Blind Image Steganalysis Based on Contourlet Transform

Natarajan V[1] and R Anitha

Department of Applied Mathematics and Computational Sciences,
PSG College of Technology, Coimbatore, India.
[1]kvn.psg@gmail.com
[2]anitha_nadarajan@mail.psgtech.ac.in

ABSTRACT

This paper presents a new blind approach of image Steganalysis based on contourlet transform and non linear support vector machine. Properties of Contourlet transform are used to extract features of images, and non linear support vector machine is used to classify the stego and cover images. The important aspect of this paper is that, it uses the minimum number of features in the transform domain and gives a better accuracy than many of the existing steganalysis methods. The efficiency of the proposed method is demonstrated through experimental results. Also its performance is compared with the state of the art wavelet based steganalyzer (WBS), Feature based steganalyzer (FBS) and Contourlet based steganalyzer (WBS). Finally, the results show that the proposed method is very efficient in terms of its detection accuracy and computational cost.

KEYWORDS

Steganalysis, Contourlet transform, Structural similarity measure, Non linear support vector machine

1. INTRODUCTION

Steganography is the art and science of hiding secret messages by embedding them into digital media while steganalysis is the art and science of detecting the hidden messages. The goal of a high quality steganography is hiding information imperceptibly not only to human eyes but also to computer analysis. The obvious purpose of steganalysis is to collect sufficient evidence about the presence of embedded message and to break the security of the carrier. Steganalysis can be seen as a pattern recognition problem also since based on whether an image contains hidden data or not, images can be classified into Stego or Cover image classes.

Steganalysis is broadly classified into two categories. One is meant for breaking a specific steganography. The other one is universal steganalysis, which can detect the existence of hidden message without knowing the details of steganography algorithms used. Universal steganalysis is also known as blind steganalysis and it is more applicable and practicable [1,2] than the specific steganalysis. Based on the methods used, steganalysis techniques are broadly classified into two classes; signature based steganalysis and statistical based steganalysis. Specific signature based steganalysis are simple, give promising results when message is embedded sequentially, but hard to automatize and their reliability is highly questionable [3,4].

The first blind steganalysis algorithm to detect embedded messages in images through a proper selection of image quality metrics and multivariate regression analysis was proposed by Avcibas

et al.[5,6]. In universal steganalysis, using statistical methods and identifying the difference of some statistical characteristic between the cover and stego image becomes a challenge. Due to the tremendous increase in steganography, there is a need for powerful blind steganalyzers which are capable of identifying stego images.

This paper proposes a new approach to blind steganalysis does not need any knowledge of the embedding mechanism. This approach utilizes contourlet transform to represent the images .A Gaussian distribution is used to model the contourlet subband coefficients and since skewness and kurtosis of a distribution could be analyzed using the first four moments, the first four normalized statistical moments are considered as the features along with the similarity measure among the medium frequency bands. The experimental results show the efficiency of our approach when analyzed with various steganography methods.

The rest of the paper is organized as below. Section 2 gives a brief description of related work and section 3 discusses the proposed method. Experimental evaluation of the proposed steganalyzer is given in section 4 and section 5 concludes this paper.

2. RELATED WORK

With the inception of data hiding techniques, the research on steganalysis started in the late 90's.Detailed survey of steganalysis is reported by Arooj Nissar et al.[7]. The first universal steganalyzer was proposed by Avcibas et al.[5]. The same authors improved their previous method in [6]. Jiang N et al. proposed a blind steganalyzer using support vector machine to classify the stego image and cover image. For the first time, Farid et al [8,9] modelled a blind steganalyzer using supervised learning and indicated that the supervised learning is effective for detecting stego images without knowing the statistical property of images and steganography methods.

Xuan et al. presented a blind steganalysis method, which was based on statistical moments of wavelet histogram characteristic functions and Bayes classifier [10]. Experimental results indicated that this method worked better for LSB, spread spectrum like steganography, F5 and Outguss steganography methods. Lie et al.[11] indicated that in general no single feature is capable of differentiating stego and plain images effectively and a combination of features extracted in different domain will be generally more promising. By means of extracting features from spatial and DCT domain, this technique had a good effect for BMP images, including spatial domain and DCT domain hiding techniques.

Another blind steganalysis method with high detection ratio was proposed by Luo Xiang Yang et al based on best wavelet packet decomposition[15]. However, the methods based on wavelet high order statistics cannot perform very well on spatial domain steganography such as LSB steganography.

Hedieh Sajedi et al. [12] presented an universal approach to steganalysis called Contourlet Based Steganalysis(CBS), which used statistical moments as well as the log errors between the actual coefficients and predicted coefficients of the contourlet transform as features for analysis. After feature extraction, a non linear SVM classifier was applied to classify cover and stego images. This method converts the image into grayscale and then processes it. CBS detection rate is very low when message is embedded in medium frequency subbands and this idea is used in [13] to develop a new contourlet based steganography algorithm. So if the algorithm in [13] is used to embed the message, then CBS [12] cannot detect successfully.

The modern steganography techniques [14], [15], [16] places embedding changes in those regions of images that are hard to model and hence increasingly more complex statistical descriptors of covers are required to capture a large number of dependencies among cover elements that might be disturbed by embedding. This historical overview clearly underlies a pressing need for efficient features to facilitate further development of Steganalysis.

To address the complexity issues arising in Steganalysis today, in the next section we propose contourlet based Steganalysis using enhanced multiclass support vector machine. By exploring several different possible features for the contourlet transform, we arrive at a rather simple, yet powerful design that appears to improve detection accuracy for all steganographic systems we analyzed so far.

This paper is a journal version of our recent conference contribution which uses neural network for classification [17]. The main difference is change of classifiers, in order to increase the detection accuracy of the proposed method and a comparison of detection accuracy between the different classifiers.

3. PROPOSED SCHEME

The objective of the proposed scheme is to select the most relevant features using statistical characteristics of the subband coefficients, thus reduce the dimensionality of feature set and increase the accuracy of detection. In this paper, the first four normalized moments of high frequency, low frequency subband coefficients and structural similarity measure of medium frequency sub band coefficients are taken as the feature set. With these five features, a non linear support vector machine is trained for further classification. The block diagram of the proposed model is given in figure.1. The following sub sections briefly explain contourlet transformation and how the feature set is extracted from images.

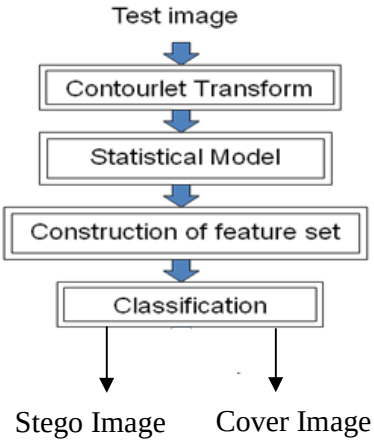

Figure 1. Block diagram for proposed scheme

3.1. Contourlet Transform

The Contourlet transform is a two-dimensional extension of the wavelet transform proposed by Do and Vetterli [18,19] using multiscale and directional filter banks. The contourlet expansion is composed of basis images oriented at various directions in multiple scales with flexible aspect ratio that could effectively capture smooth contours of all images. The contourlet employs an efficient tree structured implementation, which is an iterated combination of Laplacian Pyramid (LP) [20] for capturing the point discontinuities, and the Directional Filter Bank(DFB) [21] to gather nearby basis functions and link point discontinuities into linear structures. Contourlet transform is more powerful than the wavelet transform in characterizing images rich of directional details and smooth contours [18, 19].

Let the image be a real-valued function I(t) defined on the integer valued Cartesian grid $[2^l, 2^l]$. The Discrete Contourlet Transform with scale j, direction k and level n of I(t) is defined as follows [19,21]:

$$\lambda_{j,k,n}(t) = \sum_{i=0}^{3} \sum_{m \in Z^2} d_k(m) \psi_{j,n}^{(i)}(t)$$

where $d_k(m)$ is the directional coefficient and

$$\psi^{(i)}{}_{j,n}(t) = \sum_{m \in Z^2} f_i(m) \phi_{j,n+m}(t)$$

where $\phi(t)$ is the scaling function and $f_i(t)$ is the spatial domain function.

Furthermore, the current existing steganalysis algorithms are limited to the domain of wavelet and DCT transforms. Therefore, identifying stego (constructed by embedding data into their contourlet coefficients) and cover image from the image data set is not easy by these steganalysis algorithms. This fact motivates us to develop efficient steganalysis algorithm in contourlet domain. In this paper, contourlet subband based features are used for steganalysis.

Subband Coefficient Modelling

The coefficients in the produced sub bands of contourlet transformed image are very appropriate to obtain the texture feature due to coarse to fine directional details of the image in these subbands. Besides, the distribution of the subbands coefficients is symmetric and unimodal with mean skewness approximately near to zero, though they have not exactly Gaussian distribution [22]. These special characteristics of subband coefficients make them suitable for modelling by Gaussian distribution with density function.

$$f(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-1/2\left(\frac{x-\mu}{\sigma}\right)^2} \qquad -\infty \prec x \prec \infty$$

where μ and σ are the mean and standard deviation of all the coefficients of subbands.

3.2. Feature Extraction

There are various methods in the literature to extract the relevant features of digital images based on different transforms or filtering techniques. Even though the accuracy of classifiers is based on the number of suitable features, higher the number of features slower will be the classification. So identifying a minimum number of features which can produce efficient classification is a challenge. In this paper, only 5 features have been used which is very less compared to the number of features used in the existing steganalysis.

Contourlet transform is more sparser than wavelet as the majority of the coefficients have amplitudes close to zero. Also the moments of contourlet coefficients are more sensitive to the process of information hiding. The first four normalized moments of the high frequency and low frequency subband coefficients are more sensitive to the process of steganography. Since these moments could be a good measure for skewness and kurtosis due to information hiding, the first four normalized moments are extracted as features. Moments are computed as below:

$$m_k = \frac{E(X-\mu)^k}{\sigma^{2k}} \qquad k=1,2,3 \text{ and } 4.$$

where X represents the coefficients of contourlet sub bands. Since these moments alone are not sufficient to detect the changes in the medium frequency subbands, another feature namely structural similarity measure (SSIM) is also included. For estimating SSIM, medium frequency band is split into two equal number of subband groups X and Y respectively. SSIM includes three parts: Luminance Comparison(LC), Contrast Comparison(CC) and Structural Comparison(SC) and they are defined as below[23,24,25]:

$$CC(x,y) = \frac{2\sigma_x\sigma_y}{\sigma^2{}_x + \sigma^2{}_y}$$

$$LC(x,y) = \frac{2\mu_x\mu_y}{\mu^2{}_x + \mu^2{}_y}$$

$$SC(x,y) = \frac{\sigma_{xy}}{\sigma_x\sigma_y}$$

$$SSIM(X,Y) = [LC(X,Y)][CC(X,Y)][SC(X,Y)]$$

The similarity of the whole image (I) is

$$SSIM(I) = \frac{\sum_{j=1}^{n} SSIM_j}{n}$$

where n is the number of middle frequency sub bands in the image. Feature set consists of the first four normalized moments m_k(k=1,2,3,4) and the similarity measure SSIM(I).

3.3. Classification

A three back propagation Neural Network (NN) is used as a classifier for identifying stego images as well as images[17]. The power of back propagation is that it enables us to compute an effective error for each hidden unit, and thus derive a learning rule for the input to hidden weights. Non linear Support Vector Machine (NSVM) classifier is used for effective classification of stego images and cover images in this work.

4. EXPERIMENTAL RESULTS

The proposed steganalysis is implemented using MATLAB 7.6.0 with Matlab scripts. The experiments are conducted on a personal computer with a 1 GB RAM and P-IV processor. For training we have used 12,200 images from Computer Vision image dataset and INRIA image dataset. It contains 5,500 cover images and 6,700 stego images which are generated by different embedding algorithms like LSB, Jsteg, F5, Contsteg etc.,Washington image dataset [26] is used for testing the proposed steganalytic method. 100 images are used to test the proposed scheme, with 60 cover images and 40 stego images.

In order to analyze the proposed method, ten typical steganography methods are used. Table 1 gives a comparison of the average detection accuracy between NN classification and non linear support vector classification with same feature set. From this table, one can see that non linear support vector machine classifies stego images and cover images more accurately. Figure.2. depicts the performance comparison of NN classifier and NSVM classifier in classifying stego images.

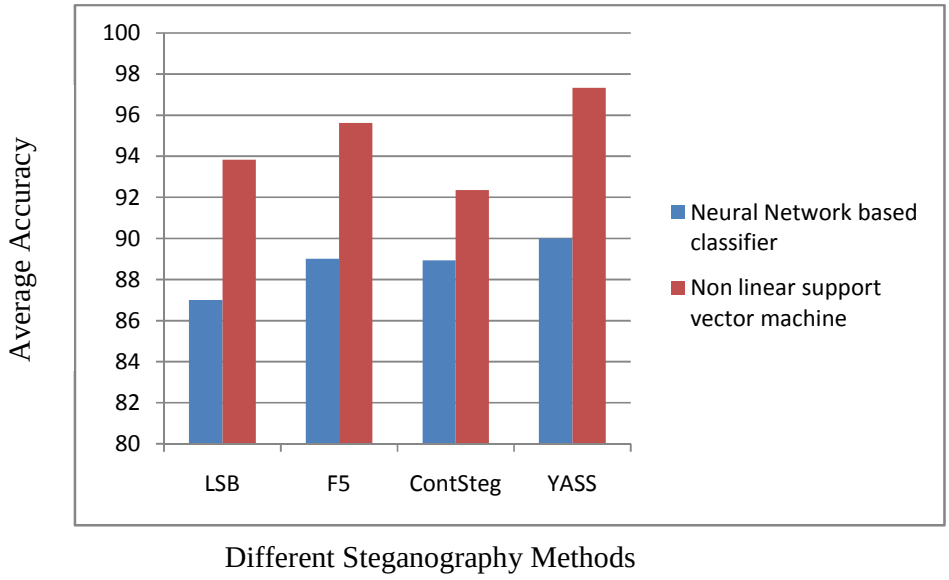

Figure 2. Performance comparison of Neural Network and non linear Support vector machine based classifiers

Table 1. Average correct detection rates for natural images and stego images

Steganography Methods	Classifier	Average correct detection rates						
		Embedding rates			Different image size			
		100%	50%	25%	512X512	256X256	128X128	64X64
LSB	NSVM	0.945	0.922	0.904	0.952	0.976	0.937	0.902
	NN	0.922	0.912	0.894	0.975	0.973	0.895	0.870
PMK	NSVM	0.936	0.911	0.901	0.967	0.942	0.915	0.889
	NN	0.916	0.901	0.886	0.970	0.911	0.876	0.883
LTSB	NSVM	0.941	0.921	0.940	0.921	0.934	0.918	0.904
	NN	0.939	0.901	0.874	0.893	0.913	0.878	0.846
Jsteg	NSVM	0.936	0.977	0.954	0.900	0.929	0.931	0.897
	NN	0.906	0.970	0.854	0.902	0.899	0.873	0.870
F5	NSVM	0.950	0.971	0.977	0.957	0.951	0.931	0.894
	NN	0.910	0.969	0.898	0.985	0.942	0.973	0.763
Jphide	NSVM	0.977	0.919	0.921	0.909	0.948	0.907	0.863
	NN	0.971	0.899	0.828	0.889	0.884	0.801	0.744
Model based	NSVM	0.946	0.915	0.918	0.917	0.915	0.891	0.812
	NN	0.926	0.875	0.781	0.911	0.905	0.813	0.771
Peturb Quantization	NSVM	0.947	0.920	0.925	0.954	0.955	0.898	0.797
	NN	0.940	0.870	0.825	0.865	0.856	0.828	0.701
Congsteg	NSVM	0.928	0.917	0.908	0.905	0.957	0.903	0.823
	NN	0.921	0.897	0.878	0.870	0.856	0.831	0.723
YASS	NSVM	0.966	0.936	0.914	0.941	0.987	0.912	0.853
	NN	0.956	0.906	0.844	0.901	0.892	0.879	0.733

The relevancy of the extracted features used in this steganalysis is evaluated using error estimation. Table 2 and figure 3 display the sample Median Absolute Error (MAE) which exhibits a higher error than bias for all the embedding algorithms. So it is clear that, with this minimum dimensional feature set, proposed method can able to detect the stego image.

Algorithm	MAE	Bias
LSB	$5.91X10^{-3}$	$-1.70X10^{-4}$
PMK	$8.38X10^{-3}$	$-5.29X10^{-4}$
LTSB	$9.07\ X10^{-3}$	$1.51X10^{-4}$
Jsteg	$3.23X10^{-3}$	$-2.89X10^{-4}$
F5	$6.63\ X10^{-3}$	$-3.78X10^{-4}$
JPHide	$7.19X10^{-3}$	$-1.31X10^{-4}$
Model based	$4.82\ X10^{-3}$	$-2.51X10^{-4}$
Perturb Quantization	$2.33\ X10^{-3}$	$1.28X10^{-4}$
YASS	$4.19X10^{-3}$	$1.87X10^{-4}$
ContSteg	$3.25X10^{-3}$	$0.58X10^{-4}$

Table 2. Median absolute error and bias for the proposed method

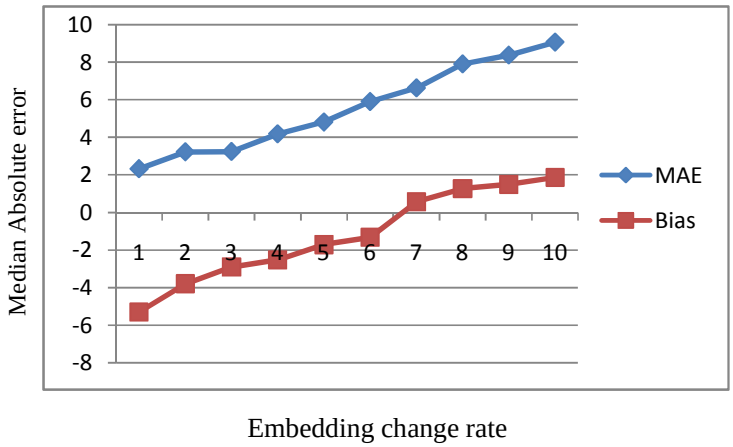

Figure 3. Median Absolute Error(MAE) and Bias of proposed steganalyzer, with respect to embedding rates

4.1 Comparison with prior art

The proposed work is compared with the state of the art Wavelet-based steganalysis (WBS)[9], Feature based Steganalysis(FBS)[27] and Contourlet-Based Steganalysis (CBS) [12] methods and the results show significant improvement and they are tabulated in Table 3. Figure 4 shows the comparison of the performance of the proposed method with other steganalysis methods against some steganography methods. The Data set used in the proposed scheme for comparison is the Washington dataset which is used in ContSteg [13] and CBS[12].

Table 3. Accuracy of WBS,FBS,CBS and proposed steganalysis methods on detection of stego-image produced by ContSteg

Secret Data Size(bits)	Steganalysis Method	Average detection Accuracy (%)
	WBS	51
	FBS	53
5000	CBS	59
	Proposed method	77
	WBS	53
	FBS	54
10,000	CBS	63
	Proposed method	89
	WBS	58
	FBS	61
15000	CBS	68
	Proposed method	93

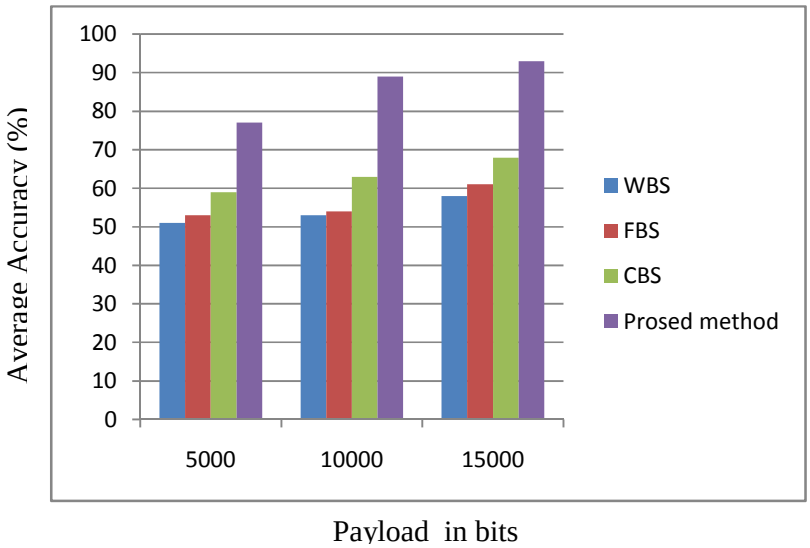

Figure 4. Comparison of Proposed method with WBS,FBS and CBS

The correct detection rate is improved in the proposed method compared to existing steganalysis schemes [12]. Especially proposed scheme is independent of file formats and image types. The new method based on statistical steganalysis utilizes fewer features than rest of the methods. Hence, it is fast and the computational cost of the new method in extracting the features and detecting the stego image are much less than that of the methods based on feature extraction.

5. CONCLUSIONS

In this paper, we propose a steganalysis blind detection method based on contourlet transform and non linear support vector machine. This method extracts the statistical moments and structural similarity of the contourlet coefficients as the feature set. The performance of the proposed scheme is illustrated using various testing metrics. The average correct detection rate is improved, at the same time the dimension of the feature set and the average run time is reduced in this proposed scheme. Furthermore, the method proposed here is an universal blind scheme, which is independent of image type and file format.

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Authors

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Natarajan Venkadahalam received his B.Sc. degree in Mathematics from Bharathiyar University in 2008 and M.Sc. degree in Mathematics from Anna University, Coimbatore in 2010. He is currently working as a Research Associate in Smart and Secure Environment Project sponsored by NTRO, Govt. of India, New Delhi. His research interests include Watermarking, Steganography and Cryptographic protocols, Network security.

Dr.R Anitha received her M.Sc. degree in Mathematics from Madurai Kamaraj Uiversity, M.Phil. and Ph.D. degree from Bharathiar University, Coimbatore. She is presently an Associate Professor in the department of Applied mathematics and computational Sciences at PSG College of Technology, Coimbatore, India. Her current research is in the areas of cryptography, steganography and cyber security. She has served on the committees of several conferences.