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Ahmed Ibrahim
Edith Cowan University

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SUITABILITY OF LACUNARITY MEASURE FOR BLIND STEGANALYSIS

Ahmed Ibrahim
School of Computer and Security Science, Edith Cowan University, Perth, Australia
a.ibrahim@ecu.edu.au

Abstract
Blind steganalysis performance is influenced by several factors including the features used for classification. This paper investigates the suitability of using lacunarity measure as a potential feature vector for blind steganalysis. Differential Box Counting (DBC) based lacunarity measure has been employed using the traditional sequential grid (SG) and a new radial strip (RS) approach. The performance of the multi-class SVM based classifier was unfortunately not what was expected. However, the findings show that both the SG and RS lacunarity produce enough discriminating features that warrant further research.

Keywords
Blind Steganalysis, Lacunarity, Sequential Grid, Radial Strip, Differential Box Counting, DCT, Steganography, Outguess, F5

INTRODUCTION

Steganalysis deals with detecting content embedded covertly in digital media such as images, also known as steganography. There has been tremendous interest in the research of steganography and steganalysis over the past decade; hence many techniques have been developed in both areas, each trying to outdo the other in its own way. The goal of steganography is to avoid detection, and that of steganalysis is to defeat this purpose (Johnson & Jajodia, 1998b), thus making this the gist of all the techniques that have been developed in both these areas.

This paper deals with ascertaining the suitability of using lacunarity measure as the features for the classification algorithm used in blind steganalysis. In doing so, this paper introduces two novel approaches; 1) using lacunarity for blind steganalysis, and 2) measuring lacunarity from the frequency domain, whereas in majority of published literature, it has been applied within the spatial domain (Barros Filho & Sobreira, 2008; Zeng, Zhang, Van Genderen & Wang, 2012).

The two steganographic algorithms used to test the proposed approach are Outguess (Provos, 2001) and F5 (Westfeld, 2001). They both embed the secret message within the frequency domain during the JPEG compression process. Similar to existing research (Lyu & Farid, 2003), Support Vector Machines (SVM) have been used as the classifier for the blind steganalysis. The features used to train the classifier are the lacunarity measure derived using Differential Box Counting (DBC). The reminder of the paper is organised as follows. The background provides a foundation about steganalysis, steganographic feature domain and lacunarity. This also includes the two approaches for lacunarity measure proposed. The methodology describes the sample images and the different parameters used for lacunarity estimation and classifier training. The results section presents the outcome of the classification and several visualisations followed by a detailed discussion. Finally conclusions are drawn and future research direction is presented in the last section.

BACKGROUND

Blind Steganalysis

The different approaches used in steganalysis can be generally categorised into three; visual steganalysis, statistical steganalysis, and blind steganalysis. In visual steganalysis, the image is visually observed for any abnormal artefacts or obvious signs of being tempered, which can be caused due to the degradation incurred by certain types of steganography. Johnson and Jajodia's (1998a, 1998b) analysis of cover and stego image pair characteristics and Westfeld and Pfitzmann's (2000) approach for analysing the Least Significant Bit are two examples of visual steganalysis. Statistical steganalysis is highly effective compared to any other approach;

however, it can only be used only for specific types of steganography (Fridrich, 2005). The Chi-square attack by Westfeld and Pfitzmann (2000) and DCT coefficient histogram distortion detection by Zhang and Ping (2003) are such examples.

Both the visual and statistical steganalysis suffer huge limitations. Visual steganalysis can only detect steganography performed within the spatial domain and not the frequency domain. Statistical steganalysis approaches have been thwarted by developing better versions of the same steganographic technique, or completely new algorithms, thereby rendering the initial statistical signatures useless.

Blind steganalysis tries to overcome the static nature of the aforementioned steganalysis approaches by using classification techniques, allowing it to be more universally applicable for both known and unknown steganographic algorithms.

Steganographic Feature Domain

A key aspect of any steganalysis technique is the investigation of the steganographic feature domain (SFD). The SFD primarily depends on the type of steganography, i.e. depending on whether the message is hidden by manipulating the spatial or the frequency domain. The steganographic tools used for the purpose of this paper are Outguess (Provos, 2001) and F5 (Westfeld, 2001). Both these tools embed the message in lossy JPEG image files using the quantised DCT coefficients.

DCT (Discrete Cosine Transform) is a process used by JPEG file format to transform successive *8 x 8* pixel blocks resulting in 64 DCT coefficients per block. The DCT coefficients $F(u,v)$ of a single block of pixels $f(x,y)$ can be represented by the following equation.

$$F(u,v) = \frac{1}{4} C(u)C(v) \left[\sum_{x=0}^{7} \sum_{y=0}^{7} f(x,y) \times \cos\frac{(2x+1)u\pi}{16} \cos\frac{(2y+1)v\pi}{16} \right] \qquad (1)$$

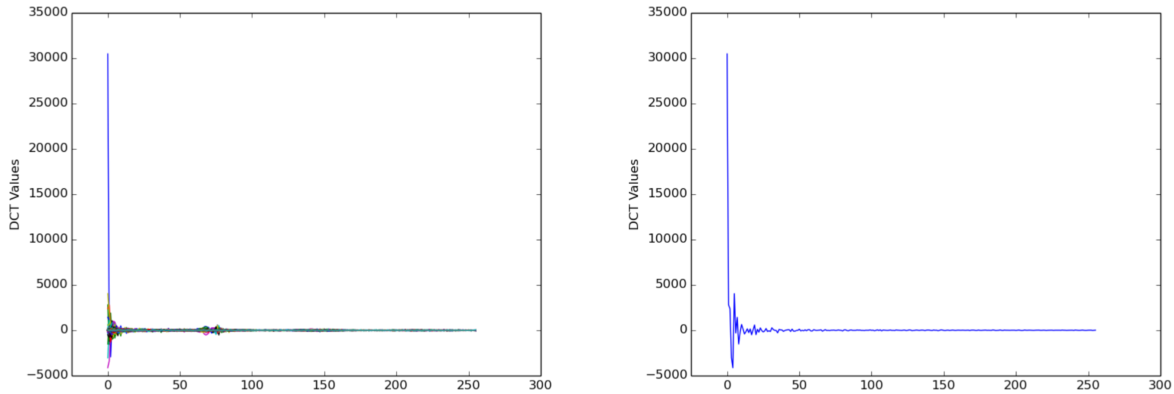
where: $C(u), C(v) = 1/\sqrt{2}$ when $u, v = 0$

$C(u), C(v) = 1$ otherwise

The quantised DCT coefficients $F^Q(u,v)$ are then obtained by equation (2).

$$F^Q(u,v) = IntegerRound\left(\frac{F(u,v)}{Q(u,v)} \right) \qquad (2)$$

where: $Q(u,v)$ = 64 element (*8 x 8*) quantisation matrix



(a) All rows of DCT array superimposed *(b) First row DCT array*

Figure 1: DCT array of size 256 x 256, x-axis moved to show large value of DC coefficient

Both Outguess and F5 use the least significant bits (LSB) of these quantised DCT coefficients as the SFD. However, they differ in their embedding approach. Outguess first selects redundant bits to limit detectable degradation and uses a RC4 encrypted hidden message to derive a pseudo-random number generator (PSRNG) to make the final bit selection (Provos, 2001). F5 uses permutative straddling to scatter the embedding and matrix encoding to increase the embedding efficiency (Westfeld, 2001). Both algorithms use a user provided pass key for randomizing the bit selection process, which is also reversible during the decoding stage to extract the hidden message.

Lacunarity

Lacunarity is the analysis of distributions of gaps among a range of pixel values (either binary or greyscale) in different scales to distinguish between spatial patterns (Plotnick, Gardner, Hargrove, Prestegaard, & Perlmutter, 1996). The higher the lacunarity, the higher the variability of its gaps and heterogeneity of the texture. A texture is the spatial variability of pixel tones in a digital image. The multi-scaling fractal nature of natural textures have intrigued researchers to employ lacunarity to analyse patterns, especially in the fields of medical and biological research (Barros Filho & Sobreira, 2008).

The term lacunarity was introduced by Mandelbrot (1982) to further describe different textures with the same fractal dimension. In addition to Mendelbrot's (1982) approach, there are different methods to calculate lacunarity. Many algorithms (Dong, 2000; Allain & Cloitre, 1991; Sarkar & Chaudhuri, 1992) have been fundamentally derived from the original box-counting algorithm used to estimate the fractal dimension of an image.

The two most commonly used lacunarity algorithms are the Gliding Box (GB) by Allain and Cloitre (1991) and Differential Box Counting (DBC) by Dong (2000). The GB algorithm is limited in capturing the complexity in certain types of images in contrast to the DBC algorithm. This is because it is applied to binary images, which only has two possible values per pixel. The DBC algorithm on the other hand can be applied to greyscale images with a wider range of 256 values per pixel. This makes it superior to its counter parts in revealing sharp grey level variations in the image intensity surface (Dong, 2000).

Even though DCT is from the frequency domain, it can still be considered as a texture; because it too has varying ranges of values demonstrating gaps. This means that it can be treated similar to a problem in the spatial domain. Figure 1a shows a DCT values array superimposed with all the rows in an image. As it can be observed, there are extremely high values towards the origin and only small variations towards the tail section. A 3D visualisation can be seen in figure 6a and 6b. Thus, DBC is applicable to estimate the textural complexity of the DCT values, which is further discussed below.

Differential Box Counting (DBC) Algorithm

The DBC algorithm discussed here was proposed by Dong (2000), which is based on the GB algorithm by Allain and Cloitre (1991) and DBC algorithm by Sarkar and Chaudhuri (1992). According to the GB algorithm (Allain & Cloitre, 1991), consider a box that glides over a lattice overlaid on the image. The distribution of mass *n(M,r)* is defined as the number of gliding boxes with radius *r* and mass *M*. The probability distribution *Q(M,r)* is obtained by dividing *n(M,r)* by the total number of boxes. The lacunarity at scale *r* can then be obtained by dividing the mean-square deviation of variations of *Q(M,r)* by its square mean.

$$\Lambda(r) = \frac{\sum_{M} M^2 Q(M,r)}{\left[\sum_{M} MQ(M,r)\right]^2} \qquad (3)$$

where: $\Lambda(r)$ = lacunarity at box size $r \times r$

M = mass or pixels of interest

$Q(M,r)$ = probability of M in box size $r \times r$

The mass *M* required for equation (3) can be calculated based on DBC algorithm (Sarkar & Chaudhuri, 1992). A gliding box of size $r \times r$ is placed at the upper left corner of an image window of size $W \times W$. The size of the window is such that $r < W$ and an odd number to allow the computed value to be assigned to the centre pixel. The odd number size for *W* and assignment at the centre pixel was not necessary in this case as this paper only deals with DCT values, which is further explained in the methodology section. The grey level intensities within the *r x r* gliding box is then covered by a column of cubes of size *r x r x r* and assigned the values 1,2,3,… starting from the bottom to the top. The relative height of the *r x r* gliding box column is calculated using the minimum and maximum box numbers *u* and *v* respectively using equation (4).

$$n_r(i, j) = v - u - 1 \tag{4}$$

where: $n_r(i, j)$ = relative height at image coordinates *i* and *j*

v = cubic box with minimum pixel value

u = cubic box with maximum pixel value

Equation (4) however, gives a negative value if both minimum and maximum values fall in the same box (Myint, Mesev, & Lam, 2006), instead, a positive one is used (Barros Filho & Sobreira, 2008) as shown below.

$$n_r(i, j) = v - u + 1 \tag{5}$$

The mass is then obtained by moving the *r x r* gliding box through the *W x W* image window by using

$$M_r = \sum_{i,j} n_r(i, j) \tag{6}$$

where: M_r = mass of the greyscale image

$n_r(i, j)$ = relative height at image coordinates *i* and *j*

The lacunarity can then be calculated by replacing *M* in equation (3) using M_r in equation (6). This gives the lacunarity of the *W x W* image window. Figure 2 illustrates the vertical boxes stacked based on the pixel values.

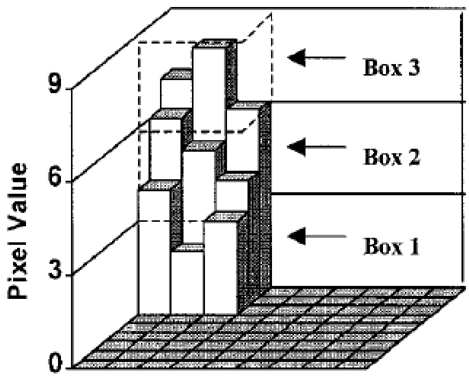
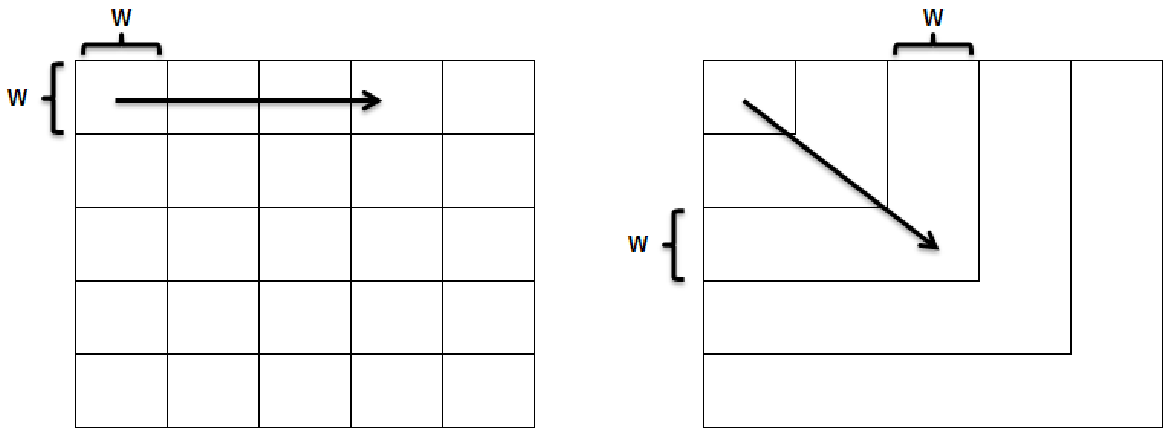


Figure 2: DBC Method (source: Dong, 2000)

Sequential Grid and Radial Strip Lacunarity

For the purpose of the investigation, two separate approaches were taken to calculate the lacunarity measure. The two approaches only differ in the way in which *W x W* window is selected. The first approach uses the exact way explained above starting from the top left index *(i=0,j=0)* of the DCT array and proceeds sequentially in a fixed grid (figure 3a) with width *W*, hence the term *sequential grid (SG)*. The second approach uses the same width *W* for the window but it advances radially as a strip (figure 3b), hence the term *radial strip (RS)*.



(a) Sequential Grid (SG) *(b) Radial Strip (RS)*

Figure 3: Windowing approach for lacunarity

METHODOLOGY

All images used were *256 x 256* greyscale images of JPEG format. To ensure all cover images were consistent and initially clean from any hidden messages, they were all acquired using an iPhone camera as opposed to obtaining from a third-party source. The images consisted of a mix of outdoor and indoor pictures with no particular preference. For the initial pre-processing, all images were cropped to size, colour converted to greyscale and all EXIF information removed. To create the stego images, all images were embedded with the same secret message and pass key for consistency. Thus creating three separate sets of images; Cover, Outguess, and F5.

The steganographic features used for the classification is the lacunarity derived from the DCT coefficients using SG and RS approaches. The complete dataset consisted of 1,224 samples for the Cover, Outguess and F5 each with a total of 3,672 per lacunarity method. Since DCT is performed in *8 x 8* blocks, the lacunarity was localised based on this constraint. The window size was set at *W=8* and the gliding box size was *r=2*. The DCT array was segmented to non-overlapping windows and the gliding box used a size of *r_sigma=r* to glide the boxes horizontally and vertically.

From the complete dataset, half was used for training the classifier while the other half was used for testing and in both cases the classes were balanced. The classifier was trained using a Multi-Class Support Vector Machine (MC-SVM). The classifier was cross validated using a *k-fold* scheme with *k=10* on the training dataset.

In order to obtain the optimal parameters for the MC-SVM, an exhaustive grid search method was used with *C={1, 10, 100, 1000}*, using a LINEAR kernel and *C={1, 10, 100, 1000}* and *gamma-value={0.001, 0.0001}* using a RBF kernel. Once the optimal parameters were obtained, classifier performance was then measured using the test dataset. The results are presented in the next section.

RESULTS

The lacunarity calculation with the above parameters of a 2D DCT array of size *256 x 256* results in a 2D SG lacunarity array of size *32 x 32* (1,024 features per sample) and a 1D RS lacunarity array of size *1 x 32* (32 features per sample). Figure 4 visualises the 2D SG lacunarity for Cover, Outguess and F5 images in the top row. It also shows the difference between the stego images and the cover images. (Cover-Cover) is blank because it is the same array and (Outguess-Cover) and (F5-Cover) differences can be clearly observed in the bottom row. Figure 5 shows the same for the RS lacunarity. However, because it is a 1D array, for the purpose of illustration, it has been visualised in a 2D format.

The following are the optimal parameters and training results for the MC-SVM blind classifier using lacunarity measure.

Lacunarity	Kernel	C	Gamma-value	Precession	Recall	F1-score	Mean accuracy
SG	Linear	100	-	0.34	0.34	0.34	0.34
RS	RBF	1	0.001	0.36	0.33	0.18	0.33

Table 1: MC-SVM classification results for lacunarity measure

		Predicted		
		Cover	**Outguess**	**F5**
Actual	**Cover**	221	198	193
	Outguess	213	212	187
	F5	231	192	189

Table 2: Confusion Matrix for SG Lacunarity using test dataset

		Predicted		
		Cover	**Outguess**	**F5**
Actual	**Cover**	5	604	3
	Outguess	3	605	4
	F5	5	603	4

Table 3: Confusion Matrix for RS Lacunarity using test dataset

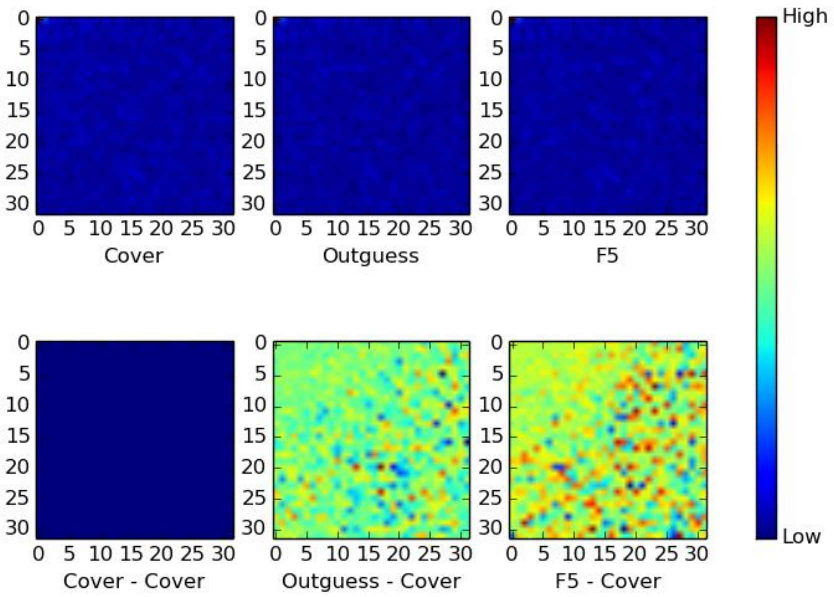


Figure 4: 2D visualisation of sequential grid (SG) lacunarity for Cover, Outguess, and F5 images (top row) and their differences with Cover image (bottom row) respectively

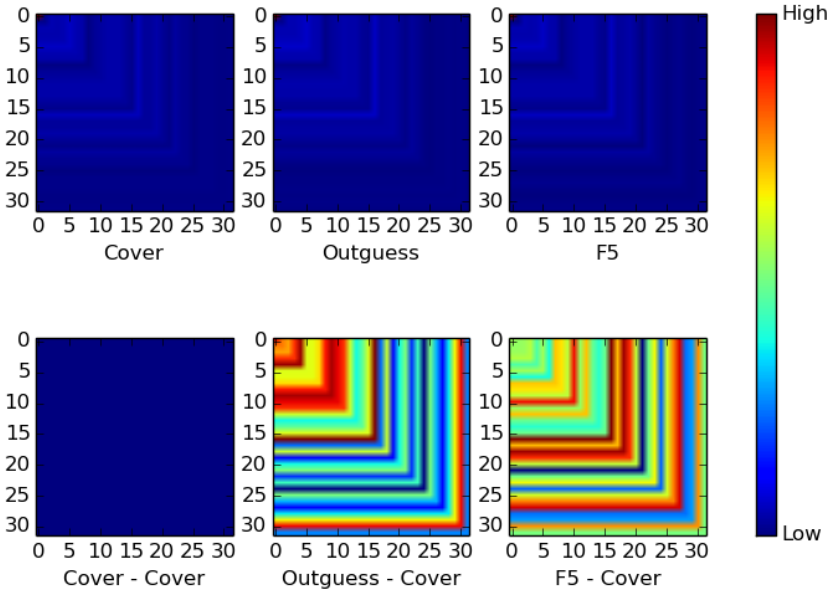
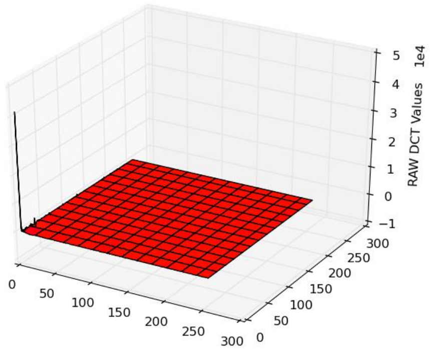
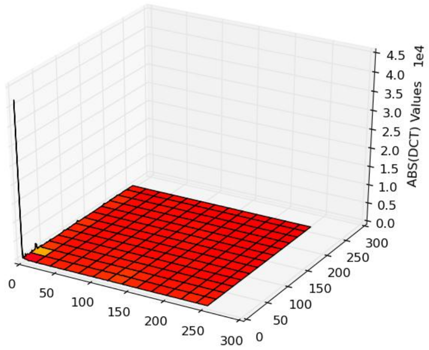


Figure 5: 2D visualisation of radial strip (RS) lacunarity for Cover, Outguess, and F5 images (top row) and their differences with Cover image (bottom row) respectively

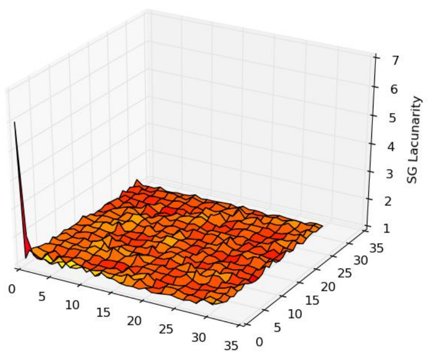
The following (figure 6) are the 3D illustrations for the DCT values and lacunarity datasets.



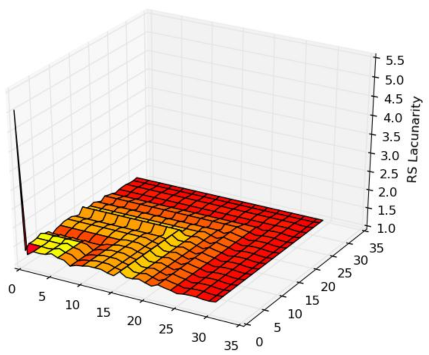
(a) RAW DCT Values



(b) ABS() of DCT Values



(c) SG Lacunarity of ABS(DCT)



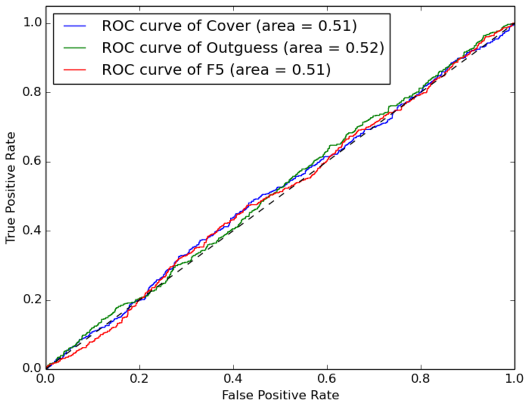
(d) RS Lacunarity of ABS(DCT)

Figure 6: 3D Visualisation for Cover Image

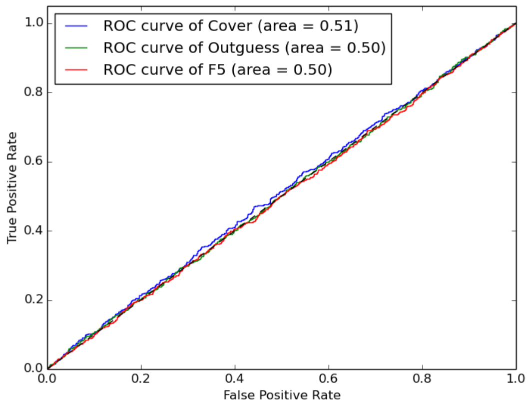
DISCUSSION

The results of these experiments were certainly not what was expected. After a much closer look, certain things can be ascertained about the different factors that may have contributed to the outcome.

Based on the visualisations in Figure 4 and 5, it can be observed that the Cover, Outguess and F5 images produce different features for both SG and RS lacunarity measures. The differences between the Cover and the stego-images suggest that there possibly could be discriminating features to help classify each type of image respectively. However, the classification results in table 1 show very poor performance with respect to the F1 score and mean accuracy. The confusion matrices presented in table 2 and 3 give more insight into how the classifier recognises each class after training. While both matrices are significantly different, both are unsatisfactory. Even though the blind steganalysis of SG lacunarity based features seemed very much random, one may lean towards suggesting that the RS lacunarity features produce very good results for classifying Outguess, but then again it also classifies everything else as Outguess. The following figure 7 encapsulates all this information visually. Since all the curves are almost exactly on the diagonal, it can be said that any classification done is as good as a random guess.



(a) ROC curves for SG Lacunarity



(b) ROC curves for RS Lacunarity

Figure 7: ROC Curves for test dataset

As there have been no previous studies done for blind steganalysis using lacunarity, it was important to investigate why the blind steganalysis performed so poorly. Thus, the trained classifier was retested using the same dataset used to train it in the first place. As expected, table 4 shows 100% accuracy for SG lacunarity, but, table 5 showed a very different outcome for RS lacunarity. This is in no way reflective of the classifiers' ability to identify unknown cases, but it gives an insight into the actual dataset or features used for training. Based on this factor alone, two conclusions could be made.

1. The dataset based on SG lacunarity features are more suitable for classification. The poor performance could be because the training data was insufficient with only 612 training samples per class.

2. The RS lacunarity dataset is unsuitable for training the classifier. Apart from having just 612 samples per class, it is only made up of 32 features per sample in contrast to the 1,024 features in the SG lacunarity dataset. This could be the reason why it predicts most of the samples as Outguess due to lack of discriminating features between classes.

		Predicted		
		Cover	**Outguess**	**F5**
Actual	**Cover**	612	0	0
	Outguess	0	612	0
	F5	0	0	612

Table 4: Confusion Matrix for SG Lacunarity using training dataset

		Predicted		
		Cover	**Outguess**	**F5**
Actual	**Cover**	143	356	113
	Outguess	121	383	108
	F5	133	349	130

Table 5: Confusion Matrix for RS Lacunarity using training dataset

Furthermore, another factor consistently mentioned in literature is the steganographic capacity of the cover image. This certainly has a significant effect (Fridrich, Pevny & Kodovsky, 2007) on the ability for steganalysis detection.

Even though all image samples used for training and testing were consistent in terms of dimension, colour map, and all three datasets; the file size of the image samples are dispersed (figure 9). This contributes to different embedding capacities as it can be observed in figure 8. It shows the file size against the embedding capacity for both Outguess and F5. The steganographic capacity tends to increase with the file size of the image file. This is because larger file size translates to more bits that can be potentially manipulated to hide the message. For consistency, the same secret message and pass key was used to embed throughout all image samples. However, because of different embedding capacity, the footprint left by the embedding process will also vary inconsistently making it difficult for the classifier to discriminate.

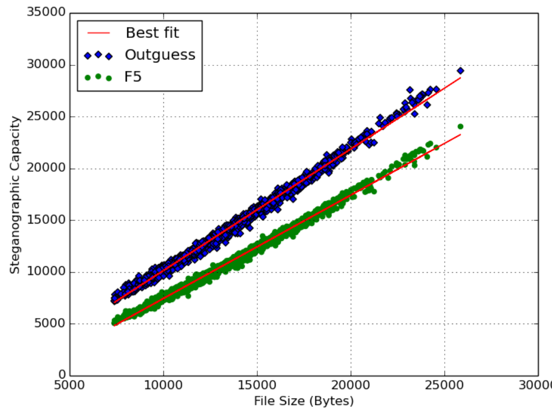


Figure 8: Steganographic capacity VS file size for Outguess and F5

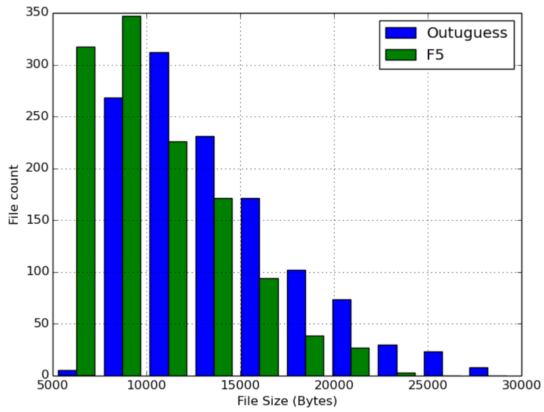


Figure 9: File size distribution histogram for Outguess and F5

CONCLUSION AND FUTURE RESEARCH

The purpose of the research was to find out the suitability of using lacunarity measure as a suitable feature for blind steganalysis. The DBC lacunarity measure was extracted from the DCT values from the Cover images and Outguess and F5 stego-images. Two approaches were used to measure the lacunarity based on the traditional sequential grid (SG) method and a new approach, i.e. radial strip (RS), introduced based on the direction of the DCT values dispersion. The differences among the Cover and stego-images suggested potential discriminating features. However, test results showed very poor performance even after an exhaustive grid search for optimisation.

Further investigation revealed that despite the poor results, the SG lacunarity dataset is more suitable compared to the RS lacunarity dataset. This however does not necessarily provide enough evidence to answer the initial question of whether lacunarity is suitable for blind steganalysis. To answer this, the following are some alternative directions that can be taken to further the research.

1. Further training need to be conducted with more samples for SG lacunarity dataset to see if it can actually classify unknown images.
2. The dataset need to be reconstructed based on Cover images with a similar range of file size and embedding capacity to serve as a control.
3. Some of the published literature (Lyu & Farid, 2004) has shown better classification performance for blind steganalysis by using two-class and one-class SVM instead of multi-class SVM. Thus, this is a potential alternative to investigate, even for RS lacunarity.

In conclusion, the suitability of lacunarity measure for blind steganalysis is yet to be discovered as current results still pose more questions. The presence of discriminating features among Cover and stego-images in the SG and RS lacunarity datasets do however pose encouraging avenues to further investigation.

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