IMPROVING POSTERIOR BASED CONFIDENCE MEASURES
IN HYBRID HMM/ANN SPEECH RECOGNITION SYSTEMS

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ABSTRACT

In this paper, building upon previous work by others [7], we define and investigate a set of confidence measures based on hybrid Hidden Markov Model/Artificial Neural Network (HMM/ANN) acoustic models. All these measures are using the neural network to estimate the local phone posterior probabilities, which are then combined and normalized in different ways. Experimental results will indeed show that the use of an appropriate duration normalization is very important to obtain good estimates of the phone and word confidences.

The different measures are evaluated at the phone and word levels on both an isolated word task (PHONEBOOK) and a continuous speech recognition task (BREF). It will be shown that one of those confidence measures is well suited for utterance verification, and that (as one could expect) confidence measures at the word level perform better than those at the phone level. Finally, using the resulting approach on PHONEBOOK to rescoring the N-best list is shown to yield a 34% decrease in word error rate.

1. INTRODUCTION

In hybrid HMM/ANN speech recognition systems, ANNs are capable of providing good estimates of the posterior probability of an HMM state(phone) given an acoustic feature vector (possibly including context). These local posterior probabilities may be combined in different ways to produce an estimate of the global posterior probability (i.e., a confidence measure) of a recognized unit given the acoustic observations. Alternatively, these local posteriors are also well suited to compute the entropy of the ANN output distribution averaged over the segment for which we want to estimate the confidence level. We thus start this paper by describing the confidence measures at the phone level and at the word level that were used in the present study.

2. CONFIDENCE MEASURES

2.1. Posterior Based Confidence Measures

Normalized Posterior based Confidence Measures (NPCMs) are defined in three different ways: one at the phone level and two at the word level using two different kinds of duration normalization.

At the phone level, the normalized posterior based confidence measure, denoted NPCM(\(k\)), is defined as the logarithm of the global phone posterior probability computed as the product of the local phone posteriors along the optimal state sequence, and normalized by the duration of the phone in frames. For a phone \(q_k\), beginning at frame \(b\) and ending at frame \(e\), this frame-based confidence level is defined as

\[
\text{NPCM}(k) = \frac{1}{e - b + 1} \sum_{n=b}^{e} \log p(q_k^n | x_n)
\]  

This normalization compensates for different phone durations, as otherwise short phones would be favored.
Similarly, we can also define a word level confidence measure. For a word \( w \), consisting of a sequence of \( J \) phone segments \((q_1, \ldots, q_J)\), the frame-based NPCM \((w)\) will thus be defined according to:

\[
\text{frame-basedNPCM}(w) = \frac{1}{\sum_{j=1}^{J} (e_j - b_j + 1)} \sum_{j=1}^{J} \sum_{n=b_j}^{e_j} \log p(q^n_j | x_n) \tag{2}
\]

where \( b_j \) and \( e_j \) are respectively the first and last frame of phone segment \( q_j \) of the considered word.

At the word level, we also define another confidence measure called phone-based NPCM \((w)\), and involving a double normalization taking into account the number of frames in each phone and the number of phones in each word, yielding the following estimate:

\[
\text{phone-basedNPCM}(w) = \frac{1}{J} \sum_{j=1}^{J} \left( \frac{1}{e_j - b_j + 1} \sum_{n=b_j}^{e_j} \log p(q^n_j | x_n) \right) \tag{3}
\]

For comparison purposes, those confidence level estimates will be assessed against other alternatives such as:

- **Mean Posterior Confidence Measures (MPCMs)**: MPCMs at phone and word levels are computed as NPCMs in (1), (2) and (3), except that we compute the average of local posteriors (and phone normalization, at the word level) before taking the logarithm.

- **Posterior Probability Confidence Measures (PPCMs)**: the confidence measures equivalent to (1) and (2), but resulting from a straight accumulation of local posteriors, without any normalization.

- **Scaled Likelihood Confidence Measures (SLCMs)**: we also tested all the above measures by dividing the local posterior probabilities by the a priori probabilities \( p(q) \) estimated on the training data, thus yielding estimates of local and global scaled likelihoods \( p(x_n | q) / p(x_n) \).

However, since application never provided us with relevant confidence measures and, consequently, results at the word level will not be reported. \(^1\)

## 3. EXPERIMENTAL SET UP

The confidence measures were evaluated in terms of their ability to predict whether a particular hypothesis (phone or word) is correct or incorrect, and experiments were carried out on two databases:

- **PHONEBOOK** [2], a large isolated word telephone speech database. A training set of 21 lists of 75 words each pronounced by 11 speakers was used, together with 5 test sets each with a disjoint set of 75 words and 11 speakers (making this task speaker and vocabulary independent).
- **BREF** [4], a continuous, read speech microphone database. 3,736 utterances were used for training and 242 utterances with a 2,300 word lexicon for testing.

The phone models were repeated state HMMs (with self-loops and minimum duration equal to half the average duration) with an ANN (multilayer perceptron, in our case) output associated with each state/phone. Nine feature vectors, \( X_{n+4}^{n+4} = \{ x_n, \ldots, x_{n-1}, x_n, x_{n+1}, \ldots, x_{n+4} \} \), were used as input to the ANN. Each feature vector consisted of 12 RASTA-PLP coefficients, 12 Δ RASTA-PLPs, Δ log energy, and Δ Δ log energy.

The test sets were recognized using Viterbi decoding, generating word and phone level hypotheses and segmentations. Confidence levels were then estimated at the phone and word level for each hypothesis using each of the measures described above.

For the evaluation, the decoding results and reference words (word sequences) and phone sequences were aligned so that each hypothesis could be marked as correct or incorrect, allowing the evaluation of the performance of each of the confidence measures in hypothesis test statistics. To do this, and to allow fair comparisons between different systems, the number of correct and incorrect hypotheses in the test sets were equalized by counting the number of incorrect hypotheses and selecting the same number of correct hypotheses from the test sets. This has the effect of artificially raising the recognizer’s error rate to 50%. Evaluation sets at both phone and word levels were constructed accordingly.

Finally, and following [7], we considered this confidence based hypothesis test: “a recognition hypothesis is rejected whenever its confidence score falls below a threshold”. Thus, two types of errors may occur: TypeI error corresponding to the rejection of a correct hypothesis and TypeII error corresponding to the acceptance of an incorrect hypothesis. The performance of confidence measures is then evaluated in terms of TypeI and TypeII errors.

\(^1\) It is believed that this entropy based measure will be more appropriate when measuring the reliability of different features, independently of the recognized hypotheses, as opposed to assessing the confidence of recognized hypotheses.
and the Classification Error Rate may be defined as:

\[ \text{CER} = \frac{\text{Type I errors} + \text{Type II errors}}{\text{total hypotheses in evaluation set}} \]  \hspace{1cm} (5) 

4. EXPERIMENTAL RESULTS

4.1. PHONEBOOK

First we investigated the phone confidence measures on the evaluation set defined for phones (2,400 hypotheses). Figure 1 shows a comparison of the performance of the confidence measures \( \text{NPCM}(k) \), \( \text{MPCM}(k) \), \( \text{PPCM}(k) \), and \( \text{EBCM}(k) \). The figure reads like this: The horizontal axis shows the percentage of hypotheses that were rejected and is a function of the confidence threshold. The vertical axis shows the CER which is a measure of the percentage of incorrect hypotheses rejected.

In Figure 1, it is shown that \( \text{NPCM}(k) \) and \( \text{MPCM}(k) \) significantly outperform \( \text{PPCM}(k) \) and \( \text{EBCM}(k) \) at the phone level. \( \text{PPCM}(k) \) probably fails because of its lack of duration normalization, which makes it towards accepting short phone hypotheses and rejecting long ones. \( \text{EBCM}(k) \) is a less powerful confidence measure when used for utterance verification: since it does not make explicit use of label information it is independent of the recognition results. Our investigations showed that the EBCM is more suited to assessing the quality of the recognition model (as opposed to assessing the confidence of the output results). From Figure 1, we conclude that \( \text{NPCM}(k) \) and \( \text{MPCM}(k) \) are basically yielding the same good performance and are both able to detect many of the incorrect hypotheses.

We also investigated confidence measures at the word level, on the evaluation set that was previously defined for words (586 hypotheses). Figure 2 shows the performance of the \( \text{frame-based MPCM}(w) \) and both \( \text{frame-based} \) and \( \text{phone-based NPCM}(w) \) and \( \text{MPCM}(w) \) word confidence measures. As for the phone level, the \( \text{PPCM}(w) \) performs poorly because of its lack of duration normalization. With regard to both \( \text{NPCM}(w) \) and \( \text{MPCM}(w) \), it is clear from the figure that the \( \text{phone-based} \) measures (involving the double normalization in terms of number of phones and number of frames per phone) perform significantly better than the \( \text{frame-based} \) measures (with the normalization involving only the number of frames in each word). One possible reason for this could be that when a hypothesized word shares many phones with the correct word, but has several extra phones, those extra phone HMMs are forced to match poor acoustic segments. Very often, in order to get the best recognition match, those phones will have minimal duration in the Viterbi backtrace. Furthermore, since those recognized phones are incorrect, they will usually have poor posterior probability scores. Consequently, a confidence measure that is more sensitive to those few frames of poor posterior probability should be better to identify the unreliable words. Since the \( \text{frame-based} \) confidence measure weights frames equally, while the \( \text{phone-based} \) confidence measure weights phones equally, incorrect phones have a better chance to have an impact on the confidence measure with the latter measure.

In Figure 2, it can be seen that its CER between (0, 50) and (37.5, 12.5) is basically a straight line, meaning that for rejection rates of up to 37.5\% only incorrect hypotheses are rejected (straight line going from (0, 50) to (50, 0) and corresponding to the optimal solution). In other words, for this evaluation set, 3/4 of the errors can be detected without any false rejection.

Figure 3 shows histograms of the \( \text{frame-based NPCM}(w) \) and \( \text{phone-based NPCM}(w) \) confidence scores. It can be observed that the distributions for correct and incorrect words are indeed much better separated for the \( \text{frame-based NPCM}(w) \) measure. The doubly normalized \( \text{phone-based} \) confidence measure is more discriminant than the simple \( \text{frame-based} \) measure, which corroborates further our previous discussion.

Finally, we tested our best confidence measure, i.e., \( \text{phone-based NPCM}(w) \), to rescore the N-best list resulting
from a Viterbi search providing us with the N-best recognition hypotheses, as well as the phone segmentation associated with each hypothesis. Rescoring the 5-best hypotheses reduced the error rate from 7.1% down to 4.7% (see [2] for comparative results), i.e., a 34% relative improvement.

4.2. BREF

Posterior based confidence measures at the word level were also investigated on the BREF database on an evaluation set of 1,600 word hypotheses and similar results and conclusions were obtained.

Unfortunately, it was also observed that the use of multiple pronunciations tends to reduce the difference between the different approaches, as well as the overall performance of the confidence measures. This can be explained by the fact that, when adding alternative pronunciations, all word likelihoods, including those for wrong hypotheses, are increased, resulting in poor confidence scores.

5. CONCLUSIONS

In this paper, we investigated HMM/ANN confidence measures based on posterior probabilities and showed that posterior based measures are yielding very good performance not only at the phone level, as initially shown in [7], but also at the word level, provided that the appropriate normalization is used. These conclusions were tested on both isolated word (PHONEBOOK) and continuous speech (BREF) tasks.

In the same framework, we are now investigating the possibility to automatically adapt the language model scaling factor as a function of our best confidence measure (e.g., computed for the previous hypothesized word), as initially proposed in [5].

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6. REFERENCES