

## THE ANALYSIS OF SPEAKER INDIVIDUAL FEATURES BASED ON AUTOREGRESSIVE HIDDEN MARKOV MODELS

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### ABSTRACT

The speech-based analysis of speaker individual features has found wide application area. In order to analyse the speaker individual features it is necessary to use high frequencies and accurate spectrum estimation methods. It was found out that the best way to analyse the personal voice individuality is to use bark scaled spectrum estimation based on arithmetic Fourier transform. For each of 10 speakers the autoregressive hidden Markov model was trained. The experiments show that such models provide high accuracy of person identification based on bark-cepstrum analysis and high sampling frequency.

### INTRODUCTION

The speech-based analysis of speaker individual features has found wide application area and can be used in order to solve many modern tasks: speaker identification and verification, diagnostics of speech producing tract disease, secure remote access systems [1], [2]. Speech signal by its nature has two aspects. Firstly, speech of the person is defined by physical parameters, such as vocal tract length, glottal size and so on. Secondly, the speech producing is impossible without neural control of the articulators, which defines the personal learned abilities such as dialect or regional accents, pronunciation, speed and timing of the articulators. These two reasons find the reflection in speech signal non-linearity, and it is necessary to implement more or less nonlinear model. First reason reflects mostly in person speech characters obtained after spectrum analysis. We can model the personal learned abilities if to take into consideration the speech characters interrelations between close frames. Correlation of feature vectors between close frames gives us the useful information about speaker pronunciation mode. From this viewpoint statistical methods based on hidden Markov models (HMM) are very attractive [1], [3]. Flexible and powerful mathematical apparatus lets to easily use them for effective temporal information modeling. But for the best results speaker individual feature task requires the development and designing of a hidden Markov model with special structure and parameters. Discrete and continuous hidden Markov models are well-studied now for the isolated word recognition task. The recognition accuracy for such models is high enough, but as usual hidden Markov models are used together with neural networks because of their low characteristics at the acoustical modeling level.

The assumptions of standard hidden Markov models do not take into consideration interrelations between close frames of the same phonetic unit and loose

important information about acoustical structure of the phoneme. All character vectors within the phoneme are assumed to be independent. The experimental results show that it is not truth in many cases. In order to eliminate this drawback of hidden Markov models we introduce an autoregressive hidden Markov model for the task of speaker individual features analysis.

### SPEECH PARAMETERS FOR SPEAKER INDIVIDUAL FEATURES ANALYSIS

The character vector used for speech analysis greatly influences the speech analysis performance. In order to provide the high accuracy we have to use apriory knowledge about human speech producing and perception. In particular, the knowledge of main psycho-acoustical principles gives us the possibility to cut information not grasping by human ear. Now human ear is the best tool for speech analysis and it is not a bad idea to model it in order to solve different speech analysis tasks. The usage of psycho-acoustical principles lets to form speech parameters that reflect all essential speech features. Psycho-acoustical parameters include absolute threshold of hearing, critical bands, simultaneous and temporal masking [4]. Here we briefly review the psycho-acoustical parameters in order to include them to the speech feature vector estimation process.

The absolute threshold of hearing is characterized by the amount of energy needed in a pure tone such that it can be detected by a listener in a noiseless environment. The threshold is well approximated by the nonlinear function

$$T_q(f) = 3.64(f/1000)^{-0.8} - 6.5e^{-0.6(f/1000-3.3)^2} + 10^{-3}(f/1000)^4 \quad (1)$$

Using the absolute threshold of hearing represents the first step towards perceptual speech analysis. For the next step it is useful to consider how the ear actually does spectral analysis. It turns out that a frequency-to-place transformation takes place in the inner ear, along the basilar membrane. Different regions in the cochlea are "turned" to different frequency bands. This process was deeply investigated and the term "critical band" was established. In the experimental sense, critical bandwidth

can be loosely defined as the bandwidth at which subjective responses change abruptly. For example, the perceived loudness of a narrowband noise source at constant sound pressure level remains constant even as the bandwidth is increased up to the critical bandwidth. For an average listener, critical bandwidth is conveniently approximated by

$$BW_c(f) = 25 + 75 \left[ 1 + 1.4(f/1000)^2 \right]^{0.69(\text{Hz})} \quad (2)$$

Although the function  $BW_c$  is continuous, for practice it is useful to present the ear as a discrete set of bandpass filters. A distance of 1 critical band is referred to as “one bark”. In order to convert frequencies from Hertz to bark scale we use the function

$$z(f) = 13 \arctan(0.0076f) + 35 \arctan \left[ \left( \frac{f}{7500} \right)^2 \right]^{(\text{Bark})} \quad (3)$$

Often for the discrete set of filters the following approximation of this function called mel-scale, is used

$$\text{Mel} = 2595 \log_{10} (1 + f/700) \quad (4)$$

Such psycho-acoustical principles can be used for all speech analysis tasks, for example, for speech recognition. It was shown that for the better personal features modeling it is necessary to use high frequency domain (above 10 kHz) and high dynamical range for the representation of input speech signal (not less than 16 bits/sample). The effectiveness of such approach is obvious because for high-accuracy speech analysis tasks we can use necessary information about high frequencies without significant processing time increasing.

To provide the high accuracy of signal processing and wide dynamical range it is reasonable to use spectrum estimation methods with low level of calculation errors. One of such methods is based on the arithmetic Fourier transform (AFT) [5], [6]. This choice can be explained by several reasons. The main drawbacks of using FFT for speech recognition are that it is impossible to use free analysis window length and there is the strict relationship between the speech sampling frequency and the FFT spectral resolution. AFT has no restrictions for the number of input points and do not require complex component calculations. That is why there is no the necessity to store even/odd coefficients and use complex memory addressing typical for the most FFT algorithms. The AFT properties make it to be very attractive for the VLSI realization to solve the tasks of signal Fourier analysis, in particular, speech recognition tasks. Especially we want to note that AFT is very suitable from the viewpoint of perceptual speech signal processing. Mel-scale frequencies and thresholds can be easily defined using AFT, much more convenient than using FFT.

The accumulated AFT-based spectrum values within the certain frequency range (channel) can be used as speech parameters:

$$S_{avg} = \frac{1}{N} \sum_{n=0}^N \omega(f_{mel}, n) S(f_{mel}), \quad (5)$$

where  $N$  - number of spectral samples,  $\omega(f_{mel}, n)$  - weight function.

Let  $S_i$  - spectral power of within the channel  $i$ . Then  $\{S_1, S_2, \dots, S_L\}$  - vector of speech parameters, where  $L$  - number of used channels. AFT spectrum can be estimated with any accuracy within the necessary range, therefore this method of spectrum estimation is very attractive to form mel-parameters. To increase the robustness we can perform the cos transformation of speech parameters. This transformation forms coefficients like the cepstral coefficients, but they are based on other principals. Thus, using the values of signal energy within the spectr range  $E_i = \log(S_i)^2$  we obtain the “mel-cepstr”:

$$C_k = \sum_{i=1}^L E_i \cos(k(i-1/2)\pi/L), \quad 1 \leq k \leq K, \quad (6)$$

where  $K$  - desired number of “mel-cepstr” values.

## HIDDEN MARKOV MODEL BASED ON AUTOREGRESSIVE PRINCIPLES.

Speech signal is produces by a non-stationary nonlinear process, and for analysis we need to present it as part-stationary signal. In this case we can apply a statistical model for speech features within the quasi-stationary parts of the signal. The main task of hidden Markov modeling is to estimate the probability that the given speech signal (process of feature vectors observation) is generated by the given hidden Markov model (process of transitions between hidden stationary states with certain statistics).

Let we have a certain word spoken by  $M$  speakers constructed from  $L$  phoneme-like units. Let  $Q^* = \{1, 2, \dots, L, \dots, L\}$  is a set of HMM states, which are used to build word models. The word for given speaker can be modeled by the sequence of  $L_i$  discrete stationary states  $q_n \in Q^*$ ,  $L_i \leq L$  with immediate transitions between states. For each word HMM defines:

- stationary state sequence  $Q = \{q_1, q_2, \dots, q_n, \dots, q_N\}$  which models the temporal speech structure (hidden process);
- acoustic vector sequence  $O = \{O_1, O_2, \dots, O_n, \dots, O_N\}$  which models local-stationary properties of speech signal (observable process).

Formally the hidden Markov model for the speaker  $m$ ,  $m = 1, 2, \dots, M$ , can be indexed as  $\lambda_m = (\pi, W, B)$ , where

- 1)  $W = (w_{ij}) = P(q_n = j | q_{n-1} = i)$  - state transition probabilities matrix with size  $L_m \times L_m$ ,
- 2)  $B = \{b_j(O_n)\}$  - probability distribution of acoustic observation vector appearance at state  $j$ .

3)  $\Pi = (\pi_i) = P(q_1 = i)$ - initial probabilities matrix with size  $L_m \times 1$ .

To design a set of hidden Markov models for person identification we assume:

- the given word model is presented by the sequence of elementary speech units (phones and phonemes). Discrete stationary HMM states are directly connected to the elementary speech units.

- the word of each person is presented by a single hidden Markov model, which described the statistical variations in word pronunciation speed.

- acoustical signal belonged to the given speaker is a realization of part-stationary process (within 20-70ms intervals speech signal is assumed to be a stationary one).

To use this technique for speech recognition we have to develop algorithm for the estimation of aposteriory probability  $P(\lambda_m | O)$ ,  $m=1,2,\dots,M$ . The speaker  $W$  which provides the maximum  $P(\lambda_m | O)$  is to be accepted as the identification result:

$$w = \underset{m \in M}{\operatorname{argmax}} P(\lambda_m | O). \quad (7)$$

In general case we can only estimate the probability  $P(\lambda_m | O)$  using given data and HMM assumptions. For this purpose we apply Bayes rule which presented  $P(\lambda_m | O)$  as

$$P(\lambda_m | O) = \frac{P(O | \lambda_m) P(\lambda_m)}{P(O)}. \quad (8)$$

The calculation of aposteriory probability has two stages: probability likelihood function  $P(O | \lambda_m)$  calculation for the given model  $\lambda_m$  which depends on the acoustical data, and apriory probability  $P(\lambda_m)$  estimation. At the identification stage  $P(O)$  is constant as the rule,  $P(\lambda_m)$  can be easily found based on the linguistic language analysis, tha is why the main task is to calculate  $P(O | \lambda_m)$ , which is called the acoustical likelihood function. We have to provide effective and fast calculation algorithm for  $P(O | \lambda_m)$  using the given series of acoustical vectors  $O = \{o_1, o_2, \dots, o_N\}$  and hidden Markov model  $\lambda_m$ .

Let discuss the conditions to solve the speaker identification task based on hidden Markov model and autoregressive principles [3]. The main task of identification is to estimate the acoustical probability likelihood function  $P(O_1 O_2 \dots O_N | \lambda_m)$  for different HMMs  $\lambda_m, m = 1, 2, \dots, M$ . Let perform the calculation of acoustical probability likelihood function using the popular forward-backward procedure. Then we suppose that the assumption  $P(O_n, q_n | q_{n-1}, \dots, q_1, O_{n-1}, \dots, O_1) = P(O_n, q_n | q_{n-1})$  typical for standart HMM is not valid more. The probaility of acoustical vector  $O_n$  appearance depends on not only the current state  $q_n = j$ , but the previous

states  $q_{n-1} = i, q_{n-2}, \dots, q_{n-p}$  too. This assumption suits the real speech signals. Such dependence can be linear and nonlinear. In order to decrease the number of free parameters for HMM we use only linear dependence.

Let's consider the state sequence  $Q = \{q_1, q_2, \dots, q_n, \dots, q_N\}$  and appropriate observation vector sequence  $O = \{O_1, O_2, \dots, O_n, \dots, O_N\}$ , where  $O_n = \{x_1, x_2, \dots, x_k, \dots, x_K\}$ - observation vector, which consists from  $K$  parameters. For each state  $q_n = j$  it is necessary to define  $b_j(O_n)$ . We assume that the vector sequence  $O$  components suit to the  $p$ -order autoregressive model  $AR(p)$ :

$$x_n = - \sum_{i=1}^p a_i x_{n-i} + \varepsilon_n, \quad (9)$$

where  $\varepsilon_n$ -Gaussian independent random values with

zero-mean and dispersion  $\sigma^2$ ,  $a_k$  - autoregressive coefficients (linear prediction coefficients).

Using this assumption for each state  $q_n = j$  at time  $n$  we can write the following expression

$$b_j(x_n | x_{n-1}, x_{n-2}, \dots, x_{n-p}) = \frac{1}{(2\pi\sigma_j^2)^{1/2}} \exp \left\{ - \frac{1}{2\sigma_j^2} \left( x_n + \sum_{i=1}^p a_i^j x_{n-i} \right)^2 \right\} \quad (10)$$

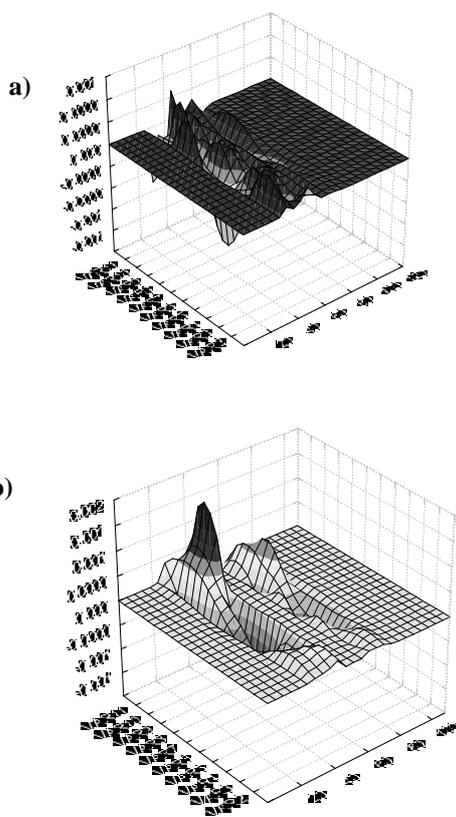
It is possible to show that for large  $K$  the probability density  $b_j(O_n)$  can be written in following manner

$$b_j(O_n) = \prod_{n=1}^K b_j(x_n | x_{n-1}, \dots, x_{n-p}) = \frac{1}{(2\pi\sigma_j^2)^{K/2}} \exp \left\{ - \frac{1}{2\sigma_j^2} \sum_{n=1}^K \left( x_n + \sum_{i=1}^p a_i^j x_{n-i} \right)^2 \right\} \quad (11)$$

In such a way the autoregressive hidden Markov model is a model of twice stochastic random process. Firstly, the model state sequence which presents the temporal speech structure, is the sample function of first-order Markov process. Secondly, the observable process which is defined by local properties of speech signal, is the random process too and it is modeled by  $p$ -order autoregression process  $AR(p)$ .

## DATA BASE AND EXPERIMENT

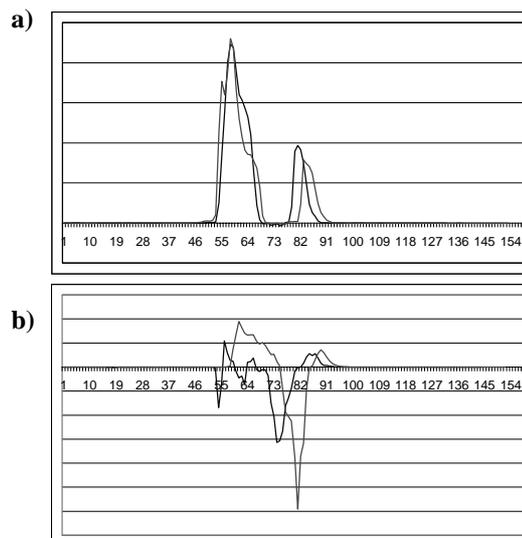
For speaker individual features analysis the following data base was created. The belarussian word “busel” was spoken 20 times by 10 speakers. Recording was done simultaneously with sampling frequency 44125Hz and 11025Hz in 16-bit format and the achieved realizations were processed by digital second order filter. To form the sequence of acoustic vectors the methodic “frame-by-frame” was used with window length 30 ms and frame length 10 ms. Each signal sample was weights by Hamming function. During the experiment bark, mel, and scharf-cepstrums were built for all word realizations from the data base. It was found out that the best way to analyse the personal voice individuality is to use bark scale for spectrum estimation. In fig.1a-b there are bark-cepstrums for two different speakers and the same word “busel”.



**Fig.1** 10 bark- cepstrums for two different speakers and the same word “busel”.

In fig.2 a, b there are the 2<sup>nd</sup> bark-cepstrum coefficients for two speakers for different sampling frequencies. It is obvious that the higher sampling frequency leads to more essential differences for individual speech features.

For each speaker the scatterplots of all cepstrum coefficients were build. It was found that close speech frames separated up to 70 ms are not statistically independent in time. The statistical independence



**Fig.2** 2<sup>nd</sup> bark-cepstrum coefficients for two different speakers

- a) sampling frequency 11025 Hz
- b) sampling frequency 44125 Hz

assumption of standard hidden Markov models is not valid and has to be removed. For each speaker the autoregressive hidden Markov model was trained using pronunciations of the word “busel”. The experiments show that such models for 10 speakers provide high accuracy of person identification based on bark-cepstrum analysis and high sampling frequency.

## REFERENCES

1. H. A. Boulard and N. Morgan Connectionist Speech recognition: A Hybrid Approach. Kluwer Academic Publishers, Boston M.A., 1994
2. D.A. Reynolds, Speaker identification and verification using Gaussian mixture speaker models //Speech Communication, №17(1-2), pp.91-108, 1995
3. B.H. Juang, L.R.Rabiner, Mixture autoregressive hidden Markov models for speech signals //IEEE Trans. on Acoustics Speech and Signal Processing, ASSP-33, №6, pp.1404-1412, 1985
4. J.Picone,"Signal Modeling Techniques in Speech Recognition", Proc. of the IEEE, vol.81, No.9, Sept. 1993.
5. E.I.Bovbel, I.E.Kheidorov, Speech Parameters Vector Based on Arithmetic Fourier Transfrom //Proc. of XI European Signal Processing Conference EUSIPCO 98. pp.713-717, 1998
6. V.G.Atlas, D.G.Atlas, E.I.Bovbel, 2-D arithmetic Fourier transform using Bruns method //IEEE Trans. on Circuits and Systems, vol.44, №6, pp.546-552, 1997.