Universal Steganalysis to Images with WBMC model

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Abstract—We propose a Wavelet based Markov Chain (WBMC) model for nature images, which can present statistic divergence between cover image and steg image prominently. Based on Markov chain empirical matrix, we discussed the difference between low frequency domain and high frequency domain generalized by step process, and then defined two models: WBMC_L model and WBMC_H model respective to construct our WBMC model. This model relied most on the statistic relativity of coefficients. At last, many experiment results are given to support our theory.

Keywords—steganalysis; Markov Chain; wavelet coefficients

I. INTRODUCTION

Over the past few years increasingly sophisticated techniques for information hiding have been developing rapidly. Research in steganalysis with images has advanced considerably over the past decade. Also, techniques for universal steganalysis have begun emerge. The goal universal steganalysis attempts to detect the presence of an embedded message independent of the embedding algorithm and, ideally, the image format, embedding specific approaches to steganalysis take advantage of particular algorithmic details of the embedding algorithm. With the growing number of steganography tools, universal approaches are clearly necessary in order to perform any type of generic, large-scale steganalysis.

This paper focuses on universal image steganalysis. There have various techniques been developed to detect steganography, Farid [1], [2] constructed the features from higher order moments of distribution of wavelet coefficients from several high-frequency subbands and their local linear prediction errors. Also Sullivan et al. [3] have argued that investigate detection-theoretic performance benchmarks for steganalysis when the cover data are modeled as a Markov chain. There analysis using an MC model provides meaningful results under the condition of a steganalyst incorporating one level of dependency for detection.

In this paper, we first discussed the properties of wavelet coefficient and Markov chain; then proposed a WBMC model; at last have shown the experimentation.

II. WAVELET BASED MARKOV CHAIN

The universal steganalysis problem is inherently difficult as there are various embedding methods to chose. The general way is to find useful statistic divergence. In this section, we will introduce our WBMC model, which depend on the dependence of adjacent pixel presented in wavelet coefficients. It is the most important section in this paper.

A. The property of wavelet coefficients

Wavelets have emerged as an interesting tool for signal processing in the last two decades. There we will only give the simple theory of wavelet. Now, we will introduce three important properties of the wavelet coefficients that much referenced to the relativity.

First, Locality and Compression: A wavelet atom is localized both in time and frequency. It states that many signals can be well approximated by a small number of their wavelet coefficients. This parsimonious property can be statistically modeled by centered, heavy tailed distributions [4]. Second, Clustering: The wavelet coefficients are locally correlated. If a wavelet coefficient is large/small, then its adjacent coefficients are likely to be large/small [5]. Third, Zero-mean: The wavelet high frequency coefficient approximate to the Gaussian white noise distribution [6].

B. WBMC model

Markov chain is a timely separated sequence whose probability of one element only depends on the one before it. With various hiding methods, we investigate a new MC model with wavelet coefficient. For the three previous property of wavelet transform we discussed in the prior section, the WBMC model can present excellence in universal detection. No mater the embedding is occurred in special domain or frequency domain, this impress can be likely apperceived by WBMC model.

(i) MC model. It is defined that if a sequence is finitely in both state and time, and its conditional probability contents,

\[ P(X_{m+n} = a_j | X_{m} = a_i, X_{m+1} = a_{i_2}, \ldots, X_{m+n-1} = a_{i_{m+n-1}}) \]

this sequence is called a Markov chain [7]. Probability \( P_y(m,m+n) \Delta P(x_m = a_j | X_m = a_i) \) is the conditional probability referenced the MC transitional probability which denote the probability of MC transformed from the state \( a_i \) at the time \( m \) to the state \( a_j \) at the time \( m+n \).

For our condition in this paper, we only discuss when \( P_y(m,m+n) \Delta P_y(n) \) (that means \( m \) is useless in this
expressions) and $n=1$. Then the empirical matrix (sometimes called one step transitional probability matrix) is defined as:

$$X_{new} = \begin{bmatrix} a_1 & a_2 & \ldots & a_m \\ p_{i1} & p_{i2} & \ldots & p_{in} \\ p_{21} & p_{22} & \ldots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ a_n & p_{n1} & \ldots & p_{nm} \end{bmatrix} = \hat{P}(1)\Delta\hat{P}$$

The WBMC model is divided into two models: WBMC_L model and WBMC_H model. First, we need to declare something. All wavelet coefficients get from first order two-dimension wavelet transform. The WBMC_L model is get from vector approximation and WBMC_H model is get from vectors horizontal, vertical and diagonal detail coefficients. For the Markov chain is a discrete finite sequence, but the wavelet coefficient is infinite and no longer be integers, so we should have those coefficient been quantized.

(ii) WBMC_L model. The low frequency of the wavelet coefficient can present most of the relativity of an image. So we can see that, as Fig.1, in the one step transitional matrix, most of the point is centralized in the diagonal. After quantization, the real number sequence became an integer one. And the one step transitional matrix also has also been quantized at the same time, (to present the quantization we only show a part of the matrix, and the same to Fig.2). Let $\{W_n, n=1,2,\ldots,L\}$ be an MC on finite set $\omega$ which is got from the quantized wavelet coefficient of low part see Fig.1. And $\omega$ must be the rounding value set of wavelet coefficient, for $\omega = \{0.5,1,0.1,5,0\}$ (50 is not the max value of those rounding values, but for our model, that is enough). For a realization $\tilde{w} = (w_1,w_2,\ldots,w_L)^T$, the empirical matrix is $\hat{P}(\tilde{w}) = (n_*/(L-1))$, where $n_*$ is the number of transitions from $w_i$ to $w_j$ in $\tilde{w}$.

(iii) WBMC_H model. The high frequency of the wavelet coefficient is a kind of Gaussian white noise which is zero-mean distribution [6] in the one step transitional matrix of Markov chain model. This is shown in the Fig.2. It is because of that without of the low part, the high frequency part can detail the independent and identically distribution (i.i.d.) of an image.

The same as WBMC_L model, we also quantized the transitional matrix, which is shown in Fig.2.

Let $\{W_n, n=1,2,\ldots,L\}$ be an MC on finite set $\omega$ which is got from the quantized wavelet coefficient of high part. And $\omega$ must be the rounding value set of wavelet coefficient, for $\omega = \{0.5,1,0.1,5,0\}$ (50 is not the max value of those rounding values, but for our model, that is enough). For a realization $\tilde{w} = (w_1,w_2,\ldots,w_L)^T$, the empirical matrix is $\hat{P}(\tilde{w}) = (n_*/(L-1))$.

C. The Effect of Hiding Process to Our Model

Now we discuss a reality that adds an i.i.d. message signal to a non-i.i.d. cover. It is not surprising then that the statistical effect is decreasing the dependence of the cover [8]. But there are some differences for different hide methods. To a spread spectrum hidden method, it mostly weak the low frequency dependence. Reflect in our WBMC_L model, it is very clearly seen in a shift of probability away from the main diagonal. Fig.3. But for the perturbation quantization hidden method, the WBMC_L model will be low efficient. So we designed the WBMC_H model that can find the spread of the centralization in evidence. It’s shown in Fig.4.
III. EXPERIMENTATIONS

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In this section, we will do some experiment to support our theory. To achieve optimal detection, we employed the framework of intelligence detection. So, we need an image database, a vector of features and a classifier. First, let’s talk about the image database.

A. Image Database

We got all 6000 experiment images from the web site ‘http://www.freefoto.com’ to construct our entire database. Then we confuse them together. Now we use half of the 6000 images for training and half for testing. Before any experiment, we embed the stego images to fit it. Used stego programs are: F5r11, H4PGP and OutGuess, and each one can set the embed rates freely.

B. Our Features

For each of RGB level, we chose the following features. From the theory we introduced in section II. part B., we designed the feature vector of 20-dimension $M(1,2,...,20)$. For the first 10-dimension $M(1,2,...,10)$ is got for WBMC_L and the other 10-dimension $M(11,12,...,20)$ is got for WBMC_H.

The first 10-dimension is get from the empirical matrix of WBMC_L model. It’s the sum of ten diagonals near the main diagonal, and they are parallel lines. With the empirical matrix $P(w) = (n_j/(L-1))$, we define the feature values: $M(i) = \sum_{j=1}^{10} P(j, j+i)$ (Fig.5). The second 10-dimension got from the empirical matrix of WBMC_H model. It’s only ten quantized probability from zero to ten in the level direction. We define those feature values as: $M(i) = P(i-11,0), (i = 11,12,...,20)$ (Fig.5).

![Fig.4.Effect of PQ hiding process to WBMC_H model, we can see the spread from the point (0,0).](image)

![Fig.5.The feature values of WBMC_L (left), and the feature values of WBMC_H (right).](image)

There, we formulate steganalysis problem as an image classification problem where trained classifiers are employed to differentiate stego images from cover images of interest automatically. We chose the One Class SVM classifier [9] for our detection. In the binary classification, a linear SVM classifier seeks a hyperplane that separates training data of two classes with the largest classification margin, which probably has the best generalization ability among all possible separating hyperplanes. Using SVM for classification can reduce the risk of overfitting the training data, the classifier merely memorizing correspondence of training data and class labels, thus will not work on data outside of the training set.

C. Results

There are some experiments, and the results are shown in Fig.6, Fig.7 and Fig.8. Those figures are all made by the probability of false alarm and miss detection. Their definitions are:

\[
\Pr(\text{false alarm}) = \frac{\text{number of normal images identified as steg}}{\text{total number of normal images}}
\]

\[
\Pr(\text{miss detect}) = \frac{\text{number of steg images identified as normal}}{\text{total number of steg images}}
\]

In Fig.6, we embed the stego database with three embedding method respectively, which embedding in three domains: spatial domain, DCT domain and DWT domain at the embed rate 0.01. From the fig we can see, with a single embed method, error rates are better enough. But when we confuse those three embedded images together to be our stego image database, the error rate does rise obviously. In Fig.7, to show the multfeature detect capability, we only use the two feature $M(1,2,...,10)$ and $M(11,12,...,20)$ as the feature vector respectively, and also have contrasted with the WBMC model vector. It’s easy to find the higher detection capability of WBMC model. In Fig.8, we have contrasted WBMC model to other models such as MC model detection and Histogram based detection, with the database of multstego images.
IV. CONCLUSION

In this paper, we introduced a WBMC model of image for steganalysis. We analyzed the property of wavelet coefficients at high and low frequency respectively, and then find the different statistic relativity of coefficients in different frequency. That statistic relativity can all be presented in an empirical matrix of Markov chain model in different way, that can previously present the divergence between stego and cover images. However, further work is needed such as prove the model under an information theory framework, find a better vector and classifier and find other model more than MC to present the statistic relativity.

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