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Fusion of clonal selection algorithm and harmony search method in optimisation of fuzzy classification systems

Xiaolei Wang*, Xiao-Zhi Gao and Seppo J. Ovaska

Department of Electrical Engineering,
Helsinki University of Technology,
Otakaari 5 A, FI-02150 Espoo, Finland
Fax: +358-9-451-2432
E-mail: xiaolei@cc.hut.fi
E-mail: gao@cc.hut.fi
E-mail: seppo.ovaska@tkk.fi
*Corresponding author

Abstract: This paper presents a hybrid optimisation method based on the fusion of the clonal selection algorithm (CSA) and harmony search (HS) technique. The CSA is employed to improve the harmony memory members in the HS method. The hybrid optimisation algorithm is further used to optimise Sugeno fuzzy classification systems for the Fisher Iris data and wine data classification. Computer simulations results demonstrate the remarkable effectiveness of our new approach.

Keywords: clonal selection algorithm; CSA; harmony search method; HS method; hybrid optimisation methods; fuzzy classification systems.

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Biographical notes: Xiaolei Wang received her BSc in Technical Physics from Heilongjiang University, China in 2001. She received her MSc (Hons.) from Helsinki University of Technology, Finland in 2005. She is now working towards her DSc (Tech.) at the same university.

Xiao-Zhi Gao received his DSc (Tech.) from Helsinki University of Technology, Finland in 1999. Since 2004, he has been working as a Docent at the same university. He is an Associate Editor of the *Journal of Intelligent Automation and Soft Computing* and an Editorial Board Member of the *Journal of Applied Soft Computing* and *Journal of Hybrid Computing Research*. Dr. Gao has published more than 150 technical papers on refereed journals and international conferences. His current research interests are neural networks, fuzzy logic, evolutionary computing, swarm intelligence and artificial immune systems with their applications in industrial electronics.

Seppo J. Ovaska received his DSc (Tech.) in Electrical Engineering from Tampere University of Technology, Finland in 1989. He is currently a Professor in the Faculty of Electronics, Communications and Automation at Helsinki University of Technology, Finland. His research interests are in computationally intelligent hybrid systems, evolutionary computation, artificial life and artificial immune systems. During his career, he has published more than 80 journal articles and more than 140 conference publications. He is a recipient of two Outstanding Contribution Awards and the Most Active SMC Technical Committee Award of the IEEE Systems, Man and Cybernetics Society.

1 Introduction

Biology-inspired computational intelligence methodologies have attracted great research attention from numerous communities. For example, artificial immune systems (AIS), inspired by the immunology, are an emerging kind of soft computing methods. As an important branch of the AIS, the clonal selection algorithm (CSA) stems from the clonal selection mechanism that describes the basic natural immune response to the stimulation of non-self cells (antigens) (Dasgupta, 2006; Wang et al., 2004; Wang et al., 2006). The harmony search (HS) method is a meta-heuristic optimisation algorithm firstly proposed by Geem et al. (2001). It is inspired by the underlying principles of the musicians' improvisation of harmonies. During the recent years, the HS method has been successfully applied in the fields of function optimisation (Lee and Geem, 2005), mechanical structure design (Kang and Geem, 2004) and pipe network optimisation (Geem et al., 2002). Unfortunately, empirical study has shown that the HS method usually suffers from a slow search speed. To overcome this drawback, we propose a novel optimisation approach that combines the CSA and HS together. The diversity maintenance capability of the CSA can accelerate the convergence speed of the HS in our hybrid optimisation method.

Pattern classification refers to the problem of partitioning the feature space into multiple regions and categorising the objects into different classes defined on these regions (Chang and Lilly, 2004). Fuzzy logic has been widely employed in the data classification area. One of the essential considerations in constructing fuzzy systems is the generation of the fuzzy rules as well as membership functions for each fuzzy set. Generally, some clustering algorithms can be utilised to divide the pattern space into subspaces and map the centre of each cluster into a rule, which results an initial fuzzy model. After that, the coarse fuzzy system is optimised by adjusting the structures and parameters. For instance, the genetic algorithms (GA) are used to tune the membership functions, tailor the fuzzy rules and select the most suitable fuzzification and defuzzification methods (Shi et al., 1999; Setnes and Roubos, 2000). The data classification rate is improved after the fine-tuning procedure. In our paper, the fuzzy c-means clustering algorithm is first applied to build up the fuzzy classification system from only the training data. This rough fuzzy model is next optimised by the proposed hybrid optimisation algorithm.

The rest of this paper is organised as follows. We briefly introduce the working principles of both the CSA and HS method in Sections 2. In Section 3, by merging the CSA and HS together, we propose a hybrid optimisation technique, in which the HS memory (HM) members are improved by the CSA. The fuzzy classification systems are discussed in Section 4. The new optimisation algorithm is employed to optimise the Sugeno fuzzy classification systems for the Fisher Iris data and wine data classification in Section 5. Finally, in Section 6, we conclude our paper with some remarks and conclusions.

2 CSA and HS method

2.1 Clonal selection algorithm

Inspired by the clonal selection principle (CSP), the CSA has been studied and applied to deal with demanding optimisation problems due to its superior search capability compared with the classical optimisation techniques (Wang et al., 2004). The CSP explains how an immune response is mounted, when a non-self antigenic pattern is recognised by the B cells. In the natural immune systems, only the antibodies that can recognise the intruding antigens are selected to proliferate by cloning (Timmis et al., 2008). Hence, the fundamental idea of the CSA is that those cells (antibodies) capable of recognising the non-self cells (antigens) will proliferate. The flow chart of a basic CSA is shown in Figure 1 and it involves the following nine iteration steps (Wang, 2005).

1 Initialise the antibody pool P_{init} including the subset of memory cells (M).

2 Evaluate the fitness of all the antibodies (affinity with the antigen) in population P.

3 Select the best candidates (P_r) from population P, according to their fitness.

4 Clone P_r into a temporary antibody pool (C).

5 Generate a mutated antibody pool (C_1). The mutation rate of each antibody is inversely proportional to its fitness.

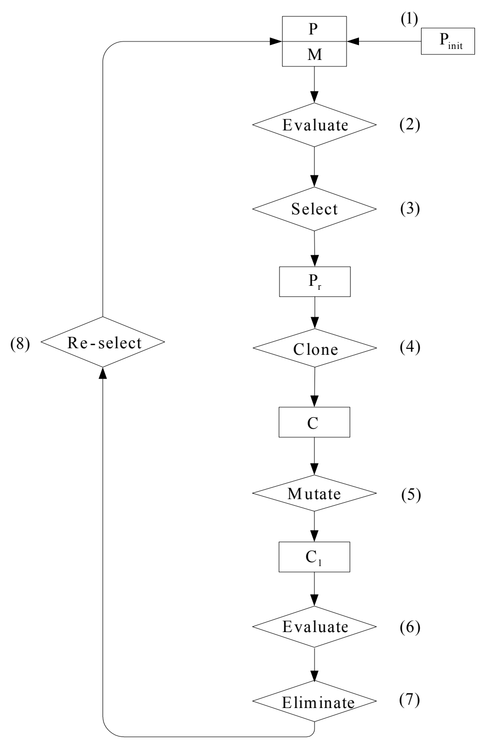
6 Evaluate all the antibodies in C_1.

7 Eliminate those antibodies similar to the ones in C and update C_1.

8 Reselect the antibodies with better fitness from C_1 to construct memory set M. Other improved individuals of C_1 can replace certain existing members with poor fitness in P to maintain the whole antibody diversity.

9 Return back to Step 2, if the preset performance criteria are not met. Otherwise, terminate.

Figure 1 Flow chart of basic CSA



We emphasise that a unique mutation operator is used in Step 5, in which the mutated values of the antibodies are inversely proportional to their fitness by means of choosing different mutation variations. That is to say, the better fitness the antibody has, the less it may change. The similarity among the antibodies can also affect the overall convergence speed of the CSA. Thus, the strategy of antibody suppression inspired by the immune network theory (Dasgupta, 2006) is introduced to eliminate the newly generated antibodies, which are too similar to those already in the candidate pool (Step 7). With such a diverse antibody pool, the CSA can effectively avoid being trapped into the local minima and provide the optimal solutions to the multi-modal problems (Wang et al., 2006). In summary, the antibody cloning and fitness-related mutation are the two remarkable characteristics of the CSA.

2.2 HS method

As we know, when musicians compose harmonies, they usually try various possible combinations of the music pitches stored in their memory. This kind of efficient search for a perfect state of harmonies is analogous to the procedure of finding the optimal solutions to engineering problems. The HS method is inspired by the principles of the above harmony improvisation (Geem et al., 2001). Figure 2 shows the flowchart of the essential HS method, in which there are four principal steps involved.

Step 1 Initialise the HM. The HM consists of a number of randomly generated solutions to the optimisation problems under consideration. For an n-dimension problem, an HM with the size of N can be represented as follows:

$$\mathrm{HM} = \begin{bmatrix} x_1^1, x_2^1, \cdots, x_n^1 \\ x_1^2, x_2^2, \cdots, x_n^2 \\ \vdots \\ x_1^N, x_2^N, \cdots, x_n^N \end{bmatrix} \tag{1}$$

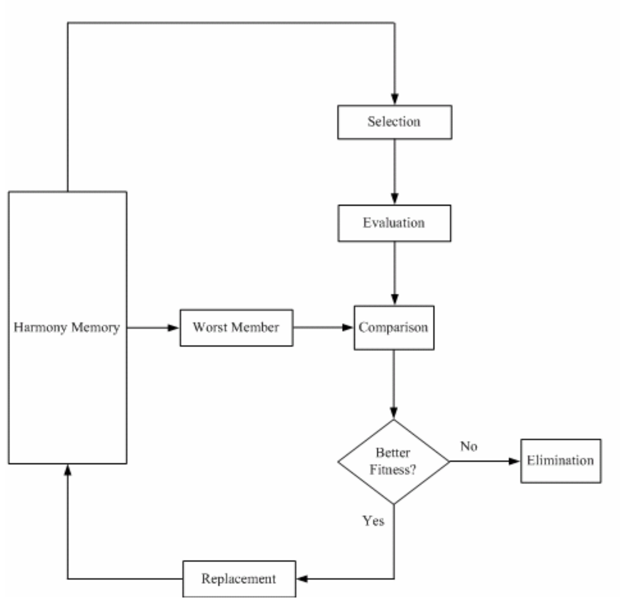
where $\left[x_1^i, x_2^i, \cdots, x_n^i\right]$ $(i = 1, 2, \cdots, N)$ is a solution candidate.

Step 2 Improvise a new solution $\left[x_1', x_2', \cdots, x_n'\right]$ from the HM. Each component of this solution, x_j', is obtained based on the harmony memory considering rate (HMCR). The HMCR is defined as the probability of selecting a component from the HM and 1-HMCR is, therefore, the probability of generating it randomly. If x_j' comes from the HM, it is chosen from the jth dimension of a random HM member and it can be further mutated depending on the pitching adjust rate (PAR). The PAR determines the probability of a candidate from the HM to be mutated. The improvisation of $\left[x_1', x_2', \cdots, x_n'\right]$ is similar to the production of offspring in the GA (Poli and Langdon, 2002) with the mutation and crossover operations. However, the GA usually creates new chromosomes using only one (mutation) or two (crossover) existing ones, while the generation of new solutions in the HS method makes full use of all the harmony members.

Step 3 Update the HM. The new solution from Step 2 is evaluated and if it yields a better fitness than that of the worst member in the HM, it will replace that one. Otherwise, it is eliminated.

Step 4 Repeat Step 2 to Step 3 until a termination criterion is met.

Figure 2 HS method

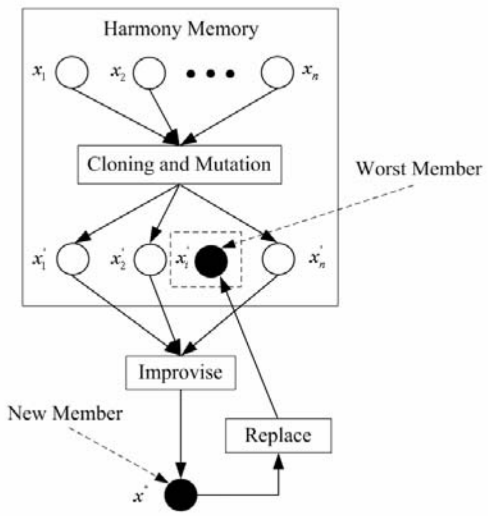


Similar with the GA and particle swarm optimization algorithms (Engelbrecht, 2005), the HS method is a random search technique. It does not need any prior domain knowledge, such as the gradient information of the objective functions. Nevertheless, different from those population-based approaches, it utilises only a single search memory to evolve. Hence, the HS method has the interesting advantage of algorithm simplicity. Note that the HM stores the past search experiences and plays an important role in its optimisation performance. In the next section, we deploy the CSA to improve the fitness of all the members in the HM so that the convergence speed of the original HS method can be accelerated.

3 Hybrid optimisation algorithm

In the past decade, hybridisation of evolutionary algorithms has gained considerable popularity, which can overcome their individual drawbacks while benefit from each other's strengths. In this section, we develop a hybrid optimisation technique based on the fusion of the CSA and HS method. As aforementioned, the elite maintenance policy is a distinguishing property of the HS method and has a central effect on its behaviours. However, the update of the HM highly depends on the past search experiences. This inherent shortcoming limits the search ability of the regular HS method, especially in handling complex optimisation problems. In our novel approach, the CSA is employed to improve the fitness of the solution candidates in the HM. That is to say, all the members of the HM are regarded as the individual antibodies and they can evolve in the population of the CSA. For example, $\left[x_1^i, x_2^i, \cdots, x_n^i\right]$ is updated to $\left[x_1'^i, x_2'^i, \cdots, x_n'^i\right]$ so as to gain a better affinity with the antigen after a certain number of the CSA iterations. The CSA-based update of the HM members is indeed embedded into the HS method as a separate fine-tuning approach. Figure 3 illustrates how the CSA is merged with the HS method in our hybrid optimisation scheme.

Figure 3 Hybrid optimisation method based on fusion of CSA and HS



The proposed hybrid optimisation algorithm takes the advantages from both the CSA and HS method. The CSA-aided tuning strategy can provide a set of diverse members for the HM, which results in an improved convergence capability to deal with the premature problem. In addition, it should be stressed that the CSA only moderately increases the computational complexity of the original HS method. In Section 5, we will demonstrate the enhanced performance of this hybrid algorithm over the CSA and HS method in the optimisation of fuzzy classification systems.

4 Fuzzy classification systems

Generally, in an n-input-single-output fuzzy classification system, a representative classification rule is:

Rule l IF x_1 is A_1^l and x_2 is A_2^l and … and x_n is A_n^l, THEN y is C_m,

where $l = 1, \cdots, L$, L is the number of fuzzy rules, $m = 1, \cdots, M$, M is the number of data classes, n is the number of input variables and $A_j^l \, (j = 1, 2, \cdots, n)$ is a fuzzy set associated with feature variable x_j. Here, vector $X = \left[x_1, x_2, \cdots, x_n\right]$ in the antecedent part consists of the input variables and C_m in the consequent part is the class label. In this paper, we only consider the asymmetric triangular membership function for those input variables:

$$\mu(x; a, b, c) = \max\left(0, \min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right)\right) \tag{2}$$

where a, b and c are the adaptive membership function parameters. Based on the given input data, the initial fuzzy system with a set of pre-defined rules according to the number of data classes can be obtained using some data clustering algorithms. The fuzzy c-means clustering method is a popular data clustering technique, which groups data or objects with high similarity and generates the partitions so that each object belongs to one or more clusters. In other words, it allows a data object to be classified into several clusters with different membership degrees. Furthermore, the parameters of the membership functions associated with the fuzzy sets can be optimised by the aforementioned optimisation methods.

In our fuzzy data classification scheme, we select the Sugeno fuzzy system with the singleton consequents representing different data classes. To evaluate the performance of the optimised membership functions, an objective function is defined as follows (Chang and Lilly, 2004; Setnes and Roubos, 2000):

$$J = \frac{1}{K}\sum_{k=1}^{K} e_k \tag{3}$$

where K is the number of the data samples in the training set and e_k is the classification error of a given data pattern. e_k is calculated as:

$$e_k = \begin{cases} 0, & \text{if classification is correct} \\ 1, & \text{if classification is incorrect} \end{cases} \tag{4}$$

Therefore, the task of the proposed hybrid optimisation method is to optimise the membership functions in the above Sugeno fuzzy classification system by minimising the objective function so that its data classification rate can be maximised. In the next section, the Fisher Iris data and wine data are used as two representative testbeds for examining this approach.

5 Simulations

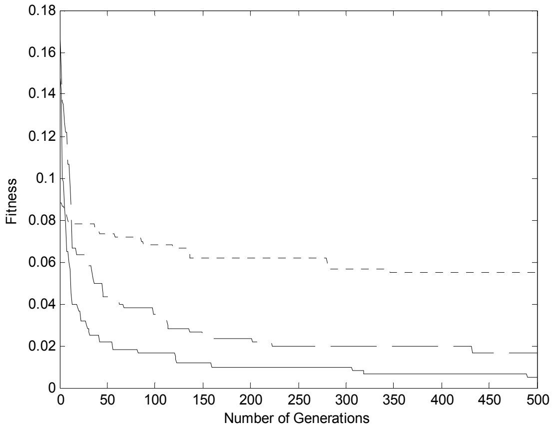
5.1 Fisher Iris data classification

The Fisher Iris data is a well-known challenging benchmark for the data classification techniques, which consists of four input measurements, sepal length (SL), sepal width (SW), petal length (PL) and petal width (PW), in 150 data sets (Fisher, 1936). A total of three species are involved, i.e., setosa, versicolor and virginica, and each species contains 50 samples. To perform the Iris data classification based on the output y of our Sugeno fuzzy classification system, the following principles are deployed:

$$\text{iris} = \begin{cases} \text{Setosa, if } y < 0.4 \\ \text{Versicolor, if } 0.4 \le y \le 0.9 \\ \text{Virginica, if } y > 0.9 \end{cases} \tag{5}$$

In the simulations, N instances from each Iris species are randomly selected as the training data and the remaining instances (T) are regarded as the test data. All the input variables are normalised within the range of [0, 1]. For the hybrid optimisation algorithm, we set HMCR = 0.8, PAR = 0.8, the number of the HM members is five and the maximum number of the antibody clones is four. The CSA, HS method and proposed optimisation algorithm are applied to optimise the aforementioned Sugeno fuzzy classification system. Figure 4 illustrates the performance comparison of their convergence speeds. Here, N = 10 and the test data have a total of 120 individual sets. Note that the results in Figure 4 are the average of ten independent runs. Obviously, our hybrid optimisation method can achieve the smallest classification error and the corresponding classification rate is 99.2%.

Figure 4 Convergence procedures of CSA, HS and hybrid algorithm in optimisation of Sugeno fuzzy classification system for Fisher Iris data classification



Notes: N = 10
dotted line: CSA
dash line: HS method
solid line: hybrid algorithm.

In a typical trial, a Sugeno fuzzy classification system with three rules is optimised, which results in only two misclassifications. The following three rules are available:

1 IF SL is small and SW is large and PL is small and PW is small, THEN Iris is setosa.

2 IF SL is large and SW is small and PL is medium and PW is medium, THEN Iris is versicolor.

3 IF SL is medium and SW is small and PL is large and PW is large, THEN Iris is virginica.

Figures 5 and 6 show the initial and optimised membership functions of small, medium and large, respectively.

Figure 5 Initial membership functions of Sugeno fuzzy classification system

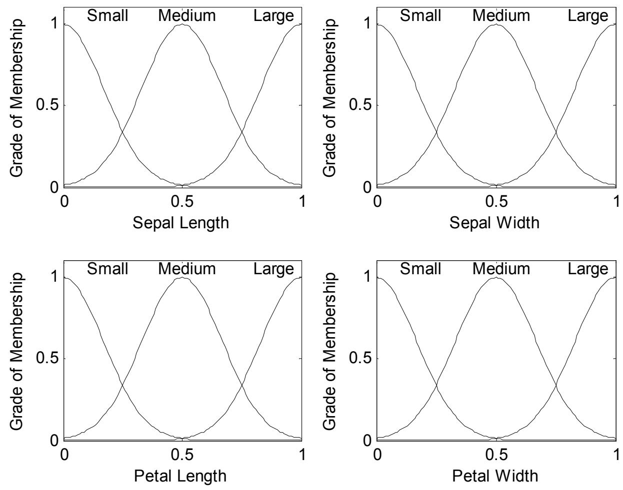
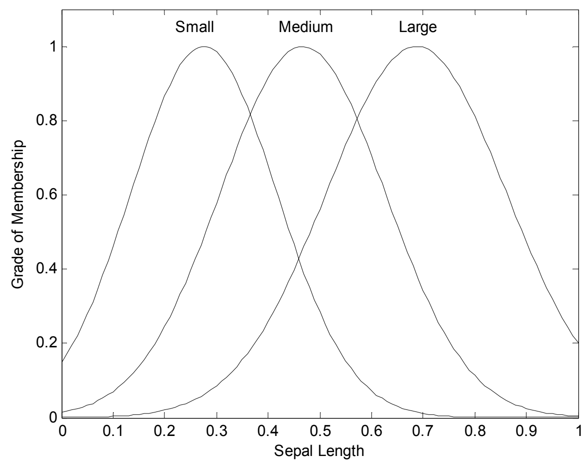
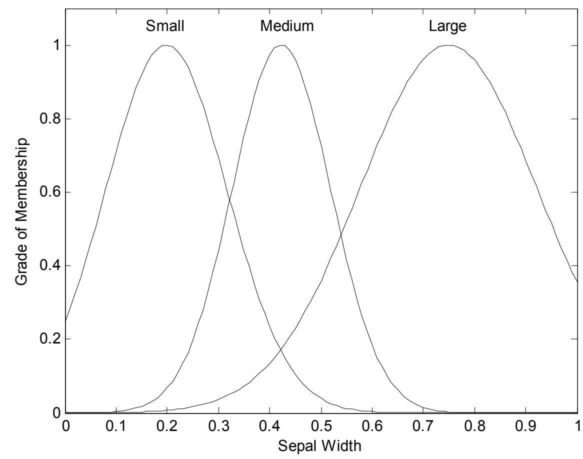


Figure 6 Membership functions of Sugeno fuzzy classification system optimised by hybrid optimisation algorithm for Fisher Iris data classification, (a) membership functions of SL (b) membership functions of SW (c) membership functions of PL (d) membership functions of PW

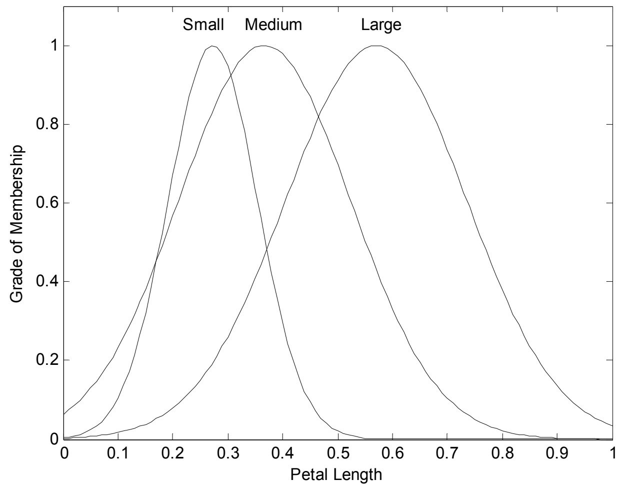


(a)

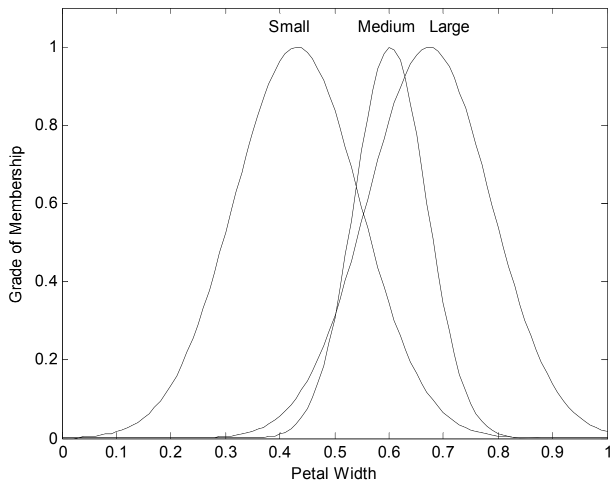


(b)

Figure 6 Membership functions of Sugeno fuzzy classification system optimised by hybrid optimisation algorithm for Fisher Iris data classification, (a) membership functions of SL (b) membership functions of SW (c) membership functions of PL (d) membership functions of PW (continued)



(c)



(d)

We further simplify our Sugeno fuzzy classification system by using only three input features, i.e., SW, PL and PW and assigning two membership functions to each of them. The three new fuzzy classification rules are as follows:

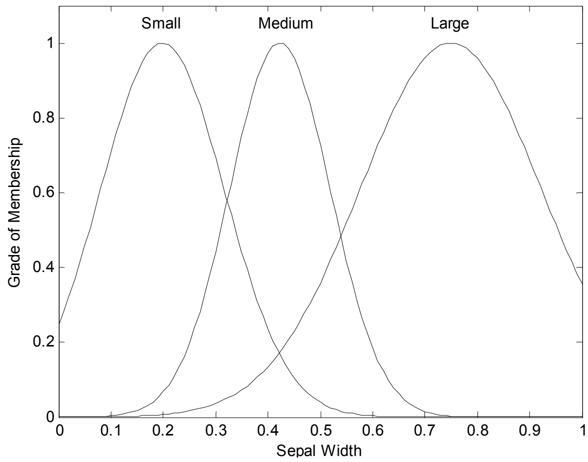
1 IF SW is large and PL is small and PW is small, THEN Iris is setosa.

2 IF SW is small and PL is small and PW is small, THEN Iris is versicolor.

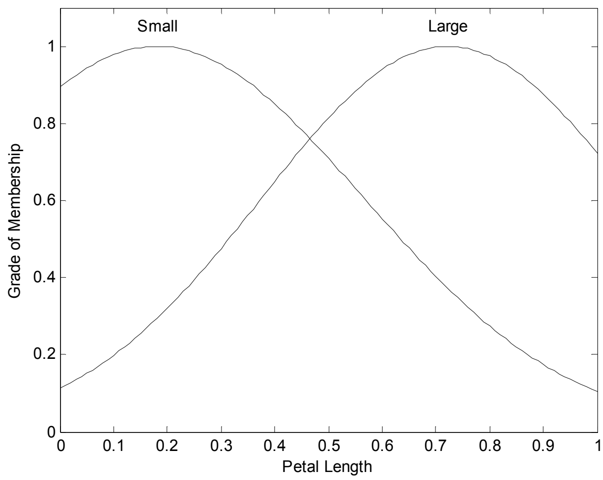
3 IF SW is large and PL is large and PW is large, THEN Iris is virginica.

The optimal membership functions acquired by the hybrid optimisation method are shown in Figure 7 and a classification rate of 99% has been achieved in this case.

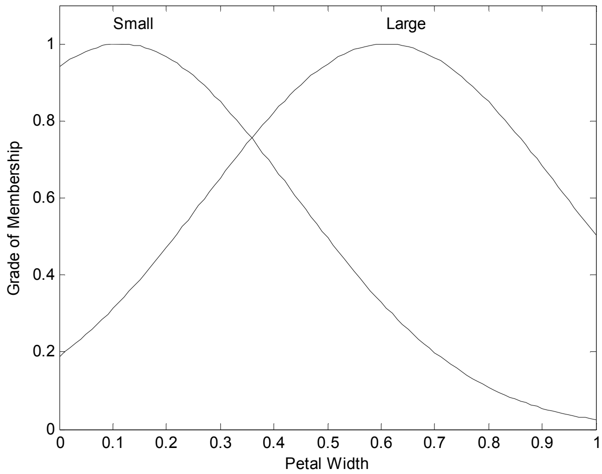
Figure 7 Membership functions of simplified Sugeno fuzzy classification system optimised by hybrid optimisation algorithm for Fisher Iris data classification, (a) membership functions of SW (b) membership functions of PL (c) membership functions of PW



(a)



(b)



(c)

Moreover, we examine the effectiveness of our hybrid algorithm in the optimisation of the same Sugeno fuzzy classification system with different numbers of training data sets, as given in Table 1. The results are also the average of ten separate runs. Misclassifying the patterns of virginica into versicolor is the main factor affecting the overall recognition rate and the classification of setosa is nearly 100% correct. Additionally, the fuzzy rules extracted by the fuzzy c-means clustering method can influence the classification rate. Table 2 gives the performance comparison between our scheme and other existing solutions from several references. It is clearly visible that the Fisher Iris data classification rate of the Sugeno fuzzy classification system can be significantly improved with the hybrid optimisation method.

Table 1 Classification results of Fisher Iris data using CSA, HS and hybrid method

Algorithms	*CSA*	*HS*	*Hybrid method*
$N = 10$, $T = 40$			
Misclassifications (training)	3	2	0.2
Classification rate (training)	90%	93.3%	99.3%
Misclassifications (test)	6.4	4.2	1
Classification rate (test)	94.7%	96.5%	99.2%
$N = 20$, $T = 30$			
Misclassifications (training)	3.8	3.2	0.2
Classification rates (training)	93.7%	94.7%	99.5%
Misclassifications (test)	3.4	3	0.6
Classification rates (test)	96.2%	96.7%	99.3%
$N = 40$, $T = 10$			
Misclassifications (training)	4.2	3.8	0.6
Classification rates (training)	96.5%	96.8%	99.5%
Misclassifications (test)	1.6	1.4	0.2
Classification rates (test)	94.7%	95.3%	99.3%

Table 2 Fisher Iris data classification comparisons of results from different references

References	*Number of features*	*Number of rules*	*Classification rates*
Shi et al. (1999)	12	4	98%
Setnes and Roubos (2000)	8 and 12	2 and 3	99.3% and 98.9%
Russo (2000)	18	5	100%
Chang and Lilly (2004)	7	5	99.3%
This paper	6 and 12	3	99% and 99.3%

5.2 *Wine data classification*

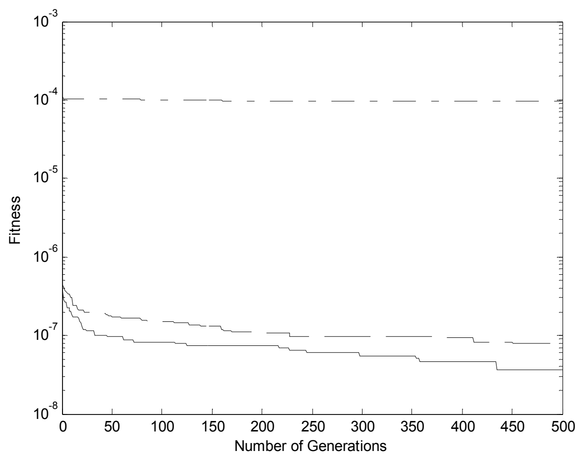
The wine data contains the chemical analysis of 178 wines that are brewed in the same region of Italy, but derived from three different cultivars. Each pattern consists of 13 features: alcohol content (Alc), malic acid content (Mal), ash content, alcalinity of ash (Ash), magnesium content (Mag), total phenols (Tot), flavanoids (Fla), non-flavanoids phenols (nFlav), proanthocyaninsm (Proa), colour intensity (Col), hue, OD280/OD315 (OD2) of diluted wines and praline (Pro). The numbers of the patterns in these three classes are 59, 71 and 48, respectively (Chang and Lilly, 2004).

Like in the Fisher Iris data classification, the output y of the Sugeno fuzzy classification system is based on the following classification rules:

$$\text{wine} = \begin{cases} \text{Class 1, if } y < 0.33 \\ \text{Class 2, if } 0.33 \le y \le 0.67 \\ \text{Class 3, if } y > 0.67 \end{cases} \tag{6}$$

Figure 8 illustrates the convergence speed comparison among the CSA, HS method and proposed hybrid algorithm. The results are the average of ten independent runs. $N = 20$ and 118 sets of wine data are used as the test data. As we can observe, the hybrid optimisation method yields the best classification performance.

Figure 8 Convergence procedures of CSA, HS method and hybrid algorithm in optimisation of fuzzy classification system for wine data classification



Notes: $N = 20$
dash-dotted line: CSA
dash line: HS method
solid line: hybrid algorithm.

As an illustrative example, the initial membership functions of flavanoids and colour intensity in the simplified Sugeno fuzzy classification system are demonstrated in Figure 9. Figure 10 shows the optimised membership functions of small, medium and large. The following seven rules are utilised:

1 IF Mal is small and Tot is large and Fla is large and Col is medium and Hue is large and OD2 is large and Pro is large, THEN wine is Class 1.

2 IF Mal is small and Tot is small and Fla is medium and Col is small and Hue is large and OD2 is large and Pro is small, THEN wine is Class 2.

3 IF Mal is large and Tot is small and Fla is small and Col is large and Hue is small and OD2 is small and Pro is medium, THEN wine is Class 3.

Figure 9 Initial membership functions of flavanoids and colour intensity in fuzzy classification system for wine data classification

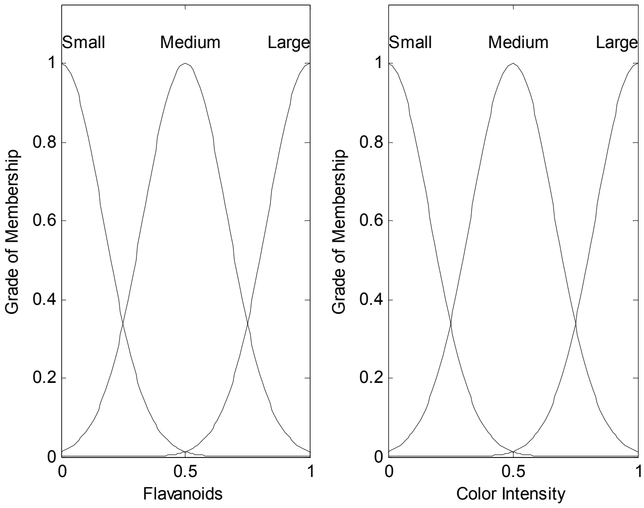


Figure 10 Membership functions of simplified Sugeno fuzzy classification system optimised by hybrid optimisation algorithm for wine data classification

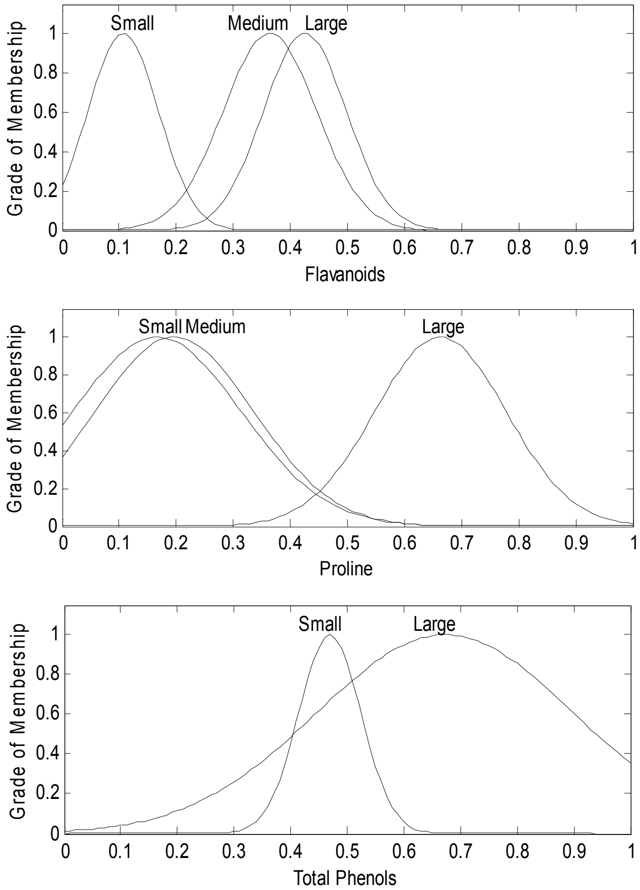
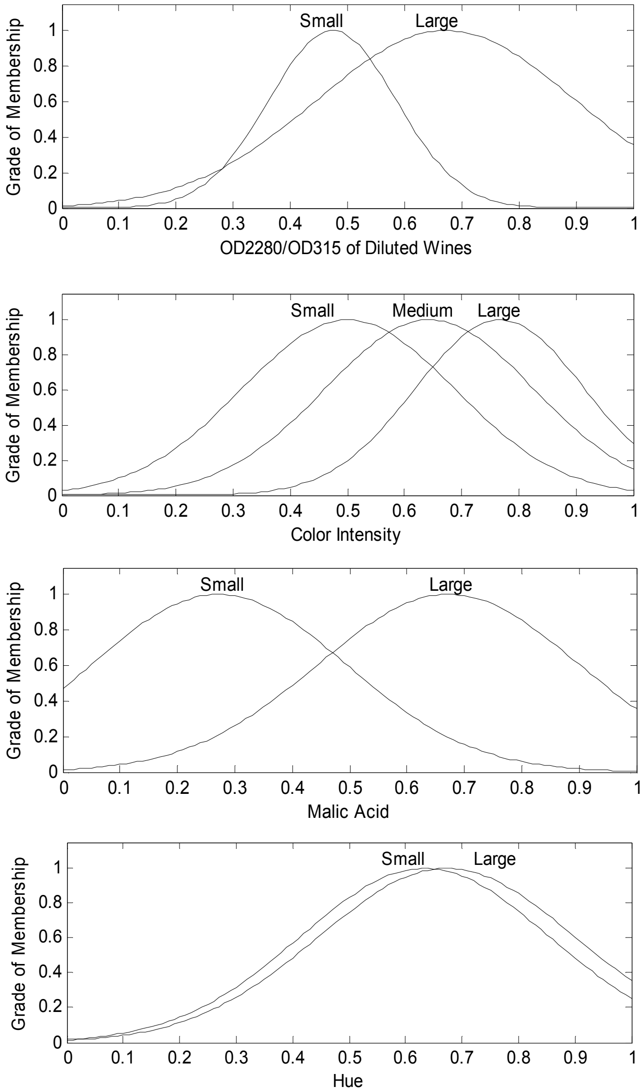


Figure 10 Membership functions of simplified Sugeno fuzzy classification system optimised by hybrid optimisation algorithm for wine data classification (continued)



Similarly, we explore the efficiency of our hybrid algorithm in the optimisation of the same Sugeno fuzzy classification system with different numbers of training data sets, as given in Table 3. The results here are the average of ten separate trials as well. Compared with both the CSA and HS method, employment of the proposed hybrid optimisation method leads to the optimal wine data classification results.

Table 3 Classification results of wine data using CSA, HS and hybrid method

Algorithms	*CSA*	*HS*	*Hybrid method*
$N = 10$			
Misclassifications (training)	12	10	3
Classification rate (test)	93.2%	94.3%	98.3%
$N = 30$			
Misclassifications (training)	10	9	1
Classification rates (test)	94.3%	94.9%	99.4%

6 Conclusions

In this paper, a new hybrid optimisation scheme based on the fusion of the CSA and HS method is proposed and it is further applied to optimise Sugeno fuzzy classification systems for the popular Fisher Iris data and wine data classification. The CSA and HS method are combined together and both of their search capabilities are fully utilised in the novel optimisation algorithm. Simulation results demonstrate that our approach can achieve a better classification performance than that of the original CSA and HS method. We are going to investigate the applications of the proposed hybrid optimisation technique in more real-world problems.

Acknowledgements

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