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Steganalysis Techniques: A Comparative Study

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A Thesis

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Abstract

Steganography is the art of hiding information within cover objects like images or audio/video files. It has been widely reported that there has been a surge in the use of *steganography* for criminal activities and therefore, implementing effective detection techniques is an essential task in digital forensics. Unfortunately, building a single effective detection technique still remains one of the biggest challenges. This report presents a comparative study of three *steganalysis* techniques. We investigated and compared the performances of each technique in the detection of embedding methods considered. Based on the results of our analysis, we provide information as to which specific *steganalysis* technique needs to be used for a particular *steganographic* method. Finally, we propose a procedure which may help a forensic examiner to decide an order in which different steganalysis techniques need to be considered in the detection process to achieve the best detection results in terms of both time and accuracy.

1 Introduction

1.1 Steganography

Steganography is the art of hiding information within innocuous cover carriers in ways such that the hidden message is undetectable. In Greek, ‘stego’ means ‘covered’ or ‘secret’ and ‘graphy’ means ‘to write’ and therefore, *steganography* becomes “covered or secret writing”. The information to be hidden is embedded into the cover object which can be a text matter, some image, or some audio /video file in such a way that the very existence of the message is undetected by maintaining the appearance of the resulted object exactly same as the original. The main goal of *steganography* is to hide the fact that the message is present in the transmission medium.

1.2 History

Steganography has a very long history dating back many centuries. It has been used by Greeks since ancient times for secret communications. There are many stories that mention about the use of secret communications in the past. One famous story is about a king who made one of his slaves shave his head, tattooed a message there and after his hair grew back, sent his slave to deliver that message without any suspicion from his opponents. Similarly, there are stories about the use of wax tablets for secret communications. Wax tablets were used for writing and sending messages. Many a times, to hide the message, it was written on wooden boxes, that were used to carry wax, instead of wax tablets itself and thus the message could be delivered without interception. During World War II, many invisible inks were used. Messages were written on paper with liquids like juice or urine which were normally invisible but when paper was heated, the message reappeared.

1.3 Cryptography vs. Steganography

Cryptography is the science of encrypting data in such a way that one can not understand the encrypted message, whereas in *steganography* the mere existence of data is concealed, such that even its presence cannot be noticed. Using cryptography might raise some suspicion whereas in *steganography* the existence of secret message is invisible and thus not known. We can think of *steganography* as an extension of cryptography, and it is commonly used under the circumstances where encryption is not allowed.

1.4 Steganography vs. Watermarking

Watermarking is another branch of *steganography* and it is mainly used to restrict the piracy in digital media. In *steganography* the data to be hidden is not at all related to the cover object. The main intention of using *steganography* is secret communication, but in watermarking the data to be hidden is related to the cover object. It is extended data or attribute of the cover object and the main intention while using watermarking is to stop piracy of digital data.

There are three main attributes related to the information hiding; *capacity*, *security*, and *robustness*. While using *steganography*, our goal is to achieve high *capacity* and *security* whereas watermarking requires high *robustness*.

1.5 Basic Embedding and Extraction process

Below is the basic flow of embedding and extraction process

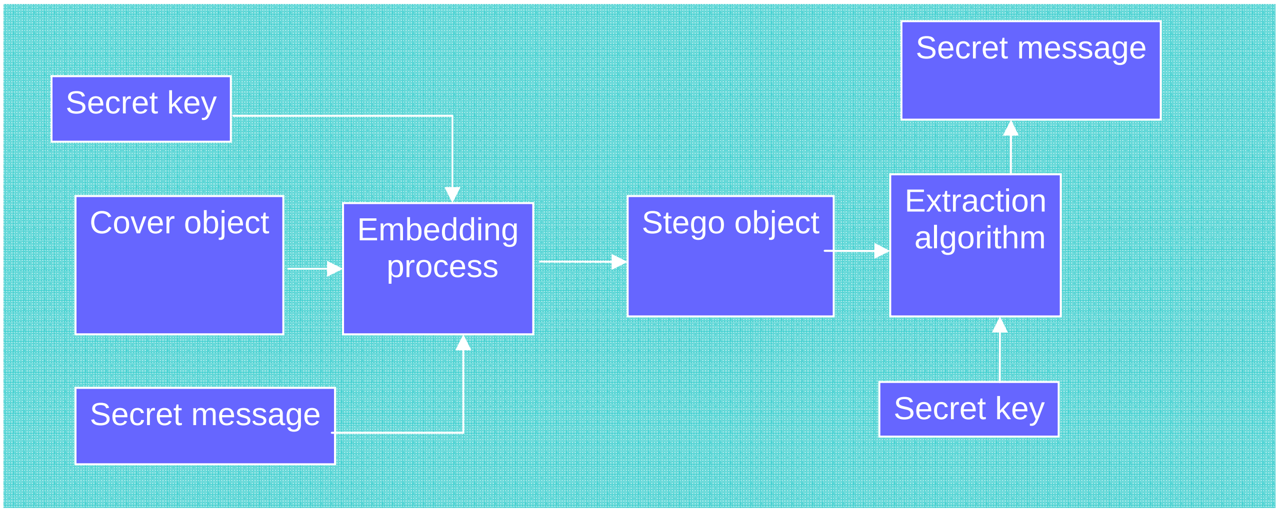


Figure 1: Basic Embedding and Extraction flow

As shown above, secret message is embedded into the cover object by using an embedding algorithm and the resulted object is called a *stego* object. A *stego* object is one which looks exactly same as the cover object but it contains hidden information. To add more security, the data to be hidden is encrypted with a key before embedding. To extract the hidden information one should have this key.

Most of the embedding methods use a secret key for encrypting the message before embedding. In some of these methods secret key is also used to select locations in the cover object where information will be hidden, thus adding more security to the embedding process.

1.6 Terminology

- *Cover* (container) – the message into which the information is hidden.
- *Embedding message* – information to be hidden, a secret message.
- *Stego* – the resulted message after embedding the secret message into cover
- *Stego Image*: Image with the hidden information.
- *Non-stego Image*: Natural image with no hidden information.

- *True Positive*: while testing, if a test image is correctly detected as a *stego image*; it is treated as *True positive*.
- *True Negative*: while testing, if a test image is correctly identified as a *non-stego image*, it is treated as *True Negative.*
- *False Positive*: while testing, if a test image is incorrectly detected as a *stego image*, it is treated as *False Positive*.
- *False Negative*: while testing, if a test image is incorrectly identified as a *non- stego image*, it is treated as *False Negative.*

1.7 Modern Steganography

With the advancement of technology in this digital age, most of the communication is carried out using some form of digital media. Similarly, *steganography* is also increasingly being used in the digital format through the use of digital media. Because of the wide spread use of internet for communication, it has become a preferable medium for digital *steganography*.

Any digital format can be used for *steganography* like images, video etc., but images are still the most widely used medium and are very suitable to hide the information. There is a lot of work being done on *steganography* based on images as compared to other formats like audio/video, and therefore, we have mainly concentrated on the images and the remainder of this paper deals mainly with *steganography* in images.

1.8 Steganography in Images:

Steganography in images is mainly classified into:

>*Least significant bit (LSB) insertion method*.

>*Masking and filtering*.

>*Algorithms and transformation*.

Least significant bit insertion method:

This is the most common method used. In this type, the data to be hidden is inserted into the least significant bits of the pixel information. In digital format the images are represented with numerical values of each pixel where the value represents the color and intensity of the pixel.

Images are mainly of two types:

24-bit images

8-bit images

24-bit images: These images have 24 bit value for each pixel in which each 8 bit value refers to the colors *red blue* and *green*. We can embed 3 bits of information in each pixel, one in each *LSB* position of the three 8 bit values in 24 bit value.

Increase or decrease of value by changing the *least significant bit* doesn't change the appearance of the image, such that the resulted *stego image* looks exactly same as the *cover image*.

8-bit images: In these images 1 bit of information can be hidden in each pixel. As in 8-bit images maximum number of colors that can be present are only 256 colors, the color variation may occur and therefore, care should be taken in considering the *cover image*.

Images with gray palette are good choice as the difference between the adjacent colors is less.

Advantages:

- There is less chance for degradation of the original image.
- More information can be stored in an image (hiding capacity is more).

Disadvantages:

- Less robust, the hidden data can be lost with image manipulation.
- Hidden data can be easily destroyed by simple attacks.

Masking and Filtering:

Masking refers to covering a signal by a different signal in such a way that the first signal is not apparent. This is based on the human visual acuity which cannot detect slight changes. Masking is mainly used in watermarking techniques. This is not pure *steganography* as here we extend the image information as well as other attributes of the image.

Since much of the data is integrated into the image, the data wont be lost even if the image manipulation is done like compression, cropping etc.

Algorithms and Transformations:

Data is embedded into the cover image by changing the coefficients of transformation of an image, such as *discrete cosine transform coefficients*. If we embed information in spatial domain, it may be subjected to the losses if the image undergoes any image processing technique like compression, cropping etc. To overcome this problem we embed the information to be hidden in frequency domain. As the digital data is not continuous, to analyze the data of the image, we apply transformations to the image. We embed the data to be hidden by changing the values of the transformation coefficients accordingly.

There are mainly three transformation techniques:

1. *Fast Fourier transformation technique (FFT)*
2. *Discrete cosine transformation technique (DCT).*
3. *Discrete Wavelet transformation technique (DWT).*

The main implementation techniques are same in all three but our main concentration in this paper is on *JPEG images* and they use *DCT* for compression. The information is hidden in the *LSB*'s of the *DCT coefficients* of a *JPEG image*.

1.9 Thesis Organization

The remainder of this thesis is structured as follows:

Chapter 2: explains brief overview of *steganalysis* and the classifications of *steganalysis* based on information available.

Chapter 3: presents the review of related work done in the field of *steganalysis*. It covers all the *steganalysis* techniques analyzed in our study.

Chapter 4: gives the overview, procedure and details of our study.

Chapter 5: presents the general data preparation process and the details of data sets we prepared for our experiments

Chapter 6: includes details of the software used in our study for embedding and detection.

Chapter 7: includes results and analysis of all the experiments.

Chapter 8: presents our proposed procedure for the detection of *steganography* in general.

Chapter 9: includes our concluding remarks.

2 Steganalysis

Steganalysis is the practice of attacking *steganography* methods for the detection, extraction, destruction and manipulation of the hidden data in a *stego* object.

Attacks can be of several types for example, some attacks merely detect the presence of hidden data, some try to detect and extract the hidden data, some just try to destroy the hidden data by finding the existence without trying to extract hidden data and some try to replace hidden data with other data by finding the exact location where the data is hidden.

Detection is enough to foil the very purpose of *steganography* even if the secret message is not extracted because detecting the existence of hidden data is enough if it needs to be destroyed. Detection is generally carried out by identifying some characteristic feature of images that is altered by the hidden data. A good steganalyst must be aware of the methods and techniques of the *steganography* tools to efficiently attack.

Classification of attacks based on information available to the attacker:

1. *Stego* only attack: only *stego* object is available for analysis.

2. Known *cover* attack: both *cover* and *stego* are known.

3. Known message attack: in some cases message is known and analyzing the *stego* object pattern for this embedded message may help to attack similar systems.

4. Chosen *stego* attack: *steganographic* algorithm and *stego* object are known.

5. Chosen message attack: here *steganalyst* creates some sample *stego* objects from many steganographic tools for a chosen message and analyses these *stego* objects with the suspected one and tries to find the algorithm used.

6. Known stego attack: *cover* object and the *steganographic* tool used are known.

Different Approaches of Steganalysis:

Visual attacks: By analyzing the images visually, like considering the bit images and try to find the difference visually in these single bit images.

Structural attacks: The format of data file often changes as the data to be hidden is embedded, identifying these characteristic structural changes can detect the existence of image, for example in palette based *steganography* the palette of image is changed before embedding data to reduce the number of colors so that the adjacent pixel color difference should be very less. This shows that groups of pixels in a palette have the same color which is not the case in normal images.

Statistical attacks: In these type of attacks the statistical analyses of the images by some mathematical formulas is done and the detection of hidden data is done based on these statistical results. Generally, the hidden message is more random than the original data of the image thus finding the formulae to know the randomness reveals the existence of data.

3 Related Work

In the paper [2] "Detecting Steganographic Messages in Digital Images Using Higher Order Statistics" it is shown that in natural images, strong higher order statistical regularities within a wavelet like decomposition exist and when the information is hidden these statistics are significantly altered. The decomposition is based on separable quardrature mirror filters (QMF's). It splits the frequency space into multiple scales and orientations. This is accomplished by applying separable low pass and high pass filters along the image axis generating a vertical, horizontal, diagonal and low pass sub bands. Subsequent scales are generated by recursive filtering of low pass sub bands.

The statistics of *mean*, *variance*, *skewness* and *kurtosis* of the sub band coefficients at each orientation and at scale i=1, 2...n form the first order statistics. Second order statistics are based on error statistics, calculated from the current and expected sub band coefficients. Expected sub band coefficients are calculated from the neighboring coefficients. The total of 12(n-1) error statistics plus 12(n-1) coefficient statistics which is a total of 24(n-1) statistics forms a feature vector. This feature vector is used to discriminate between the images that contain the hidden information and those that do not contain any hidden information.

From the experiments conducted, it is shown that *stego images* and *non-stego images* can be classified using feature vectors of the images by using the d*iscriminant analysis methods* in which first classifier is trained with the train data before we classify the test image to find which class it belongs to. This method needs a huge amount of train data.

Westfeld and Pfitxmann [13] found that embedding encrypted data into an image changes the histogram of its color frequencies. Encrypted data likely contain 1 and 0 bits equally. Because of this nature, when encrypted data is used for embedding, if the original image has color X more than color Y (where X and Y are adjacent colors), after the embedding process, X changes more often to Y than Y changing to X as a result of which the difference in frequencies of X and Y is reduced after embedding.

Niels Provos [5] found that exactly the same concept explained in [13] applies if the information is embedded in the *LSB* of the *DCT* coefficients in *JPEG images.* But instead of color frequency histogram, here the *DCT* coefficient frequency histogram is analyzed. To find whether the image has any hidden information *DCT* coefficient histograms of the original and modified image are compared but in general, as we are left with only one image to determine whether it's a *stego* or normal image, we don't have an option of having an original image to compare the frequency histograms with the suspected image. It is shown that we can estimate the original image histogram from the given image by calculating the expected *DCT* coefficients of the original image from the existing image by taking the average of adjacent coefficients.

And finally, the difference between expected and original distributions X^2 value is calculated. And from this, probability P is determined which, tells us the probability of embedding in the test image. *Stegdetect* calculates the probability of hidden information in different parts of the image. Selection of the position of image where the probability is calculated depends on the *steganography* technique we are trying to find. And also, from the graph plot between the probability and the position in the image, it is shown that the common pattern is observed for the images embedded with a same steganographic technique and also it is showed that the patterns are different for different steganographic techniques. These patterns are used to find the specific technique used for embedding. For an image with no embedded information i.e. for a normal image the probability is zero at all places of the image.

Jessica Fridrich [10] showed that *F5 steganography* method can be broken. It is shown that by embedding the information into the *JPEG image* by *F5* method will significantly alter the *DCT* coefficient histogram of the image and the changes caused to the histogram is directly proportional to the length of the message but in general for the comparison of histograms original image is not available. It is shown that if the test image is decompressed, crop by 4 pixels in both directions in spatial domain and recompress with the same quantization tables of the original image the histogram obtained from the resulted image will be equal to the original image (before embedding). A preprocessing step is performed before recompressing by doing a blurring operation to remove any furious frequencies due to the discontinuity at block boundaries. A beta value is calculated with the use of the low frequency *DCT* coefficients of the test image and recompressed image obtained. This beta value represents the percentage of embedding. For natural images without any hidden information this value should be very close to zero. A threshold value is selected for the detection of *stego images.* For example if the threshold value is 0.5, for an image if the calculated beta value is greater than 0.5 it is considered as *stego* or image with possible hidden information.

In [12] Guillermito El Loco listed all the *steganography* methods he could break. All the attacks were listed by analyzing the raw data of the test file such that all of these are structural attacks to find any changes made to the structure of the file. For all the broken methods while analyzing the raw data with the help of a Hex editor he was able to find the signatures embedding methods leave in the file. These signatures are not visible when an image is seen but they can be found when its raw data is looked using special editors. By experimenting with few test images he was able to detect the location of the signatures present in the file like password being stored at a particular location in the file, having a comment in the file. Data being present at the end of the file, for example, as *JPEG file* format has a special character which tells the end of the *JPEG file.* Some *steganography* methods just add the hidden information at the end which can be easily identified by looking at the raw data of the file to find the information after the end of *JPEG* file character.

4 Our Study

In this section we explain:

- General overview of our study
- Different techniques compared.
- Embedding methods considered for the performance comparison of *steganalysis* techniques.
- Details of comparison.

4.1 Overview

The main goal of our study was to do the performance analysis of three different s*teganalysis* techniques and compare the detection accuracy of each technique in *JPEG* images. To analyze the performance of a given *steganalysis* technique, we tested on various test images and the performance was determined based on the number of correctly detected test data. Comparison was made based on the number of *true negatives*, *true positives* and *misclassified* resulted for each *steganalysis* technique used in the detection of embedding methods.

4.2 Problem Statement

There is no single *steganalysis* technique which is able to efficiently detect all the *steganography* methods available. To analyze a suspicious image in a forensic investigation, forensic experts have to run all available *steganalysis* techniques blindly for the detection of possible *stego* involved, without the specific knowledge of the ones that are efficient in the detection of specific *steganography* methods. This results in the use of more time and resources for the investigation.

4.3 Contribution

Our motivation in writing this thesis is to summarize the enormous amount of work that has been done in the field of *steganalysis* of images. It is our aim to have all the results together in one place so that readers interested in *steganography* could easily view the results of the performance of each *steganalysis* technique considered in this paper and be able to compare them.

Contributions of Our Thesis:

(i) We did a comparative analysis of the performance of *steganalysis* techniques (*stegdetect* and *discriminant analysis based on feature vectors collected from higher order statistics*) in the detection of each *steganography* method considered (*Jsteg, Jphide, F5, Outguess* (new)).

(ii) We did a comparative analysis of the performance of the *steganalysis* technique *breaking the F5* algorithm with the best technique from two *steganalysis* techniques mentioned above (*stegdetect, discriminant analysis*) in the detection of *F5* embedding method

(iii) Based on the results of our analysis, we provide information as to which specific *steganalysis* technique needs to be used for what particular *steganographic* method and finally we propose a procedure which may help a forensic examiner to decide the order in which the different *steganalysis* techniques need to be considered in the detection process to achieve the best detection results in terms of both accuracy and time.

4.4 Steganalysis Techniques Compared

Steganalysis techniques, compared and analyzed are listed below for the detection of *steganography* in *JPEG* images.

- *Stegdetect*
- *DA (FLD) Discriminant Analysis based on Fisher Linear Discriminant classification*
- *DA (SVM) Discriminant Analysis based on Support Vector Machines*
- *Breaking F5*

Both *DA (FLD)* and *DA (SVM)* are classification methods. The detection logic in both is same i.e., the features used for the classification are same and only the methods used for the classification are different.

4.5 Embedding Methods Considered

Steganography or embedding methods for *JPEG* images considered for the performance analysis of above mentioned *steganalysis* techniques are

- *Jsteg*
- *F5*
- *Outguess (new)*
- *Jphide*

4.6 Procedure

In our study, any *steganalysis* detection test involves the detection of two sets of our test data, one with unmodified images and other with the modified images created by the embedding method whose detection was being analyzed. In an ideal scenario, if the *steganalysis* technique is hundred percent accurate, it should detect correctly all images under modified data set as *stego images* and all the images under unmodified set as *non-stego images*.

The results obtained with the test data are compared with the expected results to calculate the number of *TN (true negatives)* and *TP (true positives)* for each test. These numbers along with the number of *misclassified* images were used to analyze the performance of detection technique for each *steganographic* method.

True Negatives (TN) are the number of images from the unmodified image set which are correctly identified as *non-stego* images i.e., no *steganography* is detected in these images.

True Positives (TP) are the number of images in the modified image set which are correctly identified as *stego images* i.e., a possible *steganography* is detected.

In our study, first we compared the performance of two *discriminant analysis techniques (DA) (FLD)* and *DA (SVM)*. Each of these methods uses *Fisher linear discriminant* and *support vector machines* as classifiers respectively.

Subsequently, we compared *stegdetect* and *DA (SVM*) with three different data sets. Images were same in all the data sets but the embedding message size in creating each of the data set were different.

Finally, we analyzed and compared the performance of *breaking F5* technique and the resulted best technique from *stegdetect* vs. *DA (SVM)* in the detection of *F5 steganography* method.

5 Data Preparation

5.1 Overview

To analyze the performance of different *steganalysis* techniques considered, we needed to have test set of images to experiment with. As we were testing the *steganalysis* techniques that detect the presence of hidden information in the images, the test data needed to include both *non-stego images* (not modified) and *stego images*(with the secret message). Also, *DA (FLD)* and *DA (SVM)* needed a significant number of train data for training the classifiers and to find the threshold value for the test data classification. Therefore, data preparation was the first and a very important step in our work.

5.2 Procedure

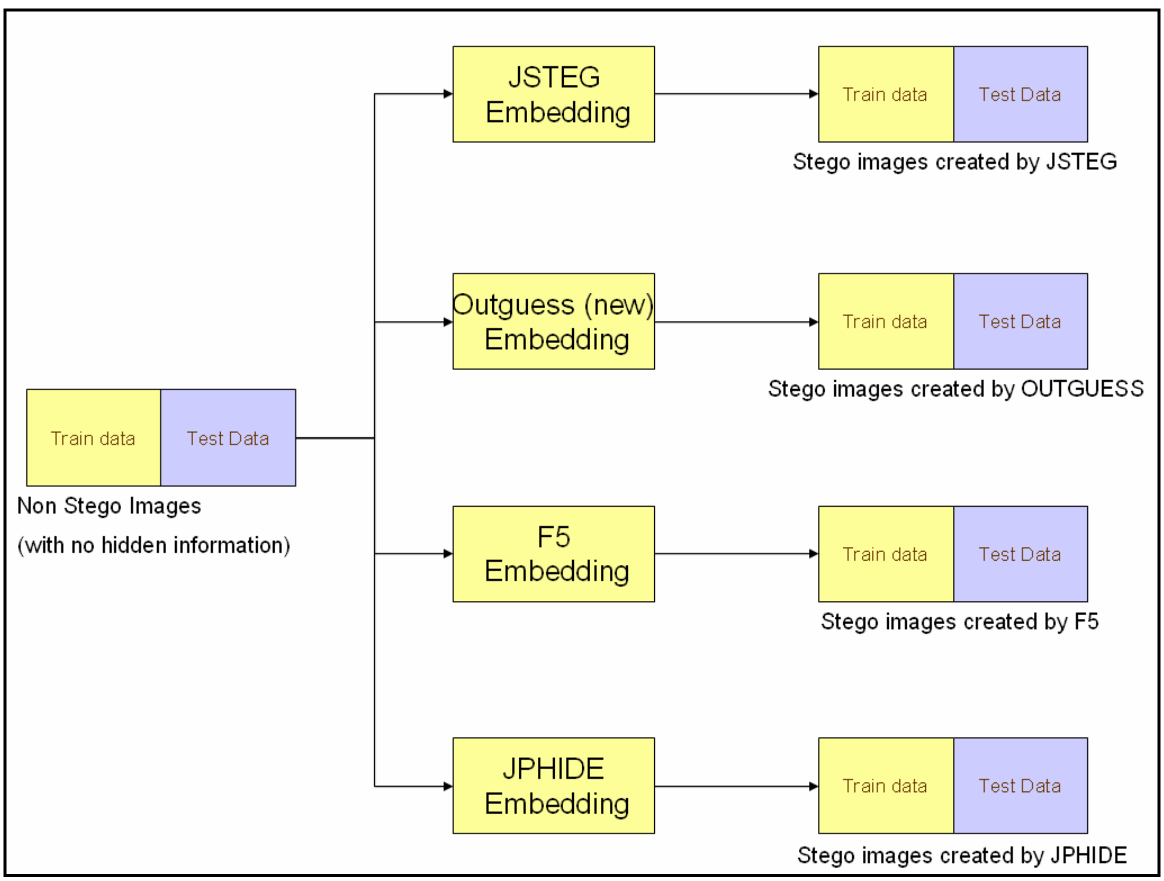


Figure 2: Basic flow for Test data creation

Shown above is a brief representation of data creation process. We created the *stego image* sets for each of the *steganography* methods by hiding a message into the *cover images* (*non-stego images*) by using corresponding embedding tools of *steganography* methods. From the process shown above, we created the data set needed. A data set consists of one subset of *non-stego images* and four subsets of *stego images* generated by embedding a secret message into the unmodified (*non-stego*), using the four embedding methods considered for this study.

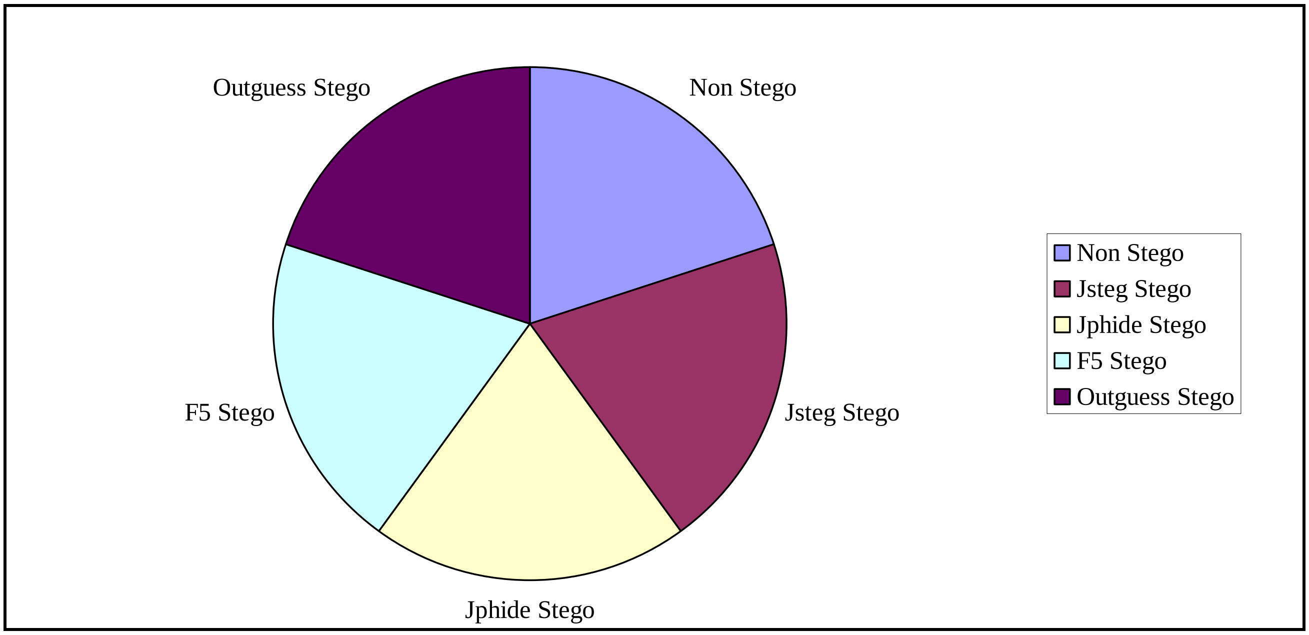


Figure 3: General Data set representation.

As discussed above, we needed the *train data* for *steganalysis* techniques based on classification so we divided the above obtained each subset image into train data and test data (see diagram below shown for only one subset). Similarly all the subsets were divided into *train data* and *test data.*

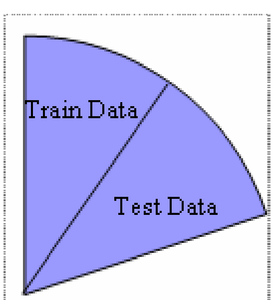


Figure 4: Train and test data representation in a subset

5.3 Details

For our experiments we created three data sets by the above mentioned process. In all these three data sets the *non-stego image* subsets are same and taken from a database of *JPEG* images with the sizes ranging from 6KB to 243KB. From these *non-stego images* the *stego image* subsets are generated by the embedding process as shown in figure 2. These *stego image* subsets differ in the three data sets because of the embedding message size we chose while creating them.

In the process of creating above mentioned three data sets, embedding message sizes chosen for the embedding processes were 5 percent, 4 percent and 3 percent of the *cover image* size into which the message is embedded.

Exceptions were present with respect to the embedding size for *F5* and *Outguess (new)* embedding methods which calculated maximum capacity it could embed before embedding process. For *F5* we tried to embed a message with size equal to the above mentioned message sizes. If the message size was larger than the expected capacity, it embeds the maximum allowable data from the message and discards the rest of the message. In *Outguess* it did not embed any information if the message was larger than the allowable capacity. Therefore, for this method we first tried to embed very large message and the log was captured in a text file which had the maximum allowable capacity. Then we created a message with maximum allowable size which was used for the embedding. In most cases the maximum allowable message size was less than 5% of the image size.

Because of the embedding problem explained above for *Outguess*, two data sets among the three created did not have *Outguess stego image* subset.

5.4 Summary of Data sets

To avoid any confusion, in this section we listed the details of each data set created separately. Details include the embedding message size used in the embedding process to create the *stego image* subsets, and the number of images considered as *train data* and *test data* from these data sets.

Data Set 1

Non-stego images: Taken from the image database.
Jsteg stego images: Created from *Jsteg* embedding method by embedding a message with size equal to 5 percent of the *cover image* size.
Jphide stego images: Created from *Jphide* embedding method by embedding a message with size equal to 5 percent of the *cover image* size
F5 stego images: Created from *F5* embedding method by embedding a message with size equal to 5 percent of the *cover image* size or maximum allowable embedding size if 5 percent of the *cover image* size was greater than maximum allowable embedding size.
Outguess stego images: Created from *Outguess (new)* embedding method by embedding a message with size equal to maximum allowable embedding size

Below table shows the number of train and test data images for each subset mentioned above

	Train data	Test data
Non Stego	1000	1200
Jsteg Stego	1000	1200
Jphide Stego	1000	1200
F5 Stego	1000	1200
Outguess Stego	1000	1200

Table 1: Number of images in Data Set 1

Data Set 2

Non- stego images: Taken from the image database.

Jsteg stego images: Created from *Jsteg* embedding method by embedding a message with size equal to 4% of the cover image size.

Jphide stego images: Created from *Jphide* embedding method by embedding a message with size equal to 4% of the cover image size

F5 stego images: Created from *F5* embedding method by embedding a message with size equal to 4 percent of the cover image size or maximum allowable embedding size if 4 percent of the cover image size was greater than maximum allowable embedding size.

	Train data	Test data
Non Stego	1000	1200
Jsteg Stego	1000	1200
Jphide Stego	1000	1200
F5 Stego	1000	1200

Table 2: Number of images in Data Set 2

Data Set 3

Non stego images: Taken from the image database.

Jsteg stego images: Created from *Jsteg* embedding method by embedding a message with size equal to 3 percent of the *cover image* size.

Jphide stego images: Created from *Jphide* embedding method by embedding a message with size equal to 3 percent of the *cover image* size

F5 stego images: Created from *F5* embedding method by embedding a message with size equal to 3 percent of the cover image size or maximum allowable embedding size if 3 percent of the cover image size was greater than maximum allowable embedding size.

	Train data	Test data
Non Stego	1000	1200
Jsteg Stego	1000	1200
Jphide Stego	1000	1200
F5 Stego	1000	1200

Table 3: Number of images in Data Set 3

6 Implementation Details

In this chapter we explained implementation details of several processes used.

- We provided the details of generation of random message for embedding.
- We listed different embedding tools used.
- We presented the details of *steganalysis* techniques and how the results were interpreted.

6.1 Generation of Embedding Message

In the process of creating *stego images* with both *train* and *test* data for our experiments, hidden message was embedded into the original set of *non-stego images* by using the embedding tools to create *stego image* subsets for each embedding method considered. The hidden message used for embedding was a random message and was different for every embedding. Random message was generated before the embedding process by writing the random characters with *ASCII* value ranging from 0-255 on to a text file, each character being 1 byte of information. We wrote *N* characters to a text file to generate *N bytes* of message.

6.2 Embedding

This section gives only a brief outline of the embedding tools used in our data creation process with download locations. More information on the usage and implementation details can be found in the documentation provided along with the software. All of the embedding tools listed here are open source.

Jsteg

UNIX version of this software was downloaded from this location [25] and code used the standard *JPEG* library. To be specific, it was a modification made to the standard library itself. The usage is pretty straight forward. An option *–steg* is added to the compression command *cjpeg* to embed the message and we extract the message using decompression *djpeg* command.

Jphide

UNIX version of this software was downloaded from this location [25]. A shell script for the automation of embedding for all the images by generating random message before embedding process was used but *Jphide* uses a *getpass()* command which asks for a password at the command prompt. Because of this, the automation of embedding process for all the images without user interaction was not possible and so we had to modify the source code of *Jphide* by hard coding a string in place of *getpass()* as password for the automation to work.

F5

The source code was downloaded from [26] location. *F5* calculates the maximum allowable embedding size before the embedding process and if the message size is larger than the allowable message size, maximum allowable message is embedded and the rest of the message is discarded.

Outguess (new)

This tool was downloaded from [16]. The new *Outguess* calculates the maximum allowable size and only embeds if the embedding message is less than maximum allowable size. If the message size is larger it simply discards the entire message and no information will be hidden. To create *Outguess stego images* for our test data, we embedded maximum allowable message into each image of unmodified image set. To find the maximum allowable message size, we first tried to embed very large amount of data (maximum image size in the unmodified image set) into each image and collected the log in a text file which is then parsed for the maximum allowable message size for each image. Having found maximum allowable message size for each image we then embedded the message with maximum allowable message size into all the images to form *Outguess stego image* set.

6.3 Detection

In this section we explain the implementation details of detection process by all the *steganalysis* techniques considered for our study, which involved the tools used in each process and details of the interpretation of results.

Stegdetect

Stegdetect software written by Niels Provos was downloaded from [16]. It's an open source code and this was used without any modifications by calling its executable from a shell script. The shell script was written for automation of detection for all the test images and the output was written to a text file, this text file was then parsed and the results were interpreted for all the images which in turn were compared with the expected results to calculate the total number of *true negatives* and *true positives*.

Any image which was identified as *negative* or *skipped (false positive likely)* was considered a *negative image* that is, as an image with no hidden information. Image which was identified as a possible *steganography* of any method was considered as a *positive.*

Note: If an image with the hidden information embedded by *Jsteg* was identified as an *Outguess (old)(***),* it was considered as a *true positive*, or as a correct detection, even though the method of embedding was not correctly identified. This is because our main aim in this whole thesis was to compare the total number of images correctly detected as *stego* and *non-stego images*.

DA (FLD) and DA (SVM)

As explained above, in both these techniques the feature vectors used for classification of data were same and only the tools used for the classification were different. A matlab routine written by Hany Farid downloaded from [23] was used for the extraction of feature vector for an image, but as this code extracts the feature vector for an *8 bit* gray scale image this was modified to extract the feature vector for a *24 bit JPEG* color image. Feature vector length for a gray scale image is 72 i.e. 72 features were collected for each image but for color *JPEG* image the feature vector was extracted in the similar way as gray scale images but for all the three color components separately which makes the length of feature vector for a color image equal to 216 (72*3). Also additional logic was added to extract the feature vectors for *N* number of images and the feature vector of *n* images were stored in an [Nx216] array. These feature vectors were used for the classification of images. For *DA (FLD), Fisher linear discriminant classifier* was used and for *DA (SVM), LIBSVM* [18] which is an open source tool for the classification, *SVM (support vector machines)* was used.

DA (FLD): Here we give a brief introduction of *FLD*. For more details of the implementation of *two class FLD* refer [2].

This is one of the most commonly used general methods in a simple *two class classification* problem. For the *train data*, the within class mean and between class mean of the two classes were calculated by using these within class scatter matrix and between class scatter matrix. Now the *train data* were projected on to the one dimensional subspace which was defined by the maximal generalized eigen value and eigen vector solution of the scatter matrices calculated above. From these projections a threshold value was selected which best classified the *train data*. Now *test data* was projected on to the same axis to find the class it belongs to. The threshold value calculated above is used as a divider between the two classes to determine into which class the *test data* fell. For our experiment the two classes were *non-stego images* and *stego images* and we represented them as -1 and +1 respectively, for *test data*. After we determine into which class the image fell, we further calculated *true positives*, *true negatives* and *misclassified* numbers.

DA (SVM): *SVM (support vector machines)* are used for classification in which the *training data* are mapped on to a higher dimensional space to find the hyper plane which separates the classification data into different classes. The mapping function which is used to map the train data in to the higher dimensional place is called *kernel*. For *SVM* classification in our study, non linear *RBF kernel* was used and the parameters for this kernel C and gamma values were calculated by a parameter selection tool in the *LIBSVM*. A tool in *LIBSVM* was used for this whole process of classification which takes everything from scaling the data to parameter selection for the classification. Parameters were selected by cross validation on the *train data* with brut force search

For every classification we generated 2 text files, train.txt and test.txt, which contained the feature vectors of train and test images formatted as required by *LIBSVM* [18] for the classification. Details of the format of these *train* and *test files* can be found in the documentation of the software or for more details refer [18]. As *LIBSVM* takes only the numeric data as input, each image was labeled as -1 or +1, -1 for the *non-stego images* and +1 for the *stego images*. In general this labeling was required only for the *train data* but we added the labeling for the *test data* too to find the accuracy of the classification. The output of the classification for the *test data* was a predict file where all the test images were classified as either –1, or +1. The results from this predict file was compared against the expected results to calculate total number of *TP (true positives) and TN (true negatives).*

Breaking the F5 algorithm

This is implemented in the matlab, paper[10] “Steganalysis of JPEG Images: Breaking the F5 Algorithm” written by Jessica Fridrich was implemented with some extra logic as the paper[10] talks about only gray scale images. But in our experiment, as we were testing on 24 bit jpeg color images, the code was implemented for the *JPEG* color images. To accomplish this we had to consider only the luminance component from the *JPEG* color components leaving the chrominance component in calculating the beta value. The code uses different open source libraries. For the decompression and recompression of images, *cjpeg* and *djpeg* from the standard *JPEG* library were used. And to find the quantization tables of a test *JPEG* image which were used in the recompression process after cropping the image in spatial domain, we used Matlab *JPEG* Tool Box written by Phil Sallee [24].

The preprocessing step before the recompression of an image was the uniform blurring operation done to the image to remove any spurious frequencies due to the discontinuity at block boundaries. This was necessary to reduce the *false positives*. For gray scale images studied in paper [10] this was done by convoluting the image with the 3x3 kernel shown below

0	2.7183	0
2.7183	-9.8731	2.7183
0	2.7183	0

But for our study, since we considered the color *JPEG* images, we experimented with the above kernel used in the paper, 1/9 Kernel shown below and without using the blurring operation.

.

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

From the tests we conducted (not shown), we found that removing the preprocessing step (blurring operation) explained in the paper [10] gave good results for the *JPEG* images. Kernel used in the paper [10] for the preprocessing step was for the gray scale images and it was not good for the *JPEG* images. So, we completely removed this step as this was an extra step for the reduction of *false positives* and not the main part in the detection. The results shown here for *breaking F5* in this thesis are without the preprocessing step.

The beta values for each *test image* were calculated as explained in the paper. We chose the threshold value ‘T’ to classify the data as one which best classifies from random values we considered. For the test, *images* with the beta value less than threshold T were considered as images with No hidden information (*non-stego Image*) and images with beta value greater than the threshold T were considered as images with hidden information (*stego Image*).

7 Results and Analysis

In this section we present all the results for each *steganalysis* technique in the detection of embedding methods considered. We show the comparison charts to compare the performances for all the experiments.

All the experiments presented in this section were conducted with the data sets created in data preparation process. More details of data sets are explained in chapter 5. Table below lists the comparison experiments and data sets used for each experiment.

Experiment number	Techniques Compared	Data Set used
Experiment 1	DA (FLD) vs. DA (SVM)	Data Set 1
Experiment 2	Stegdetect vs. DA (SVM)	
Experiment 2.1	Stegdetect vs. DA (SVM)	Data Set 1
Experiment 2.2	Stegdetect vs. DA (SVM)	Data Set 2
Experiment 2.3	Stegdetect vs. DA (SVM)	Data Set 3
Experiment 3	DA (SVM) vs. Breaking F5	Data Set 1

Table 4: Data sets for each experiment

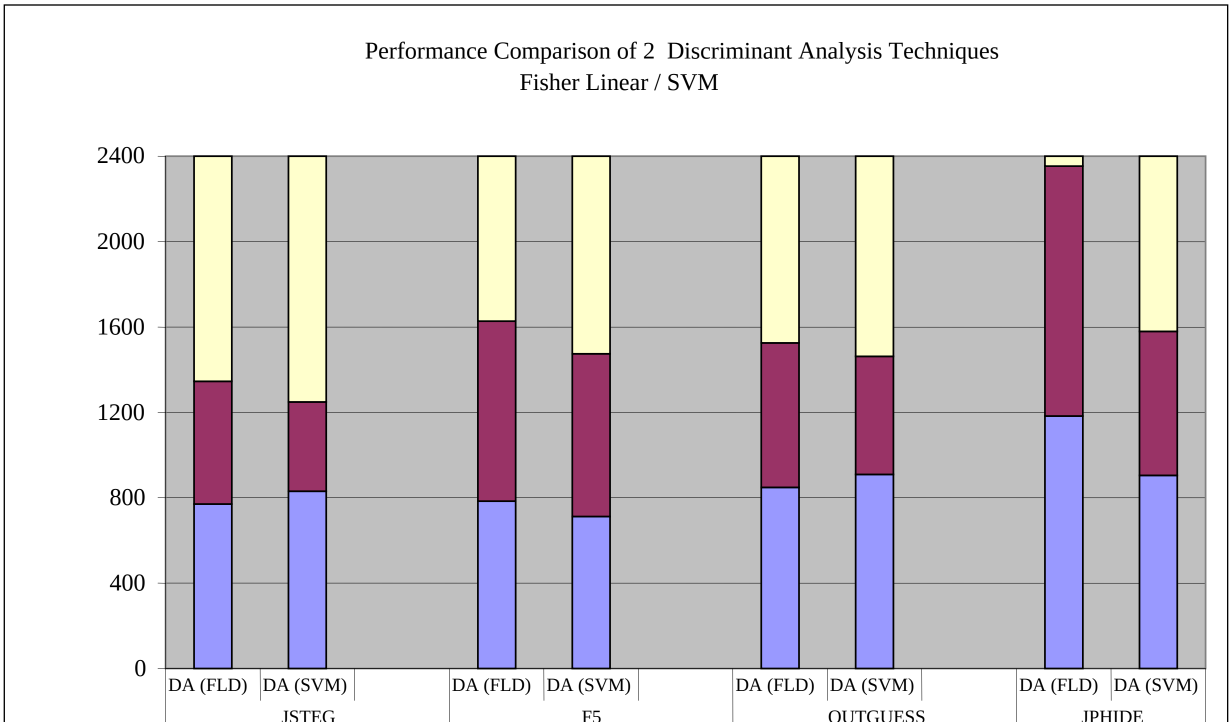
Stegdetect does not detect *F5* and *Outguess (new)*, it detects *F5* only when a message is embedded with the comment. We tested the detection of these using *stegdetect,* if it could detect just the mere presence of hidden message even though it could not detect the correct method *(F5 or Outguess)* used to embed by considering the fact that mere detection of a *stego image* is enough to foil the whole purpose of *steganography*. For *stegdetect* if an image was detected as *positive* it was considered as a *true positive,* though it did not identify the embedding method used correctly. We have included the charts to illustrate both the individual performances and for comparison of the techniques even though they are showed in comparison graphs in Experiment 2, we were not trying to compare the performance of *stegdetect* for these methods.

7.1 Experiment 1: DA (FLD) vs. DA (SVM)

Overview

In this experiment we analyzed and compared the performance of *discriminant analysis technique* by using 2 different classifiers. The features considered for the classification in both the techniques were same only the classification methods were different. The two classifiers used were *Fisher linear discriminant (FLD)* and *Support Vector Machines (SVM)*. We tested for all the four embedding methods *Jsteg*, *F5*, *Outguess (new)* and *Jphide*.

Results



	JSTEG DA (FLD)	JSTEG DA (SVM)	F5 DA (FLD)	F5 DA (SVM)	OUTGUESS DA (FLD)	OUTGUESS DA (SVM)	JPHIDE DA (FLD)	JPHIDE DA (SVM)
True Negatives	1054	1151	772	925	875	938	46	820
Misclassified	575	418	844	763	676	552	1172	674
True Positives	771	831	784	712	849	910	1182	906

Figure 5: DA (FLD) vs. DA (SVM)

Analysis

From the above results we see that for all the embedding methods considered, the number of misclassified are less in *DA (SVM)* when compared with the *DA (FLD)*. From the above results we concluded that *DA (SVM)* is better than *DA (FLD)*. From the above conclusion *DA (SVM)* was considered for the comparison with other *steganalysis* techniques in the below experiments.

7.2 Experiment 2: Stegdetect vs. DA (SVM)

Overview

In this experiment we analyzed and compared the performance of *stegdetect* and *discriminant analysis technique DA (SVM),* the classifier used in *discriminant analysis technique* is *support vector machines (SVM)*. We have compared the results for all the three data sets we have collected.

The three experiments shown in this section are conducted with the data sets as listed below

Experiment 2.1: Data Set 1
Experiment 2.2: Data Set 2
Experiment 2.3: Data Set 3

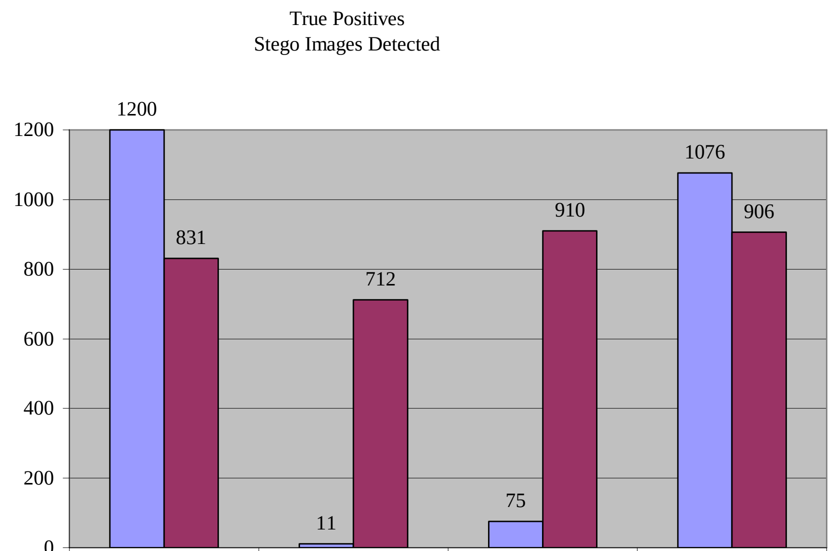
Results

Table and charts below show all the results for both *stegdetect* and *discriminant analysis* for all three tests with Data sets 1, 2 and 3.

Data Set 1 (Embedding Size = 5% of the image size)					
	Stegdetect			Discriminant Analysis (SVM)	
	True Positives	True Negatives		True Positives	True Negatives
Jsteg	1200	1123		831	1151
F5	11	1123		712	925
Outguess(new)	75	1123		910	938
Jphide	1076	1123		906	820
Data Set 2 (Embedding Size = 4% of the image size)					
Jsteg	1199	1123		805	1120
F5	10	1123		656	908
Jphide	1059	1123		778	785
Data Set 3 (Embedding Size = 3% of the image size)					
Jsteg	1200	1123		793	1080
F5	10	1123		743	807
Jphide	1054	1123		785	670

Table 5: True Negatives and True Positives for Stegdetect vs. DA (SVM)

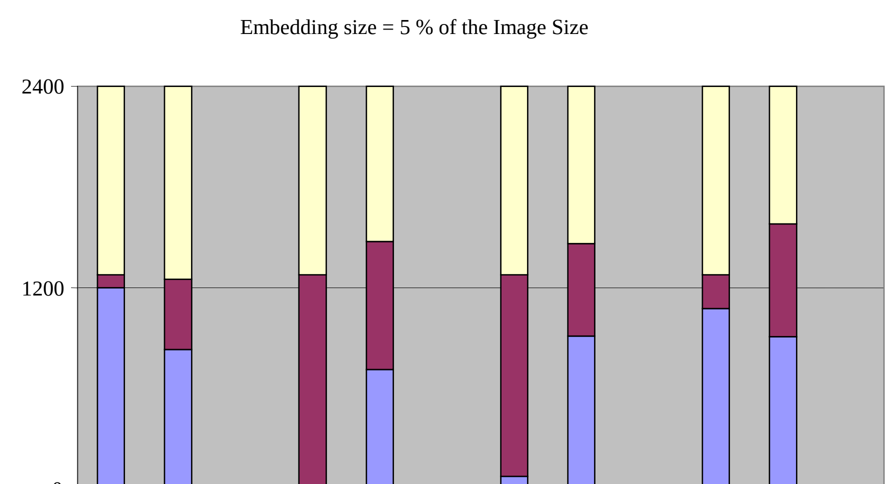
Experiment 2.1



	Jsteg	F5	Outguess(new)	Jphide
Stegdetect	1200	11	75	1076
Discriminant analysis	831	712	910	906

Figure 6: True Positives for Data Set 1

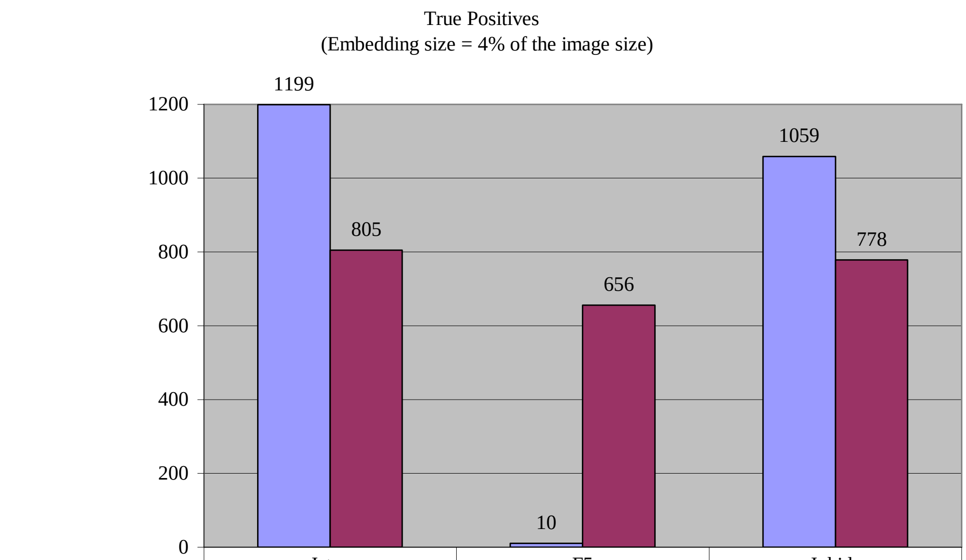
Above Figure 4 shows the detection of steganographic methods *Jsteg*, *Jphide*, F5 and OUTGUESS (new) by Stegdetect and Discriminant Analysis (SVM)



	Jsteg		F5		Outguess(new)		Jphide	
	SD	DA	SD	DA	SD	DA	SD	DA
True Negatives	1123	1151	1123	925	1123	938	1123	820
Misclassified	77	418	1266	763	1202	552	201	674
True positives	1200	831	11	712	75	910	1076	906

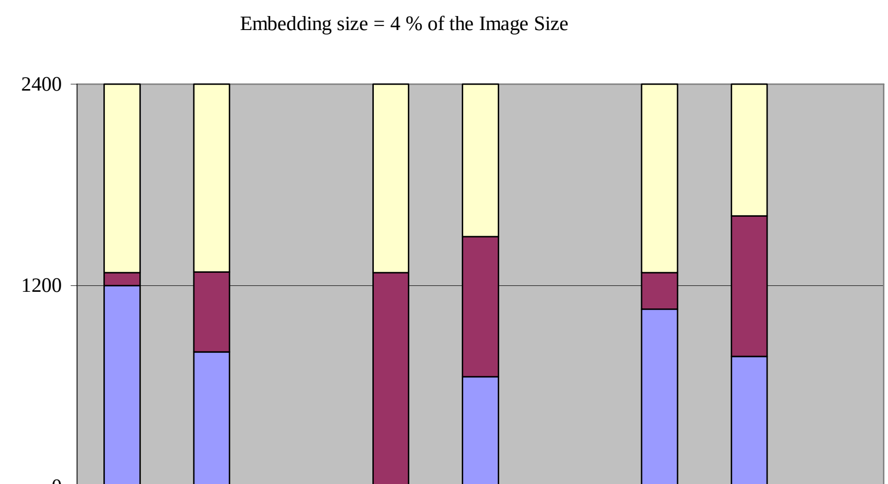
Figure 7: Stegdetect vs. DA (SVM) for Data Set 1.

Experiment 2.2



	Jsteg	F5	Jphide
Stegdetect	1199	10	1059
Discriminant analysis	805	656	778

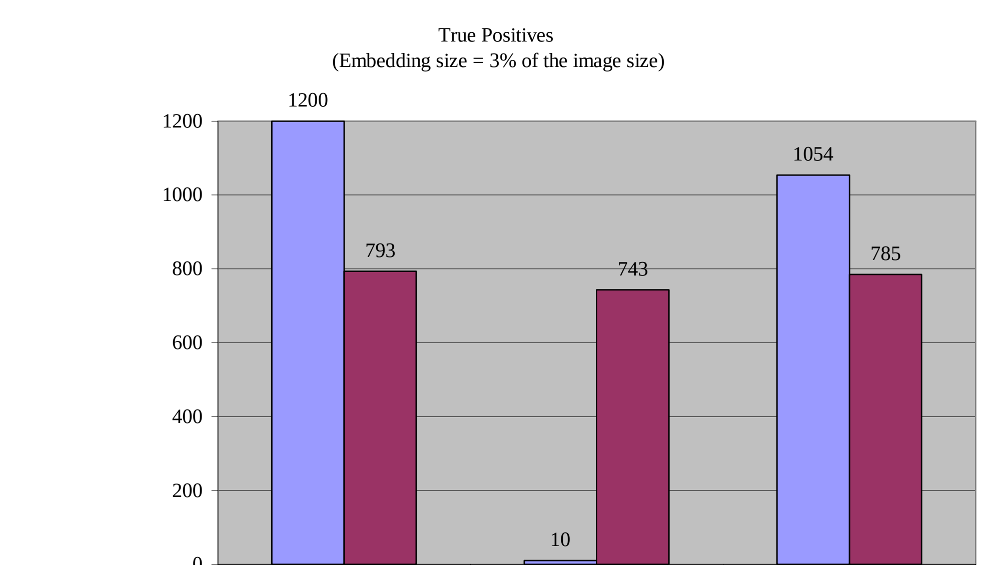
Figure 8: True Positives for Data Set 2



	SD	DA		SD	DA		SD	DA	
	Jsteg			F5			Jphide		
True Negatives	1123	1120		1123	908		1123	785	
Misclassified	78	475		1267	836		218	837	
True positives	1199	805		10	656		1059	778	

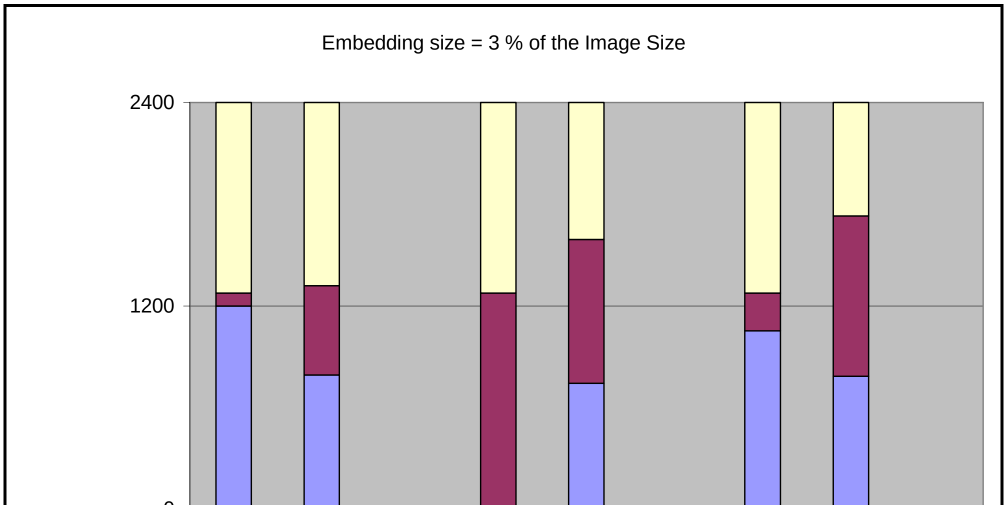
Figure 9: Stegdetect vs. DA (SVM) for Data Set 2

Experiments 2.3



	Jsteg	F5	Jphide
Stegdetect	1200	10	1054
Discriminant analysis	793	743	785

Figure 10: True Positives for Data set 3



	Jsteg SD	Jsteg DA		F5 SD	F5 DA		Jphide SD	Jphide DA	
True Negatives	1123	1080		1123	807		1123	670	
Misclassified	77	527		1267	850		223	945	
True positives	1200	793		10	743		1054	785	

Figure 11: Stegdetect vs. DA (SVM) for Data set 3.

Analysis

From all the above figures (in experiment 2.1, 2.2 and 2.3) shown the performance of *stegdetect* and *DA (SVM)* for 3 different datasets created with varying embedding sizes, it is evident that stegdetect performed better in the detection of *Jsteg* and *Jphide.*

As explained earlier *stegdetect* does not detect *F5* and *Outguess* (new) technically, but they were considered for test by *stegdetect* if they could be identified as *stego* with any other embedding methods. By looking at the results we could see that *stegdetect* could detect very few *Outguess* (new) and *F5 stego images* and because of such low numbers they were considered not detectable by *stegdetect.* The results for these in *DA (SVM)* were acceptable, although not very good, among them the detection of *Outguess* (new) was better than the detection of *F5.*

One more observation was that if we looked at only the results of *DA (SVM)* it was evident that it could detect all the embedding methods with an acceptable accuracy as they were better than random guessing. It could be used for the detection of any *steganography* method irrespective of the algorithm used.

If we look at the results from the embedding method point of view, considering both the *steganalysis* techniques, *F5* was the less detectable method. Because of this, we added a new *steganalysis* technique for detecting *F5* in our study and we compared the results of *F5* detection by *DA (SVM)* with the new technique *breaking F5* in the next experiment.

7.3 Experiment 3: DA (SVM) vs. Breaking F5

Overview

In this experiment we analyzed and compared the performance of *discriminant analysis DA (SVM)* and *breaking F5* techniques in the detection of embedding method *F5.*

Results

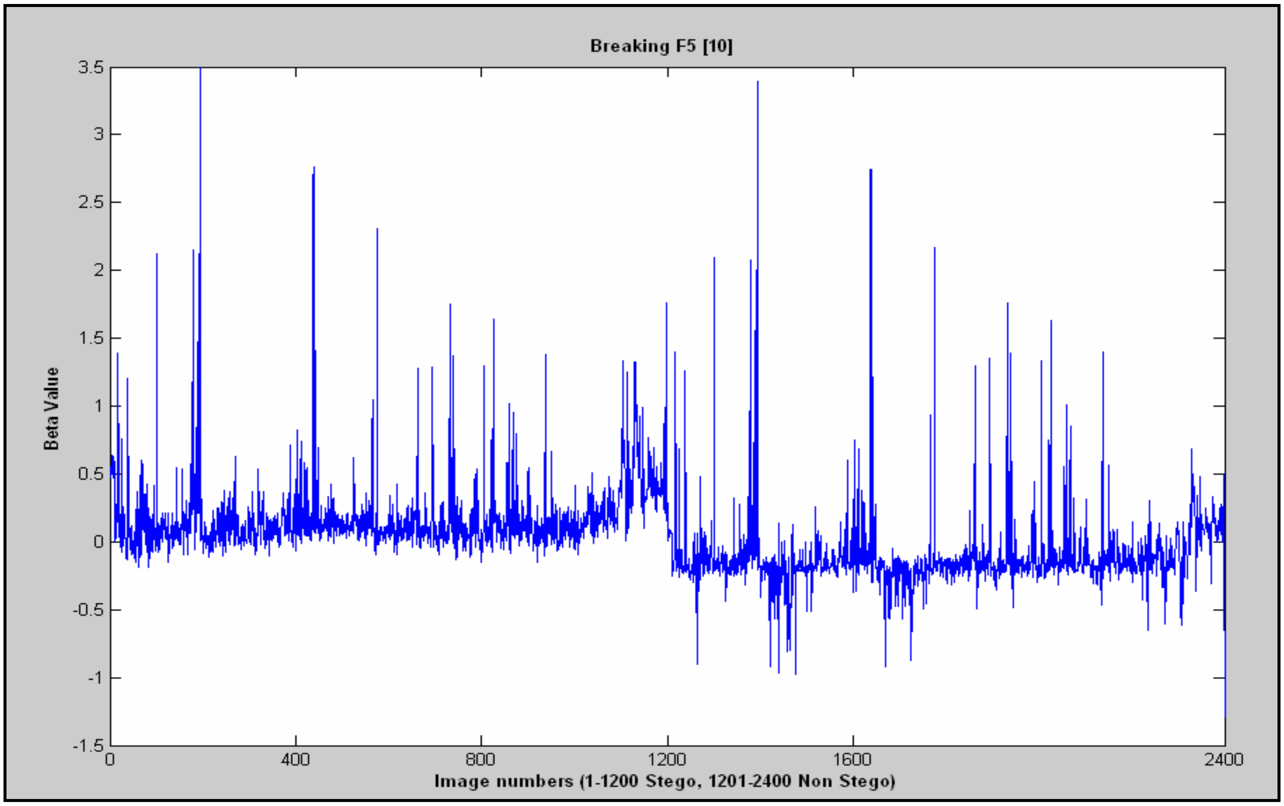


Figure 12: Graph plot of beta values in breaking F5

Figure 12 above shows the graph plot of beta values for a set of 2400 test images in which the first 1200 images are *stego images* and the next 1200 images are *non-stego images*. From the graph we could see that for all *stego images* beta value is generally greater than the beta value of *non-stego images* with few exceptions in the *non-stego images* which are considered as *False Positives*. For a Threshold value of T equal to the beta value of -0.0488 we got the best classification with TP=1138 and TN=938.

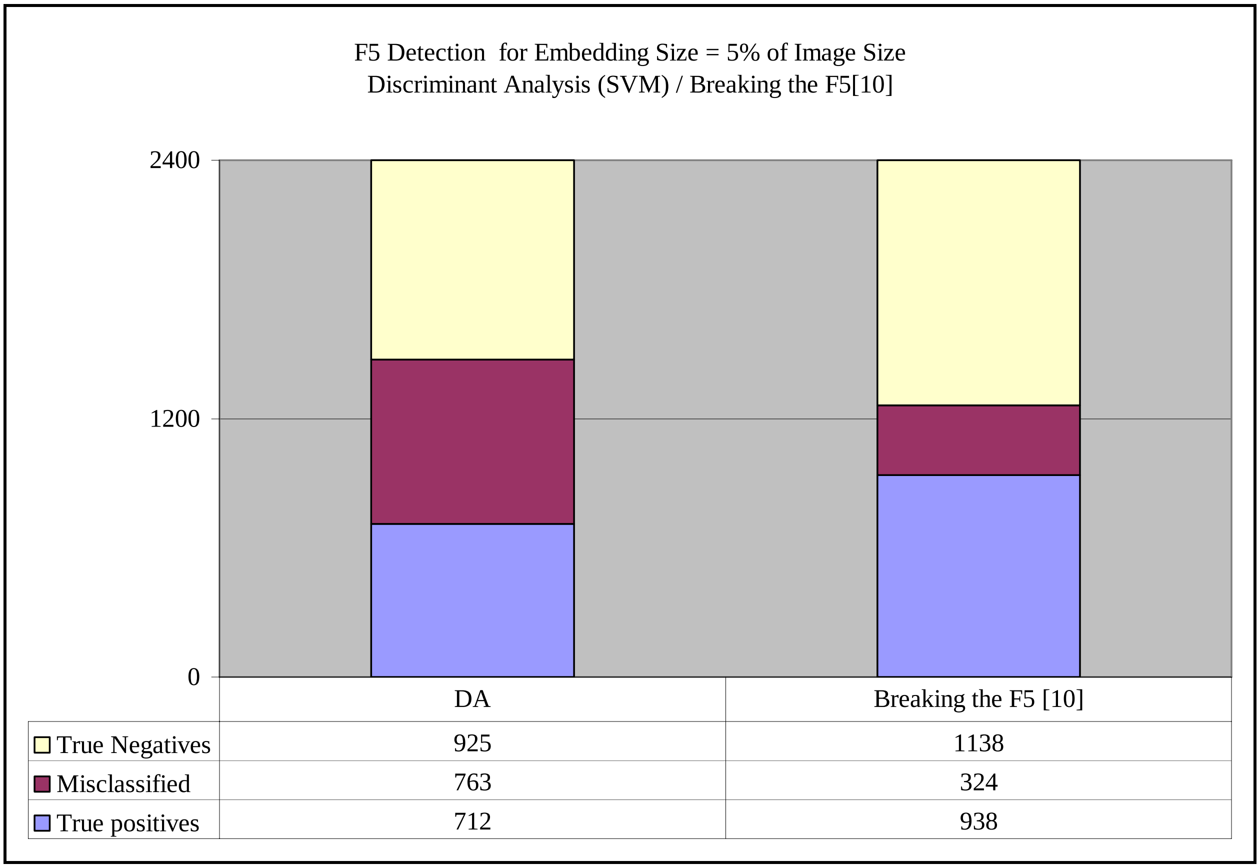


Figure 13: DA vs. "Breaking the F5" for F5 detection.

Figure13 above compares the detection performance of *F5 steganography* method in *Discriminant Analysis (SVM)* and *breaking the F5* [10], from the results we clearly see that the detection accuracy for *breaking the F5* is better than *discriminant analysis (SVM).*

7.4 Summary of Analysis

From Experiment 1 it was found that *discriminant analysis* method with *support vector machines* as classifier, *DA (SVM)* performs better in the classification of *non-stego* and *stego images* when compared with the *discriminant analysis* with *Fisher Linear Discriminant, DA (FLD).* Since the features used for the classification in both were same we concluded: for the features we extracted from the images, nonlinear *LIBSVM* classifier is good in classifying when compared to linear standard *FLD* classifier.

From Experiment 2 it was found that

(1) Detection of *Jsteg* and *Jphide* was very good by *stegdetect* when compared to the detection by *DA (SVM).*

(2) *F5* and *Outguess (new)* were not detected by *stegdetect.*

(3) Detection results for *F5* and *Outguess (new)* by *DA (SVM)* were acceptable although not very good.

(4) *DA (SVM)* could detect all the embedding methods.

(5) With the decrease in embedding size of the hidden message detection accuracy also decreases in both *stegdetect* and *DA (SVM)* for all the embedding methods.

From Experiment 3 it was found that *breaking F5* was better in the detection of *F5* embedding method when compared with *DA (SVM).*

8 Proposed Procedure

From our tests and analysis it was found that we were not able to detect all the embedding methods with any one single *steganalysis* technique efficiently, it was found that *Jsteg* and *Jphide* were detected well by *stegdetect* and detection of *F5* was good in *breaking the F5* technique, *Outguess (new)* is only detected by the *Discriminant analysis*.

Without the above information that helps in determining which detection technique works well for what particular embedding method, a forensic examiner who is investigating a case with suspicious *stego image* will run all the detection tools available for the detection which takes lot of time and resources.

Based on our analysis we propose a procedure for a forensic expert in investigating the suspected *stego images*, an order in which to try the different *Steganalysis* techniques for the detection.

From the above experiments and analysis of the results, we saw that *steganalysis* techniques which attacked specific embedding methods by finding the signatures of embedding methods were more efficient in the detection than the universal blind *steganalysis* technique like the one we tested and analyzed.

Also, because of the overheads included in training with the huge number of *train data* we suggest that *discriminant analysis method* be tried at the end, if the suspected image is not detected by any other technique. *Universal blind steganalysis* techniques are useful in detecting the new and unknown embedding methods.

This type of procedure is also useful when possible embedding method information is available. In such cases the forensic investigator can try the technique which best detects the suspected possible embedding method first instead of randomly choosing techniques. For example, consider an investigator who is trying to detect a *stego image* created by *F5* and has the information that the possible embedding method is *F5*. Without the knowledge of performance of *steganalysis techniques*, he might end up trying the *discriminant analysis* method first which not only takes a significant amount of time but also needs large train data.

Below is the basic flow chart which best describes our procedure for the detection of methods we considered in this study.

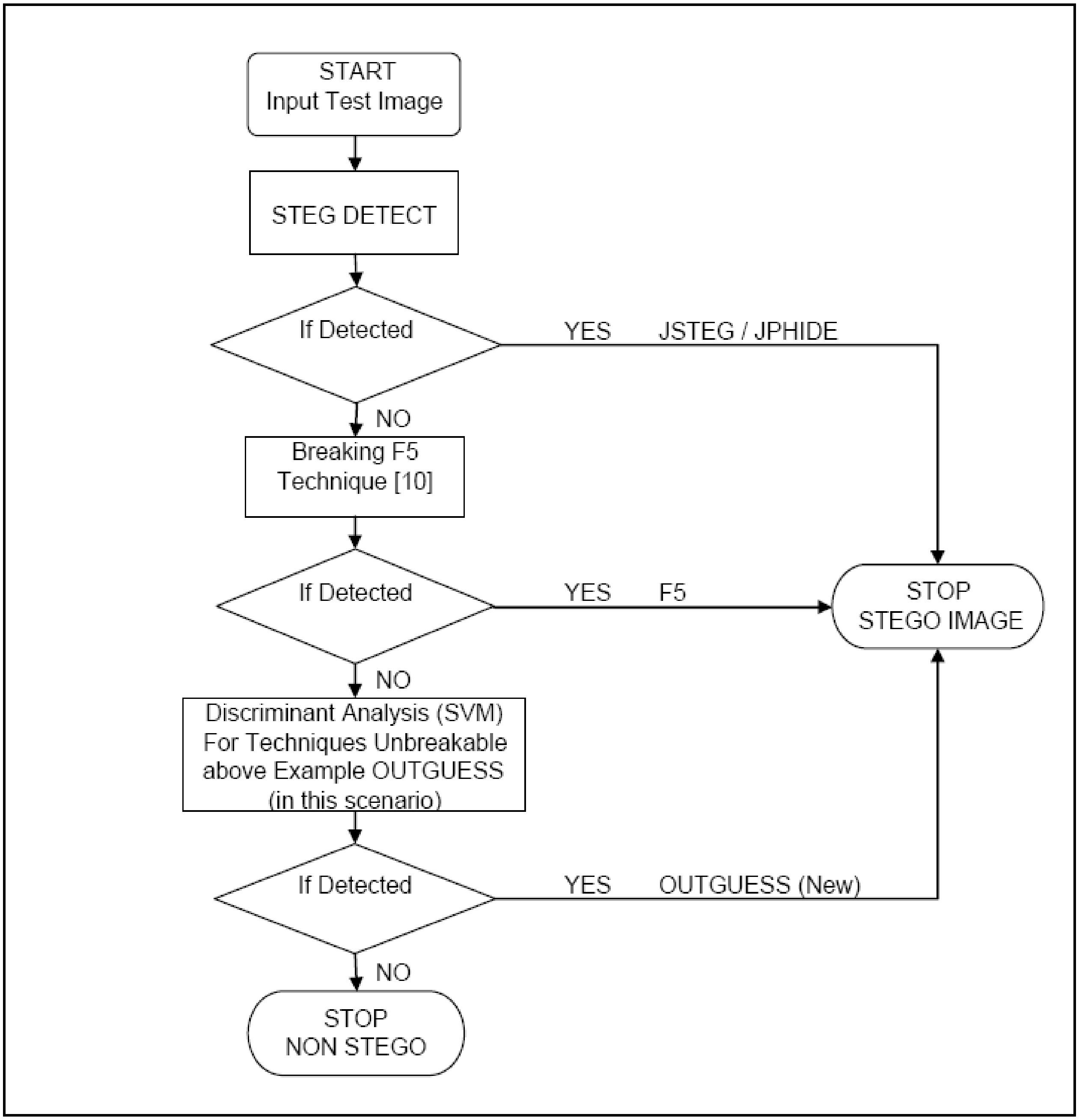


Figure 14: Proposed procedure flow chart

9 Conclusions

From the above analysis it was found that detection of *Jsteg* and *Jphide* in *stegdetect* and the detection of *F5* by *breaking F5* [10] were better when compared to *discriminant analysis.*

From the proposed procedure, although we can not completely reduce the work of a forensic examiner in trying different *steganalysis* techniques, still with this kind of analysis if there is any information of possible *steganography* method used in the test file, we can suggest as to which *steganalysis* technique may be tried first. For the ones with no information, the order shown in the proposed procedure can be followed while trying different techniques to reduce investigation time and for better accuracy in the detection.

Also, we can say that universal *steganalysis* technique like *DA* in our work should be the last option after all the individual attacks like *stegdetect* for *Jphide* & *Jsteg* and *breaking F5* for *F5*. Although we are saying universal *steganalysis (DA)* is the last option, it still has a very important place in the field of *steganalysis* as it can be used for the detection of any *steganography* method in general without the knowledge of algorithm it uses for embedding. More work on this need to be done to improve the performance.

This type of analysis with all the available *steganalysis* techniques, both commercial and open source will help forensic experts to achieve best results in less time.

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Vita

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