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Bio-Inspired Computational Algorithms for Improved Image Steganalysis

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Abstract

Acquiring the best image features that best distinguishes a stego and clean image is a challenge in image steganalysis. Though higher order models acquire all these features, they pose problems due to computational complexity in terms of time and space. This demands optimization of the feature sets. Compared to the existing statistical feature optimization techniques, genetic algorithm based optimization techniques are evolving to be more promising. The existing deterministic methods of optimization have the limitation of converging into local minima as compared to the evolutionary methods which tend to converge to the global minima. **Objectives:** This paper intends to review the various genetic algorithm based feature optimization techniques applicable for image steganalysis of JPEG images and identify the best algorithm that converges to global minima. **Method/Analysis:** The methods analysed include the stochastic (metaheuristic) algorithms that make use of the random behaviour of plants and animals. The Antlion behaviour based optimization technique (ALO) has been implemented and analysed for JPEG stego images. The movement of ants are modelled as random walk and the traps built by antlions are assumed proportional to their fitness. The antlions shoot sand outwards to pull the ants inside the pits. This causes sliding down of the ants into the pits to the most minimum position. The coding of the optimization is implemented in Matlab with images taken from the standard BOSS database. **Findings:** The feature set after feature extraction has a dimension of 2000 × 48600 with 1000 cover and 1000 clean images. Considering these vectors as the initial positions of the ants in the Ant Lion Optimizer, for a payload of 0.5 in embedding logic the classification accuracies are studied. The convergence of this optimizer is proved according to the convergence curve for 300 iterations. After optimization, the reduced feature set is used to classify the image as cover or stego image. SVM, MLP and the fusion classifiers - Bayes, Decision template and Dempster Schafer are used. For low levels of embedding changes, the classification by MLP and Fusion schemes is good. For medium and high levels of embedding changes, the classification by Fusion schemes alone is good. It has been identified that the proposed steganalyser gives best results for Bayes fusion classification (69%) scheme when Antlion behaviour is used as optimizer. **Applications/Improvements:** This research has implemented a novel method of image feature optimization that improves steganalysis. The optimized feature set is 100 times less in dimension assuring reduced computational complexity in time and space. Improved version of this research may include a different selection mechanism or using a different optimization function.

Keywords: Bio-Inspired Algorithms, Evolutionary Algorithm, Fusion Classifiers, Stochastic Optimization, Swarm Intelligence

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1. Introduction

Digital image steganalysisis of two types - Embedding specific and Universal. Universal or blind steganalysisis a two class optimized classification problem where the given image is classified as a clean or stego image. Each image acts like a sample point in the feature space. Universal steganalysis considers different types of image features for classification. Literature shows that researchers have used features like image quality metrics[1], wavelet statistics[2], Binary similarity measures[3], higher order image statistics[4], noise residue based features[5], features based on moments of Characteristic Functions Using Wavelet Decomposition[6], statistical analysis of the empirical matrix and the projection histogram[7] and so on. Recent research by J. Kodovsky, J. Fridrich, and V. Holub[8-17] show that steganalysis with rich models (features from 10000 to 30000) created from diverse model are more accurate, but demand proper reduction of feature sets to choose the most appropriate features. Owing to the many possible ways of feature extraction, the need for choosing the most appropriate features has risen. This necessitates the selection of important features by proper feature selection algorithm. Feature set reduction or optimization under steganalysis is a growing field of research. The non stochastic methods of feature reduction used in the recent past include the Principal Component Analysis (PCA) which is a linear method based on the covariance matrix[18]. A special case of PCA, the independent component analysis[19-21] is a non linear method. Unlike these methods which work on the statistical measures, the random projections (Project Pursuit), principal curves, Self organizing Maps[22], and other distance measures based on Euclidean distance, Manhattan distance[19] have been used. Though each of these methods are effective, the problem of local optima convergence prevails in all. To overcome this critical issue, global optimization techniques based on bio inspired algorithms are evolving. This research has presented the various methods of such bio inspired genetic algorithm based optimization techniques for image feature reduction and hence steganalysis.

2. Genetic Optimization

Genetic based optimization techniques are stochastic (metaheuristic) algorithms that make use of the random behavior of animals and plants and use random operators in determining the global minima[23]. The randomization may seem unreliable but these algorithms are good in avoiding local minima compared to deterministic algorithms. These algorithms proceed by setting up random solutions called candidate solutions[24]. These candidate solutions are iteratively improved by approximating to the global optima till a required level of satisfaction. The major advantages of these algorithms are simplicity, avoidance of local minima, independent of problem definition and solution derivation. Most of the evolutionary algorithms consider the problem and solution derivation as black box and use only the problem formulation for evaluating the candidate solutions. Thus evolutionary optimization depends on the given inputs and obtained outputs and not on the nature of the problem.

3. GA based Optimization Algorithms

3.1 Fire Fly Algorithm

The firefly algorithm is based on the flashing behavior, whose primary aim is to attract other fireflies. The flash pattern is short and rhythmic[25,26] and differs for different fireflies. These flashes are used by the fireflies to communicate and attract potential prey. Based on this behavior, a metaheuristic local search algorithm has been developed where; the brightness is associated with the objective function. The three rules that govern the movement of one fireflyto another and hence the optimality conditions are - the fireflies are unisex insects and they move towards more brighter flies, the brightness of the flash is directly proportional to the degree of attractiveness, brightness is directly dependent on the objective function[27]. The optimization problem considers two points - the variation in light intensity and the formulation of attractiveness.

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary global optimization technique. According to the perception of the environment, each agents in the swarm adopts stochastic behavior and undergo unsupervised learning. The four vectors (solutions) include, the current position, the best possible position, the best possible position of the neighborhood and the velocity of the particle. The objective function is defined in terms of the best possible positions. Combined with the superior performance of Support Vector Machines (SVM), PSO provides better classification accuracy[20]. A variant of PSO, the Genetic Quantum Particle Swarm Optimization (GQPSO) was used by Gong[21] to reduce the attributes in network intrusion detection. GQPSO extracts the combined normalized mutual information between the attributes and hence is more efficient. Guoming Chen et al., have worked on decomposition of an image into 12 sub bands[22] (4 sub bands in a three level Haar transform). Along with the original image, 13 sub bands are used to derive 39 features, with the first three moments of characteristic functions they show that detection rate of PSO based steganalysis is high compared to original methods.

3.3 Harmony Search Algorithm

Harmony search algorithm is a stochastic based evolutionary algorithm used by the musicians to build a new note based on the near optimal solution. HS algorithm can be easily implemented with very few parameters which act as the musical notes. The solution that maximizes optimization criteria is the harmony chosen. Harmony search algorithm along with the SVM has been used for image steganalysis[23]. The harmony memory is updated when a new harmony is better than the worst harmony. Generation of a new harmony memory depends on parameters like pitch, randomization and memory considerations. The consideration rate of Harmony memory (HMCR), depends on the probability of choosing one value from the historic stored values in harmony memory.

3.4 Binary Encoded Genetic Algorithm

Reduction of JPEG features by Binary Coded Genetic algorithm led to improved feature selection and classification[24]. The optimal feature subset was based on defined number of features. The genetic operations executed on parents resulted in child binary strings with better chances of accuracy for JPEG steganalysis. Here the string or solution gives the number of optimal features. Each string evaluates according to the objective function (fitness function). The best solution (string) is identified by the survival of the fittest principle and next generation is created. The generation creation continues until convergence. A binary value of 1 means that the feature participates in evolution and if the binary value is 0 then that feature is removed. A hybrid crossover operator gives diverse offspring. Vasily Sachnev[24] use uniform crossover and two point crossover to generate eight offspring for a pair of parents. The best pair among these will replace their parents. Their proposed BCGA algorithm was able to search the optimal number of features and the optimal feature set.

3.5 GA based Regression

Xiao Yi Yu and Aiming Wang[25] have proposed a genetic algorithm based logistic regression model for classification of stego and clear images. Their model involves transform selection and feature selection followed by regression model. The entire model is controlled by the genetic algorithm. Each feature is coded as a gene in the model[25]. The gene coding process involves coefficient generation by selection, indexing and transformation methods. Cloning, crossover, mutation and evaluation are the processes in evolution. The steganographic techniques used for testing were generic LSB, non blind spread spectrum method[26], adaptive LSB[27], random ± 1 embedding[28], DCT block SS method[29] and generic quantization index modulation method[30]. The candidate features used were the higher order statistics like Empirical Matrices (EM) and Characteristic Function (CF). Their results show that the genetic classification gives the best accuracy compared to fusion classifiers.

3.6 Bee Colony Algorithm

The artificial Bee Colony (ABC) optimization divides the colony of bees into three categories - employee bees, onlooker bee and scouts. Each employed bee is assigned a food source where it is assumed to dance and those whose food source is abandoned turn into a scout which hunts for new source of food. If the nectar in new food source is higher than that in the old source, the scout bee forgets the old source and it memorizes the new location[31]. The choice of food sources by onlookers is based on the probability of dancing associated with that food source.

3.7 Ant Colony Optimization

The ant colony optimization is a metaheuristic algorithm to detect the shortest path. The optimal solution is obtained by use of previous knowledge and local heuristics. The real ants leave a substance called pheromone to mark the shortest path that was travelled towards food source. Any ant in random space detects this odorous pheromone to identify the shortest path. Each ant traversing through that path leaves additional pheromone and hence the probability of an ant choosing a path is directly proportional to the number of ants that have already chosen that path. While these algorithms aim at optimizing the path, optimization of features from a feature set is proposed by Al Ani[32]. He proposes a wrapper evaluation function and a mutual information evaluation function to estimate the performance of the optimized feature sets.

3.8 Ant Lion Optimization

The Antlions or Doodlebugs are net-winged insects which hunt their prey during their larvae stage. These larvae dig a cone shaped pit in sand by circular movement and to a pointed bottom to trap the prey. Once a prey (an ant) gets trapped in, the antlion catches the prey. The ALO algorithm considers the movement of the ants as data in random space and the hunting by the antlions as the fitness function. The movement of the ants are modeled as random stochastic walk in search of food. The position of the ants are the variables for optimization. The fitness function is used to evaluate each ant. Also the position of the hiding antlion and their fitness are evaluated[33]. The conditions for optimization are

- Random walks are considered for the movement of the ants and the antilions.
- The pits built by antlions is proportional to their fitness level (larger the pit, larger the probability of the antlion catching a prey).
- The elite antlion catches an ant in each iteration
- Fitter ants are assumed to be caught by the antlions.
- The antlions reposition themselves to the position of the latest prey and again start building pits.

4. Proposed Steganalyser Framework

This section presents the implementation of the proposed optimized image classification for steganalysis. The implementation and analysis of problem is segmented into four stages.

- Creating steganographic images from raw images: The modified F5 (non shrinkage F5) steganographic algorithm is implemented to create stego images. The stego images are obtained for different PRNG seed (embedding capacity).
- Extracting the image features: The 48600 features (24300 uncalibrated and 24300 calibrated) features of DCT coefficients in JPEG domain.
- Optimizing the image features by ALO: Implementation of the Antlion Optimizerto get optimized features of the images.
- Classifying the optimized features: Ensemble based classifiers which combine SVM and MLP and their fusion by Bayes, Decision tree and Dempster Schafer schemes are used.

4.1 Image Data Base

The images used in this research were acquired from BOSS (Break Our Steganographic Systems) database [34]. These are raw images in two different data sets, the BOSSBase and BOSSRank. The BOSSBase has 9074 uncompressed images acquired from 7 different cameras. This data base is declared for public usage by Steganalysers. Full resolution images in raw format were taken from different cameras like Canon EOS, Leica, Panasonic, NIKON and Pentax. These images are resized and cropped to get 512x512 images[34]. For our research 1000 images from BOSSBase were converted into JPEG images by MATLAB code with quality factor of 75. These 1000 cover images (clean images) are further subjected to steganographic embedding to create another 1000 images (stego images). This provides a data set of 2000 images for optimisation and classification.

4.2 Creating Steganographic Images from Raw Images

The steganographic embedding scheme implemented is the modified F5 algorithm. The original F5 algorithm[35] embeds the secret information in non zero AC coefficients of the DCT parameters of image. If a coefficient becomes zero (shrinkage effect), the information is re-embedded into next non zero coefficient. Even though F5 algorithm uses the syndrome coding or matrix embedding scheme to increase embedding efficiency, the effect of shrinkage limits the embedding capacity. The embedding capacity is ‘s’ bits in every ‘2s-1’ pixels. To avoid this shrinkage, nsF5 (non shrinkage F5) was developed. Based on wet paper codes, nsF5 uses syndrome coding similar to matrix coding which uses a binary matrix of order ‘s x m’. nsF5 provides higher embedding efficiency than F5 by reducing shrinkage. This nsF5 embedding logic has been

A. Few of the raw images (from BOSS datbase) used in research

implemented in this research work using MATLAB code and stego images have been created for different values of AC DCT coefficients in JPEG domain.

4.3 Feature Extraction

Since embedding uses JPEG domain, the extracted features are the DCT features and their dependencies in JPEG domain. The features chosen include the combined calibrated features of Markov and DCT features used by Kodovsky and Fridrich[36]. The extended version of this feature extractor extracts the co-occurrence matricesfor every pair of DCT mode based on 6 parameters. A pair of DCT coefficient is defined as

$$Q(\Delta i,\Delta j,k1,l1,k2,l2)=\{[A^{(i,j)}]k1,l1::[A^{(i+\Delta i,j+\Delta j)}]k2,l2 \tag{1}$$

where, Δi, Δj, k1, l1, k2, l2 are the 6 parameters, $[A^{(i,j)}]_{k1,l1}$ is the (k,l)th DCT coefficient in the (i,j)th block (k,l) vary from 0 to 7. (i) varies from 1 to M and (j) varies from 1 to N for image of dimension M × N. The algorithm also considers truncation of the coefficients $[A^{(i,j)}]_{k1,l1} = \mathrm{trunc}_Z([A^{(i,j)}]_{k1,l1})$. $\mathrm{trunc}_Z(x) = x$ where $x \in [-Z, Z]$. Thus the extended algorithm calculates the inter-block dependencies in terms of the co-occurrence matrices as

$$CC=\frac{1}{N(i)N(j)}\sum_{i=1}^{N(j)}\sum_{j=1}^{N(j)}|\{[a,b]\in Q(\Delta i,\Delta j,k1,l1,k2,l2)\,|\,a=s,b=t\} \tag{2}$$

A systematic construction of the co-occurrence matrices is done based on the significance of the mutual information on a set of DCT coefficients from two modes. For a fixed value of truncation constant, each pair of DCT mode gives a co-occurrence matrix of dimension 81. For all possible 'P' pairs, the combined co-occurrence matrices has a dimension P × 81. When subjected to calibration, the dimensionality doubles yielding 2 × P × 81. This final feature set is a rich set of dimension 48600 × 1 for each image. This set of features is universal and are independent of any specific embedding technique. The embedding invariants when correlated with the disturbed cover image statistics may be useful for universal steganalysis.

4.4 The Ant Lion Optimizer

As indicated in previous section, the extracted rich set of features may lead to more accurate classification of stego images against cover images but at the cost of computational complexity. This time space complexity in computation has been challenged by many statistical methods but not as good as bio- inspired methods. These nature inspired meta-heuristic algorithms as discussed in section 3, enable to get a reduced set of optimal values from a random search space. This research work has implemented the Ant Lion Optimization algorithm discussed in section 3.8. The implementation has considered the following operations

The walk of ants is random in search space and hence is modeled by

$$Y(t) = [0, CS(2a(t_1)-1), CS(2a(t_2)-1), \ldots CS(2a(t_n)-1)] \quad (3)$$

where 'a' is a stochastic function, 't' is the step size of random walk, 'n' is the number of iterations and 'CS' is the cumulative sum. A sample random space walk for a chosen feature vector is shown in Figure 1. This corresponds to the feature vector of the first stego image generated with a payload of 0.5 and a PRNG seed of 19 (random choice of DCT coefficients for embedding).

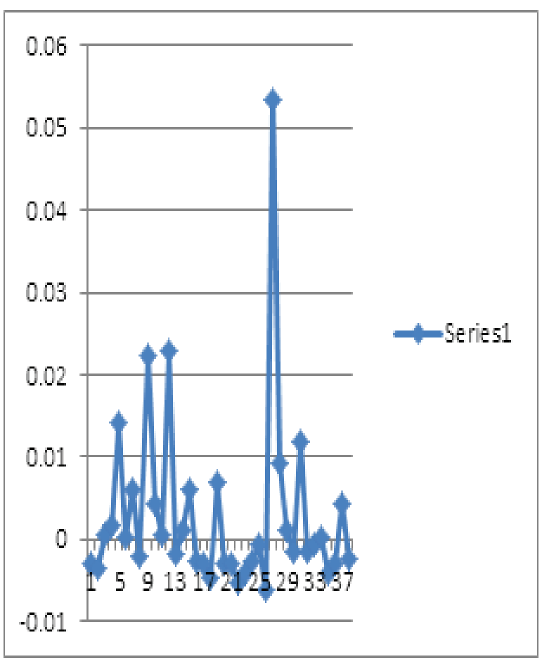


Figure 1. Sample Random walk of Ants and Antlions (Feature vector to be optimized).

The movement of the antlions in search of ants is also considered as random as that of the ants and the position of these antlions correspond to the particular solution during optimization. The fitness values of the antlions are stored in each iteration in matrix form.

$$OP = \begin{bmatrix} f(A1,1 & A1,2 & A1,m) \\ & \vdots & \\ f(A2,1 & A2,2 & A2,m) \\ (An,1 & An,2 & An,m) \end{bmatrix} \quad (4)$$

Where $A_{i,j}$ is the j[th] dimension of the i[th] ant in the search space, OP is the fitness values of antlions, 'f' is the objective function used for optimization.

The trapping of the ants in the antion's pits is modeled in terms of two parameters MN and MX. MN corresponds to the minimum of all the variables in an iteration and MX corresponds to the maximum of all the variables in an iteration. These are mathematically depicted as

$$MN_i^t = antlion_j^t + MN^t \quad (5)$$

$$MX_i^t = antlion_j^t + MX^t \quad (6)$$

Here $antlion_i^t$ shows the position of the chosen j[th] antlion in t[th] iteration. These equations show the random walk of ants around a selected antlion in a hyper sphere according to the values of MN and MX.

The traps built by antlions are proportional to their fitness and the antlions shoot sand outwards to pull the ants inside the pits. This causes sliding down of the ants into the pits to the most minimum position possible in each iteration. This iterative decrease in the step size of the random walks is modeled as

$$MN_i^t = \frac{MN_i^t}{I} \text{ and } MX_i^t = \frac{MX_i^t}{I} \quad (7)$$

Here I = 10 t/T, 't' is the current iteration number and 'T' is the maximum number of iterations. These equations mimic the reducing search space of an ant inside the pit and assures sliding down to most optimal (global minima) position. The most optimal value corresponds to the hunting position of the elite antlion. The reducing search space is represented in terms of the best optimal positions (solutions) in each iteration.

Thus the Antlion Optimizer gives the optimally reduced set of image features by correlating the original (high dimensional) feature set to the random search space of ants and the antlions. The reduced features are the optimal best solutions after the maximum number of iterations. In our research, the high dimensional feature set has 48600 features which are reduced to 486 features after Antlion optimizer.

4.5 Classifier Framework

Classification is the most crucial part in steganalysis as it decides whether an image is true (clean) image or stego image. We have implemented two main classifiers SVM and MLP and fused versions of them. SVM (Support Vector Machine) is a powerful classifier and works under the principle of non-linear mapping, where the input vectors are mapped to high dimensional feature space. MLP (Multi Layer Perceptron) is another popular pattern recognition or classification network. MLP is a powerful classifier working under the principle of back propagation training[37]. MLP also has many free parameters so that the input associates with high output response[38]. Owing to their high performance, we intend to choose SVM and MLP classifiers. We opted for fusing SVM and MLP classifiers with three different fusion schemes, namely Bayes method, Decision Template scheme and Dempster Schafer method. The accuracy of these fusion methods have been studied to identify the best method suitable for image steganalysis.

5. Analysis of Results

The combination of clean and stego images after feature extraction is a feature set of dimension 2000 × 48600 since 1000 cover images and 1000 stego images are considered for analysis. These are considered as the initial positions of the ants in the antlion optimizer. The reduced feature set has 2000 × 486 features. The analysis for a payload of 0.5 and different values of PRNG seed in the embedding logic shows the classification accuracy for the individual and fusion classifiers as in Table 1.

The performance of the optimizer shows the optimal solutions in the search space as in Figure 2. The most elite antlion position is at the global optima as in Figure 2 where the minimum and maximum boundary values of features are considered as -100 and +100.

The convergence of this optimizer is proved according to the convergence curve for 300 iterations. The optimization function shows the convergence to global minima rather than local minima. After optimization, the reduced feature set is used to classify the image as cover or stego image. The classifier performances are illustrated in Table 1.

The performance measure used to compare the classifiers is 'Classification Accuracy'. The percentage of correct prediction is called as classification accuracy and is calculated as, Accuracy = (TP + TN)/(TP + TN + FP + FN), where TP is number of True Positive, TN is number of True Negative, FP is number of false Positive and FN is number of False Negative. For low levels of embedding changes, the classification by MLP and Fusion schemes is good. For medium and high levels of embedding changes, the classification by Fusion schemes alone is good.

Table 1. Classification Accuracies of the Proposed Steganalyser

Original Feature set size	Optimized Feature set size	Payload during Embedding	PRNG seed during embedding	SVM	MLP	Bayes	Decision Tree	Dempster Schafer
2000 × 48600	2000 × 486	0.5	19	0.2778	0.6389	0.6667	0.6111	0.5833
			55	0.3611	0.4722	0.5556	0.5833	0.5000
			80	0.4444	0.4444	0.5278	0.4444	0.4444
			99	0.3333	0.4167	0.5833	0.5278	0.5556
			150	0.2222	0.3333	**0.6944**	0.6389	0.7222
Average Classification Accuracy				0.32776	0.4611	**0.60556**	0.5611	0.5611

Comparison of the classifiers shown in Figure 3 depicts Bayes classifier as the best.

Based on the above results, it can be seen that the proposed steganalyser gives best results for Bayes fusion classification (69%) scheme when Antlion behaviour is used as optimizer.

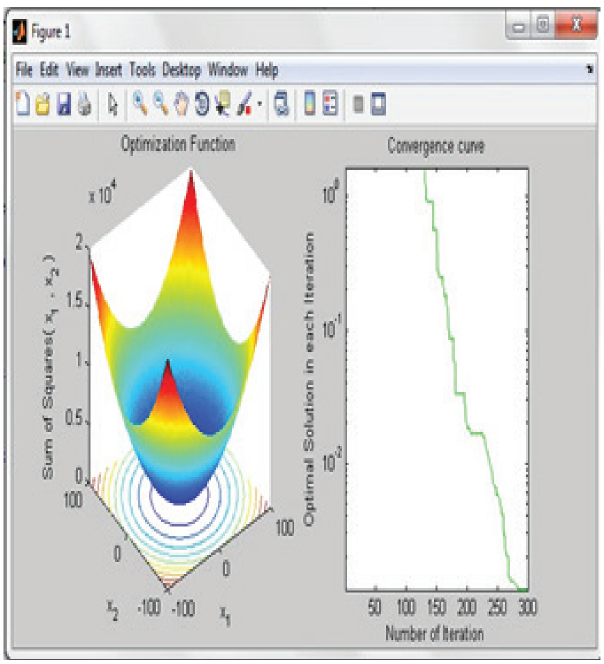


Figure 2. Optimization function and Convergence of Antlion Optimizer.

6. Conclusion

As genetic algorithm based optimization techniques are fast emerging, this paper has reviewed their application to image steganalysis. The most common methods of bio-inspired algorithms tend to optimize the feature sets, hence they can be applied for reducing the parameters of image models in image steganalysis. The algorithms discussed in this paper include the fire fly algorithm, Particle Swarm Optimization, Harmony Search Algorithm, Binary Encoded Genetic Algorithm, GA based Regression, Bee Colony Algorithm, Ant Colony Optimization. Among these Particle Swarm Optimization and Binary Encoded

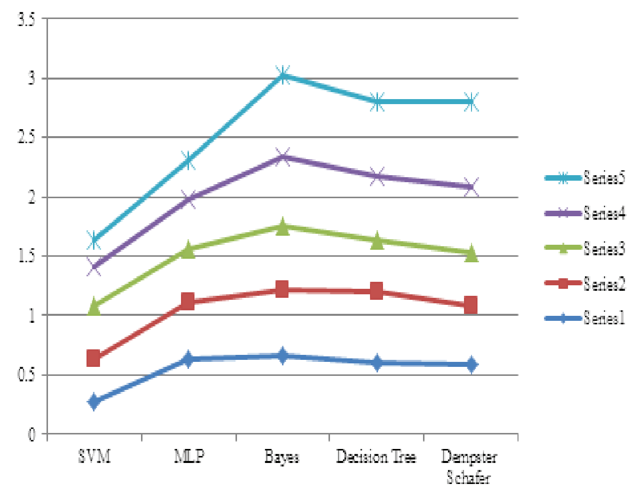
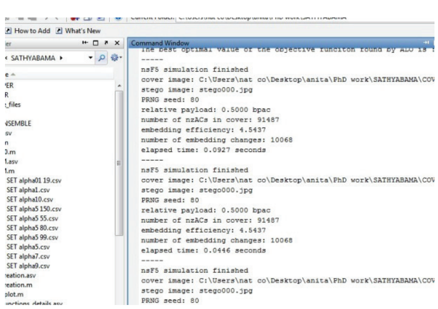
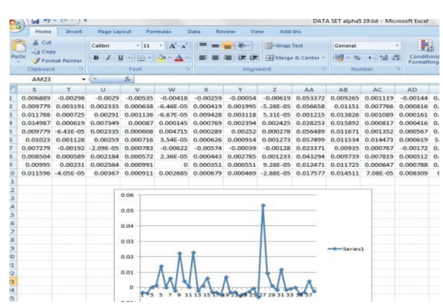


Figure 3. Comparison of classifiers for the data set.

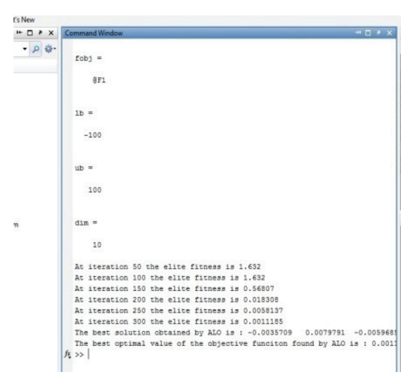
B. Simulation Results



Matlab output for embedding logic



Sample of data set extracted from images for optimization



Matlab output of Optimizer

Genetic Algorithm have been already applied for image steganalysis. The most promising algorithms are Ant Colony optimization, Artificial Bee Colony optimization and Antlion optimization. The Antlion optimizer has been implemented in Matlab and verified by optimizing the original feature set of 48600 features to 486 features. This reduction in feature set enables easy and good classification by MLP and Bayes fusion classifiers with best classification accuracy. This research proves that Bio-inspired optimization algorithms like ALO can best support in accurate image steganalysis.

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