Overview Feature Selection using Fish Swarm Algorithm

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Abstract. Feature selection is a process of representing wanted features based on the requirement needed by selecting the best subset of a dataset without changing the originality of the dataset. The aim of feature selection is to obtain most optimal feature subset to represent the data and for that purpose feature selection offered a few methods. This paper gives an easy understanding of the feature selection concept and the available methods in feature selection. As nowadays metaheuristics is catching attention researchers in many fields and feature selection is one of them, this paper intentionally brief feature selection using metaheuristics that implement Fish Swarm Algorithm (FSA) in the feature selection process. FSA classified as one of the Swarm Intelligence (SI) techniques have several advantages mainly to solve optimization problems. A number of previous works are reviewed. Based on the reviewed and the outcome results that has been tested using high dimensional, real-valued benchmark data sets, FSA reflect good performance among others SI.

1. Introduction
Nowadays, dealing with huge amount of high dimensional data that involved various of domains such as healthcare, bioinformatics, maritime, social media, business, online education and more is a trend. Hence, in having good deal of data, the data demands for effective and efficient data management. Data mining and machine learning are techniques offered to help discover knowledge from these data of various domains where data become scattered in high dimensional space, adversely affecting techniques designed for low-dimensional. Besides, a large number of features tend overfitting the model techniques applied and may lead to downgrade performance on unseen data. Feature selection is one of the methods to tackle the concerns.

Feature selection is a process of selecting a subset of necessary features from a requirement. The main goal is to discover a minimal subset of features from a certain problem domain and the result of subset reflect a high accuracy at the same time. Generally, feature selection is used for four reasons; 1) To simplify data so the data easier to be used and interpreted by users especially researchers. 2) To short time consuming by selecting only important feature to process. 3) To avoid the curse of dimensionality. 4) To enhance generalization by reducing overfitting which generally refers to reduction of variance. Once all these are presented together, the noise, irrelevant, redundant or misleading feature is removed successfully [5] and a good feature selection is produced.

Feature selection offered three main methods; filter, wrapper and embedded. As feature selection closely related to the dimensional size of data so different size of data needs a different approach. The filter method evaluates the relevance of features only focused on the intrinsic properties of the data.
Filter usually used as a processing step which selection of features doesn't cooperate with any learning algorithm. The wrapper method assesses the best of feature subsets using the performance of a learning algorithm. Meanwhile, the embedded method combines feature selection and classifier construction using an integrated computational process. Before going further, Figure 1 shows the general framework of feature selection and Figure 2 illustrated how each method of feature selection works.

Refer Figure 2, feature selection methods start by generating subset but the process continue differently. Differ to wrapper and embedded methods, filter method directly selects the best subset before passed the best subset to the learning algorithm. Whereby, the others two methods generate best subset by working together with learning algorithm. Unlike the others, the embedded method combines together the qualities of both filter and wrapper methods. Normally, feature selection assessed the qualities of individual features. However, recently the pattern changed. The evaluation metrics concept has been developed to judge the quality of a given feature subset as a whole. It
allowed a good quality solution to be discovered without resorting to exhaustive search and nature inspired metaheuristics is the best implementation [5].

The paper is organized as follows. A brief about the feature selection concept is provided in Section 2. In Section 2, the background of feature selection is introduced. The depth of paper continues in Section 3 where the taxonomy of FSA is described. The taxonomy of FSA includes the intro of FSA, FSA flow chart and FSA for feature selection. Next, previous studies related feature selection in FSA are reviewed. Finally, the conclusion of the paper is summarized in Section 5.

2. Feature Selection Concept

In feature selection, searching an optimal subset of features is a challenge when solving feature selection problems, hence proper conceptual understanding of feature selection is a must. Consider a couple sets of m, (Χ, Y), where X is non empty set of finite objects and Y is a non-empty finite set of feature. Decision of the selection is based on Y = {A ∪ Z} where A = {a₁, .... , aₙ} is the set of input feature and Z is the decided features criteria. The features criteria can be qualitative or quantitative. The main target of the feature subset search algorithm is to determine a set of features B ⊆ A that has highest evaluation score f (B) and minimum subset size |B|. Figure 3 illustrates the example into set concept.

![Figure 3. Feature Selection in Set Concept](image)

Based on Figure 3, in feature selection mapping, a m dataset name that contains X and Y. X is the information of all feature and Y is the significant feature. The intersect of X and Y produce set of A and Z where the intersect between these two create B. A represent the possible significant feature based on certain criteria and B represents a possible subset of signature feature when mapping into the feature selection concept. The result of intersect represents the significant feature based on certain criteria. In feature selection the result of A and Z which is B must evaluate its quality. The quality of B done by the subset evaluation function, f: B → R where f (B) ∈ [0,1] , f (⌀) = 0. Best quality of subset is from high score of evaluation. Hence, to get high score the number of desired number of feature need to be calculated. Therefore, problem in feature selection can be stated as equation below:

\[ Y = \max_{B \subseteq X, |B|=d} f(B) \]  

(1)

Where d represent the desired number of feature in selected subset.

Based on Equation 1, B is the possible subsets of significant feature and for a given data set with N features, multiple subsets either equal or almost equal optimal may exist. The task of feature selection can be seen as a search for optimal feature subsets through the competing 2N candidates. The
optimality of feature depends on the problem at hands. Based on that, the optimal feature selection problem relates to NP-hard and heuristic approaches able to deal with these kind problems. Therefore, several techniques have been developed to evaluate of discovered feature subset.

As mentioned in the previous section feature selection offered three different types of methods. These methods will reduce unwanted features and only significant features are remain. Filter method relies on general characteristics of the data to evaluate and select feature subsets without involving any mining algorithm as its use as a proxy measure instead of error rate to score a feature subset. Generally, it adopts statistical functions to evaluate the quality of the each feature. As a result, it has a tendency to select redundant features due the measure did not consider the interaction between features. Then, the selected features will be ranked and evaluated by using either univariate or multivariate techniques. However, this technique is fast and scalable to most the high dimensional problems.

Wrapper method wrapped together of feature selection and learning process to find the best feature subset by using a predictive model. Typically, it requires extensive computation to search for best features, but it is simple to implement. Compared to filter, wrapper has higher accuracy performance. However, wrapper has a high tendency to have fitting problem as it use iterative process to evaluate the best feature subset. In wrapper, Sequential or Greedy and Global or Random Search are the evaluation techniques used.

Embedded performed well as feature selection by integrating feature selection as part of the learning process and normally specifically to given learning machine. Compared to others two methods, the searching and selection process of features’ subset is built into classifier construction. Based on Hancer et al (2017), embedded method is more efficient than wrapping method as it able to avoid the iterative process in finding the best feature subset. Add to that, the learning process will be identified the best feature in the development phase. This cause computational process is more complex compared to wrapper method. However, compared among these three methods offered by feature selection, embedded has a higher performance accuracy especially for a classification model.

However, recently two new techniques in feature selection are introduced. They are hybrid and ensemble methods. Actually, hybrid is the combination of filter and wrapper where filter is used to select the best features while wrapper is used as learning algorithm to evaluate the feature subset. Both filter and wrapper have their own advantages hence by combining these two methods through hybridization better performance can be achieved in term of accuracy and computational complexity [4,23]. However, ensemble method selects a different feature subset from an original dataset. Among them, a group of the best feature is created and it has two different types of techniques to act as a classifier. They are heterogeneous and homogenous.

In the process of developing methodology for a good feature selection, there are two main problems related to feature selection that must be concerned and solved. They are construction of feature evaluation and application of a strategy to search for optimal features. Evaluation and search are the keys to solving problems in developing good feature selection models. These two criteria are compulsory for a feature selection method. Evaluation of feature is important to measure the quality of a candidate subset and it is an important element to increase the classification ability of a feature subset. By the same token, a good feature evaluation can reflect high accuracy of the classification process. Second, the search involves finding strategy to select an optimal feature selection and must rely on the defined evaluation. Distance, correlation, consistency and mutual information are the factors determine the connection between evaluation and search in a feature selection. Search for an optimal subset an important process in feature selection. Heuristic search not promising the best subset even it has an acceptable solution in a reasonable time.

Hence, recently metaheuristic inspired from nature triggered the researchers to implement it in order to solve feature selection problem. Based on the previous research, each natured inspired metaheuristics have its own advantages and disadvantages in dealing with different dataset. However, the results reflect the performance of feature selection increase by using metaheuristics approaches. Recently, swarm intelligent algorithms are widely used due for many reasons [3, 22]. Able to share
information among multiple agents lead the algorithms to self-organization, co-evolution and learning during iterations. These helped in providing high efficiency of performance. The multiple agent also beneficial for the feature selection because it easily can be parallelized so it more practical especially in large scale optimization. Swarm intelligence based on optimization algorithm such as particle swarm optimization (PSO), harmony searches (HS), ant colony optimization (ACO) and fish swarm algorithm (FSA) are among metaheuristics catches the researches. Among them, FSA has flexible and simple to be implemented and gives higher accuracy of feature selection result as it has advantages in term of speed of convergence and fault tolerance [6,13].

3. Fish Swarm Algorithm (FSA)

The fish lives in a group without a leader, however, has self-organized and has the ability to accept information about the environment by a sense organ. Then the fish do a stimulant reaction by control of tail and fin to find areas that have a high concentration of food. This situation inspired Dr. Xiaolie Li in 2002 to propose FSA [9]. Based on the purposed FSA, FSA technically builds up with two main components. They are parameters and functions which both related to behavior of fish and surrounding factors.

Parameters include the size of the movement of fish (Step), the visual distance of fish individual (Visual), the crowd factor of the fish (δ) and distance between two fish donated by $X_i$ and $X_j$ ($d_{ij} = \| X_i - X_j \|$), where $X=(X_1,X_2,X_3,....,X_n)$ and $Y= f(x)$. $X$ represents an individual state in fish population and $Y$ represents food concentration value or objective function. Visual and Step played the most important role among the four parameters. Visual determines the range of search, and Step determines the convergence speed and accuracy of optimization. Additionally, the value of Visual and Step are fixed. The larger the value of both parameters, FSA moves faster toward global optimum because the fish can explore larger space around them and move larger step in each iteration. Meanwhile, by defining small value of both parameters, the local search process is more stable and accurate [20, 21].

Three behaviors of fish include Search, Follow and Swarm and are translated as basic functions in FSA. Search or also known as prey is the most basic fish’s behavior. Once the fish detects a region with a high concentration of food, it will directly toward that region. The concentration of food represents the objective function value. The higher objective function, it is easier to find the global extreme value and converges. When one fish discovers more food, the other fish will share with it. In FSA adaptation, if there is another state has a higher concentration of food than current state, the fish will move toward it. Swarm behavior, fish tend to swarm naturally to avoid the danger and to guarantee the existence of the colony. The danger here is referring to preventing fish from trapping into sub-optimal [7]. This reflects either to move toward the center or not, and the decision depends on the crowd factor.

The value of Visual and Step have a great effect on the behavior of fish. As an example, when the size of Visual is narrow, the search behavior and swarm behavior are dominated [2, 20]. The fish tends to search most high food concentration in the Visual. Then the swarm behavior will decide either to move toward it or not. The higher value of Visual and Step, thus a faster global optimal was achieved. This concept encourages the researchers to employ FSA to solve many optimization problems in various research areas. Recently, FSA is aggressively implemented in feature selection, prediction and classification [13, 17, 19, 24].
3.1. FSA Flow Chart

Based on Figure 4, the state vector of fish swarm is shown as

\[ X = (X_1, X_2, X_3, \ldots, X_n) \]  \hspace{1cm} (2)

where, \( X \) represents the fish.
and the visual position is presented as

\[ X_v = (X_{v1}, X_{v2}, X_{v3}, \ldots, X_{vn}) \]  \hspace{1cm} (3)

where, \( X_v \) represents the fish position in Visual.

The above functions (1), (2) worked by:
\[ X_{vi} = X_{vi} + \text{Visual} \times \text{Rand()} \hspace{0.5cm} ; i \in (0,1] \]  \hspace{1cm} (4)

where, \( X_{vi} \) is the condition of fish in Visual.
From above equations, Equation (2) represents the state of fish and Equation (3) represents the fish position in Visual. Equation (4) represents how Equation (2) and (3) work together, and it shows the coward factor in FSA. Equation (5) shows how the next fish is determined by the distance between two fish and the value of Step. Then the behaviors of fish which represent the functions in the FSA will be processed as indicated in Equations (6) to (10).

\[ X_{\text{next}} = X + \frac{(X_v - X)}{||X_v - X||} \times \text{Step} \times \text{Rand()} \]  
(5)

where,

\( X_{\text{next}} \) is the next fish in Visual.

Search behavior, swarm behavior and follow behavior are represented in Equations (6), (9) and (10) respectively. They will be executed once the related conditions are fulfilled. Otherwise Equation (7) and (8) are executed. The process continues until the condition is fulfilled by repeating Equation (6). The process will be repeated until optimal point obtained. When the condition is satisfied, the current optimal value based on the result obtained will be updated. Finally, once the termination condition is fulfilled, then the final result is recorded. Figure 4 shows the flowchart of FSA regarding
to Equations (2) to (10).

Compared to the other swarm intelligent algorithms, FSA is an efficient algorithm in terms of its accuracy, appropriate to tolerate with fault, avoiding local minimum, more flexible and has high convergence speed [5,15,18]. Although the existing method such as PSO works well for optimization, there is problem of falling into the local optimum solution easily. FSA is able to avoid falling into the local optimum easily by controlling the parameter of FSA [11].

3.2. FSA for Feature Selection

This section provides a key concept mapping how feature selection problems are translate into optimization problems and be solved by implementing FSA. In optimization problem, predetermined number of variable is a must process. Variable in optimization is equivalents to features in feature selection. Differ to optimization problems, the number of features is not fixed in a subset. Therefore, the size of the evolving potential subset should be reduced similar to the optimization of subset evaluation score. Table 1 reflects further mapping FSA to feature selection concept and Figure 5 shows the flow how FSA works in feature selection.

| Fish Swarm Algorithm | Optimization          | Feature Selection                  |
|----------------------|-----------------------|-----------------------------------|
| Fish                 | Variable              | Feature                           |
| Step                 | Parameter             | Distance                          |
| Visual               | Parameter             | Feature Space                      |
| Distance Between Fish| Parameter             | Distance relates to mutual information |
| Search Behavior      | Function              | Subset Evaluation                  |
| Follow Behavior      | Function              | Subset Evaluation                  |
| Swarm Behavior       | Function              | Subset Evaluation                  |
Refer Figure 5, implementation of FSA in feature selection can be divided into four main actions; initialization, assessment of the fitness, augmentation steps of fish swarm and output the optimal feature subset. The initialization of feature subsets of each fish consist of two main steps. First, representation of fish and second distance and center of fishes. During the representation of position, each position of fish that has same character is placed in a feature subset. Then the distance and number of fishes are defined. At this time, it involved Equation (2) and (3) which work perfectly together with Equation (4) and (5).

Assessment of fitness involved the assessment fitness value of the attribute subcategory of every fish. In FSA fitness function represent the food concentration and it also a factor of selection fish behavior. During augmentation steps of fish swarm, the behavior functions are tested. These functions act as subset evaluation and subset that fulfilled the condition will approved as the optimal subset. These evaluation also act as halting condition to select the best subset of features. Equations (6), (9), and (10) are the halting target to be achieved by fulfilled their conditions in order to execute Equation (7) and (8).

4. Recent Studies of FSA in Feature Selection
Despite FSA conquered in various fields for multiple purpose, FSA recently has been applied in many areas as a feature selection method. This includes in image and speech recognition, computer network, gene selection and etc. The structure of FSA that contain flexible parameters and functions proved to be highly successful in the different fields. Besides, the result of experiment implemented FSA show FSA achieve better performance than other methods [13]. Hence, FSA in feature selection most probably will reflect same result which able to achieve high performance in many terms.
Tsai and Lin (2011) focus on effect of FSA behaviour for optimization especially during the evolution process. The basic FSA is reformulate using particle swarm optimization (PSO) algorithm. The proposed technique was tested on eight different benchmark functions. The results reflect the proposed FSA needs less effort to set parameters. Generally, the proposed method increase the step free status, stability, speed and accuracy. However, there is slightly improvement need in term of computation time. Chen et al (2015), proposed FSA for rough set reduction (RST) to cover the limitation of RST that inadequate for finding a global minimal reduct. FSA that consists of searching, swarming and following functions triggered them to apply the functions to find the minimal subset among the features. As mentioned earlier, the fitness function and fish position play important roles besides the FSA function. Then it was tested with some data from UCI dataset. The results are compared with heuristic methods and population-based algorithms and it shown the propose algorithm reflect a good tool for finding a minimal subset of feature selection without losing the dataset information. The result implementation of FSA reflects and proved, FSA has strong search capability in problem space, able to find minimal reduct efficiently and able to converge quickly.

Lin et al (2015), improve feature selection for classification by improving basic FSA, modified fish swarm algorithm (MFSA) and used support vector machine (SVM) as a classifier. The modification of FSA involved adjustment of visual parameter and searching function which the visual became more dynamic and searching is focused on the best fish swarm. They used ten datasets from the UCI database with different number of records, features, classes and fields. Every datasets are tested by using both approach FSA and MFSA. The results demonstrate MAFSA has high accuracy of classification compared to FSA. Other related to SVM is Nalluri et al (2017). They applied FSA with support vector machine (SVM) to select feature among the medical dataset with minimum number of features. The performance is assessed by evaluating the algorithm on nine different datasets. Using nine datasets which are binary and multiple imbalanced class. Among them, three are large and the rest are small datasets. The results are compared to the metaheuristic algorithm. From the results, the proposed method provides high classification accuracy with features subset with few features. The improvement is recorded from 3.15% to 22.84%.

In 2016, Luan et al implement FSA to overcome the problem of low solution precision and slow resolving speed of exiting reduction algorithms for feature selection purpose. Having a good feature selection, attribute reduction (AR) is an important step in pre-processing phase. Hence, taking advantages of FSA, they implement FSA in rough set. To strengthen the implementation, Cauchy distribution function, multi-parent crossover operator, modified minimal generation gap model and mutation operator are applied. As the result they covered the limitations of FSA which are slow convergent speed and converging to a local minimum. Some data from UCI dataset are used to identify how well the proposed method works. From the results, the proposed method improves the performance by not only having fast convergence speed also reflect high accuracy of attribute reduction for feature selection.

Chen et al (2017) using rough set theory as they believed it an effective method to feature selection. The current approaches inadequate for finding a global minimal reduct so FSA is applied. Based on the review, they justified FSA has capability to overcome the problem as the FSA discover the best combination of features as the fish swim within the subset space. They define three foraging fish behavior to find optimal subset and a fitness function for evaluating best solution. Results reflect, FSA based on neighborhood reduction is suitable to deal with numerical data.

Differ to other, Manikandam and Kalpana (2017) focus on big data area. The most worrisome problems in data includes data streams and data heterogeneity. Hence, dimension of databases need to reduce in order obtaining only relevant feature and feature selection techniques play important role. They used FSA approach to search a subset of features that relevant data to represent an accurate description of the certain dataset. As searching is combinational problem and can cause big time consuming, FSA is applied to overcome the situation. Classification and regression tree (CART) is combined with FSA. Results proved FSA achieved better performance from the other methods by 7.91% when compared with MI-CART and FSO with random forest increased accuracy by 7.31%.
when compared with MI-random forest. These results are obtained from used data, Product review database from Amazon with total 235 000 positive and 147 000 negative reviews records in database. Table 2 shows the summary of feature selection using HS in the literature from 2011- 2017.

Table 2. Summary of feature selection using FSA

| Author (Year)             | Application                                                                 | Method / Implementation                          |
|---------------------------|-----------------------------------------------------------------------------|--------------------------------------------------|
| Tsai and Lin (2011)       | 10 Benchmark Functions Data                                                 | FSA with PSO                                      |
| Chen et al (2015)         | UCI Datasets                                                                | FSA with Rough Set                                |
| Lin et. al (2015)         | UCI Datasets                                                                | MFSA with SVM                                     |
| Luan et al (2016)         | UCI Datasets                                                                | FSA with Rough Set                                |
| Chen et al (2017)         | UCI Datasets                                                                | FSA-based neighbourhood rough set reduction      |
| Manikandam and Kalpana (2017) | Product Review from Amazon along with synthetic data                          | FSA with CART                                     |
| Nalluri et al (2017)      | 1. UCI database 2. SRBCT from Shenzhen University                            | FSA with SVM                                      |

5. Conclusion
Consider a feature selection space with large size that has large number of feature subsets where each feature subset potentially to be mapped as point or variable or valuable feature in such a space. The total N features will be assigned as 2N kinds of subsets which have different lengths and features number for each subset and the least length and highest classification quality is considered as the optimal subset. This triggered researchers to propose different strategies to improve feature selection. Their main objective is to identify more compact and better quality feature subsets. Its proven by a number of evaluations has been developed. From the reviews, it can be concluded feature selection using FSA gives a good performance and reflect a good result in various research area compared to others. In FSA view, fish are put into the feature space known as Visual where each fish takes one position. This reflects each fish represent as feature. During searching for food, the fish will swim toward best position and through this their position will change. They have to communicate to each other through the space and search around the locally and globally best positions. To achieve that FSA offered a good and position converge. Through this, FSA show high potential to discover minimal subset that can lead to a good performance of feature selection. Hence, to realize it, a few steps are highlighted. They are presentation of position, distance and center of fishes, position update strategies, fitness function and halting condition.

It has proven FSA good at identifying the high performance in solution space within a reasonable time. There are many strategies that have been proposed to improve and enhance the capabilities of FSA so better results are performed. Parameter of FSA catches more attraction of researches to do some modification and adjustment within it compared to function to FSA. Generally, function or behavior of FSA is more focus in order to speed up performance time of feature selection meanwhile parameter of FSA has high contribution in determines the relevant or wanted feature for feature selection process. The review as discussed in the previous section.

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