NEW TIME-FREQUENCY DERIVED CEPSTRAL COEFFICIENTS FOR AUTOMATIC SPEECH RECOGNITION

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ABSTRACT

The goal is to improve recognition rate by optimisation of Mel Frequency Cepstral Coefficients (MFCCs): modifications concern the time-frequency representation used to estimate these coefficients. There are many ways to obtain a spectrum out of a signal which differ in the method itself (Fourier, Wavelets,...), and in the normalisation. We show here that we can obtain noise resistant cepstral coefficients, for speaker independent connected word recognition.The recognition system is based on a continuous whole word hidden Markov model. An error reduction rate of approximately 50% is achieved. Moreover evaluation tests demonstrate that these results can be obtained with smaller databases: halving the training database have small effects on recognition rates (which is not the case with traditional MFCCs).

1 INTRODUCTION

The subject is about optimizing cepstral estimation for speaker independent continuous speech recognition using HMMs. These adaptations take place in the first stage of cepstral calculation, the time frequency transformation.

This paper points out that a significant gain can be obtained by choosing the time-frequency transformation and its normalisation. Gains are of two kinds:

- 50% Error reduction.
- 50% Training database size reduction.

We study the most often used coefficients: the MFCCs (Mel Frequency Cepstral Coefficients). The first part of this paper is a short reminder of the classical computation method for these coefficients. The second part is the explanation of the different improvements proposed here. The last part exposes the results and the database used for the tests.

2 MFCC estimation

MFCCs are used to describe the short-term spectral envelope of a speech signal. Several studies have shown the importance of using a Mel frequency scale. There are two main steps in calculating MFCCs:

- Calculating the log-magnitude spectrum out of a filter-bank.

  This step can be simulated by computing the power spectrum, passing it through a filter-bank and using a log function.

- Calculating the cosine transform of the filter-bank output.

The figure 1 presents the different stages of Cepstrum computation. For more information see [RJ93].

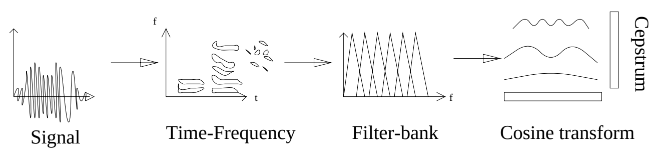

Figure 1: Signal to cepstrum

3 Possible Improvements

The power spectrum is often estimated by FFT, but this may not be the best time-frequency transformation. For instance a wavelet transform can be used to obtain the spectrum, with a different time-frequency accuracy compromise. We use here a wavelet transform defined by M Unser [Uns94]:

$$W_x(t,a) = \frac{1}{\sqrt{a}} \sum_{T=-\infty}^{+\infty} x(t+T) g(a,T) e^{\frac{-i\Omega T}{a}}$$

In this formula : a is the scale factor, linked to the frequency by :

$$f = \frac{\Omega}{2\pi a}$$

g is a window the size of which depends on a, according to :

$$g(a,t) = \frac{1}{\sqrt{2\pi}} e^{\frac{-t^2}{2a^2}}$$

A good choice of the scale factor a allows to simulate a Mel scale filter bank.

We can compare this transfom with the short term Fourier transform [Coh89] defined by:

$$S_x(t,f) = \sum_{s=-\infty}^{+\infty} h(s)x(t+s)e^{-2i\pi fs}$$

(where h(s) is a window, for instance a gaussian). The latter can be seen as a Wavelet transform, with

$$a = \frac{\Omega}{2\pi f}$$

and g(a,f) = h(t).

The main difference is the size of the time window: constant for Fourier and variable for wavelets. Likewise the notion of scale in wavelets can be seen as a change of variable in Fourier analysis.

On the two figures 2, 3 we can notice the different time/frequency accuracy compromises between the two methods.

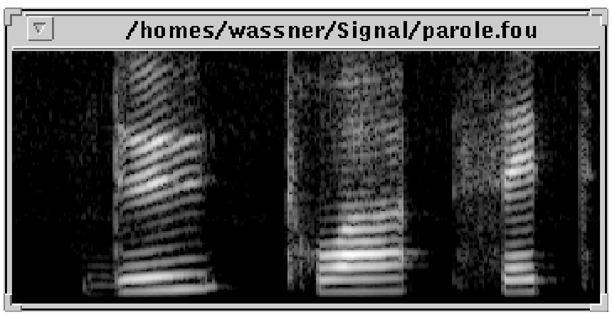

Figure 2: Fourier analysis of speech.

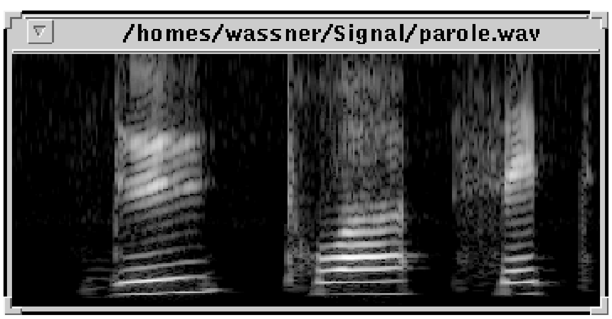

Figure 3: Wavelet analysis of speech.

In the classical cepstrum calculation, a log transformation is used to modify the power spectrum. Generally this transformation is done after the filter-bank. We will see that performing this transformation before the filter bank is more interesting in our case. (See figures 4 and 5 to compare the two different filtered spectra)

Moreover we can notice that in certain noisy conditions this log-transformation has much too low energy dynamics (certain low energy time-frequency zones

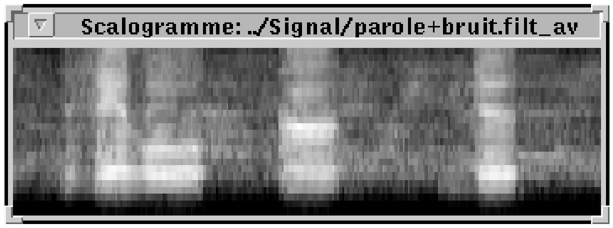

Figure 4: Filtered spectrum : log before filters.

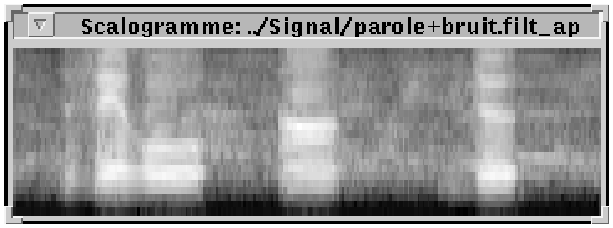

Figure 5: Filtered spectrum : log after filters.

can be interpreted as noise). Therefore other energy-transformation functions (see figure 6) have been experimented:

$$log2(x) = (\frac{log(x)}{log(M)})^2 * log(M)$$

$$sigm(x) = \frac{1}{1 + 0.0004 * e^{x/M*\alpha+5}} * log(M)$$

Where M is the value of the maximum energy found in the time-frequency plane, from the speech signal studied.

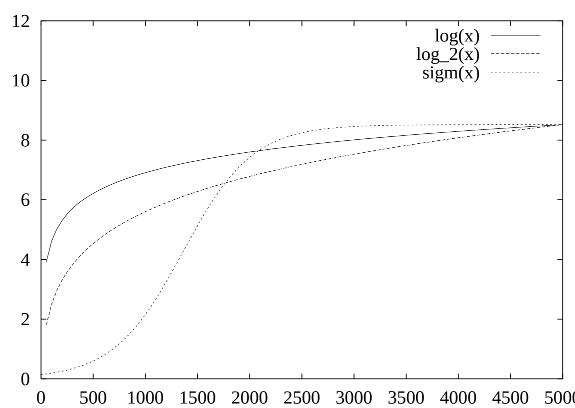

Figure 6: Different energy transformation functions.

4 Experiments and results

The test protocol was the same for all experiments, only the speech parametrisation was different. An initialisation and a re-estimation have been made on the models (HInit and HRest HTK(1.5) programs).

Two of these experiments have been done using HTK's HCode program for parametrisation, in order to obtain references. The other experiments have been done using a specific program (HCepstre).The Markov model used are "left-right" models representing words.

The default HTK-like parameters used are:

- Mel scale
- Number of cepstrum coefficients : 12
- Number of filters : 24
- Cepstral liftering (sin) : 22
- Pre-emphasis coefficient : 0.98
- Frame-rate : 10 ms
- Window size : 25 ms for Fourier (variable for wavelets).

Each MFCC vector is composed of 12 cepstral coefficients, with energy, slope, and acceleration. This leads to a 39 elements vector per frame.

These parameters come from the HTK guideline [Ent94]. Nothing proves that they are the best, but they are quite widely used.

Three sub-databases have been used, two extracted from "Polyphone" [CCLK96] and one from "Computer95". These two databases have been collected by IDIAP and the Swiss Telecom PTT from French spoken telephone speech. The words used are the french digits (0-9) for all the three sub-databases, added with the word "diese" (hash) and "etoile" (star) in the extracts from "Polyphone".The Polyphone database is low noise (people are calling from home). Computer95 is recorded from the annual computer forum at Lausanne, with a high background speech noise. The three sub-databases have different speakers (for more information see the table 1).

	speaker	words
learning (Polyphone)	498	2962
Evaluation (Polyphone)	429	2574
Test (Computer95)	376	3760

Table 1: Databases' composition

Table 2 presents the main interesting experiments and their results (in percentage). First we can notice the important gain compared to the reference experiment (1). The improvement seems larger on the Computer95 database. In fact the gain is a reduction of 50% of the number of errors on both Polyphone and Computer95.

We have noticed that putting the log function before the filter-banks leads to better results. Then we have choosen, for all the other experiments, to place the energy transformation before the filter-bank (except for the experiment 1,3,12). More information on this choice can be found in [Was95].

	Parametrisation	polyphone	Computer
1	MFCC reference (HTK)	92.70	65.48
2	MFCC log before filters	97.40	79.36
3	MFCC log after filters	91.18	62.13
4	MFCC sigmoid (60)	93.28	67.31
5	MFCC sigmoid (30)	96.70	75.11
6	MFCC sigmoid (15)	96.27	80.88
7	MFCC sigmoid (10)	95.18	81.33
8	MWCC, $\Omega = 9$, log	96.89	80.40
9	MWCC, $\Omega = 11$, log	97.47	82.61
10	MWCC, $\Omega = 9$, log2	96.70	81.62
11	MFCC, log2	93.59	71.86
12	MFCC (HTK) with small learning database	87.61	59.81
13	MWCC, $\Omega = 11$ with small learning database	96.15	80.16

Table 2: Results

Remarks:
- MWCC are mfcc calculated on a spectrum obtained by wavelet-transform.
- log, log2, sigmoid (with a parameter) are energy transformation functions.(this transformation is done before the filter-bank, except for the experiment 1,3,12.)
- Experiments 12 and 13 have been made using only 45% of the learning data base, in order to study the learning speed (in terms of database size)

In experiments 4, 5, 6 , 7, where a sigmoid is used instead of a log, we can notice that for the sigmoid parameter α, the best value seems to be the same on the different databases. This may indicate the existence of an optimal function for all conditions.

Experiments 12 and 13 indicate the possibility of learning twice quicker, in terms of database size, with very little loss. Even with a halved database, we reach better results than with the classical MFCCs on the whole database.

We may also point out that the energy normalisation function is closely linked with the time frequency method used to obtain the spectrum. There is a difference of 3% on Polyphone and 10% on Computer95 between the couples (MWCC, log2) and (MFCC, log2).

A context re-estimation (using HTK's HERest) with 390 new speakers (2340 words) taken from Polyphone database leads to the results reported in table 3.

	Parametrisation	Polyphone	Computer95
1	MFCC reference (HTK)	96.81	76.54
9	MWCC, $\Omega = 11$, log	97.98	83.48

Table 3: Results after context re-estimation

The new parametrisation is again better. The difference becomes very short on the Polyphone database but is always important on the Computer95 database. The important thing is that context re-estimation is nearly useless with the new parametrisation.

5 Conclusion

The cepstrum computation in its widely used form, appears clearly not to be an optimal solution. By keeping the same theoretical framework and calculating coefficients with more care, the cepstrum may give better results both for recognition rate and learning speed (related to database size). This can be very interesting in terms of cost reduction for training databases.

Acknowledgments

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