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Feature selection using multi-objective CHC genetic algorithm

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Abstract

Most of the datasets contain redundancies and inconsistencies in terms of features or instances or both. Therefore, datasets always need pre-processing before applying data mining algorithms. Feature selection is an important pre-processing task that prefers non-redundant and informative features. In addition, feature selection is a multi-objective problem with conflicting criteria like accuracy and reduction rate. This paper proposes a multi-objective CHC algorithm (a genetic algorithm with cross-generational elitist selection, heterogeneous recombination, and cataclysmic mutation) for feature selection. The algorithm, named as MOCHC-FS, combines the idea of non-dominated sorting with CHC genetic algorithm to arrive at a set of non-dominated solutions. The proposed algorithm is validated on twenty datasets available on UCI dataset repository. The results affirm that MOCHC-FS algorithm finds a range of optimal solutions that simultaneously fulfil both objectives of relatively higher accuracies and more reduction rates. Finally, a single feature subset is extracted from the set of non-dominated solutions. Accuracy and reduction rate are recorded for various experimental datasets by using KNN classification algorithm on the selected features only.

Keywords: Feature Selection; Genetic Algorithm (GA); Multi-objective Genetic Algorithm (MOGA); CHC; Multi-objective CHC (MOCHC); KNN.

1. Introduction

Today massive datasets with many features are frequently available for data analytics and machine learning applications. These datasets often consist of redundant and unimportant features and instances. The existence of noisy and superfluous features hampers the performance of machine learning algorithms. Thus, everybody needs some data reduction mechanisms to apply machine learning algorithms in an effective manner. In fact, the process of data reduction comprises the selection of more useful and appropriate features or instances or both [1–7]. This study solely deals with the problem of feature selection (FS) in context to KNN (K-nearest neighbour) classifier.

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The KNN algorithms performance depends upon the value of the factor K and number of features in the dataset. The large number of features in datasets makes the application of KNN infeasible due to the curse of dimensionality and scalability problems. Therefore, we need to reduce the dimensionality of the training data by eliminating the redundant attributes.

Since feature selection can be posed as a search and optimization problem, hence, it can be solved effectively using evolutionary algorithms. The review of the related literature shows that the CHC, a variant of genetic algorithm with cross-generational elitist selection, heterogeneous recombination, and cataclysmic mutation, performs best for the problem of instance selection [7]. CHC is a nontraditional genetic algorithm which simultaneously performs an elitist selection, recombination operator, and a restart process for avoiding convergence to suboptimal regions [8].

Accuracy and reduction rates are two conflicting objectives as maximization of data reduction may cause drop in accuracy and vice versa. As a result, feature selection should be dealt as multi-objective problem. Many authors have employed multi-objective GA for solving the problem of feature selection [6,9–15]. We have not come across any application of multi-objective CHC for the problem of features selection. Rathee et al. [7] have developed MOCHC for solving the problem of instance selection within multi-objective environment [7]. In this paper, we propose a Multi-objective CHC (MOCHC-FS) to tackle the problem of feature selection. The suggested algorithm finds a set of Pareto-optimal solutions rather than arriving at a single best solution. Therefore, the users can have numerous choices of reduced feature subsets and select the one that suits their preferences. The main contribution of this paper is the design a CHC algorithm in a multi-objective framework with the help of NSGA-II to find several sets of non-dominated solutions with trade-off between accuracy and reduction rates. Further, the features occurring in various non-dominated solution are combined to form a beneficial single feature subset. The experimental comparative analysis shows the superiority of the proposed approach.

Rest of the paper is structured as follows. Section 2 illustrates the necessary background for feature selection and multi-objective optimization methods. Section 3 gives details of the proposed algorithm: MOCHC-FS for feature selection. Section 4 gives experimental design and results. The last section 5 concludes the paper.

2. Related Work

This section gives a detailed review of feature selection, Multi-objective GA and Multi-objective CHC algorithm.

2.1. Feature Selection

The main idea of feature selection is to identify revealing and pertinent features from datasets. Feature selection reduces the computational cost by decreasing dimensionality of data through elimination of redundant and extraneous features. Feature selection algorithms are categorized into three models- filter models, wrapper models and hybrid models [16–21]. Wrapper approaches often give better results instead of the filters in terms of accuracy. However, filter approaches run many times faster than wrappers. Hybrid models achieve better efficiency by combining both filter and wrapper approaches. Many authors have worked on hybrid model for selecting most important features [16,17,22,23]. Evolutionary Algorithms (EAs) are well known for searching optimal solution for the problem of feature selection [1,22,24,25].

2.2. Multi-objective Optimization for Feature Selection

As FS consists of multiple objectives, for that reason, feature selection problem can be better solved using multi-objective meta-heuristics [6,9–11,15,16,26]. Multi-objective optimization involves optimization of several contradictory objective functions simultaneously. In such situations, there is no single optimal solution; however, there exists many solutions which are better to each other on one or another objective function. Pareto optimal solutions will be used for these kinds of problems to find best trade-off among the objective functions. It generates multiple solutions and the set of all these multiple non-dominated solutions is called Pareto optimal set. These multiple solutions help a user to select a solution according to his/her choice in their application domain. In general, FS is treated as a multi-objective problem as it has two main conflicting objectives such as accuracy and reduction rate. We need to maximize the classification accuracy and increase the reduction rate simultaneously. Xue et al. (2013) [15] have designed a differential evolution based multi-objective approach for feature selection by maximizing classification accuracy and minimizing the number of features from the dataset. Ahuja and Ratnoo (2015) [16] have designed a hybrid approach for feature selection in which they devise a MOGA at filter phase and a simple GA at the wrapper phase. The authors have compared their Hybrid MOGA with Filter, Wrapper and Hybrid GA approaches. At filter phase, MOGA provides feature subsets of non-dominated solutions optimized on some criterion as an input to the wrapper phase. Paul and Das (2015) [11] have developed a feature selection and weighting decomposition based multi-objective algorithm in which, the inter-class and intra-class vectors are simultaneously optimized by the proposed algorithm for obtaining best possible number of features. The objective function contains penalty and a repairing mechanism which is used to reduce the irrelevant features from the dataset. The authors have compared MOEA/D approach to numerous feature selection methods such as SFS, SBS, FS-FS, FR-FS, BBA-FS, RB-FS, DEMOFS and MOGA-FS. The results of MOEA/D outperform all of these approaches in both accuracy and feature reduction rates.

2.3. The CHC Genetic Algorithm

CHC genetic algorithm, first developed by Eshelman in 1991, consists of a cross-generational elitist selection, heterogeneous recombination, and cataclysmic mutation. It is a variation of Genetic Algorithm (GA) which has proven to be very effective for the purpose of feature and instance selection as well as dual selection [5,7,27–29]. CHC algorithm differs from simple GA regarding the way selection, crossover and mutation operators are applied. The fundamental steps of the CHC algorithm are given below:

- **Selection:** Only those pairs which differs from each other by some bits according to given threshold (d=L (length of chromosome)/4) are permitted to mate.
- **HUX Crossover:** The uniform crossover is performed by CHC algorithm. It randomly swaps half of the non-matching bits from the parents whose hamming distance is greater than specified threshold (d).
- **Mutation:** No mutation is applied at the recombination stage of the CHC algorithm. It is only applied whenever convergence occurs and the threshold (d) reaches zero.
- **Restart Process:** A restart process is initiated that infuses some diversity into the population by using cataclysmic mutation. It uses one copy of the best performing individuals as a template string and the remainder of the population is generated by mutating 35% of the bits in the template string.

Multi-objective genetic algorithm (MOGA) includes NSGA-II (non-dominated sorting genetic algorithm) [30], Pareto archived evolution strategy (PAES) and strength Pareto evolutionary algorithm 2 (SPEA2). Out of all of the MOGAs, NSGA-II is the most commonly applied MOGA. Yet, MOCHC has been implemented for solving instance selection problem only [7].

3. The proposed Multi-Objective CHC (MOCHC-FS)

The proposed Multi-Objective CHC (MOCHC-FS) algorithm hybridizes the design of Pareto-based non-dominated sorting (NSGA-II) [30] and CHC genetic algorithm to tackle feature selection problem. The algorithm optimizes data reduction rate and KNN classification accuracy simultaneously. The non-dominated sorting and substitution/replacement strategy of NSGA-II provides the multi-objective setting for the two distinctive objectives, i.e., feature reduction rate and classification accuracy whereas the CHC algorithm puts together a selection method, HUX crossover operator and a restart process.

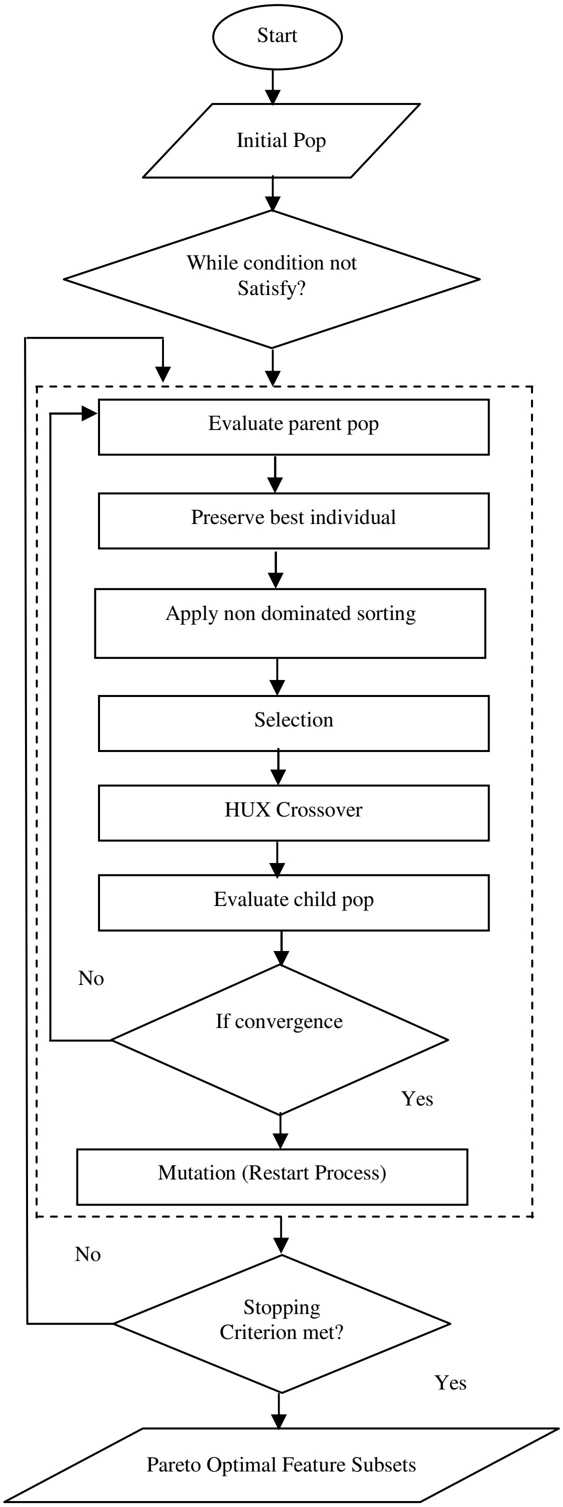

Figure 1: Flowchart of MOCHC-FS for Feature Selection

The main purpose of the proposed MOCHC-FS is to preserve elitism as well as diversity in the population regarding both objectives. Figure 1 shows the flowchart of the proposed algorithm: MOCHC-FS for feature selection. The sorting is done using non-dominated sorting of NSGA-II. Further, if size of the new population is larger than the original size of population, in that case, chromosomes are chosen one-by-one from the most recently added front based on the crowding distance mechanism. Whenever GA population is close to convergence, a resume process is started by simple bit-flip mutations; usually 35% of the bits are mutated.

Chromosome Representation

The GA population is initialized randomly. Each chromosome represents a set of features. The chromosome matches to a series of the digits, 1's and 0's. The 0 bit indicates the absence of a feature, while the 1 bit points to the presence of a feature.

Fitness Function

The two important objectives, i.e., maximizing classification accuracy and minimizing the number of features are used in the fitness function.

$$Fitness = \{f1 = Acuracy; f2 = \left(1 - \frac{|RS|}{|DS|}\right) * 100\} \quad (1)$$

The fitness function considers f1 as the accuracy of the classifier and f2 as the data reduction where RS and DS are the reduced and original datasets.

CHC Operators

The CHC algorithm uses elitist strategy as selection approach based on hamming distance and HUX crossover operator. The HUX operator exchanges half of those bits which are differing in the parent chromosomes. Mutation is applied with a high probability i.e. 35% only when the algorithm converges to sub-optimal areas.

4. Experimental Design and Result Analysis

We have implemented the MOCHC-FS algorithm in MATLAB. The other experimental information is given below.

4.1. Datasets Description

The MOCHC-FS algorithm is applied to twenty datasets available in UCI datasets repository. Table 1 shows the characteristics of these datasets.

Table1. Description of the Datasets.

Sr. No.	Datasets	#Features	#Instances	#Classes	Sr. No.	Datasets	#Features	#Instances	#Classes
1.	Spambase	57	4701	2	11.	German	24	1000	2
2.	Waveform	40	5000	3	12.	Zoo	17	101	7
3.	Ionosphere	34	351	2	13.	Mushroom	22	5644	2
4.	WDBC	30	569	2	14.	Chess	36	3196	2
5.	Vehicle	24	1000	2	15.	Splice	60	3190	3
6.	Wine	13	178	3	16.	Vote	16	232	2
7.	Breast Cancer	10	683	2	17.	Connect-4	42	67557	3
8.	WBC	9	699	2	18.	Flare	11	1066	6
9.	Glass	9	214	6	19.	Tic-Tac-Toe	9	958	2
10.	Iris	4	150	3	20.	Lymph	18	148	4

4.2. Genetic Parameters

The setting of parameters is a key issue for the success of any genetic algorithm. However, this work has only tuned the parameters experimentally and we do not claim these to be optimal. The employed parameters for the proposed algorithm are: chromosome length according to the number of features within a dataset, generations count = 80, population size = 40, difference threshold = 1/4 of the length of chromosomes (based on hamming distance), mutation rate = 0.35 (mutation takes place only on convergence), no. of elite kids = 10%, stalling generations = 10.

4.3. Results

Although, we have applied MOCHC-FS on 20 datasets, it is not possible to give the Pareto optimal fronts for all the datasets. Here, we show the Pareto fronts for two datasets only (Ionosphere and WDBC) in figure 2(a) and figure 2(b).

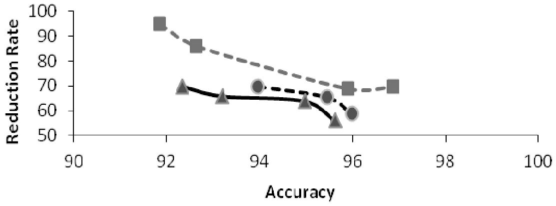

Figure 2 (a): Pareto Fronts for Ionosphered Dataset

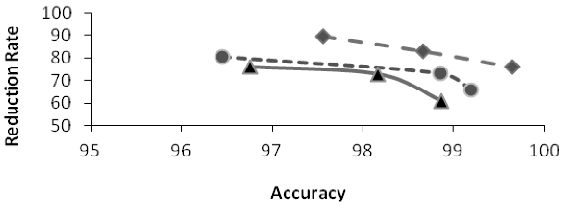

Figure 2 (b): Pareto Fronts for WDBC Dataset

A user can select any of the feature subset from the Pareto fronts that suits his/her requirements with respect to the cost or any other criteria for gathering the observations on the selected features. However, we have taken all the features occurring in more than 50 percent of the non-dominated solutions as the feature subset for further experiments and comparisons. The results using the selected features are recorded for accuracy and reduction rate in Table 2.

Table 2. Results of MOCHC-FS accuracy, KNN accuracy, reduction rates, total no. of features and selected no. of features

Datasets	KNN Accuracy	MOCHC-FS Accuracy	% Feature Reduction	Total #Features	Selected #Features
Spambase	81.89	99.26	98.43	57	2
Waveform	89.90	98.78	97.56	40	2
Ionosphere	90.00	97.56	96.96	34	2
WDBC	97.76	99.79	88.88	30	4
Vehicle	65.17	78.52	94.73	24	2
Wine	100	100	92.30	13	2
Breast Cancer	97.46	98.67	72.34	10	3
WBC	96.32	97.31	88.88	9	2
Glass	95.34	96.19	66.66	9	3
Iris	98.33	98.66	50.00	4	2
German	61.00	100	95.00	24	2
Zoo	100	100	93.75	17	2
Mushroom	95.78	98.18	90.90	22	2
Chess	99.52	98.56	83.33	36	6
Splice	72.17	75.90	76.66	60	14
Vote	98.92	98.20	89.50	16	2
Connect-4	97.99	84.70	86.79	42	5
Flare	95.99	78.36	90.90	11	2
Tic-Tac-Toe	88.68	82.75	88.88	9	3
Lymph	86.66	98.43	88.86	18	3

The table also gives the total number of features and the number of selected features by MOCHC-FS for respective datasets. Further, the table also includes the accuracies obtained by the KNN using full feature set and MOCHC-FS using only the reduced subset of features. The table shows that the proposed MOCHC-FS achieves higher accuracy on 14 datasets whereas KNN gets higher accuracy only on four datasets. The accuracies on two datasets are same. The proposed algorithm attains reduction rate in the range of 66 percent to 98 percent. Overall, we can say that MOCHC-FS successfully removes several irrelevant and superfluous features from the dataset without any significant compromise on accuracy.

Next, the results of the MOCHC-FS algorithm are compared with two recent multi-objective approaches- MOEA/D (Multi-objective Evolutionary Algorithm based on decomposition) [11] and Hybrid MOGA (Hybrid Multi-objective Genetic Algorithm for FS) [16]. The comparison is made on the datasets that were found common with the respective works. These results are given in Table 3 and 4.

Table 3. Comparison between MOEA/D and proposed MOCHC-FS.

Datasets	MOEA/D		MOCHC-FS	
	Accuracy	Reduction Rate	Accuracy	Reduction Rate
Spambase	88.48	54.38	99.26	98.43
Waveform	83.65	60.00	98.78	97.56
Ionosphere	88.31	66.17	97.56	96.96
WDBC	94.06	55.00	99.79	88.88
Vehicle	65.26	49.44	78.52	94.73
Wine	96.05	46.90	100	92.30
Breast Cancer	96.53	57.00	98.67	72.34
WBC	96.05	53.33	97.31	88.88
Glass	67.76	51.11	96.19	66.66
Iris	97.27	50.00	98.66	50.00

Table 4. Comparison between Hybrid MOGA and proposed MOCHC-FS

Datasets	Hybrid MOGA		MOCHC-FS	
	Accuracy	Reduction Rate	Accuracy	Reduction Rate
German	76.30	82.50	100.00	95.00
Zoo	95.50	57.81	100.00	93.75
Mushroom	99.42	89.54	98.18	90.90
Chess	97.32	77.22	98.56	83.33
Splice	87.53	75.00	75.90	76.66
Vote	96.30	91.87	98.20	89.50
Connect-4	72.65	81.42	84.70	86.79
Flare	73.45	79.09	78.36	90.90
Tic-Tac-Toe	77.24	55.55	82.75	88.88
Lymph	86.56	66.66	98.43	88.86

According to the Table 3, MOCHC-FS achieves superior accuracies and reduction rates in all the datasets as compared to MOEA/D. Further, MOCHC-FS obtains higher accuracy in 8 datasets out of 10 datasets when compared with Hybrid MOGA as shown in table 4. In case of reduction rates, percentage of feature reduction is higher in 9 datasets out of 10 datasets. It is quite clear from the results (Table 3 and 4) that MOCHC-FS for feature selection outperforms other evolutionary approaches in terms of both classification accuracy and reduction rates.

We have applied Wilcoxon signed rank test for further confirmation if the proposed algorithm for feature selection is significantly better than the other algorithms. It is a non-parametric statistical test used to test the null hypothesis for comparing paired samples. The results are summarized in Table 5.

Table 5. Wilcoxen Rank test results for Accuracy and Reduction Rate.

Accuracy	MOEA/D		Hybrid MOGA	
	V	p-value	V	p-value
MOCHC-FS	55	0.001953	47	0.04883
Reduction Rate	MOEA/D		Hybrid MOGA	
	V	p-value	V	p-value
MOCHC-FS	45	0.009152	52	0.009766

The test results confirm the supremacy of MOCHC-FS over the other two multi-objective algorithms for selection of features. The p-value for the comparison of MOCHC-FS with MOEA/D and Hybrid MOGA are 0.001953 and 0.04883 which are less than 0.05 (significance level). Therefore, we can reject the null hypothesis and accept the alternate hypothesis that MOCHC-FS is significantly better than the MOES/D and Hybrid MOGA at a significance level 0.05. For reduction rates, the p-values are 0.009152 and 0.009766, which are again far less than 0.05. This confirms that MOCHC-FS is better than the two algorithms regarding reduction rates as well.

5. Conclusion

Selecting relevant and useful features is crucial for enhancing the performance of and classification algorithms like KNN. Superfluous and noisy features confuse data mining algorithms in general and do not allow these algorithms to achieve their optimal performance. The performance of KNN classifier degrades in the existence of large number of features due to curse of dimensionality problem. This paper has suggested MOCHC-FS, a hybridization of CHC and NSGA-II algorithms, to deal with the problem of feature selection. The proposed MOCHC-FS has effectively discovered a pool of Pareto-optimal solutions. The results achieved by the proposed approach are affirmative across all the datasets with high accuracy and considerable reduction rates. In future, we would like to confirm these results for massively large datasets for dual data selection by using parallel multi-objective CHC genetic algorithm.

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