Multiple Feature Extraction and Hierarchical Classifiers for Emotions Recognition

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Abstract. The recognition of the emotional states of speaker is a multi-disciplinary research area that has received great interest in the last years. One of the most important goals is to improve the voiced-based human-machine interactions. Recent works on this domain use the prosodic features and the spectrum characteristics of speech signal, with standard classifier methods. Furthermore, for traditional methods the improvement in performance has also found a limit. In this paper, the spectral characteristics of emotional signals is used in order to group emotions. Standard classifiers based on Gaussian Mixture Models, Hidden Markov Models and Multilayer Perceptron are tested. These classifiers have been evaluated in different configurations with different features, in order to design a new hierarchical method for emotions classification. The proposed multiple feature hierarchical method improves the performance in 6.35% over the standard classifiers.

1 INTRODUCTION

In the last years, the recognition of emotions has become in a multi-disciplinary research area that has received great interest. This plays an important roll in the improvement of human-machine interaction. For example, security application of the fear emotional manifestation in abnormal situations is studied in [1]; in [2], real-life emotion detection using a corpus of agent-client spoken dialogs from a medical emergency call center is studied; in [3], a framework to support semi-automatic diagnosis of psychiatric diseases is proposed.

The use of biosignals (like ECG, EEG, etc.), face and body images is an interesting alternative to detect emotional states [4,5,6]. However, methods to record and use these signals are more invasive, complex and impossible in some real applications. Therefore, the use of speech signals clearly becomes a feasible option. Most of the previous works in emotion recognition have been based in the analysis of speech prosodic features and spectral information. For the classifier, Gaussian Mixture Models (GMM), Hidden Markov Models (HMM) and several other standard techniques have been explored [7,8,9,10].

Very few works have been presented using some combination of standard methods. In [11], two classification methods: stacked generalization and unweighted vote, were applied in emotion recognition. These classifiers improved

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modestly the performance of traditional classification methods. In [12], a multiple stages classifier with support vector machines (SVM) is presented. Two class decision is repetitively made until only one class remains, and hardly separable classes are divided at last. Authors build this partition based on expert knowledge or derived it from the confusion matrices of a multiclass SVM approach. A two stages classifier for five emotions is proposed in [13]. In this work, a SVM to classify five emotions into two groups is used. Then, HMMs are used to classify emotions within each group.

In this work, an analysis of spectral features is made in order to define groups of similar emotions. Emotions are grouped based on their properties and a hierarchical classifier is designed. The proposed classifier is evaluated in the same experimental condition than standard classifiers, with important improvements in the recognition rates.

In the next section, the emotional speech data base and an acoustical analysis of emotions are presented. Section 3 describes the feature extraction and classification methods. The method here proposed and the experiments are also explained. Section 4 deals with the classification performance and discussion. Finally, conclusions and future works are presented.

2 ACOUSTIC ANALYSIS OF EMOTIONS

2.1 Emotional Speech Corpus

The emotional speech signals used were taken from an emotional speech data base [14], developed by the Communication Science Institute of Berlin Technical University. This corpus had been used in several studies [8,9,15] and allows the development and evaluation of an speaker independent recognizer[4].

The corpus, consisting of 535 utterances, includes sentences performed in 6 ordinary emotions, and sentences in neutral emotional state. These emotions covers the “big six” emotions set except for boredom instead of surprise. Sentences are labeled as: happiness (joy) (71), anger (127), fear (69), boredom (81), sadness (62), disgust (46) and neutral (79).

The same texts were recorded in german by ten professional actors, 5 female and 5 male, which allows studies over the whole group, comparisons between emotions and comparisons between speakers. The corpus consists of 10 utterances for each emotion type, 5 short and 5 longer sentences, from 1 to 7 seconds. To achieve a high audio quality, these sentences were recorded in an anechoic chamber with 48 kHz sample frequency (later downsampled to 16 kHz) and were quantized with 16 bits per sample. A perception test with 20 subjects was carried out to ensure the emotional quality and naturalness of the utterances, and those more confused were eliminated.

[4] The corpus is freely accessible from http://pascal.kgw.tu-berlin.de/emodb/.

2.2 Acoustic Analysis

The psychological conceptualization of affects, with two-dimensional and three-dimensional models, is widely known in the categorization of emotions [16,17,18]. These models are often used to group emotions in order to define classes. For example, those associated with low arousal and low pleasure versus those associated with high arousal and high pleasure. In this work the psychological information will be discarded and emotions would be characterized only by spectral information. As the main goal is performance improvement, the focus has been oriented to find discriminative acoustic features. It was studied how to take advantage from this acoustic evidence in the classification, without taking into account information from the phychological level or the taxonomy of human emotions.

For every utterance, the mean of the log-spectrum (MLS) on each frequency band, along the frames, were calculated. Then, the average of the mean log-spectrums (AMLS) over all the utterances with same emotion were computed

$$AMLS_k(f) = \frac{1}{N_k}\sum_{i=1}^{N_k}\frac{1}{T_i}\sum_{t=1}^{T_i}\log\|v(t,f)\|\,, \qquad (1)$$

where f is a frequency band, N_k is the number of sentences for the emotion class k, T_i is the number of frames in the utterance i and $v(t,f)$ is the discrete Fourier transform of the signal in the frame t.

The most important information to discriminate between emotion classes was found between 0 and 1200 Hz. In Figure 1, this information is shown for each emotional class. As it can be seen in the figures, some emotions have spectral similarities between them. For example, it can be noticed a similar shape and a maximum between 240 and 280 Hz in Joy, Anger and Fear. A minimum is present close to 75 Hz in Joy, Anger, Fear and Disgust. On the other hand, Boredom, Neutral and Sadness have similar shape and a peak between 115 and 160 Hz.

So, it is possible to define groups using this spectral information. For example, a group could contain Joy, Anger, Fear emotions (JAF) whereas other contains Boredom, Neutral and Sadness emotions (BNS) and finally Disgust emotion alone in a third group. On the other hand, emotion similarities used to propose the groups keep a relationship with accuracies and errors present in confusion matrices [8,9,19]. This relevant knowledge for emotion grouping will be used in the next section to define a hierarchical classifier.

3 PROPOSED METHOD

In this section, a new multiple feature hierarchical classification method based on the acoustic analysis described above is presented.

3.1 Features Extraction and Classification Methods

For every emotion utterance, three kinds of characteristics were extracted: MLS, mel frequency cepstral coefficients (MFCCs) and prosodic features. The MLS

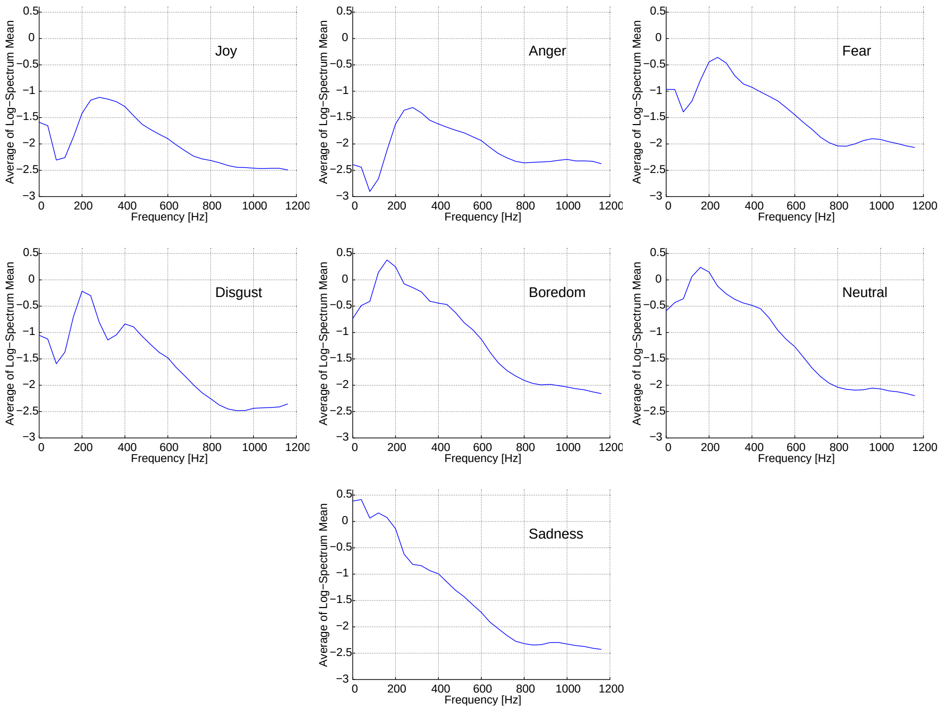

Fig. 1. Average of Mean Log-Spectrum for all emotion classes.

were computed as defined in Section 2.2. The spectrograms and the MFCC parametrization were calculated by using Hamming windows of 25 ms with a 10 ms frame shift. The first 12 MFCC plus the first and second derivatives were extracted [20].

The use of prosodic features in emotion recognition has been discussed extensively and classic methods to calculate the *Energy* and the F_0 along the signals have been used here [21]. Many parameters can be extracted from them; therefore the minimum, mean, maximum and standard deviation, over the whole utterances, were used. This set of parameters has been already studied and the experiments reported an important information gain to distinguish emotions [8,12,22]. Combinations of features were arranged in vectors and every dimension was independently normalized by the maximum from the feature vectors set.

In this work, some standard one-level classifiers (Fig. 2) are used as baselines. Classifiers are based on well known techniques: Multilayer Perceptron (MLP), GMM and HMM. The MLP is a class of artificial neural network and it consists of a set of process units (simple perceptrons) arranged in layers. In the MLP the nodes are fully connected between layers without connections between units

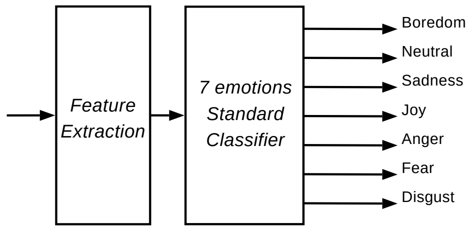

Fig. 2. Structure of standard one-level classifier for 7 emotions.

in the same layer. The input vector (feature vector) feeds into each of the first layer perceptrons, the outputs of this layer feed into each of the second layer perceptrons, and so on [23]. The input of the neuron is the weighted sum of the inputs plus the bias term, and its activation is some function (linear or nonlinear) of the input:

$$y = \mathcal{F}\left(\sum_{i=1}^{n} \omega_i x_i + \theta\right) \tag{2}$$

where x_i are the inputs and ω_i the weighting factors.

Although Gaussian distributions have important analytical properties, they have limitations to model multimodal data. Superposition of multiple distributions would fit better the real data distribution. *Mixture of Gaussians* is a superposition formed as a finite linear combination of simple Gaussian densities and it is widely used in statistical pattern recognition [24]:

$$p(\mathbf{x}) = \sum_{k=1}^{K} \omega_k \mathcal{N}(\mathbf{x}|\mu_k, \Sigma_k), \tag{3}$$

where $\mathcal{N}$ is a single normal density defined by μ_k and Σ_k. The mixing coefficients verify $\sum_k \omega_k = 1$ and $0 \leq \omega_k \leq 1$ for all k. By using a sufficient number of Gaussians, and by adjusting their means and covariances as well as the coefficients in the linear combination, almost any continuous density can be approximated to arbitrary accuracy [24].

The HMMs are basically statistical models that describe sequence of events and it is a very used technique in speech and emotions recognition. In classification tasks, a model is estimated for every signal class. Thus, it would take into account as many models as signal classes to recognize. During classification, the probability for each signal given the model is calculated. The classifier output is based on the model with the maximum probability of generating the unknown signal [25]. Here, the problem is presented as:

$$\hat{E} = \arg\max_{E} P(E|A), \tag{4}$$

where A is the sequence of acoustic features taken from speech signal and E represent the emotion.

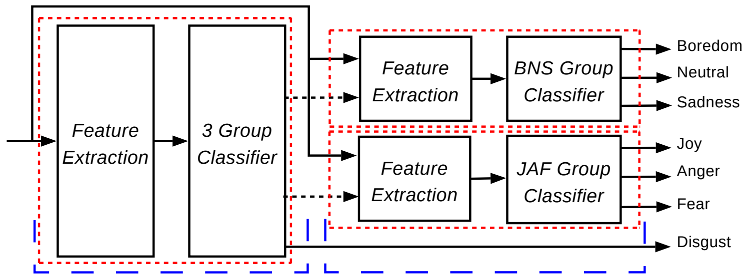

Fig. 3. General structure of the hierarchical classifier for 7 emotions.

Based in previous studies [7], the GMM and a two state HMM were picked. Tests increasing the number of Gaussian components in the mixtures were performed to find the optimal structure. In order to optimize the MLP performance, different number of neurons in hidden layer were tested.

3.2 Hierarchical Classifiers

The main motivations for the development of a hierarchical classifier are to take advantage of spectral emotion similarities to improve the emotion recognition rate. We also used the fact that better results can be achieved when the number of emotions decrease for the same standard classifier. Furthermore, the main differences between specific emotions are more evident with a particular feature vector and the best classification is obtained through a specialized classifier and structure. As can be seen from Fig. 3, the hierarchical classifier is defined in two levels. In a first stage the emotion utterance would be classified in one of 3 groups (BNS, JAF or Disgust), then it would be classified again in its corresponding block group (if it is not Disgust) and finally the emotion label is obtained.

To define the hierarchical model structure in each block, several configurations of MLP and HMM with different parameter vectors, were evaluated. Finally, the model stages were chosen and assembled with classifiers that achieved better results in isolated block tests.

In every MLP block test, 15 feature vectors were tested in 3 different hidden layer configurations (90, 120 and 150 perceptrons). Table 1 shows the number of characteristics for each vector and what kind of features it includes. For example, the feature vector FV14 includes 12 MFCC, the F_0 mean and the Energy mean. On the other hand, a 36 coefficients vector was used for HMM tests (12 MFCCs plus delta and acceleration), like in [7].

In MLP experiments, 60% of data was randomly selected for training, 20% was used for the generalization test and the remaining 20% was left for validation. The MLP training was stopped when the network reached the generalization peak with test data [23]. In HMM cases, the 20% used for test was added to the standard train set.

Table 1. Feature vectors used in MLP tests.

Parameters	FV12	FV14	FV16	FV18	FV20	FV30	FV32	FV34	FV36	FV38	FV42	FV44	FV46	FV48	FV50
12 MFCC	•	•	•	•	•						•	•	•	•	•
30 Mean Log-Spectrum						•	•	•	•	•	•	•	•	•	•
$\mu(F_0)$, $\mu(E)$		•	•	•	•		•	•	•	•		•	•	•	•
$\sigma(F_0)$, $\sigma(E)$			•		•			•		•			•		•
$Min(F_0)$, $Max(F_0)$				•	•				•	•				•	•
$Min(E)$, $Max(E)$				•	•				•	•				•	•

4 RESULTS AND DISCUSSIONS

In order not to favor one of the emotions over the others, in the experiments the same number of utterances was used for every emotion. This balanced partition has 46 randomly selected utterances for each emotion. Every utterance has one label according to the expressed emotion and represents only one pattern.

A comparative analysis between GMM and HMM for recognition of seven emotions was presented in [7]. Better results were achieved with a two state HMM with mixtures of 30 Gaussians, using a MFCC parametrization including delta and acceleration coefficients. The best result with GMM was with mixtures of 32 Gaussians. Here, the same systems with the balanced partition were tested in order to obtain the baseline reference's to compare results. The classification rate were 63.49% with GMM and 66.67% with HMM. In this work, the number of output nodes in the MLP equals the number of seven emotions and the performance was 68.25% for the network composed by FV46 input neurons and 90 hidden neurons (considered here as the baseline for MLP classification).

For the Stage I in the hierarchical classifier, three different options were evaluated: (a) to re-group HMM baseline outputs into 3 groups ($\mathrm{HMM}^7\mathrm{g}^3$); (b) to model each group with one HMM (HMM^3); and (c) to use a MLP with 3 output neurons. In HMM cases, the number of Gaussian components in the mixture was set to 30 (as best results in [7]). Table 2 shows the MLP results for each feature vector with train and validation data. Best results obtained for Stage I are summarized in Table 3. It can be seen that MLP achieved the best result but it is the worst classifying Disgust. This could be because MLP is not a good classifier when the classes are unbalanced.

For each block in Stage II, HMM and MLP tests were done using the partition data to evaluate the blocks in an isolated form. In HMM case, tests altering the number of Gaussian components in the mixture, increasing by two every time, were performed. A HMM with 26 Gaussians in the mixtures achieved a 74.07% for JAF test, while only 4 Gaussians achieved a 77.78% for the BNS case. The MLP results for JAF and BNS classification could be seen in Table 4 and Table 5 respectively. Best results for the isolated blocks of Stage II are shown in Table 6.

Table 2. Results of MLP classification for 3 Groups. Classification rate in [%].

Input	Best Net	Train	Validation
FV12	12+90+3	98.98	85.71
FV14	14+90+3	95.92	87.30
FV16	16+90+3	97.96	87.30
FV18	18+150+3	98.47	79.37
FV20	20+90+3	100.00	77.78
FV30	30+90+3	100.00	87.30
FV32	32+90+3	99.49	85.71
FV34	34+120+3	**98.98**	**88.89**
FV36	36+90+3	99.49	84.13
FV38	38+120+3	100.00	82.54
FV42	42+120+3	92.86	87.30
FV44	44+150+3	96.94	84.13
FV46	46+150+3	94.39	85.71
FV48	48+90+3	100.00	80.95
FV50	50+150+3	100.00	82.54

Table 3. Performance of Stage I classification models.

	HMM grouped	HMM	MLP
JAF	88.89	77.78	88.89
BNS	85.19	92.59	100.00
D	66.67	88.89	55.56
average	84.13	85.71	**88.89**

Table 4. Results of JAF with MLP in isolated classification. Classification rate in [%].

Input	Best Net	Train	Validation
FV12	12+150+3	98.81	81.48
FV14	14+150+3	90.48	85.19
FV16	16+150+3	95.24	74.07
FV18	18+90+3	86.90	74.07
FV20	20+120+3	85.71	77.78
FV30	30+90+3	98.81	77.78
FV32	32+120+3	100.00	70.37
FV34	34+90+3	100.00	77.78
FV36	36+120+3	76.19	74.07
FV38	38+90+3	73.81	77.78
FV42	42+90+3	100.00	81.48
FV44	44+90+3	100.00	85.19
FV46	46+90+3	**100.00**	**85.19**
FV48	48+90+3	100.00	85.19
FV50	50+150+3	100.00	85.19

The best HMM and MLP models for JAF and BNS were extracted. These blocks were evaluated in cascade with each first stage model. In Table 7, the

Table 5. Results of BNS with MLP in isolated classification. Classification rate in [%].

Input	Best Net	Train	Validation
FV12	12+90+3	84.52	66.67
FV14	14+90+3	100.00	74.07
FV16	16+90+3	100.00	66.67
FV18	18+150+3	96.43	48.15
FV20	20+150+3	94.05	51.85
FV30	30+90+3	100.00	74.07
FV32	32+120+3	92.86	74.07
FV34	34+90+3	96.43	66.67
FV36	36+90+3	92.86	62.96
FV38	38+120+3	100.00	59.26
FV42	42+150+3	96.43	70.37
FV44	44+150+3	**97.62**	**81.48**
FV46	46+120+3	100.00	77.78
FV48	48+90+3	95.24	59.26
FV50	50+120+3	97.62	66.67

Table 6. Best results for isolated Stage II classification.

Group	Stage II model	Performance
JAF	MLP	85.19
	HMM	74.07
BNS	MLP	81.48
	HMM	77.78

Table 7. Final test of hierarchical model.

Stage I		Stage II				
Model	Disgust	JAF		BNS		Best
		HMM	MLP	HMM	MLP	
HMM^7g^3	66.67	66.67	**74.07**	62.96	70.37	71.43
HMM^3	**88.89**	55.56	62.96	74.07	77.78	73.02
MLP	55.56	66.67	**74.07**	77.78	**81.48**	**74.60**

performance for JAF and BNS blocks with both models are shown for each model in Stage I. The performance for the best combination considering each model in Stage I are: 71.43% for HMMs re-grouped (HMM^7g^3), 73.02% for 3 HMMs (HMM^3) and 74.60% for MLP.

Finally, the best hierarchical model is formed by a MLP with FV34 and 120 hidden neurons in the Stage I; a MLP with FV46 and 90 hidden neurons for the JAF block and a MLP with FV44 and 150 hidden neurons for the BNS block. Figure 4 shows the best hierarchical model configuration. As can be seen, spectral and some prosodic features (FV34) are the best to classify the 3 groups. However, the MFCC are required to improve the recognition in both blocks of the Stage II.

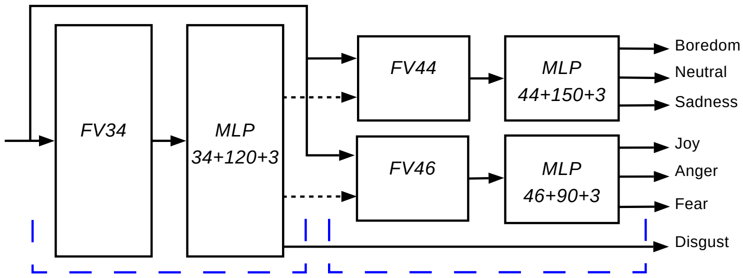

Fig. 4. Best hierarchical classifier for 7 emotions.

Table 8. Results of standard classifiers and hierarchical model.

Model	Performance
GMM	63.49
HMM	66.67
MLP	68.25
Hierarchical	**74.60**

In Table 8 is shown a comparison between standard classifiers and the best hierarchical classifier here proposed. Results show that hierarchical method improves the performance in 6.35% over the best standard classifier.

5 CONCLUSIONS AND FUTURE WORKS

In this paper a characterization of emotions and their similarities based on the acoustical features was presented. A new hierarchical method for emotion classification supported by such acoustic analysis was proposed. Experiments with different number of inputs and internal structure for MLP and tests increasing the number of Gaussians in mixtures for HMM were performed for each block. The results show that the hierarchical model improves recognition rates of the standard one-stage classifiers. Furthermore, it was showed that prosody combined with spectral features improves the results in the emotion recognition task.

In future works will improve cross-validation tests with more data for the hierarchical model. Although the speaker independent results are good, tests in gender dependent frameworks are also planned. This will allow taking more advantage of specific spectral information. Also, it is planned to carry out similar analyses on other languages.

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