Test of several external posterior weighting functions for multiband Full Combination ASR

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Abstract

Information about speech reliability can be extracted and then integrated in a recogniser by various means. The full combination (FC) approach allows the weighting of the posterior values estimated locally in the time frequency representation, according a speech reliability measure. Since most of the speech segments are voiced, we use a method exploiting the harmonicity of speech to derive these weights. We test this method together with the direct integration of the a priori SNR. Then, we run speech recognition with different kind of weighting functions. The weights are continuous or binary values. This corresponds to a soft or to a hard decision function about the speech reliability, which is derived from an observable harmonicity index. Using a binary decision process, the effect is, for each time frame, to collapse the set of combinations of sub-bands into a single combination. On the other hand, we substitute empirical values to these terms, including functions of the a priori SNR, which are continuous or discrete, but not based on a probabilistic estimation. We establish the average scores in % WER for a panel of noises at different level, stationary or not, narrow-band or wide-band. All these functions are found to be sub-optimal comparatively to the constant weighting, but a robustness of the FC for narrow-band noises is observed.

1 Introduction

Preliminary experiments leads us to expect that multistream speech recognition can be made more robust with the inclusion of estimates of the stream’s reliability$^{[5,2]}$. In this field, reliability or weighting factors are empirically estimated, or calculated using a probabilistic method. Several techniques are available for generating subband speech reliability. However these often require a frame duration which is too long to provide accurate estimates in an environment where the noise changes rapidly. The SNR estimation proposed in$^{[6]}$ demonstrate this situation. In this paper we propose a short term reliability$^{[1]}$ measure based on a harmonicity index.

We will see that this harmonic index is well correlated with the SNR and provides solutions for estimation of weighting factors. We will compare this kind of weights to optimal estimation using the true SNR value. The multistream recognition is performed by the Full Combination model$^{[7,3]}$, allowing an entry point for external posterior weighting based on a speech reliability measure.

2 The Full Combination ASR

Multistream ASR aims to make an adaptive fusion of the different sources, according to the match between each stream and the set of trained data. In our case a stream $J$ will be one of the 16 combinations of $d=4$ subbands, including the empty stream of data $x_0$. We shown$^{[7]}$ that full-band posterior $P(q_k|X)$ for each phoneme can be written into a weighted sum of all combination of subband according to the reliability of corresponding subband posterior. If we assume that the best estimates of posterior is produced by the cleanest data, then the weighting factor for the stream $x_j$ corresponds to the probability that the “data of $x_j$ better matches the data of the training set” (this event is called $L_j$). Using Bayes we estimate the posterior of the full band $X$ as:

\[ P(q_k|X) = \sum_{j=0}^{2d-1} P(q_k,L_j|X) \approx \sum_{j=0}^{2d-1} P(q_k|x_j) P(L_j|X). \]  

(Eq0)
In our approach each basic event is relative to the local time frequency cell subband: \(P(SNR_i > T_i)\) where \(SNR_i\) is its SNR. This local probability is given by a detector which is more or less sensitive (good detection) and specific (noisy cells detected as noisy). Therefore a continuous weighting factor is more appropriate than a binary one as this will be confirmed by this study.

It has been shown that (1) FC is more efficient than other common subband models [7], and (2), avoiding the need to train \(2^d - 1\) experts because good estimates of subband combinations can be obtained from a product of the \(d\) subband experts. We will only use this approximation approach AFC. Let \(|J|\) be the number of subbands in the stream \(J\). If we assume that the subband data vectors \(x_i\) are independent given class \(q_k\) we then have:

\[
P(x_j|q_k) \approx \prod_{i \in J} P(x_i|q_{k_i}),\text{ then}^2:
\]

\[
P(q_k|x_j) \frac{p(x_j)}{p(q_k)} \approx \prod_{i \in J} \frac{P(q_k|x_i)}{P(q_k)} = P(q_k|x_j)
\]

(1)

\[
P(q_k|x_j) \approx \frac{\prod_{i \in J} P(q_k|x_i)}{p^{|J|-1}(q_k)} \cdot \Theta
\]

(2)

**Link with partial recognition**

The estimation technique for weighting factors which is introduced by the AFC model can be empirical or, preferably, derived from a probabilistic approach as shown in the next section. Then let \(C_i\) be: “Time frequency cell feature vector in subband \(i\) matches the clean speech vector” \(^3\). Assuming that all \(C_i\) are independent (which is almost always the case for non-adjacent subbands [8]), then weight for a stream \(J\) will be estimated as:

\[
P(L_j|X) = \prod_{i \in J} P(C_i|x_i) \prod_{i \notin J} (1 - P(C_i|x_i)).
\]

Partial recognition is run if the probability \(P(C_i|x_i)\) is binary. In that case, the cells where speech is occluded by noise are ignored and FC is similar to a partial recognition process[4]. In [2] we performed a marginal partial recognition which remains feasible thanks to spectral redundancy of formants. However this model is limited by its noise detection performance. Probabilistic model carries more information than a binary mask indeed the local noise detector is not perfect and corresponding soft decision probabilities can be assigned to the terms \(P(L_j|X)\) of AFC. We will now compare AFC to partial recognition, under various conditions (we use prefix B for binary functions, S for Soft).

3 A Probabilistic estimation of short time speech reliability from harmonicity

We develop here technique for estimating the probability that a cell is corrupted by noise. Most speech is composed of voiced segments. Therefore, the autocorrelation of the demodulated signal can be used as a basis for differentiating between harmonic signal and noise. An interesting property is that this differentiation has been shown to be efficient with a time window in the same range than the average phoneme duration [2], and in a frequency domain divided in four subbands.

A correlogram of a noisy cell is less modulated than a clean one. We use that fact to estimate the reliability of a cell for which time and frequency definitions are compatible with the recognition process (125 ms of duration). Before the autocorrelation, we compute the demodulated signal after Half Wave Rectification followed by Band-Pass Filtering in the pitch domain ([90, 350] Hz). We calculate for each cell the ratio \(R_i = R_1/R_0\), where \(R_1\) is the local maximum in time delay segment corresponding to the fundamental frequency and \(R_0\) the cell energy. This measure is comparable to the HNR index [9]. We construct the histogram of \(R_i\) relatively to its local SNR. Initial data population comprised 60 sentences of the training set added gaussian white noise at \((SNR = [-21 \ldots -18 \ldots 39]dB)\). The distribution of \(R_i\) relative to local SNR, Fig 1, show the strong correlation between SNR and \(R_i\) which has been demonstrated in [1]. We extract from these distributions the Probability Density Function at a given cell \(P(SNR_i = T_i|R_i, x_i)\) where \(SNR_i\) is the local SNR of the cell.

Based on the histograms we construct the Cumulative Density (Fig.2) of each subband for a given SNR threshold \(T_i: P(C_i|x_i) = P(SNR_i > T_i|R_i, x_i)\). For various subbands we get functions (called Spro) with similar graphs that are shifted on the \(R_i\) axis depending on the subband definition. We set \(T_i\) at 0dB according to experimental results [3]. The left part of the Spro function is built upon very few samples, so the function is not well defined, but this is not a major issue because only a few test samples are concerned.

Partial recognition (Bpro) is easily derived: if \(P(C_i) > 1/2\) then \(P(C_i) = 1\) else 0. Actually this
chosen as $sqXR = sqrt(1/(1 + 1/(10^{SNR/10})))$. The same decision threshold as the previous method is applied ($BsqXR$) corresponding roughly to $SNR = 0$ dB.

We also studied another empirical weight $(Srel)$ derived from a detector of speech pause [6]. In a similar way we estimate the relative SNR index $P(C_i) = (SNR_i - SNR_{iMIN})/(SNR_{iMAX} - SNR_{iMIN})$ where $SNR_{iMIN}$ and $SNR_{iMAX}$ are the extreme values determined from statistics on the noisy subset. $SNR_{iMIN} = -64$ dB for all subbands $i$. $SNR_{iMAX}$ equals [63, 54, 52, 43] dB for each respective subband.

The different methods are listed below with their characteristics. For all the binary functions $T_d = 0.5$, fullband = no weight. Soft functions: blind = probe, given (equalised) / $BsqXR = empirical$, given / $Srel = empirical$, given / $SqXR = empirical$, estimate / $Spro = proba$, estimate. Binary function: $BsqXR = empirical$, given / $BsqR = empirical$, estimate / $Bpro = proba$, estimate.

5 Recognition evaluation

We use a hybrid ANN/HMM system and Numbers95, a multispeaker free format numbers telephone speech database. Our model is trained on 9 consecutive data frames. The posterior probabilities estimated by the ANN (about 1500 hidden units), divided by their priors, are passed as scaled likelihoods to a HMM for decoding using a 1 to 3 repeated-state model. No language model is used. For AFC only five ANN are trained: 1 for full band and 1 for each subband. We choose 1 subband for approximately each formant, and we carefully defined the subband with the minimal frequency overlap using the PLP filter bank. Frequency ranges are in Hz $115-629, 565-1370, 1262-2292, 2122-3769, 115-3769$. The respective extracted coefficients are 5, 5, 3, 3, 11.

We tested two narrow band noises 300 Hz wide and centered in different subband. We also use a nonstationary noise composed of periodic sequences $[1, 2, 3, 4, 3, 2, 1]$ of respective noisy subband number[2]. We used natural factory noise from NoiseX and a Daimler car noise. Tests were constructed by averaging scores obtained with 200 utterances repeated at 6 different SNRs from -12 to 18 dB, by step of 6 dB, silence included. All the features are processed by Jrrasta (which is referenced in [5]).

6 Discussion and conclusion

We tested various approaches to weight the posterior values estimated locally in the time frequency representa-
of noise so SNR of the input signal and posteriors reliability might no longer be strongly correlated. On the other hand, intrinsic weighting factors compatible with the FC formalism could improve the model [3]. This factors could be derived from outputs of the recognition system as well as a priori knowledge about the streams' reliability (e.g. the weighting of each subband or each stream by its reliability for speech recognition, knowing a priori that lower frequency subbands carry more phonetic information, or knowing that the larger streams are more reliable).

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References


