

Universal Steganalysis for image Based on Genetic Algorithm and Grey-SVC

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Abstract: The isolated samples can produce some effect on distinguishing the best classifying plane, which becomes one of causes of less performance of universal steganalysis that uses Support Vector Machines (SVM) as classifier. This paper proposes a new universal steganalysis algorithm for image based on Genetic Algorithm (GA) and Grey Support Vector Machines (GSVM). The algorithm firstly catches characteristic of noise signal in wavelet domain of image, then utilizes GA search samples which are used to train, and finds the best characteristic of species, finally makes grey relational degree between sample characteristic and the best characteristic of species participate in training of SVM, thus constructs a GSVM to be a classifier of steganalysis. The result testing on the large numbers of images indicates that the proposed universal steganalysis algorithm has less false positive rate and better classifying performance compared to Holotyak's algorithm which has the same characteristic with above algorithm, which indicates that GSVM can reduce effect of isolated samples.

Keywords: Steganalysis, Genetic Algorithm, Grey Relational Analysis.

1. Introduction

The purpose of steganalysis is to reveal the existence of secret information in the media. At present, there are many steganalysis methods for specific information hiding. However, with the development of steganography, the variety of methods makes the detection of hidden information very difficult. As a result, the development of steganalysis always falls behind that of steganography. It is an obviously important research content of steganalysis to the images which may contain hiding information and is completely blind to the steganography algorithm that may be used. This method is not limited to a single steganography algorithm, and can be applied to several steganography algorithms, so it is also called general steganalysis.

Famous general steganalysis techniques, such as I. Avci et al use the multiple two-value similarity test of the lowest and second-lowest plane of the image as feature space, adopt SVM classification algorithm [1]. Siwei et al. further used QMF to analyze image wavelet coefficients and higher-order statistics of prediction errors, and trained One-class SVM [2]. T. Holotyak et al. proposed a new method to extract noise component features in image wavelet domain and classify them with two-class SVM [3]. The similarity of these techniques is that they all use SVM as the classifier, but in the SVM method, the support vector to determine the optimal classification hyper-plane is located at the edge of the class, and the outlier samples are often located near the edge of the class. For this problem, Linear Unsupportable Vector Classifier introduces slack variables to allow certain quantity of misclassified samples existing. These misclassified samples will affect the identification of the optimal classification plane, thus affecting the performance of classifier, and become one of the reasons for the low performance of the analysis.

This paper proposes a new general image steganalysis method using GSVM as classifier. Firstly, select 33 high-order noise statistics in T. Holotyak's general steganalysis as feature vector, and using



genetic algorithm on Training samples to search, obtaining the optimal class feature vectors. Secondly, calculate the correlation degree between the feature vectors of different training samples and the optimal class feature vectors applying grey correlation analysis. Then make it participating in the training of SVM, in order to reduce the influence of the classification error of outlier samples on the objective function of SVM. The SVM trained in this way is called GSVM. Finally, use the trained GSVM to detect and classify. Experimental results on a large number of image samples show that the proposed classifier has a better performance and higher detection accuracy compared with T. Holotyak's universal steganalysis using same feature vector.

2. Genetic algorithm and grey correlation analysis

The first systematic GA was proposed by J. H. Holland [4]. GA start to iterate initial population (parent generation), which is constituted through gene coding on possible solution set of the problem, calculate fitness of the parent individual, and jump out from the iteration if it satisfy optimization criteria. Otherwise, form a new individual (filial generation) through selection, intersection, gene recombination or mutation operations, insert it into parent generation, and start cycle again until satisfying optimization criteria, so that the population evolve to a state containing approximately optimal solution.

After finding the optimal solution, use Grey Relational Analysis (GRA) to calculate the grey relational degree between it and possible solution in the parent generation. The calculation of grey relational degree is described as following [5]:

Let reference sequence

$$x_0 = (x_0(1), x_0(2), \dots, x_0(n))$$

n represents the number of elements in the array. Sequence to be compared

$$x_i = (x_i(1), x_i(2), \dots, x_i(n))$$

i represents the number of sequences to be compared, and the number of elements in the sequence to be compared is the same as in the reference sequence. The grey correlation coefficient of x_i and x_0 at the point k is

$$\vartheta(x_0(k), x_i(k)) = \frac{\Delta_{min} + \rho\Delta_{max}}{\Delta_{0i}(k) + \rho\Delta_{max}}$$

Where $\Delta_{min} = \min_k \min_i |x_0(k) - x_i(k)|$, $\Delta_{max} = \max_k \max_i |x_0(k) - x_i(k)|$,

$\Delta_{0i}(k) = |x_0(k) - x_k(k)|$; $\rho \in (0,1]$ is a pre-set constant, which is called resolution coefficient, generally taken $\rho = 0.5$. The gray correlation degree is

$$\gamma(x_0, x_i) = \frac{1}{n} \sum_{k=1}^n \vartheta_{0i}(k)$$

3. Steganalysis method based on GS

3.1. Fe nature extraction

After 1 layer db8 wavelet transformation of the image, noise signal can be obtained by using the denoising filter proposed by M. K. Mihcak et al [6]. According to literature [3], the noise signal is uniquely determined by its Probability Distribution Function (PDF). Write PDF as p, apply exponential kernel e^x , and perform Taylor expansion to map p to a parameter space, as follows:

$$M(x) = \int_{-\infty}^{\infty} p(t)e^{tx} dt = \int_{-\infty}^{\infty} p(t)(1 + tx + \frac{t^2 x^2}{2!} + \dots + Q_n(t))dt =$$

$$1 + m_1 x + \frac{m_2}{2!} x^2 + \dots + R_n(x)$$

The above equation as a polynomial expression of the noise signal in the wavelet domain. Statistically, it is regarded as Moment generation function, which can be obtained by its coefficient matrix, where m_i is the moment of i order, Q_n and R_n approach 0 with the increasing of n . Therefore, the moment can be taken as its characteristic, and the complexity of the calculating p can be avoided. After a lot of experiments, finally the 11 moments normalized by the standard deviation $\sqrt{m_i}$ of the second moment are selected in the subband as the feature vectors, that is $m_i' = \frac{m_i}{\sqrt{m_2^i}}, i = 4, 6, \dots, 24$ (the PDF of the noise signal obtained by the denoising filter in literature [6] has parity symmetry), and a 33-dimensional feature vector can be obtained by calculating in the three subbands LH, HL and HH.

3.2. The optimal class feature generating

The feature vectors of the positive class samples (stegano-image samples) in the training samples are taken as the initial population of GA, and the real number coding method is adopted. Establishing cost function of the sample i as

$$\Psi_i = 1 - \frac{1}{n} \sum_{j=1}^n \gamma(T_i, T_j)$$

Where $\gamma(T_i, T_j)$ represents the grey correlation degree between sample i and j in the population. The smaller it is, the more similar the sample is to the rest of the population, and the more representative it is of the population as a whole. The cost function values of all samples make up the set of cost functions $\Psi = \{\Psi_1, \Psi_2, \dots, \Psi_n\}$ for the population. Rank-scale method is adopted [7], after the cost function values in the set are arranged in ascending order, the fitness of the samples ranked in the j th place is

$$\phi_j = \frac{n}{\sqrt{j} \sum_{i=1}^n \frac{1}{\sqrt{i}}}$$

Using the above formula, calculating the fitness of all samples in the population. The adaptation mechanism of roulette is performed according to the fitness. The selected individuals proceed genetic operation of single point crossover and mutation to form the intermediate population and combine with the parent population. The cost function and fitness of all samples of combined population are calculated, and the previous n samples with high fitness are taken as the next generation population to start the next iteration. When the population contains samples ϕ_i less than 0.05, loop ends. The feature vector of this sample is the one of the optimal class; or other condition are satisfied, the sample feature with the smallest cost function is the optimal class at the end of the cycle.

3.3. GSVM classifier constructor

The optimal class feature generated above denoted as x_0 , then the grey correlation degree $\gamma(x_0, x_i)$ between it and the training samples noted as $\gamma_0(x_i)$, introducing $\gamma_0(x_i)$, the training sample set can be expressed as:

$$(x_1, y_1, \gamma_0(x_1)), (x_2, y_2, \gamma_0(x_2)), \dots, (x_l, y_l, \gamma_0(x_l))$$

Wherein, $x_j \in R^n$ is the feature vector of the sample, $y_i \in \{-1,1\}$ is the class identifier, $0 < r_0(x_j) \leq 1$ is the gray correlation degree between sample feature and class feature, $j = 1, \dots, l$, $\phi: x \subseteq R^n \rightarrow x \subseteq H$ is the transformation from the original feature space to a high-dimensional feature space. Then the nonlinear classification problem in literature [8] is transformed into a quadratic programming problem solving the following decision variables $(w, b, \varepsilon)^T$:

$$\left\{ \begin{array}{l} \min_{w,b,\varepsilon} \frac{1}{2} \|w\|^2 + C \left(\sum_{j=1}^l \gamma_0(x_j) \varepsilon_j \right) \\ s.t. \quad y_j ((w^T, \phi_j) + b) + \varepsilon_j \geq 1, j = 1, 2, \dots, l \\ \varepsilon_j \geq 0, j = 1, 2, \dots, l \end{array} \right. \quad (1)$$

Wherein, $C > 0$ is a self-defined penalty factor, ε_i is the classification error in the objective function of the support vector machine, as can be seen from expression (1): small $\gamma_0(x_j)$ can reduce the influence of ε_i in it, or it can be considered that the corresponding sample x_j is not important.

The kernel function $K(x_j, x_i) = \phi(x_i, x_j)$ is introduced, then the inner product operation on the higher dimensional space only needs to be carried out on the original space, and the dual programming expression of equation (1) becomes:

$$\left\{ \begin{array}{l} \min_a \frac{1}{2} \sum_{j=1}^l \sum_{i=1}^l a_j a_i K(x_j, x_i) - \sum_{j=1}^l a_j \\ s.t. \quad \sum_{j=1}^l a_j y_j = 0 \\ 0 \leq a_j \leq \gamma_0(x_j) C, j = 1, 2, \dots, l \end{array} \right.$$

The grey correlation degree $\gamma_0(x_j)$ between the best class features and training samples is introduced into the samples, and the trained SVM classifier is called grey SVM classifier.

4. Analysis of experimental results

By comparing the algorithm proposed in this paper with the algorithm in literature [3], the performance of the algorithm is analyzed. In fairness, the algorithm should be carried out under the same conditions. So like the literature [3], the experimental images also originate from [9] and consists of 2375 TIFF format, 32-bit color scanned images stored in 1500×2100 pixel. Similarly, the sample images were also converted to a grayscale image. Embedding method is the classic LSB with embedding rates of 0.25 bpp (bits per pixel), 0.5 bpp, 0.75 bpp and 1.0 bpp. FIG.1 (a) and FIG.1 (b) respectively show the ROC (Receiver Operating Characteristic) classification performance curves of the algorithm in this paper and the algorithm in literature [3] on the above image set. As can be seen from the figure, the performance of the algorithm proposed in this paper is better than that of the algorithm in literature [3], that is, the false positive rate under the same True positive rate is smaller. This is because the grey correlation degree between the optimal class features of positive class samples (stego-image) and training samples is introduced when training the classifier, which reduces the outlier points in negative class samples (original images), that is, the influence of the original images close to positive class samples on the classification error in the objective function of support vector machine, so the probability of taking negative class samples as positive class samples is reduced.

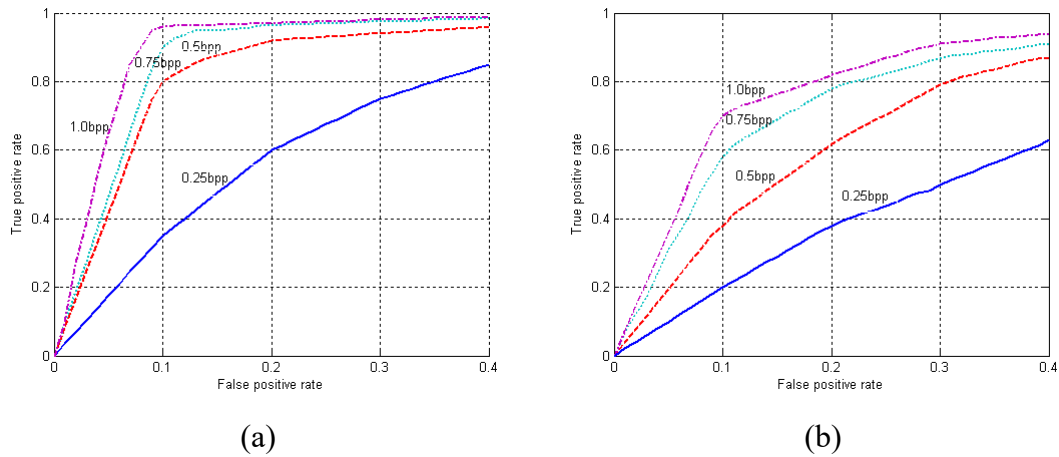


Fig1 The experiment result of steganalysis to different embedded capacity: (a) The experiment result of the proposed method; (b) The experiment result of Holotyak's method

The following is to measure the performance of the proposed algorithm from the final classification result. The same image set as mentioned above, divide these images into two groups in a 4:1 ratio and make four copies of each. Using the classical LSB method, the embedding rate is 0.25bpp, 0.5bpp, 0.75bpp and 1.0bpp to embed secret information into the four copies of the image respectively. In the experiment, the first group of images without embedded secret information and a copy of the first group of images with embedded secret information constitute a training sample set to train the above constructed GSVM, and then the trained GSVM is used to test the second group of images without embedded secret information and the second group of images with the same embedding rate embedded secret information. The other three copies with embedded secret information were also used in the same way, and a total of four groups of test data are obtained. Table 1 shows the comparison between the correct detection rate of the original image and the stego-image in the above experiment and the correct detection rate of the method in literature [3]. It can also be seen from the table that the performance of the algorithm proposed in this paper is better than that in literature [3]. The reason is that the function of outliers is weakened in the training of classifier.

Tab.1 Correct Classification result of original images and stegano images

Embedding rate(bpp)	Original images (%)		Stegano images (%)	
	Proposed algorithm	Holotyak's algorithm	proposed algorithm	Holotyak's algorithm
0.25	75%	70%	65%	48%
0.50	82%	75%	89%	68%
0.75	85%	78%	94%	78%
1.00	86%	79%	96%	80%

5. Conclusions

In this paper, a new general image steganalysis algorithm based on GA and GSVM is proposed. In SVM training, grey correlation degree between samples and class features is introduced to construct GSVM, which reduces the effect of outliers. In addition, GA is used to search for the best class features as a reference sequence when calculating the grey correlation degree, so that the calculated grey correlation degree can truly reflect the degree of correlation between samples and classes. Finally, the trained GSVM is used for detection. Experimental results show that the universal steganalysis algorithm proposed in this paper has a lower error acceptance rate and a higher correct detection rate under the same conditions. However, the noise characteristics of Holotyak were only tested in this paper. The

next research focus is to seek better classification features, train the constructed GSVM, and form a more effective general steganalysis.

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