Application of New Qualitative Voicing Time-Frequency Features for Speaker Recognition

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Abstract. This paper presents original and efficient Qualitative Time-Frequency (QTF) speech features for speaker recognition based on a med-term speech dynamics qualitative representation. For each frame of around 150ms, we estimate and binarize a subband voicing activity estimation of 6 frequency subbands. We then derive the Allen temporal relations graph between these 6 time intervals. This set of temporal relations, estimated at each frame, feeds a neural network which is trained for speaker recognition. Experiments are conducted on fifty speakers (males and females) of a reference radio database ESTER (40 hours) with continuous speech. Our best model generates around 3% of frame class error, without using information of frame continuity, which is similar to state of the art. Moreover, our QTF generates a simple and light representation using only 15 integers for coding speaker identity.

1 Introduction

Classical models of speech recognition assume that a short term analysis of the acoustic signal is essential for accurately decoding the speech signal. Most of these systems are based on maximum likelihood trained Gaussian mixture speaker models, with diagonal covariance matrices. They can use for example principal component analysis from the output of 24 mel frequency channels, or more usually around 256 components calculated from the cepstral coefficients and deltas [1], voice recognition feature for speaker recognition such as since such features compensate characteristics of speakers [2].

This paper presents an alternative view, where the time scale requires an accurate description, longer than the phonetic segment, wedded to the dynamics of TF voicing level intervals. We assume that voicing reflects a singular property of the modulation spectrum that may provide a qualitative framework to generate a speaker identity model.

A variety of studies have shown that intelligibility depends on the integrity of the low-frequency modulation spectrum [3]. Within reverberant environments the greatest impact of acoustic reflection is between 2 and 6Hz. An effect of reverberation is to jumble the spectral content of the acoustic signal across both time and frequency, particularly that portion of the spectrum below 1500Hz. Although, reverberation is known to interfere with intelligibility; the basis for its deleterious impact is not well understood. On the other hand, it has been established that phonological perception is a SB process [4]. Moreover, this can be linked to speech production dynamics [5]. This has inspired various algorithms for robust speech recognition [6, 7], also linked to the TF voicing level [6, 8]. This time-frequency dynamics seems therefore to be important in speech perception, and because a natural representation for timely events has been proposed by Allen J.F., we proposed a quantific time-frequency dynamics for robust speech features extraction paradigm [9], that an approach is presented here for a specific task of speaker recognition.

2 Features Extraction

2.1 Voicing Extraction

We use the voicing measure [6, 10], correlated with SNR and equivalent to the *harmonicity index* (HNR) [11, 12] to estimate the average voicing per utterance. It is extracted from the autocorrelogram of a demodulated signal. In the case of Gaussian noise, the correlogram of a noisy frame is less modulated than a clean one [11]. The peaks in the autocorrelogram of the demodulated frame isolate the various harmonics in a signal. This can be used to separate a mixture of harmonic noises and a dominant harmonic signal. It is interesting that such separation can be efficiently accomplished, using a time windows of duration in the same range as the average phoneme duration.

Before the autocorrelation we compute the demodulated signal after half wave rectification, followed by pass-band filtering in the pitch domain ([90,350]Hz). For each frame of 128ms, we calculate the ratio $R = R1/R0$, where $R1$ is the local maximum in time delay segment corresponding to the fundamental frequency, and $R0$ is the cell energy. This measure is strongly correlated with SNR in the 5-20dB range [11]. Figure 1 demonstrates explicitly the voicing levels for each SBs and each frame. These values will be thresholded to get qualitative dynamic features that will be used to estimate the speaker identity. The subband (SB) definitions are following Fletcher studies, followed by other ones like in ALLEN J.B. papers [4, 5, 6].¹ Here are the definitions of SB range (Hz):[216 778 ; 707 1631 ;1262 2709; 2121 3800 ; 3400 5400 ; 5000 8000].

¹ Note that ALLEN J.B and ALLEN J.F. are two different authors, the first worked on speech analysis, the second on generic time representation. Our model is based on both approaches.

Fig. 1. From Voicing to the Allen’s Interval : (a) voicing signal (b) the voicing level by SB (c) the binarized voicing levels by SB using ${}^sT_{b_i}$ threshold

2.2 Allen Interval Graphs

A temporal intervals algebra has been defined in [13, 14], where 13 atomic relations are depicted between two time intervals. From ours observations to the voicing levels by SB (cf fig. 1-(b)), we propose to apply the J.F. Allen’s time representation for each SBs and each voicing activity regions (that can be 200 ms long). We present Allen’s time relationships in the figure 2. X is the sliding interval which gives, progressively with Y , the 13 Allen intervals relations. We can define the algebraic distance d between the two nearest interval to 1 and we increment it as we moved away from the interval relation. This will give us the numeric values for each relation that we use in this paper. The “b”symbol is coded into “1”, “m”into “2”, ... for the 13 relations of the figure 2. Moreover, the “no-relation” is also coded into “0”, this can occurred between two SBs if one or both have no frame with enough voicing level.

In order to obtain and to characterize exactly these six SB intervals we binarize the voicing matrix sM_R (s mean that for each speaker we build his own voicing matrix). First of all, we must find the best threshold for each sub-waveband to use it after. Indeed, after some experiences we have noticed that it is better to set one threshold for each SB. Thus we are looking for the best threshold which gives a fixed percent (30% , 50% and 70%) of 1 in each waveband by binarising the voicing matrix sM_R . We first look for the threshold ${}^sT_{b_i}$ values in:

$\Upsilon = \left[mean({}^sM_{R_{b_i}}) - \tau , mean({}^sM_{R_{b_i}}) + \tau \right]$, by steps of 0.01 with $\tau = 0.4$, such that:

$$\frac{Card({}^sR_{b_i}(t) > {}^sT_{b_i})}{Card({}^sw)} = P \pm \varepsilon, \quad (1)$$

Relation	Symbol	Illustration	Inverse Symbol
X before Y	b		a
X meets Y	m		mi
X overlaps Y	o		oi
X starts Y	s		si
X during Y	d		di
X finishes Y	f		fi
X equals Y	eq		

Fig. 2. The interval construction structure with the 13 symbols. (no=“no-relation”).

where t is the time of speaker s , T is threshold used, b_i represents a SB with $i \in \{1..6\}$, and P defines the percent of 1 in the binarized interval. ε is a percent of tolerance ($\pm 1\%$), and ${}^s w$ is the total number of frames for speaker s .

If not any threshold value satisfies the previous conditions, then we set ${}^s T_{b_i} = mean({}^s M_{R_{b_i}})$.

After this iterative threshold research, we have generated per speaker voicing frame a threshold vector ${}^s T = [{}^s T_1 \ {}^s T_2 \ {}^s T_3 \ {}^s T_4 \ {}^s T_5 \ {}^s T_6]$, where T_i represents the threshold by SB. By applying ${}^s T$ to ${}^s M_R$ we obtain the binarized matrix, which a short sample is represented on Fig. 1-c. We then extract the Allen’s graph per speaker for all frame having at least 4 binarized voicing interval simultaneously equal to 1.

The Allen graph corresponding to the figure 1-c is represented by atomic relation matrix in figure 3 (we characterize in bold the relations which are non redundant and useful). For each speaker, we obtain full graphs which will be used to discriminate one from the other by using a Multi-Layer Perceptron (MLP). In the next paragraph, we introduce a brief explanation of this method.

All Allen graphs are symmetric to the first diagonal (see 3). Each of the seven relations has an inverse relation in the same graph. This is due to the logic between two intervals: if the interval A is BEFORE B, in the same time we can assure that B IS AFTER A. Thus the useful information is contained in the 15 first relations which are ordered from left to the right, beginning from subband I’1 to subband I’5. For our example, one input vector at time t of our Multi Layer Perceptron Classifier is $QTF(t)=[di \ di \ di \ oi \ oi \ d \ d \ d \ s \ oi \ d \ oi \ f \ d]$. We see on figure 4 the histogram of all QTF vectors for “Yves Decaens”.

$$\begin{array}{c}
I'_1 \\ I'_2 \\ I'_3 \\ I'_4 \\ I'_5 \\ I'_6
\end{array}
\begin{pmatrix}
I'_1 & I'_2 & I'_3 & I'_4 & I'_5 & I'_6 \\
eq & di & di & di & oi & oi \\
d & eq & d & d & d & d \\
d & di & eq & s & oi & d \\
d & di & si & eq & oi & f \\
o & di & o & o & eq & d \\
o & di & di & fi & di & eq
\end{pmatrix}$$

Fig. 3. The second part of the figure 1-c Allen graph correspondences. The top-right triangle of this matrix contains the 15 relations values that will be given to an MLP for Id. speaker modelisation. Then they will be sorted from 1 to 15 as $1 = (I'_1, I'_2)$, $2 = (I'_1, I'_3)$, ..., $15 = (I'_5, I'_6)$. We needn't to use down-left triangle of this matrix due to the symmetric relation between both triangles.

The “no-relation” occurs when some binarized SBs only containing zeros. We see that that the “no-relation” represents around 10% of all relations. See also Tab. 1 for an estimation of the discriminative power of this relation.

In figure 5 we present the log ratio of the QTF normalized distributions of two speakers (Yves Deceans and Patricia Martin), whos both have spoken about 50 minutes. It shows well the strong differences for certain relations and certain SB couples. We demonstrate in this paper that this information is discriminative for a speaker identification task training a simple MLP.

For this purpose, we train with these 15 integers a MLP using the Torch toolbox [15]. It's a machine learning library written in simple C++ and distributed under BSD License. Torch is currently developed by IDIAP team. Torch has been designed to be essentially time efficient, modular, as it is a research oriented library. Our MLP is based on the Last Mean Square criterion (other Machine Learning algorithm could have been used, like Support Vector Machines SVM).

3 Database

Our experiments are conducted on a corpus issued from the Phase 1 of ESTER 2006 evaluation campaign (Evaluation Campaign for the Rich Transcription of French Broadcast News) [16]. ESTER implements three tasks, named transcription (T), segmentation (S) and information extraction (E). We have focused our work on SVL Speaker tracking and SRL Speaker diarization. This acoustic corpus Phase 1 is issued from two different sources, named France Inter (Inter) and Radio France International (RFI). It contains about 40 hours of manually transcribed radio broadcast news. This corpus is divided into three separated parts for training, developing and testing activities respectively. The training part (train) contains 30 hours and 40 minutes and the development part (dev) 4 hours and 40 minutes. The test part (test) contains 4 hours and 40 minutes. The unseen source in the test data is meant to evaluate the impact of the knowledge of the document source on performances.

4 Experimental Results and Interpretation

We give class error rate results left column in table 1, and their falsification in right columns in the same Table. We see that the best parametrisation is given for 70% of ‘active’intervall in each SB, yielding to a class error rate of 2.5%. Comparison with ESTER Phase 1 results [17] are promising: we get the same order of speaker identification for this task on continous broadcast news.

Table 1. In the “Real Data” column are presented the class error results for the 50 speakers id. with different P values (MLP methods $P = 0.3, 0.5$ or 0.7). The best score is around 2.5%. In the “Falsified Data” column we find for comparison a model falsification with only two relations: no-relation versus all other relations (see text).

MLP method			Real data				Falsified data			
	Parameters		The_class_error				The_class_error			
	data Set	nhu	iter	Train	Dev	Test	iter	Train	Dev	Test
	Nb	Nb	Nb	%	%	%	Nb	%	%	%
0.3	-	300	1206	8.57	12.37	12.21	132	85.21	85.01	84.95
	27338	600	1678	9.97	16.18	16.27	123	85.15	84.44	85.29
	-	600	1472	8.20	13.62	13.30	110	85.14	84.21	84.50
	-	1000	1242	26.16	32.93	33.68	138	84.99	85.74	86.12
0.5	-	300	1431	8.58	13.32	13.11	95	85.22	84.60	84.96
	27306	600	1940	6.62	9.05	9.11	140	85.23	85.33	84.80
	-	600	675	34.95	43.22	42.58	128	85.24	84.86	84.57
	-	1000	1560	10.20	15.17	15.11	130	85.07	85.24	85.70
0.7	18166	600	874	1.56	2.68	3.01	159	86.03	86.74	86.03
	-	300	819	1.49	2.7	2.92	141	85.75	86.56	85.90
	-	600	873	1.44	2.55	2.46	149	86.11	86.41	86.25
	-	1000	923	1.46	2.57	2.48	150	86.11	86.92	86.01

We run a falsification experimentation to verify if each relation encodes useful information, or if only the difference between “no-relation” and all other relations is relevant. Thus, in each set (train, dev and test), we have just used a 1 bit input parameter for our MLP, replacing all atomic relations different to the “no-relation” by 1, and keeping all the no-relation (originally coded by 0). The table 1 on the right gives this falsification results: we observe that the worst score is approximately 85%, telling that most of the coding information is given by the nature of the relations. But we also mesure that this is better than the random system (around 93% cf. formula²). This demonstrates that the no-relation contains by itself some speaker identity information.

² Let P_k be the frequency of the class C_k , the error rate of a random classifier is:

$$ER_{rand} = 1 - \sum_{k=1}^c (P_k)^2 = 1 - \sum_{k=1}^c \left(\frac{card(C_k)}{\sum_{k=1}^c card(C)} \right)^2$$

where c is the number of classes and $card(C_k)$ is the number of images in the class C_k .

Fig. 4. Histogram of the QTF MLP inputs for the men speaker “Yves DECAENS”. Each atomic relation is in abscissa from left to right (no:no-relation, b:before, m:meets, o:overlaps, s:starts, d:during, f:finishes, eq>equals, and respective symmetric ones: a, mi, oi, si, di, fi and eq). Each of the 15 MLP inputs (from left blue for the SB couple (I1,I2), to right red dark for the SB couple (I5,I6)). We note that the QTF distributions are varying more across relations than across each SB couples. The first input in dark blue on the left of each histogram (i.e for the couple (I1,I2)) has a majority of “no relation” and “during”. The 15th input (node for couple (I5,I6)), in the right of each histogram, has a majority of “during” relation, ie the voicing interval in subband 5 is most of the time included in the voicing interval of SB 6. The “meeting” relations are not present for this speaker. The “equal” relation seems to be an informative kind of relation, showing great contrast across each SB couple.

Fig. 5. This figure shows the logarithm (10) ratio between the QTF normalized distributions. The atomic relations and SB couples orders are the same than in previous figure. As we can see there are often large differences between at least half of the relations or SB couples. The MLP have learned with success each of these singularities distributions and then discriminats well speaker identity. Note that this figure represents only a part of the QTF processed information: it may exists another intra-frame discriminative information between the 15 parameters calculated on each frame, that is erased in this global histogram summing all training frames.

5 Discussion and Conclusion

A better optimisation could be obtained by combining different parameters for each subband. Moreover this preliminary iterative threshold research should be replaced by more global optimisation scheme. The total number of MLP weights is around 39000 ($=600 \cdot (15+50)$), which is smaller than usual parameters size. Nevertheless our approach generates the same order of errors than other experiments conducted on ESTER Phase 1 using classical MG HMM model on

classical spectral parameters. Another major difference and originality of our qualitative approach remains its parcimonious and simple integer representation of each speaker in a very small integer subspace (50 speakers identity coded in $[0 : 13]^{15}$).

A systematic falsification of each relation will give for each relation an idea of its amount of information for encoding speaker identity information. This should show if speakers are discriminated by particular relations, or if only the joint set of each relation encodes the speaker identity. Some experiments are currently testing our qualitative model on ESTER phase 2, which is a bigger database, with more speakers, and with published SRL and SVL scores with MG HMM models [17].

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