sensed Measurements," accepted at the 17^{th} International Conference on Electronics, Computers and Artificial Intelligence ECAI 2025, Targoviste, Romania.

8.3 Perspectives for further developments

Several research directions for further developments have been identified:

- An important development would be to thoroughly assess the algorithm's resilience to different types of attacks and improve the security layers accordingly.

- A natural next step would be to test the method against a real SPC setup, using the acquired data in the process

- Another research prospect would be to expand the scenario for other types of input data across different fields where data acquisition is done using the compressive sensing theory.

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