Evolutionary feature selection for emotion recognition in multilingual speech analysis

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***Abstract*—In the case when conventional feature selection methods do not demonstrate sufficient performance, alternative algorithmic schemes might be applied. In this paper we propose an evolutionary feature selection technique based on the two-criteria optimization model. To diminish the drawbacks of genetic algorithms, which are used as optimizers, we design a parallel multi-criteria heuristic procedure based on an island model. The effectiveness of the proposed approach was investigated on the Speech-based Emotion Recognition Problem, which reflects one of the crucial aspects in the sphere of human-machine communications. A number of multilingual corpora (German, English and Japanese) were engaged in the experiments. According to the results obtained, a high level of emotion recognition was achieved (up to a 11.15% relative improvement compared with the best F-score value on the full set of attributes).**

Keywords—feature selection, multi-objective genetic algorithm, island model, emotion recognition

I. INTRODUCTION

In recent years there has been a growing interest in the sphere of *Evolutionary Machine Learning*. However, some researchers highlight the negative sides of the *Evolutionary Computation* and *Machine Learning* integration. Firstly, it is always necessary to investigate a number of algorithms to define the most effective one for the problem considered because the performance of evolutionary algorithms varies significantly for different problems. Secondly, these methods require more computational resources compared with alternative non-evolutionary algorithms. Therefore, in this study we attempt to develop a feature selection technique for classification problems based on a genetic algorithm with these drawbacks removed.

Generally, the feature selection procedure can be organized as the *wrapper* approach or the *filter* one [1]. The first technique involves classification models to evaluate the relevancy of each feature subset. Although it requires high computational resources, this approach demonstrates adjustment to an applied classifier. The second technique is referred to the pre-processing stage because it extracts information from the data set and reduces the number of attributes, taking into consideration such measures as consistency, dependency, and distance. This approach needs significantly fewer calculations therefore it is rather effective in the sense of computational effort. On the one hand, the filter attribute selection procedure does not cooperate with a learning algorithm and so ignores its performance entirely. However, on the other hand, it might be effectively used in combination with an ensemble of diverse classifiers, which is quite reasonable in the case when one does not know one particular reliable and effective model. Therefore, in this paper we propose the evolutionary feature selection procedure which corresponds to the filter scheme.

We designed the attribute selection approach as a two-criteria optimization model and applied a modified multi-objective genetic algorithm to find solutions. To overcome the disadvantages of the evolutionary search, an island model is used to involve genetic algorithms which are based on different concepts. Moreover, this model allowed us to parallelize calculations and, consequently, to reduce the computational time.

The effectiveness of the proposed approach has been investigated on the *Speech-based Emotion Recognition Problem* which reflects one of the crucial questions in the sphere of human-machine communications [2]. In the experiments conducted a number of multilingual databases (English, German, and Japanese) are used.

In the previous research it was found that there was no classification model which demonstrated the highest performance for all of the corpora [3]. Therefore, we combined the developed filter technique with the ensemble of classifiers (Multilayer Perceptron, Support Vector Machine, and Linear Logistic Regression) which showed high effectiveness separately. The classification results obtained after the application of the developed pre-processing method were compared with the classification quality on the full databases (without feature selection) and after the application of Principal Component Analysis (PCA).

The rest of the paper is organized as follows: in Section II a brief description of the related work is presented, Section III contains the details of the evolutionary feature selection scheme. The speech-based emotion recognition problem and the corpora used are introduced in Section IV. The experiments

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conducted, the results obtained, and the main inferences are included in Section V. The conclusion and future work are presented in Section VI.

II. Related Work

Yang and Hanovar (1998) used a one-criterion genetic algorithm (GA) to determine relevant attributes in order to improve the quality of classification realized with neural networks [4]. Li Zhuo *et al.* (2008) accomplished the classification of hyperspectral images with a support vector machine; they also engaged a one-criterion GA to remove non-informative features [5]. In both cases the feature selection procedure was combined with supervised learning algorithms based on the wrapper approach scheme.

Lanzi (1997) offered to apply a heuristic method to extract attributes before executing the classification [6]. The inconsistency rate was used by a GA to assess the relevancy of reduced data sets. Due to the implementation of the filter approach it became possible not only to achieve the high performance of the C4.5 inductive algorithm but also to lower the computational cost.

Development of multi-objective optimization algorithms allowed researchers to embed these methods in the feature selection procedure to take into account several criteria. Venkatadri and Srinivasa (2010) introduced a set of measures such as *Attribute Class Correlation, Inter- and Intra-Class Distances, Laplasian Score, Representation Entropy* and *the Inconsistent Example Pair measure* to estimate the quality of reduced databases. They investigated various combinations of these criteria by means of the Non-dominated Sorting Genetic Algorithm (NSGA-II) [7]. Hamdani *et al.* (2007) also implemented NSGA-II to attain a compromise between the number of extracted attributes and the classification accuracy evaluated with the 1-NN classifier [8]. These are examples of MOGA realization in the framework of the filter and the wrapper approach respectively.

III. Evolutionary Feature Selection Scheme

A. Two-criteria Filter Approach

Feature selection with the filter approach is based on estimating statistical metrics such as *Attribute Class Correlation, Inter- and Intra- Class Distances, Laplasian Score, Representation Entropy* and *the Inconsistent Example Pair measure* which characterize the data set relevancy. In this case we also introduce the two-criteria model, specifically, *the Intra-class distance* (IA) and *the Inter-class distance* (IE) are used as optimized criteria:

$$IA = \frac{1}{n}\sum_{r=1}^{k}\sum_{j=1}^{n_r} d(p_j^r, p_r) \rightarrow min, \quad (1)$$

$$IE = \frac{1}{n}\sum_{r=1}^{k} n_r d(p_r, p) \rightarrow max, \quad (2)$$

where p_j^r is the j-th example from the r-th class, p is the central example of the data set, $d(...,...)$ denotes the Euclidian distance, p_r and n_r represent the central example and the number of examples in the r-th class.

The scheme of the filter method is shown in Figure 1.

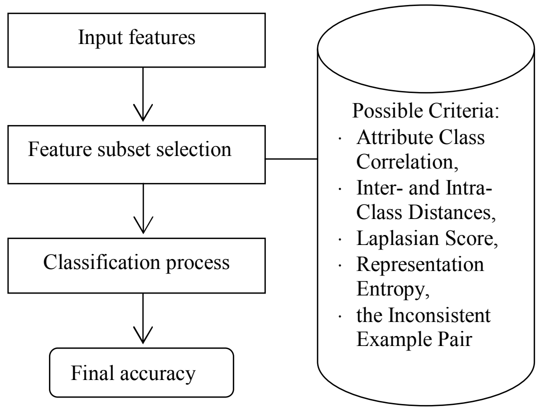

Fig. 1. General filter approach scheme.

As a feature selection technique we use a multi-objective genetic algorithm (MOGA) operating with binary strings, where *unit* and *zero* correspond to a relative attribute and an irrelative one respectively.

B. Multi-objective Genetic Algorithms

The common scheme of any MOGA includes the same steps as any conventional one-criterion GA:

Generate the initial population
Evaluate criteria values
While (stop-criterion!=true), do:
{Estimate fitness-values;
Choose the most appropriate individuals with the mating selection operator based on their fitness-values;
Produce new candidate solutions with recombination;
Modify the obtained individuals with mutation;
Compose the new population (environmental selection);
}

In contrast to one-criterion GAs, the outcome of MOGAs is the set of non-dominated points which form the Pareto set approximation.

Designing a MOGA, researchers are faced with some issues which are referred to fitness assignment strategies, diversity preservation techniques, and ways of elitism implementation. Therefore, in this study we investigate the effectiveness of MOGAs, which are based on various heuristic mechanisms, from the perspective of the feature selection procedure.

As we have noticed, MOGAs return the set of candidate-solutions which cannot be preferred to each other. Taking into account this fact, we have proposed a way to derive the final solution based on the set of non-dominated points. It is assumed that the outcome of the MOGA is N binary strings (the set of non-dominated solutions). Each chromosome should be decoded to the database reduced, according the rule: if a gene is equal to '0' then eliminate the corresponding attribute, and if a gene is equal to '1' then include the respective feature in the database reduced. In short, we obtain N different sets of features and train N various classifiers based on these data. For each test example the engaged models vote for different classes according to their own predictions. The final decision is defined as a collective choice based on the majority rule.

Taking into consideration predictions of several classifiers is a good alternative to choosing one particular solution from the set of non-dominated points. In fact, candidates, which demonstrate high effectiveness on the training data, might often be the worst on the test data. Therefore, to avoid such cases, we use the scheme described.

Non-Sorting Genetic Algorithm II (NSGA-II) [9], *Preference-Inspired Co-Evolutionary Algorithm with goal vectors (PICEA-g)* [10], and *Strength Pareto Evolutionary Algorithm 2 (SPEA2)* [11] were used as tools to optimize the introduced criteria (1), (2).

TABLE I. BASIC FEATURES OF THE MOGA USED

MOGA	Fitness Assignment	Diversity Preservation	Elitism
NSGA-II	Pareto-dominance (*niching mechanism*) and diversity estimation (*crowding distance*)	Crowding distance	Combination of the previous population and the offspring
PICEA-g	Pareto-dominance (*with generating goal vectors*)	Nearest neighbour technique	The archive set and combination of the previous population and the offspring
SPEA2	Pareto-dominance (*niching mechanism*) and density estimation (*the distance to the k-th nearest neighbour in the objective space*)	Nearest neighbour technique	The archive set

In Table 1 there are the basic features of each method.

C. Island Model of Genetic Algorithm

An *island model* [12] of a GA implies the parallel work of several algorithms. A parallel implementation of GAs has shown not just an ability to preserve genetic diversity, since each island can potentially follow a different search trajectory, but also could be applied to separable problems. The initial number of individuals M is spread across L subpopulations: $M_i=M/L,\ i=1,\dots,L$. At each T-th generation algorithms exchange the best solutions (*migration*). There are two parameters: *migration size*, the number of candidates for migration, and *migration interval*, the number of generations between migrations.

Moreover, it is necessary to define the island model topology, in other words, the scheme of migration. We use the fully connected topology that means each algorithm shares its best solutions with all other algorithms included in the island model. The multi-agent model is expected to preserve a higher level of genetic diversity. The benefits of the particular algorithm could be advantageous in different stages of optimization. Therefore, in this study NSGA-II, PICEA-g, and SPEA2 are involved as parallel working islands.

IV. SPEECH-BASED EMOTION RECOGNITION

A. Problem Definition

One of the obvious ways to improve the intellectual abilities of spoken dialogue systems is related to their personalization. While communicating, machines should perceive the qualities of the user (as people usually do) such as age, gender and emotions to adapt its answers for the particular speaker.

In this paper we consider one particular aspect of the personalization process that is *speech-based emotion recognition*. Generally, any approach used to solve this recognition problem consists of three main stages.

At first, it is necessary to extract acoustic characteristics from the collected utterances. At the «INTERSPEECH 2009 Emotion Challenge» an appropriate set of acoustic characteristics representing any speech signal was introduced. This set of features comprised attributes such as power, mean, root mean square, jitter, shimmer, 12 MFCCs and 5 formants. The mean, minimum, maximum, range and deviation of the following features have also been used: pitch, intensity and harmonicity. The number of characteristics is 384. To get the conventional feature set introduced at INTERSPEECH 2009, the Praat [13] or OpenSMILE [14] systems might be used. Secondly, all extracted attributes or the most relevant of them should be involved in the supervised learning process to adjust a classifier. At the final stage, the signal that has to be analysed is transformed into an unlabelled feature vector (also with the usage of the Praat or OpenSMILE systems) and then the trained classification model receives it as the input data to make a prediction.

B. Corpora Description

In the study a number of speech databases have been used and this section provides their brief description.

The *Emo-DB* emotional database (German) [15] was recorded at the Technical University of Berlin and consists of labelled emotional German utterances which were spoken by 10 actors (5 female). Each utterance has one of the following emotional labels: neutral, anger, fear, joy, sadness, boredom or disgust.

The *SAVEE* (Surrey Audio-Visual Expressed Emotion) corpus (English) [16] was recorded as a part of an investigation into audio-visual emotion classification from four native English male speakers. The emotional label for each utterance is one of the standard set of emotions (anger, disgust, fear, happiness, sadness, surprise and neutral).

The *LEGO* emotion database (English) [17] comprises non-acted American English utterances extracted from an automated bus information system of the Carnegie Mellon University at Pittsburgh, USA. The utterances are requests to

TABLE II. STATISTICAL DESCRIPTION OF THE USED CORPORA

Database	Language	Full length (min.)	Number of emotions	File level duration		Notes
				Mean (sec.)	*Std. (sec.)*	
Emo-DB	German	24.7	7	2.7	1.02	Acted
SAVEE	English	30.7	7	3.8	1.07	Acted
LEGO	English	118.2	3	1.6	1.4	Non-acted
UUDB	Japanese	113.4	4	1.4	1.7	Non-acted

the Interactive Voice Response system spoken by real users with real concerns. Each utterance is annotated with one of the following emotional labels: angry, slightly angry, very angry, neutral, friendly, and non-speech (critical noisy recordings or just silence). In this study different ranges of anger have been merged into a single class and friendly utterances have been deleted. This pre-processing results in a 3-class emotion classification task.

The *UUDB* (The Utsunomiya University Spoken Dialogue Database for Paralinguistic Information Studies) database (Japanese) [18] consists of spontaneous Japanese human-human speech. The task-oriented dialogue produced by seven pairs of speakers (12 female) resulted in 4,737 utterances in total. Emotional labels for each utterance were created by three annotators on a five-dimensional emotional basis (interest, credibility, dominance, arousal, and pleasantness). For this work, only the pleasantness and arousal axes are used. The corresponding quadrant (anticlockwise, starting in the positive quadrant, and assuming arousal as abscissa) can also be assigned emotional labels: happy-exciting, angry-anxious, sad-bored and relaxed-serene.

There is a statistical description of the used corpora in Table II.

V. PERFORMANCE ASSESSMENT

A. Experiments and Results

Several experiments were conducted to investigate the effectiveness of the approach proposed on the human emotion recognition problem.

Firstly, we applied a set of conventional classifiers [19] to full databases (the number of attributes was equal to 384). In previous research [3] the following models showed high performance:

- *Support Vector Machine – SMO.* To design a hyperplane separating sets of examples Sequential Minimal Optimization (SMO) is used for solving the large scale quadratic programming problem.
- *Multilayer Perceptron – MLP.* A feedforward neural network with one hidden layer containing [(NumberOfFeatures+NumberOfClasses)/2+1] - neurons is trained with the error backpropagation algorithm (BP).
- *Linear Logistic Regression – Logit.* This linear model describes the relationship between labels and independent variables using probability scores.

For each classifier the *F-score* metric was evaluated to estimate the results of the 6-fold cross-validation procedure (and further, in the next experiments): the more effective the classifier used, the higher F-score value obtained (Table III, 'without feature selection' rows).

Secondly, we repeated the classification procedure after the application of Principal Component Analysis (the conventional attribute selection method) with the threshold values 0.75 and 0.95 (Table III, 'PCA(0.75)' and 'PCA(0.95)' rows).

The next experiment was based on the two-criterion feature selection model (1), (2). NSGA-II, PICEA-g, and SPEA2 were used as optimizers in combination with SMO, MLP, and Logit classifiers. In Table III rows 'NSGA-II', 'PICEA-g', and 'SPEA2' reflect the results obtained with the application of these MOGAs separately. All algorithms were provided with the same amount of resources (90 generations and 150 individuals in populations). For each MOGA the following settings were defined: binary tournament selection, uniform recombination and the mutation probability $p_m=1/n$, where n is the length of the chromosome.

Then the island model including 'NSGA-II', 'PICEA-g', and 'SPEA2' was applied to solve the two-criterion feature selection problem (1), (2). All islands had an equal amount of resources (90 generations and 150/3 = 50 individuals in populations), the migration size was equal to 10 (in total each island got 20 points from two others), and the migration interval was equal to 10 generations. Due to the properties of the filter approach, it became possible to use an ensemble of classifiers (SMO, MLP, and Logit) after the feature selection procedure (Table III, 'Island model (NSGA-II, PICEA-g, SPEA2)' rows). The usage of the island model and the ensemble of classifiers is described in detail in Figure 2.

B. Discussion

The first experiment revealed that there was no one classifier which demonstrated the highest effectiveness for all of the corpora.

In most cases the application of Principal Component Analysis led to the deterioration of the classifier performance.

The usage of the evolutionary feature selection procedure contributed to the classification quality for most of the corpora. However, we may notice that different MOGAs provide the highest F-score values for different classifiers and different databases. Moreover, for SAVEE and LEGO the classification models which led to the best results on the full set of attributes (MLP and SMO respectively) were outperformed by other models (Logit and MLP respectively) after the feature selection procedure. This implies that we cannot predict the most

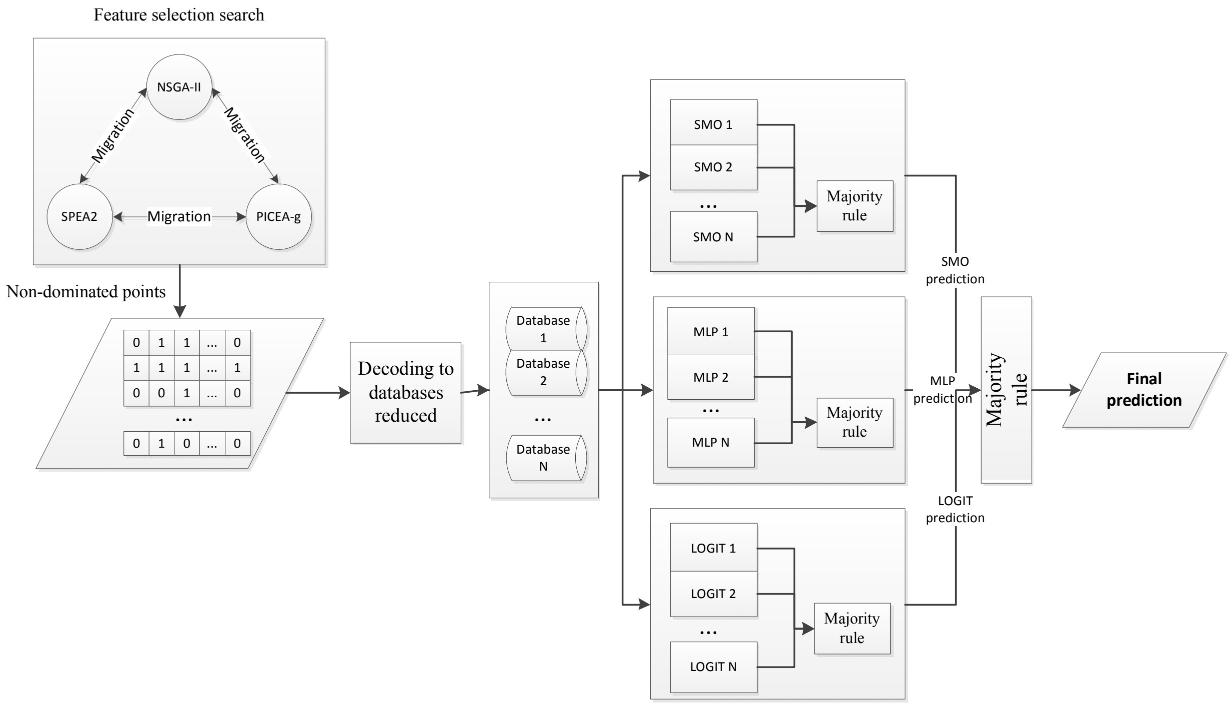

Fig. 2. The proposed evolutionary feature selection scheme in combination with the ensemble of classifiers.

TABLE III. EXPERIMENTAL RESULTS

Database	**Feature Selection Method**	**Average Number of Selected Features**	**F-score Values, %**		
			SMO	***MLP***	***LOGIT***
Emo-DB	Without Feature Selection	384.00	82.58	82.98	80.46
	PCA (0.75)	49.67	79.61	74.71	77.04
	PCA (0.95)	136.80	73.62	73.87	76.39
	NSGA-II	165.16	82.77	**86.07**	82.56
	PICEA-g	180.88	83.06	84.74	84.09
	SPEA2	159.49	82.93	85.69	85.64
	Island model (NSGA-II, PICEA-g, SPEA2)	166.89	**86.26**		
SAVEE	Without Feature Selection	384.00	59.31	61.82	60.82
	PCA (0.75)	46.67	57.86	57.46	59.86
	PCA (0.95)	130.7	46.18	50.63	51.80
	NSGA-II	163.67	66.61	67.70	**69.84**
	PICEA-g	186.06	64.80	68.81	64.28
	SPEA2	166.74	64.48	67.55	66.82
	Island model (NSGA-II, PICEA-g, SPEA2)	165.94	**68.71**		
LEGO	Without Feature Selection	384.00	71.08	64.77	70.71
	PCA (0.75)	59.83	68.05	67.19	69.03
	PCA (0.95)	162.50	70.06	66.08	70.58
	NSGA-II	145.21	70.19	71.86	70.36
	PICEA-g	166.48	70.47	71.98	70.22
	SPEA2	151.18	70.61	**72.71**	70.58
	Island model (NSGA-II, PICEA-g, SPEA2)	150.68	**71.29**		
UUDB	Without Feature Selection	384.00	50.44	41.94	50.88
	PCA (0.75)	46.67	48.48	47.53	49.61
	PCA (0.95)	156.80	49.37	47.93	49.89
	NSGA-II	141.47	50.12	50.44	50.50
	PICEA-g	167.50	50.34	50.22	**50.91**
	SPEA2	145.68	50.37	50.19	50.59
	Island model (NSGA-II, PICEA-g, SPEA2)	146.85	**51.02**		

effective combination of a MOGA and a classifier in advance. Therefore, it is reasonable to apply a general approach which is based on an island model and an ensemble of classifiers (Figure 2).

The results provided with the combination of different MOGAs and the ensemble of classification models are compared with the highest F-score values obtained with one of the MOGAs and one of the classifiers separately (these values are highlighted in Table 3).

A t-test (with the significance level p=0.01) was used for comparison. As a result, for all of the corpora there was no difference between the best results obtained in the previous experiment (with a classifier and a MOGA which realized a feature selection search) and the F-score values provided with the island model of MOGAs and the ensemble of classifiers.

The application of the proposed approach allowed us not only to achieve the highest F-score values but also to reduce the number of features significantly (approximately by a factor of two) and to save the computational time owing to the parallel work of the island model (roughly by a factor of 2.5 because the additional time was spent on the migration process).

VI. CONCLUTIONS

The proposed evolutionary feature selection scheme based on an island model includes a number of algorithms and, therefore, does not require additional experiments to expose the most appropriate MOGA for the problem considered. It saves computational time due to the parallel work of islands. Besides, this approach might be effectively used as a pre-processing stage in combination with an ensemble of classifiers.

According to the results obtained, a high level of emotion recognition was achieved (up to 11.15% relative improvement for the SAVEE database compared with the best F-score value on the full set of attributes). Thus, the described evolutionary feature selection technique is an effective alternative to conventional dimension reduction procedures such as Principal Component Analysis.

Moreover, there are some other aspects related to speech-based recognition of human qualities of the user such as gender and speaker identification. Consequently, the proposed schemes might be applied to solve these problems.

From the view point of the algorithms improvement, the use of the self-configuration approach [20] will improve their performance because of the problem specific fine adjustment of parameters which are currently chosen in the ad hoc mode.

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