Data Hiding in Digital Images : A Steganographic Paradigm

A thesis submitted in Partial Fulfillment of
the requirements for the Award of the degree of

Master of Technology
in
Computer Science and Engineering

by

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May, 2008

Certificate

This is to certify that the thesis titled **Data Hiding in Digital Images : A Steganographic Paradigm** submitted by **Piyush Goel, Roll No. 03CS3003**, to the Department of Computer Science and Engineering in partial fulfillment of the requirements of the degree of **Master of Technology in Computer Science and Engineering** is a bonafide record of work carried out by him under my supervision and guidance. The thesis has fulfilled all the requirements as per the rules and regulations of this Institute and, in my opinion, has reached the standard needed for submission.

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Acknowledgments

It is with great reverence that I wish to express my deep gratitude towards Prof. Jayanta Mukherjee for his astute guidance, constant motivation and trust, without which this work would never have been possible. I am sincerely indebted to him for his constructive criticism and suggestions for improvement at various stages of the work.

I would also like to thank Mr. Arijit Sur, Research Scholar, for his guidance, invaluable suggestions and for bearing with me during the thought provoking discussions which made this work possible. I am grateful to Prof. Arun K. Majumdar for his guidance and the stimulating discussions during the last semester. I am also thankful to Prof. Andreas Westfeld, Technical University of Dresden, Germany, for clearing some of my doubts through email.

I am grateful to my parents and brother for their perennial inspiration.

Last but not the least, I would like to thank all my seniors, wingmates and my batchmates especially Mayank, Udit , Joydeep , Prithvi, Lalit, Arpit, Sankalp, Mukesh, Amar and Umang for making my stay at IIT Kharagpur comfortable and a fruitful learning experience.

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Abstract

In this thesis a study on the Steganographic paradigm of data hiding has been presented. The problem of data hiding has been attacked from two directions. The first approach tries to overcome the Targeted Steganalytic Attacks. The work focuses mainly on the first order statistics based targeted attacks. Two algorithms have been presented which can preserve the first order statistics of an image after embedding. Experimental Results reveal that preserving the image statistics using the proposed algorithm improves the security of the algorithms against the targeted attacks. The second approach aims at resisting Blind Steganalytic Attacks especially the Calibration based Blind Attacks which try to estimate a model of the cover image from the stego image. A Statistical Hypothesis Testing framework has been developed for testing the efficiency of a blind attack. A generic framework for JPEG steganography has been proposed which disturbs the cover image model estimation of the blind attacks. This framework has also been extended to a novel steganographic algorithm which can be used for any JPEG domain embedding scheme. Experimental results show that the proposed algorithm can successfully resist the calibration based blind attacks and some non-calibration based attacks as well.

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Chapter 1

Introduction

1.1 Steganography

Steganography is the art of hiding information imperceptibly in a cover medium. The word ”Steganography” is of Greek origin and means ”covered or hidden writing”. The main aim in steganography is to hide the very existence of the message in the cover medium. Steganography includes a vast array of methods of secret communication that conceal the very existence of hidden information. Traditional methods include use of invisible inks, microdots etc. Modern day steganographic techniques try to exploit the digital media images, audio files, video files etc

Steganography and cryptography are cousins in the spy craft family. Cryptography scrambles a message by using certain cryptographic algorithms for converting the secret data into unintelligible form. On the other hand, Steganography hides the message so that it cannot be seen. A message in cipher text might arouse suspicion on the part of the recipient while an ”invisible” message created with steganographic methods will not. Anyone engaging in secret communication can always apply a cryptographic algorithm to the data before embedding it to achieve additional security. In any case, once the presence of hidden information is revealed or even suspected, the purpose of steganography is defeated, even if the message content is not extracted or deciphered. According to [1] , *“Steganography’s niche in security is to supplement cryptography, not replace it. If a hidden message is encrypted, it must also be decrypted if discovered, which provides another layer of protection.”*

Another form of data hiding in digital images is **Watermarking**. Digital watermarking is the process of embedding auxiliary information into a digital cover signal with the aim of providing authentication information. A watermark is called robust with respect to a class of transformations if the embedded information can reliably be detected from the marked signal even if degraded by any transformation within that class. Typical image degradations are JPEG compression, rotation, cropping, additive noise and quantization.

Steganography and watermarking differ in a number of ways including purpose, specification and detection/extraction methods. *The most fundamental difference is that the object of communication in watermarking is the host signal, with the embedded data providing copyright protection. In steganography the object to be transmitted is the embedded message, and the cover signal serves as an innocuous disguise chosen fairly arbitrarily by the user based on its technical suitability.* In addition, the existence of the watermark is often declared openly, and any attempt to remove or invalidate the embedded content renders the host useless. *The crucial requirement for steganography is perpetual and algorithmic undetectability.* Robustness against malicious attack and signal processing is not the primary concern, as it is for watermarking. The difference between Steganography and Watermarking with respect the three parameters of payload, undetectability and robustness can be understood from Figure 1.1.

As mentioned, steganography deals with hiding of information in some cover source. On the other hand, Steganalysis is the art and science of detecting messages hidden using steganography; this is analogous to cryptanalysis applied to cryptography. The goal of steganalysis is to identify suspected packages, determine whether or not they have a payload encoded into them, and, if possible, recover that payload. Hence, the major challenges of effective steganography are:-

1. **Security of Hidden Communication**: In order to avoid raising the suspicions of eavesdroppers, while evading the meticulous screening of algorithmic detection, the hidden contents must be invisible both perceptually and statistically.

2. **Size of Payload**: Unlike watermarking, which needs to embed only a small amount of copyright information, steganography aims at hidden communication and therefore usually requires sufficient embedding capacity. Requirements for higher payload and secure communication are often contradictory. Depending on the specific application scenarios, a trade off has to be sought.

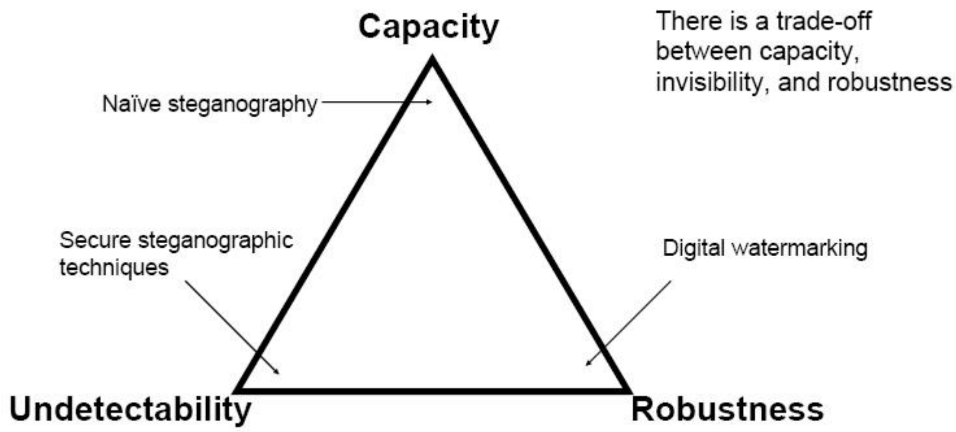


Figure 1.1: Tradeoff between embedding capacity, undetectability and robustness in data hiding.

One of the possible ways of categorizing the present steganalytic attacks is on the following two categories :

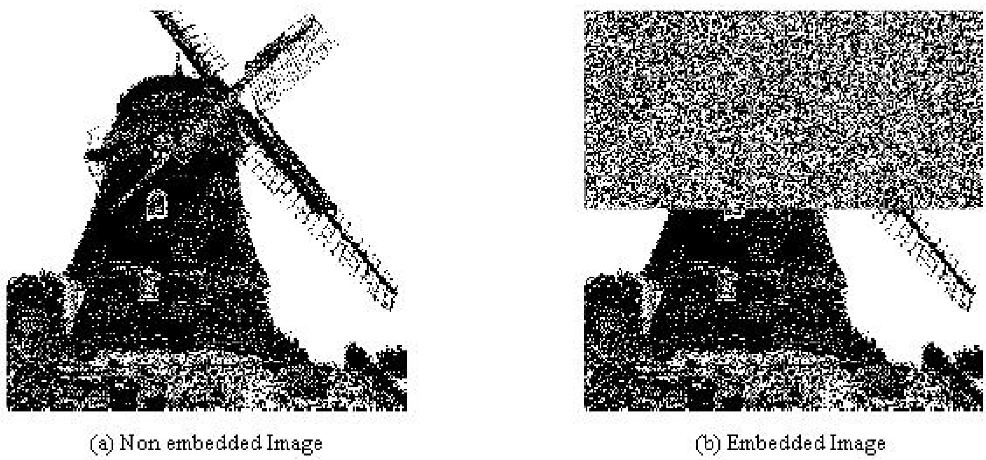


Figure 1.2: Visual attacks for detecting hidden messages in an image layer

1. **Visual Attacks**: These methods try to detect the presence of information by visual inspection either by the naked eye or by a computer. The attack is based on guessing the embedding layer of an image (say a bit plane) and then visually inspecting that layer to look for any unusual modifications in that layer as shown in Figure 1.2.

2. **Statistical Attacks**: These methods use first or higher order statistics of the image to reveal tiny alterations in the statistical behavior caused by steganographic embedding and

hence can successfully detect even small amounts of embedding with very high accuracy. These class of steganalytic attacks are further classified as **'Targeted Attacks'** or **'Blind Attacks'** as explained in detail in the next few sections.

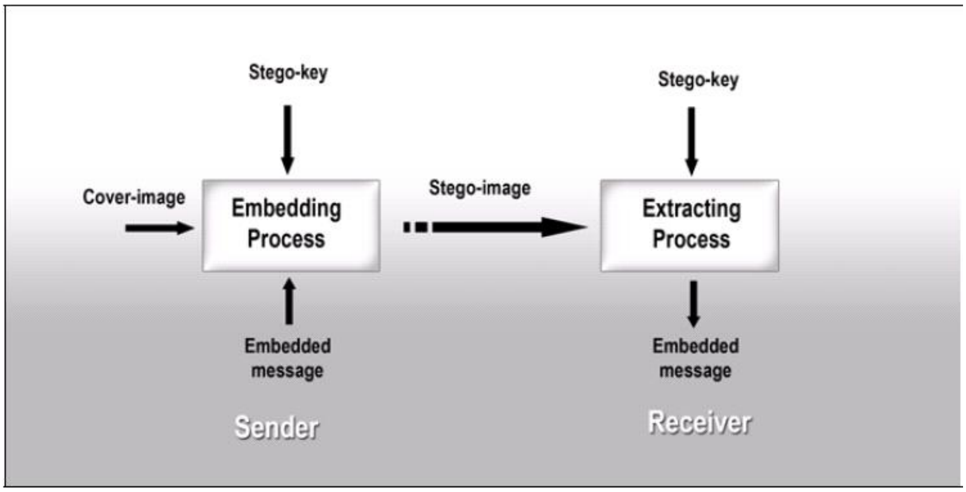


Figure 1.3: A generalized steganographic framework

1.2 A Steganographic Framework

Any steganographic system can be studied as shown in Figure 1.3. For a steganographic algorithm having a stego-key, given any cover image the embedding process generates a stego image. The extraction process takes the stego image and using the shared key applies the inverse algorithm to extract the hidden message.

This system can be explained using the *'prisoners problem'* (Figure 1.4) where Alice and Bob are two inmates who wish to communicate in order to hatch an escape plan. However communication between them is examined by the warden, Wendy. To send the secret message to Bob, Alice embeds the secret message 'm' into the cover object 'c', to obtain the stego object 's'. The stego object is then sent through the public channel. In a pure steganographic framework, the technique for embedding the message is unknown to Wendy and shared as a secret between Alice and Bob. In private key steganography Alice and Bob share a secret key which is used to embed the message. The secret key, for example, can be a password used to seed a pseudo-random number generator to select pixel locations in an image cover-object for embedding the secret message. Wendy has no knowledge about the secret key that Alice and

Bob share, although she is aware of the algorithm that they could be employing for embedding messages. In public key steganography, Alice and Bob have private-public key pairs and know each other's public key. In this thesis we confine ourselves to private key steganography only.

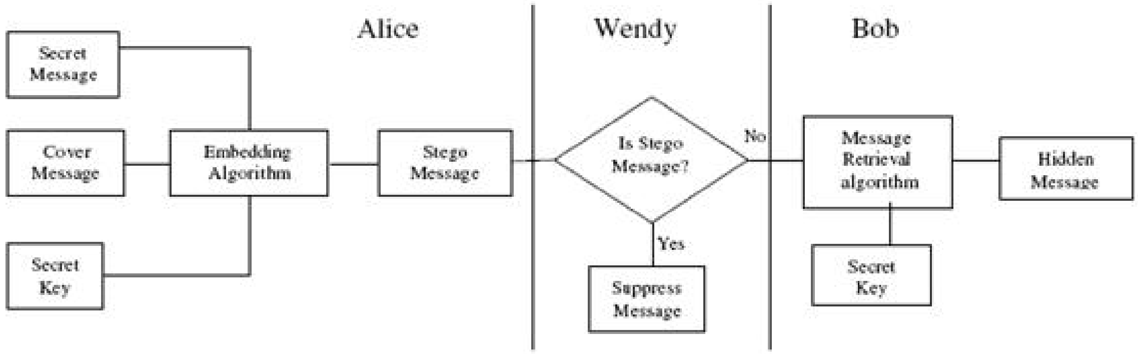


Figure 1.4: Framework for Private Key Passive Warden Steganography.

1.3 Organization of the Thesis

This thesis is organized as follows : In Chapter 2, *"Literature Survey"*, we give a background of the existing state of the steganographic research. We cover briefly the main categories of steganographic algorithms covered till date although the survey is not exhaustive and we may have missed out some of the algorithms. We also present a survey on the two categories of Steganalytic Attacks, "Targeted" and "Blind" and briefly describe the attacks especially the attacks that are relevant to this thesis. In Chapter 3, *"Statistical Restoration"*, we present the motivation for working on this approach in steganography and present some of the existing algorithms based on this approach. We introduce two new algorithms for data embedding with statistical preservation and make a comparative analysis of the proposed algorithms with the existing ones. In Chapter 4, *"Spatial Desynchronization"*, we first study the calibration based blind attacks and analyze two of the existing attacks using a novel Statistical Hypothesis Testing Framework to test their effectiveness against steganographic embedding. We introduce a new framework for JPEG steganographic algorithms called "Spatial Desynchronization" and extend this framework to a new steganographic scheme called "Spatially Desynchronized Steganographic Algorithm". We make a comparative analysis of the proposed algorithm with the existing techniques with respect to the statistical hypothesis testing framework introduced in the same chapter and also with respect to two more metrics of evaluation (Area under ROC, Detection Accuracy). The thesis is concluded in Chapter 5 with the concluding remarks. We also try to identify and present some avenues of future research. Also, the papers included in the bibliography and the source code of all the algorithms and attacks implemented in the course of this work have been attached in the form of a CD with the thesis.

Chapter 2

Literature Survey

In this chapter we provide the necessary background required for this thesis. In section 2.1 we discuss briefly some of the existing steganographic techniques. In section 2.2 we present some of the steganalytic attacks proposed till date as a counter measure to the steganographic algorithms.

2.1 Existing Steganographic Techniques

The steganographic algorithms proposed in literature can broadly be classified into two categories.

1. Spatial Domain Techniques

2. Transform Domain Techniques

Each of these techniques are covered in detail in the next two subsections.

2.1.1 Spatial Domain

These techniques use the pixel gray levels and their color values directly for encoding the message bits. These techniques are some of the simplest schemes in terms of embedding and extraction complexity. The major drawback of these methods is amount of additive noise that creeps in the image which directly affects the Peak Signal to Noise Ratio and the statistical properties of the image. Moreover these embedding algorithms are applicable mainly to lossless image compression schemes like TIFF images. For lossy compression schemes like JPEG, some of the message bits get lost during the compression step.

The most common algorithm belonging to this class of techniques is the Least Significant Bit (LSB) Replacement technique in which the least significant bit of the binary representation of the pixel gray levels is used to represent the message bit. This kind of embedding leads to an addition of a noise of $0.5p$ on average in the pixels of the image where p is the embedding rate in bits/pixel. This kind of embedding also leads to an asymmetry and a grouping in the pixel gray values (0,1);(2,3);...(254,255). This asymmetry is exploited in the attacks developed for this technique as explained further in section 2.2. To overcome this undesirable asymmetry, the decision of changing the least significant bit is randomized i.e. if the message bit does not match the pixel bit, then pixel bit is either increased or decreased by 1. This technique is popularly known as *LSB Matching*. It can be observed that even this kind of embedding adds a noise of $0.5p$ on average. To further reduce the noise, [2] have suggested the use of a binary function of two cover pixels to embed the data bits. The embedding is performed using a pair of pixels as a unit, where the LSB of the first pixel carries one bit of information, and a function of the two pixel values carries another bit of information. It has been shown that embedding in this fashion reduces the embedding noise introduced in the cover signal.

In [4], a multiple base number system has been employed for embedding data bits. While embedding, the human vision sensitivity has been taken care of. The variance value for a block of pixels is used to compute the number base to be used for embedding. A similar kind of algorithm based on human vision sensitivity has been proposed by [5] by the name of Pixel Value Differencing. This approach is based on adding more amount of data bits in the high variance regions of the image for example near *"the edges"* by considering the difference values of two neighboring pixels. This approach has been improved further by clubbing it with least significant bit embedding in [6].

According to [20], *"For a given medium, the steganographic algorithm which makes fewer embedding changes or adds less additive noise will be less detectable as compared to an algorithm which makes relatively more changes or adds higher additive noise."* Following the same line of thought Crandall [7] have introduced the use of an Error Control Coding technique called *"Matrix Encoding"*. In Matrix Encoding, q message bits are embedded in a group of $2^q - 1$ cover pixels while adding a noise of $1 - 2^{-q}$ per group on average. The maximum embedding capacity that can be achieved is $\frac{q}{2^q-1}$. For example, 2 bits of secret message can be embedded in a group of 3 pixels while adding a noise of 0.75 per group on average. The maximum embedding capacity achievable is $2/3$ = 0.67 bits/pixel. F5 algorithm [17] is probably the most popular implementation of Matrix Encoding.

LSB replacement technique has been extended to multiple bit planes as well. Recently [3] has claimed that LSB replacement involving more than one least significant bit planes is less detectable than single bit plane LSB replacement. Hence the use of multiple bit planes for embedding has been encouraged. But the direct use of 3 or more bit planes leads to addition of considerable amount of noise in the cover image. [8] and [9] have given a detailed analysis of the noise added by the LSB embedding in 3 bit planes. Also, a new algorithm which uses a combination of *Single Digit Sum Function* and *Matrix Encoding* has been proposed. It has been shown analytically that the noise added by the proposed algorithm in a pixel of the image is $0.75p$ as compared to $0.875p$ added by 3 plane LSB embedding where p is the embedding rate.

One point to be observed here is that most of the approaches proposed so far are based on minimization of the noise embedded in the cover by the algorithm. Another direction of steganographic algorithm is preserving the statistics of the image which get changed due to embedding. Chapter 2 of this thesis proposes two algorithms based on this approach itself. In the next section we cover some of the transform domain steganographic algorithms.

2.1.2 Transform Domain

These techniques try to encode message bits in the transform domain coefficients of the image. Data embedding performed in the transform domain is widely used for robust watermarking. Similar techniques can also realize large-capacity embedding for steganography. Candidate transforms include discrete cosine Transform (DCT), discrete wavelet transform (DWT), and discrete Fourier transform (DFT). By being embedded in the transform domain, the hidden data resides in more robust areas, spread across the entire image, and provides better resistance against signal processing. For example, we can perform a block DCT and, depending on payload and robustness requirements, choose one or more components in each block to form a new data group that, in turn, is pseudo randomly scrambled and undergoes a second-layer transformation. Modification is then carried out on the double transform domain coefficients using various schemes. These techniques have high embedding and extraction complexity. Because of the robustness properties of transform domain embedding, these techniques are generally more applicable to the *"Watermarking"* aspect of data hiding. Many steganographic techniques in these domain have been inspired from their watermarking counterparts.

F5 [17] uses the Discrete Cosine Transform coefficients of an image for embedding data bits. F5 embeds data in the DCT coefficients by rounding the quantized coefficients to the nearest data bit. It also uses Matrix Encoding for reducing the embedded noise in the signal. F5 is one the most popular embedding schemes in DCT domain steganography, though it has been successfully broken in [42].

The transform domain embedding does not necessarily mean generating the transform coefficients on a blocks of size 8×8 as done in JPEG compression techniques. It is possible to design techniques which take the transforms on the whole image [10]. Other block based JPEG domain and wavelet based embedding algorithms have been proposed in [11] and [25] respectively.

2.2 Existing Attacks

The steganalytic attacks developed till date can be classified into visual and statistical attacks. The statistical attacks can further be classified as

1. Targeted Attacks

2. Blind Attacks

Each of these classes of attack is covered in detail in the next two subsections along with several examples of each category.

2.2.1 Targeted Attacks

These attacks are designed keeping a particular steganographic algorithm in mind. These attacks are based on the image features which get modified by a particular kind of steganographic embedding. A particular steganographic algorithm imposes a specific kind of behaviour on the image features. This specific kind of behaviour of the image statistics is exploited by the targeted attacks. Some of the targeted attacks are as follows:

1. **Histogram Analysis**: The histogram analysis method exploits the asymmetry introduced by LSB replacement. The main idea is to look for statistical artifacts of embedding in the histogram of a given image. It has been observed statistically that in natural images

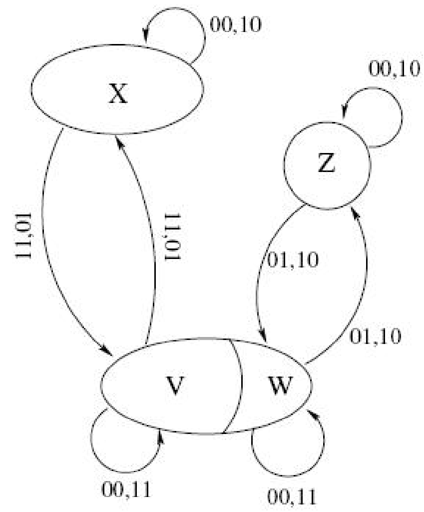


Figure 2.1: Flipping of set cardinalities during embedding

(cover images), the number of odd pixels and the number of even pixels are not equal. For higher embedding rates of LSB Replacement these quantities tend to become equal. So, based on this artifact a statistical attack based on the ***Chi-Square Hypothesis Testing*** is developed to probabilistically suggest one of the following two hypothesis:

Null Hypothesis H_0*: The given image contains steganographic embedding*

Alternative Hypothesis H_1*: The given image does not contain steganographic embedding*

The decision to accept or reject the Null Hypothesis H_0 is made on basis of the observed confidence value p. A more detailed discussion on Histogram Analysis can be found in [37].

2. **Sample Pair Analysis :** Sample Pair Analysis is another LSB steganalysis technique that can detect the existence of hidden messages that are randomly embedded in the least significant bits of natural continuous-tone images. It can precisely measure the length of the embedded message, even when the hidden message is very short relative to the image size. The key to this methods success is the formation of 4 subsets of pixels (X, Y, U, and V) whose cardinalities change with LSB embedding (as shown in Figure 2.1), and such changes can be precisely quantified under the assumption that the embedded bits are randomly scattered. A detailed analysis on Sample Pair technique can be found in [34]. Another attack called RS Steganalysis based on the same concept has been independently proposed by [38].

3. **HCF-COM based Attack:** This attack first proposed by [43] is based on the Center of Mass (COM) of the Histogram Characteristic Function (HCF) of an image. This attack was further extended for LSB Matching by [39]. This attack observes the COM of a cover/stego image (C(H_C)/C(H_S)) and its calibrated version obtained by down sampling the image (C($H_{\hat{C}}$)/C($H_{\hat{S}}$)). It has been proved empirically that :

$$C(H_C) \approx C(H_{\hat{C}}) \tag{2.1}$$

$$C(H_C) - C(H_S) > C(H_{\hat{C}}) - C(H_{\hat{S}}) \tag{2.2}$$

From Equations 2.1 and 2.2, a dimensionless discriminator for classification can be obtained as $\frac{C(H_S)}{C(H_{\hat{S}})}$. By estimating suitable threshold values of the discriminator from a set of training data, an image can be classified either as cover or stego.

Some other targeted attacks also exist in literature which have not been covered in this survey. A detailed survey can be found in [35]

2.2.2 Blind Attacks

The blind approach to steganalysis is similar to the pattern classification problem. The pattern classifier, in our case a *Binary Classifier*, is trained on a set of training data. The training data comprises of some high order statistics of the transform domain of a set of cover and stego images and on the basis of this trained dataset the classifier is presented with images for classification as a non-embedded or an embedded image. Many of the blind steganalytic techniques often try to estimate the cover image statistics from stego image by trying to minimize the effect of embedding in the stego image. This estimation is sometimes referred to as *"Cover Image Prediction"*. Some of the most popular blind attacks are defined next.

1. **Wavelet Moment Analysis (WAM)**: Wavelet Moment Analyzer (WAM) is the most popular Blind Steganalyzer for Spatial Domain Embedding. It has been proposed by [40]. WAM uses a denoising filter to remove Gaussian noise from images under the assumption that the stego image is an additive mixture of a non-stationary Gaussian signal (the cover image) and a stationary Gaussian signal with a known variance (the noise). As the

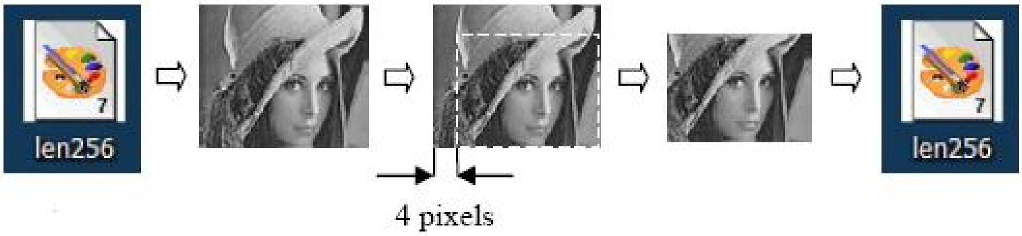


Figure 2.2: Calibration of the stego image for cover statistics estimation

filtering is performed in the wavelet domain, all the features (statistical moments) are calculated as higher order moments of the noise residual in the wavelet domain. The detailed procedure for calculating the WAM features in a gray scale image can be found in [40]. WAM is based on a 27 dimension feature space. It then uses a Fisher Linear Discriminant (FLD) as a classifier. It must be noted that WAM is a state of the art steganalyzer for Spatial Domain Embedding and no other blind attack has been reported which performs better than WAM.

2. **Calibration Based Attacks**: The calibration based attacks estimate the cover image statistics by nullifying the impact of embedding in the cover image. These attacks were first proposed by [14] and are designed for JPEG domain steganographic schemes. They estimate the cover image statistics by a process termed as $Self\ Calibration$. The steganalysis algorithms based on this self calibration process can detect the presence of steganographic noise with almost 100% accuracy even for very low embedding rates [14, 28]. This calibration is done by decompressing the stego JPEG image to spatial domain and cropping 4 rows from the top and 4 columns from the left and recompressing the cropped image as shown in Figure 2.2. The cropping and subsequent recompression produce a "calibrated" image with most macroscopic features similar to the original cover image. The process of cropping by 4 pixels is an important step because the 8×8 grid of recompression *"does not see"* the previous JPEG compression and thus the obtained DCT coefficients are not influenced by previous quantization (and embedding) in the DCT domain. The details of these attacks are covered in Chapter 4.

3. **Farid's Wavelet Based Attack**: This attack was one of the first blind attacks to be proposed in steganographic research [13] for JPEG domain steganography. It is based on the

features drawn from the wavelet coefficients of an image. This attack first makes an n level wavelet decomposition of an image and computes four statistics namely Mean, Variance, Skewness and Kurtosis for each set of coefficients yielding a total of $12 \times (n-1)$ coefficients. The second set of statistics is based on the errors in an optimal linear predictor of coefficient magnitude. It is from this error that additional statistics i.e. the mean, variance, skewness, and kurtosis are extracted thus forming a $24 \times (n-1)$ dimensional feature vector. For implementation purposes, n is set to 4 i.e. four level decomposition on the image is performed for extraction of features. The source code of this attack is available at [32]. After extraction of features, a Support Vector Machine (SVM) is used for classification. We would like to mention that although in [32] a SVM has been used for classification we have used the Linear Discriminant Analysis for classification.

Some other blind attacks have also been proposed in literature. [30] have modeled the difference between absolute value of neighboring DCT coefficients as a Markov process to extract 324 features for classifying images as cover or stego. [28] have extended the features of [14] to 193 and clubbed them with 72 features derived by reducing the 324 extracted by [30].

2.3 Summary

In this chapter, we have covered some of the necessary background needed for the rest of the thesis. Some other concepts and definitions may be used from time to time and they shall be explained as and when needed.

Chapter 3

Statistical Restoration

Statistical undetectability is one of the main aspects of any steganographic algorithm. To maintain statistical undetectability, the steganographic techniques are designed with the aim of minimizing the artifacts introduced in the cover signal by the embedding technique. The main emphasis is generally on minimizing the noise added by embedding while increasing the payload. This is an important consideration in the design of embedding algorithms, since the noise added effects the statistical properties of a medium. As already mentioned previously, the algorithm which makes fewer embedding changes or adds less additive noise generally provides better security than the algorithm which makes relatively more changes or adds higher additive noise [33].

From the point of view of the steganalyst, the attacks are designed to examine a signal and look for statistics which get distorted due to embedding. These statistics range from marginal statistics of first and second order in case of targeted attacks[34, 38, 39] and upto 9th order statistics for blind attacks [40]. *So, in order to defeat these steganalytic attacks, there has been a shift from the above mentioned data hiding paradigm. Algorithms have been proposed which try to restore the statistics which get distorted during the embedding procedure and are used for steganalysis.*

In this chapter we review some of the existing schemes based on this approach of preserving the marginal statistics of an image in section 3.1. In section 3.2 we propose a new algorithm which inherently preserves the first order statistics of the cover image during embedding. In section 3.3, a steganographic method is proposed which explicitly preserves the first order statistics during embedding. We provide experimental results to show that the two proposed schemes give better performance than existing restoration methods. The chapter is finally concluded in section 3.4.

3.1 Introduction

In steganographic research several algorithms have been proposed for preserving statistical features of the cover for achieving more security. Provos' Outguess algorithm [18] was an early attempt at histogram compensation for LSB hiding, while Eggers et al [41] have suggested a more rigorous approach to the same end, using histogram-preserving data-mapping (HPDM) and adaptive embedding respectively.

Solanki et al [21, 22] have proposed a statistical restoration method for converting the stego image histogram into the cover histogram. This algorithm is based on a theorem proved by [36] which tries to convert one vector x into another vector y while satisfying a Minimum Mean Square Error (MMSE) criterion. The algorithm considers the stego image histogram as source vector x and tries to convert it into the cover image histogram i.e. the target vector y. All the bins of the source histogram are compensated by mapping the input data with values in increasing order. This algorithm suffers from the following limitations:

1. The algorithm assumes the cover image to be a Gaussian cover and does not give good results for non-Gaussian cover images.

2. The algorithm ignores low probability image regions for embedding due to erratic behavior in low probability tail.

3. The algorithm has been tried specifically for Quantization Index Modulation algorithm [23] and it has not been tested for some well known embedding schemes like LSB Replacement, LSB matching etc.

To overcome the above limitations we propose two algorithms for preserving the cover image statistics after embedding. The first algorithm is designed to inherently preserve the first order statistics during embedding itself. The algorithm makes an explicit attempt at restoring the cover image histogram after embedding. These algorithms are discussed in detail in the next two sections.

3.2 Embedding by Pixel Swapping

The main motivation the steganographic algorithm proposed in this section is to embed data such that the histogram of the image does not get modified. Such a requirement entails an embedding procedure which does not modify the pixel values such that the corresponding bin value in the histogram is changed. We propose a simple yet effective algorithm called ***"Pixel Swap Embedding"*** which embeds message bits into the cover image without making any modifications to the image histogram. The main idea is to consider a pair of pixels such that their difference is within a fixed threshold value. To embed a value of 0 check if the first pixel is greater than the second pixel or not. Otherwise swap these two gray level values. Similarly pixel value of 1 can be embedded by making the value of first pixel lesser than the second pixel. The algorithm is discussed formally in the next subsection.

3.2.1 Algorithm Pixel Swap Embedding

The algorithm is summarized below.

Algorithm: *Pixel Swap Embedding (PSE)*

Input: *Cover Image* (I)

Input Parameters: *Message Stream* (α), *Threshold* (ϵ), *Shared Pseudo Random Key* (k)

Output: *Stego Image* I_s

Begin

1. (x_1,x_2) = Randomize(I,k)

2. *If* $|x_1 - x_2| \leq \epsilon$

   then goto Step 3

   Else goto Step 1.

3. *If* $\alpha(i) = 0$

   If $x_1 \geq x_2$

   then Swap(x_1,x_2)

   $i = i + 1$

   Else $i = i + 1$

   goto Step 1

Else goto step 4.

4. *If* $\alpha(i) = 1$

   If $x_1 \leq x_2$

   then Swap(x_1,x_2)

   $i = i + 1$

   Else $i = i + 1$

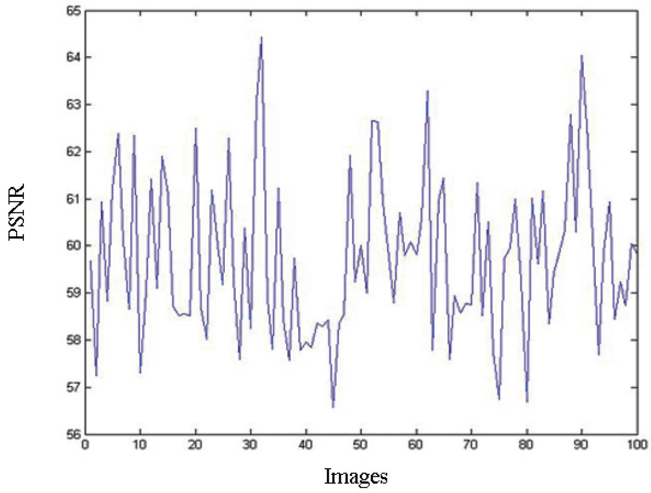
   goto Step 1

   Else goto step 1.

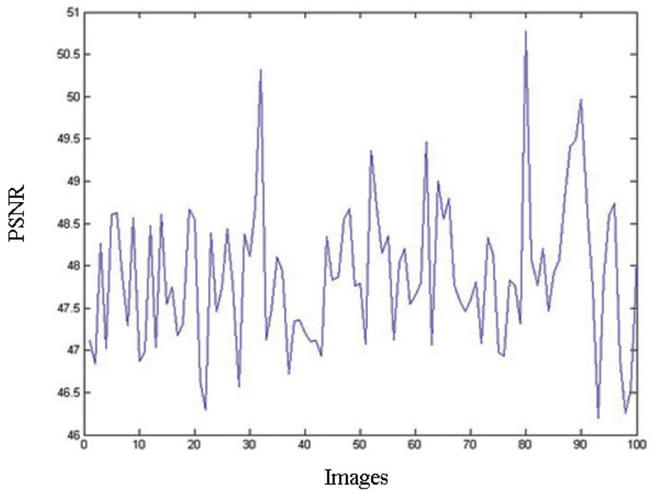
End *Pixel Swap Embedding*

The Randomize(I,k) function generates random non-overlapping pairs of pixels (x_1,x_2) using the secret key k shared by both ends. Once a pair (x_1,x_2) has been used by the algorithm it cannot be reused again. The function Swap(x_1,x_2) interchanges the grayvalues of the two pixels x_1 and x_2. The extraction of the message bits is a simple inverse process of the above algorithm. It is easily understood that this scheme automatically preserves the values of all image histogram bins since no extra value is introduced in the cover. Hence it can resist the attacks based on first order statistics.

One important point to be observed here is that the threshold ϵ used in the algorithm directs the trade off between the embedding rate and the noise introduced in the cover signal. The noise added shall be limited as long as ϵ is kept small. We tested the algorithm for ϵ = 2 and ϵ = 5 i.e effectively we are making modifications to the Least Significant Planes of the pixel graylevel but without changing the bin value of the two grayvalues. The achievable embedding rate would be high for images having low variance than for images having high variance as the number of pixel pairs satisfying the condition in Step 2 of the PSE algorithm would be higher in the former case than in the latter case. The plots of the maximum achievable embedding rates using PSE algorithm is shown in Figures 3.2(a) and 3.2(b). To verify that the noise added by PSE algorithm, we plotted the Peak Signal to Noise Ratio (PSNR) values obtained for one hundred grayscale images as shown in Figures 3.1(a) and 3.1(b). It can be observed that the PSNR values are constantly above 57 dB for ϵ = 2 and above 46 dB for ϵ = 5. This reduction in PSNR values is due to the increase in the achievable embedding rate as we increase ϵ. In the next subsection we analyze the security of the PSE algorithm against the first order statistics



(a) PSNR for ϵ=2



(b) PSNR for ϵ=5

Figure 3.1: PSNR for the Pixel Swap Embedding Algorithm for different values of ϵ.

based targeted attacks.

3.2.2 Security Analysis

To check the robustness of the PSE algorithm we conducted security tests on a set of one hundered grayscale images [16]. All the images were converted to the Tagged Image Format (TIFF) and resized to 256×256 pixels. PSE was tested against the Sample Pair attack proposed in [34]. As explained in 2.2.1 Sample Pair is a targeted attack based on the first order statistics of the cover image and tries to exploit the distortion which takes place in the image statistics. Also, a similar kind of attack called RS-Steganalysis has been proposed independently by [38] which is based on the same concept of exploiting the first order statistics of the cover image. Hence, in this work we have tested the performance of our schemes against Sample Pair Attack only assuming that it will give similar performance against RS- Steganalysis as well.

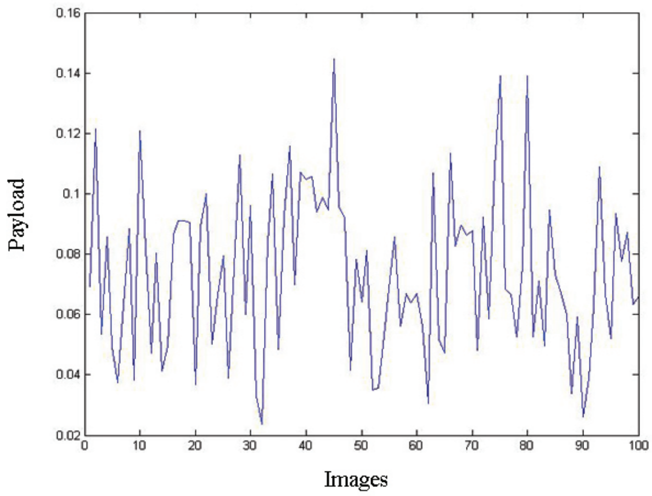
The performance of PSE against Sample Pair has been shown in Figure 3.3. Data bits were hidden in the images as the maximum possible embedding rates for ϵ = 5. It can be observed that the message length predicted by Sample Pair Attack is much less than the actual message length embedded in the image.

In the next section we introduce the second algorithm based on the idea of statistical preservation which explicitly tries to match the cover image histogram after embedding.

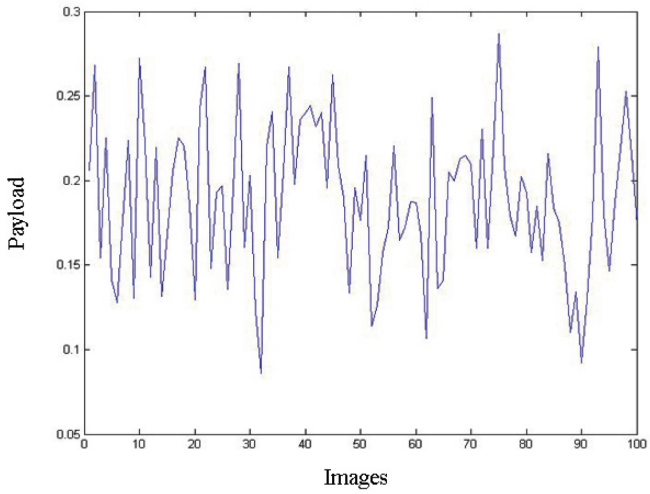
3.3 New Statistical Restoration Scheme

In this section we propose a new statistical restoration scheme which explicitly tries to convert the stego image histogram into the cover image histogram after completion of embedding. As mentioned in 3.1, the restoration algorithm proposed in [21, 22] gives good results only under the assumption that the cover image will be close to a Gaussian Distribution. The proposed scheme tries to overcome this limitation and provides better restoration of image histogram for non-Gaussian cover distributions as well.

The histogram $h(I)$ of an gray scale image I with range of gray value $[0 \dots L]$ can be interpreted as a discrete function where $h(r_k) = \frac{n_k}{n}$ where r_k is k^{th} gray level, n_k is the number of pixels with gray value = r_k and n is the total number of pixels in the image I. Histogram $h(I)$ can also be represented as $h(I) = \{h(r_0), h(r_1), h(r_2), \dots, h(r_{L-1})\}$ or simply, $h(I) = \{h(0), h(1), h(2), \dots, h(L-1)\}$. Let us represent the histogram of the stego image $\hat{h}(I)$ as



(a) Maximum achievable embedding rate for ϵ=2



(b) Maximum achievable embedding rate for ϵ=5

Figure 3.2: Maximum Achievable Embedding Rates for PSE Algorithm for different values of ϵ.

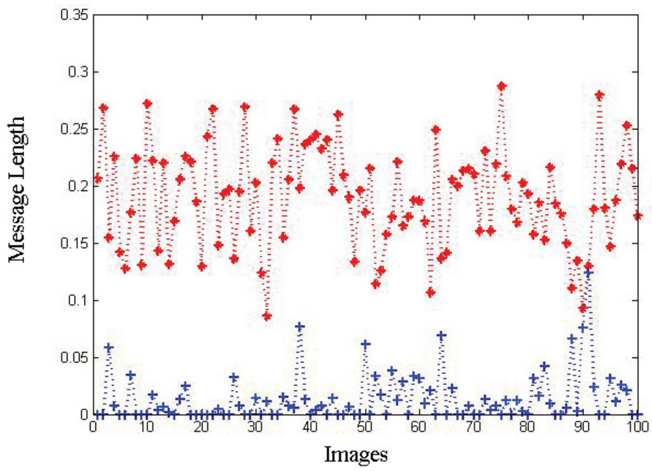


Figure 3.3: Result of testing PSE algorithm against Sample Pair Attack for ϵ = 5. Red Plot: Actual Message Length, Blue Plot: Predicted Message Length

$\hat{h}(I) = \{\hat{h}(0), \hat{h}(1), \hat{h}(2), \ldots, \hat{h}(L-1)\}$. We then categorize the image pixels into two streams, *Embedding Stream* and the *Restoration Stream*. During embedding we maintain the meta data about those pixels which get changed during embedding and the amount of change in those pixels. Then we compensate the histogram with the pixels from the *Restoration Stream* using the meta data information such that the original histogram of the cover can be restored. So by restoration we try to equalize $\hat{h}(I)$ and $h(I)$. The algorithm is formalized in the next few subsections.

3.3.1 Mathematical Formulation of Proposed Scheme

The proposed restoration scheme is dependent on the embedding scheme. The whole idea of embedding and restoring is that some of image pixels are used for embedding and rest are used for restoration. Without loss of generality, we can say that if number of pixels used for embedding is greater than 50% of the whole image then complete restoration is not possible but converse is not always true. One cannot say that if number of available compensation pixels are greater than or equal to 50% of the whole image, then full compensation is possible. But we can certainly see that the probability of full compensation increases with increase in the number of pixels available for compensation. So a trade off has to be sought between the embedding rate and restoration percentage in order to get the optimum embedding procedure. For better understanding of the algorithm some definitions are described next.

Let the cover image, stego image (i.e. embedded but not yet compensated) and compensated stego image (stego image after compensation) be defined by C, S and R respectively. Suppose C_{ij}, S_{ij} and R_{ij} represent the $(i, j)^{th}$ pixel of C, S and R images respectively ($0 < i < m$, $0 < j < n$, m is number of rows and n is number of columns of image matrices).

$Embed\ Matrix(\Psi)$**:** It is a $m \times n$ characteristic matrix representing whether a pixel has been used for embedding or not.

$$\Psi(i,j) = \begin{cases} 1 & \text{if } (i,j)^{th} \text{ pixel is used for embedding} \\ \\ 0 & \text{if } (i,j)^{th} \text{ pixel is not used for embedding} \end{cases} \tag{3.1}$$

$Compensation\ Vector(\Omega)$**:** It is a one dimensional vector with length L where L is number of existing gray levels in the cover image (C). $\Omega(k)$ = u means that u number of pixels with gray value k can be used for restoration.

$Changed\ Matrix(\Gamma)$**:** It is a $L \times L$ matrix where L is number of existing gray levels in the cover image (C). $\Gamma(x, y) = \lambda$ means during embedding λ number of pixels are changed from gray value x to gray value y.

$Changed\ Matrix$ (Γ) is computed as given below:

$$\Gamma(x,y) = \sum_{i=0}^{m}\sum_{j=0}^{n} eq(C_{ij}, x) \times eq(S_{ij}, y) \times \epsilon_{ij} \tag{3.2}$$

where

$$eq(a,b) = \begin{cases} 1 & \text{if } a = b \\ \\ 0 & \text{if } a \neq b \end{cases} \tag{3.3}$$

$Compensation\ Matrix(\xi)$**:** It is a $L \times L$ matrix where L is number of existing gray levels in the cover image (C). $\xi(x, y) = \lambda$ means during embedding number of times x is changed to y minus number of times y changes to x is λ.

$Compensation\ Matrix$ (ξ) has been formed as following:

$$\xi = UT(\Gamma - \Gamma^T) \tag{3.4}$$

where $UT(M)$ means upper triangulation of matrix M.

3.3.2 Algorithm Statistical Restoration

The statistical restoration algorithm is summarized below:

Algorithm: *Statistical Restoration Algorithm (SRA)*

Input: *Cover Image (I)*

Input Parameters: $Compensation\ Matrix$ *(ξ),* $Changed\ Matrix$ *(Γ)*

Output: *Stego Image (I_s)*

Begin

for all $k \in \xi(i, j)$ *do*

{

1. $k = \xi(i, j)$

2. *If* $k > 0$, k number of pixels with gray value i from the set of pixels used for compensation are changed to gray value j for full compensation.
   Else k pixels with gray value j from the set of pixels used for compensation are changed to gray value i for full compensation.

3. Modify the $Compensation\ Vector$ (Ω) to reflect the pixel changes under taken in step 2 as in Equation 3.5 below

$$\Omega(i) = \begin{cases} \Omega(i) - k & \text{if } \Omega(i) > k \\ \\ 0 & \text{if } \Omega(i) \leq k \end{cases} \tag{3.5}$$

}

End *Statistical Restoration Algorithm (SRA)*

In the above algorithm we have made the assumption that for $\Omega(i) < k$, full compensation is not possible. Further research can be possible to improve this situation.

3.3.3 Restoration with Minimum Distortion

The additional noise added due to compensation is an important issue. The goal is to design a restoration procedure in such a way that additional noise should be kept minimum. In the SRA algorithm, the noise introduced depends on the embedding algorithm used. The total noise (η) introduced at the time of restoration can be estimated by

$$\eta = \sum_{i=0}^{L-1} \sum_{j=1}^{abs[\hat{h}(i)-h(i)]} abs(i - k_j) \tag{3.6}$$

where $\hat{h}(i)$ and $h(i)$ is the histogram of the stego and cover images respectively. $L - 1$ is the no. of bins in the histogram. k_j ($0 \leq k_j \leq L - 1$) is a bin that is used to repair at least one unit of data in i^{th} bin.

Lemma 3.3.1 *With any restoration scheme the minimum total noise* $\sum_{i=0}^{L-1} abs[\hat{h}(i) - h(i)]$.

Proof: The total noise (η) introduced at the time of restoration is

$$\eta = \sum_{i=0}^{L-1} \sum_{j=1}^{abs[\hat{h}(i)-h(i)]} abs(i - k_j) \tag{3.7}$$

where $1 \leq abs(i - k_j) \leq L - 1$. η is minimum when $abs(i - k_j) = 1$. Substituting $abs(i - k_j) = 1$ in Equation 3.7 we get

$$\eta = \sum_{i=0}^{L-1} abs[\hat{h}(i) - h(i)] \tag{3.8}$$

Lemma 3.3.2 *The total noise (η) added by the SRA algorithm is minimum if maximum noise per pixel due to embedding is* 1.

Proof: Since the SRA algorithm is based on pixel swapping strategy introduced in 3.2 i.e. if a the gray level value α of a pixel is changed to β during steganographic embedding, at the time of restoration, a pixel with gray level value β is changed to α.

During embedding with ± 1 embedding, the gray level value of a pixel, x can be changed into either $x + 1$ or $x - 1$. Hence during restoration the proposed scheme restores bin x value is repaired from either bin $x + 1$ or $x - 1$ according to embedding. It is to be noted that maximum noise that can be added during restoration for one member of a bin is at most 1 since we are using only the neighboring bins for compensation. Hence, with ± 1 embedding scheme (or any other steganographic scheme where noise added during embedding per pixel is at most 1), the proposed scheme increments or decrements gray value by 1 i.e. $abs(i - k_i) = 1$.

From Equation 3.7, the total noise (η) introduced at the time of restoration is

$$\eta = \sum_{i=0}^{L-1} \sum_{j=1}^{abs[\hat{h}(i)-h(i)]} abs(i - k_j)$$

and for the SRA algorithm $abs(i - k_i) = 1$, substituting this value in Equation 3.7, we get

$$\eta = \sum_{i=0}^{L-1} \sum_{j=1}^{abs[\hat{h}(i)-h(i)]} (1)$$

or

$$\eta = \sum_{i=0}^{L-1} abs[\hat{h}(i) - h(i)]$$

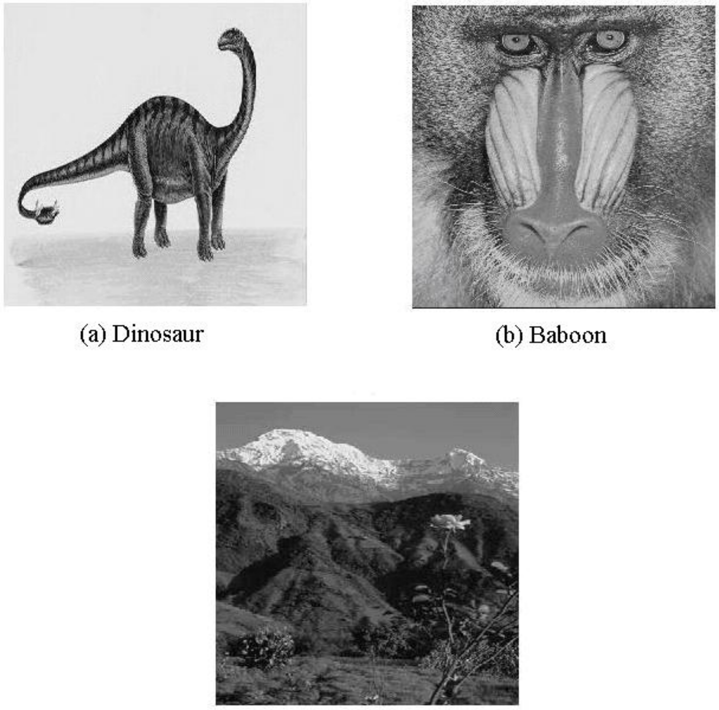
So from $Lemma$ 1 and 2, we can conclude that the SRA algorithm adds minimum amount of noise during restoration if maximum noise per pixel due to embedding is at most 1.

3.3.4 Experimental Results

For testing the performance of the SRA algorithm we conducted experiments on a data set of one hundred grayscale images 3.4. Least Significant Bit replacement with embedding rate 0.125 bits/pixel is used as the embedding method. All of the images used in our experiment had non-Gaussian histograms. Figures 3.5a, 3.6a and 3.7a image histograms of the three test images (Dinosaur, Baboon, and Hills) respectively. Figures 3.5b, 3.6b and 3.7b show the difference histograms of the two images before compensation. Figures 3.5c, 3.6c and 3.7c depict the difference Histogram after compensation using Solanki. et als scheme and Figures 3.5d, 3.6d and 3.7d show the compensation results using the proposed SRA algorithm respectively. It may be seen that the proposed scheme provides better restoration than Solanki. et. al's scheme. Figure 3.8 shows the scatter plot of the reduction in the difference histogram for Solanki's scheme against proposed scheme. It can be observed that reduction in difference histogram is more for the SRA algorithm.

3.3.5 Security Analysis

As already mentioned above many steganalysis techniques use first order statistical features to detect stego images [34, 38, 39]. If the SRA algorithm is used then it may be possible to reduce



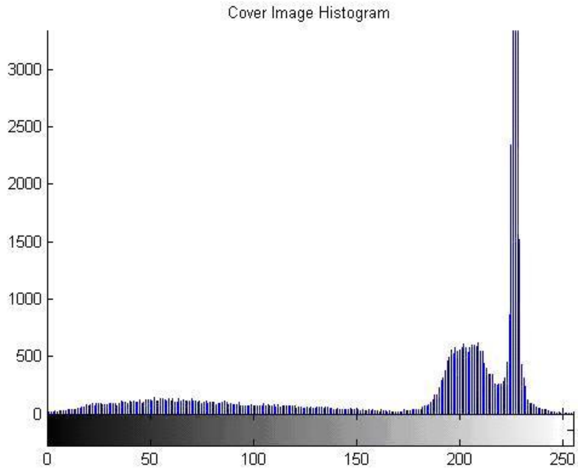
(a) Dinosaur (b) Baboon

(c) Hills

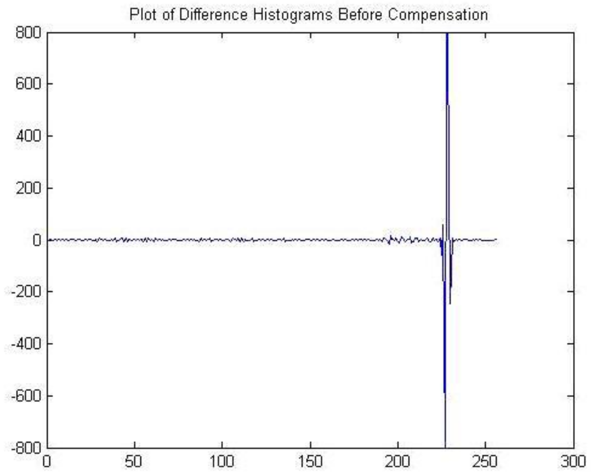
Figure 3.4: Sample Test Images

detection rate of the steganalyzer substantially. Also since SRA algorithm can be applied to any arbitrary cover distribution, it can be used to restore the first order statistics after embedding for most steganographic methods both in compressed and spatial domain. Histogram based attacks like Chi Square Attack [37] and HCF COM based attack [39] can be successfully resisted using the proposed scheme. It should be noted that the SRA algorithm can be used for preserving the histograms of the compressed domain coefficients as well, but this will lead to addition of large noise in the spatial domain. We tested the performance of the Sample Pair Attack on SRA algorithm for one hundred test images and plotted the Receiver Operating Characteristic (ROC) Curve as shown in Figure 3.9. LSB Matching was used as the embedding algorithm at an embedding rate of 0.25 bpp. It can be seen that the performance of Sample Pair Attack is as good as random guessing.

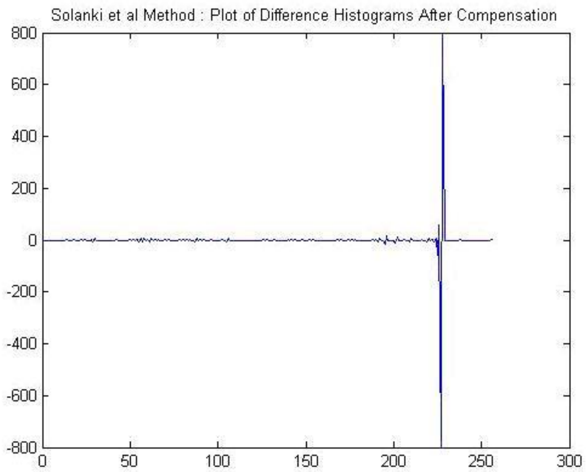
We also compared the performance of the SRA algorithm and Solanki's scheme for two embedding rates of 0.25 and 0.35 bpp. In can be seen in the Figures 3.10(a) and 3.10(b) that the detection rate of SRA is less than the detection rate of Solanki's scheme. This fact can be easily understood since SRA algorithm can restore the statistics in a better way and hence it is able to resist the first order statistics based attacks.



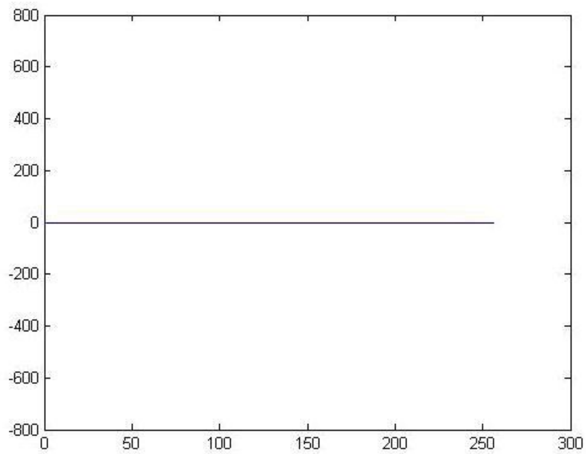
(a) Histogram of Dinosaur



(b) Uncompensated Difference Histogram



(c) Compensated Difference Histogram using Solanki's Method



(d) Compensated Difference Histogram using proposed SRA Algorithm

Figure 3.5: Results for Dinosaur

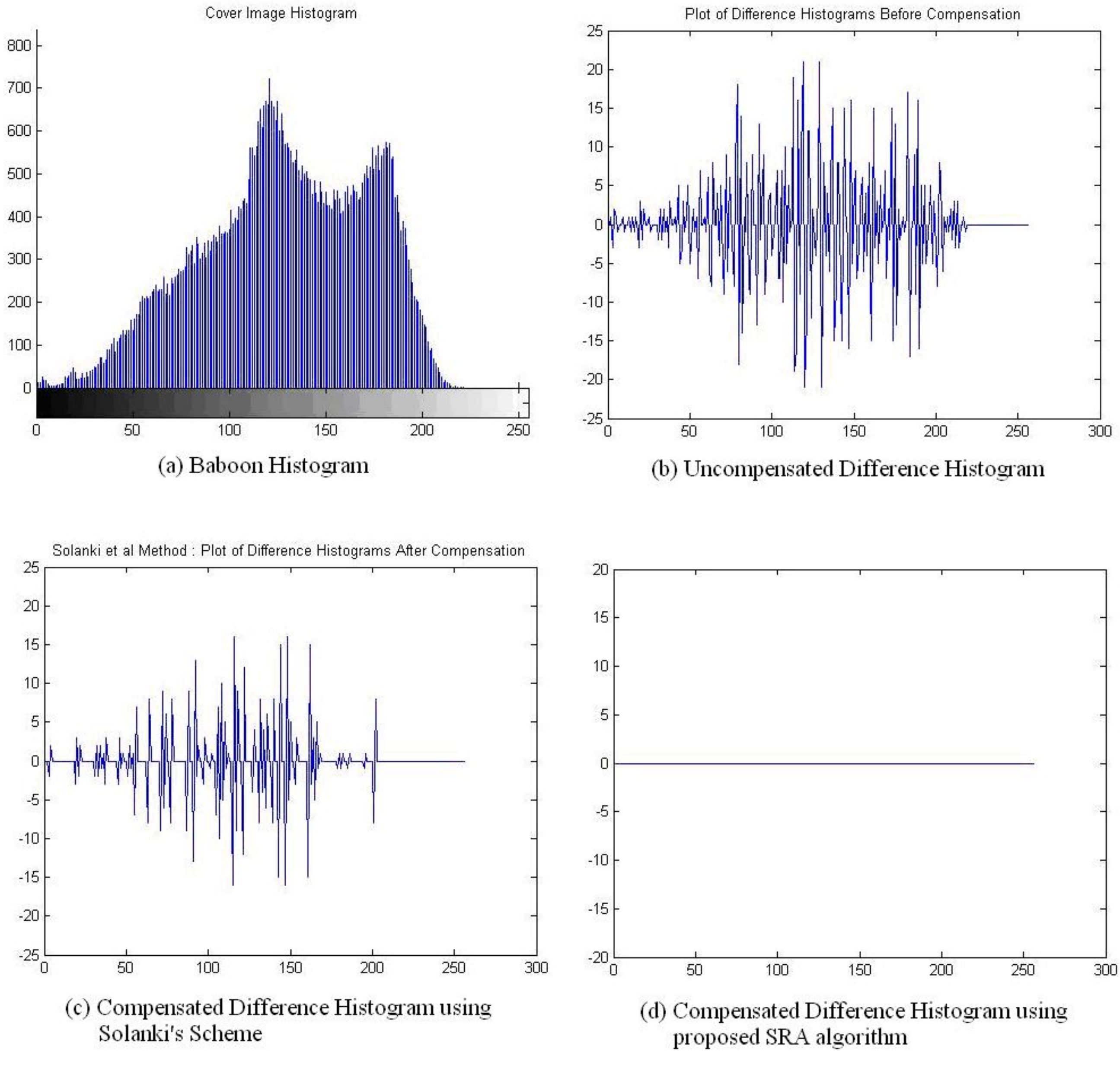
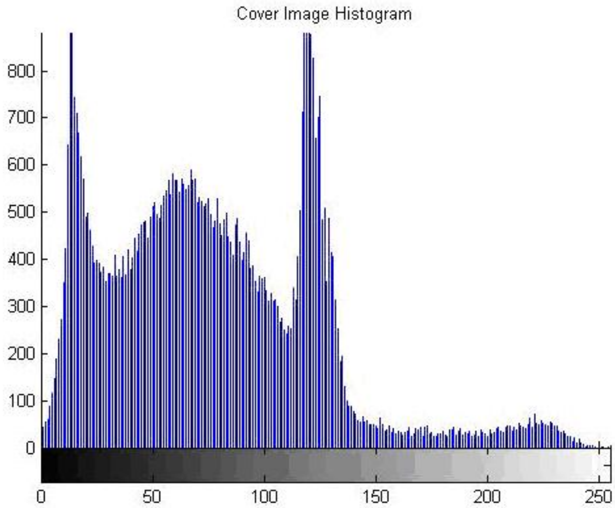
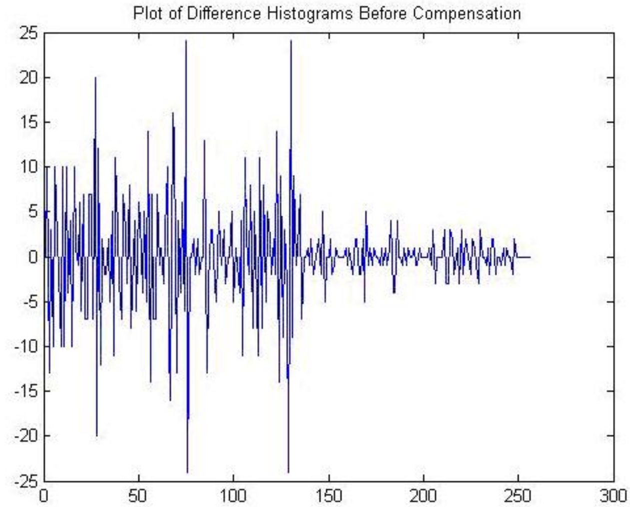


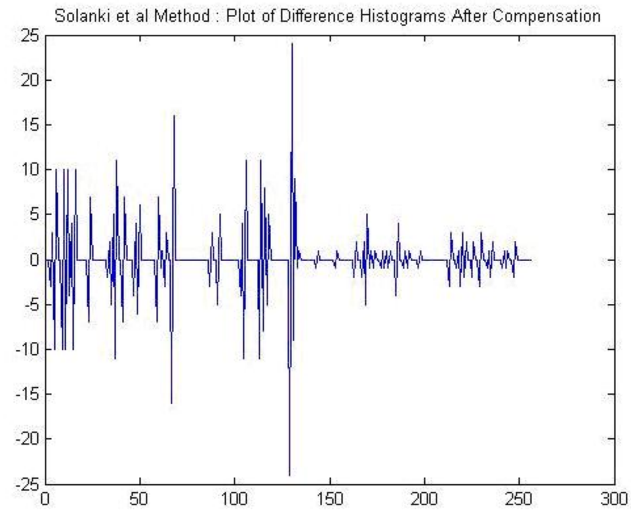
Figure 3.6: Results for Baboon



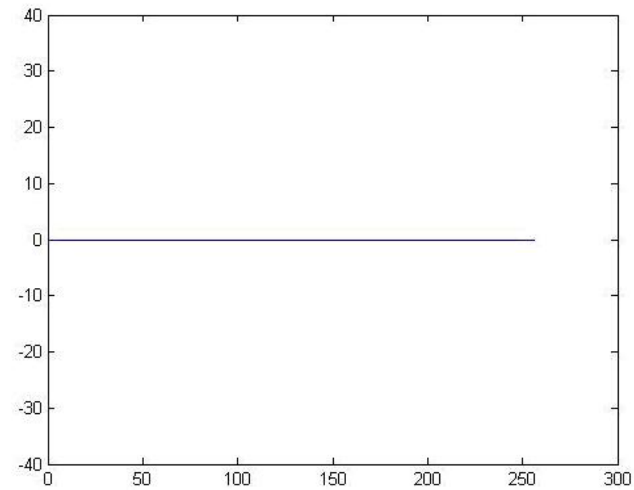
(a) Hills Histogram



(b) Uncompensated Difference Histogram



(c) Compensated Difference Histogram using Solanki's Scheme



(d) Compensated Difference Histogram using proposed SRA algorithm

Figure 3.7: Results for Hills

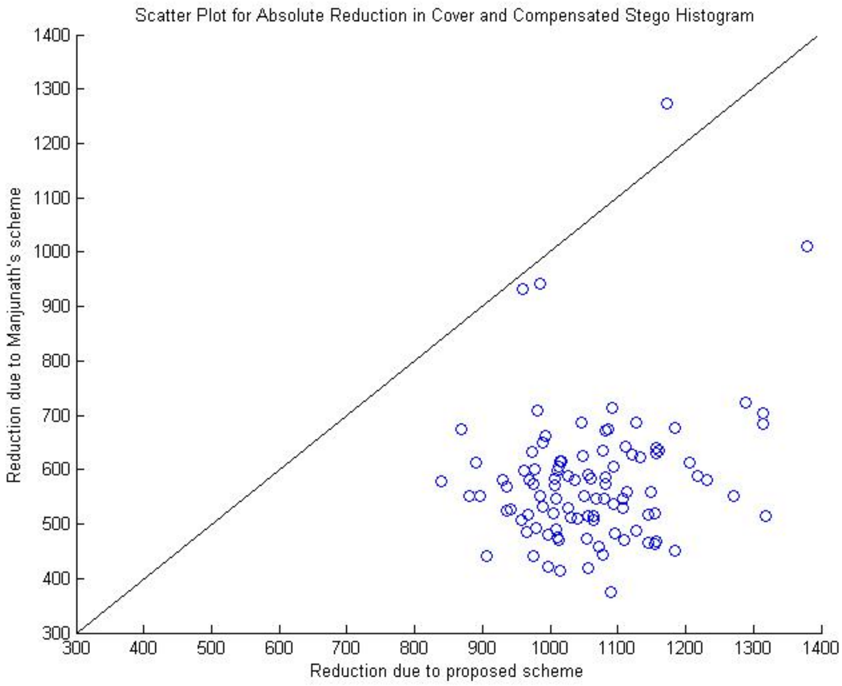


Figure 3.8: Scatter Plot showing amount of reduction in difference histogram using SRA algorithm and Solanki's Scheme

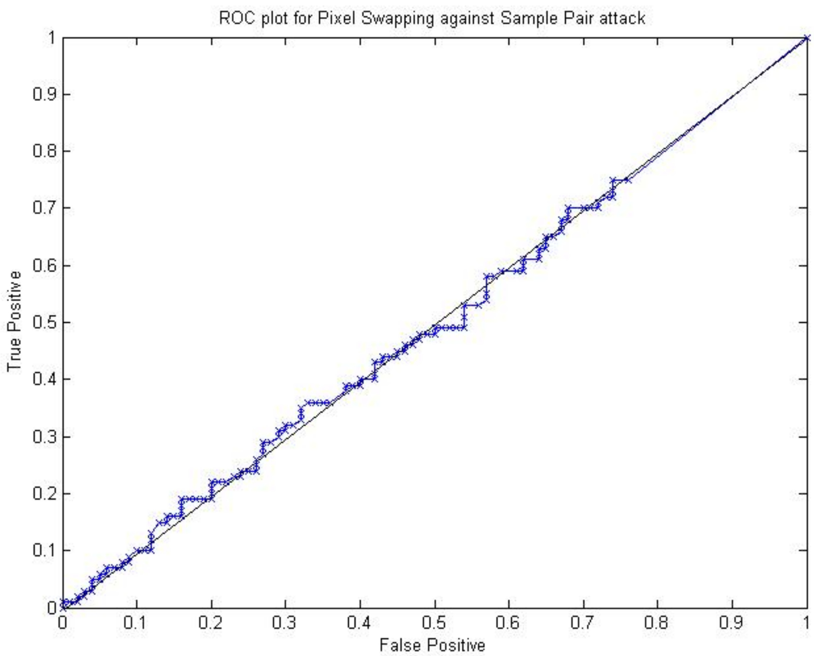
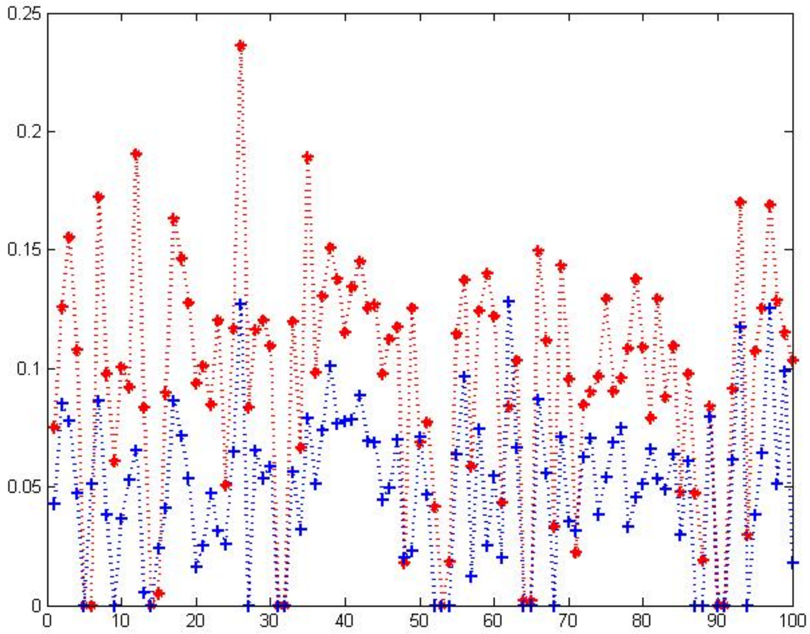
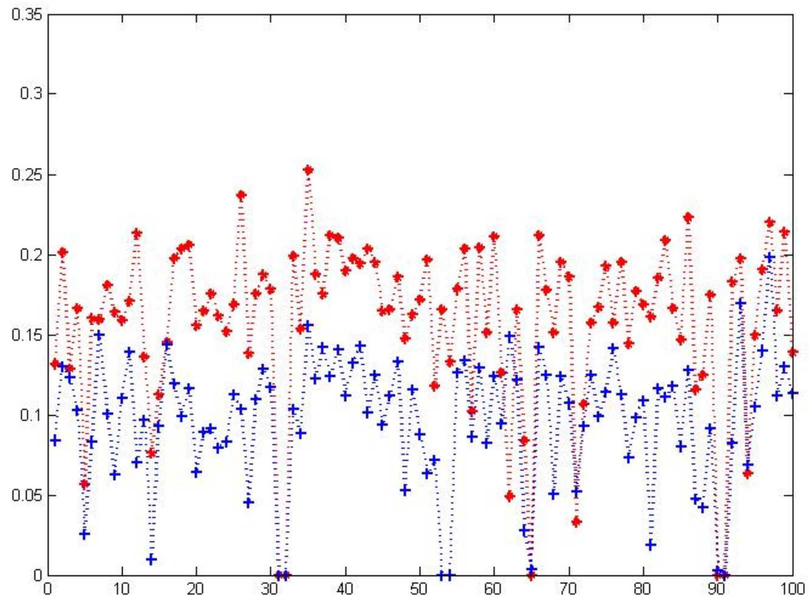


Figure 3.9: ROC plot of Sample pair steganalysis on SRA scheme with an average embedding rate of 0.25 bpp



(a) Embedding Rate = 0.25 bpp



(b) Embedding Rate = 0.35 bpp

Figure 3.10: Comparison of SRA algorithm and Solanki's scheme against Sample Pair Attack. X-axis: Images, Y-axis: Predicted Message Length, Red Plot: Solanki's Scheme, Blue Plot: SRA Algorithm

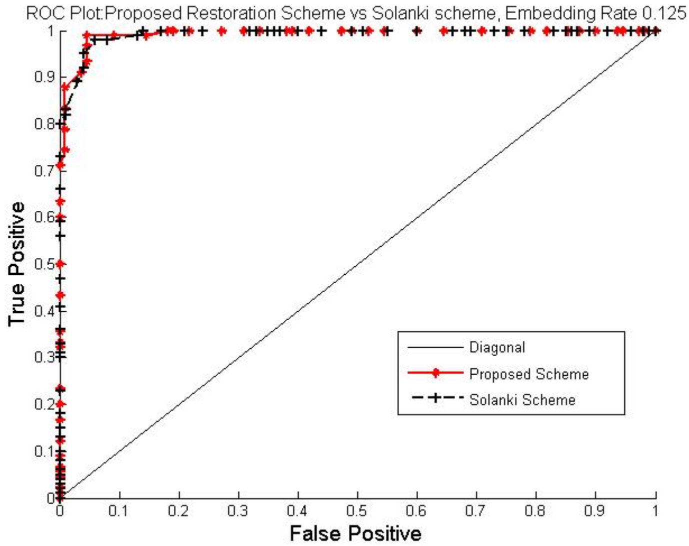


Figure 3.11: ROC plot of WAM steganalysis on SRA algorithm and Solanki's scheme with an average embedding rate of 0.125 bpp

To check that whether preserving only the marginal statistics of the cover image can improve the performance of a steganographic scheme against blind attacks, we tested the performance of the proposed SRA algorithm and Solanki. et. al's scheme against the Wavelet Analysis Moment (WAM) attack proposed in [40]. The results of our experiments have been shown in Figure 3.11. LSB Matching has been used as the steganographic scheme with an embedding rate of 0.125 bpp. It should be noted that WAM attack can detect LSB Matching with very high accuracy even for low embedding rates of 0.25 bpp. So, the tests were conducted for low rates since during restoration although we restore the marginal first order statistics, we introduce an additional noise in the cover signal which can effect the robustness of the steganographic scheme. It can be observed from the ROC plot that even after compensation of the first order statistics after embedding using the both the schemes, the WAM attack can easily detect the stego images. This high accuracy can be attributed to the fact that even though we have been able to preserve that first order statistics, while restoration an additional amount of noise gets added to the cover image which can disturb the higher order statistics of the image which are used by the blind attack. The feature space of the blind attack is highly sensitive to even small amount of noise which gets added to the cover image.

3.4 Summary

In this chapter two new algorithms have been proposed which are able to preserve the first order statistics of a cover image after embedding and thus making the data hiding process robust against first order statistic based steganalytic attacks. Moreover the proposed SRA algorithm does not assume any particular distribution for the cover image and hence gives better performance than existing restoration scheme given in [21, 22] especially for non-Gaussian covers. It must be mentioned that the additional noise added during restoration is dependent on the embedding algorithm for proposed scheme and is a topic of future research. It was also observed that preservation of only the marginal statistics does not increase the robustness of a steganographic algorithm against blind steganalytic attacks as they are based on extremely high order statistical moments which are sensitive to even small amounts of additive noise.

Chapter 4

Spatial Desynchronization

In this chapter a new steganographic framework is proposed which can prevent the calibration based blind steganalytic attack in JPEG steganography. The calibration attack is one of the most successful attacks to break the JPEG steganographic algorithms in recent past. The key feature of the calibration attack is the prediction of cover image statistics from a stego image. To resist the calibration attack it is necessary to prevent the attacker from successfully predicting the cover image statistics. The proposed framework is based on reversible spatial desynchronization of cover images which is used to disturb the prediction of the cover image statistics from the stego image. A new steganographic algorithm based on the same framework has also been proposed. Experimental results show that the proposed algorithm is less detectable against the calibration based blind steganalytic attacks than the existing JPEG domain steganographic schemes.

4.1 Introduction

Joint Photographics Expert Group (JPEG) image format is perhaps the most widely used format in the world today and a lot of steganographic algorithms have been developed which exploit the code structure of JPEG format. For example in JPEG steganography, Least Significant Bits of non-zero quantized Discrete Cosine Transform (DCT) coefficients are used for embedding [17, 18, 19]. However this causes significant changes in DCT coefficients and it is often used as a feature for steganalysis. Westfeld's F5 algorithm [17] tries to match the host statistics by either increasing, decreasing, or keeping unchanged, the coefficient value based on the data bit to be hidden. Provos's OutGuess [18] was the first attempt at explicitly matching the DCT histogram so that the first order statistics of the DCT coefficients can be maintained after embedding. Sallee [19] proposed a model based approach for steganography where the DCT coefficients were modified to hide data such that they follow an underlying model. Perturbed Quantization proposed in [20] attempts to resemble the statistics of a double-compressed image. Statistical restoration method proposed by [21, 22] is able to perfectly restore the DCT coefficients histogram of the cover after embedding, thus providing provable security so long as only the marginal statistics are used by the steganalyst.

Significant research effort has also been devoted to developing steganalytic algorithms for detecting the presence of secret information in an innocent looking cover image as already covered in section 2.2. The blind attacks, first proposed in [12] and [13] try to estimate a model of an unmodified image based on some statistical features. One of the existing approaches for predicting the cover image statistics from the stego image itself is by nullifying the changes made by the embedding procedure to the cover signal. The most popular attacks based on this approach was proposed by Pevny and Fridrich [14]. They estimated the cover image statistics by a process termed as $Self\ Calibration$. The steganalysis algorithms based on this self calibration process can detect the presence of steganographic noise with almost 100% accuracy even for very low embedding rates [14, 28].

In this chapter, we propose a new steganographic framework called *Spatial Block Desynchronization* which attempts to resist the calibration based steganalytic attacks by preventing the successful prediction of the cover image statistics from the stego image. We also introduce a new steganographic scheme called *Spatially Desynchronized Steganographic Algorithm ($SDSA$)* based on the same framework. We use a novel Statistical Hypothesis Testing Model to show that the proposed $SDSA$ scheme is more robust against calibration attack than Quantization Index Modulation (QIM)[23] and "yet another steganographic scheme"(YASS)[15]. We also evaluate the security of $SDSA$ against several blind steganalysis attacks and compare the performance of the algorithm against YASS[15], which is also found to be quite robust against calibration based attacks [14, 28].

The rest of the chapter is organized as follows: In section 4.2 we discuss the calibration based attacks and also present statistical tests to demonstrate its effectiveness. The possible counter measures for resisting calibration attacks are discussed in section 4.3. The proposed scheme is described in section 4.4, Experimental results are presented in section 4.5 finally the chapter is concluded in section 4.6.

4.2 Calibration Attack

As already discussed in section 2.2.2, the process of self-calibration, tries to minimize the impact of embedding in the stego image in order to estimate the cover image features from the stego image. This calibration is done by decompressing the stego JPEG image to spatial domain and cropping 4 rows from the top and 4 columns from the left and recompressing the cropped image. The next two subsections briefly explain the calibration attacks proposed in [14] and [28] respectively.

4.2.1 23 Dimensional Calibration Attack

Let C and S be the cover and corresponding stego images and $\hat{C}$ and $\hat{S}$ be the respective cropped images. The feature set for cover images (say F_{23C}) and the stego images (say F_{S23}) are 23 dimensional vectors which are computed using the following equations

$$F_{23C}^{(i)} = \left\| g^{(i)}(C) - g^{(i)}(\hat{C}) \right\|_{L_1} \tag{4.1}$$

$$F_{23S}^{(i)} = \left\| g^{(i)}(S) - g^{(i)}(\hat{S}) \right\|_{L_1} \tag{4.2}$$

where L_1 represents the L_1 *NORM* of the two feature vectors, $i = 1, 2, \ldots 23$ and g are vector functionals which are applied to both cover and cropped cover and stego and cropped stego images. These functionals are the global DCT coefficient histogram, co-occurrence matrix, spatial blockiness measures etc. The complete set of functionals can be found in [14]. For the rest of the chapter, we use the notation **23 DCA** to refer to the 23 Dimensional Calibration Attack.

4.2.2 274 Dimensional Calibration Attack

In the 274 dimensional calibration attack, 193 extended DCT features and 81 Markov features are combined to form a 274 dimensional feature set which is then used to train the steganalytic classifier. 193 DCT features have been derived by extending the features of 23 DCA [14] and the 81 Markov features are derived from the 324 dimensional Markov features proposed in [30] which models the difference between absolute value of neighboring DCT coefficients as a Markov process. Let C and S be the cover and corresponding stego images and $\hat{C}$ and $\hat{S}$ be the respective cropped images. The feature set for cover images (say F_{274C}) and the stego images (say F_{274S}) are 274 dimensional vectors which are computed using the following equations

$$F_{274C}(z) = \gamma^{(i)}_{(j)}(C) - \gamma^{(i)}_{(j)}(\hat{C}) \tag{4.3}$$

$$F_{274S}(z) = \gamma^{(i)}_{(j)}(S) - \gamma^{(i)}_{(j)}(\hat{S}) \tag{4.4}$$

where $z = 1, 2, \ldots 274$, $\gamma^{(i)}$ denote the vector functionals where $i = 1, 2, \ldots 21$ and $j = 1, 2, \ldots \sigma^i$ where $\sum_{i=1}^{21} \sigma^i = 274$. Each $\gamma^{(i)}$ yields σ^i features. These functionals are the global DCT coefficient histogram, co-occurrence matrix, spatial blockiness measures etc. The complete set of 21 functionals can be found in [28]. The most important difference between 23 dimensional attack and 274 dimensional attack is that in 274 dimensional attack absolute differences between cover image and cropped cover image vectors (stego image and cropped stego image vectors) are taken as cover (stego) features unlike the 23 dimensional attack where L_1 norm of the difference of the various functionals are taken as the feature set. For the rest of the chapter, we use the notation **274 DCA** to refer to the 274 Dimensional Calibration Attack.

4.2.3 Statistical Test for Calibration Attack

In this subsection, we propose a new *Statistical Hypothesis Testing Framework* to check the following:

- Sensitivity of the features used in the calibration attacks.
- Effectiveness of the self-calibration process.

We extract the steganalytic features from the cover images and the corresponding stego images using the calibration attacks as explained above. We then apply the Rank-Sum Test [29] (also called the Wilcoxon-Mann-Whitney test) which is a non-parametric test for assessing whether two samples of observations come from an identical population. The two hypothesis are formulated as follows:

Null Hypothesis H_0*: The two samples have been drawn from identical populations*

Alternate Hypothesis H_1*: The two samples have been drawn from different populations*

The Rank-Sum test computes the U statistic for the two samples to accept or reject the null hypothesis. The U statistic for the two samples are defined as follows:

$$U_1 = W_1 - \frac{n_1 \times (n_1 + 1)}{2} \tag{4.5}$$

$$U_2 = W_2 - \frac{n_2 \times (n_2 + 1)}{2} \tag{4.6}$$

where W_1 and W_2 are the sums of the ranks alloted to the elements of the two sorted samples and n_1, n_2 are the sizes of the two samples. The detailed discussion on Rank-Sum test can be found in [29].

We have used the Rank-Sum Test available in the Statistical Toolbox of MATLAB version 7.1 for our experiments. We measure the *p-value* from the Rank Sum Test where p is the probability of observing the given result by chance if the null hypothesis is true. Small values of p increase the chances of rejecting the null hypothesis whereas high values of p suggest lack of evidence for rejecting the null hypothesis. QIM has been used as the steganographic algorithm.

We first check the sensitivity of the features used by 23 DCA and 274 DCA. The 23 and 274 dimensional feature vectors are separately reduced to a single dimension using Fisher Linear Discrimant(FLD) Analysis [31] for both the cover image features and the stego image features. These single dimension values are labeled as the cover image sample and the stego image sample for each of the attacks. We then test the hypothesis that the two samples are drawn from an identical population or not. The test is applied on samples of size one thousand each drawn from the cover image population and the stego image population respectively. The p value observed from the test is recorded in Table 4.1 for both attacks at various embedding rates. It can be observed that with the increase of embedding rate from 0.05 $bpnc$ to 0.10 $bpnc$, the p-value between the cover and the stego sample decreases to zero implying that the separation between cover and stego population increases with increase of the embedding rate thus showing that the features are indeed sensitive to the embedding.

In the second test, we test the effectiveness of the self-calibration process. This test has only been applied to 274 DCA because for 23 DCA the final features are computed using Equations 4.1 and 4.2 and it is not possible to calculate these features for a cover(stego) image

Table 4.1: p value of the Rank-Sum Test for 23 DCA and 274 DCA

Embedding	p-value	
Rate	23 DCA	274 DCA
0.05	2.1556×10^{-8}	3.179×10^{-87}
0.10	0	0
0.25	0	0
0.50	0	0

and its cropped version individually. For the cover and the cropped cover images, we extract the two 274 dimensional vectors α_C and $\alpha_{\hat{C}}$ using the following equations:

$$\alpha_C(z) = \gamma^{(i)}_{(j)}(C) \tag{4.7}$$

$$\alpha_{\hat{C}}(z) = \gamma^{(i)}_{(j)}(\hat{C}) \tag{4.8}$$

where $z = 1, 2, \ldots 274$. There are 21 vector functionals denoted as $\gamma^{(1)}, \gamma^{(2)}, \ldots \gamma^{(21)}$ and $j = 1, 2, \ldots \sigma^i$ where $\sum_{i=1}^{21} \sigma^i = 274$. Each $\gamma^{(i)}$ produces σ^i features as mentioned in subsection 4.2.2. α_C and $\alpha_{\hat{C}}$ are 274 dimensional vectors.

Next we calculate the L_2 **NORM** (L_2^C) between α_C and $\alpha_{\hat{C}}$ using the following equation:

$$L_2^C = \sqrt{\sum_{i=1}^{274}[\alpha_C(i) - \alpha_{\hat{C}}(i)]^2} \tag{4.9}$$

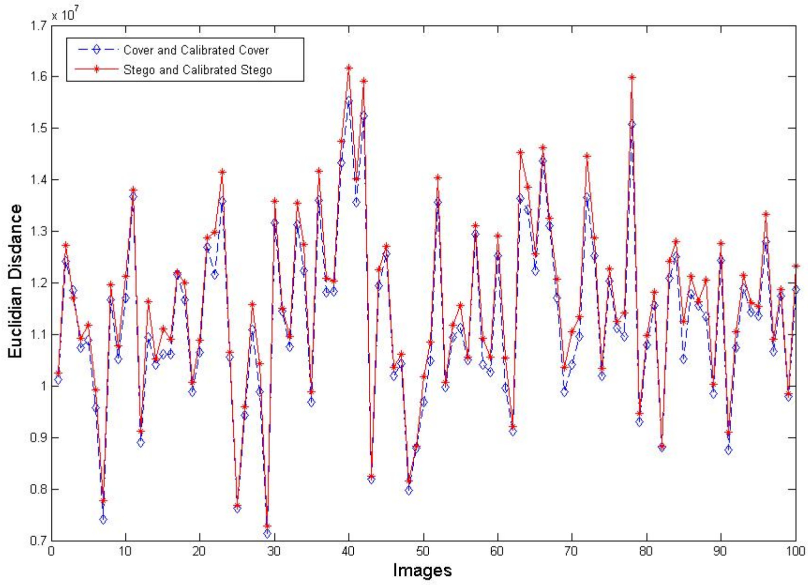
where α_C and $\alpha_{\hat{C}}$ are 274 dimensional vectors.

We similarly calculate the L_2 NORM (L_2^S) between α_S (stego) and $\alpha_{\hat{S}}$ (cropped stego). These two single dimensional values, L_2^C and L_2^S, are treated as two separate samples. We then test the hypothesis that these two samples have been drawn from an identical population or not. This hypothesis testing is done for different embedding rates of the QIM algorithm and the p-value obtained from these tests are presented in Table 4.2. It can be observed that when the embedding rate increases the p value decreases significantly. Thus we can conclude that the L_2 NORM between stego and cropped stego increases with the increase of embedding rate. This fact can also be observed in Figures 4.1 and 4.2. At embedding rate of 0.05 there is a very small difference between the L_2 NORM of Cover and Cropped Cover and the L_2 NORM of Stego and

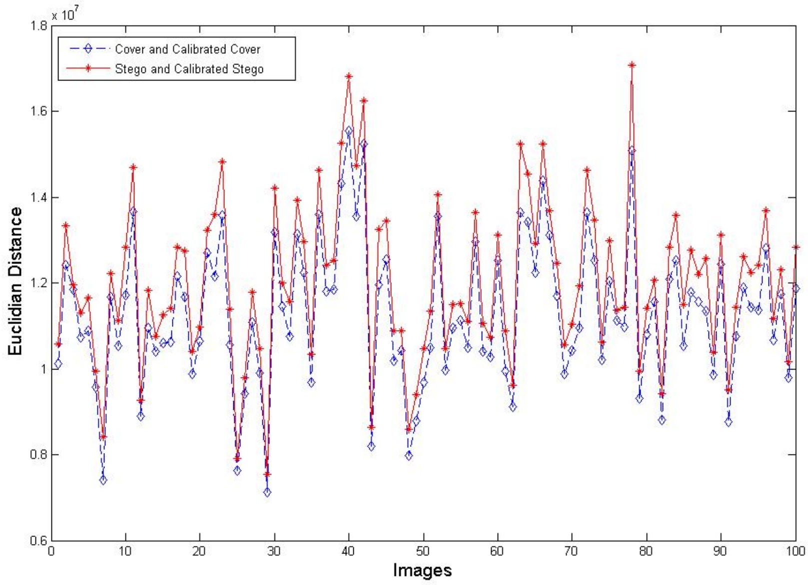
Table 4.2: p value of the Rank-Sum Test for 274 DCA for testing the Self Calibration Process

Embedding Rate	p value
0.05	0.1907
0.10	0.0059
0.25	1.028×10^{-16}
0.50	0

Cropped Stego (Figure 4.1(a)). With the increase of embedding rate (i.e., Emb. Rate = 0.10, 0.25 and 0.50), this difference also increases (Figure 4.1(b), 4.2(a) and 4.2(b)). Hence we can conclude that statistics drawn from the cropped stego image can be used for approximating the cover image statistics.



(a) At Embedding Rate 0.05



(b) At Embedding Rate 0.10

Figure 4.1: L2 Norms of Cover/Stego and Cropped Cover/Cropped Stego for QIM Algorithm against 274 DCA for Embedding Rates 0.05 and 0.10

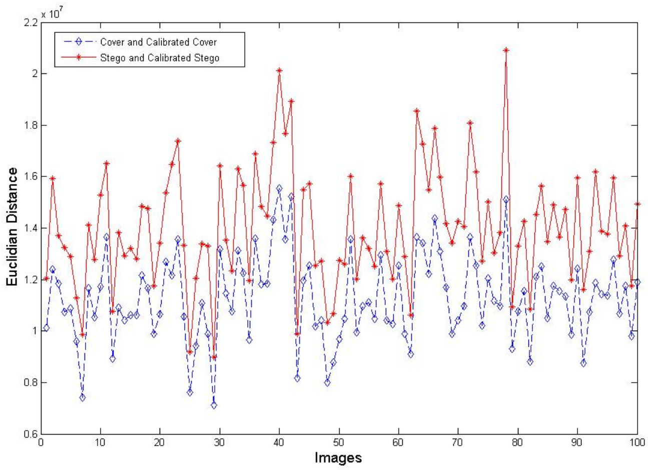
4.3 Counter Measures to Blind Steganalysis

As mentioned above, the crux of blind steganalysis is its ability to predict the cover image statistics using the stego image only. So a secure steganographic embedding might be possible if the steganographer can somehow disturb the prediction step of the steganalyst. Some techniques following the same line of thought have been proposed in steganographic literature. In [24], it has been argued that estimation of cover image statistics can be disturbed by embedding data at high embedding rates. By embedding data with high strength, the cover image is distorted so much that the cover image statistics can no longer be derived reliably from the stego image. But embedding at high rates will obviously increase the visual distortion introduced in the image. Moreover as pointed out in [15], it might be possible to detect the embedding by testing a stego image against an approximate model of a natural image.

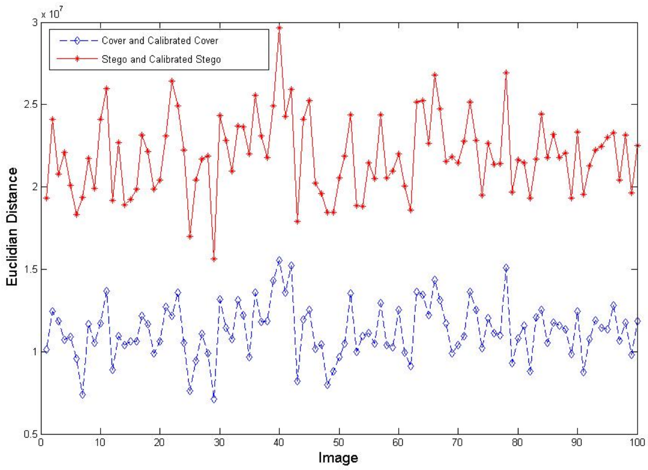
In [15] the authors have suggested the use of randomized hiding to disable the estimation of the cover image statistics. It has been observed that due to randomization of hiding, even if the embedding algorithm is known to the steganalysts, they are unable to make any concrete assumptions about the hiding process. This approach has been extended to a successful steganographic algorithm called ”yet another steganographic scheme” (YASS). It has been experimentally shown that the YASS algorithm can resist many blind attacks with almost 100% success rate. But the main limitation of the YASS algorithm is that it is unable to achieve high embedding rates.

In [26], the authors have suggested two modifications to the original YASS algorithm to improve the achievable embedding rates. Firstly they randomize the choice of the quantization matrix used during the embedding step. This choice of quantization matrix is made image adaptive by using high quality quantization matrices for blocks having low variance and low quality matrices for blocks having high variance values since a block having high variance by itself supports high embedding rates as the number of non-zero AC coefficients increase in the block.

The second modification is targeted towards reducing the loss in the message bits due to the JPEG compression of the embedded image. The JPEG compression is considered as an ”attack” which tries to destroy the embedded bits, thereby increasing the error rate at the decoder side. Since the parameters of this attack i.e. the quality factor used for compression are known after embedding, an iterative process of embedding and attacking is suggested so that



(a) At Embedding Rate 0.25



(b) At Embedding Rate 0.50

Figure 4.2: L2 Norms of Cover/Stego and Cropped Cover/Cropped Stego for QIM Algorithm against 274 DCA for Embedding Rates 0.25 and 0.50

the system converges towards a low error rate. The suggested modifications have been able to improve the embedding rate upto some extent while maintaining the same levels of security. But clearly the iterative step of embedding and attacking increases the complexity of the algorithm. It will be shown in the next few sections that the proposed scheme can achieve even higher embedding rates at same levels of security. In the next subsection we introduce our concept of spatial block desynchronization for resisting the blind steganalytic attacks.

4.3.1 Spatial Block Desynchronization

In the JPEG image format, an image is divided into non-overlapping blocks of size 8×8. The information contained in these blocks is then compressed by taking the 2D Discrete Cosine Transform of the block followed by quantization step which are then used for embedding data bits. A slight alteration of this spatial block arrangement can desynchronize the whole image. Such alteration of the spatial block arrangement of an image is termed as *Spatial block desynchronization*. For example, 8×8 non overlapping blocks for embedding can be taken from a subimage of the original cover image or we can say the block arrangement is slightly shifted from standard JPEG compression block arrangement. A formal description of spatial block desynchronization is given below.

Let I be a gray scale image of size $(N \times N)$. A subimage of I can be obtained by removing u rows from the top and v columns from left. Let us denote the cropped image by $\hat{I}_{u,v}$. The size of image $\hat{I}_{u,v}$ is $(N-u) \times (N-v)$. Let us denote the cropped portion of the image by $I^{\delta}_{u,v}$ i.e I, $\hat{I}_{u,v}$ and $I^{\delta}_{u,v}$ are related by the following equation

$$I^{\delta}_{u,v} = I - \hat{I}_{u,v} \tag{4.10}$$

So, the image I is partitioned into $\hat{I}_{u,v}$ and $I^{\delta}_{u,v}$. The said partitioning is depicted pictorially in Figure 4.3. In Figure 4.3, the partition $\hat{I}_{u,v}$ is denoted by portion labeled as EFGC and $I^{\delta}_{u,v}$ by the portion labeled as ABEFGD.

An image I can be divided into a set of non overlapping block of size $n \times n$ (as shown in Figure 4.3). Let this set be denoted by $P^{(n\times n)}_{I}$ and a block B is an element of set $P^{(n\times n)}_{I}$. In Figure 4.3, these blocks are drawn with dashed lines. For JPEG compressed images $n = 8$ and the set of blocks is denoted by $P^{(8\times 8)}_{I}$. Now the cropped image $\hat{I}_{u,v}$ can be divided into a set of non overlapping blocks of size $m \times n$. Let this set be denoted by $P^{(m\times n)}_{\hat{I}_{u,v}}$. In Figure 4.3,

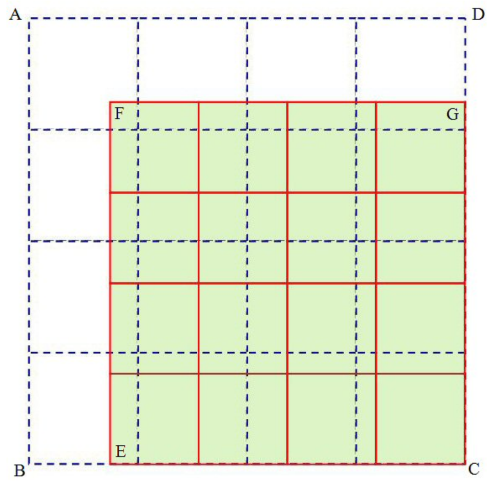


Figure 4.3: Block Diagram of Spatial Block Desynchronization

$P^{(m\times n)}_{\hat{I}_{u,v}}$ set of blocks is drawn with solid lines. The spatial arrangement of $P^{(m\times n)}_{\hat{I}_{u,v}}$ (where the actual embedding is done) is shifted from $P^{(n\times n)}_{I}$. This spatial shifting of $P^{(m\times n)}_{\hat{I}_{u,v}}$ achieves the required spatial desynchronization.

Another possible way of spatial desynchronization is to use a block size other than 8×8 i.e using blocks of sizes $m\times n$ where $m\neq 8$ and $n\neq 8$. In such a case, the quantization matrix Q has to be changed accordingly to size $m\times n$ at the time of data embedding. This deynchronization can be strengthened further with the help of randomization. In this case, the removal of rows and columns and also the sizes of the blocks can be chosen randomly using a shared secret key. Also, the matrix Q can be a shared secret between the two communicating parties. Since at the steganalysis stage the image statistics are derived using blocks of sizes 8×8, the steganalyst is not able to capture effectively the modifications made during the embedding process. Even if it is known that embedding has been done using blocks of different sizes, it is difficult to track the portions of the image containing the embedded information due to randomized hiding.

It should be noted that once the quantized DCT coefficients have been obtained, any JPEG steganographic scheme can be employed for embedding. In the next section we explain a new steganographic scheme based on the concept of spatial block desynchronization.

4.4 The Proposed Algorithm

The main aim of the proposed scheme is to embed data in a spatially desynchronized version of the cover image so that the cover image statistics cannot be easily recovered from the stego image. The cover image is desynchronized by the partitioning scheme discussed above. The cropped version of the image $\hat{I}_{u,v}$ is used for steganographic embedding using any DCT domain scheme. After embedding, this embedded portion of the image is stitched with $I^{\delta}_{u,v}$ to obtain the stego image I_s. The JPEG compressed version of I_s is communicated as the stego image. Below a stepwise description of the algorithm is given.

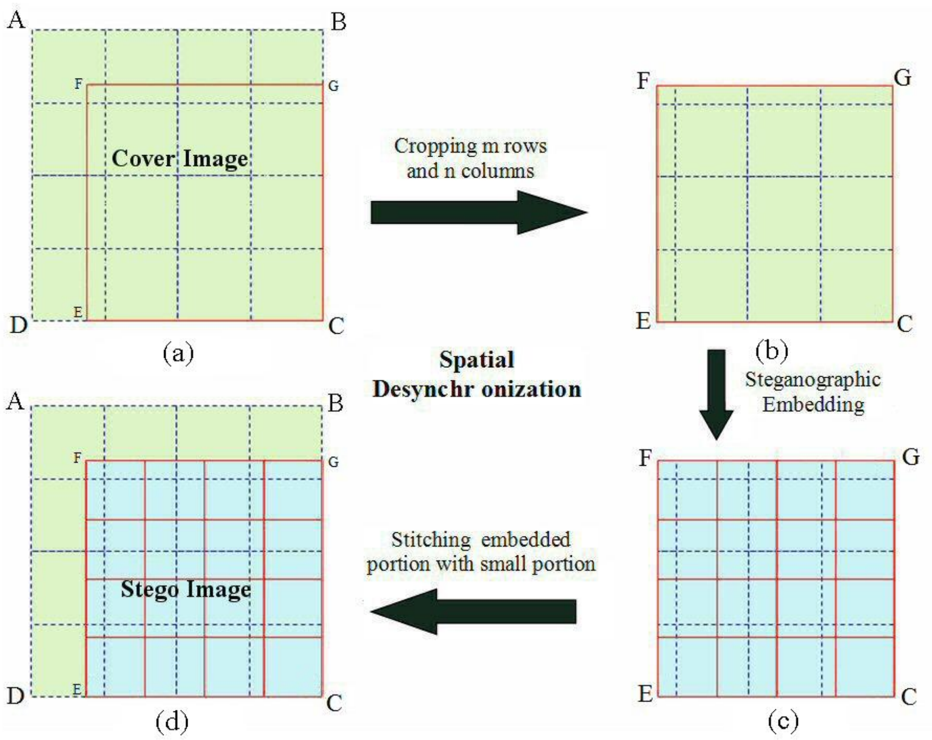


Figure 4.4: Block Diagram of Proposed Method

4.4.1 Spatially Desynchronized Steganographic Algorithm (SDSA)

The algorithm is summarized below.

Algorithm *Spatially Desynchronized Steganographic Algorithm (SDSA)*

Input: *Cover Image* I

Input Parameters: *Rows and Columns to be cropped (u,v), Block size* $(m \times n)$*, Quantization Matrix* (Q)

Output: *Stego Image* I_s

Begin

1. Partition the cover image I into $\hat{I}_{u,v}$ and $I^{\delta}_{u,v}$ by cropping u topmost rows and v leftmost columns.

2. Perform $m \times n$ non-overlapping block partitioning on $\hat{I}_{u,v}$. Let us denote this set of blocks by $P^{(m\times n)}_{\hat{I}_{u,v}}$.

3. Choose a set of blocks from $P^{(m\times n)}_{\hat{I}_{u,v}}$ (using a key shared by both ends) and perform the embedding in each of the selected blocks using any standard DCT based steganographic scheme. The quantization matrix Q which is a shared secret is used for obtaining the quantized coefficients.

4. Apply dequantization and Inverse Discrete Cosine Transform (IDCT) to the set of blocks used for embedding in Step 3.

5. Join $I^{\delta}_{u,v}$ with the resulting image obtained at Step 4. This combined image is the output stego image I_s which is compressed using JPEG compression and communicated as the stego image.

End *Spatially Desynchronised Steganographic Algorithm* $(SDSA)$

The SDSA algorithm has been shown pictorially in Figure 4.4. Figure 4.4(a) shows the unmodified cover image from which the cropped image $\hat{I}_{u,v}$ (Figure 4.4(b)) is extracted. This portion is labeled as EFGH in Figure 4.4(a). $\hat{I}_{u,v}$ is then divided into non overlapping blocks size $m \times n$ as shown by solid lines in Figure 4.4(c). A DCT domain steganographic scheme is then applied to some of these blocks and $\hat{I}_{u,v}$ is finally attached with $I^{\delta}_{u,v}$ to obtain the stego image I_s as shown in Figure 4.4(d).

23 DCA crops 4 rows and 4 columns from the top and the left of the image and uses the remaining portion of the image for estimating the cover image statistics. To disturb this calibration step, at the time of embedding u rows and v columns (where $u, v \neq 4$ $or\ any\ multiple\ of$ 8) should be cropped from the left and the top of the image. Thus the cover image is spatially desynchronized before actual embedding is done. During steganalysis, the steganalyst uses the stego portion of the image itself as a reference for estimating the cover image statistics and

hence is not able to distinguish the cover image statistics from the stego image statistics. It should be noted that if u consecutive rows and v consecutive columns are cropped from an image, then $u, v \neq 4\ or\ any\ multiple\ of\ 8$ because such kind of cropping will realign the blocks of the partitioned image I_2 with the original cover image and hence in effect there won't be any desynchronization during embedding.

Also since the embedded image undergoes JPEG compression before being communicated to the decoding end, some of the embedded data bits might get lost in the process because of the quantization step during JPEG compression. This quantization loss occurs for almost all the DCT domain embedding schemes. We try to circumvent this problem by embedding data mainly in the low-frequency DCT coefficients. Also embedded data can be made secure by adding some redundant bits in the data stream and using error-control coding techniques. This problem of using error-control coding for securing the data bits has been addressed in [23] albeit at the cost of low embedding rate. We would like to mention here that in our implementations of QIM, YASS and SDSA we have not included any error-control technique. Hence we shall be comparing the raw versions of the three schemes. In the next section we verify our claim using statistical hypothesis testing.

4.4.2 Hypothesis Testing

In this subsection, we use hypothesis testing to validate our claim that the SDSA algorithm does disturb the self-calibration process of a steganalytic attack. We extract the steganalytic features from the cover images and the corresponding stego images as explained in section 4.2.3. for all the three schemes. Once again we observed the p values obtained from the Rank-Sum Test which are presented in Tables 4.3 and 4.4. It can be seen that for all embedding rates the p-value of the SDSA algorithm is greater than the p-value of both YASS and QIM scheme indicating that the SDSA algorithm generates a stego image population which is statistically closer to the cover image population than the populations generated by YASS and QIM. It should be noted that even though the p-values obtained are small but for the purpose of comparison it is significantly higher for the proposed scheme than that of QIM and YASS.

Table 4.3: p-value of Rank Sum Test for 23 DCA

Embedding Rate (bpnc)	QIM p-value	YASS p-value	SDSA 8x8 p-value
0.05	2.15×10^{-8}	0.0042	0.1180
0.10	0	2.44×10^{-4}	0.0065
0.25	0	1.12×10^{-24}	4.23×10^{-6}
0.50	0	0	7.53×10^{-10}

Table 4.4: p-value of Rank Sum Test for 274 DCA

Embedding Rate (bpnc)	QIM p-value	YASS p-value	SDSA 8x8 p-value
0.05	0.1907	0.7947	0.8652
0.10	0.0059	0.6734	0.7853
0.25	1.028×10^{-16}	0.3170	0.5213
0.50	0	9.27×10^{-6}	0.3525

4.5 Experiments and Results

For testing the performance of the SDSA algorithm we conducted experiments on a data set of two thousand test images [16] which were divided into two equal sets of one thousand cover images and one thousand stego images. Each image was resized to 256×256 with a JPEG quality factor of 75%. For ease of comparison we have used QIM as the data embedding algorithm and compare the performance of the SDSA algorithm with the original YASS[15] and the QIM scheme itself. It has already been reported in [15] that YASS surpasses some of the standard data hiding techniques like OutGuess[18] and StegHide[27]. So SDSA has not been compared with OutGuess and StegHide. The embedding rate is expressed in terms of the non-zero DCT coefficients available after quantization of the whole cover image i.e. in terms of *bits per non-zero coefficients (bpnc)*. We tested the performance of SDSA against 23 DCA and Farid's 92 Dimensional Attack proposed in [13]. Farid's Attack is a DCT domain steganalysis attack and it was used to test whether SDSA and spatial desynchronization can be used to defeat steganalysis algorithms not based on self-calibration. The source code of the attack is available at [32]. Area under the ROC and the Detection accuracy (P_{detect})[15] which is computed using equations 4.11 and 4.12 have been used as the evaluation metrics.

$$P_{detect} = 1 - P_{error} \tag{4.11}$$

$$P_{error} = \frac{1}{2} \times P_{FP} + \frac{1}{2} \times P_{FN} \tag{4.12}$$

where P_{FP}, P_{FN} are the probabilities of false positive and false negative respectively. A value of $P_{detect} = 0.5$ shows that the classification is as good as random guessing and $P_{detect} = 1.0$ shows a classification with 100% accuracy.

Two possible cases of SDSA were tested during the experiments. In the first case after cropping of rows and columns from the left and the top of the image, $\hat{I}_{u,v}$ is divided into blocks of size 8×8. In the second case, $\hat{I}_{u,v}$ is divided into blocks of sizes 10×10. The quantization matrix was adjusted accordingly by replacing the additional rows and columns by 50 which is the quantization index for the highest frequency component at a JPEG quality factor of 75%. We use the notation *SDSA* 8×8 and *SDSA* 10×10 respectively for the two cases of the SDSA algorithm. 5 rows and 5 columns were cropped for both SDSA 8×8 and SDSA 10×10 i.e. $u = 5$ and $v = 5$. YASS scheme was implemented using a big block size of 10 and a quality

Table 4.5: Area under ROC for QIM, YASS and SDSA against 23 DCA

Embedding Rate (bpnc)	QIM	YASS	SDSA 8x8	SDSA 10x10
0.05	0.3071	0.0580	0.0534	0.0570
0.10	0.4032	0.0702	0.0574	0.0615
0.25	0.4947	0.1116	0.0744	0.1327
0.45	0.50	0.3459	0.1201	0.2305

Table 4.6: Detection Accuracy of QIM, YASS and SDSA against 23 DCA

Embedding Rate (bpnc)	QIM	YASS	SDSA 8x8	SDSA 10x10
0.05	0.7585	0.5305	0.5100	0.5300
0.10	0.8500	0.5600	0.5275	0.5450
0.25	0.9770	0.5950	0.5350	0.5850
0.45	1.000	0.7760	0.5720	0.6500

factor of 75% for embedding.

Tables 4.5 and 4.6 report the performance of the two versions of SDSA, QIM and YASS against 23 DCA for different embedding rates. Tables 4.7 and 4.8 present the results of testing the different schemes against Farid's 92 Dimensional Attack. The results have been reported upto 4 decimal places to highlight the difference in performance of SDSA and YASS at low embedding rates. Tables 4.5 and 4.7 contain the Area under the ROC and Tables 4.6 and 4.8 contain values of P_{detect} at different embedding rates. It can be seen that for all embedding rates SDSA clearly outperforms both QIM and YASS schemes for both the steganalytic attacks especially at high embedding rates of 0.25 $bpnc$ and 0.45 $bpnc$ at which Area under ROC and P_{detect} of SDSA is significantly less than that of QIM and YASS. It should be pointed out that in [15], the authors have used only 19 low frequency AC coefficients in a block for embedding but for achieving the embedding rate of 0.45 $bpnc$ this number had to be increased to 25. Also it can be observed that although SDSA 10×10 gives better results than YASS, its detection rate is slightly higher than SDSA 8×8. This can be attributed to the fact that as we increase the size

Table 4.7: Area under ROC for QIM, YASS and SDSA against Farid's 92 Dimensional Attack

Embedding Rate (bpnc)	QIM	YASS	SDSA 8x8	SDSA 10x10
0.05	0.1082	0.0989	0.0844	0.0980
0.10	0.1125	0.1030	0.0853	0.1000
0.25	0.1987	0.1572	0.1044	0.1368
0.45	0.4960	0.2670	0.1360	0.2420

Table 4.8: Detection Accuracy of QIM, YASS and SDSA against Farid's 92 Dimensional Attack

Embedding Rate (bpnc)	QIM	YASS	SDSA 8x8	SDSA 10x10
0.05	0.5700	0.5140	0.5120	0.5090
0.10	0.6000	0.5210	0.5195	0.5100
0.25	0.6750	0.5900	0.5310	0.5870
0.45	0.9750	0.6750	0.5600	0.6650

of the embedding block the number of blocks available for embedding decrease and thereby increasing the embedding density i.e. the bits/block and hence increasing the detection rate.

4.6 Summary

In this chapter, a new steganographic framework is proposed to resist calibration based blind steganalytic attacks. The proposed framework which is based on spatial block desynchronization to disturb the successful prediction of cover image statistics from the stego image which is the key feature of calibration based steganalytic attacks. The proposed framework has been extended to a new steganographic algorithm called "Spatially Desynchronized Steganographic Algorithm (SDSA)". A comparative study with existing steganographic schemes has been carried out at different embedding rates on the basis of Area under the ROC and Detection Accuracy. It has been found that proposed algorithm shows better results than existing schemes in terms of detectability against calibration based steganalytic attacks.

Chapter 5

Conclusions and Future Directions

5.1 Conclusions

In this thesis we have explored two different approaches to steganography. The first approach was aimed at preservation of the marginal statistics of a cover image. The preservation of marginal statistics helps in defeating the targeted attacks designed for specific steganographic algorithms. We covered two kinds of algorithms under this approach. The first algorithm was designed to inherently preserve the first order statistics of the cover image while embedding itself. It has been shown that this approach is able to resist first order statistics based targeted attacks while maintaining an acceptable quality of the stego image. The second algorithm was an attempt at explicitly restoring the marginal statistics of the image after data has been embedded in the image. It was found that under a specified constraint the suggested algorithm is optimal in terms of the noise added due to the restoration procedure. It was also observed that although the restoration of the image statistics can resist targeted attacks, it does not improve the security of an embedding algorithm against blind attacks. This observation was attributed to the fact that the restoration process acts as an additional source of noise in the cover signal which can be captured during feature extraction and classification. This factor limits the applicability of this approach to only targeted attacks.

The second approach studied in this thesis aims at hampering the steganalysts ability to effectively estimating the statistics for classification. A new statistical model for testing the efficiency of calibration based blind attacks was proposed. It was found that the calibration step is indeed able to estimate an image model. To counter this, a generalized framework has been proposed which disturbs this model estimation of the attack. It is based on embedding data such that the stego population remains statistically closer to the cover population and the difference between these two cannot be observed in the statistics drawn from the two populations. The framework was extended to a new algorithm for JPEG domain steganography. This algorithm was evaluated in the proposed statistical testing framework and it was found that the algorithm is successful in breaking the calibration based blind attacks.

5.2 Future Directions

During the course of this work, some potential directions of future research were identified. Firstly, it was observed that most of the steganographic research till date has been towards designing algorithm which generate stego images which are as close to the cover as possible. All the algorithms study the behavior of the cover image while ignoring the message bit stream. It may be possible to design some encoding functions, which given a cover image and an embedding algorithm can modify the message stream such that it becomes more suitable for embedding than the original bit stream. This kind of steganography can be useful even in the "Active Warden Framework" of steganography because firstly the modified message stream will be introducing less artifacts in the cover. Secondly, even if the embedding algorithm is known to the attacker, the exact message sequence cannot be reconstructed unless the attacker has the knowledge of the encoding function.

Another possible direction of research can be formulated as a problem of *"Image Retrieval"*. It is based on searching for a suitable cover image given a message sequence and the embedding algorithm. This may be possible through maintaining a huge image database and given any message sequence and a pseudo-random key for generating embedding locations, we search for a cover image from the database that will generate a stego image with minimum amount of changes. The change criterion considered for searching can be dependent on the features used by the corresponding steganalytic attacks. Some other possible ideas can be borrowed from the field of *"Visual Cryptography"* which encrypts a message by distributing the decoding key into different images such that the message can be broken only by a proper combination of these images.

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