Speaker State Recognition: Feature Selection Method based on Self-adjusting Multi-criteria Evolutionary Algorithms

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Abstract: In supervised learning scenarios there are different existing methods for solving a task of feature selection for automatic speaker state analysis; many of them achieved reasonable results. Feature selection in unsupervised learning scenarios is a more complicated problem, due to the absence of class labels that would guide the search for relevant information. Supervised feature selection methods are "wrapper" techniques that require a learning algorithm to evaluate the candidate feature subsets; unsupervised feature selection methods are "filters" which are independent of any learning algorithm. However, they are usually performed separately from each other. In this paper, we propose a method which can be performed in supervised and unsupervised forms simultaneously based on multi-criteria evolutionary procedure which consists of two stages: self-adjusting multi-criteria genetic algorithm and self-adjusting multi-criteria genetic programming. The proposed approach was compared with different methods for feature selection on four audio corpora for speaker emotion recognition and for speaker gender identification. The obtained results showed that the developed technique provides to increase emotion recognition performance by up to 46.5% and by up to 20.5% for the gender identification task in terms of accuracy.

1 INTRODUCTION

Speaker state analysis problems such as speaker emotion recognition and speaker gender identification are complicated and challenged classification problems due to the high dimensionality. For solving such classification problems it is necessary to perform determination of irrelevant features (attributes) in data sets (feature selection). All data may have consequences of effects such as noise (natural factor), voice distortion (human factor); the attributes may have a low level of variation, correlate with each other that leads to a deterioration of the classification performance. If standard techniques of feature selection do not demonstrate sufficient effectiveness, an alternative way is an application of the methods based on evolutionary techniques that are effective for high-dimensional and poorly structured problems.

The proposed approach for feature selection includes two stages with two evolutionary algorithms: modified genetic algorithm and genetic programming. First stage is the pre-processing procedure with modified genetic algorithm (Pre-processing with Sorting - PS) using multi-criteria optimization as an unsupervised feature selection algorithm and the second stage is the multi-criteria genetic programming (MCGP) with an artificial neural network (ANN) as a supervised feature selection algorithm, where structure of ANN models by genetic programming (GP) procedure are created. The optimization of the ANN structure with choosing optimal amount of neurons and layers was proposed in (Loseva, 2015a). In fact, the efficiency of GP applications depends on its parameters and setting reasonable parameters requires the expert knowledge. Therefore, we also proposed a new self-adjusting procedure, which allows choosing the optimal combination of evolutionary operators (EO) automatically. This self-adjusting procedure is a modification of the existing self-tuning and self-configuring evolutionary approaches that are presented in (Sergienko and Semenkin, 2010; Semenkin and Semenkina, 2012).

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We investigate the efficiency of the proposed algorithmic schemes on the sets of acoustical data for speaker state recognition problems (emotion recognition and gender identification) which reflect one of the main questions in the area of human-machine communications. It turns out that by using the proposed evolutionary technique we could significantly improve efficiency of the recognition tasks.

This paper is organized as follows: related done works are listed in Section 2. Section 3 describes the proposed approach for feature selection using multi-criteria evolutionary algorithms (GA, GP) with six criteria of efficiency. In Section 4 all used databases are described. All experiments in this work on the comparative analysis of the novel hybrid method and other methods for feature selection are presented in Section 5. Conclusions and directions for future work are presented in Section 6.

2 SIGNIFICANT RELATED WORK

Various classifiers (support vector machine, linear discriminant analysis, naive Bayes, decision tree, multi-layer perceptron) for speaker state recognition problems were compared in (Loseva, 2014) on Berlin, UUDB, LEGO databases of emotional speech (see Section 4). These results showed the highest value (maximum) of precision using ANN classifiers and one-criterion genetic algorithm (OGA) for feature selection (Loseva, 2014). Also the results of emotion recognition with feature selection have been presented in (Sidorov et al., 2014). The authors have achieved the high value of precision on the databases Berlin, UUDB, LEGO with different methods of feature selection such as: one-criterion Genetic Algorithm (OGA) (Holland, 1975), Principal Component Analysis (PCA) (Akthar and Hahne, 2012), Information Gain Ratio (IGR) as it was done in (Polzehl et al., 2011) and SPEA (Zitzler and Thiele, 1999) using Multi-layer Perceptron (MLP) as a classifier. In this research the authors noted that the reduced with the SPEA method feature set was a twice less than the original dimensionality.

3 HYBRID ALGORITHM FOR FEATURE SELECTION

3.1 Self-adjusting Multi-criteria Modified Genetic Algorithm

In (Holland, 1975) basic algorithmic scheme of GA is presented. The first stage of PS method is a preprocessing of initial feature set from the database. Selection on the first stage is based on estimating statistical metrics such as *Variation level, Distance between clusters* (Venkatadri and Srinivasa, 2010), *Laplacian Score* (He et al., 2005), which characterize the data set quality by its power of locality preserving. The fitness functions are follows:

- The first fitness function - Variation level:

$$FitGA_r^1 = \frac{1}{1+\delta_r^2}, \tag{1}$$

where δ_r^2 - dispersion value of r - *th* feature.

- The second fitness function - Laplacian Score: Let L_r denote the Laplacian Score of the r-th feature. Let f_{ri} denote the i-th sample of the r-th feature, i=1,…,m. Laplacian Score calculates as follows:

1. Construct a nearest neighbor graph G with m nodes. The i-th node corresponds to x_i. Put an edge between nodes i and j if x_i and x_j are "close", i.e. x_i is among k nearest neighbors of x_j, or x_j is among k nearest neighbors of x_i. When the label information is available, one can put an edge between two nodes sharing the same label.
2. If nodes i and j are connected, put:

$$S_{ij} = \begin{cases} e^{\frac{-\|x_i - x_j\|}{t}}, i = j \\ 0, otherweise \end{cases}, \tag{2}$$

where t is a suitable constant. The weight matrix S of the graph models is the local structure of the data space.

3. For the *r-th* feature, we define:

$$f_r = [f_{r1}, f_{r2}, f_{r3}, ..., f_{rm}]^T,\ D = diag(S \cdot 1),$$
$$1 = [1,...,1]^T,\ L = D - S, \tag{3}$$

where the matrix L is often called graph Laplacian (Fan and Chung., 1992). Recall that given a data set, we construct a weighted graph G with edges connecting nearby points to each other. S_{ij} evaluates the similarity between the *i-th* and j-th nodes. Thus, the importance of a feature can be thought of as the degree it respects the graph structure. To be specific, a “good” feature should the one on which two data points are close to each other if and only if there is an edge between these two points.

Laplacian Score calculates by formula (4):

$$L_r = \frac{\sum_{ij}(f_{ri} - f_{rj})^2 S_{ij}}{Var(f_r)}, \tag{4}$$

where $Var(f_r)$ is the estimated variance of the *r-th* feature.

Therefore, the second fitness function *r-th* feature by formula (5) is calculated:

$$FitGA_r^2 = L_r, \tag{5}$$

- Third fitness function - Distance between clusters (DC):

$$FitGA_r^3 = \frac{\sum_{k=1}^{K}\sum_{p=1}^{X_k}\frac{\| x_p^k - x^k \|^2}{X_k}}{\frac{1}{K}\sum_{k=1}^{K}\| x^k - x^{k+1} \|^2}, \tag{6}$$

where x_g^k is *g-th* object for *k-th* class, x^k is the central object, X_k - amount of object *k-th* class, K - amount of classes.

As a feature selection technique on this stage we use a multi-criteria modified genetic algorithm operating with binary strings, where *unit* and *zero* correspond to a relative attribute and an irrelative one respectively. Each feature is the individual from initial population (initial feature set), which is sorted by the PS procedure after estimation as "1" - effective, "0" - not effective, as it in Figure 1 is presented.

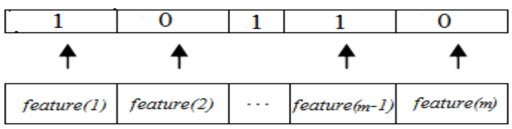

Figure 1: The representation of the determination effectiveness of features in population by PS procedure.

The PS procedure works as follows:

1. Estimate criteria values for all individuals from the current population.
2. To calculate average value of efficiency each feature from initial feature set by formula (7):

$$A = \sum_{r=1}^{R}\sum_{f=1}^{F} Fit_r^f;\ Value = F \cdot \frac{A}{R}, \tag{7}$$

where K - amount of classes, R- amount of features, Fit_f^r - fitness function of r - th feature, $f = \overline{1, F}$, F -amount of fitness function.

3. To sort features as "0" - not effective, if *A>Value*, and "1" - effective, if *A<=Value*.
4. To select features with rang "1" to intermediate population (set).

3.2 Self-adjusting Multi-criteria Genetic Programming

In the second stage, the MCGP algorithm using self-adjusting technique is applied. The selected on the first stage feature subset is the total feature set for selection procedure on this stage. After working MCGP the found by the algorithm features are the final subset of features.

In (Koza, 1992) the basic scheme of genetic programming is presented. In the MCGP method the ANN classifiers is used as a learning algorithm. In our evolutionary procedure we use genetic programming operating with trees (tree encoding). The ANN model is encoded into the tree. A tree is a directed graph consists of nodes and end vertex (leaves). In nodes may stay one operator from the multiplicity *F* {+, <} and there are objects from the multiplicity *T* {IN_1, IN_2, IN_3,..., IN_n - input neurons (feature subsets), F_1, F_2, F_3, F_4 ..., F_N - activation functions (neurons)} in the leaves. Each input neuron corresponds to one feature. The operator "+" from multiplicity *F* indicates formation all neurons in one layer and the operator "<" indicates formation all layers in ANN (Figure 2).

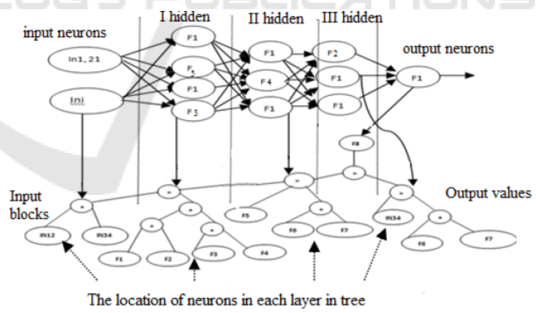

Figure 2: Schematic representation ANN in tree.

In this case we introduce the three-criteria model, specifically, *Pair correlation level, Complexity of ANN structure and Classification accuracy* are used as optimized criteria:

- The first fitness function: Pair correlation level:

$$FitGP^1 = \frac{1}{1 + \text{measure}} \to \max, \tag{8}$$

where "measure" is a maximum of pair correlation values between input neurons in ANN:

$$measure = \max(\mathrm{corr}_t), \qquad (9)$$

where corr_t is pair correlation value of two (x^t, y^t) ANN input neurons, $t = \overline{1,T}$ T - amount of all possible pairs of ANN input neurons. corr_t by formula (10) is calculated:

$$corr_t = \frac{\sum_i^M (x_i^t - \bar{x}^t)(y_i^t - \bar{y}^t)}{\sqrt{\sum_i^M (x_i^t - \bar{x}^t)^2} \sqrt{\sum_i^M (y_i^t - \bar{y}^t)^2}}, \qquad (10)$$

where M - amount of objects in x^t.

- The second fitness function: Classification accuracy:

$$FitGP^2 = \frac{P}{V}, \qquad (11)$$

where P is the amount of correctly classified objects; V is the amount of classified objects.

- The third fitness function: Complexity of ANN structure:

$$FitGP^3 = n \cdot N_1 + \sum_{i=1}^{L-1} N_i N_{i+1} + N_L \cdot l, \qquad (12)$$

where n is the amount of input neurons; N_i is the amount of neurons in the i-th layer; i is the number of hidden layers; L is the amount of hidden layers in ANN; l is the amount of output neurons in ANN.

In evolutionary algorithms there are different types of operators and necessary to do different initial settings. To avoid choosing the algorithm settings it is reasonable to apply the self-adjusting procedure. The developed approach (MCGP) works as follows:

Step 1. Initialization

Create a population of individuals. Each individual is a tree as a representation of ANN.

Step 2. Weight factors optimization

Optimization of the neural network weighting factors by OGA. The criterion for stopping the OGA is the maximum value of classification accuracy.

Step 3. Choosing evolutionary operators

In this step all combinations of EO have equal probabilities of being selected. In other step is necessary to recalculate probability values for new combinations of EO. All combinations with different types of operators were formed: two types of selection operators (tournament, proportion), two types of mutation operators (strong, weak) and one type for recombination (one-point) were used.

Step 4. Evaluation of criteria values

Estimate criteria values for all individuals from the current population.

Step 5. Generation of new solutions

- Selection two individuals for recombination by VEGA (Vector Evaluated Genetic Algorithm) method (Ashish and Satchidanada, 2004).
- Recombination of two selected individuals for creation a new descendant.
- Mutation of a descendant.
- Evaluation a new descendant.
- Compilation new population (solutions) by each created descendant.

Step 6. Resources reallocation

Choose a new combination of EO by recalculation of the probability values. For recalculation need to estimate the EO combination effectiveness by formula (13) for each descendant, which was created by this EO combination:

$$Fit\_Oper_p = \frac{1}{I_p} \cdot \sum_{d=1}^{I_p} \sum_{f=1}^{F} FitGP_f^{\ d}, \qquad (13)$$

where Fit^d_f is fitness f-th descendent by d-th criterion; I_p is amount of descendants which were created by chosen variant of EO combination.

The number of added fitness functions may be different; it depends on the algorithm. After comparing values (Fit_Oper_p), the variant of EO with highest value calls a “priority” variant. A combination of EO with the lowest probability value changes on the “priority” variant. The recalculation of probabilities is implemented for each iteration of the algorithm. If all combinations on a "priority"

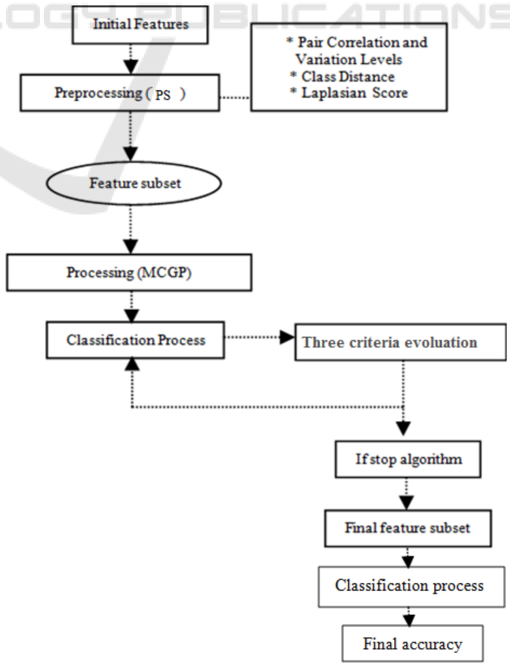

Figure 3: Schematic representation of the PS+MCGP algorithm.

option have been replaced, all probability values are cleared. New variants of EO combination are generated again.

Step 7. Stopping Criterion

Check the stop-criterion: if it is true, then complete the working of MCGP and select the best individual as a representation of ANN from population, otherwise continue from the second step. The chosen best ANN is the model with relevant set of features, which equals to the set of input neurons in ANN.

Both described stages are called as a PS+MCGP algorithm. The schematic representation of the PS+MCGP algorithm is presented in Figure 3.

4 DATABASES

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

The *Berlin* emotional database (Burkhardt et al., 2005) was recorded at the Technical University of Berlin and consists of labeled 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 *UUDB* (The Utsunomiya University Spoken Dialogue Database for Paralinguistic Information Studies) database (Mori et al., 2011) consists of spontaneous Japanese human-human speech. The task-oriented dialogue was 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 pleasantness (or evaluation) and the arousal axes are used.

The *LEGO* emotion database (Schmitt et al., 2012) comprises non-acted American English utterances extracted from an automated bus information system of the Carnegie Mellon University in Pittsburgh, USA. The utterances are requests to 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 single class and friendly utterances have been deleted. These preprocessing results are represented as a 3-classes emotion classification task.

The *RSDB* (Russian Sound Data Base) (Loseva, 2015b) was created, which consists of voices of people from 14 to 18 and from 19 to 60 years old both human`s gender (man, woman). Each utterance is annotated with one of the following emotional labels: angry, neutral, happy. The database was created in Krasnoyarsk on the recording studio "WAVE" in 2014.

5 EXPERIMENTS AND RESULTS

To estimate the performance of the PS+MCGP usage in speech-based recognition problems, a number of experiments were conducted. The proposed approach was applied for all considered databases. The following methods for feature selection were also applied in this study: OGA, IGR. These methods have been included to conduct classification experiments with Sequential Minimal Optimization (SMO) (Platt, 1998). The conventional OGA-based feature selection is used as the supervised technique. From early works (Liu et al., 2001), (Golub et al., 1999), (Nguyen and Rocke, 2002), it is obvious that best accuracy for cross-validation from training set is used as a classification accuracy. Therefore, in this study we used the OGA procedure, with one-criteria for testing data as mentioned in equation (14):

$$Fitness = accuracy\,(ind), \tag{14}$$

where is the *accuracy* (*ind*) is the cross-validation accuracy of the SMO classifier trained using the feature subset of training data represented by *ind.*

In order to provide statistical comparison of the proposed methods, the classification procedure was tested several times (15 times). Firstly, it was fulfilled by SMO (without feature selection) and secondly by the earlier proposed methods (Brester et al., 2014). In order to determine the number of selected features using the IGR method, a grid bases consist of Russian human speech. A statistical description of the used corpora can be found in Table 1.

Table 1: Databases description.

Data base	Language	Data base size	Features	Emotion classes	Speak ers
Berlin	German	535	45	7	10
UUDB	Japanese	1514	45	4	10
LEGO	English	4827	29	5	291
RSDB	Russian	800	20	3	300

Table 2: Average accuracy for emotion recognition.

Data base	Baseline SMO	SMO IGR	SMO OGA	SMO PS+MCGP
Berlin	12.99	16.9(35)	15.1(26)	**25.1(23)**
UUDB	86.04	85.5(40)	83.3(30)	**87.7(25)**
LEGO	13.46	20.3(19)	20.7(15)	**45.2(16)**
RSDB	32.38	23.8(15)	34.4(12)	**80.9(10)**

Table 3: Average accuracy for gender identification.

Data base	Baseline SMO	SMO IGR	SMO OGA	SMO PS+MCGP
Berlin	24.30	**99.1(38)**	21.3(25)	92.5(24)
UUDB	34.77	65.4(39)	31.8(28)	**87.1(26)**
LEGO	36.89	61.2(17)	64.6(18)	**70.3 (15)**
RSDB	53.89	73.6(16)	52.8(15)	**94.1(12)**

The optimization technique with 10 steps was applied, i.e. for Berlin database: first 5, 10, 20, ..., 45 features. The data sets were randomly divided into training and test samples in a proportion of 80 - 20%. In all experiments PS+MCGPs were provided with an equal amount of resources. The final solution is the relevant feature set that is determined by amount of input neurons in ANN in the second part of the described algorithm. Tables 2 and 3 contain the relative classification accuracy for the described corpora. In parentheses there is the average number of selected features (Tables 2, 3). The columns entitled SMO Baseline contain results which were achieved with the baseline feature selection methods. Similarly, the columns titled SMO PS+MCGP, SMO IGR and SMO OGA contain results obtained with PS+MCGP, IGR, OGA feature selection procedures correspondingly.

6 CONCLUSIONS AND FUTURE WORK

An application of the proposed hybrid algorithm in order to select the relevant features and maximize the accuracy of particular tasks could decrease the number of features and increase the accuracy of the system simultaneously. In most of the cases, the PS+MCGP approach outperforms other algorithms. Also the MCGP approach is able to create (select) the optimal variant of the ANN classifier which could be applied for improving effectiveness of speaker state recognition problems. It should be noted that the number of selected features using the IGR, OGA methods is quite high. It means that in some cases the number of features was equal to 41, i.e. an optimal modeling procedure has been conducted without feature selection at all.

The usage of effective classifiers may improve the performance of the proposed approach. Thus, it is important to estimate efficiency of classifiers in cooperation with feature selection algorithms for comprehensive improvement of recognition systems.

Additionally, the proposed approach can be applied to improve the effectiveness of „real-time" (on-line) systems. On-line processes always accompany by different types of effects such as noise, voice distortion, etc. that should be processed in real time. Therefore, it can be useful to involve the developed algorithm into on-line systems. For example, the proposed approach can be applied for improving real-time recognition of a psycho-emotional state of a human. We assume, a study in this direction allows creating a state recognition procedure for real-time systems more accurate.

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