A Hybrid Feature Selection Technique based on Improved Discrete Firefly and Filter Approach for Blind Image Steganalysis

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***Abstract*— Feature Selection is a preprocessing technique with great significance in data mining applications that aims at reducing computational complexity and increase predictive capability of a learning system. This paper presents a new hybrid feature selection algorithm based on Discrete Firefly optimization technique with dynamic alpha and gamma parameters and t-test filter technique to improve detectability of hidden message for Blind Image Steganalysis. The experiments are conducted on important dataset of feature vectors extracted from frequency domain, Discrete Cosine Transformation and Discrete Wavelet Transformation domain of cover and stego images. The results from popular JPEG steganography algorithms nsF5, Outguess, PQ and JP Hide and Seek show that proposed method is able to identify sensitive features and reduce the feature set by 67% in DCT domain and 37% in DWT domain. The experiment analysis shows that these algorithms are most sensitive to Markov features from DCT domain and variance statistical moment from DWT domain. The results are compared with DPSO (Discrete Particle Swarm Optimization) and well known multivariate feature selection techniques.**

Keywords- Discrete Firefly Algorithm, Feature Selection, Steganalysis, t-Test, DCT, DWT

I. INTRODUCTION

Steganalysis is science of breaking steganography which is the science of embedding hidden messages in innocent looking cover documents such as text, images, audio, video files [1]. It forms an important area of digital forensics. Steganalysis is broadly categorized as Blind and Specific Steganalysis. Blind image steganalysis is able to detect hidden message irrespective of underlying embedding technique and is found to be more practical, while specific steganalysis is beneficial only for known steganography tools [2].

Steganalysis can be considered a pattern recognition problem with two classes. The performance of a classifier is dependent on two parameters; classifier and features extracted from images. Various methods have been provided in literature to improve performance of steganalysers by increasing feature space starting from 274 features given by Fridrich [3], which were further extended to 548 [4].CF*7850 compact rich model for DCT domain further extended to 48,600 [5]. Farid et al [6] presented 72 wavelet features based on CF and PDF moments that provide improved accuracy. Recently Han Zong et al have proposed 126 wavelet features [7] based on entropy, energy and combinations of PDF moments. Some of the features may not be relevant to classification and may degrade the performance of the classifier.

The objective of applying feature selection for steganalysis is to reduce computational complexity and increase the classification accuracy. Feature selection methodology based on Mutual Information was proposed by Xia et al that improves the efficiency of learning system [8]. Different evolutionary algorithms based methods presented in literature are MBEGA based on Markov Blanket [9], Localized Generalization Error Model (L-GEM) [10], Genetic Algorithm (GA) based on higher order statistics[11], Particle Swarm Optimization Algorithm (PSO) [12] employing SVM and neural networks as classifier. All these feature selection techniques have been found to enhance performance of a classifier for blind image steganalysis.

A novel metaheuristic Firefly algorithm was proposed by Yang [13]. It has been successfully employed for applications like flowshop scheduling problems to minimize the makespan [14]. Banati and Bajaj [15] combined rough set theory with firefly algorithm. Yang Xin-She proved that Firefly algorithm outperforms GA and PSO and GA in terms of efficiency and success rate [16].

In this paper we present a new hybrid Discrete Firefly algorithm (DFA) based wrapper technique with dynamic alpha parameter in combination with t-test filter feature selection algorithm to find the most relevant reduced subset of features. The aim of reducing feature space is to improve accuracy to classify unseen images as cover or stego and improve speed of the learning system. The proposed work is applied on images generated from four steganography tools nsF5, PQ, Outguess and JPHS. The features extracted are from DCT 274 feature vector as given by Fridrich [3] and DWT 72 feature vectors given by Farid [6]. The proposed algorithm provides insight in the statistical features which provide maximum information about underlying embedding algorithms. The results from improved DFA are compared with Global Best Particle Swarm Optimization (DPSO).

To our knowledge there is no such study that uses discrete firefly algorithm (DFA) for feature selection in Blind Image Steganalysis. The rest of the paper is organized as follows section II explains the hybrid proposed framework of firefly and t-test algorithm, section III describes improved discrete firefly algorithm. Features extracted from DCT and DWT domains are briefly discussed is section IV. Experiment results and analysis are explained in section V followed by concluding remarks in section VI.

II. PROPOSED FRAMEWORK

Blind Steganalysis can be defined as a two class pattern recognition problem. Let's assume that 'm' features are generated from an input feature space F_i where i=1,2…..m and that pattern from F are associated with 'c' classes whose label comprise of the set C={1,2..c}. Since ours is a two class problem C= {1, 2}. Given a training data set (x_i,y_i) i=1…N $x_i \in f$, $y_i \in C$ our aim is to find a classifier f: F->C that exhibits good generalization ability on unseen patterns.
We have employed SVM using Gaussian kernel in our work for training procedure. It is a state-of-the art classification algorithm that has shown to give successful results in pattern recognition. Accuracy of the classifier is taken as the parameter to measure performance of the feature subset thus obtained.

The main steps of this framework can be described as follows:

Input: Training data set and Test set - $X^F \cup Y^F$ Feature space- F with '*n*' features, Cover feature vectors $X^F = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$, Stego feature vectors $Y^F = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n\}$.
Output : Accuracy, Number of features, Computation time, Sensitive features.

1) for i=1 to N where N number of datasets
2) Apply classifier to above data set and obtain the Accuracy
3) Apply DFA feature selection technique
4) Calculate three attributes Acc(i), features(i) and time(i)
5) end for
6) Selectedfeatures(S)=features(1)||features(2)….||features(N,j) // perform logical or
7) //To find most sensitive of these selected features apply t-test technique
8) Rank selected features with t-test filter technique
9) for i=5 to S step 5
10) Calculate accuracy with SVM t-acc(i)
11) end for
12) get the best subset of features (Bs) with max(t-acc(i)) and also index of features
13) Find the frequency of various statistical features selected within Bs(top feature subset).
14) All N training datasets are combined to form a single dataset with selected features only
15) N test sets are applied to find the accuracy with selected features and compared without feature selection.

III. IMPROVED DISCRETE FIREFLY ALGORITHM

Firefly algorithm is a novel stochastic optimization algorithm motivated by social behavior of fireflies. It was presented by Xin-She Yang at Cambridge University [13]. The flashing light of fireflies usually attracts mating. The rate of flashing, the periodic flash, and the amount of time plays a significant role in bringing both sexes together. The firefly's flash is a signal system that attracts other fireflies. The flashing light forms the objective function that is to be optimized.

A. Parameter Settings

For our experiment we have set the parameter values as follows:

i) Alpha parameter controls the randomness and we have defined it as follows for our application of feature selection for steganalysis.

$$\alpha = (1 - \Delta)S_c \tag{1}$$

where

$$S_c = (|\mathrm{f}| - |\mathrm{di}|)/|\mathrm{f}| \tag{2}$$

where |f| is the number of total features, $|d_i|$ is number of selected features in each iteration where i=1……N, N is the total number of iterations, and Δ=0.95.

ii) Gamma parameter (γ) has also been made to depend on the number of features selected in each iteration.

$$\gamma = 1/\sqrt{S_c} \tag{3}$$

iii) Beta parameter – defines attractiveness of one firefly to another. It can be function β(r) can be any monotonically diminishing function such as follows:

$$\beta(r) = \beta_0 \, e^{-\gamma p} \tag{4}$$

where $p=r^m$ (m>=1), $\beta_0 = 1$, γ =1/sqrt(S_c).

The distance between any two fireflies i and j at Z_i and Z_j is the Cartesian distance as follows:

$$r_{ij} = \sqrt{\sum_{l=1}^{d} (Z_{i,l} - Z_{j,l})^2} \tag{5}$$

iv) Position: The new position is calculated as follows:

$$z_i = z_i + \beta(\mathrm{r})\ (z_j - z_i) + \alpha(\mathrm{rand} - .5) \tag{6}$$

v) Objective Function **-** The objective function is a metric that relates to the brightness of a firefly. The brightness can be taken proportional to the value of the objective function for a maximization problem. For our experiments we have taken accuracy obtained through SVM classifier using Gaussian kernel as objective function.

vi) Discretization: The discretization of position of firefly *i* is performed with the help of sigmoid function as given in equation 4.

$$S(z_{il})=\frac{1}{1+e^{-z_{il}}} \qquad (7)\ zij(t+1) = \begin{cases} 1 & if\ r3j(t) < S(zij) \\ 0 & otherwise \end{cases}$$

B. Algorithm

The value of α and γ values are updated with each iteration based on number of features selected. This helps to control the randomness of Discrete Firefly algorithm and move towards target with improved accuracy.

- Calculate objective function for d dimension f(z), $z=(z_1,z_2,\ldots,z_d)^T$
- Initialize a population of fireflies z_i(i= 1,2, . . , n)
- Determine the light intensity Li at z_i by $f(z_i)$.
- Assign values to light absorption coefficient γ, α, β_0, Δ
- while (t<MaxIterations)
- for i=1:m //all m fireflies
- for j=1:i
- if ($L_i > L_j$)
- Move firefly i towards j in all d dimensions applying equation 6
- else
- Move firefly i randomly
- end if
- Apply sigmoid function to change real values to binary form
- Determine new solutions and revise light intensity
- end for j
- end for i
- Rank the fireflies according to light intensity and find the current best
- Calculate the new α and γ values using equation 1 and 3 resp.
- end while

IV. FEATURES EXTRACTED

A. DCT Features

Some embedding algorithms attempt to maintain the statistics of cover medium by minimizing the embedding distortion in order to improve the steganography security, hence appropriate steganalysis features are very crucial for high detection rate.

TABLE I. FRIDRICH's 274 FEATURES

Functional	Dimensionality
Global histogram H_l	11
5 AC histograms h^{ij}_l	5 X 11
11Dual histograms g_{ij}^d	11 X 9
Variation V	1
2 Blockiness B_α	2
Co-occurrence matrix	25

A feature set comprising of 193 features derived from DCT coefficients [1] and 81 features [30] derived from Markov model of DCT plane were able to achieve good performance independently with certain limitations. To overcome the limitation of single feature set method, such as biased detection for different embedding algorithms, the DCT and Markov features were merged to produce a 274-dimensional feature vector [2] and consists of following features.

C. DWT Features

Farid [6] extracted 72 dimension feature set from three level quadrature mirror filter wavelet coefficients. Four statistical moments: mean, variance, kurtosis and skewness are extracted from wavelet coefficient of each nine high frequency subbands, generating 36 features. Another set of 36 features is extracted from predicted errors of nine high frequency subbands to form 72-dimensional feature vector for steganalysis.

V. EXPERIMENT RESULTS AND ANALYSIS

We have performed experiments on two sets of dataset; first by taking dataset obtained by each embedding algorithm independently and second dataset is combination of all training dataset in one and testing with corresponding datasets. The datasets are evaluated for three performance measures a) number of features reduced b) classification accuracy and c) computation time.

A. Dataset

We have prepared an image database with varying image pattern of 2000 jpeg images of resolution ranging from 800x600 and 1024x768. All the images were resized to 640x480 and converted to grey scale. Each cover image is embedded with varying message capacity to generate 2000 stego images using four popular embedding algorithms F5 [18], PQ [19], Outguess [20] and JPHS [20]. Feature vector of 274 DCT features [3] and 72 wavelet coefficient features [6] are extracted from all cover and stego images. Total number of images generated are (4000x4x2) 32000 images.

For all our experiments we have selected 1200 original cover images and equivalent 1200 stego images for training dataset, creating a dataset of 2400 images for 4 embedding algorithm and 2 set of feature vectors (2400x4x2=19200). The remaining 800 images are used to generate test dataset generating a total of 1600x4x2=12800 images with different embedding capacities used to evaluate the performance of the generalized model generated by training dataset.

B. *Evaluation of features reduced*

In our experiments we have first used SVM classifier to train with all 274 DCT and 72 DWT features respectively. We have then applied our improved nature inspired algorithm Discrete Firefly algorithm and compared with optimization algorithm Discrete PSO. The number of iterations for each algorithm is 30 and population size is 25. The various parameters set for DFA are already explained in section III and parameter used for DPSO are as used by original algorithm (Constriction coefficient=2 and inertia weight=1). In all these algorithms fitness function is obtained by training the selected features with SVM [17] Gaussian kernel and averaging the accuracy by 10-cross validation.

The proposed Discrete Firefly Algorithm reduces the DCT features by almost 67% and DWT by 38% as shown in Figure 1(a) and Figure 1(b). However, reduction of features should not be at the cost of classification accuracy.

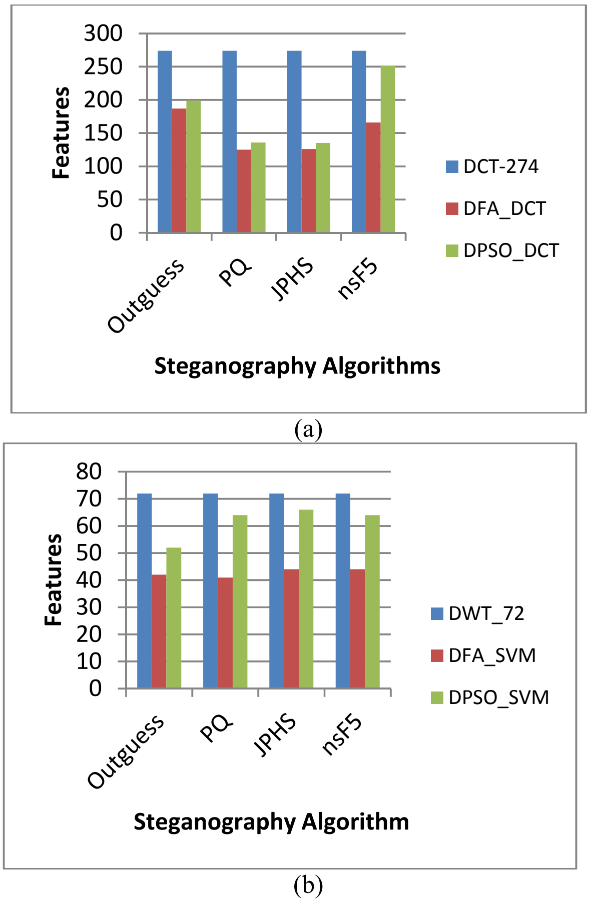


Fig 1. Relationship of features for stego tools (a) DCT 274 features (b) DWT 72 features

C. *Evaluation of Classification Accuracy*

The accuracy of features before performing feature selection and after applying feature selection techniques are as shown in Table II. The proposed discrete firefly is compared with three well known multivariate feature selection techniques a) multiple regression (mLR) [21] b) bhattacharya distance (Bhat) [22] c) mRmR (Minimum Redundancy Maximum Relevance [23].

As observed from Table II using all features does not provide good predictive ability, however it degrades the performance of SVM classifier.

The evolutionary algorithms such as Discrete Firefly, PSO can improve the predictive accuracy by almost 2-8% with a reasonable computational effort and also remove redundant features. SVM being sensitive to irrelevant attributes performs better with reduced feature subset.

D. *Evaluation of Computation Time*

The computation time for both DCT and DWT features is lowest for Discrete Firefly as shown in Figure 2 for four steganography embedding techniques as compared to DPSO.

E. *Effectiveness of DFA with combined dataset*

To test the effectiveness of the proposed algorithm an experiment is performed by combining all four steganographic algorithms and applying most sensitive features found by DFA to the combined dataset. A logical OR is performed on all features selected for all four algorithms using DFA to obtain the feature subset of most sensitive features. The selected feature set is ranked by applying t-test a filter feature selection technique and through forward selection an optimal feature subset is discovered for each steganography embedding algorithm as shown in Table III.

As observed from Table III Accuracy is improved by 5-10% with features selected through our proposed algorithm. We can also observe that nsF5 requires maximum number of features to be detected as compared to other embedding algorithms and JPHS is the weakest of all embedding algorithms.

F. *Selection of Sensitive Feature Subset*

A final experiment is performed to find the most sensitive feature subset. The best accuracy is achieved by top 90 features ranked through t-test for DCT 274 features and 45 features for DWT. The occurrence of different features in top 90 for DCT is as shown in Figure 3(a). As observed Markov features are most sensitive to hidden information. As observed from Figure 3(b) variance statistical moment contribute the most and skewness the least in steganalysis. There is higher percentage of redundant features in DCT feature set as compared to DWT feature set.

TABLE II. COMPARISON OF CLASSIFICATION ACCURACY

	Accuracy DCT – 274			
	Outguess	**PQ**	**JPHS**	**nsF5**
DCT-274	69.6	97.8	70.16	64.2
DFA	**70.4**	**99.2**	**78.6**	**71.1**
DPSO	70.1	98.6	75.3	67.2
mRmr	65.9	96.7	72.3	67.2
mLR	69.3	98.2	73.6	66.6
Bhat	66.5	97.6	74.5	69.6
	Accuracy DWT 72			
DWT-72	66.6	95.6	72.2	60.6
DFA	**67.2**	**98.8**	**77.5**	**66.8**
DPSO	65.6	96.4	74.4	66.2
mRmr	62.5	95.3	73.5	63.4
mLR	66.3	97.4	75.6	65.1
Bhat	65.7	97.3	74.7	64.2

TABLE III. MEASURES OF COMBINED DATASET

	Without FS		**With FS**	
	Accuracy	**Feat**	**Accuracy**	**Feat**
Outguess_DCT	67.4	274	72	70
PQ_DCT	89.8	274	97	45
JPHS_DCT	66.42	274	81.42	40
nsF5_DCT	65.6	274	66.2	90
Outguess_DWT	64.2	72	65.4	45
PQ_DWT	83.6	72	88.7	20
JPHS_DWT	69.5	72	72	30
nsF5_DWT	56.5	72	59.3	35

#FS-Feature Selection, Feat-Features

The experiment results demonstrate that the following three goals are achieved a) proposed algorithm increases correct classification rate b) it reduces the number of features to be trained by classifier c) identifies the most relevant and sensitive features to detect hidden information.

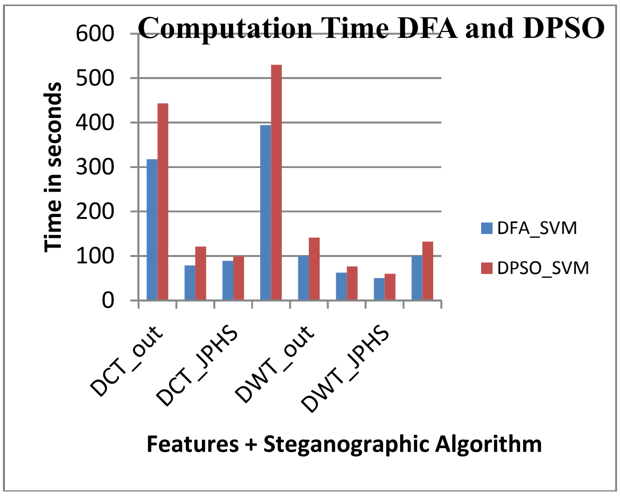
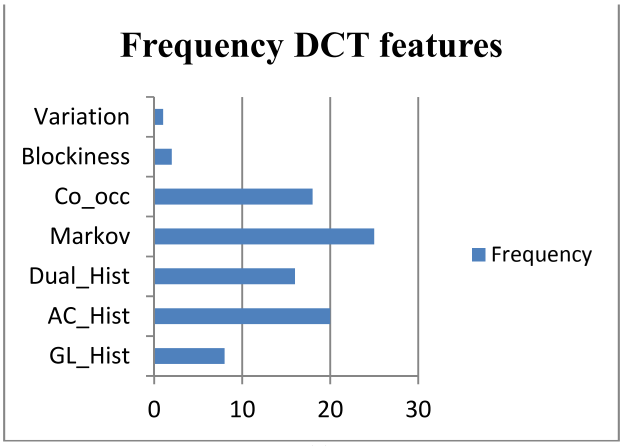
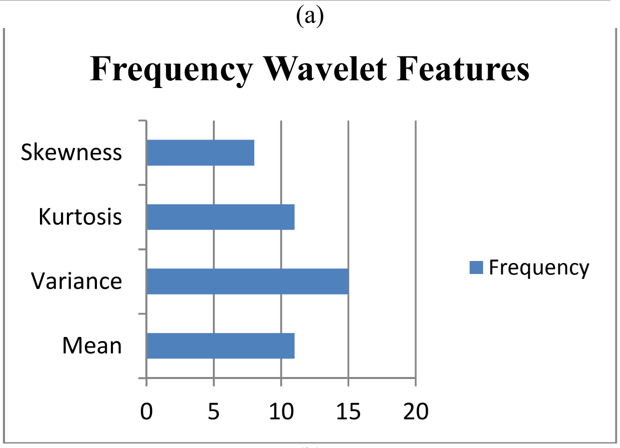


Fig 2. Comparison of Computation Time for DFA and DPSO



(a)



(b)

Fig 3. Frequency of (a) DCT and (b) DWT features after feature selection

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VI. CONCLUSION

We have addressed the problem of image steganalysis in this paper. Various statistical features from DCT and DWT domain have been extracted from the image and used to investigate two stochastic wrapper feature selection algorithms. The experiments are performed for four advance embedding algorithms nsF5, Outguess, PQ and JPHS. A new method for selecting best features set using dynamic discrete firefly algorithm in fusion with t-test filter technique has been proposed that improves the classification accuracy by 4-10% and reduces the features set dimensionality by almost 67% for DCT features and 37.5% for DWT features. It outperforms Discrete Particle Swarm Optimization and well known multivariate feature selection algorithms in terms of classification accuracy. The hybrid approach applied is capable of finding feature subsets which is most sensitive to hidden information. We are able to analyse that the four steganography tools used in our experiments are sensitive to markov features from DCT domain and variance from DWT features. The future scope shall be to analyse the algorithm for high dimensional features such as SPAM and CF*. The firefly algorithm shall be applied in combination with other filter approaches to further reduce the number of features.

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