ISEA: Image Steganalysis using Evolutionary Algorithms

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Abstract— NP-hard problems always have been attracting scientists’ attentions, and most often seen in the emerging challenging issues. The most interesting NP-hard problems emerging in the world of data science is Curse of dimensionality (CoD). Recently, this problem has penetrated most of high technology domains like advanced image processing, particularly image steganalysis. The universal and smarter steganalysis algorithms provide a huge number of attributes, which make working with data hard to process. In large data sets, finding a pattern which governs whole data takes long time, and yet no guarantee to reach the optimal pattern. In general, the purpose of the researchers in image steganalysis stands for distinguishing stego images from cover images. In this paper, we investigated recent works on detecting stego images, particularly those algorithms that adopted evolutionary algorithms. Thus, our work is categorized as supervised learning which consider ground truth to evaluate the performance of given algorithm. The objective is to provide a comprehensive understanding of evolutionary algorithms which are attempted to solve this NP-hard problems.

Keywords: Image steganalysis, Image classification, Feature extraction, Feature selection, Curse of dimensionality, Dimension reduction, NP-hard problem, Data science

1. Introduction

Last two decades, in this world of technologies, the majority of communication goes through the magic of Internet. Upon developing technologies, it is totally obvious that internet users prefer friendly technologies to ease their life, such as planing, contacting friends, talking online, sending E-mail, etc. By increasing the users and the advanced technologies, the risk of third party spying has proliferated. Researchers believe that having secure data communication has the highest priority \textsuperscript{11}. Moreover, the number of generated data has increased significantly which generates high dimension problem, curse of dimensionality (CoD), and is required to be analyzed deeply which needs a long time and is not sufficient yet. Scientists have found the CoD problem as a NP-hard problem \textsuperscript{2, 3} and attempted to solve it. Thus, detecting the suspicious files, which includes embedded messages or images, plays an important role in the world of steganalysis and steganography. Further, enhancing this process of detecting versus decreasing the number of required features becomes a challenging issues in data science. Although research studies have been done on offline data sets to improve the process and attempted to solve the NP-hard problem, scientists are looking for to propose a process to do the same process online and real-time. In this study, we provide the research studies and proposed methods which have attempted to improve the process and solve the NP-hard problem.

Curse of dimensionality (CoD) are generated upon extracting or gathering too much information. In general speaking, the more information we have, the better and more accurate training model we may have \textsuperscript{4}. However, the large number of features (information) that can be extracted from a single image could be problematic. This richness of features is known as the curse of dimensionality (CoD). It makes our data to have redundancy or poor data available Steganography is an advanced skill and communication method that allows the hidden secret messages to be sent through an innocuous covert multimedia \textsuperscript{5}. The most appropriate covert multimedia involves images, audios, videos even text files, or internet protocols \textsuperscript{6}. The cover multimedia, when the secret messages are embedded into them, turn into stego multimedia which is a practical example of suspicious files. The idea behind this is that the stego covert multimedia and the related cover must look as identical as possible, otherwise the risk of attack is likely. Thus, the goal of steganography is always to conceal the embedded data (messages or images), and then technically to consider professional criterion,PSNR, to accept a single steganography algorithm.

Steganalysis is an highly skilled art and advanced science to detect stego images. It has been considered a challenging issue lately, however, researchers have tried to solve the problems\textsuperscript{7, 8}. First, researchers extract important features based on preferred extraction strategies \textsuperscript{9, 10, 11}. The goal of these features is to provide a distinguishing border between stego images and cover images. After that, researchers adopt machine learning algorithms to make a proper model to predict stego images from cover images. Concretely, the second part will not yield a better accuracy unless the related and proper features had extracted in the first part.

1.1 Motivation

Having large amount of extracted features, steganalysis suffers from the curse of dimensionality problem, which stands as one of the challenging points. As a matter of fact,
extracting important features play the main role in steganalysis. Lately, a large number of research studies are proposed to improve steganalysis performance with a huge number of features like CC-C300 with 48600 features[7], PHARM with 12600 features [8]. Further, researchers have attempted to propose a new universal (blind) approach, which is a technique to detect stego images that are manipulated by an unknown steganography algorithm. In other words, universal approach avoid analyzing specific steganography algorithm. So, the goal of universal approach stands for discovering hidden messages with the presence of an unknown steganography algorithm. In spite of considering the universal approach, it has a big drawback, the number of features has proliferated exponentially during the feature extraction (FE). This approach adversely affect machine learning algorithm by making it difficult to learn the model, and training process takes quite a long time which yields a high time complexity problem. Moreover, there is a high chance of increasing the correlations among features. The higher correlation probably causes classifier to face problem of well or bad training, which called an over-fitting or under-fitting problem respectively. The generated model will also not be able to predict test data correctly. Researchers have proposed several approaches [12][13] to solve this problem and train classifier to learn properly. 

Recently, a large number of methods have been proposed for steganalysis. Some research studies rely on deep learning [12] which tries to enhance the detection accuracy while considering high dimensional images. Broroumand et. al [5] proposed a new convolutional neural network (CNN) architecture called SRNet for steganalysis. SRNet is the first steganalysis network that is independent of many introduced design elements proposed lately. However, although deep learning enhances the performance of steganalysis significantly, it still keeps high time complexity issues. A long side of deep learning, Evolutionary algorithms (EA) [13] have been proposed for steganalysis and improve the performance of steganalysis better than deep learning. EA provides a new environment that steganalysis remains as low time complexity as possible. Researchers adopted evolutionary algorithms for a wide variety of purposes in steganalysis like : feature selections, the most probable sub-images in spatial domain, etc.

Evolutionary algorithms is one of the young computational algorithms which was invented not more than 28 years.[13] A large number of techniques have been proposed as an evolutionary algorithm. In this study, we focus on those evolutionary algorithms, have attempted to improve steganalysis such as Artificial Bee Colony (ABC) [14] , Particle Swarm Optimization (PSO) [15], Firefly Algorithm (FA) [16] and Grey Wolf Optimizer(GWO) [12]. The common processes among the evolutionary algorithm includes population initialization, Cross-Over and reproduction, fitness calculation, competition and selection of the best individuals out of population and Mutation.[18] This process is repeatedly computed until the condition satisfied or the loop ended.

1.2 Organization

After introducing the domain, problem statement and possible solutions. In the rest of this paper, we are eager to focus on aforementioned evolutionary algorithms in detail as follows. In section 2, we will give general structure of image steganalysis using evolutionary algorithm. In the next section, we will dig into the Artificial Bee Colony and it’s application to steganalysis. Then, we will work on Particle Sawrm Optimization. After that, in section 6, we will focus on Firefly algorithm. Section 7 provides another evolutionary algorithm, Grey Wolf Optimizer, and presents related works with respect to steganalysis. Section 8 discusses the common generated data sets in research studies. Finally, we summarize this paper in section 9. Figure [1] presents the overall view of this study in detail which clarifies the sections of this paper.

2. Image steganalysis using evolutionary algorithms

Recently, Researchers sought to find a way to optimize the process of steganalysis particularly in image domain. After all, they obtained a successful results which will be discussed in this study. The general overviews of the combination of evolutionary algorithm and steganalysis are shown Figure [2].

As mentioned in the introduction section, researchers attempted to solve CoD problem using evolutionary algorithm. The goal of applying EAs is to minimize the number of feature dimension as small as possible with respect to the performance. The evolutionary algorithms, which are used to solve the problem, tend to decrease the number features. The new feature dimension is accepted if the performance of
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steganalysis preserves the performance or improve it. Evolutionary algorithms most likely choose the feature dimension, which yields the higher performance in comparison with other feature dimensions. This study keeps technical and complex words more often. So, in order to provide an easy way to understand the terms and algorithms, Table 1 provides all abbreviations have been used in this study.

3. Image steganalysis using artificial bee colony

The idea of artificial bee colony (ABC) algorithm has been developed by Karaboga [14], which is a more likely suitable for continues and discrete optimization problems. ABC algorithm is a powerful optimization algorithm, which simulates the foraging behavior of honeybees to find the best food source. ABC works based on three types of bees. One employed, one onlooker, one scout. ABC starts by employed bee then onlooker for cross over, after that scout starts his task based on "limit". Limit plays an important role for scout which allows scout to find a new source and update the solution. ABC runs up to the limit condition satisfied. So, one of employee bees that their work ended, converted into scout. Note that, in each iteration, we only have a single scout on specific condition satisfactory with respect to limit. Scout does like mutation and limit looks the probability of mutation. In a given algorithm always the number of employed bees are the same as onlooker bees which the sum of them equals to the population. Researchers have proposed a new customized version of ABC to solve their problems. There are plenty of ABC applications particularly for image processing in [19], [20], [21], but not limited to those. Simplicity, flexibility, robustness and ability to explore local solutions are the reasons that ABC looks more probable a popular algorithm. The most important advantages of ABC is it's power to solve any problem, and simplicity which stands for the minimum number of parameters to be tuned. Therefore, ABC seems to be far better than other evolutionary algorithms like Genetic Algorithm (GA). However, ABC suffers from lower convergence rate in sequential processing and not quite fast to compute precise solutions. These are the reasons that ABC may not obtain the best food source.

Ghareh Mohammadi and Saniee Abadeh in [19] proposed a new steganalysis method named IFAB, which helps steganalysis to enhance the performance of distinguishing stego images from the cover images. Authors adopted a wrapper-based feature selection technique by customizing the original ABC into discrete ABC algorithm. ABC selects the feature subsets, and a classifier is employed to evaluate every feature subset generated by the algorithm. According to the study in [19] would be considered the beginning of applying evolutionary algorithm on steganalysis according to the published date, other related papers published after this paper and referenced this paper. IFAB significantly minimized the feature dimension and selected 80 features out of 686 SPAM attributes. IFAB also shrinks the CC-PEV feature dimension properly by selecting 250 features out of 548. The final accuracy of IFAB is 60.98 and 68.22 for SPAM and CC-PEV data set, respectively.

Ghareh Mohammadi and Saniee Abadeh in [21] presented an improved evolutionary algorithm approach for image steganalysis to enhance IFAB, named IFAB-KNN. IFAB-KNN also provides a wrapper based feature selection algorithm. k-Nearest Neighbor (KNN) is an embedded machine learning algorithm within ABC and helps ABC to evaluate each subsets of features carefully. Concretely, KNN plays a main role as a fitness function for evaluating subset features in ABC. IFAB-KNN outperforms IFAB with the new updated tuning parameters while it keeps the same number of selected features at the end.

Ghareh Mohammadi and Saniee Abadeh in [20] presented a new hybrid approach to steganalysis named, region based Image Steganalysis using Artificial Bee colony (RISAB). RISAB enables ABC to search in image space, particularly spatial domain, to find the most probable sub-image which carries the hidden messages. As a matter of fact, the likelihood of embedding messages in sub-image which provides the best amount of intensity and energy, which are greater than other parts of given images. RISAB is a combination of applying IFAB over whole image, and a sub-image which is selected by ABC. The goal of paper is to investigate whole images to seek for such a sub-image. Then, they extracted features twice. First, they extracted features from whole given images. Second, they extracted the same features from the sub-image which is found in earlier phase. The features are the same features which IFAB [19] presented that are the best subset for SPAM and CC-PEV. Having extracted the features, They made a data set of both extracted features. This new data set visualizes instances in a proper way that classifier will be able to train and make a model what covers
Table 1

| Abbreviations | Definition |
|---------------|------------|
| General       |            |
| AUC           | Area Under Curve |
| EA(s)         | Evolutionary Algorithms |
| FS            | Feature Selection |
| FE            | Feature Extraction |
| SVM           | Support vector machine |
| KNN           | K-Nearest Neighbor |
| LSBR          | LSB Replacement |
| LSBM          | LSB Matching |
| LSBMR         | LSBM Revisited |
| LSBR2 or 2LSB | Two bit LSBR |
| LSBRmod5      | Modulo 5 LSBR |
| SW            | Similarity weight |
| AUC           | Area Under Curve |
| Nature-inspired |            |
| ABC           | Artificial Bee Colony |
| PSO           | Particle Swarm Optimization |
| FA            | Firefly Algorithms |
| GWO           | Grey Wolf Optimizer |
| Proposed EA.  |            |
| IFAB          | Image steganalysis using FS based on ABC |
| IFAB-KNN      | IFAB-K-Nearest Neighbour |
| RISAB         | Region based Image Steganalysis using ABC |
| DyFA          | Dynamic firefly algorithm |
| APSO          | Adaptive inertia weight-based PSO called |
| LFGWO         | Levy Flight-based Grey Wolf Optimizer |
| GRASP-BGWO    | Greedy Random Adaptive Search |
| GLBPSO        | Global Local PSO |
| ASPO-AUC      | Adaptive inertia weight-based PSO called- AUC |
| Steganography |            |
| LSB           | Least Significant Bit |
| Feature Extractor |        |
| SPAM          | Subtractive pixel adjacency matrix |
| CC-PEV        | Cartesian Calibrated features extracted by PEVny |
| SRM           | Spatial Rich Model |
| PSRM          | Projected SRM |

Table 2

| Paper | Evolutionary algorithm | Proposed method | Year |
|-------|------------------------|-----------------|------|
| [19]  | Artificial bee colony  | IFAB            | 2014 |
| [21]  | Artificial bee colony  | IFAB-KNN        | 2014 |
| [20]  | Artificial bee colony  | RISAB           | 2017 |
| [23]  | Particle swarm Optimization | HYBRID   | 2016 |
| [24]  | Particle swarm Optimization | APSO   | 2018 |
| [25]  | Particle swarm Optimization | PSO-AUC | 2016 |
| [26]  | Particle swarm Optimization | GLBPSO  | 2017 |
| [27]  | Particle swarm optimization | Mi-APSO | 2018 |
| [28]  | Firefly algorithm      | DyFA           | 2018 |
| [29]  | grey wolf optimizer    | GRASP-BGWO     | 2019 |
| [30]  | Grey wolf Optimizer    | LFGWO          | 2019 |

whole instances. Authors considered either given images and a certain part of images. This is the reason, this approach outperforms IFAB. The final data set for SPAM and CC-PEV involves 160 and 500 features respectively.

Ghahreh Mohammadi and Saniee Abdeh were capable of applying professionally ABC on two different areas: one data, one spatial domain. They proposed two new methods: IFAB and RISAB. Both of them significantly increased the performance of steganalysis with respect to their dimension reduction properties.

4. Image steganalysis using particle swarm optimization

Particle Swarm Optimization (PSO) \cite{15} is an optimization method to solve non-linear optimization problems, presented by Kennedy and Eberhart. PSO is inspired by the behaviour of a flock of birds or fish swarms. Authors attempted to propose a new version of PSO to solve optimization problems \cite{23, 24}. In this section, we investigate the papers which have adopted PSO for steganalysis.

Chhikara \textit{et. al} \cite{23} proposed a new hybrid approach using PSO for steganalysis named HYBRID. They proposed a hybrid filter and wrapper based feature selection approach to deal with the computational complexity in image steganalysis. Authors examined their approach for attacking different steganography algorithms. The customized PSO improved the classification accuracy of detecting stego images and cover images. Not only it improved the performance, but also it reduced time complexity too. Authors enhanced the accuracy of classification significantly for SPAM and CC-PEV up to 10 percent, and 14 percent for different steganography algorithms, respectively.

Researchers in \cite{25, 24} presented a novel approach to solve the problem of discovering the message embedded in a certain covert multimedia. They considered another filter-based feature selection algorithm for steganalysis. Authors introduced an Adaptive inertia weight-based PSO called APSO. APSO is adopted for steganalysis with two main phases: first, feature selection which plays the important step and training section to make a classification model. APSO uses a novel fitness function which provides Area Under Curve (AUC) to evaluate selected feature subset. The latter step, authors used several classifiers such as SVM, DT, NB, and KNN. The SVM obtained the best result in comparison with others, when the hyper-plane experienced the largest distance between support vectors of given stego and cover classes. ASPO-AUC decreased the feature dimension and selected top 140 features out of 686 SPAM attributes and 363 features out of 548 features. The final accuracy of APSO using SVM yields 82.62 and 87.72 for SPAM and CC-PEV data set, respectively. Although these methods yield a better result using PSO in comparison with IFAB and RISAB, they still have the time complexity problem sensible on large data

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we investigate the application of FA to steganalysis. The authors introduced a new wrapper-based feature selection to that end, named Global Local PSO (GLBPSO). They adopted backpropagation neural networks to evaluate the selected feature subsets by GLBPSO. The GLBPSO algorithm improves the standard PSO by having global and local best PSO simultaneously. In this study, researchers tried to use Chen, decrease it’s dimension and select the best feature subset. The prediction performance of GLBPSO provides no more than 7 percent improvement in comparison with the basic results where performance is calculated based on all features. GLBPSO reduced features down to 282 feature out of 486 features. Furthermore, Kaur and Singh [27] proposed a new feature selection leveraging mutual information and adaptive PSO (MI-APSO) using area under curve for image steganalysis, MI-APSO has also inspired from IFAB as a feature selection and improved the performance of image steganalysis.

5. Image steganalysis using firefly algorithm

Yang introduced a new evolutionary algorithm in named Firefly algorithm (FA) which is inspired by the flashing behaviour of the fireflies. FA aims to attract other objects, particularly their mates through their light. Yang presented this algorithm based on the following assumption: non of fireflies are opposite genders. It means that the possibility of attacking other mates is the same. Second, the rate of attraction has a direct relation with their light, the more lighter the high rate of attraction. Third, if no brightest firefly exists, mates tend to move towards one of the fireflies very randomly. Researchers developed and tailored FA to work well with steganalysis.

It is worth mentioning that firefly algorithm can improve convergence rate problem of ABC properly. In this section we investigate the application of FA to steganalysis.

Chikara et al [28] proposed a new dynamic algorithm to steganalysis, named DyFA. They customized carefully firefly algorithm for universal steganalysis. Feature selection (FS) plays the main role of DyFA, which alleviates the computational complexity of universal steganalysis. FA provides two important parameters alpha and gamma, which help FA to converge faster per each iteration. Basically, tuning these parameters seems important for FA to do it’s task perfectly. In addition, DyFA applied a hybrid FA which combines the filter method (t-test and regression) and wrapper method for FS. The result of given DyFA is reduced features significantly almost 77 − 93 percent of feature dimension, with improving the accuracy of distinguishing stego images from cover images about 2 − 10 percent. CC-PEV and SPAM are used by DyFA that decreased the feature dimension properly. Accuracy for SPAM has enhanced by 9 − 15 percent and CCPEV shows an improvement of 10 − 13 percent. The result shows that FA outperforms IFAB. But DyFa also still need to be tuned to decrease time complexity.

6. Image steganalysis using grey wolf optimizer

Mirjalili et al [17] recently proposed a new evolutionary algorithm based on the concept of grey wolf society named Grey Wolf Optimizer (GWO). GWO outperforms other evolutionary algorithms in searching the solution of nonlinear functions in multidimensional space. The GWO algorithm mimics the leadership hierarchy and hunting mechanism of gray wolves. The leadership hierarchy is simulated based on using behaviour of different types of grey wolves such as alpha, beta, delta, and omega. Basically, The GWO inspired grey wolf hunting procedure which involves three main phases. First, seeking for prey which is considered as exploration, encircling prey and lastly attacking prey which provides exploitation, through which it is done for optimization problem.

The GWO is a population based algorithm which employs a collective behavior of wolves for seeking the optimal solution. Concretely, GWO starts with the exploration of search space and exploits gradually, using the three main steps. GWO provides the most important parameter for adjusting step size, named A, controls convergence by setting the exploration and exploitation rates. The GWO is well-known for its low computational cost. However, it still has some negative points like slow convergence rate and traps in local optima at times. It is more obvious that controlling the exploration and exploitation trade-off defined by "A" which plays the main role in GWO.

Pathak et al [30] proposed a new version of GWO for solving steganalysis using feature selection called levy flight-based grey wolf optimization (LFGWO). LFGWO improved the drawback of GWO and implemented professionally for seeking the most prominent features in feature space. The fitness function, they used, includes one of the decision tree classifiers, called random forest. The main advantage of LFGO over similar works seems its better convergence precision. They also examined 5 different classifiers such as SVM, LDA, RF, KNN, ZeroR to analysis the performance of image steganalysis method over selected features. It is worth mentioning that the LDA here is used as a classifier. LDA also is used in general as a feature reduction algorithm. The LFGWO extracted 84 out of 686 and 89 out of 1000 features from SPAM and AlexNet extracted features, respectively. Although LFGWO obtained better result than IFAB [19] and IFAB-KNN [21], IFAB and IFAB-KNN extracted less number of features, 80 out of 686 for SPAM. The result shows that 84 looks are the most proper subsets rather than 80, particularly for SPAM.

Veena et al [29] introduced an optimized method to attack
a well-known steganography algorithm, Least Significant Bit (LSB). Authors mainly focused to seek for optimal features by the proposed hybrid technique of Greedy Randomized Adaptive Search – Binary Grey Wolf Optimization (GRASP-BGWO). They succeeded in enhancing classification accuracy of the used ensemble logistic regression classifier while shrinking the features.

Veena in et al [29] introduced five different spatial LSB algorithms: LSB Replacement (LSBR), LSB Matching (LSBM), Revisited (LSBMR), Two bit LSBR (LSBR2 or 2LSB) and Modulo 5 LSBR (LSBRmod5). The authors applied GRASP-BGWO and observed that the detection process is highly dependent on the three important properties: training algorithms, payloads and features. According to [29], GRASP-BGWO did excel all existing decent works like SRM, PSRM and SPAM even in low volume payload per pixel. The proposed hybrid method, GRASP-BGWO, helped to improve performance by 12 – 13 percent while having at most 400 features for given 6 class classification in different aforementioned spatial LSB images. For further information about GRASP-BGWO, I highly recommend that you read [29]. In addition to given GRASP-BGWO and its performance on LSBR, , Shojae Chaeikar and ashmadi in [32] presented a novel ensemble Similarity weight (SW) image steganalysis which leverages a low dimension method for LSB detection. The ensemble SW steganalysis comprises three main steps. First, SW analysis. The second step is to adopt SVM classifier. The third step makes a decision. The former step computes the pixel and channel similarity weights of the given object and generate PSW and CSW data sets. The latter one compares the data sets with their corresponding reference profiles. The last step is considered to take generated data sets from the second step to make the final decision.

7. Generative data set for steganalysis

In the given research studies in previous sections, Authors mostly take advantage of well-known image data sets such as Breaking Out Steganography System (BOSS) (BOSSbase 1.01) , and data sets of images 1000 Pictures and Photo-bucket.

Researchers have adopted the most common feature extractors. One of them is proposed in [9] for Subtractive Pixel Adjacency Matrix (SPAM) feature extraction from spatial domain of the digital images and [10][11] for extracting Cartesian Calibrated features extracted by PEVny (CC-PEV) features from transforming domain of the digital images. The details of features are mentioned in table 3 and table 4, respectively. It worth mentioning that CC-PEV involves 548 feature vectors which provides 274 features from the original given image and the second half from the calibrated respective image[11]. Table 3 only shows the features would be extract from original images. In addition, the same number of features also extracted from the calibrated images. Then, the sum of both remains 548.

There are still other important and state of the art feature extractors that researchers took them into account which are Spatial Rich Model (SRM)[34] which provides 34,671 features, and another one is Projected SRM (PSRM) that extracts 12,870 features [35], and CHEN[31]. Chen is presented in 2008 which is the first common feature extractor that generates 486 features. Chen takes advantage of using both inter and intra block Markov-based features.

8. Discussion and conclusion

By the passage of time, image steganalysis gets smarter and stronger. However, it has been struggling with new steganography. Concretely, researchers try to propose as universal steganalysis as possible to attack all steganography algorithm successfully. Image steganalysis always has some defects; according to the papers are considered in this study, the common problem with state of the art image steganalysis

| Table 3 |
| --- |
| **THE CC-PEV FEATURE VECTOR REPRESENTATION**[10] |
| Features vectors | No. of Dim. | Total of Dim. |
| 1 Global histogram | 11 | 11 |
| 5 AC histograms | 5 * 11 | 55 |
| 11 Dual histograms | 11 * 9 | 99 |
| 1 Variation | 1 | 1 |
| 1 Blockiness | 2 | 2 |
| 1 Co-occurrence matrix | 5 * * | 25 |
| 1 Calibrated Markov | 9 * 9 | 81 |
| total : | 274 |

| Table 4 |
| --- |
| **THE SPAM FEATURE VECTOR REPRESENTATION**[9] |
| Features vectors | No. of Dim. | Total of Dim. |
| 1 Markov-horizontal and vertical | 343 | 343 |
| 1 Markov-major and minor diagonal | 343 | 343 |
| total : | 686 |

| Table 5 |
| --- |
| **THE ALEXNET FEATURE VECTOR REPRESENTATION**[33] |
| Kernel | No. of Dim. | Total of Dim. |
| 3 1st layer is a Con. layer | 11 * 11 | 11 * 11 * 3 |
| 48 2nd layer is a Con. layer | 5 * 5 | 5 * 5 * 48 |
| 48 3rd layer is a Con. layer | 5 * 5 | 5 * 5 * 48 |
| 384 4th layer is a Con. layer | 3 * 3 * 192 | 3 * 3 * 192 |
| 256 5th layer is a Con. layer | 3 * 3 * 192 | 3 * 3 * 192 |
| total : | 4096 neurons each. |
| Reduced : | 1000 neurons each. |
algorithms is curse of dimensionality. This problem may cause the algorithms to fail to make a proper model and distinguish stego images from cover ones. Not only that, but this problem likely increase the time complexity of learning all input data.

Among a large number of state-of-the-art approaches accomplished to solve this problem, evolutionary algorithms are the most commonly, successfully algorithms associated. In this study, we examined those algorithms were adopted to solve the defects of image steganalysis with respect to the curse of dimensionality. Four evolutionary algorithms have succeeded to alleviate this problem while they improved the performance of image steganalysis. One Artificial Bee Colony (ABC), one Particle Swarm Optimization (PSO), one Firefly Algorithms, one Grey Wolf Optimizer (GWO). Fig 3 shows the distribution of evolutionary algorithms.

Evolutionary algorithms have used for a particular goal, here solving the problem of curse of dimensionality. Mostly they are adopted for feature selection, to that end. Fig 4 represents that majority of evolutionary algorithms used for steganalysis worked on different types of feature selection. The figure shows that mostly in the research studies wrapper-based feature selection have been used carefully, the rest stands for other goals such as searching a sub-image provides high likelihood of having embedded messages. It is worth mentioning that majority of researchers almost used SPAM and CC-PEV as their feature extractors according to fig 5. SPAM stands for the most commonly used feature extractors and it also has been used within other state of the art feature extractors like SRM [35] and PSRM [35].

Evolutionary algorithms have adopted for image steganalysis since 2014, researchers started using ABC, as it is more likely a powerful optimization tool, which is tailored for image processing. A number of research studies with innovative solution are technically proposed to improve aforementioned traditional evolutionary algorithms. However, they have also problems, which cause to fail to converge successfully (find the global minimum) because of following reasons: sensitivity to initial and noisy conditions, being greedy, having biased assumptions, having some parameters to be fine-tuned and lastly being in-deterministic. [36]. Majority of evolutionary algorithms also suffer from having high computational cost, however, they are more robust to find the best solution.

This paper will be very helpful for the researchers who are currently working or will work on the image processing, particularly in image steganalysis, and would like to explore other evolutionary algorithms and apply them to produce a novel approach for images processing. This research study shows that a large number of evolutionary algorithms are left yet to work considering future research challenges that can
be overcome by the use of the rest but powerful evolutionary algorithms.

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