Block Dependency Feature Based Classification Scheme for Uncalibrated Image Steganalysis

Deepa D. Shankar, T. Gireeshkumar, K. Praveen, R. Jithin, and Ashji S. Raj

TIFAC CORE in Cyber Security, Amrita Vishwa Vidyapeetham, Coimbatore, India
{sudee99,gireeshkumart,praveen.cys,
jithn_r550,ashjisraj}@gmail.com

Abstract. Steganalysis is a technique of detecting hidden information sent over a communication medium. In this paper, we present a powerful new blind steganalytic scheme that can reliably detect hidden data in JPEG images. This would increase the success rate of steganalysis by detecting data in transform domain. This scheme is feature based in the sense that features that are sensitive to embedding changes and being employed as means of steganalysis. The features are extracted in DCT domain. DCT domain features have extended DCT features and Markovian features merged together to eliminate the drawbacks of both. The blind steganalytic technique has a broad spectrum of analyzing different embedding techniques. The feature based steganalytic technique is used in the DCT domain to extract about 23 functionals and classify the dataset according to these functionals. The feature set can be increased to about 274 features by merging both DCT and Markovian features. The extracted features are being fed to a classifier which helps to distinguish between a cover and stego image. The classification is also done with inter block dependency features and intra block dependency features within the 274 features. Support Vector Machine is used as classifier here.

Keywords: Steganalysis, DCT, Extended DCT, Markov, Support Vector Machine.

1 Introduction

Steganography is a means of communication in a covert manner so that anyone who inspects the message being exchanged cannot collect enough evidence to prove that the message has data hidden in it. Steganography should thus make the communication invisible. In this paper we propose a new steganalytic technique which can be applied to different steganographic schemes and image format. However it can be ideally used in JPEG format.

Steganalysis can be broadly classified as Blind Steganalysis and Targeted Steganalysis. Targeted Steganalysis are designed for a particular steganographic algorithm. This technique is more robust since it has good detection accuracy for that specific technique when they used against the particular steganographic technique. Blind Steganalysis are schemes which are independent of any specific embedding technique are used to alleviate the deficiency of targeted analyzers by removing their dependency on the behavior of individual embedding techniques To achieve this, a set of distinguishing statistics that are sensitive to a wide variety of embedding operations

R. Kannan and F. Andres (Eds.): ICDEM 2010, LNCS 6411, pp. 189–195, 2011.

are determined and collected. These statistics, taken from both cover and stego images are used to train a classifier, which is subsequently used to distinguish between cover and stego images.

Blind steganalysis is composed of two important components. These are feature extraction and feature classification. In feature extraction, a set of distinguishing statistics are obtained from a data set of images. There is no well defined approach to obtaining these statistics, but often they are proposed by observing general image features that exhibit strong variation under embedding. The second component, feature classification, operates in two modes. First, the obtained distinguishing statistics from both stego and cover images are used to train a classifier. Second, the trained classifier is used to classify an input image as either being a clean image or carrying a hidden message. Previous literature [1] state only the application of JPEG images in the either DCT domain or in the spatial domain [3] in terms of embedding and extraction. Feature based steganalysis [1] [4] is a technique wherein certain features that are sensitive to embedding changes but insensitive to image content is extracted. This paper intends to merge both DCT and Markovian features [2] with a possibility of eliminating the drawbacks of both with a feature selection. In order to reduce further computational complexity or costs, and to obtain reasonable success, SVM is used as a classifier for the DCT domain. Fridrich et al [2] used standard 274 features by merging DCT and Markov features for JPEG steganalysis.

In the next section, we will discuss about the general architecture of the system. Section 3 will deal with the implementation issues regarding the architecture. The experimental results are discussed in section 4. Section 5 will have a short note on the future work.

2 Implementation Details

The concept of feature extraction is combined with linear classification to devise an analytic system mainly for JPEG images. It has been understood in literature survey that calculating the features directly in JPEG domain is more sensitive to a wider type of embedding algorithms. The direct calculation also enables a more straight forward interpretation of the influence of individual features on detection as well as easier formulation of design principles leading to more secure steganography.

2.1 Feature Extraction

The goal of the paper is to merge new feature set which gives a better detection rate than any other steganalytic technique. The proposed feature set is used to construct a general linear classifier. The first step is to extract the features, and then Principal Component Analysis is used to find the optimal feature subset to improve the algorithm efficiency. Then the Support Vector Machine is designed with respect to accuracy, reliability and cost to give best results. The classification is then done on the same set of features, but differentiated as interblock dependency features and intra block dependency features [1, 2]. The SVM is trained by the obtained features and then it is subjected to testing on images which were used during training and also on images which are not trained. Fig. 1 shows the overall representation of the system.

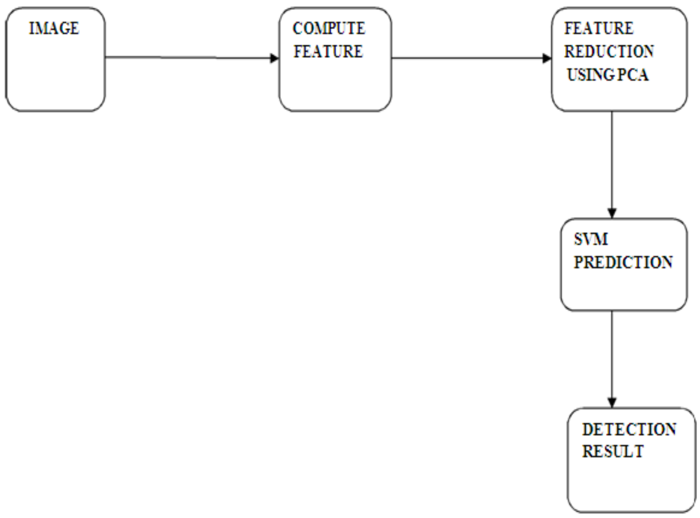

Fig. 1. System Architecture

Three types of features are extracted in DCT domain. They are First Order features, Extended DCT features and Markov features. The original DCT features [1] have 23 functional in them. The original DCT features can be extended to extended DCT features [2] which can extract about 193 functionals. The features of extended DCT are extracted within a range of -5 to +5 since DCT follows a Gaussian function and most of the important information is concentrated in values around zero. Another set of features is the Markov features [2] whose dimensionality can be reduced to 81.While the extended DCT features model inter-block dependencies between DCT coefficients, the Markov features capture intra-block dependency among DCT coefficients of similar spatial frequencies within the same 8X8 block. Hence they have been merged to eliminate the drawbacks of both. Markov features are also normalized to central values from -4 to +4. Another reason for merging the set is that the classifiers employing each feature set individually have complementary performance. Markov features are unable to detect short message lengths..All features in the merged feature set are uncalibrated. The same set of Extended DCT features are again distinguished as inter block dependency features and intra block dependency feature for low embedding rate. Here, the embedding is done by using two steganographic algorithms, F5 and PVD [9,10].

The Markov feature set as proposed in [2] models the difference between absolute values of neighboring DCT coefficients as a Markov process. The Markovian functionals taken together will comprise of 324 features. This has increased dimensionality, which can be reduced by taking the average of the four 81 dimensionality features. Thus we get a combined set of Extended DCT and Markov features as 274.

2.2 Feature Reduction

PCA or Principal Component Analysis is used to analyze the effective dimensionality of DCT and spatial based feature space. This is used to reduce the dimensionality of features and hence to retrieve optimal dataset. The extracted dataset is fed into a PCA. Relevant features were extracted from a total set of data. These data have the maximum amount of information which helps to classify the cover images and stego image from a dataset that is inputted [7].

2.3 Support Vector Machine Based Classification

Support Vector Machine is a supervised learning technique for classification. There are many techniques for classification like Neural Network, perceptron, Fisher Linear Discriminant and SVM. Out of this, SVM is widely popular in Machine Learning since it maps the data from the original space into a high dimensional feature space.

When the kernel function is linear, the resulting SVM is a maximum margin hyperplane.Given a training sample, the hyper plane splits a given training sample in such a way that the distance from the closest cases to the hyper plane is maximized. The complexity of SVM depends on the training samples. Hence we can conclude that SVM guarantees generalization to a great extend [8].

3 Result and Discussion

3.1 Database of Images

One of the important aspects of any performance evaluation work is the dataset employed in the experiments. The dataset needs to include a variety of textures, qualities and image formats. A set of 420 images were taken both from JPEG format and compressed to a size of 256 X 256. We choose a large amount of JPEG format due to its wide popularity in transmission through the internet. A practical evaluation of project is presented by testing unconditional steganalysis for two different algorithms with diverse embedding mechanism: F5 and PVD. Unless stated otherwise, all results were derived on samples from the testing set that were not used in any form during training. 420 datasets of cover image and stego image is taken for analysis. Out of this, the images are used to extract different features like first order features, Extended features etc.Many features of these datasets maybe irrelevant. Hence these features maybe removed for better performance. This dimensionality reduction may be achieved by using Principal Component Analysis. The output of Principal Component Analysis is given to a linear SVM. Out of the 420 datasets used, 340 are used to train the SVM.80 datasets are used for testing.

3.2 Principal Component Analysis

A set of feature that have different statistics are extracted. The features are again reduced to obtain another set with lower feature dimensionality. This is only in terms of statistical outlook. The features can be further reduced by means of Principal Component Analysis. The first value found is called the Principal Component. The lower values are ignored after finding the Eigen values and Eigen vectors thus reducing the dimensionality. The Principal Component Analysis will reduce the dimensionality but may have a probability of eliminating the best features [7].

3.3 Linear SVM

The dimensionality reduction needs to be done because the classifier used here is linear SVM. There are many classifiers like Neural Network, perceptron, Fisher Linear Discriminant, SVM etc. Out of these, SVM is considered to be more powerful in terms of classification. The feature reduction is mainly due to the use of linear SVM to reduce the cost and computational complexity. Since the steganalysis system used was Blind, the SVM has to be trained before any testing occurs. Out of the 420 images, 340 images were used to train the data and the rest 80 were used to test the data [8].

A random set of 50 features were first extracted from an image. The extracted features were checked without inputting in the PCA. The classification results were only 50%. The feature set dimensionality was later reduced using PCA to a set of 20 features. The result was 90%.Thus the features have been reduced to give a more accurate classification. The reduced features are also proved to be a set of better features than before reduction. Two random steganographic algorithms, PVD and F5 are used for embedding into the images. The images are taken with various percentage embedding using F5 and PVD. All 274 features are taken into consideration here. The results are tabulated in Table 2.

Table 1. Classification using SVM

Data set	Percentage classification
Feature set without using PCA	50
Feature set using PCA	90

Table 2. Classification of uncalibrated images using SVM

Embedding Percentage	10	25	50	10-25-50-75
F5	59.5	46.6	60	50
PVD	52.7	54.5	83	50

When taken as a whole feature set of 274, the results shows results ranging from 50 to 60 %.Hence features are divided as interblock dependency features and intrablock dependency features [1,2]. Moment and Global Histogram is termed as intrablock dependency features since it depends only on values within a block. Variation, Blockiness, Co-occurance and Markovian features are termed as intra block features since it pertains to the values between two consecutive blocks. Global Histogram,Variation, Blockiness,Co-occurance are also said as Extended DCT Features. The separate feature gave a good classification rate than all features taken together. Moreover, the intra block dependency features gave a better classification result than inter block dependency features.

Table 3. Uncalibrated Image Classification with Separate Features

% Embedding	Moment	Global Histogram	Variation	Blockiness	Co-occurance	Markovian
10	66	60	80	100	83.4	80
25	75	40	75	83.33	66	71.4
50	50	57.14	80	60	69.23	85
75	57	57	75	100	83	88.7
10-25-50-75	55.2	50	80	69.2	71.42	75

4 Conclusion and Future Work

A set of features for steganalysis of JPEG images with a range of quality factors was developed. We considered features that take into account the numerical changes in DCT coefficient introduced by embedding. The feature set was obtained by merging and modifying two previously proposed feature sets with complementary performance (the DCT features that capture the inter-block dependencies among DCT coefficients and Markov features which capture intra-block dependencies). According to the experiments, the new merged feature set provides better results than previous results.

The present feature based system has PCA incorporated for reduced dimensionality thereby obtaining a better feature set. This feature set is being input into the linear SVM for classification between cover and stego image. Apart from the features mentioned, it has been decided to find a set of calibrated set of 274 features and uncalibrated set of 274 features [5]. Feature selection can be done using independent component analysis. These features can be later fed to a classifier, probably a soft margin classifier with Gaussian kernel [5]. The classification accuracy of the calibrated features as compared to uncalibrated features can be estimated.

Calibration can also used as a technique to analyze separate features with various steganographic algorithms. Separate feature extraction using inters block dependency features and intra block dependency features. Another enhancement of the paper can be an introduction to estimation of payload. This is called quantification, which can be achieved by means of Support Vector Regression [6]. The next enhancement is on the detection of message length. The method consists of a sequence of estimation procedures that use spatial domain representation of the cover and stego images to estimate the length of a message embedded.

References

1. Fridrich, J.: Feature-Based Steganalysis for JPEG Images and Its Implications for Future Design of Steganographic Schemes. In: Fridrich, J. (ed.) IH 2004. LNCS, vol. 3200, pp. 67–81. Springer, Heidelberg (2004)
2. Pevn'y, T., Fridrich, J.: Merging Markov and DCT Features for Multiclass JPEG Steganalysis. In: Proceedings SPIE, Electronic Imaging, Security, Steganography and Watermarking of Multimedia Contents IX, San Jose, CA, vol. 6505, pp. 301–314 (2007)

3. Yadollapour, A., Niami, H.M.: Attack on LSB Steganography in Color and Grayscale Images using Autocorrelation Coefficients. European Journal of Scientific Research 31(2), 172–183 (2009)
4. Kharrazi, M., Sencar, H.T., Memon, N.: Performance study of common image steganography and steganalysis techniques. Journal of Electronic Imaging 15(4), 041104 (2006)
5. Kodosky, J., Fridrich, J.: Calibration Revisited. In: ACM Multimedia and Security Workshop, Princeton, NJ, vol. 8, pp. 63–74 (September 2009)
6. Pevny, T., Fridrich, J., Ker, A.D.: From Blind to Quantitative Steganalysis. In: SPIE, Electronic Imaging, Media Forensics and Security XI, San Jose, CA, January 18-22, vol. 14, pp. 0C1– 0C14 (2009)
7. Miranda, A.A., Le Borgne, Y.A., Bontempi: New Routes from Minimal Approximation Error to Principal Components. Neural Processing Letters 27(3) (June 2008)
8. Cristianini, N., Shawe-Taylor, J.: An Introduction to Support Vector Machines and other kernel-based learning methods. Cambridge University Press (2000)
9. Wu, D.-C., Tsai, W.-H.: A steganographic method for images by pixel-value differencing. Pattern Recognition Letters 24, 1613–1624 (2003)
10. Fridrich, J., Goljan, M., Hogea, D.: Steganalysis of JPEG Images: Breaking the F5 Algorithm. In: Petitcolas, F.A.P. (ed.) IH 2002. LNCS, vol. 2578, pp. 310–323. Springer, Heidelberg (2003)