REVIEW OF BIO-INSPIRED OPTIMIZATION ALGORITHMS FOR FEATURE SELECTION

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ABSTRACT

Bio-inspired computing represents the umbrella of different studies of computer science, mathematics, and biology in the last years. Bio-inspired computing optimization algorithms is an emerging approach which is based on the principles and inspiration of the biological evolution of nature to develop new and robust competing techniques. In the last years, the bio-inspired optimization algorithms are recognized in machine learning to address the optimal solutions of complex problems in science and engineering. However, these problems are usually nonlinear and restricted to multiple nonlinear constraints which propose many problems such as time requirements and high dimensionality to find the optimal solution. To tackle the problems of the traditional optimization algorithms, the recent trends tend to apply bio-inspired optimization algorithms which represent a promising approach for solving complex optimization problems. This paper presents state-of-art of fifteen recent bio-inspired algorithms namely; Genetic Algorithm (GA), Dragonfly Algorithm (DA), Moth-Flame Optimization (MFO), Particle Swarm Optimization (PSO), Cuckoo Optimization Algorithm (COA), Grasshopper Optimization Algorithm (GOA), Ant Colony Optimization (ACO), Firefly Algorithm (FA), Bee Colony Optimization (BCO), Fish Swarm Optimization (FSO), Whale Optimization Algorithm (WOA), Artificial Algae Algorithm (AAA), Elephant Search Algorithm (ESA), Chicken Swarm Optimization Algorithm (CSOA) and Grey Wolf Optimization (GWO). Optimization has been applied in almost every area of science, engineering, medical and feature selection problems. Feature selection, as a dimensionality reduction technique, aims to choosing a small subset of the relevant features from the original features by removing irrelevant, redundant or noisy features. Feature selection usually can lead to better learning performance, i.e., higher learning accuracy, lower computational cost, and better model interpretability.

1. INTRODUCTION

Nowadays, researchers in machine learning and similar domains are increasingly recognizing the importance of dimensionality reduction of analyzed data. Not only that such high-dimensional data affect learning models, increasing the search space and computational time, but they can also be considered information poor [1]. Furthermore, because of high-dimensional data and, consequently, a vast number of features, the construction of a suitable machine learning model can be extremely demanding and often almost fruitless [2]. We are faced with the so-called curse of dimensionality that refers to a known phenomenon that arises when analyzing data in high-dimensional spaces, stating that data in high-dimensional space become sparse [3]. To overcome problems arising from the high-dimensionality of data, researchers use mainly two approaches. The first one is feature extraction, which comprises the creation of a new feature space with low dimensionality. The second one is feature selection that focuses primarily on removal of irrelevant and redundant features of the original feature set and, therefore, the selection of a small subset of relevant features. The feature selection problem with n features has 2n possible solutions (or feature subsets).

The Feature Selection (FS) problem involves identifying a subset of features [4]. An FS algorithm identifies and selects the subset of features that are relevant to the task to be learned. The classifier that is built with an efficient subset of relevant features gives better predictive accuracy than a classifier built from the complete set of features. Other advantages of FS include a reduction in the amount of training data needed, a process that is simpler and easier to understand, reduced computation time, and more accurate classification. Many researchers [5] [6] have identified that the presence of irrelevant features may have a negative impact on the performance of learning systems. The predictive accuracy of a particular target concept might not be affected by the irrelevant features. Redundant features are those features that, although relevant to a target concept, provide information that is already provided by another feature and therefore do not contribute toward prediction. Randomly class-correlated features are the features that are highly correlated with the target class. Irrelevant and redundant features are worthless; hence, removing them can improve the learning process. FS is the process of identifying and removing the inappropriate, redundant, and randomly class-correlated features [7].

Bio-inspired optimization algorithms are based on the structure and functioning of complex natural systems and tend to solve problems in an adaptable and distributed fashion. They are a problem solving methodology derived from the structure, behavior and operation of natural system and remarkably flexible and adaptable nature. Exploring the Bio-inspired algorithms is the enormous computational efforts to solve optimization problems by the conventional algorithms which tend to increase the problem size. They have the ability to describe and resolve complex relationships from intrinsically very simple initial conditions and rule. Bio-inspired optimization can solve the problems of almost all areas including wireless sensor networks, computer networks, security, robotics, biomedical engineering, control systems, parallel processing, data mining, power systems, production engineering, medical, image processing and many more. Designing for Bio-inspired algorithms involves choosing a proper representation of problem, evaluating the quality of solution using a fitness function and defining operators so as to produce new set of solutions.

2. FEATURE SELECTION TECHNIQUES

In this section, we have discussed the various feature selection techniques present in the literature. The removal of irrelevant, redundant, and noisy features speeds up the algorithm and reduces the error rate. In general, there are three common methods for FS: wrapper, filter, and embedded.

2.1 Filter-based Feature Selection

The important characteristics of the data are used to assess the importance of feature for addition in the subset of features. This technique is alienated into two different categories: Rank Based and Subset Evaluation Based. Rank based category uses some univariate statistical techniques to evaluate the rank of each individual feature without considering the interrelationship between features. This technique flops to identify redundant features. Subset Evaluation Based category uses multivariate statistical techniques to evaluate the rank of the entire feature subset. The advantage of the multivariate statistical technique is, it considers feature dependency, no need of classifier and it is more efficient than wrapper technique in terms of computational complexity. The main drawback of the multivariate technique is, it slower and less stable as compared to the univariate ranking technique. Joint Mutual Information and Maximum of The Minimum Nonlinear Approach filter techniques produces the best trade-off between accuracy and stability.

2.2 Wrapper-based Feature Selection

This technique incorporates supervised learning algorithm in the process of feature selection. It ranks features based on the subset evaluation technique. Correlation and dependencies between the features are considered while selecting the features. Considering the bias of the prediction algorithm helps in optimizing the performance of the algorithm. In support vector machine (SVM), weight is assigned to each feature during the learning of SVM. The main drawback of the wrapper technique is computational expensiveness due to searching of the optimal set from large space of dimensionality. Wrapper technique has a high risk of overfitting. SVM- Recursive Feature Elimination (RFE) and Greedy Forward Selection (GFS) strategy are some examples of the wrapper method.

2.3 Embedded Technique

These methods benefit from qualities of filter and wrapper methods combined. They are implemented using algorithms with inbuilt feature selection methods. They are based on learning about which feature contributes the most to the accuracy of the model as it is being created. Embedded methods have three types: pruning methods, models with inbuilt mechanisms for feature selection and regularization models. Pruning methods begins by using all the available features to train a model. This step is followed by an attempt to eliminate the features by setting the value as 0 of corresponding coefficients without reducing the performance. These methods use models such as recursive feature elimination with a support vector machine (SVM) which is a supervised machine learning algorithm that can be used for both classification and regression challenges.

3. BIO-INSPIRED OPTIMIZATION METHODS

In the recent, many bio-inspired optimization methods have been proposed by researchers. These algorithms differ from the other meta-heuristic algorithms as they are designed based on the biological behavior of plants or animals, in specific animal behavior. This section reviews recent novel bio-inspired optimization techniques.

3.1 Genetic Algorithm (GA)

Genetic Algorithms proposed by Holland in 1975 [9] [10] are numerical optimization algorithms inspired by Natural selection and Natural Genetics. They follow the principles of Charles Darwin theory of survival of the fittest. However its great performance in optimization, GA has been regarded as a function optimizer. GA techniques differ from more traditional search algorithms in that they work with a number of candidate solutions rather than one candidate solution. Each candidate solution of a problem is represented by a data structure known as an individual. A group of individuals collectively comprise what is known as a population. GAs is initialized with a population of random guesses. GA includes operators such as Reproduction, Crossover, Mutation and Inversion.

3.2 Dragonfly Algorithm (DA)

Dragonfly, also known as Odonata include more than 3,000 varieties of species. There are two stages in their life cycle, the nymph stage and the adult stage. They predate in both the stages and tend to swarm for hunting (static) and migration (dynamic). These two swarming behaviors inspire toward the exploration and exploitation phases of optimization. During hunting (static swarming), they form subswarms which characterize the exploration phase. During dynamic swarming (migration), dragon flies move in bigger groups in a particular direction which characterize the exploitation phase. Mirjalili has modeled the behavior of dragon flies to the three primitive behavior of swarms defined by Reynold namely separation, alignment, and cohesion. These three primitives combined with the two objectives of the swarm, attraction toward the food source and repulsion away from the enemies form the five primitive corrective patterns between the individual dragon flies in a swarm.

3.3 Moth-Flame Optimization (MFO)

Moths are butterfly like species with two stages in life namely the larvae stage and adult stage. The adults are capable of flying in night with moonlight as reference based on the transverse orientation mechanism for navigation (Frank, Rich, & Long core, 2006). They maintain a fixed angle with respect to the moon light to travel in straight lines. In spite of transverse orientation flight, moths are misguided by artificial lights and tend to fly spirally when they follow these lights that are close compared to the distant moon. In their spiral movement, moths finally converge toward the artificial light. This converging behavior can be modeled into an optimization algorithm called moth-flame optimization (MFO) algorithm (Mirjalili, 2015b).

3.4 Particle Swarm Optimization (PSO)

By observing the flocking behaviour of birds, J. Kennedy and R. Ederhart proposed PSO algorithm [11] [12] in 1995. Flocks of birds fly around in large swarms looking for food, whenever a bird locates a food source, all other birds in the flock move towards the source [13] [14]. The individual birds in the flock communicate with other birds thereby allowing all the flock to converge on the food source. The larger the number of birds in a flock, the better is the chance that they can locate good food sources in an area in a shorter time, thereby increasing the success rate of the flock as a whole. The PSO algorithm mimics this behaviour, in which individual components of a group work together to optimize the problem solving efficiency of the whole.

3.5 Cuckoo Optimization Algorithm (COA)

The cuckoo search algorithm (Rajabioun, 2011) characterizes the egg laying and breeding strategy for optimization. The initial population, called as habitat is an array depicting the current living position. The cuckoos lay eggs in around this habitat and the maximum range is taken as egg laying radius. In a habitat, each cuckoo lays eggs in some other bird's nest and the number of eggs also differs. The worst habitats are abandoned by the cuckoos and after certain immigrations (iterations), most of the cuckoos gather in the best habitat (global minimal position).

3.6 Grasshopper Optimization Algorithm (GOA)

Grasshoppers appear in swarms in two stages of their life, namely their nymph and adulthood stages. Their swarming behavior in terms of exploration and exploitation has been modeled (Saremi, Mirjalili, & Lewis, 2017) as GOA to model architectural structures. The movement of the grasshoppers are influenced by gravity, social interaction, and wind direction. The repulsive and attractive forces among the grasshoppers are used for exploration and exploitation, respectively. The balance between these forces is maintained by a coefficient of comfort zone.

3.7 Ant Colony Optimization (ACO)

Ants and ant colonies are one of nature's typical examples of a swarm based problem solver. Marco Dorigo in 1992 proposed the ACO algorithm [15] [16] drawing inspiration from this. Ants start from their nest and randomly search for food sources leaving pheromones in its path; on locating one it lays a pheromone trail back to its nest[17] [18]. Any other free ant that happens upon this pheromone trail picks it up and follows it to the food source while adding pheromones to the path. As more ants use the trail to the food source, the trail represents the best solution for reaching the food source from the nest. ACO algorithm consists of independent components that try to find the best path to a target from a starting point, both points existing in the same environment. The pheromone trail laid by each component represents that component's solution or path for the problem. A greater number of components using the same trail signify the higher quality of that particular path or solution.

3.8 Firefly Algorithm (FA)

Firefly algorithm [19] [20] was proposed in 2008. It was inspired by intra population, species specific, communication strategy of fireflies, particularly, reproductive behavior between them. Fireflies have unique adaptation, an organ for producing light by a process bioluminescence. This is an evolution of communication method using biochemical like pheromones seen in other insects [21] [22]. The primary purpose of bioluminescence as used by fireflies is to signal reproductive fitness of that individual. It is in nature that fireflies that are able to produce more intense light; are able to attract more mates, increasing reproductive success of that individual. This positive genetic feedback system has led to evolution of fireflies with light producing ability of highest order. It is observed that even though the primary criteria in attraction between fireflies are light intensity, there is second contradicting parameter is the distance between light producer and observer as the intensity by physical laws decreases with distance. This means that a distant brighter source may be at disadvantage compared to a dimmer but closer source. The brighter the light emitted by a firefly as observed by other fireflies, the more likely they are to move towards that firefly. This leads to convergence of various individuals of swarm into areas with higher emission intensity. This property is utilized by firefly algorithm in order to solve continuous optimization problems.

3.9 Bee Colony Optimization (BCO)

The BC (Bee Colony) algorithm is based on the behavior of the bees in nature and is classified as for- aging behavior and mating behavior. Proposed by Karaboga and Basturk (2007), BC simulates the intelligent foraging behavior of a honey bee. A BC contains three groups: worker bees, onlookers, and scouts. Onlooker bees wait in the dance region to make a decision about selecting a food source. Worker bees visit the food source. Scout bees perform a random search to determine new food sources. The position of a food source corresponds to a potential solution to the optimization problem, and the nectar quantity of a food source matches the class of the associated solution. A swarm of virtual bees is produced and begins to move arbitrarily in two- dimensional search space. Bees act together when they locate some target nectar and the solution is attained from the intensity of bee interactions [23].

3.10 Fish Swarm Optimization (FSO)

Li et al. (2002) proposed an innovative swarm intelligent algorithm inspired by the natural schooling behavior of fish called FSA (Fish Swarm Algorithm) [24]. FSA possesses a powerful ability to keep away from local minimums to attain global optimization. FSA replicates three distinctive behaviors: searching, swarming, and following. Searching is a random search for food, with an inclination toward food concentration. Swarming tries to satisfy food intake needs, engage swarm members, and attract new swarm members. In the following, neighboring individuals follow the fish that locates the food. The parameters involved in FSA are the visual distance (visual), maximum step length (step), and a crowd factor. FSA effectiveness is primarily influenced by the visual and step parameters.

3.11 Whale Optimization Algorithm (WOA)

Whales are the biggest mammals among all animals and they are extravagant animals. There are some important main parts of this animal such as humpback, killer, blue, and finback. Whales never sleep because as they need to breathe most of the time from the seas and oceans. Moreover, half of the brains can only sleep. Wales live alone or in groups. Some of their parts such as the killer whales can live in a family most of their life. The humpback whales are considered as the biggest whales, and their favorite prey is small fish and krill species. **W**hales have basics cells in specific regions of their brains [25]. These cells are in charge of judgment, feelings and emotions, and the behavior of humans. But whales are different than human by their twice number of these cells which represent the main advantage of their smartness. Whales behave smart like a human but with low level; can learn, think, communicate, and have emotions as a human does, Whales can develop their dialect as well. The special hunting way of humpback whales is considered as the main interesting point of these whales which can be defined as bubble-net feeding method.

3.12 Artificial Algae Algorithm (AAA)

AAA is a recent bio-inspired algorithm, and it is mimic the living lifestyles and behavior of microalgae [26]. This algorithm has been based simulated based on microalgae lifestyles such as the algal tendency, reproduction, and adaptation to the surrounding environment to change the dominant species. Therefore algae have three main basic processes called, evolutionary process, helical movement, and adaptation. The population in this algorithm is composed of algal colonies. The algal cells in algal colonies will grow if it receives enough light and then the algal colony will grow to a bigger size. However, in the growing process, the algal colony may not grow enough due to they suffer from insufficient light. In helical movement, each algal colony will be able to move towards the best algal colony.

3.13 Elephant Search Algorithm (ESA)

ESA belongs to the group of contemporary met heuristic search optimization algorithms. This algorithm mimics the behavior and characteristics of an elephant, and its strategy is based on dual search mechanism, or the search agents can be divided into two groups [27] Elephants live in groups, and an elephant group is divided into several subgroups or clans under the leadership of the oldest one in the main group. The ESA mimics the main characteristics and features of herds of elephants. The social structures of elephants are different, where male elephants prefer to live in isolation and females prefer to live in family groups, the spatial enhancement is considered by the female of elephants while male elephants are responsible for the targets of exploration.

3.14 Chicken Swarm Optimization Algorithm (CSOA)

CSOA is a recent optimization algorithm that mimics the behaviors of the chicken swarm and their hierarchal order [30,31]. The swarm of chicken can be described by different groups; each group consists of only one rooster and many chicks and hens. There is a competition in this warm between different chickens with a specific hierarchal order. The hierarchal order in this swarm is important in the social lives of chickens such as flock structure, the hens, the chicks and the mother hens. The behavior of the chicken swarm varies with male or female. The head rooster will positively search for the food, and fight with chickens who are around the search area of the group. The chicken that forages for food will be consistent with the head roosters, and the submissive chicken will be standing in the same location of the group to search for their food. Generally speaking in this swarm, there is a competition between chickens; however, chicks search for the food around their mother. This swarm is based on several groups, and each group consists of a rooster, a couple of hens, and chicks. In this case, the chickens with best several fitness values will be considered as roosters, while the chickens with worst several fitness values can be assigned to chicks and the others can be the hens which can choose the group to live in. This hierarchal order and relationship between hens and chicks will be updated every several time steps, say S. Therefore, chickens will follow their group-mate rooster to search the food, while chicks search the food around their hens.

3.15 Grey Wolf Optimization (GWO)

The GWO algorithm is one of the recent meta-heuristic algorithms which has been introduced by Ref. [31]. The main inspiration techniques in this algorithm are based on hunting and social leadership of grey wolves (Canis Lupus) which belong to the Canidae family. Gray wolves usually live in groups, and the leader of the group is called alpha and is responsible for some activities such as making decisions about sleeping place and hunting. Their second wolf is called beta, and he helps the wolf alpha in making decisions. The third gray wolf is called omega and is responsible for providing the information to all the other wolves. The all other remaining gray wolves are called delta and are responsible for dominating the omega. The main phases of the GWO algorithm of gray wolves are based on the following steps: (i) track, chase and approach the prey; (ii) pursue, encircle and harass the prey; (iii) attack toward the prey. In the designing process of the GWO, the fittest solution is supposed to be the alpha (α) wolf. The second best solution is called beta (β) and third best solutions is called delta (ð) wolves. The other candidate solutions are considered to be omega (μ) wolves.

CONCLUSION

Bio inspired algorithms are creating a paradigm shift in the realm of Computer Science. These algorithms are inspired by nature and so their boundaries are boundless. So is the way of providing solutions to Computer Science problems. By hybridizing the algorithms we can proceed to the next generation modelling and computing. This work renders a summary of various algorithms to afford optimization and enhanced feature selection. There are arena where there are still notably demanding work for the researchers to provide solution by hybridizing the algorithms to offer perfect solution for new arising domains in engineering and technology. More specifically, there are innumerable ways and means to explore and hybridize a new approach or an algorithm. In conclusion, fifteen bio-inspired optimization algorithms are presented and analyzed in this paper: Genetic Algorithm (GA), Dragonfly Algorithm (DA), Moth-Flame Optimization (MFO), Particle Swarm Optimization (PSO), Cuckoo Optimization Algorithm (COA), Grasshopper Optimization Algorithm (GOA), Ant Colony Optimization (ACO), Firefly Algorithm (FA), Bee Colony Optimization (BCO), Fish Swarm Optimization (FSO), Whale Optimization Algorithm (WOA), Artificial Algae Algorithm (AAA), Elephant Search Algorithm (ESA), Chicken Swarm Optimization Algorithm (CSOA) and Grey Wolf Optimization (GWO) which have been inspired by the social behavior of animals. There are several simulation stages are involved in the developing process of these algorithms which are (i) observation of the behavior and reaction of the animals in the nature, (ii) designing a model that represent the behavior of these animals (iii) converting into mathematical module with some assumptions and setting up of the initial parameters, (iv) developing the pseudo code to simulate the social behavior of these animals (v) testing the proposed algorithm theoretically and experimentally, and redefine the parameter settings to achieve better performance of the proposed algorithm.

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