Step 5 (Selective breeding): Employ the fitness function (10) to evaluate each child string in the offspring set. After this, select the best N_{pop} individuals from the current population and the offspring set to form the next generation.
Step 6 (Termination test): If a pre-specified generation number has not been reached, go to Step 2, otherwise terminate the search procedure and return the best individual in the population as the final solution for building the fuzzy dissimilarity model.

6 Evaluation Results

We have applied our proposed approach to the problems of classification and diagnosis. In this section we illustrate a case study made on the well-known benchmark problem of wine data classification. The wine data can be downloaded from the address ftp.ics.uci.edu/pub/machine-learning-databases. It consists of 178 samples with 13 continuous features from three classes.

Each feature difference x_i (i=1, 2, ..., 13) was assigned with three fuzzy sets $A(i, 1)$, $A(i, 2)$, and $A(i, 3)$ to build fuzzy rules for assessing the dissimilarity between cases. The membership functions of these three fuzzy sets, as illustrated in Fig. 4, can be interpreted with linguistic terms such as *small, medium, and large* respectively. The GA was set into force to search for the rule premises under different consequences (dissimilarity=1.0, dissimilarity=0) and to optimize the parameters (corresponding to the circle in Fig. 4) of the fuzzy set membership functions at the same time. The objective of the GA was to discover the fuzzy knowledge base to maximize the fitness function in (10). The learnt fuzzy rules were employed as evaluation criteria to determine the dissimilarities of cases, which were then used in solution filtering for estimating impossibility degrees of candidate solutions.

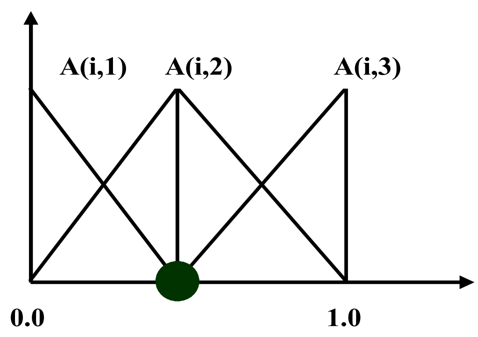

Fig. 4. The three membership functions for the difference on feature x_i

To test the feasibility of learning fuzzy dissimilarity rules from a small number of cases, we randomly selected 33% of the cases from the wine data set as the case base used for learning and the remaining cases as test data containing query problems. The fuzzy rules learnt from the case base were then used for dissimilarity assessment in case-based classification of the problems in the test data set. We performed such tests 10 times. Table 1 illustrates the classification accuracy on the test data in the 10 tests. It is interesting to observe that, despite the small case bases with about 66 instances in each, very good classification accuracy was still achieved by our CBR system employing the learned fuzzy dissimilarity models.

Table 1: Classification accuracy on test data

Numbers of tests	Classification accuracy
1	97.48%
2	90.76%
3	94.12%
4	93.22%
5	92.44%
6	93.28%
7	91.53%
8	90.76%
9	90.76%
10	94.96%
Average	92.93%

In table 2, we compare our work with some other machine learning approaches in terms of classification accuracy (on test data) and the numbers of cases used for learning. The classification accuracy we obtained is rather close to the best result among the other works. In the other aspect, we employed a much lower number of cases for learning than any other work as indicated in the table. It demonstrates that our system can survive with learning from a small amount of examples. This is an attractive advantage distinguishing our CBR system from other supervised learning systems for classification.

Table 2: Comparison with other methods

Learning methods	**Accuracy**	**Number of cases for learning**
This paper	92.93%	59 ~ 60
C4.5 [40]	90.14%	160 ~ 161
Ho [41]	93.72%	160 ~ 161
Hu [42]	91.63%	160 ~ 161
Elomaa [43]	94.40%	160 ~ 161
SOP-1 [44]	92.70%	160 ~ 161
MOP-1 [44]	96.01%	160 ~ 161