SOLVING THE HUMAN STATUS DETECTION PROBLEMS BY AUTOMATICALLY GENERATED NEURO-FUZZY CLASSIFIERS

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Abstract: This study is focused on the application of automatically generated neuro-fuzzy systems for solving complex detection problems such as human status detection. In this study a person's reaction while listening to music, namely, whether person liked the music or disliked, was determined as well as person's state beforehand, in other words, whether this person listened to the music or not at all. Thus, firstly each person's condition was monitored by using non-contact Doppler sensors and then the gathered data were collected and pre-processed so that two classification problems could be formulated. The aim was to automatically generate the neuro-fuzzy classifiers by the new optimization algorithm, firstly introduced in this study and called MADEGA, to solve the mentioned detection problems. These problems were also solved by other well-known and frequently used data mining tools. Experimental results demonstrated that neuro-fuzzy classifiers automatically generated by the MADEGA approach can properly determine the human status and reaction. Besides, proposed approaches outperformed alternative data mining tools used in this study. Therefore, mentioned neuro-fuzzy classifiers can be used for solving more complex problems related to the automated detection of a human's status and even of an operator's condition of other various complex systems.

Key words: neural networks, fuzzy logic, human status detection, sensors, classification.

1. INTRODUCTION

Nowadays in the era of the Internet of Things or IoT automated detection of human status or reaction to something at a given moment became one of the most interesting and relevant problems [1]. This kind of problems is related to concepts such as Industry 4.0 which is based on IoT concepts [2] and can be formulated for different complex systems with human operators.

Various state-of-the-art methods, such as artificial neural networks (ANNs) [3], support vector machines (SVM) [4], Bayes classifier [5] as examples, and their modifications have been proposed to solve these problems. Some of these methods, especially the ones that are considered as the network-based methods, can be trained with population-based evolutionary algorithms [6]. In that case the time it takes to select the network parameters generally depends on the size of the datasets formed for the mentioned detection problems.

One of the network-based classifiers is the neuro-fuzzy classifier [7]. Neuro-fuzzy classifiers combine the description and interpretability of classification techniques based on fuzzy logic with the learning capabilities of artificial neural networks. In this study a new population-based evolutionary optimization algorithm called MADEGA was developed for the neuro-fuzzy systems training. Its basic idea consists in cooperative work of four well-known evolutionary algorithms, which are used cooperatively with a given probabilities that can change during the optimization process.

To be able to determine person's current status at a given moment their state should be monitored for a while. This monitoring can be done by standard sensors, which are usually applied to human bodies, but that may cause the inaccuracy in obtained measurements due to the noise. So, in this study to achieve the higher efficiency the non-contact sensors (designed in Aichi Prefectural University) [8], which use the Doppler Effect for data retrieval, were applied for human condition monitoring. These sensors' data processing technique has low computational complexity, which makes it possible to implement them with small-scale processors so that the battery life can be prolonged, and it is one of the most important factors in the IoT context.

To prove the workability and usefulness of the proposed approach, namely, of the neuro-fuzzy classifiers automatically generated by the MADEGA algorithm, two problems related to the human status and reaction while listening and not listening to music were solved. Measurements obtained by the non-contact vital sensing for each person that participated in the experiments were formalized and pre-processed. Thus, two human status detection problems were formulated as two classification problems.

Also other data mining tools were used to solve the classification problems described in the next section of this paper: support vector machines (SVM) [4], *k* nearest neighbours (*k*-NN) [9], decision trees (DT) [10], the Hybrid Evolutionary Fuzzy Classification Algorithm (HEFCA) [11] and standard artificial neural networks [3]. Comparison of the obtained results by all mentioned classifiers is demonstrated.

Thus, in this paper firstly a description of the formulated classification problems is given. Then the proposed approach, to be more specific, the neuro-fuzzy systems generated by the MADEGA algorithm, is introduced. In the next section, the experimental results obtained by various data mining tools are discussed, and finally, some conclusions are given in the last section.

2. PROBLEM STATEMENT

In this paper human status detection problems related to the person's reaction while listening and not listening to music were considered. Thus, first of all ten people of different gender and age (so that their health condition was diverse) were invited to participate in experiments conducted by the Japanese research group in Aichi Prefectural University.

Participants' condition was monitored by using non-contact vital sensors designed by mentioned Japanese research group [8] over three stages: listening to music that a person admitted to like and to music that the same person admitted to dislike in three different time periods each, and sitting in silence (not listening to music or anything at all) in two different time periods. These sensors use the Doppler Effect, thus, the respiration was extracted by digital signal processing of the frequency deviation.

During experiments participants were seated in front of a desk and then their breathing and heartbeat were monitored by a Doppler sensor installed 30 cm away from their chests. The Doppler sensor module was equipped with two output ports, called *I*- and *Q*- channels. The outputs from the two ports were enhanced by two amplifiers so that the voltages were sampled by a data logger. The model numbers and specifications of the equipment are listed in the Table 1.

Table 1. Equipment description

Equipment	***Description***
Data logger	*GL-900 (GRAPHTECH)*
Sampling	*100 Hz, 16 bits*
Doppler sensor module	*NJR4262 (New Japan Radio) Frequency 24 GHz*

Then the ARS technique [12] was applied to the received signals to pre-process them. So, in the end 8 data sequences were obtained for each participant in the conducted experiments: 3 data sequences for 3 time periods when a person was listening to the music that this person admitted to like, 3 data sequences for 3 time periods when a person was listening to the unpleasant music, and 2 data sequences for 2 time periods of silence. Moreover, each pre-processed data sequence consisted of 4 real-valued features, to be more specific, the deviation of the respiratory rate, voltage, the average value of the respiratory rate and the variance of the respiratory rate.

The obtained data were then normalized and labelled. Finally, two human status detection problems were formulated as two classification problems. The first human status detection problem was called "listened", for this problem each data sequence was labelled as "1" if the person that participated in the experiments listened to the music at a given moment and "0" otherwise. The second human status detection problem was called "liked", it consisted in determining whether the person that participated in the experiments liked the music (in that case the data sequence was labelled as “1”) or disliked it (in that case the data sequence was labelled as “0”).

The datasets for both human status detection problems are briefly described in table 2.

Table 2. Description of the formulated classification problems

Problem	*Classes*	*Dataset sizes*
1	*1 – listened to music* *0 – did not listen to music*	*1: 60 instances* *0: 20 instances* *whole set: 80 instances*
2	*1 – liked music* *0 – disliked music*	*1: 30 instances* *0: 30 instances* *whole set: 60 instances*

The dataset for the problem “listened” was imbalanced due to the fact that the number of instances of the first class “listened to music” was equal to 60, while the number of instances for the second class “did not listen to the music” was equal to 20. Thus, this problem was harder to solve by the proposed neuro-fuzzy classifiers as well as by the other well-known alternative classification algorithms.

Finally, the dataset for the second human status detection problem contains of only 60 instances, where half are from the class “liked music” and another half are from the class “disliked music”.

3. PROPOSED APPROACH

In this study neuro-fuzzy classifiers proposed in [13] were adapted for solving the human status detection problems. For this purpose they were modified by using new evolutionary optimization technique MADEGA. To be more specific, generation of the neuro-fuzzy classifiers is performed automatically as the solving of the unconstrained real-valued optimization problem. Thus, in this section firstly neuro-fuzzy classifiers are described and then the new optimization technique is introduced.

3.1. Neuro-fuzzy classifiers

In the neuro-fuzzy classification methods, the feature space is partitioned into multiple fuzzy subspaces that are controlled by fuzzy if-then rules, which can be represented by network structure. Generally the neuro-fuzzy classifiers consist of the following layers: input layer, fuzzy membership layer, fuzzification layer, defuzzification layer, normalization layer and output layer [7].

The structure of neuro-fuzzy classifiers is demonstrated in the Figure 1. Example presented here shows the case of the feature space with two features, which form the input layer. In the end in this example the classifier separates data instances into two classes, which represent the output layer. Every feature is defined with three linguistic terms, thus, there are nine fuzzy rules of the following form:

$$R_q\text{: IF } x_{p1} \text{ is } A_{q1} \text{ and } \ldots \text{ and } x_{pn} \text{ is } A_{qn} \text{ then class is } Class\ k, \tag{1}$$

where R_q is the q-th fuzzy rule, $x_p = (x_{p1}, \ldots, x_{pn})$ is the set of n features or input variables of the p-th sample from the train set, A_{qi} is a fuzzy set for the i-th variable and *Class k* is the class number.

This classifier uses weight coefficients in the defuzzification layer, they affect the fuzzy rules and improve the classification flexibility. The initial parameters of the neuro-fuzzy system are obtained by k-means clustering method, which is also used to formulate the fuzzy if-then rules [14].

There are 3 groups of the real-valued parameters of the neuro-fuzzy classifiers that should be selected for each problem: the center matrices of the Gaussian membership functions, the width matrices of the Gaussian membership functions, the weight matrix among the rules and the classes. These parameters can be adjusted by population-based evolutionary algorithms during the training stage of the neuro-fuzzy system.

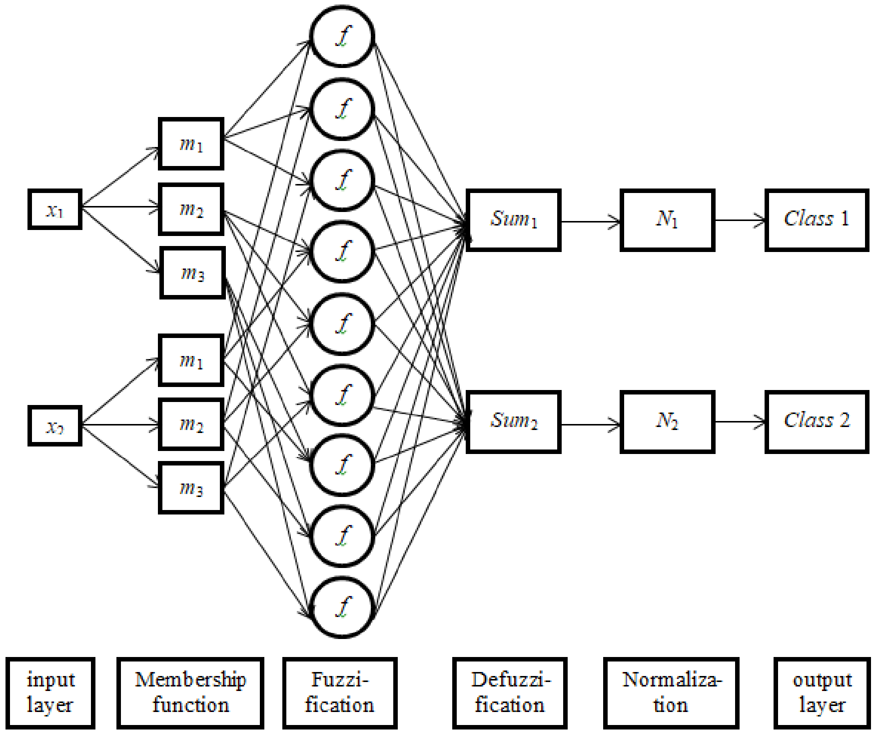

Fig. 1. Example of the neuro-fuzzy classifier's structure

In this study the adaptive neuro-fuzzy networks have been trained using new cooperative evolutionary optimization technique MADEGA. The aim is to use the mentioned algorithm to determine neuro-fuzzy classifiers' optimal parameters from the cost function, namely from the classification error, which should be minimized.

3.2. Optimization technique MADEGA

A new optimization technique based on cooperative work of four population-based evolutionary algorithms, namely Matrix Adaptation Evolution Strategy (MA-ES) [15], Success-History based Adaptive Differential Evolution (SHADE) [16] algorithm with two different mutation strategies (DE/rand/1 and DE/current-to-best/1) [17] and Genetic Algorithm with Success History based Parameter Adaptation (SHAGA) [18], was developed. The new technique is called MADEGA. Its main idea consists in generating of one population in such a way that each individual in that population can use operators of one of the mentioned evolutionary algorithms with a given probability, which changes periodically according to operators' successfulness.

So first of all, the initialization step is performed, to be more specific, a set of N points, called individuals, in the search space of the dimensionality D is randomly generated within the given lower and upper bounds for each dimension. For each individual its objective function value is evaluated.

It should be noted, that initially all operators (MA-ES, SHADE and SHAGA) are used for a given individual from the population with the same probabilities. After each g iterations these probabilities change: they can increase or decrease, however, they can't be lower than the p_{min} value (it's done so that to keep the search diversity).

The procedure for probabilities estimation can be described as follows. The first step consists in calculating of the number of times each operator was used. The second step consists in estimating of the objective function improvements and their number for each operator. If after g iterations objective function value is improved at least once, then the median of improvements is calculated, otherwise it is equal to 0. Finally, the probability of using a giving operator is determined according to its median value over g iterations, but if there are no improvements, then all probabilities stay the same.

Additionally, the success-history based position adaptation of potential solutions was applied to improve the search diversity of the mentioned evolutionary component-algorithms. The key concept of the proposed technique can be described as follows.

An external archive for best found positions is created. The maximum size of this archive is chosen by the end-user and stays the same during the optimization process. Thus, at the beginning the external archive is empty and then its size can increase to the maximum value.

For each individual in the population if an improved position is discovered, then the previous one will be stored in the external archive. Later when individuals change their position in the search space according to the formulas given for the considered operator, they can use the individuals stored in the external archive with some probability p_a.

4. EXPERIMENTAL RESULTS

4.1. Experimental settings

In this paper the neuro-fuzzy classifiers have been automatically generated by using the population-based evolutionary optimization algorithm MADEGA described in the previous section. Thus, each set of neuro-fuzzy system's parameters was encoded as an individual of the population. Also it should be noted that both classification problems have two classes and for both of them each data sequence has four features. So, there were 24 parameters or variables (namely 12 parameters for center matrix and 12 parameters for width matrix) for the Gaussian membership functions that were adjusted.

The initial parameters of the neuro-fuzzy system are obtained by *k*-means clustering method and these parameters are used to determine the lower and upper bounds for them by using 3σ rule. The population size N was equal to 100. Also initially all operators (MA-ES, both SHADE versions and SHAGA) were used with the same probabilities $p_i = 0.25$ ($i = 1, \ldots, 4$). These probabilities change after each $g = 7$ iterations, the minimal probability value was $p_{min} = 0.04$.

The maximum number of function evaluations to generate neuro-fuzzy classifiers' structures by the mentioned optimization technique was equal to 100000. The maximum archive size was equal to 100 and individuals stored there were used with the probability $p_a = 0.05$. All mentioned parameter settings were chosen according to the previous experiments conducted on test benchmark problems.

In addition other classifiers were also used to solve these problems, including some well-known state-of-the-art classification methods implemented in the RapidMiner 5.3 software. To be more specific, the following approaches were used: SVM, *k*-NN, DT and standard ANN. Also the HEFCA was applied to the mentioned two human status detection problems as instance selection modification so without it. Results for the listed classifiers were taken from [19].

4.2. Numerical results

Datasets for both classification problems were divided into training set, which contained 70% of instances, and the test set with the remaining 30% of instances. Instances for both sets, train and test, were chosen randomly, and the division was implemented in such a way that the instances belonging to both classes were present in the training and test sets respectively.

To perform the comparison of the mentioned classifiers (the ones implemented in the RapidMiner 5.3 software as well as the proposed neuro-fuzzy approach) 20 independent program runs were made.

In addition to the classical accuracy criterion the F-score value with parameter $\beta = 1$ was used for evaluating the obtained results for each class respectively. Tables 3 and 4 show the results achieved by all tested algorithms for the "listened" and the "liked" classification problems respectively. In these tables, the best values of the F-

score criteria and accuracy (the portion of correctly classified instances) received during one of the program runs out of 20 are demonstrated, because the idea was to find the best model for a given real-world problem.

Table 3. Results obtained for the "listened" problem

Classifier	***F-score***		***Accuracy***
	"listened"	***"didn't listen"***	
k-NN	*0.8657*	*0.3077*	*0.7750*
SVM	*0.8571*	*0.0000*	*0.7500*
DT	*0.8571*	*0.0000*	*0.7500*
ANN	*0.8571*	*0.0000*	*0.7500*
HEFCA (instance selection)	*0.7434*	*0.3830*	*0.6380*
HEFCA (no instance selection)	*0.8406*	*0.0000*	*0.7250*
Proposed approach	***0.8400***	***0.4286***	***0.7500***

Table 4. Results obtained for the "liked" problem

Classifier	***F-score***		***Accuracy***
	"liked"	***"disliked"***	
k-NN	*0.6667*	*0.6316*	*0.6500*
SVM	*0.4889*	*0.6933*	*0.6167*
DT	*0.6250*	*0.2500*	*0.5000*
ANN	*0.6071*	*0.6562*	*0.6333*
HEFCA (instance selection)	*0.5862*	*0.6129*	*0.6000*
HEFCA (no instance selection)	*0.5714*	*0.6250*	*0.6000*
Proposed approach	***0.7500***	***0.7857***	***0.7000***

The membership functions of the rules corresponding to the results demonstrated in the above mentioned tables 3 and 4 for both human status detection problems are shown in figures 2 and 3 respectively.

The computational complexity of the neuro-fuzzy classifiers is slightly larger than for the mentioned state-of-the-art algorithms like *k*-NN, SVM, ANN or DT implemented in RapidMiner 5.3 software system. Nevertheless, this difference is not very significant and it only appears during the training procedure, while the application of the trained neuro-fuzzy classifiers to new data takes very short time (unlike some of the above mentioned standard classifiers), which is important for operation in the real-world.

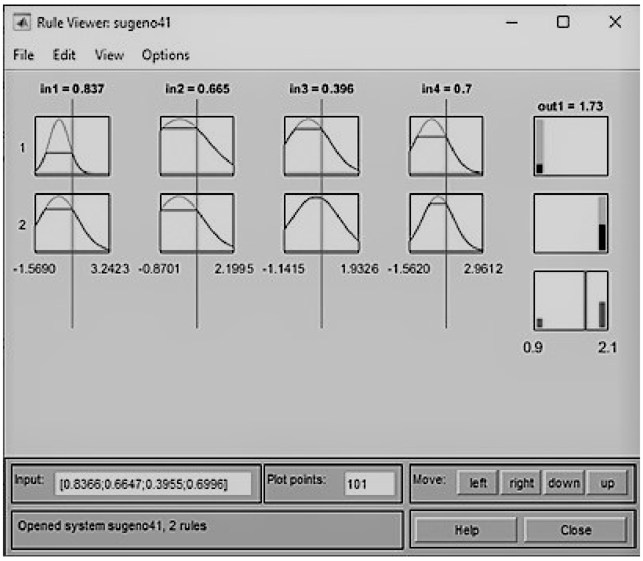

Fig. 2. Example of membership functions for the classification problem "listened"

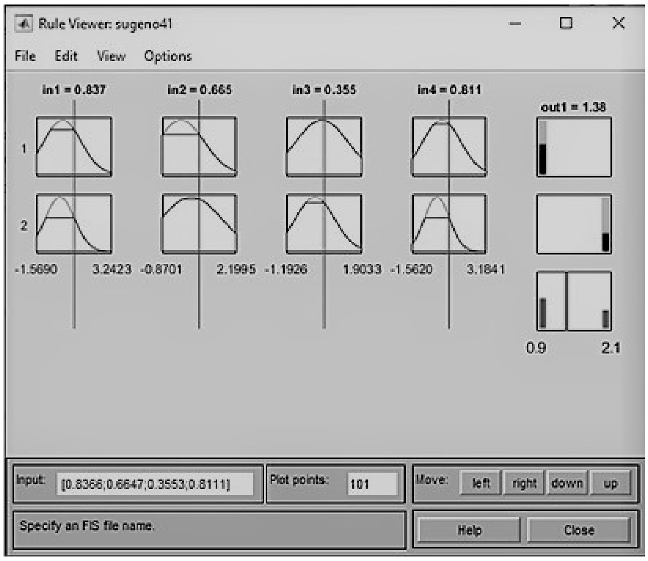

Fig. 3. Example of membership functions for the classification problem "liked"

Moreover, the proposed approach demonstrates better results in terms of accuracy and *F*-score measure for each class established for both human status detection problems. Therefore, it was established that the neuro-fuzzy classifiers automatically generated by the population-based evolutionary optimization algorithm MADEGA is more useful for these problems, which databases were created by non-contact sensors [8]. Thus, the neuro-fuzzy systems introduced in this study are more efficient for the automated human status detection problems.

6. CONCLUSION

In this paper a new algorithm for automated generation of the neuro-fuzzy classifiers, namely the MADEGA approach, was introduced. To be more specific the neuro-fuzzy classifiers generation was realized as solving the unconstrained real-valued optimization problem. The proposed approach was shown to perform better than state-of-the-art classification methods on the human status detection problems, for which the databases were created by means of the non-contact sensors for vital data retrieval using Doppler Effect. In particular, in this paper two human status detection problems were formulated as classification problems. It was demonstrated that neuro-fuzzy classifiers, automatically generated by the optimization algorithm called MADEGA, achieved the best results for the described detection problems. Thus, the proposed approach for the problem statement combined with neuro-fuzzy classifiers automatically generated by the optimization approach MADEGA can be used for other problems concerning the human status detection.

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