Speech Emotion Recognition Using Fourier Parameters

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Abstract—Recently, studies have been performed on harmony features for speech emotion recognition. It is found in our study that the first- and second-order differences of harmony features also play an important role in speech emotion recognition. Therefore, we propose a new Fourier parameter model using the perceptual content of voice quality and the first- and second-order differences for speaker-independent speech emotion recognition. Experimental results show that the proposed Fourier parameter (FP) features are effective in identifying various emotional states in speech signals. They improve the recognition rates over the methods using Mel frequency cepstral coefficient (MFCC) features by 16.2, 6.8 and 16.6 points on the German database (EMODB), Chinese language database (CASIA) and Chinese elderly emotion database (EESDB). In particular, when combining FP with MFCC, the recognition rates can be further improved on the aforementioned databases by 17.5, 10 and 10.5 points, respectively.

Index Terms—Fourier parameter model, speaker-independent, speech emotion recognition, affective computing

1 Introduction

Speech emotion recognition, which is defined as extracting the emotional states of a speaker from his or her speech, is attracting more attention. It is believed that speech emotion recognition can improve the performance of speech recognition systems [1] and is thus very helpful for criminal investigation, intelligent assistance [2], surveillance and detection of potentially hazardous events [3], and health care systems [4]. Speech emotion recognition is particularly useful in man-machine interaction [1], [6].

To effectively recognize emotions from speech signals, the intrinsic features must be extracted from raw speech data and transformed into appropriate formats that are suitable for further processing. It is a longstanding challenge in speech emotion recognition to extract efficient speech features. Researchers have performed many studies [6]-[12]. First, it is found that continuous features including pitch-related features, formants features, energy-related features, and timing features deliver important emotional cues [7], [11], [31]. In addition to time-dependent acoustic features, various spectral features such as linear predictor coefficients (LPC) [32], linear predictor cepstral coefficients (LPCC) [33] and mel-frequency cepstral coefficients (MFCC) [44] play a significant role in speech emotion recognition. Bou-Ghazale and Hansen [34] found that the features based on cepstral analysis, such as LPCC and MFCC, outperform the linear features of LPC in detecting speech emotions. Next, the Teager energy operator (TEO), introduced by Teager [35] and Kaiser [36], can be used to detect stress in speech [37]. There are also other TEO-based features proposed for detecting neutral versus stressed speech [38]. Although the abovementioned features are useful for recognizing specific emotions, there is no sufficiently effective feature to describe complicated emotional states [13].

It has been demonstrated that voice quality features are related to speech emotions [14], [15], [39], [40], [42], [53]. According to an extensive study by Cowie et al. [11], the acoustic correlations with voice quality can be grouped into voice level, pitch, phrase and feature boundaries and temporal structures. There are two popular approaches for determining voice quality terms. The first approach depends on the fact that speech signals can be modeled as the output of a vocal tract filter excited by a glottal source signal [32]; hence, voice quality can be measured by removing the filtering effect of the vocal tract and by measuring the parameters of the glottal signal [41]. However, the glottal signal must be estimated by exploiting the characteristics of the source signal and the vocal tract filter because neither of them is known [1]. In the second approach, voice quality is represented by the parameters estimated from speech signals. In [39], voice quality was represented by jitter and shimmer. The system for speaker-independent speech emotion recognition used the continuous hidden Markov model (HMM) as a classifier to detect some selected speaking styles: angry, fast, question, slow and soft. The baseline accuracy was 65.5 percent when using MFCC features only. The classification accuracy was improved to 68.1 percent when MFCC was combined with jitter, 68.5 percent when MFCC was combined with shimmer and 69.1 percent when MFCC was combined with both of them. In [53], the voice quality parameters were estimated by spectral gradients of the vocal tract compensated speech signal and were applied in [40], [42] for classifying utterances from the Berlin emotional database [18] to improve speaker-independent emotion classification. To the best of our knowledge, Yang and Lugger [15] first proposed a set of harmony features, which came from the well-known psychoacoustic harmony perception in music theory, for automatic emotion recognition. The following emotions were selected for classification: anger, happiness, sadness, boredom, anxiety, and neutral. The accuracy was 70.9 percent when using voice quality features and standard features.

Despite these contributions, further study regarding voice quality in delivering emotions is needed. Acoustic interpretation explains that the unique quality (tone) of each instrument is due to the unique content and structure of a harmonic sequence. According to music theory [49], the harmony structure of an interval or chord is mainly responsible for producing a positive or negative impression on listeners. In this paper, we propose a set of harmonic sequences, named Fourier parameter (FP) features, to detect the perceptual content of voice quality features rather than the conventional ones. The new FP features will be evaluated on different speech databases. It is one of the first attempts to apply a new set of FP features, in particular, with the first- and second-order differences for speaker-independent speech emotion recognition. Both Bayesian classification and support vector machines (SVM) are evaluated.

The main contributions of this paper for speaker-independent emotion recognition are summarized as follows: 1) proposing a new FP model using FP features and their first- and second-order differences for speech emotion recognition; 2) proposing to further improve speaker-independent speech emotion recognition by combining FP and MFCC features; 3) performing extensive validations on three speech databases in two languages. This paper is organized as follows. Section 2 presents the Fourier parameter model based on Fourier series. Section 3 details the FP features for speech emotion analysis and the evaluations on a German database and a Chinese database. Section 4 discusses the experimental results of speaker-independent speech emotion recognition. Concluding remarks are drawn in section 5.

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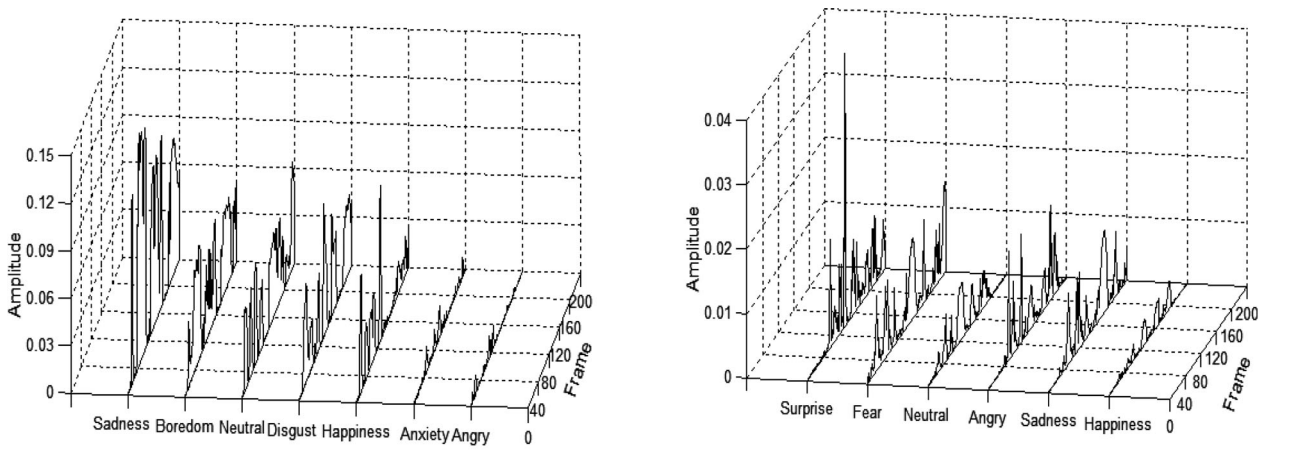
Manuscript received 11 May 2014; revised 15 Oct. 2014; accepted 26 Dec. 2014. Date of publication 13 Jan. 2015; date of current version 3 Mar. 2015.
Recommended for acceptance by K. Hirose.
For information on obtaining reprints of this article, please send e-mail to: reprints.org, and reference the Digital Object Identifier below.
Digital Object Identifier no. 10.1109/TAFFC.2015.2392101



(a) Speech signals uttered in German with seven emotion types, sadness, boredom, neutral, disgust, happiness, anxiety/fear and angry

(b) Speech signals uttered in Chinese with six emotion types, surprise, fear, neutral, angry, sadness and happiness

Fig. 1. The mean of H_3 for speech signals with different emotions from the German and Chinese databases.

2 Fourier Parameter Model of Speech

Fourier series [43] is one of the most principal analytical methods for mathematical physics and engineering. Fourier analysis has been extensively applied for signal processing, including filtering, correlation, coding, synthesis and feature extraction for pattern identification.

In Fourier analysis, a signal is decomposed into its constituent sinusoidal vibrations. A periodic signal can be described in terms of a series of harmonically related (i.e., integer multiples of a fundamental frequency) sine and cosine waves. In other words, a speech signal can be represented as the result of passing a glottal excitation waveform through a time-varying linear filter, which models the resonant characteristics of the vocal tract [17]. A speech signal $x(m)$ that is divided into l frames can be represented by a combination of an FP model as in (1):

$$x(m) = \sum_{k=1}^{M} H_k^l(m)\left(\cos\left(2\pi\frac{f_k^l}{F_s}m\right) + \varphi_k^l\right), \tag{1}$$

where F_s is the sampling frequency of $x(m)$, H_k^l and φ_k^l are the amplitude and phase of the kth harmonic's sine component, l is the index of the frame, and M is the number of speech harmonic components.

The harmonic part of the model is a Fourier serial representation of a speech signal's periodic components. When a nonperiodic component is sampled, its Fourier transform becomes a periodic and continuous function of frequency.

The discrete Fourier transform (DFT) is derived from sampling the Fourier transform of a discrete-time signal at N discrete frequencies, which correspond to the integer multiples of the fundamental sampling interval $2\pi/\mathrm{N}$. For a finite duration discrete-time signal $x(m)$ of length N samples, DFT is defined as (2), where $H(k)$ are FPs from k = 0 . . . N-1.

$$H(k) = \sum_{m=0}^{N-1} x(m)e^{-j\frac{2\pi}{N}mk} \quad \mathrm{k} = 0, 1, 2, \ldots, N\text{-}1. \tag{2}$$

3 Fourier Parameter Features for Speech Emotion Analysis

In this section, a new model is proposed, with special attention on three speech emotion databases in two different languages, to extract FP features.

3.1 Emotion Databases

Three databases are considered: a German emotional corpus (EMODB) [18], a Chinese emotional database (CASIA) [45] and a Chinese elderly emotional speech database (EESDB) [54], which are summarized as follows. EMODB was collected by the Institute of Communication Science at the Technical University of Berlin. It has been used by many researchers as a standard data set for studying speech emotion recognition. EMODB comprises 10 sentences that cover seven classes of emotion from everyday communication, namely, anger, fear, happiness, sadness, disgust, boredom and neutral. They could be interpreted in all emotional contexts without semantic inconsistency. EMODB is well annotated and publicly available.

CASIA was released by the Institute of Automation, Chinese Academy of Sciences. It is composed of 9,600 wave files that represent different emotional states: happiness, sadness, anger, surprise, fear, and neutrality. Four actors (two females and two males) simulated this set of emotions and produced 400 utterances in six classes of different emotions.

The EESDB database includes seven classes of emotions (angry, disgust, fear, happy, neutral, sadness and surprise). The sources of this database came from a part of Chinese TV statements presented by 11 elderly people over 60 years old (five females and six males).

In the first step, two speech emotion databases, EMODB and CASIA, are employed to validate the method for extracting FP features.

3.2. Fourier Parameter Features

Harmonics include frequency, amplitude and phase. It has been reported that harmonic frequency features are effective for speech emotion recognition [15]. In this study, we also make use of harmonic amplitude and phase features. For every frame, FP is estimated by Fourier analysis. As shown in (2), H_k^l is the lth frame's FP. The ith FP amplitude is H_i. It then leads to the average values of H_i. In other words, a new speech feature vector H_k may be evaluated for all frames in the speech signal from 1 to l (number of frames). Fig. 1 shows the averaged H_3 among various emotions for one person. It is observed that amplitudes vary with different classes of emotions. We also discern the mean of each phase of speech with different emotions, but the difference is trivial.

3.3 Global Fourier Parameter Features

It has been reported [1] that global features are superior in terms of classification accuracy and computational efficiency. Therefore,

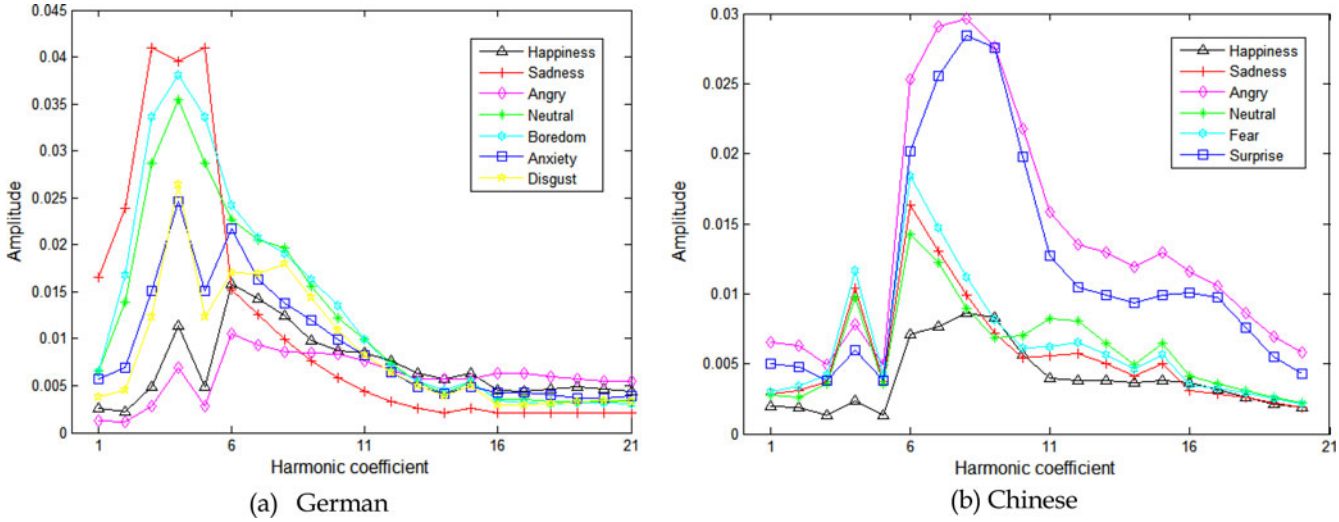


Fig. 2. The means of H_1 to H_{20} with different emotions.

the mean, maximum, minimum, median and standard deviation of the amplitudes of the first 20 Fourier parameters are calculated as in [1], [7], [15], [46] and [47].

Fig. 2a shows that the means of H_1 to H_{20} are different with regard to seven emotions. The average values of H_3 for sadness, boredom and neutral are higher than disgust, happy and anxiety. The peak of every emotion is at the lower harmonics. For example, the peaks of happy and angry emotions are obtained at the sixth harmonic; the peaks of neutral, boring, anxious and disgusted emotions are obtained at the fourth harmonic. It is also observed that the variation of the low-order FPs for every emotion is large, while the high-order FPs is relatively smooth. The amplitudes of happy and angry emotions are below those of neutrality before the former 10 harmonics. Similar results have been observed by Ramamohan and Dandapat [19] in which angry and happy emotions have higher values of energy compared to those with neutral emotion.

Fig. 2b shows the means of six emotions from CASIA. The amplitudes of anger and surprise are higher than those of other emotions, while happy is lower. The variation of happiness is relatively smooth, while anger and surprise are obvious. It also shows that the peaks of happiness, surprise and anger lie at the eighth harmonic, and the peaks of neutrality, sadness and fear lie at the sixth harmonic.

It is noteworthy that among these speech databases, the same emotions between the German speech database and the Chinese speech database may have different FP features. The angry emotion from the Chinese speech database is higher than the other emotions, while the German database is lower. Moreover, the happy emotion in both databases is low. The reason is that different countries have different cultures so that the ways in which they convey and perceive emotions are different [25].

4 Speaker-Independent Recognition

Speaker-independent emotion recognition is one of the latest challenges in the field of speech emotion recognition. It is able to cope with unknown speakers and thus has better generalization than those speaker-dependent approaches [4]. Until now, there have been quite a few studies reported on speaker-independent emotion recognition [4], [15], [16], [48]. Yang and Lugger [15] proposed a set of harmony features derived from the pitch contour and employed them for the speaker-independent recognition of six classes of emotions: happiness, boredom, neutrality, sadness, anger, and anxiety. Ruvolo et al. [16] made use of the hierarchical aggregation of features to combine short-, medium- and long-scale features. They employed MFCC and LPCC for speaker-independent experiments. Bitouk et al. [48] defined three classes of phonemes in the utterance, namely, stressed vowels, unstressed vowels and consonants, and further calculated the statistics of fundamental frequency, first formant, voice intensity, jitter, shimmer and the relative duration of voiced segments for speaker-independent experiments. Kotti and Paternò [4] extracted 2,327 features in total for speaker-independent recognition that were related to the statistics of pitch, formants, and energy contours as well as spectrum, cepstrum, autocorrelation, voice quality, jitter, shimmer and others.

4.1 Feature Extraction

Both MFCC and FP features are extracted for speaker-independent emotion recognition. Continuous features [1] such as fundamental frequency (F0) [7], energy and zero-crossing rate (ZCR) are also extracted.

4.1.1 MFCC Features

MFCC was first introduced and applied to speech recognition in [44]. It has been popularly used for speech emotion recognition [25], [34], [40]. By considering the reaction of human ears to different frequencies, the Mel frequency is determined according to the characteristics of human audition.

In this study, MFCC features were extracted for comparison with the proposed FP features. For emotion recognition, MFCC features usually include mean, maximum, minimum, median, and standard deviation. All speech signals were first filtered by a high-pass filter with a pre-emphasis coefficient of 0.97. The first 13 MFCCs and the associated delta- and double-delta MFCCs were extracted to form a 39-dimensional feature vector. Its mean, maximum, minimum, median and standard deviation were further derived out, which led to a 195-dimensional MFCC feature vector in total.

4.1.2 Fourier Parameter Features

We extracted a set of FP features from speech signals as described in Sections 3.2 and 3.3. Here, the first 120 harmonic coefficients were extracted. The dynamic features were extracted so that temporal derivative features may improve the performance of emotion recognition [20]. In other words, the FP feature vector is comprised of amplitude (H), first-order difference (ΔH) and second-order difference ($\Delta\Delta H$). Their minimum, maximum, mean, median and

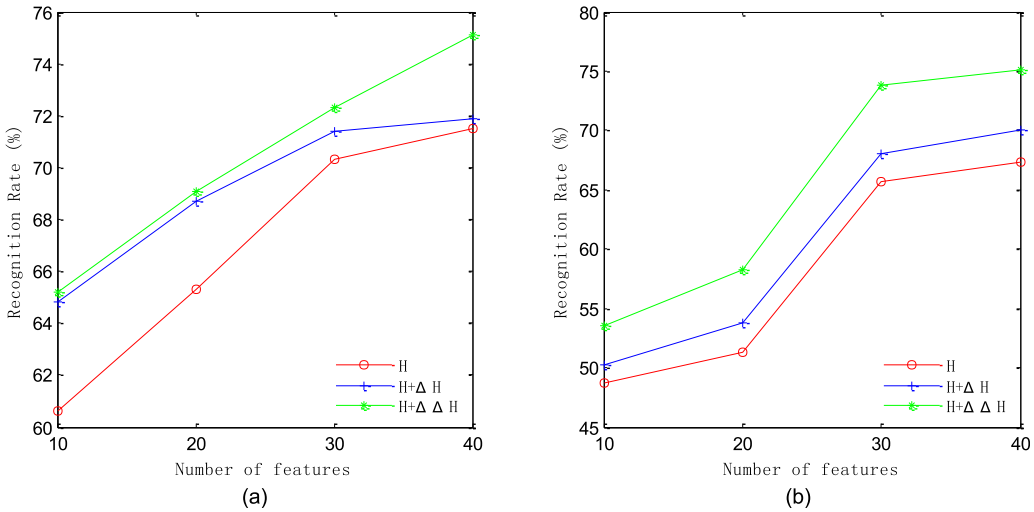


Fig. 3. Result of six-class emotion recognition using H, $H+\Delta H$ and $H+\Delta\Delta H$(a) EMODB database and (b) CASIA database. The *x*-axis represents 1 to n number Fourier parameters.

standard deviation were also computed. There were a total of 1,800 features for speaker-independent speech emotion recognition.

4.1.3 *Continuous Features*

Continuous features are important in delivering the emotional cues of speakers [7], [9], [11] and thus have been widely used in speech emotion recognition [1], [7], [22]. F0 or pitch is a prosodic feature, which provides the tonal and rhythmic properties of the speech. Energy refers to the intensity of the speech signal and reflects the pause and where the accent of the voice signal is. ZCR reflects the time when adjacent samples of a voice signal are going to change the symbol. In our earlier studies, the feature set with F0, energy, and ZCR has been better than other common feature sets including formant and LPCC [56]. In this study, the minimum, maximum, mean, median, and standard deviation of F0, energy and ZCR were also calculated for comparison with the proposed FP features.

4.2 Feature Normalization

Normalization is an important aspect for a robust emotion recognition system [30]. The goal is to eliminate speaker and recording variability while keeping the effectiveness of emotional discrimination [51]. In particular, it could compensate for speaker variability. Here, z-score normalization [51] was adopted for feature normalization.

For a given FP feature H from a speech signal of a speaker s, its mean value, $E(H^s)$, and its standard deviation, $std(H^s)$, were first derived out. Then, the normalized feature was estimated by the following (3):

$$\widehat{H^s} = \frac{H^s - E(H^s)}{std(H^s)}. \tag{3}$$

4.3 Support Vector Machine Classification

With respect to emotional speech recognition, many classifiers including the Gaussian mixture model (GMM), artificial neutral networks (ANN) [22], hidden Markov model [23] and support vector machine [21], [24], [25] have been studied more than once. SVM makes use of convex quadratic optimization that is advantageous in making a globally optimal solution. SVM has demonstrated good performance on several classical problems of pattern recognition [26], including bioinformatics, text recognition and facial expression recognition [27]. It was also used for speech emotion recognition [4], [28], [29], [50] and outperformed other well-known classifiers [1].

There are two different families of solutions aiming to extend SVM for multiclass problems [52]. The first solution follows the strategy of "one-versus-all", while the second solution follows the strategy of "one-versus-one". We selected the second method by using LIBSVM [58] because it is more convenient in practice [52]. FP features were fed as inputs to the SVM classifier with the Gaussian radial basis function kernel, where the controlling parameters have been evaluated for c $\in$ (0, 10) and $\gamma \in (0, 1)$.

4.4 Experiment Results

We first used 40 FP features for speech emotion recognition. As shown in Fig. 3, the recognition rate increased with increments of 10 FP features. Moreover, the recognition rates increased when the first- and second-order differences were incorporated.

The third- and fourth-order differences were also evaluated, but their contributions were not as effective. The same protocol was used with the phase features and their differences. The recognition rate was as low as approximately 55 percent. It suggests that the phase feature is not that are efficient for speech emotion recognition, which has also been demonstrated in [19].

TABLE 1
Confusion Matrix of Emotion Recognition Using 120 FP Features on the German Database (%)

	Happ.	Bored.	Neutr.	Sad.	Angry	Anxi.
Happ.	92.92				1.25	5.83
Bored.	1.11	71.48	10.22	1.25	12.44	3.5
Neutr.		2.54	87.46	4.44		5.56
Sadn.				91.21		8.79
Angry		1.71			98.29	
Anxi.		3.08	1.25	2.08	1.67	91.92

TABLE 2
Confusion Matrix of Emotion Recognition Using 120 FP Features on the CASIA Database (%)

	Happ.	Surpri.	Neutr.	Sadn.	Anger	Fear
Happ.	81		2	4	11	2
Surpri..		84		3	10	3
Neutr.			75	16		9
Sadn.	11	8	2	67	6	6
Anger				6	86	8
Fear.		3	4	5	7	81

TABLE 3
Confusion Matrix of Emotion Recognition Using 120 FP Features on the EESDB Database (%)

	Happ.	Sadn.	Anger	Neutr.
Happ.	41.5	28.9	14.7	14.9
Sadn.	2	83.6	9.4	5
Anger	2.6	8.6	88.8	
Neutr.	4.2	2.9	2.8	90.1

Happ. = *happiness*, *Surpri.* = *surprise*, *Neutr.* = *neutrality*, *Sadn.* = *sadness*, *Anxi.* = *anxiety*, *Bored.* = *boredom*

TABLE 4
The Best Feature among MFCC, FP, FP+MFCC and FEZ on Three Databases

	EMODB	CASIA	EESDB
Happ.	FP	FP+MFCC	FP
Sadn.	FP+MFCC	FP	FP
Anger	FEZ	FP+MFCC	MFCC
Neutr.	FP+MFCC	FP	FP
Bored	FP+MFCC		
Surpri.		FP+MFCC	
Fear	FP+MFCC	FP+MFCC	

The method of sequential floating forward search (SFFS) [57] was then used to reduce the inputting features and to improve the recognition rate. Table 1 shows the confusion matrix of SVM classification with 120 FP features on EMODB.

In [4], a total of 2,327 features were extracted for speech emotion recognition. The average accuracy in [4] was 83.3, 89.7 percent for happiness, 90.5 percent for neutrality, 87.7 percent for anxiety, 90.1 percent for anger, 88.6 percent for sadness and 89.3 percent for boredom. In contrast, the approach presented in this paper achieved recognition rates for happiness (92.92 percent), anger (98.29 percent), sadness (91.21 percent) and anxiety (91.92 percent). In other words, the proposed FP and FP + MFCC features improve the recognition rate at approximately 5.6 and 6.8 points versus the result of [4].

In [15], harmony features were proposed for speaker-independent emotion recognition by using a Bayesian classifier on EMODB. The rates of emotion recognition were 52.7 percent for happiness, 84.8 percent for boredom, 52.9 percent for neutrality, 87.6 percent for sadness, 86.1 percent for anger and 76.9 percent for anxiety. We also developed a Bayesian classifier with Gaussian class-conditional likelihood on EMODB. By using the same 120 FP features, the average accuracy was 79.51 percent, with 87.59 percent for happiness, 54.36 percent for boredom, 84.31 percent for neutrality, 89.60 percent for sadness, 93.62 percent for anger and 67.60 percent for anxiety. In other words, the proposed FP features are able to improve the recognition rate at approximately 6.01 points versus the best result of [15].

Tables 2 and 3 report the confusion matrices of 120 FP features on CASIA and EESDB, respectively. The recognition rate on EESDB is below that of the other two databases. The main reason might be because the emotions expressed by the elderly are usually more difficult to identify [55].

According to Tables 1 to 3, it seems that the rates of emotion recognition vary between German and Chinese. It is reasonable that different countries have different cultures, and the way in which they express their emotion is also different [25].

Fig. 4 shows the results of using MFCC, FP, MFCC+FP and F0+ENERGY+ZCR (FEZ) features on the three databases. In general, the FP features themselves achieved higher average recognition rates than MFCC and FEZ, particularly on the EMODB database. When combining the FP and MFCC features (MFCC+FP), it was able to further improve the performance of speech emotion recognition. On the contrary, the FEZ features usually led to worse performance. In other words, although continuous features deliver the important emotional cues of speakers [7], [11], [31], FEZ features did not demonstrate better performance in speaker-independent emotion recognition. We also combined FP with FEZ features, but it had little impact on recognition accuracy.

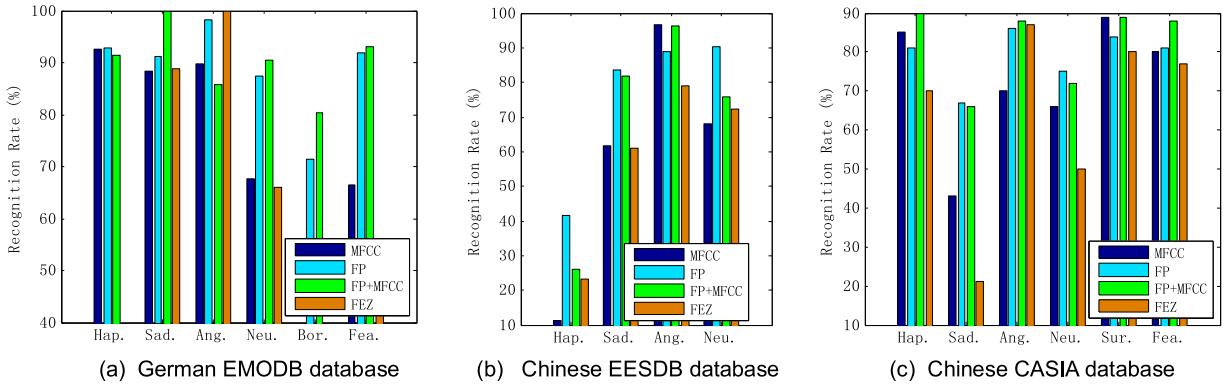
Table 4 shows the optimal combination of features by using FP, MFCC, FP+MFCC and FEZ for different classes of emotions on the three databases. With an average rate of recognition at 87.5 percent, the proposed FP features outperformed the others in all cases.

In summary, compared with MFCC features, the proposed FP features improved speaker-independent emotion recognition by 16.2 points on the German database, 6.8 points on the CASIA database and 16.6 points on the EESDB database. The performance could be further enhanced by approximately 17.5 points, 10 and 10.5 points by combining the FP and MFCC features on the aforementioned databases.

5 Conclusion

In previous studies, different features were employed for speech emotion recognition. In this paper, we proposed a new FP model to extract salient features from emotional speech signals and validated it on three well-known databases including EMODB, CASIA and EESDB. It is observed that different emotions did lead to different FPs. Furthermore, FP features were evaluated for speaker-independent emotion recognition by using SVM and a Bayesian classifier.

The study showed that FP features are effective in characterizing and recognizing emotions in speech signals. Moreover, it is possible to improve the performance of emotion recognition by combining FP and MFCC features. These results establish that the proposed FP model is helpful for speaker-independent speech emotion recognition.



(a) German EMODB database (b) Chinese EESDB database (c) Chinese CASIA database

Fig. 4. Comparisons of the recognition rates by FP, MFCC, FP+MFCC and F0+ENERGY+ZCR (FEZ).

ACKNOWLEDGMENTS

The authors would like to thank all anonymous reviewers for their critical comments. This work was partially supported by the National 111 Project under grant B14025, by the International S&T Cooperation Program of China under Grant No. 2014DFA11310, by the National Natural Science Foundation of China under Grant No. 51274078, 61203312, 61271123, 61370219, 61432004, and 61305064, by the National Key Technology R&D Program of China under Grant No. 2013BAH19F01, by the National High Tech R&D Program of China under Grant No. 2012AA011103, by the "University Featured Project" of the Ministry of Education under grant No. TS2013HFGY031, and by the Anhui Provincial Natural Science Foundation under grant KJ2014A047. Any correspondence should be made to N. An.

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