Audio Steganalysis Based on Independent Component Analysis

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Abstract

Steganalysis is the art and science of detecting messages hidden using steganography. This paper proposes steganalysis of audio signal using Independent Component Analysis. A detection method is used for detecting hidden message in compressed audio files produced by MP3Stego. Steganography can be successfully detected during the Principle Component Analysis (PCA) whitening stage. A nonlinear robust batch ICA algorithm, which is able to efficiently extract various temporally correlated sources from their observed linear mixture are used for blind steganography extraction.

***Keywords**: MP3Stego, Principle Component Analysis (PCA), Independent Component Analysis (ICA)*

1. Introduction

The objective of steganography is to enable convert communication by hiding data in digital covers such as images, audios and videos, etc. Various steganography methods and software have been widely applied. Correspondingly, steganalysis techniques are developed to detect the existence of hidden information. Steganalysis is the opposite of steganography, and aims at detecting and analyzing the hidden information in digital media. Steganalysis is the scientific technology to decide if a medium carriers some hidden messages or not and if possible, to determine the hidden messages in cover objects.

There have been two main research approaches to the problem of steganalysis, namely, technique-specific steganalysis and universal steganalysis. The former group of techniques performs very accurately when used against the steganographic technique it is targeted for. The latter group of technique, on the other hand, are effective over a wide range of techniques, while performing less accurately overall. However, since universal steganalysis is better suited to the practical setting, it attracted more interest and many effective steganalyzers are proposed.

Audio is an important communication way for people, and therefore is a convenient medium secure communications. Audio steganography is a useful means for transmitting convert battlefield information via and innocuous cover audio signal. This paper focuses on MP3 files. In order to discriminate stego audios from clear normal ones, that embed random data into a (possibly) stego file by using a certain steganographic tool. It was found that the variation in some statistical features of WAV file is significantly different between clear WAV files and stego ones which already contain hidden messages embedded by the same tool. In this paper, that can detect the existence of hidden messages, and separate signal from mixture source. Although multiple steganalysis methods were designed for detecting information hiding in uncompressed audios in the past years, the information hiding behavior in compressed audios, such as MP3 audios, has been barely explored due to the complication and the variety of the compression methods.

To present the basic principle of this new steganalysis technique based on ICA, this paper is restricted to steganalysis with the simplest ICA model. The objective of this paper is to introduce an efficient ICA based steganography detection and extraction scheme for audio steganography. A robust batch ICA algorithm is applied in the steganography detection. The simulation results and performance are shown for various types of signal.

This paper is organized as follow Section 2 presents the related work of propose system and explain the MP3Stego in Section 3. Section 4 describes the steganography detection and separation system, including both PCA whitening for steganography detection and robust batch algorithm ICA for steganography separation. Section 5 shows the testing result of proposed system.

2. Related Work

In audio steganalysis, Qingzhong Liu presented a novel stream data mining for audio steganalysis, based on second order derivative of audio streams. That extracted Mel-cepstrum coefficients and Markov transition features on the second order derivative; a support vector machine was applied to the features for discovery of the existence of covert message in digital audios [2]. M.Qiao [4] proposed feature mining and intelligent computing for MP3 steganalysis. That described a scheme for steganalysis of MP3Stego based on feature mining and pattern recognition techniques. That first extracted the moment statistical features of GGD shape parameters of the MDCT sub-band coefficients, as well as the moment statistical features, neighboring joint densities, and Markov transition features of the second order derivatives of the MDCT coefficients on MPEG-1 Audio Layer 3. Support Vector Machines (SVM) is applied to these features for detection.

Q. LIU and M. QIAO [8] described derivative based audio steganalysis. This article presented a second-order derivative-based audio steganalysis. First, Mel-cepstrum coefficients and Markov transition features from the second-order derivative of the audio signal are extracted; a support vector machine is then applied to the features for discovering the existence of hidden data in digital audio streams. Also, the relation between audio signal complexity and steganography detection accuracy, which is an issue relevant to audio steganalysis performance evaluation but so far has not been explored, is analyzed experimentally.

Christian Kraetzer and Jana Dittmann extended an existing information fusion based audio steganalysis approach by three different kinds of evaluations: The first evaluation addressed so far neglected evaluations on sensor level fusion. The second evaluation enhanced the observations on fusion from considering only segmental features to combinations of segmental and global features. The third evaluation tried to build a basis for estimating the plausibility of the introduced steganalysis approach by measuring the sensibility of the models used in supervised classification of steganographic material against typical signal modification operations like de-noising or 128kBit/s MP3 encoding [3].

Y.Huang analyzed the properties of the audio information hiding tool by MP3Stego and calculated the statistics of part23 length and stuffingBits in mp3 files. That estimated the size of embedded text accurately by calculating the variance sequence of the block length [5]. Q. Ding [6] approached to Steganalysis of Analysis-by-synthesis Compressed Speech. A steganalysis method for analysis-by-synthesis (AbS) compressed speech is proposed. In this steganalysis method, the probability difference of 0 and 1 and five statistics, including sum of histogram local flatness, sum of histogram local extremum difference, sum of histogram local variance, sum of histogram characteristic function, are used as distinguishing features. SVM classifiers are employed to discriminate stego speech from cover speech.

In this article, propose a steganalysis method of audio files. Firstly, steganography detection by Principle Component Analysis and followed by robust batch ICA algorithm for steganography extraction.

3. MP3Stego

MP3 was the research result of the Fraunhofer-IIS Institute. MP3Stego embeds compressed and encrypted data in an MP3 bit stream during the compression process. The MP3 audio encoding process is shown in Figure 1.

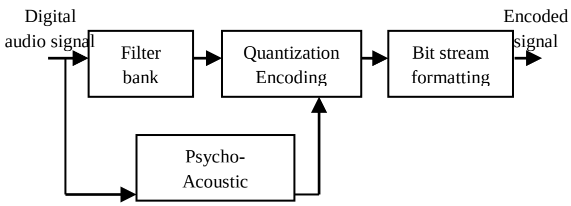

Figure 1. The MP3 Encoder

The important parts that carry out the MP3 encoding are the two loops [5]. The inner loop is a quantization and encoding loop. The outer loop is a noise control loop. It controls the quantization noise according to the threshold value and adjusts the scale factor. MP3Stego was carried out on the base of the 8 Hz-mp3 encoder. The hiding process of MP3Stego could be explained by Figure 2.

```
Static int inner_loop (...)
{    ……
 do {
    quantizerStepSize += 1.0;
    bits=quantize ( );
    switch (hiddenBit) {
          case 2:
          embedRule = 0; break;
          case 0 : case 1:
embedRule = ((bits + part2length)% 2)!=hiddenBit;
    break ;
    default ;
    ERROR (“inner loop: unexpected hidden bit”);}
} while ((bits>max_bits)|embedRule);
Return bits;
}
```

Figure 2. The simplified inner iteration loop of MP3Stego

4. Proposed Steganography Detection and Separation scheme

Independent Component Analysis (ICA) attempts to separate a set of observed signals that are composed of linear mixtures of a number of independent non-Gaussian sources into a set of signal that contain the independent source. This system requires the number of observed linear mixture input is at least equal to or larger than the number of independent sources. Mixture signal are generated by adding observed signal (X_1) and original signal (X_2) of audio file.

$$X = X_1 + X_2 \tag{1}$$

This signal is used for input data requirement of nonlinear blind extraction algorithm, robust batch ICA algorithm which is used for steganalysis process. The proposed steganography detection scheme is shown in Figure 3.

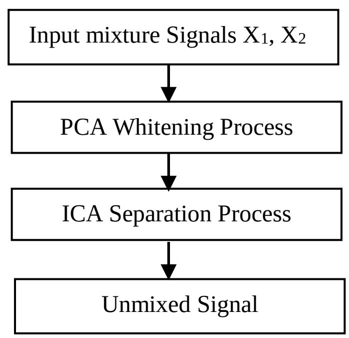

Figure 3. Block diagram of propose system

In the first stage, the two signals are taken as input and mixed them with the equation 1. The mixture signal is entered into the second stage to determine the original signal or stego signal by applying PCA (whitening process). If the input signals contain hidden messages, the third stage use ICA separation method to separate the stego signals from the input signals. The final stage displays the result of detected stego signals.

4.1. Robust Batch Algorithm for Steganography Detection and Separation

ICA is recently developed method in which the goal is to find a linear representation of non-gaussian data so that the components are statistically independent or as independent as possible. ICA is very closely related to the method called blind source separation (BSS) or blind signal separation. A robust batch algorithm which is based on the second-order statistics is used for steganography detection and blind extraction [9]. This method is based on following two stages that is PCA whitening process for steganography detection and ICA algorithm for steganography extraction.

4.2. Steganography Detection – PCA whitening

Standard Principle Component Analysis (PCA) is often useful preprocessing strategy in ICA is to first whiten the observed variables. This transform observed vector x linearly so that obtain a new vector $\tilde{x}$ which is white. Its component are uncorrelated and their variances equal unity.

$$E\{\tilde{x}\tilde{x}^T\} = I \qquad (2)$$

One popular method for whitening is to use the eigen-value decomposition (EVD) of the covariance matrix$E\{\tilde{x}\tilde{x}^T\} = EDE^T$, where E is orthogonal matrix of eigenvectors of $E\{xx^T\}$ and D is the diagonal matrix of its eigen-values$D = diag(d_1 \dots\dots d_n)$. Note that $E\{xx^T\}$ can be estimated in a standard way from the variable sample $x(1)\dots\dots x(T)$ whitening can now be done by

$$\tilde{x} = ED^{1/2}E^T X \qquad (3)$$

For example, rank of D is equal to two for steganography signal, meaning that observed and linear signal are uncorrelated. On the other hand, if the signal is not steganography, this mixtures are actually the combination of one signal only, hence, the rank of D will be reduced to one.

4.3. ICA Algorithm, Steganography Separation

After prewhitening process, ICA attempts to estimate the matrix A, or equivalent to find an unmixing matrix W [10].

$$y = WAs \qquad (4)$$

That give an estimate of the original source signal where $y^T = [y_1 \dots\dots y_N]$and W is of size N x N. It is possible to obtain such as unmixing matrix given two constraints, these being that cannot recover the source signals in the order in which they came in, and that cannot get the original signals in their original amplitude. Mixtures of signals are almost always Gaussian and it is fairly safe to assume that non Gaussian signal must therefore be source signal [1]. The amount of Gaussian-ness of signal can be specified in terms of its histogram, which is an approximation to probability density function (pdf). The degree of mutual independence between signals can be specified in terms of their joint (pdf). The cross-correlation matrix $R_{\varepsilon_i x_i}$computed in

$$R_{\varepsilon_i x_i} = E[\varepsilon_i x_i^T] = w_i^T R_{x_i x_i} - b_i^T R_{\tilde{y}_i x_i} \qquad (5)$$

where

$R_{x_i x_i} = E[x_i x_i]$ and $R_{\tilde{y}_i x_i} = E[\tilde{y}_i x_i^T] = R^T_{x_i \tilde{y}_i}$.

Based on the principle of decorrelation, the optimum $w_{i,opt}$is obtained when the cross-correlation matrix $R_{\varepsilon_i x_i} = 0$,

$$w_{i,opt} = \hat{R}^{-1}_{x_i x_i} \hat{R}_{x_i \tilde{y}_i} b_i \qquad (6)$$

where $\hat{R}$denotes the estimated matrix of R_i.

By applying standard PCA and normalization of singnals to unit variance after each deflation procedure, the autocorrelation matrix $R_{x_i x_i}$will be the identity matrix. Hence, the optimum $w_{i,opt}$can be further simplified as

$$w_{i,opt} = \hat{R}_{x_i \tilde{y}_i} b_i \qquad (7)$$

For updating the vectors b_i, the optimal minimum means squared error $E[\varepsilon_i^2]$can be written as

$$E[\varepsilon_i^2] = E[y_i^2] + b_i^T R_{\hat{y}_i\hat{y}_i} b_i - 2R_{\hat{y}_i y_i} b_i^T \quad (8)$$

The gradient of this function related to $b_i$will be given by

$$\frac{\partial E[\varepsilon_i^2]}{\partial b_i} = 2R_{\hat{y}_i\hat{y}_i} b_i - 2R_{\hat{y}_i y_i} \quad (9)$$

By using the Wiener filtering, that has the optimum vector $b_{i,opt}$

$$b_{i,opt} = \hat{R}^{-1}_{\hat{y}_i\hat{y}_i} \hat{R}_{\hat{y}_i y_i} \quad (10)$$

Thus, in a heuristical algorithm is obtained that the updating vector $b_i$can be further simplified by removing the matrix in verse and obtain

$$b_{i,opt} = \hat{R}_{\hat{y}_i y_i} \quad (11)$$

Hence, the optimum updating vectors for w_i and b_i adopted in this algorithm are (10) and (11).

5. Experimental Result

The propose steganalysis technique is implemented and tested on a set of 400 MP3 audio files. The audio samples include music types (piano,symphony,violin and rock), songs (pop,blue,classical,country and folk) ,speech (males and females) and nature noise etc. Each audio has duration of 20 seconds. This system produced the same amount of stego audio by hiding random messages in these audios. Then these MP3 files are detected and separated by PCA and ICA. Some speech signals cannot detected by PCA because source signal and observed signal has same frequency rates. Figure 4 shows mixture of observed signal and that is input for preprocessing of PCA whitening. This mixture signal is obtained from equation 1.

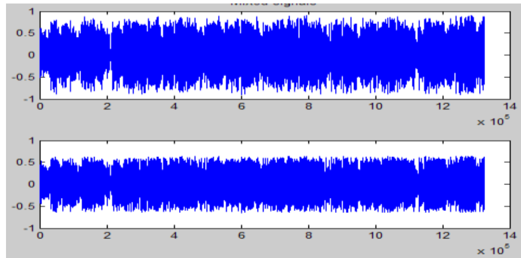

Figure 4. Mixture signal

While the PCA whitening process estimates the uncorrelated components, it is also quite useful to reduce the dimension of the data. In this application, reducing the dimension allows detecting whether the received signal is stego or not. If one of received audio streams is steganography, the PCA whitening automatically reduces the dimension to one. This Figure 5 shows the mixture signals of PCA implementation.

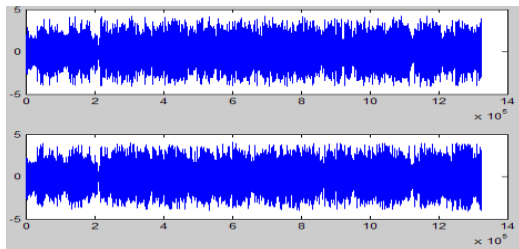

Figure 5. Whitened the observed signal

ICA performs decomposition on the whitened audio resulting that is estimated stego and original signal. ICA is used to separate the hidden message from original audio data by making process on the received observations. Then, calculate the correlation between hidden message with audio signal and pure audio signal. The observed signal of ICA implementation is shown in Figure 6.

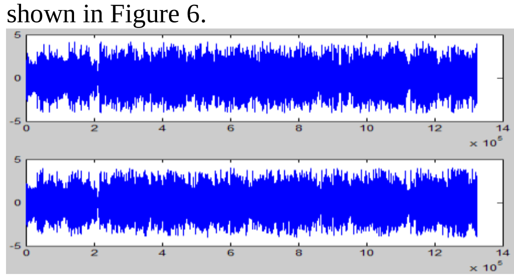

Figure 6. Wave form of ICA implementation

As in robust batch algorithm, the optimum learning rule is derived based on decorrelation principle, where it is assumed that the sources are statistically independent, which implies that the cross-correlation is ideally zero. However, in practice the signals are not perfectly independent; hence it will degrade the separation performance. Table 1 describes the result of detection performance by calculating the correlation coefficient method.

Table 1. Detection performance

	Original	Stego signal
MP3 files	400	400
error	0	25
Correct rate	100%	93.75%

The result demonstrates that the steganography has a high robustness against Gaussian noise, a desirable thing for almost all published algorithms. The steganography detection is still obtained exactly with a signal to Gaussian noise ratio about 32-35dB for this method. Gaussian noise is added, but this fact does not affect the result of steganography estimation.

6. Conclusion

In this paper, Independent Component Analysis (ICA) for audio steganalysis has been proposed. The steganography signal is detected by Principle Component Analysis (PCA) whitening process. Steganography can be separated from the mixture signal using robust batch ICA algorithm. The performance of the proposed method can be evaluated by the correlation coefficient method.

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