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Feature Selection for Image Steganalysis Using Binary Bat Algorithm

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ABSTRACT Steganography is to hide secret information in a normal cover, so that the secret information cannot be detected. With the rapid development of steganography, it's more and more difficult to detect. Steganalysis is the counter of steganography. In order to improve the detection effect, more complex high-dimensional features are proposed for steganalysis. However, this also creates huge redundancy features, which in turn consume generous time. Feature selection is a technique that can effectively remove redundant features. In this paper, we propose a new blind image steganalysis algorithm to distinguish stego images from cover images using a nature-inspired feature selection method based on the binary bat algorithm(BBA). Meanwhile, SPAM and several classifiers have been used to improve the detection effect. Furthermore, we select the ideal feature subset using BBA from the original features and use the selected feature subset to train the several classifiers. The experimental results demonstrate that our proposed method can improve the detection effect and reduces the redundant features.

INDEX TERMS Image steganalysis, feature selection, binary bat algorithm, swarm intelligence.

I. INTRODUCTION

With the development of information technologies, steganography has developed rapidly and many steganographic methods are proposed. These methods embed secret information into the normal covers, such as images, audios, texts, and videos. As these behaviors do not change the visual effect of the covers, it's hard to get alert. In the field of digital images, current steganographic methods are divided into two domains: the spatial domain and the frequency domain. In spatial domain, the methods directly embed the secret data into the covers, such as Least Significant Bit (LSB) [1] method. In frequency domain, the methods embed the secret data into the spectrum space, such as Discrete Cosine Transform (DCT) [2] and Discrete Wavelet Transformation (DWT) [3]. In the early period, steganography methods were only used to hide information without considering the changes of the image characteristics. So the researchers can easily detect the stego images with simple statistical features. This promotes the further development of steganography. Therefore, some researchers have proposed lots of steganographic methods that can keep some features unchanged. And some researchers further propose adaptive steganographic methods, such as Wavelet Obtained Weights (WOW) [4] and HUGO [5] methods for uncompressed images, JUNIWARD [6] and nsF5 [7] methods for JPEG images. At the same time, lots of unknown information hiding algorithms are more subtle [8].

Steganalysis is the opposite of steganography. As steganography will change some features of the image when embedding information into it, some researchers try to find these changed features to identify the stego images. In the early period, researchers can effectively detect the stego images according to the abnormal phenomena such as histogram anomalies and JEPG blocking effects. With the advancement of steganography, the simple statistical features mentioned above cannot effectively detect the stego images. This conversely promotes the further improvement of steganalysis. Therefore, some researchers have proposed more and more complex feature sets with high dimension to improve the detection performence of steganography. For example, in spatial domain, the feature extraction methods have subtractive pixel adjacency model (SPAM), Spatial Rich Models (SRM) [9]and so on. In the JEPG domain, the feature extraction methods have Cartesian-calibrated PEV feature set (CC-PEV), Discrete Cosine Transform Residual (DCTR) [10] and so on.

With the increase of the feature dimensions, exponentially order of training data is required which causes high computational complexity of the classifier. Further, there are

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the chances of irrelevant and redundant features which may degrade the performance of a classifier. Hence, there is a requirement of an efficient feature selection method to overcome this problem.

As the feature sets with high dimension of steganalysis contain large redundant features, it is necessary to find a way to extract the useful features. Feature selection is the technique to effectively reduce the feature dimension. Therefore, we can use the technique to select a high-efficiency feature subset and input the feature subset to the classifier to detect the stego images. Xia *et al.* [11] used Mutual Information on feature selection which efficiently improved the learning system. Meanwhile, some classic algorithms, such as the Genetic Algorithm (GA) [12], Particle Swarm Optimization Algorithm (PSO) [13], Artificial Bee Colony Algorithm (ABC) [14], Bat Algorithm (BA) [15], grey wolf optimization (GWO) and so on, are used for selecting the effective features and improving the detection accuracy.

The bat algorithm is a metaheuristic algorithm for global optimization. It was inspired by the echolocation behaviour of microbats, with varying pulse rates of emission and loudness. The idealization of the echolocation of microbats can be summarized as follows: Each virtual bat flies randomly with a velocity v_i at position (solution) x_i with a varying frequency or wavelength and loudness A_i. As it searches and finds its prey, it changes frequency, loudness and pulse emission rate r. Search is intensified by a local random walk. Selection of the best continues until certain stop criteria are met. This essentially uses a frequency-tuning technique to control the dynamic behaviour of a swarm of bats, and the balance between exploration and exploitation can be controlled by tuning algorithm-dependent parameters in bat algorithm. Compared with other algorithms, BA is much better than other algorithms in accuracy and effectiveness, and there are not many parameters to adjust.

Therefore, in this paper, we propose a new image steganalysis method using binary bat algorithm. The proposed method can select the most effective feature subset from the raw features extracted from the cover and stego images to improve the detection accuracy. As the total number of selected features is reduced, the computation time is also decreased extensively. And we use the selected feature subset to train the classifer of several classifiers which can effectively improve the detection effect.

The main contributions of our proposed method are as follows:

1) A new method for image steganalysis based on BBA is proposed.
2) For discriminating cover images from stego images in BOSSbase 1.01 dataset, several classifiers are used and compared.

The rest of this paper is organized as follows. In section II , the details of BBA will be introduced. In section III , the design of our method will be shown. In section IV , the experimental results and analysis are presented. The conclusion will be presneted in section V.

II. FEATURE SELECTION USING BINARY BAT ALGORITHM

In this section, the bat algorithm and binary bat algorithm (BBA) will be described detailly as follow, so that we can conveniently understand the bat algorithm for feature selection.

A. BAT ALGORITHM

Bats are the magical animals as they are the only mammals with wings that have advanced echolocation capabilities. Most small bats are the insectivores. And the small bats have a sonar called echolocation to detect, prey, avoid obstacles and find inhabited cracks in the dark. These bats can emit the sound waves and listen for echoes reflected from surrounding objects. The characteristics of the pulses are related to the hunting strategy.

Through observing these behaviors of the bats, an efficient bio-heuristic optimization algorithm called bat algorithm is proposed by Professor Yang. First, the bat algorithm initializes a set of random solutions, then it will iteratively search for the optimal solutions. When the optimization solutions are found, the bat algorithm will generate a new local solution by random flight around the optimal solutions, which can strengthen the search capability of the bats. Comparing to other algorithms, BA is far superior to other algorithms in terms of accuracy and effectiveness.

For the sake of simplicity, Yang used the following ideal rules:

1) All bats use echolocation to sense distance and are able to distinguish the food from the background obstacles.
2) Bats are flying randomly at position x_i with the velocity v_i, and they can automatically adjust the frequency f of the pulse, adjust the pulse emissivity $r \in [0, 1]$ according to the proximity of the target.
3) Although the loudness can be changed in many ways, he assume that the loudness changes from a large positive) value A_0 to a minimum value A_{min}.

Based on the above idealization rules, the basic steps of BA can be summarized in Algorithm 1:

According to Algorithm 1, first, we need to define some initialization parameters for the virtual bats: the d-dimensional search space, the position x_i, the velocity v_i and the frequency f_i. And in each step t, the update rules for the new solution x_t^i and velocity v_t^i are given below:

$$f_i = f_{min} + (f_{min} - f_{max})\beta \tag{1}$$

$$v_i^j = v_i^j(t-1) + [\hat{x}^j - x_i^j(t-1)]f_i \tag{2}$$

$$x_i^j(t) = x_i^j(t-1) + v_i^j \tag{3}$$

where $\beta \in [0, 1]$ is a random vector subject to uniform distribution. According to Eq. (1)-(2)and (3), we know that the variable f_i is used to adjust the velocity and the variable $x_i^j(t)$ presents the value of the position j for the bat i at the step t. Here the variable $\hat{x}^j$ is the current global best position, which is found after comparing all the solutions of all m bats.

Algorithm 1 Bat Algorithm

Input: Objective function $f(x)$, $x = (x_1, x_2, \cdots, x_n)$
Output: The current best position $\hat{x}$.
Initialize the population x_i and v_i
Initialization frequency f_i, pulse emissivity r_i and loudness A_i
while $t < T$ **do**
  for each bat b_i **do**
    Update velocity and position based on formula and generate new solutions
    if $rand > r_i$ **then**
      Select a solution among the best solutions and generate a local solution around the best solution.
    end if
    if $(rand < A_i) and (f(x_i) < f(\hat{x}))$ **then**
      Accept the new solutions and increase r_i and reduce A_i.
    end if
  end for
end while
result=Rank the bats and find the current best position $\hat{x}$.
return *result*

In order to prevent the bats falling into local extremum and increase the random searching ability for each bat, Song and Gorla [12] employed the strategy of random walks for each bat. Once a solution is selected from the current best position, the random walk is used to generate a new solution for each bat according to Eq. (4).

$$x_{new} = x_{old} + \epsilon \bar{A}(t) \tag{4}$$

where $\epsilon \in [-1, 1]$ is a random number controling the direction and stride of the walk, and $\bar{A}(t)$ is the average loudness of all bats in the step t.

In addition, the loudness A_i and the pulse rate r_i are updated for each step according to Eq. (5)-(6). Once the prey is found, the loudness A_i is usually reduced and the pulse rate r_i is increased. And the loudness can be set to any value for convenience.

$$A_i(t+1) = \alpha A_i(t) \tag{5}$$

$$r_i(t+1) = r_i(0)[1 - exp(-\gamma t)] \tag{6}$$

in which α and γ are constants. At the first step of the bat algorithm, the loudness $A_i(0)$ and the pulse rate $r_i(0)$ are usually chosen randomly. Generally, we set $A_i(0) \in [1, 2]$ and $r_i(0) \in [0, 1]$.

B. BINARY BAT ALGORITHM

As mentioned above, the basic bat algorithm is just suitable for the continuous problems in Algorithm 1, because the positions are randomness.

Therefore, in order to deal with the feature selection, we need to discretize the bat algorithm. Nakamura et al. proposed the binary bat algorithm for feature selection and image processing. In their paper, the whole search space can be modeled as a d-dimensional boolean lattice, in which the bats move across the corners of a hypercube.

In BBA, the sigmoid function is used to limit the positions of the bats according to Eq. (7)-(8).

$$S(v_i^j) = \frac{1}{1 + e^{-v_i^j}} \tag{7}$$

$$x_i^j = \begin{cases} 1 & if\ S(v_i^j) > \sigma \\ 0 & otherwise \end{cases} \tag{8}$$

The velocity v_i^j corresponds to the j dimension of bat i and $\sigma \sim U(0, 1)$ is a random number obeying uniformly distribution.

Therefore, in this paper, we use BBA to select the best feature subset of the features to improve the detection performence.

III. PROPOSED METHOD

Our proposed method using binary bat algorithm together with the classifier to find the best performence of the feature subset will be introduced in this section. And two sub-sections will be divided for deeper explanation of our approach. In subsection III-A, the structure of our approach will be presented. In subsection III-B, the details of our method will be introduced.

A. STRUCTURE OF OUR APPROACH

In this subsection, we present the whole structure of our proposed approach using binary bat algorithm together with the classifier to find the best performence of feature subset, as Fig. 1.

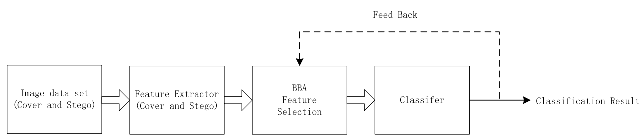

FIGURE 1. Our proposed method.

In general, the proposed images steganalysis approach contains four aspects, as Fig. 2: a feature subset selected process, an evaluation classifier, a validation process and a stopping condition in BBA. As the combinations of features grow exponentially, it is important to select an appropriate dimension of the feature subsets. First, the raw feature sets are respectively extracted from the cover and stego images. Next, a feature subset is randomly initialized. Then the selected subset will be evaluated by the classifier. The above process will iterate until the stopping condition reached. Final the best feature subset is selected. Furthermore, we will verify the best selected feature subset via 10-fold cross validation.

B. IMAGE ATEGANALYSIS WITH BINARY BAT ALGORITHM

In this subsection, we present our proposed approach detailly using bat algorithm together with the classifier to improve the detection performence as Fig. 3.

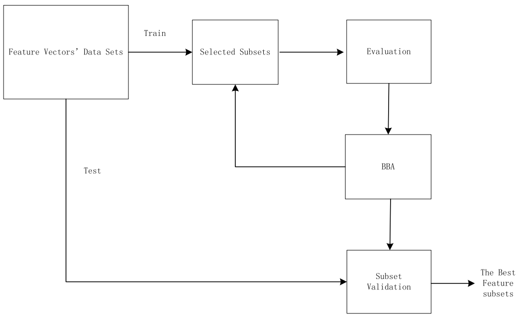

FIGURE 2. The general method of BBA-based feature selection.

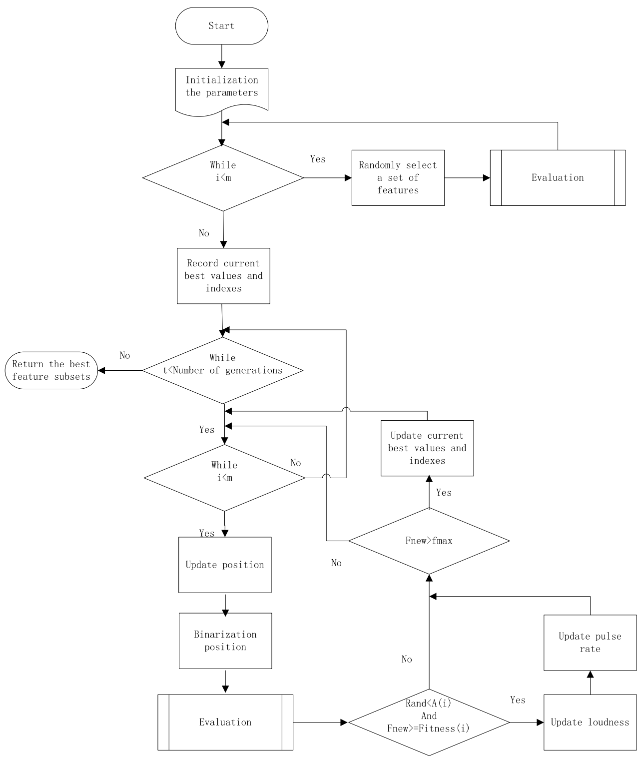

FIGURE 3. The BBA image steganalysis.

Fig. 3 shows the overall process of our approach in details. In our proposed method, the binary bat algorithm is used to select features and return the best feature subsets to improve the detection accuracy of the classifier.

Before experiments, we divide the raw feature sets into a training set $Z1$ and a validation set $Z2$. Then, we utilize the position of each bat in the search space as a subset of the features selected. After this, the classifier will be trained in $Z1$ for each bat and then the trained classifier will be evaluated over $Z2$ so as to evaluate the validity of the selected feature subset.

From Fig. 3, first we initialize the parameters of the bats and randomly select the position of each bat with the binary value, which indicates whether this feature is selected or not. If the value of the position is 1, it means the feature is selected. If the value of the position is 0, it means the feature is unselected. The selected features of each bat will compose a new subset of features as the new training set $Z1'$ and evaluating set $Z2'$. Next, we will evaluate the seleted subset using the classifier to update the fitness value and record the current best value and its index. Then we will carry out T round test to find the best feature subset and the best fitness value. In each round, we can find the current best quality and compare it with global best value. If the current best value is greater than the global best value, we will replace the global best value with the current best value and record its index. After these operations, we can get the best value and its index.

TABLE 1. The experimental parameters of the accuracies of different selected number of features.

Parameters	Value
Population size	10
Number of generations	200
A	0.25
r	0.1

IV. EXPERIMENTAL RESULTS

In this section, we will discuss the experimental results and assess the performance of our method. Also some methods will be compared in order to reveal the performance of our method. For the data set, we take the widely accepted database BOSSBase v1.01, which contains 10000 grayscale images with the size of 512×512 collecting from seven different cameras. Then we use several steganography algorithms to embed the 10000 images with the payload of 0.4 per pixel. Next, for each kind of steganography algorithm, we randomly select 5000 image pairs for training and 5000 image pairs for testing. Then the feature extractor of subtractive pixel adjacency model (SPAM) is employed to extract the features for image steganalysis. For different experiments, we choose different classifiers for testing. In order to evaluate the performance in term of classification accuracyies and reduction of the features, our experiments are all compared to the original features of SPAM with the same classifiers.

A. THE ACCURACIES OF DIFFERENT SELECTED NUMBER OF FEATURES

To determine the impact of different number of selected features on detection results, the experiments are set different number of features. First, we use Hugo algorithm to embed the covers with the payload of 0.4 per pixel. Next, we randomly select 5000 image pairs for training and 5000 image pairs for testing. The classifier is Support Vector Machine (SVM). And we limit the selection of the number of features by setting a binarization threshold in Eq. (7)-(8). The parameters of this experiment are as Table 1.

In Table 2, we can see that the threshold can be ability to efficiently select different numbers of features and the our method can improve the detection accuracy significantly. In Table 2, the detection accuracies are obviously improved, especially when the value of threshold is above 0.6. So we set

TABLE 2. The experimental accuracies of different selected number of features.

Feature Number of SPAM	Accuracy of O-riginal Fea-tures	Threshold	Feature Number of Se-lected	Accurancy of Our Method
686	55.51	0.5	358	63.79
		0.6	297	63.97
		0.7	278	67.10
		0.8	184	67.22
		0.9	89	66.35

TABLE 3. The experimental accuracies of different selected number of features.

Feature Number of SPAM	Feature Number of Seleted	Classifiers	Accuracy of original features	Accuracy of Our Method
686	106	KNN	51.07	54.84
	82	RF	59.02	62.61
	147	AdaBoost	52.78	61.56
	131	DCA	67.47	68.04
	92	NB	50.36	54.58
	110	SVM	55.51	68.08

the value of threshold 0.9 in all the rest experiments, as the dectection accuracy is high and the dimension of feature reduced mostly.

B. THE ACCURACIES OF DIFFERENT CLASSIFIERS

In the subsection IV-A, we demonstrate that our method can effectively improve the detection effect while reducing the number of features. Therefore, in this subsection, we will verify our method on different classifiers. And the parameters of this experiment are a little different from IV-A. To improve the effect in this experiment, the population size of bats is set as 20 and the umber of generations is set as 500. The rest parameters remain unchanged. And we select six classifers named: K-Nearest Neighbor (KNN), Random Forest (RF), AdaBoost, Discriminant Analysis Classifier (DCA), Naive Bayesian (NB), SVM. And all of these classifiers are native to MATLAB with the default parameters. In order to verify our method, we do two experiments. The first set of experiments is carried out on the original feature set of SPAM, the other is carried out on our method, as shown in Table 3.

In Table 3, we can see that our method improve the classification accuracies to different degrees on different classifiers. Especially for the SVM classifier, the detection accuracy is obvious improved.

C. THE ACCURACIES OF DIFFERENT STEGANOGRAPHY ALGORITHMS

In this subsection, we will verify our method on different steganography algorithms. So we respectively use the three

TABLE 4. The experimental accuracies of different selected number of features.

Steganography algorithms	Feature Number of SPAM	Feature Number of Seleted	Accuracy of original features	Accuracy of Our Method
Hill	686	136	55.16	64.11
WOW		132	52.47	64.07
Hugo		110	55.51	68.08

TABLE 5. Comparisons of different feature selection methods on SPAM.

Methods	SPAM	ABC [16]	LFGWO [19]	Proposed method
Selected feature Accuracy	55.51	66.08	67.23	68.08
Number of features	686	80	84	110

steganography algorithms: Hill, WOW, Hugo to embed the covers with the payload of 0.4 per pixel. Next, the SPAM extractor is respectively used to extract the featuers of the covers and stegos. And the parameters of this experiment are unchanged with IV-B. Similarly with other experiments, we do two experiments too. The first set of experiments is carried out on the original feature set of SPAM, the other is carried out on our method, as shown in Table 4.

This experiment also demonstrate our method can effectively improve the classification accuracies and reduce the number of features remarkably.

D. COMPARISONS WITH OTHER METHODS

In this subsection, we compare our method with other methods to reveal the performance of our method. In our experiments, two feature selection algorithms are selected to compare. As we use the same dataset:BOSSBase v1.01, the same steganography algorithm:Hugo with the same payload of 0.4 per pixel and the same classifier of SVM. As we can see in Table 4, the number of reduced features are roughly the same, while the classification accuracy of our method is higher than others.

This experiment results in Table 4 demonstrate that our method can reduce the number of features and improve the classification accuracy of image steganalysis.

V. CONCLUSION

In this paper, we propose a new blind image steganalysis algorithm to distinguish the stegos from covers using a nature-inspired feature selection method based on binary bat algorithm(BBA). The proposed method selects the most effective feature subset from the raw features extracted from the cover and stego images to improve the detection accuracy. In the experiments, using the BBA, we can select an ideal feature subset to reduce the dimension of the feature set and improve the detection accuracy. And the experimental results demonstrate that our algorithm can significantly improve the detection effect compared with other typical feature selection methods using the same classfication of SVM in image steganalysis.

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