A Universal JPEG Image Steganalysis Method Based on Collaborative Representation

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***Abstract*—In recent years, plenty of advanced approaches for universal JPEG image steganalysis have been proposed due to the need of commercial and national security. Recently, a novel sparse-representation-based method was proposed, which applied sparse coding to image steganalysis [4]. Despite satisfying experimental results, the method emphasized too much on the role of l_1-norm sparsity, while the effort of collaborative representation was totally ignored. In this paper, we focus on the least square problem in a binary classification model and present a similar yet much more efficient JPEG image steganalysis method based on collaborative representation. We still represent a testing sample collaboratively over the training samples from both classes (cover and stego), while the regularization term is changed from l_1-norm to l_2-norm and each class-specific representation residual owns an extra divisor. Experimental results show that our proposed steganalysis method performs better than the recently presented sparse-representation-based method as well as the traditional SVM-based method. Extensive experiments clearly show that our method has very competitive steganalysis performance, while it has significantly less complexity.**

Keywords*—Steganalysis; binary classification; least square; collaborative representation.

I. Introduction

Steganography is the art of information hiding, which hides data under a cover medium, such as image, video, and text. It focuses on how to establish covert communications between trusting parties and impose the requirement of concealing the presence of the secret data [1]. Steganalysis, a countermeasure technology to steganography, aims to determine whether there exists embedded secret data in given media objects [2].

Most existing steganalysis approaches utilize feature-based classification and machine learning techniques, among which the universal steganalysis method based on support vector machine (SVM) is the most famous one. With a training set consisting of clean cover and corresponding stego images with hidden data, features can be extracted from both cover and stego images and their statistics are studied to train a binary classifier, which is more likely time-consuming in training and has a certain inevitability of “over-fitting”.

To avoid these often time-consuming and potentially over-fitting problems of traditional pattern classification methods, a novel classification scheme is proposed and achieves a great success in face recognition [3], which boosts the research of sparsity-based pattern classification. A given testing sample is first sparsely coded over all the training samples, and then the classification is performed by checking which class yields the least coding error. Reference [4] applies sparse-representation-based classification (SRC) scheme to JPEG image steganalysis and outperforms the universal SVM-based method. However, this proposed sparse-representation-based steganalysis method emphasizes heavily on the role of l_1-norm sparsity. Reference [5] questions the role of sparsity in pattern classification and analyzes the principle and mechanism of SRC. In addition, it presents a general model, namely collaborative-representation-based classification (CRC), which can be much faster than SRC without sacrificing classification accuracy. CRC can also avoid the inherent problems of classical classification methods, which is of enlightening significance to image steganalysis.

In this paper, we propose a universal image steganalysis method based on collaborative representation. We still utilize all the training samples from both classes (cover and stego) to represent the testing sample, while the regularization term is changed into an l_2-norm and each class-specific representation residual in our method owns an extra divisor. Our steganalysis method not only has better detection accuracy than the traditional SVM-based method as well as the recently presented SRC-based method, but also has a fast speed due to its lower computational complexity.

The rest of this paper is organized as follows. In Section II, we briefly review sparse-representation-based classification (SRC) scheme and its application in JPEG image steganalysis. In Section III, collaborative-representation-based classification (CRC) scheme and our CRC-based JPEG image steganalysis method is presented. Extensive experiments are conducted to verify the effectiveness of the proposed method in Section IV. Finally, we conclude this paper as well as discuss future works in Section V.

II. The SRC Scheme

In many applications, high-dimensional features belonging to the same class exhibit degenerate structure. That is, they often lie on or near low-dimensional subspaces, submanifolds, or stratifications. The sparse-representation-based steganalysis method [4] exploits this underlying structure to solve a binary classification problem. Fig. 1 provides an illustration of this universal SRC-based JPEG image steganalysis method.

This work is partially supported by the National Natural Science Foundation of China (Grant No. 61402079), and China Postdoctoral Science Foundation (Grant No. 20110490343 and 2013T60090), and the Fundamental Research Funds for the Central Universities (Grant No. DUT14RC(3)103).

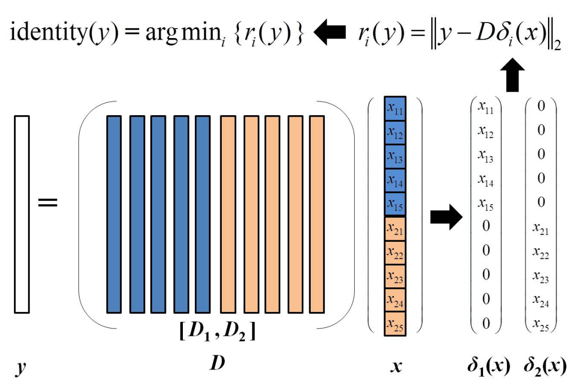

Fig. 1. Illustration of steganalysis based on sparse representation.

The training sample set, namely dictionary D, consists of samples belonging to two classes, which means there is a sub-dictionary for each class of samples. Let $D \triangleq [D_1 , D_2]$, each column of sub-dictionary D_i is a sample of the ith class, where $i = 1$ stands for "cover" and $i = 2$ stands for "stego". Given a testing sample y, we first calculate its sparse representation x over D via

$$x = \arg\min_x \left\{ \|y - Dx\|_2^2 + \lambda \|x\|_1 \right\}, \tag{1}$$

where λ is the regularization parameter to balance the coding error of y and the sparsity of x. After obtaining $x \in \mathrm{R}^n$, we can extract two vectors $\delta_1(x) \in \mathrm{R}^n$, $\delta_2(x) \in \mathrm{R}^n$ from x. For $\delta_1(x)$, we only keep the entries in x associated with class 1 (i.e. D_1) and force other entries to zeros; For $\delta_2(x)$, we only keep the entries in x associated with class 2 (i.e. D_2) and force other entries to zeros. Using only the coefficients associated with the ith class, one can approximate the given testing sample y as $y_i = D\delta_i(x)$. We then calculate the residuals between y and these approximation $D\delta_i(x)$ as

$$r_i(y) = \|y - D\delta_i(x)\|_2 , i = 1,2 . \tag{2}$$

Finally, we classify the sample y by assigning it to the object class that minimizes the residual between y and y_i:

$$\text{identity}(y) = \arg\min_i \{ r_i(y), i = 1,2 \}. \tag{3}$$

It can be seen from the above description, the core procedure of SRC scheme is that it classifies a testing sample as the class whose sub-dictionary has the lower representation error. Algorithm 1 below summarizes the complete procedure of the universal sparse-representation-based steganalysis method.

Algorithm 1: Steganalysis Based on Sparse Representation

Input: A training sample set D for two classes, a testing sample y.

1. Normalize all the columns of the dictionary D to have unit l_2-norm.
2. Code y over D by l_1-minimization as (1).
3. Calculate the residuals as (2).

Output: Identity of the testing sample y as (3).

III. Proposed Steganalysis Method

It can be seen from Section II that the SRC scheme has two key points. The first one is the l_1-norm sparsity constraint on the coding vector of testing sample y, and the second key point is the discriminability of class-specific representation residual.

For the first core, we think it unnecessary to use the strong l_1-norm. A testing sample y is represented by a linear combination of all the training samples from both classes, which is called collaborative representation (CR). It is CR but not the l_1-norm sparsity that can achieve satisfactory performance for JPEG image steganalysis. We will see in the next section, by using the much weaker l_2-norm to regularize the coding vector x, we can have better steganalysis results but with significantly lower complexity due to its analytical solution.

For the second core, (2) is not an exact formula for a binary classification model. We will analyze the detailed mechanism of residuals and provide a new way to calculate class-specific representation residuals. In our proposed steganalysis method, the testing sample y still belongs to the class that produces the lower representation error. The relationship between residuals and representation errors will be discussed in detail, which is scarce in the SRC-based steganalysis method [4]. A novel and standard formula for residuals will be described in our paper.

A. *Collaborative Representation*

A simple yet very important understanding of collaborative representation (CR) is that it uses all the training samples from both classes (cover and stego) to represent the testing sample just to solve a least square problem

$$x = \arg\min_x \|y - Dx\|_2^2 , \tag{4}$$

which means to code the testing sample y collaboratively over the whole dictionary D rather than each sub-dictionary D_i. By differentiating with respect to x, we can obtain

$$\frac{\partial \|y - Dx\|_2^2}{\partial x} = -2D^T(y - Dx), \tag{5}$$

$$\frac{\partial^2 \|y - Dx\|_2^2}{\partial x \partial x^T} = 2D^T D . \tag{6}$$

Supposing (for the moment) that D has full column rank, $D^T D$ would be positive definite and we could set the first derivative (5) to zero

$$D^T(y - Dx) = 0 \tag{7}$$

to obtain the solution

$$x = (D^T D)^{-1} D^T y . \tag{8}$$

If D has too many columns, the solution vector x of least square problem will become non-unique. It may happen when the columns of D are not linearly independent, so that D is not of full rank. This would occur, for example, if two columns in D were perfectly correlated, (e.g. $d_2 = -3d_1$). Then all the elements of x are not uniquely defined and there is more than one way to express y by a linear combination of columns in D.

If the l_1-norm regularization constraint is imposed on x as

$$x = \arg\min_x \left\{ \|y - Dx\|_2^2 + \lambda \|x\|_1 \right\} \tag{9}$$

to make the solution vector x stable, we will get a model called LASSO, which can produce a sparse representation. If the l_2-norm regularization constraint is imposed on x as

$$x = \arg\min_x \{\|y - Dx\|_2^2 + \lambda\|x\|_2^2\} \quad (10)$$

to make the solution vector x stable, we will get a model called Ridge Regression, which can shrink the elements of vector x.

In a unified view, LASSO and Ridge Regression are Bayes estimates with different priors of x. The SRC scheme employs LASSO to obtain a unique solution vector x. However, the l_1-norm is not differentiable, so it is time-consuming for iteration and the solution has an inevitability of "instability". Moreover, it is not necessary to use the strong l_1-norm. It is collaborative representation but not the l_1-norm sparsity constraint that can achieve satisfactory steganalysis performance. Our proposed CRC-based method utilizes the much weaker l_2-norm to regularize the solution vector x of least square problem, which has significantly lower complexity than SRC and SVM.

B. Mechanism of Residual

We still focus on the least square problem arising in image steganalysis, which is a binary classification model. Each column of dictionary D can be denoted by d_i. These vectors $\{d_i\}$, namely atoms, span the column space of D. We solve the least square problem by choosing appropriate x so that the residual vector $y-Dx$ is orthogonal to this space, where (7) can prove that the resulting estimate Dx is the orthogonal projection of y onto this space because $D^T(y-Dx)=0$. Since $D \triangleq [D_1, D_2]$, each column of sub-dictionary D_i is a sample of the ith class, where $i=1$ stands for "cover" and $i=2$ stands for "stego". So we can obtain

$$\hat{y} = Dx = \sum_{i=1}^{2} D_i\delta_i(x) = \sum_{i=1}^{2} y_i\ . \quad (11)$$

For each class i, let δ_i still be the function that selects the coefficients associated with class i. For x, $\delta_i(x)$ is an equilong vector whose only nonzero entries are the entries in x that are associated with the ith class. As is shown in Fig. 2, the reconstruction error by each class $e_i(y)$, which is the square of residual $r_i(y)$ in SRC, is important for binary classification. It can be derived by

$$e_i(y) = \|y - D_i\delta_i(x)\|_2^2 = \|y - y_i\|_2^2 = \|y - \hat{y}\|_2^2 + \|\hat{y} - y_i\|_2^2 . \quad (12)$$

Obviously, when we use $e_i(y)$ to determine the identity of y, it is the amount $e_i^*(y) = \|\hat{y} - y_i\|_2^2$ that works for the binary classification because $\|y - \hat{y}\|_2^2$ is a constant for both classes.

From (11), we can obtain $y_1 = \hat{y} - y_2$. According to the Sine Theorem, we can readily have

$$\frac{\|\hat{y}\|_2}{\sin(y_2, y_1)} = \frac{\|\hat{y} - y_2\|_2}{\sin(y_2, \hat{y})}\ , \quad (13)$$

where (y_2, y_1) is the angle between y_2 and y_1, and $(y_2, \hat{y})$ is the angle between y_2 and $\hat{y}$. Finally, the reconstruction error by the second class can be renewed as

$$e_2^*(y) = \frac{\sin^2(y_2, \hat{y})\|\hat{y}\|_2^2}{\sin^2(y_2, y_1)}\ . \quad (14)$$

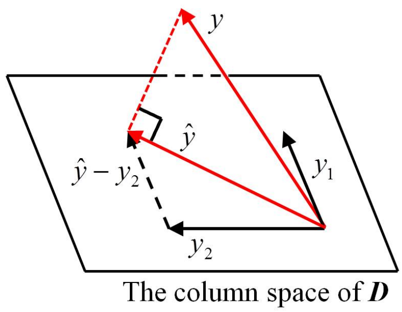

Fig. 2. Simple geometrical illustration of residuals.

We can obtain (15) in a similar way.

$$e_1^*(y) = \frac{\sin^2(y_1, \hat{y})\|\hat{y}\|_2^2}{\sin^2(y_1, y_2)} \quad (15)$$

Equations (14) and (15) show that, by using CR in a binary classification model, when we judge if y belongs to class i, we can only consider if $\sin^2(y_i, \hat{y})$ is small. Since the angle between y_1 and y_2 is fixed (i.e. $\sin^2(y_1, y_2)$ is fixed). Besides, for a testing sample y, the estimate vector $\hat{y}$ in (14) is as same as that in (15). Hence, a standard formula for residuals can be obtained.

$$r_i(y) = \frac{\|y - D\delta_i(x)\|_2}{\|\delta_i(x)\|_2}, i = 1, 2\ . \quad (16)$$

To sum up all in sub-section A and B, our method represents a testing sample y by a linear combination of dictionary atoms (i.e. collaborative representation) with an l_2-norm regularization term. Then, it classifies y individually (i.e. examine residuals of the two classes separately). Fig. 3 illustrates our proposed universal JPEG image steganalysis method based on collaborative representation. Given a new testing sample y, we first obtain x via

$$x = \arg\min_x \{\|y - Dx\|_2^2 + \lambda\|x\|_2^2\}, \quad (17)$$

where λ is still a regularization parameter. For each class i, let δ_i be the characteristic function that remains the coefficients corresponding to class i. For $x \in \mathrm{R}^n$, $\delta_i(x)$ is an equilong vector whose only nonzero entries are the entries in vector x that are associated with class i. Using only the coefficients associated with class i, one can approximate the given testing sample y as $y_i = D\delta_i(x)$. We then calculate the residuals between y and these approximation $D\delta_i(x)$ as (16). Finally, we classify y by finding the minimum of the residuals between y and y_i, which can be represented the same as (3).

Algorithm 2 summarizes the complete procedure, which is similar to the universal image steganalysis method utilizing SRC (refer to Algorithm 1).

Algorithm 2: Steganalysis Based on Collaborative Representation

Input: A training sample set D for two classes, a testing sample y.
1. Normalize all the columns of the dictionary D to have unit l_2-norm.
2. Code y over D by l_2-minimization as (17).
3. Calculate the residuals as (16).

Output: Identity of the testing sample y as (3).

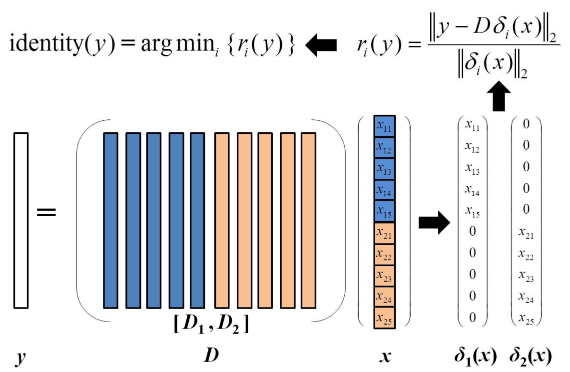

Fig. 3. Illustration of steganalysis based on collaborative representation.

There are two key changes in our proposed method. The first one is that the regularization term is changed from l_1-norm to l_2-norm. So the solution of (17) can be analytically derived as $x = Py$, where $P=(D^TD+\lambda I)^{-1}D^T$ and I is an identity matrix. Clearly, P is independent of vector y so that it can be pre-calculated. The second key change is based on the fact that $\|\delta_i(x)\|_2$ can also bring some discrimination information for classification, which can be derived from (14) and (15). Hence each class-specific representation residual in our method owns an extra divisor.

IV. Experimental Studies

A. Experimental Preparation and Instructions

1) Image Database. In this paper, we carry out our experiments on the standardized database called "break our steganography system" (BOSSbase) ver. 1.01 [8]. It contains 10,000 images acquired by eight digital cameras in the RAW format and subsequently processed by converting to 8-bit grayscale, resizing, and cropping to the size of 512×512, and finally JPEG -compressed with quality factor 85.

2) Testing Steganographic Algorithms. To demonstrate the power of our proposed steganalysis method, we steganalyze five modern steganographic algorithms: Jsteg, Outgess, MB1, F5, and nsF5.

a) The Jsteg algorithm treats DCT coefficients like bytes and changes LSB of DCT coefficients sequentially to embed a hidden message.

b) The Outgess algorithm is similar to Jsteg. It embeds the hidden message bits using the LSB embedding but skips coefficients 0 and 1.

c) The MB1 algorithm is a model-based steganography algorithm, which embeds data by modifying nonzero values of quantised coefficients of all AC DCT subbands. Meanwhile, it tries to preserve the model of some of the statistical properties of the image.

d) The F5 algorithm contains two key points. It replaces the operation of LSB flipping with decrementing the absolute value of the DCT coefficient, and its matrix encoding scheme decreases the number of embedding changes.

e) The nsF5 algorithm is an improved version of F5 (no shrinkage F5 with wet paper codes).

TABLE I. Detection Results Of Five JPEG Steganographic Algorithms For Payload 0.25 BPAC.

Steganographic Algorithms	*Classification Methods*	P_E
Jsteg	SVM	0.0000
	SRC	0.0006
	CRC	0.0000
Outgess	SVM	0.0028
	SRC	0.0120
	CRC	0.0052
MB1	SVM	0.0012
	SRC	0.0045
	CRC	0.0003
F5	SVM	0.0008
	SRC	0.0058
	CRC	0.0008
nsF5	SVM	0.0483
	SRC	0.0638
	CRC	0.0418

TABLE II. Detection Results Of Five JPEG Steganographic Algorithms For Payload 0.5 BPAC.

Steganographic Algorithms	*Classification Methods*	P_E
Jsteg	SVM	0.0000
	SRC	0.0003
	CRC	0.0000
Outgess	SVM	0.0002
	SRC	0.0082
	CRC	0.0012
MB1	SVM	0.0000
	SRC	0.0014
	CRC	0.0000
F5	SVM	0.0000
	SRC	0.0006
	CRC	0.0000
nsF5	SVM	0.0005
	SRC	0.0040
	CRC	0.0003

TABLE III. Detection Results Of Five JPEG Steganographic Algorithms For Payload 1.0 BPAC.

Steganographic Algorithms	*Classification Methods*	P_E
Jsteg	SVM	0.0000
	SRC	0.0000
	CRC	0.0000
Outgess	SVM	0.0000
	SRC	0.0052
	CRC	0.0003
MB1	SVM	0.0002
	SRC	0.0008
	CRC	0.0000
F5	SVM	0.0000
	SRC	0.0000
	CRC	0.0000
nsF5	SVM	0.0000
	SRC	0.0000
	CRC	0.0000

3) Training Images and Testing Images. We use the above five modern steganographic algorithms (Jsteg, Outgess, MB1, F5 and nsF5) to embed information in all the 10,000 images for three payloads (0.25, 0.5, 1.0 bpac), respectively. All of our experiments have been repeated 1,000 times. In each time, we randomly select 3,500 pairs (cover and its corresponding stego images) for training and the rest for testing.

4) Selection of Image Features. In all the experiments, we use the PF-274 features [9] for steganalysis.

5) Classifiers and Softwares. We adopt SVM classifier from the open source implementation provided by LIBSVM [10]. We also use the implementation of [11] provided by the SPAMS toolbox [12] to solve l_1-minimization.

6) Parameter Setting. We use SVM classifier with RBF kernel and the parameters are obtained by the cross validation. The regularization parameter λ for both l_1-minimization and l_2-minimization is set as 10^{-6}.

B. Detection Results

The performance is evaluated in a standard fashion using the detection error P_E computed from the ROC curve on the testing set [13]:

$$P_E = \min_{P_{FA}} \frac{P_{FA} + P_{MD}(P_{FA})}{2}, \tag{18}$$

where P_{FA} is the false alarm rate and P_{MD} is the missed detection rate. This error is also used to report the accuracy of detection in the entire paper. All of our experiments have been repeated 1,000 times. The average detection results rounded to four decimal places are shown in Tables I-III.

As is shown in Tables I-III, our proposed CRC-based image steganalysis method enjoys advantages over SRC. For steganographic algorithms Jsteg, MB1, and F5, our proposed method still has a similarly low detection error to SVM. Our method has a better detection result than the traditional SVM-based method for the popular steganographic algorithm nsF5. In fact, the detection result for the steganographic algorithm Outgess based on SVM slightly outweighs our method with a sufficiently small P_E yet an acceptable gap.

C. Running Time

All experiments were conducted using MATLAB R2010a on an Intel Core i5-3470 processor at 3.20 GHz combined with 3.68 GB RAM and a 64-bit Windows 7 operating system. Table IV shows the average running time. It can be observed that our proposed CRC-based steganalysis method has much less time for identifying a testing image. Moreover, CRC does not need training phase while it is very time consuming for SVM-based steganalysis method. Therefore, we can conclude that our proposed method produces effective steganalysis for JPEG image.

V. Conclusion

This paper has presented a novel universal JPEG image steganalysis method based on collaborative representation, which focuses on the least square problem arising in a binary classification model and utilizes collaborative-representation-based classification (CRC) scheme. This proposed CRC-based image steganalysis method can improve detection accuracy compared with the traditional SVM-based method and also outperforms the recently presented SRC-based method. The computational complexity of our method is also significantly lower than the other two methods.

TABLE IV. THE AVERAGE RUNNING TIME

Classification Methods	*Training Time (s)*	*Testing Time per Image (s)*
SVM	917.5	0.0004
SRC	——	3.4589
CRC	——	0.0139

a. Training time of SVM contains the time for cross validation.

Future researches will mainly focus on how to utilize collaborative representation to conduct content-mismatched steganalysis and how to make full use of the sample set to obtain a better dictionary. Besides, we will also investigate the combination of kernel-CRC and image steganalysis in a lower payload case.

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