A SURVEY ON BIO-INSPIRED COMPUTING AND REVIEW OF FEATURE SELECTION BASED SWARM INTELLIGENCE

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Abstract. *In recent decades, the rapid growth of database technology has led to the large-scale use of datasets. On the other hand, data mining applications work on high dimensional datasets. An important issue with applications is the term curse of dimensionality. The dimension of the data means the number of features or columns in the dataset. One of the dimensionality reduction techniques is feature selection, which means a subset of the original features. It reduces the dimensionality of data by eliminating irrelevant, redundant data. Recently, swarm intelligence techniques have gained more attention from the feature selection community because of their global search ability. In this paper, a comparative analysis, of different bio-inspired computing algorithms and recent feature selection methods based on swarm intelligence are reviewed. Furthermore, the basic operators, control parameters, variants and areas of application where these algorithms have been successfully applied. It also identifies and short listing the methodologies that are best suited for the problem. The strengths and weaknesses of the different bio-inspired algorithms are evaluated.*

Keywords: *Feature Selection, Evolutionary Computation Algorithms, Swarm Intelligence Algorithms.*

1. INTRODUCTION

Dimensionality reduction is one of the techniques used to eliminate features. Dimensionality reduction can improve the performance of machine learning algorithms and reduce computational complexity by removing irrelevant and redundant features. There are two types of approaches available in dimensionality reduction, feature selection and feature extraction. Feature extraction means creating a new set of features from the original features, whereas feature selection means a subset of the original features. Many feature selection methods use Meta heuristic optimization algorithms. It is used to find near-optimal solutions for all optimization problems. Meta heuristic algorithms are classified into Bio-stimulated algorithms, Nature-inspired algorithms, Physics-based algorithms, Evolutionary algorithms and Swarm-based algorithms.

Many bio-inspired algorithms have been employed with feature selections. A bio-inspired optimization algorithm [1] is an emerging approach; it is based on the inspiration of the biological properties of nature to develop techniques. It can be divided into 3 types as evolutionary algorithms, swarm intelligence algorithms and ecology-based algorithms. Evolutionary algorithms [2] are Darwin's theory of survival of the fittest and selection; Swarm intelligence is the behaviour of social insects such as ants, fireflies, fish, birds, bees, termites etc. Ecology-based algorithms are being used to balance the relationship between feasible and infeasible individuals.

This research work is organized as follows. Section 2 describes the taxonomy of bio-inspired computing, Section 3 discussed evolutionary based algorithms, Section 4 presents the swarm intelligence algorithms, Section 5 present the ecology based algorithms, Section 6 reviews swarm intelligence based feature selection algorithms which mainly are based on ACO, PSO, ABC, FA, GOA, WOA and GOA. The paper is concluded by Conclusions in Section 7.

2. TAXONOMY OF BIO-INSPIRED COMPUTING

This section gives an overview of the techniques reviewed in Bio-inspired algorithms. The classifications of different Bio-inspired computing algorithms are shown in Figure 1. It can be classified into 3 common algorithms like natural evolution based algorithms, swarm intelligence based algorithms and ecology based algorithms.

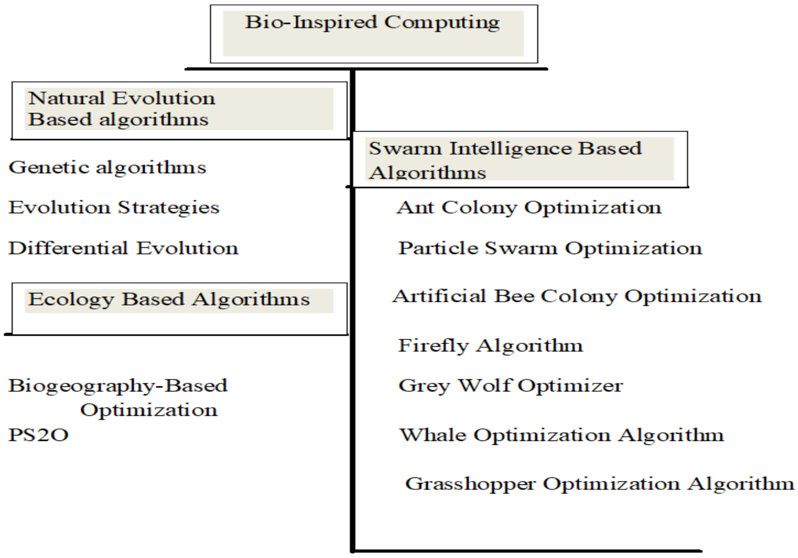

Figure 1: Taxonomy of DNA Compression Techniques

3. EVOLUTIONARY BASED ALGORITHMS

An evolutionary algorithm is a population-based Meta-heuristic algorithm inspired by nature and solves problems through the behaviors of living organisms. Evolutionary algorithms are a combination of both evolutionary computing and bio-inspired computing. The bio-inspired algorithms are based on biological evolution in nature; that is, being responsible for the design of all living beings on earth, and for the strategies they use to interact with each other.

It can be categorized into 3 types like Genetic algorithms, Evolution Strategies and Differential Evolution. These are all population based stochastic search algorithms and share a number of common features for performing with best-to-survive criteria.

3.1 GENETIC ALGORITHMS

A genetic algorithm [3] is an optimization technique based on the principles of genetics and natural selection. It was developed by John Holland and his colleagues at the University of Michigan. The phases of Genetic algorithm are Initialization of population, Fitness function, Selection, Reproduction and convergence.

3.2 EVOLUTION STRATEGIES

Evolution Strategies [4] is a type of evolutionary algorithm developed by Igno Rechenberg, Hans-Paul Schwefel and their co-workers. It is an optimization technique inspired by biological evolution and the functions may include selection, reproduction, mutation and recombination. It is commonly applied to black-box optimization problems in continuous search.

3.3 DIFFERENTIAL EVOLUTION

Differential evolution developed by Storn et al. is considered one of the population-based methods for solving complex optimization problems. Differential evolutions [5] can produce new offspring solutions through three mechanisms mutation, crossover and selection.

4. SWARM BASED ALGORITHMS

Swarm Intelligence (SI) is the concept of artificial intelligence. It was introduced by Gerardo Beni and Jing Wang. Swarm Intelligence means using the knowledge of collective objects (insects, people, etc.) together and reaching the optimal solution for a given problem. SI [6] systems are used to solve complex problems. It is the concept based on individual elements in decentralized and self-organized systems.

4.1 ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) is one of the most successful algorithms of swarm-based algorithms. ACO was first introduced by Marco Dorigo in the 1990s. It is purely inspired by foraging behavior of ants. The ants communicate via a pheromone. The pheromone is a chemical substance that insects use to send out signals to other insects. Initially it is used to solve traveling salesman problem; later it is used for different optimization problems. In ACO [7], artificial ants are a computational agent that gives solutions to optimization problems. In the first step each ant constructs a solution; in that second step, the different ants are compared, and the last step consists of updating the pheromone levels on each stage. There are three different versions [8] of ant-system: Ant Density, Ant Quantity and Ant Cycle. Ant Density &Ant Quantity; the pheromone is updated in each movement of the ant from one place to another. Whereas Ant cycle, the pheromone is updated once all the ants have completed the tour.

4.2 PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a population-based optimization technique inspired by birds of flocks and schooling in nature or insects swarming. It was proposed by Kennedy and Eberhart [9] in 1995. A collection of individuals called particles, in PSO; the particles refer to population members.

Steps in PSO

1. Generate a random population of particles: Position and Velocity.
2. Assess the position of each particle through the objective function.
3. Save each particle the best position and global best.
4. Update the velocity and the particle.
5. Go to step 2 until the stopping criteria are satisfied.

4.3 ARTIFICIAL BEE COLONY

The Artificial Bee Colony (ABC) is swarm based Meta heuristic algorithm was introduced by Karaboga [10] in 2005.ABC was inspired by the foraging behavior of honey bees. This algorithm consists of three components employed [11], onlookers' bees and scouts. The first two components are used for searching a food and third component useful for their hive. In this algorithm, the employed bees responsible for searching food using fitness values and share the information to onlooker bees. The number of employed bees or the onlooker bees is equal to the number of solutions in the population.

Steps in ABC

1. Generate food source position
2. Calculate the fitness value for each position
3. Modify neighbor positions (solutions)
4. Calculate fitness of updates position
5. Compare food positions and retain best
6. Calculate probability for positions solutions
7. Define the lowest probability for a position
8. Update position solutions
9. Go to Step 3 until the stopping criteria are satisfied.

4.4 FIREFLY ALGORITHM

Firefly Algorithm (FA) is a new Meta heuristic algorithm for optimization problems. It is inspired by the flashing behavior of fireflies. It was developed by Xin -She Yang in the year of 2008. Fireflies [12] can divide them into subgroups owed to stronger neighbor attraction over long distance attractiveness. This algorithm, randomly generated solutions called fireflies, will be assigned with a light intensity based on their performance in the objective function.

Steps in FA

1. Generate an initial population of fireflies.
2. Evaluate fitness of all fireflies from the objective function.
3. Update the light intensity fitness value of fireflies.
4. Rank the fireflies and update their position.
5. Go to Step 2 until the stopping criteria are satisfied.

4.5 GREY WOLF OPTIMIZER

Grey Wolf Optimizer (GWO) is a Meta heuristic algorithm inspired by the behavior of grey wolves in nature to hunt in a cooperative way. This algorithm developed by Seyedali Mirjalili et al. in 2014. There are four types of grey wolves [13] alpha, beta, delta and omega, where the best individual, second best individual, third best individual called α, β, δ, respectively. The remaining individuals come under the omega (ω) category.

Steps in GWO

1. Initialize the parameters like number of grey wolves, number of iterations, etc.
2. Create initial populations of grey wolves with different social hierarchy like alpha, beta, delta and omega.
3. Estimate the position of prey by alpha, beta, and delta.
4. Evaluate the position of grey wolves by the position of the grey.
5. Grade the grey wolves like the best solution called alpha, the second best solution called beta, etc.
6. Go to step 3 until the stopping criteria are satisfied.

4.6 WHALE OPTIMIZATION ALGORITHM

Whale Optimization Algorithm (WOA) is a recently developed swarm-based Meta heuristic algorithm [14] inspired by the hunting behavior of humpback whales. It was proposed by Mirjalili and Lewis in 2016. This algorithm follows bubble-net foraging behavior, which means that the whale finds its prey; it can create a bubble net along the spiral path and moves upstream to prey.

Steps in WOA

1. Initialize of search agent.
2. Calculate Fitness Value.
3. Update Whale position.
4. Apply boundary conditions and return back whales that go beyond search limits.
5. Go to step2 until the termination criteria are satisfied.

4.7 GRASSHOPPER OPTIMIZATION ALGORITHM

Grasshopper Optimization Algorithm (GOA) is a new Meta heuristic [15] algorithm and a population based algorithm inspired by the foraging and swarming behavior of grasshopper swarms in nature. It was developed by Saremi and Mirjalili, 2017. Grasshopper life cycle includes two phases called nymph and adulthood. The adulthood stage is a long range and abrupt movements where as the nymph stage is characterized by small steps and slow movements.

Steps in GOA

1. Initialize the population size, number of iterations, coefficients, and fitness function definition.
2. Assign random position of grasshoppers.
3. Evaluate the fitness of each search agent.
4. Update the position of the current search agent.
5. Check boundaries of grasshopper position.
6. Go to step3 until the termination criteria are satisfied.

5. ECOLOGY BASED ALGORITHM

The ecology-based evolutionary algorithm [16] is making attempts to balance the relationship between feasible and infeasible individuals. There can be many and complex types of interactions among the species of ecosystem. This algorithm generates considerable interest for solving real world problems. Ecology-based evolutionary algorithms are inspired by the both interspecies and intraspecies. It is more popular in solving complex multi-objective problems. It can be categorized into 2 types like Biogeography-Based Optimization and PS2O algorithm.

5.1. BIOGEOGRAPHY-BASED OPTIMIZATION

The Biogeography-Based Optimization (BBO) is used to describe the concept and models of biogeography [17]. It was developed by Simon in 2008. Biogeography is the study of the immigration and emigration of species between habitats. In BBO, each individual is termed as a habitat and has an index called the habitat suitability [18] index (HSI) to calculate its quality as a solution. It is an evolutionary algorithm that iteratively improves candidate solutions with regard to fitness functions. The operators in BBO migration and mutation are used to improve habitat solutions in the population.

Steps in BBO

1. Initialize the Habitats.
2. To compute HSI/Fitness of Habitats.
3. Perform Migration and Mutation operation.
4. Select best habitat based on HSI/Fitness value.
5. Go to step2 until the termination criteria are satisfied.

5.2. PS^{2}O

The PS^{2}O algorithm was proposed by Chen and Zhu in 2008. It is a multi-species optimizer inspired by the ideas from the co-evolution of symbiotic species in the ecosystems and it makes heterogeneous interactions between species. It is a multi-swarm approach; the interaction occurs not only between within the species but also between different species.

The following table (Table 1) summarizes the Bio-inspired computing algorithms with their control parameters, applications domain, strength and weakness of their algorithms.

Table 1: Summary of control parameters and area of application domain in Bio-inspired algorithms

Algorithm	Control Parameters	Area of Applications	Advantage	Disadvantage
Genetic Algorithm	Population size, max generation number, cross over probability, mutation probability, length of chromosome, chromosome encoding.	Robotics, Travelling and Shipment Routing	It supports multi-objective optimization.	It does not scale well with complexity.
Evolution Strategies	Population size, Maximum number of generations, Probability of crossover, Probability of mutation.	Task scheduling, car automation and Vehicle routing	Self Adaption of strategy parameters	Only applied in Continuous problems
Differential Evolution	Population size, dimension of problem, Fscale factor, probability of crossover	Image classification, filter design, chemical engineering processes and multi-objective optimization.	Reliable, accurate, robust and fast optimization technique	It is not capable of finding a new search domain.
Ant Colony Optimization	Number of ants, pheromone iterations, evaporation rate, amount of reinforcement.	Travelling Salesman Problem, Quadratic Assignment Problem, Scheduling, Vehicle routing.	Good for dynamic applications,	Convergence is guaranteed, but time to convergence is uncertain.
Particle Swarm Optimization	Number of particles, Dimension of particles, Range of particles.	Traffic Accident Forecasting, Energy-Storage Optimization, sequential ordering problem, Edge detection in noisy images, colour image segmentation.	Parallelized for concurrent processing, Efficient for global search algorithms.	Local search ability is weak.
Firefly Algorithm	Attractiveness, Randomization and absorption.	Demand Forecasting, Sensitivity Analysis.	It requires a small number of iterations.	High computational time complexity, slow convergence.
Grey Wolf Optimizer	Number of wolves, Number of iterations, problem dimension, search dimension.	Neural Network, Power System, Scheduling and Routing applications.	Simple structure so easy to implement, less storage, faster convergence.	Easy to premature, low solving accuracy.
Whale Optimization	Number of Whales,	Heterogeneous Net-	A good rate for con-	Too many parameter

Algorithm	Number of iterations, Number of variable, Random number(r).	work, Image Segmentation, Classification and Optimization.	vergence, It can handle large of decision variables, flexibility, Scalability.	tuning.
Grasshopper Optimization Algorithm	Population size, max number of iterations, coefficients, and fitness function definition.	Cloud computing, Abrupt motion tracking, Global Optimization problem.	Reasonable execution time, High accuracy, Easy to implement.	Exploiting the search space, Premature convergence in complex optimization problem.
Biogeography-Based Optimization	Number of habitats (population size), maximum migration rates, mutation rate.	Antennas and wireless communications, colour image segmentation, Satellite image classification.	An efficient algorithm for optimization. Doesn't take unnecessary computational time. Good in exploiting the solutions.	Poor in exploiting the solutions and no provision for selecting the best members from each generation.
PS^2O	Number of particles, Dimension of particles, Range of particles, Learning factors: inertia weight, maximum number of iterations.	Cooperative cognitive wireless communication, Constructing collaborative service systems (CSS).	To find a food quickly.	Take more time to allocate the food to feed.

6. FEATURE SELECTION BASED SWARM INTELLIGENCE ALGORITHMS

Feature selection is used to extract relevance data from the dataset. This section comparing the works of feature selection in swarm intelligent methods in various algorithms like ACO, PSO, ABC, FA, GWO, WOA and GOA. The following table (Table 2) consists of swarm methods comparing among the dataset, techniques, classifiers /tools, and results.

6.1 ANT COLONY ALGORITHM

Manosij Ghosh et.al (2019) proposed a filter-wrapper ACO feature selection [19] in a multi-objective manner for increasing accuracy and reducing number of features. So it can be considered as a computationally inexpensive for UCI datasets.

6.2PARTICLE SWARM OPTIMIZATION

Yu Zhou et.al (2020) proposed a model called improved discretization -based particle swarm optimization (PSO) for feature selection [20]. In this method, pre-screening process is used to reduce the size of features and then apply ranking-based cut point table are sorted the each feature and it will improve the effectiveness of the benchmark datasets.

6.3 ARTIFICIAL BEE COLONY

Artificial Bee Colony Based Feature Selection Algorithm [21] proposed by Esra Sarac Essiz et.al (2020) is effective in reducing the features and it is suitable for classification in high dimensional data. This method reduces the time without loss of accuracy in classification.

6.4 GREY WOLF OPTIMIZATION

A two-stage Improved Grey Wolf Optimization [22] called IGWO is proposed by chaonan shen et.al (2020) for feature selection on high-dimensional data. The IGWO algorithm can reduce the size of a feature, maintain high performance metrics and increase classification accuracy.

6.5 FIREFLY ALGORITHM

Sofiane-MAZA et.al (2019) proposed a firefly algorithm for feature selection [23] (FAFS) to find the best subset of the feature that gives the highest accuracy and reduces the number of features. It uses two fitness functions; they are called accuracy rate and reduction rate.

6.6 WHALE OPTIMIZATION ALGORITHM

Adel Got et.al (2021) proposed a Hybrid filter-wrapper feature selection using whale optimization algorithm [24] which uses a multi-objective approach to combine filter and wrapper for fitness functions and their experimental results show that to reduce the number of features with good classification accuracy.

6.7 GRASSHOPPER OPTIMIZATION ALGORITHM

Learning automata based improved version of Grasshopper Optimization Algorithm [25] called (LAGOA) is proposed by Chiradeep Dey et.al (2021) using two-phase mutation. The first phase reduces the number of features and the second. Phase adds relevant features which increase classification accuracy.

Table 2: Outlining the reviewed swarm intelligence based feature selection methods.

Algorithm	Algorithm/s compared with	Application	Dataset	Classifier	Accuracy		
Filter-wrapper ACO Feature Selection (WFACOFS)	Feature Selection Methods	Facial Emotion recognition System.		KNN MLP	KNN	MLP	
			Wine		100	100	
			Soy-bean-small		100	100	
			Ionosphere		97.35	98.68	
			Breast Cancer		99	99.67	
			Monk2		88.89	87.04	
			Hill-valley		55.61	64.52	
			Monk1		88.89	100	
			Arrhythmia		62.5	64.47	
			Horse		100	100	
			Madelon		100	100	
Improved discretization-based Particle Swarm Optimization Feature selection(IDPSO-FS)	Potential PSO, Aadaptive Potential PSO	Mulit-objective optimization model	Adenocarcinoma	KNN	70.56		
			Lymphoma		99.72		
			Nic		78.74		
			Colon		84.56		
			Breast2		69.44		
			Breast3		68.86		
			Brain_tumor		89.87		
			Leukemia 2		96.52		
			Brain Tumor 1		87.83		
			Lung cancer		93.18		
Improved Grey Wolf Optimization (IGWO)	Linear forward selection, correlation based feature selection methods	Neural Network	SRBCT	MLP	100		
			DLBCL		98.30		
			9Tumor		63.33		
			Leukemia 1		94.17		
			Brain tumor 1		82.50		
			Leukemia 2		97.22		
			Brain tumor 2		79.17		
			Prostate		94.33		
			Lung cancer		98.29		
			11 Tumor		93.05		
Artificial Bee Colony based Feature Selection	Traditional feature selection methods like Information Gain.	Cyber bullying detection problem	Formspring	WEKA TOOL	0.72		
Firefly Algorithm for Feature Selection(FAFS)	Particle Swarm Optimization for feature selection	Binary Classification		KNN NB LDA	KNN	NB	LDA
			Iris		96	95	98
			Wine		75.28	93.26	95.51
			Lung-Cancer		94.36	94.55	94.21
			Spambase		78.94	91.22	91.92
			Libras-Movement		98.54	96.98	95.44
			Glass		96.52	94.5	92.22
			Segmentation		96.32	94.53	93.33
			Banknote - Authentication		99.85	83.53	99.75
			Hill-Valley		96.11	93.55	94.25
			Musk		91.02	92.3	90.2
Filter-Wrapper	Single objective	Discrete problem	Breast cancer	KNN	96.70		

Guided Population Archive Whale Optimization Algorithm (FW-GPAWOA)	algorithms and Multi objective algorithms		Lymphography Spect Spectf Sports articles Vehicle Whole sale customers Optical digits Letter recognition		84.61 100 84.28 84.29 74.20 92.17 94.55 93.65
Learning automata based grasshopper optimization algorithm (LAGOA)	Binary Grasshopper Optimization Algorithm (BGOA)	Disease diagnosis	Statlog (Heart) SPECTF Heart Breast Cancer (Wisconsisn) Breast Cancer (Diagnostic) Lung Cancer Hepatitis	RF	88.24 88.21 99.26 98.46 85.71 93.00

7. CONCLUSIONS

This paper provides a comprehensive survey of bio-inspired algorithms and SI based feature selection algorithms, which covers the seven most common SI algorithms: ACO, PSO, ABC, FA, GWO, WOA and GOA. In SI algorithms, the comparative analysis and categorization of different feature selection methods are evaluated. Moreover, the strengths and weaknesses of the different bio-inspired algorithms are studied. Furthermore, the algorithms in EA and SI are heuristic population-based search and it has been applied to various optimization problems in image processing, parallel computing, financial problems, forecasting problems, bio informatics etc. Nevertheless, bio-inspired algorithms are the most powerful algorithms for optimization and have a wide impact on future generation computing.

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