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Hybrid Nature Inspired Algorithms and Rough Set Theory in Feature Selection for Classification: A Review

Ahmed Alia[1], Adel Taweel[2]

Research Assistant, Faculty of Engineering and Information Technology, An Najah national University, Nablus, Palestine[1]

Associate Professor, Dept. of Computer Science, Faculty of Engineering and Information Technology, Birzeit University, Ramallah, Palestine[2]

ABSTRACT: Feature Selection (FS) is an important process in classification to select the most relevant features that are necessary and sufficient to a target concept [3]. It aims to improve the classification accuracy and reduce the complexity of the classification model [1]. There are several approaches that have been applied to solve feature selection problems, where hybrid Nature Inspired Algorithms (NIAs) with Rough Set Theory(RST) approaches have shown success to solve filter FS in classification in reasonable time. This paper conducts a review to understand different filter FS approaches that are based on a combination of NIAs (Ant colony Optimization, Particle Swarm Optimization and Artificial Bee colony) and RST. The review shows that hybrid NIAs (ACO, PSO and ABC) with RST approaches are efficient for filter FS in classification, and the ABC algorithm, in particular,exhibits promising results.

KEYWORDS: Feature Selection, Nature Inspired Algorithms, Particle Swarm Optimization, Ant Colony Optimization, Artificial Bee Colony, Swarm Intelligence, Metaheuristic.

I. Introduction

The rapid growth in the volume of data in many fields, such as web, scientific, and business data, presents several challenges to researchers in developing more efficient data mining methods to extract useful and meaningful information [2, 3]. Datasets are often structured as a database table in which records are called objects, and columns are called features that describe each object [4]. Classification is an important example of data mining algorithms, which aims to classify each object in the dataset into different classes or groups based on key relevant features [1, 5].

Datasets, however,can have a large number of features including many irrelevant or redundant, which causes major problem for classification known as the curse of dimensionality [3, 7]. Curse of dimensionality causes exponential increase in the size of the search space, adding extra dimensions (features) and making the data sparser, for learning classification algorithm. More specifically, it causes several problems for classification [3, 7]: 1- reduces the classification accuracy, 2- increases the classification model complexity, 3- increases the computational time, and 4- complicates the problemsof storage and retrieval.

Usually, datasets have three types of features [3, 6].The first type refers to relevant features which provide useful information to learning classification algorithms. Second type refers to irrelevant features which provide no useful information to classification algorithms. Third type refers to redundant features that provide no more information than the currently selected features to classification algorithms. Redundant and irrelevant features are not useful for classification, and thus removal of these features does not affect the useful information in the datasets for classification, and reduces the curse of dimensionality problems [36.]However, usually, determining which features are relevant is a very complex task before knowing the effects of redundant or irrelevant features on classification. To address this issue, Feature Selection (FS) approaches are thus used, to determine the relevant features within classification [3]. In other words, a main objective of FS approaches is to minimize the number of selected features without significantly

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reducing the classification performance [3].

Two main principal dimensions of FS approaches are the employed Search and Evaluation mechanisms [3]. The Search mechanism uses three strategies to search for subset of features: complete, heuristic and random search. Complete Search is very expensive because it covers all combination of features. Heuristic Search is often more efficient than the complete search because it makes smart choices to select the near optimal subset without searching in all combination of features. Random search picks features at random and requires more user-defined input parameters. The Evaluation mechanism determines the relevancy of the generated feature subset candidates towards classification algorithms[3, 7].

According to evaluation strategy, FS approaches may be generally categorized into two groups: filter and wrapper approaches.In the filter approaches the feature subset is selected independently from classification algorithms, but the wrapper approaches select a feature subset using the classification algorithm itself. The filter approaches are generally much faster and more general than wrapper approaches [3].

Rough set Theory (RST) method, proposed in the early 1980s [8], is one of the effective methods to filter feature selection in classification[10].The basic solution to RST based feature selection is to generate all possible feature subsets and choose the one with highest dependency and least length [9, 10]. Unfortunately, this way is expensive and can be not suitable especially for large datasets. However FS can be viewed as an optimization problem, that is the problem of finding the best solution (i.e. most relevant features subset) from all feasible solutions (i.e. all possible features subsets) [5]. Metaheuristic approaches have been shownto provide very suitable solutions for optimization problems[11]. For this reason many approaches have been developed that combine metaheuristic algorithms and RST to solve the FS in a less expensive and more efficient way [11].

Metaheuristic algorithms represent a group of approximation techniques and provide good solutions with a reasonable computational time for solving Optimization problems[11]. Nature Inspired algorithms (NIAs) are a powerful type of metaheuristic algorithms and an efficient approach to solve FS in RST [12, 31]. NIAs take inspiration from the social behaviors of agents like ants, and bees and their methods of cooperation, by an indirect communication medium, between the agents to discover food sources [11]. NIAs have several advantages including the ease of implementation, and are able to find best/optimal solution in a reasonable time due to their efficient convergence [11]. Ant Colony Optimization (ACO) [13], Particle Swarm Optimization (PSO) [14] and Artificial Bee Colony (ABC) [15] are the famous algorithms for NIAs. The objective of this paper is to review the filter FS approaches in classification that combine NAIs algorithms, such as ACO, PSO or ABC, with RST to discover the best solution in a reasonable computational time [16–21].

The remainder of the paper is organized as follows. Section II presents the basic concepts of RST and NIAs' search mechanisms. Review of Hybrid NIAs and RST Filter FS approaches are reviewed in section III. The conclusion is drawn in Section IV.

II. Background

A. Rough Set Theory (RST)

RST was developed by Zdzislaw Pawlak [8] as a mathematical tool that deals with classificatory analysis of a data table (structured dataset). The main advantages of RST is that it needs no additional parameters/ information to analyze the data, easy to understand, and not expensive [9, 10]. RST provides RST Dependency Degree (RSTDD) to measure the dependency between the features [9, 10]. Filter FS approaches in classification use RSTDD to build an objective function to guide the search algorithms to optimal/best solution by calculating the dependencies between the feature subsets and class labels[x]. The RSTDD can be defined in equation (1)

$$\gamma_p(\mathrm{Q}) = \frac{|pos_p(Q)|}{|U|} \qquad \textit{eq. (1)}$$

Where |U| is the total number of objects, $|POS_p(Q)|$ is the number of objects in a positive region that contains all objects which can be classified to classes of Q using information in P. And $\gamma_p(\mathrm{Q})$ is the dependency between feature subset p and classes Q [19, 20.30, 31].

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Table 1: Dataset [35]

U	a	b	c	d	e
0	1	0	2	2	0
1	0	1	1	1	2
2	2	0	0	1	1
3	1	1	0	2	2
4	1	0	2	0	1
5	2	2	0	1	1
6	2	1	1	1	2
7	0	1	1	0	1

In the example dataset in table 1, {a, b,c,d}are features, {e} is class (Q), and objects (U) are {0,1,2,3,4,5,6,7).Assume P= {b, c}, Q= {e}, the degree of dependency of feature {e} upon the {b, c} is:

$$\gamma_p(\mathrm{Q}) = \frac{\{2,3,5\}}{\{0,1,2,3,4,5,6,7\}} = \frac{3}{8}$$

Notice, {2, 3, 5} objects are certainly classified into the same class. While {0, 4} objects have the same values {0, 2} for {b, c} features, but it is classified into a different class. And the same applies for {1, 6, 7} objects.

B. NIAs' Search Mechanisms

Search mechanisms play an important role in the effectiveness of each NIA. Local, global, and hybrid search are mechanisms that are used in NIAs to update the population of feature subsets to solve the FS [25].

Local Search aims to find the best possible solution to a problem (Global Optimum) by iteratively moving from current solution to better neighbor solution. But sometimes, current solution is better than all neighbor solutions, but is still worse than global optimum. In this case, the local search suffers from local optimum problem and stops searching. The advantage of local search is that it is relatively efficient (fast), but it is affected by poor initial solutions, and it does not guarantee the global convergence [12, 25].

Global Search searches for the candidate solution in all the search space until it finds the best solution or reaches maximum iterations. But it is slower [12, 25].

Hybrid Search aims to increase the convergence efficiency (to avoid be trapped in local optimum), and to guarantee the global convergence as soon as possible by using global search to generate initial solutions for local search [25].

III.HYBRID NIAS AND RST FILTER FS APPROACHES

This section briefly mentions overall categories of FS before it summarizes nine filter FS approaches in classification that combine NIA with RSTDD [16-24]. And these approaches are categorized equally according to the NIA which is used in them to three groups: Ant Colony Optimization, Particle swarm Optimization and Artificial Bee Colony.

A. Overall Categories of FS

In general, FS approaches are categorized into two groups [26, 27]: First group refers to ranked approaches which depend on single feature evaluation to select the best feature subsets. The main problem in these approaches, is that the relevant features cannot be evaluated independently from other features, therefore the ranked approaches are not capable to achieve the optimal/best feature reduction [26, 27]. To avoid this problem, many FS are implemented with feature subset evaluation instead of single feature evaluation, these approaches are the second group which is feature approaches. Feature subset approaches are categorized into three groups based on search strategy used in these approaches to complete, heuristic, and meta-heuristics approaches [27]. As mentioned earlier, metaheuristic algorithms, especially NIAs, have been shown to have faster and more efficient convergence compared to heuristic and complete algorithms [12].

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The search space of FS is large. Hence, traditional optimization algorithms are inefficient in solving feature selection problems. Therefore, meta-heuristic algorithms especially NIAs can be a good option to search for candidate feature subsets [12]. And RSTDD is widely used as an objective function with NIAs, because it is less expensive and more efficient[16, 17].

B. Ant Colony Optimization

Ant Colony Optimization (ACO) is a NIA presented by Dorigo et al in 1992 [13], it simulates the behavior of real ants that use chemical material called pheromone to find the shortest path between their nest and the food source. And when each ant finds the food it returns to nest laying down a pheromone trail that evaporate over time, then each ant follows the path that has large amount of pheromone[28].

ACO uses graph to represent the search space, features are represented as nodes, and edges between the nodes determine the best next connected feature. ACO generates number of ants and put them randomly in graph, this means each ant represents a candidate solution, in each iteration every ant uses self experience (heuristic measures) and social experience (amount of pheromone) to select the best next connected feature, then gather all subset of features for evaluation, if at least one of subset of features is the best, the algorithm stops iterating, but if no best solution in this iteration is found, the pheromone trails are updated (social experience) to help the other ants to locate a better solution and the algorithm continues until discovering the best solution or reaching maximum number of iterations[13.

A numberof approaches that combine ACO and RST have shown improvement in feature selection over the use of ACO alone [16, 17,18]. Ant Colony Optimization based on Feature Selection in Rough Set Theory (ACOFS) [16], an efficient Ant Colony Optimization approach to Attribute Reduction in rough Set theory (ACOAR) [17] and Finding Rough Set Reducts with Ant Colony Optimization (AntRSAR) [18] are examples of RST-based approaches that demonstrate improvement in feature selection over approaches.

These approaches exploits the conceptof the ants behavior, which combine the heuristic measure and amount of pheromone trails to evaluate the next connected edge to select the best connected feature to construct candidate solution. The three approaches update the pheromone trails on each edge after adding feature, but in ACOAR the pheromone values are limited between the upper and lower trail limits to increase the efficiency of the algorithm. And the heuristic measure in the AntRSAR approach uses entropy information, but ACOFS and ACOAR use RSTDD which makes ACOFS and ACOAR cost less compared to AntRSAR, because the entropy information is expensive compared to RSTDD, where after each iteration a new candidate subset of features are evaluated using RSTDD in these approaches.

However, ACO has some drawbacks. It has complex implementation and slow convergence, because it uses graph to represent the search space [11, 12]. Thusthe approaches that use ACO are very expensive, and not suitable for large datasets (maximum size of datasets that are used in the evaluation of these approaches is 69 features [16-18]).

C. Particle Swarm Optimization

Particle swarm optimization (PSO) is a NIA developed by Kennedy and Eberhart [14]. In nature, PSO simulates the movements of a flock of birds around food sources, a flock of birds moving over an area where they can smell a hidden source of food. The one who is closest to the food tweets loudly, and the other birds tweet around in its direction. This means the group of birds closer to the target tweet louder. This work continues until one of the birds find the food [14, 29].

PSO uses Particles as birds to search for the best solution in the search space, which are represented in binary representation. The position of each particle is a possible solution and the best solution is the closest position of particle to the target (food). Particles move in the search space to search for the best solution by updating the position of each particle based on the experience of its own and its neighboring particles. Each particle has three vectors, first vector represents the current position, the second one is for the velocity of the particle, and the last one represents the best previous position that is called personal best (pbest). But the algorithm stores the best solution in all particles in a vector called global best solution (gbest) [14].

Fig 1 illustrates how the PSO works in general, in the initial step, it generates particle swarms with random position and velocity, then evaluates the position of each particle using fitness/objective function, and changes the pbest to new position, if the new position is better than pbest. It checks for gbest, then the algorithm stops if the gbest arrives to good

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fitness/quality or maximum iterations, otherwise update the velocity and the position of each particle, and repeats until it converges to the best position [19].

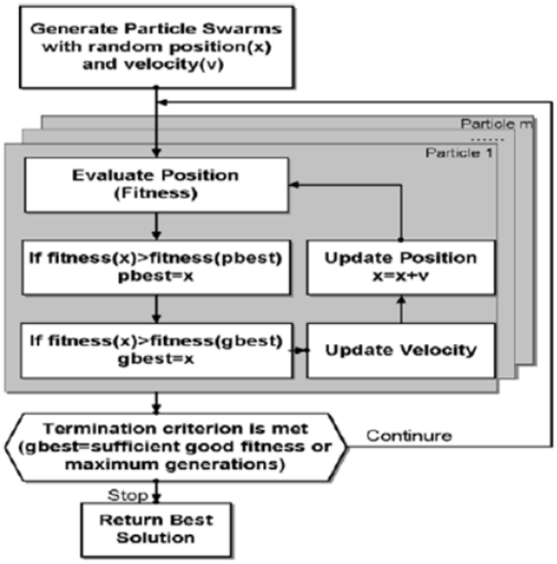

Fig 1: PSO Algorithm [21]

There are several approaches that solves FS using PSO and RSTDD.PSORSFSis a feature selection based on Rough Sets and Particle Swarm Optimization [19], while ARRSBP is An Attribute Reduction of Rough Set Based on PSO [20], however SPSO-RRuses a supervised hybrid feature selection based on PSO and rough sets for medical diagnosis[21].

Creating new candidate subset of features (i.e. position) of each particle depends on the velocity of the particle, which determines how many of the particle's bits/features should be changed. The number of bits/features that may be changed increases when the velocity increases. Thus because high velocity moves the particle far away from global optimal, and low velocity causes the local optimal, XiangyangWang, et al (in PSORSFS) [19] added limitation to the particle velocity to avoid local optima, and to achieve better near global optimal solution. However, Hongyuan Shen, et al ARRSBP [20] only changed the values of weight parameter from 0.1 to 0.9 to balance between the pbest and gbest in generations.H. Hannah Inbara, et al (SPSO-RR) [21] developed two algorithms (for medical datasets), one combines the PSO,to achieve quick reduction based on dependency degree, and the second combines the PSO and to achieve relative reduction based on relative dependency.

These approaches use difference objective function to evaluate the subset of features for each particle. The objective function in the PSORSFS approach uses RSTDD, but modifies this function by adding the number of selected features, and two parameters to control the importance of the quality of solution or the size of solution or both.The ARRSBP alters the RSTDD by adding the number of feature selected to focus on the quality and the least size of solution together.WhileSPSO-RR uses relative dependency. The latter's objective function focuses on the quality instead of the size of the solution.

In general, PSO is easy to implement, and relatively cheaper. But it is affected by the poor initial solutions [29], it has weak convergence, and could be trapped into local optimum when it is applied on large datasets (maximum size of datasets that used in the experiments of these approaches is 57 features) [14, 29].

D. Artificial Bee Colony

Artificial Bee Colony (ABC) algorithm is a NIA that is inspired by the natural foraging behavior of honey bees. ABC is proposed by Karaboga [15]. In nature, the colony consist of three types of bees, employed bees, onlooker bees, and scout bees. The foraging process starts by scout bees that move randomly to discover the food sources. When the scout

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bees find the food sources, they return to their hive and then start dancing (waggle dance) to share their information about the quality of food sources with onlooker bees, depending on this information more bees are then recruited (employed bees) to the richer food source.But if a bee finds the food source is poor, the bees call scout bees to discover randomly new source food and so on [15, 30].

The position of a food source represents a possible solution using binary representation, and the nectar amount of food source considered as the quality of the solution. Each bee tries to find the best solution. ABC combines the global search and local search to find the best solution [15, 30]. The ABC algorithm starts with *n* scout bees that select randomly population of candidate solutions as initial solutions. These solutions are evaluated, and it selects the candidate solutions that have maximum quality for local search.The remainder of the algorithm uses global search to construct a new population of candidate solutions. The quality of each solution in the new population is then evaluated, if the algorithm gets the best solution then the algorithm stops, otherwise it continues searching until it finds the best solution or arrives to maximum number of iterations [15, 30].

A number ofapproaches, in the literature, thatsolves FS using ABC and RSTDD.The first is a Novel Discrete Artificial Bee Colony Algorithm for Rough Set based feature Selection (NDABC) [22], and the second is a Novel Rough Set Reduct Algorithm for Medical Domain Based on Bee Colony Optimization BeeRSAR [23], while the third is an Independent Rough Set Theory Approach Hybrid with Artificial Bee Colony Algorithm for Dimensionality Reduction (BeeIQR) [24].

Yurong Hu, et al. [22] combined ABC and RSTDD to solve FS by changing one feature by either adding one feature or removing one randomly in local search, and using a random mechanism in global search.Suguna, et al [23, 24] proposed two similar approaches, except that in [25] the initial population started from feature core (Start from set of features), while in [24] it started randomly. In local search, more than one feature is randomly changed with some criteria, and a random strategy is used in global search.

The objective function in the NDABC approach uses RSTDD and the size of candidate solution to balance the importance of the quality and the size of the solution. In addition, this approach adds one parameter to its fitness function to control the importance of the quality or the size or both. But BeeRSAR and BeeIQR approaches calculate the indiscernibility relation for each candidate solution to determine the quality for each one.

In general, ABC is a very efficient algorithm that solves the local optimal problem by using hybrid search mechanism [11]. ABC is quick, relatively less complex, easier to implement, and uses fewer parameters compared with other NIAs[14].

IV. CONCLUSION

This paper has reviewed several approaches for filter FS in classification based on Rough Set Theory (RST) and Nature Inspired Algorithms (NIAs). The NIAs are an efficient type of meta-heuristics algorithms and are used to search for candidate feature subsets that are evaluated by RST to find the minimum feature subset with maximum classification performance.

These approaches are categorized to Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC). ANTRSA, ACOFS, ACOAR approaches use ACO, but ARRSBP, SPSO-RR and PSORSFS use the PSO. However, NDABC, BeeRSAR and BeeIQR use ABC.

From the review, NIAs are shown to be more efficient algorithms for optimization and thus suitable for FS, which is effectively an optimization problem. This is further enhanced when combined with RST, which employs dependency degree as a powerful and cheap objective function to guide NIAs to best/optimal features subsets.

ACO is seen as very complex because it uses graph representation, and it needs more parameters for its function. On the other hand, PSO uses binary representation, which makes its implementation mostly much less expensive and easier. But it is generally slow to find the best/optimal feature subset, because it uses a global search mechanism.

The convergence of ABC is more efficient compared to ACO and PSO, because ABC uses a hybrid search mechanism. Also ABC has less complexity, easier to implement, and fewer parameters compared with other NIAs [28, 30].

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BIOGRAPHY

Ahmed Fayez Alia is a Research Assistant in the Faculty of Engineering and Information Technology, An NajahNational University, Palestine. He received a Master of Computingemphasis Computer Science and Engineering in2015from Birzeit University, Palestine.His research interests include Knowledge Discovery, Information Retrieval, Big Data, Data Mining, Machine Learning, Optimization Problems.

Adel Taweel is a faculty member of the Department of Computer Science at Birzeit University. He has previously held academic posts at the Universities of Keele, Manchester, Birmingham and King's College London, where he still holds an academic position. He has led, managed and worked on several EU, USA and UK funded projects, including ePCRN, CLEF, CLEF-Services, and CLARiFi. Dr Taweel is a Coordinator and Principal Investigator of three current projects (HiCure, Diet4Elders, IMI EHR4CR) and has previously co/principle investigated and led several other projects (FP7 TRANSFoRm, PEARL, ePCRN, ENJECT, HealthConnect). He is a Charted Engineer and member of a

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number of professional institutions (BCS, IET, IEEE), and has served as a member of several UK national committees and scientific consultant for several companies and government ministries include the UK Department of Health. Dr. Taweel is an expert EU reviewer and sits on the reviewer panel of several UK research councils

Dr Taweel has published more than 90 peer-reviewed scientific publications in distributed software engineering, component-based, service-based and agent-based systems and medical informatics, and has served as a chair, a session chair of several international conferences and is a standing committee member, editorial member and reviewer of several books, and international journals and conferences.