An improved uncertainty decoding scheme with weighted samples for DNN-HMM hybrid systems

Christian Huemmer\textsuperscript{1}, Ramón Fernández Astudillo\textsuperscript{2}, and Walter Kellermann\textsuperscript{1}

\textsuperscript{1}Multimedia Communications and Signal Processing, University of Erlangen-Nuremberg, Erlangen, Germany
\textsuperscript{2}Spoken Language Systems Laboratory, INESC-ID-Lisboa, Lisboa, Portugal

\{huemmer, wk\}@int.de, ramon@astudillo.com

Abstract

In this paper, we advance a recently-proposed uncertainty decoding scheme for DNN-HMM (deep neural network - hidden Markov model) hybrid systems. This numerical sampling concept averages DNN outputs produced by a finite set of feature samples (drawn from a probabilistic distortion model) to approximate the posterior likelihoods of the context-dependent HMM states. As main innovation, we propose a weighted DNN-output averaging based on a minimum classification error criterion and apply it to a probabilistic distortion model for spatial diffuseness features. The experimental evaluation is performed on the 8-channel REVERB Challenge task using a DNN-HMM hybrid system with multichannel front-end signal enhancement. We show that the recognition accuracy of the DNN-HMM hybrid system improves by incorporating uncertainty decoding based on random sampling and that the proposed weighted DNN-output averaging further reduces the word error rate scores.

Index Terms: uncertainty decoding, robust speech recognition, observation uncertainty

1. Introduction

Since deep neural networks (DNNs) have become an important part of state-of-the-art automatic speech recognition (ASR) systems, the mismatch between training and test conditions (e.g., caused by environmental distortions) motivated various systems, the mismatch between training and test conditions a tant part of state-of-the-art automatic speech recognition (ASR) systems. However, misalignment between training and test condition data. As input features of the DNN, we append log-melspec features (extracted from a beamformer output signal) with delta coefficients and add spatial diffuseness features. It is shown that the recognition accuracy improvements by incorporating uncertainty decoding based on random sampling and that the proposed weighted DNN-output averaging further reduces the word error rate (WER) scores, especially for real-world recordings.

This paper is structured as follows: We propose a probabilistic distortion model for spatial diffuseness features in Section 2 and the uncertainty decoding scheme with weighted samples in Section 3. The DNN-HMM hybrid system is introduced in Section 4, followed by the experimental results for the 8-channel REVERB challenge task in Section 5. Finally, concluding remarks are given in Section 6.

2. Probabilistic distortion model for spatial diffuseness features

We focus on a multichannel ASR system with front-end processing in the short-time Fourier transform (STFT) domain (DFT length 512). For each microphone pair, indexed by $m = 1, \ldots, M$, the real-valued spatial diffuseness $0 < D^{(m)}_{\nu,n} < 1$ in STFT band $\nu = 1, \ldots, 257$ and at time $n$ is estimated as described in (23). The coherent-to-diffuse power ratio (CDR) $CDR^{(m)}_{\nu,n}$ is determined by inserting the estimated complex-valued coherence $\Gamma^{(m)}_{\nu,n}$ (see (6) in [24]) and the spatial coherence function of a spherically isotropic sound field $\Gamma^{(m)}_{\text{diff},\nu,n}$ (see (11) in [24]) into (1), where $\operatorname{Re}\{\cdot\}$ is the real part. Note that the CDR estimation in (1) is independent of the direction of arrival (DOA) [23] and that also other CDR estimates could be applied (see overview in [24]). The spatial diffuseness is finally obtained by inserting $CDR^{(m)}_{\nu,n}$ into

\[ D^{(m)}_{\nu,n} = (1 + CDR^{(m)}_{\nu,n})^{-1}. \] (2)
From this, the diffuseness feature vector $x_n^{(m)}$ for each microphone pair is calculated by weighting the length-257 vector
\[
d_n^{(m)} = [D_1^{(m)}, \ldots, D_{257}^{(m)}]^T
\]
by the mel-filterbank matrix $W_{\text{mel}}$ of dimensions $24 \times 257$:
\[
x_n^{(m)} = [x_1^{(m)}, \ldots, x_{24}^{(m)}]^T = W_{\text{mel}} d_n^{(m)}.
\]
These microphone-pair specific estimates are averaged to determine the spatial diffuseness feature vector $x_n$:
\[
x_n = \frac{1}{M} \sum_{m=1}^{M} x_n^{(m)}.
\]
As measure for the uncertainty of the spatial diffuseness feature vector in (5), we introduce the Gaussian distribution
\[
p(x_n | x_n) = \mathcal{N}(x_n, V_n)
\]
with mean vector $x_n$ and covariance variance
\[
V_n = \text{diag}(v_1, v_2, \ldots, v_{24}),
\]
\[
v_{n,\kappa} = \frac{1}{M-1} \sum_{m=1}^{M} (x_n^{(m)} - x_{n,\kappa})^2,
\]
where $\text{diag}\{\}$ creates a diagonal matrix from the scalar variances $v_{n,\kappa}$ ($\kappa = 1, \ldots, 24$). Note that we choose a diagonal covariance matrix $V_n$ in (5) for a computationally efficient realization of the uncertainty decoding scheme described in the following section.

3. Improved uncertainty decoding with weighted samples

As illustrated in Fig. 1(a), the posterior likelihood of the $i$th context-dependent HMM state $s_j$ in the decoding process of a DNN-HMM hybrid system is given by a nonlinear transformation of the feature vector $x_n$ at time instant $n$:
\[
p(s_j | x_n) = f_j(x_n).
\]
Assuming distortions of the feature vector $x_n$ (reflecting, e.g., measurement uncertainty) to be modeled by a latent random variable $z_n$ and the nonlinear mapping $f_j(\cdot)$ to be known, the posterior distribution in (9) reads according to (18):
\[
p(s_j | x_n) = \mathcal{E}(f_j(z_n))|x_n).
\]
In general, nonlinearities in $f_j(\cdot)$ preclude closed-form solutions of (10), which motivated piece-wise function approximations and numerical sampling schemes. In this paper, we focus on uncertainty decoding based on random sampling, as it has been shown to be promising for improving the accuracy of DNN-based ASR systems even for a small number of samples [18, 20]. As illustrated in Fig. 1(b), we draw $L$ samples $z_n^{(l)}$ from the estimated probability density function (PDF) $p(z_n | x_n)$ and average the resulting DNN outputs:
\[
p(s_j | x_n) \approx \frac{1}{L} \sum_{l=1}^{L} f_j(z_n^{(l)}),
\]
where $l = 1, \ldots, L$. This numerical sampling scheme is modified in the following by employing a MCE criterion as measure for the reliability of DNN output $f_j(z_n^{(l)})$ [21, 22]: for each sample $z_n^{(l)}$, the $j$th sample index $l$ omitted for simplicity) DNN output is identified as the most probable
\[
g = \arg \max_j f_j(z_n^{(l)})
\]
to determine the misclassification measure $e_n^{(l)}$ as the difference between the most probable and the best competing class [21]:
\[
e_n^{(l)} = f_j(z_n^{(l)}) - \max_{j \neq g} f_j(z_n^{(l)}).
\]
In other words, $e_n^{(l)}$ is the sample-specific difference between the posterior likelihoods of the two most probable HMM states and thus a confidence measure for the reliability of the classification. From (13), we propose to calculate weights
\[
\omega_n^{(l)} = e_n^{(l)} \sum_{l=1}^{L} e_n^{(l)}
\]
used for a weighted DNN-output averaging:
\[
p(s_j | x_n) \approx \frac{1}{L} \sum_{l=1}^{L} f_j(z_n^{(l)})
\]
An overview of the proposed uncertainty decoding scheme with weighted samples is illustrated in Fig. 1(c).

Figure 1: Calculation of the posterior likelihood $p(s_j | x_n)$ in a DNN-HMM hybrid system (a) without and with uncertainty decoding based on random sampling using (b) arithmetic and (c) weighted DNN-output averaging.
Finally, the relation between uncertainty decoding with weighted samples and multistream fusion should be clarified. The latter is (motivated by the human behavior dealing with unexpected data) based on experimental evidence that the error probability in human decoding is given by the product of error probabilities in different frequency bands \([28]\). Although this is conceptually different from drawing samples from a PDF, the strategies for fusing multiple streams (e.g., \([26, 27]\)) might also be of interest for improving the DNN-output averaging as part of uncertainty decoding with weighted samples.

### 4. DNN-HMM hybrid system

Besides the spatial diffuseness features of Section 3, we extract logmel-spect features and corresponding delta coefficients which have been frequently used in state-of-the-art DNN-HMM hybrid systems (often termed “log-filterbank” features). As shown in Fig. 2 the STFT-domain microphone signals are processed by an MVDR beamformer, transformed into the lower-dimensional logmel-spect domain (24 coefficients) and normalized by applying per-utterance mean and variance normalization (MVN). We append the delta coefficients and the spatial diffuseness features to create the “logmel-spect+delta+diffuseness” feature vector of length 72, which is passed through the nonlinearity \(f_j(\cdot)\) realized in our implementation as follows:

- Context extension using \(\pm 5\) frame splicing (the size of the context window has been manually optimized).
- DNN: 6 hidden layers, each with 2048 sigmoid activation functions, output layer with softmax nonlinearity and 3463 elements (context-dependent HMM states).

It should be emphasized that Fig. 2 provides an overview of the DNN-HMM hybrid system without reflecting the probabilistic distortion model of \([6]\). As the MVDR beamformer is designed to let plane waves coming from the desired look direction pass the system undistorted \([28]\), we model logmel-spect features and respective delta coefficients as deterministic point estimates without observation uncertainty. Thus, the “logmel-spect+delta+diffuseness” feature vector samples used for uncertainty decoding consist of \(L\) diffuseness feature vector samples drawn from \([\mathbf{W}_{\text{mel}}]\) appended by the logmel-spect features and respective delta coefficients (equal for all samples).

### 5. Experiments

We choose the Kaldi Toolkit \([29]\) as ASR back-end system to evaluate the DNN-HMM hybrid system on the 8-channel REVERB Challenge task \([30]\) (WSJ0 trigram 5k language model, circular microphone array with a microphone spacing of 8 cm). As first step, a GMM-HMM system is trained on the clean WSJCAMO Cambridge Read News REVERB corpus \([31]\) with feature extraction following the Type-I creation in \([32]\), which is state-of-the-art in the Kaldi recipe \([29]\). Then, we create a state-frame alignment to train the DNN on the multi-condition training sets (each of 7861 utterances) provided by the REVERB challenge \([30]\). This is realized using “Karel’s implementation” of the Kaldi Toolkit including generative pretraining (on restricted Bolzmann machines) and discriminative fine-tuning (using a mini-batch stochastic gradient descent approach) \([33]\). It should be emphasized that the front-end enhancement and feature extraction is identical during training and testing.

The evaluation test set of the REVERB-Challenge task (\(\sim 5000\) environmentally-distorted utterances) consists of ...

- artificially corrupted data (“SimData”) using measured impulse responses \((T_{\text{io}} \approx 0.25\) s, 0.5 s and 0.7 s), recorded noise sequences (added to the microphones signals with a signal-to-noise ratio of 20 dB) and source-microphone spacings of 0.5 m (“Near”) and 2 m (“Far”),
- multichannel recordings (“RealData”) in a reverberant environment \((T_{\text{io}} \approx 0.7\) s) and noisy environment with source-microphone spacings of 1 m (“Near”) and 2.5 m (“Far”).

As first experiment, we evaluate the performance of the DNN-HMM hybrid system without uncertainty decoding. Here we compare the recognition accuracy achieved by “Logmel-spect+delta+diffuseness” features (see Fig. 2) to the logmel-spect features with respective delta and acceleration coefficients extracted from a single microphone signal “Logmel-spect+delta+acceleration(1 mic)” and the beamformer output signal “Logmel-spect+delta+acceleration(MVDR)”.

It is obvious from Table 1 that spatial filtering and replacing acceleration coefficients by diffuseness features significantly improves the recognition accuracy of the DNN-HMM hybrid system, especially in scenarios with large source-microphone spacing and for real-world recordings.

| Table 1: WER scores for the REVERB challenge evaluation test set using different feature types. |
|---------------------------------|-------------------|-----------------|-------------------|-----------------|-----------------|-----------------|-----------------|
|                                | SimData           | RealData        |                                |                 |                 |                 |                 |
|                                | \(T_{\text{io}} \approx 0.25\) s | \(T_{\text{io}} \approx 0.5\) s | \(T_{\text{io}} \approx 0.75\) s | \(T_{\text{io}} \approx 0.7\) s | Near | Far | Near | Far | Near | Far | Avg. | Near | Far | Avg. | Near | Far | Avg. | Near | Far | Avg. | Near | Far | Avg. | Near | Far | Avg. | Near | Far | Avg. |
| Logmel-spect+delta+acceleration(1 mic) | 5.7 | 6.5 | 6.9 | 11.2 | 8.1 | 13.0 | 8.6 | 21.2 | 23.0 | 22.1 |
| Logmel-spect+delta+acceleration(MVDR) | 4.7 | 5.2 | 4.9 | 6.9 | 6.1 | 8.6 | 6.1 | 13.6 | 17.2 | 15.4 |
| Logmel-spect+Delta(MVDR)+diffuseness | 4.9 | 5.1 | 5.0 | 6.2 | 6.0 | 8.0 | 5.9 | 13.1 | 15.3 | 14.2 |
Next, we compare the recognition accuracy achieved by DNN-HMM hybrid system using uncertainty decoding based on ...

- the arithmetic DNN-output averaging in (11), termed “UD arithm”;
- the weighted DNN-output averaging in (15), denoted as “UD weight”.

As in other approaches deriving uncertainty from front-end enhancement (34, 35), we employ a scaling factor in (8) (manually optimized to a value of 0.1) to compensate for the inaccuracies of the variance estimation. First, the impact of the number of \( L \) samples on the recognition accuracy of the DNN-HMM hybrid system is evaluated with focus on the practically relevant case of real-world recordings. As shown in Fig. 3 the WER scores for real data (averaging the scenarios “Near” and “Far”) decrease with increasing value of \( L \), while already a small number of samples is sufficient for improving the recognition accuracy compared to the DNN-HMM hybrid system without uncertainty decoding (“No UD”). Further, replacing arithmetic (“UD arithm” in Fig. 3) by weighted (“UD weight” in Fig. 3) DNN-output averaging leads to a consistent reduction of the WER scores. It should be mentioned that no significant further improvement was observed by increasing the number of samples above \( L = 60 \). In summary, the results in Table 2 for \( L = 30 \) samples emphasize the performance gain achieved by applying uncertainty decoding based on random sampling using the proposed weighted DNN-output averaging.

| SimData | RealData |
|---------|----------|
| \( L = 0.25 \text{ s} \) | \( L = 0.7 \text{ s} \) | \( L = 0.5 \text{ s} \) | \( L = 0.7 \text{ s} \) | \( L = 0.75 \text{ s} \) | \( L = 0.7 \text{ s} \) |
| Near | Far | Near | Far | Near | Far | Ave. | Near | Far | Ave. |
| No UD | 4.9 | 5.1 | 5.0 | 6.2 | 6.0 | 8.0 | 5.9 | 13.1 | 15.3 | 14.2 |
| UD arithm (\( L = 30 \)) | 5.0 | 5.0 | 4.9 | 5.9 | 5.9 | 7.7 | 5.7 | 12.9 | 14.9 | 13.9 |
| UD weight (\( L = 30 \)) | 4.9 | 4.9 | 4.9 | 5.7 | 5.8 | 7.5 | 5.6 | 12.7 | 14.6 | 13.6 |

It is worth highlighting that uncertainty decoding based on random sampling modifies the posterior-likelihood calculation and leaves the remaining parts of the decoding procedure (e.g., grammar and language model) untouched. As a consequence, the average decoding time in our implementation is only increased by 76% for \( L = 30 \) samples (Intel i7 with 3.4 GHz, GPU: NVIDIA GeForce GTX 650 Ti) over regular decoding (no uncertainty decoding).

6. Conclusions

We advance a recently-proposed uncertainty decoding scheme for DNN-HMM hybrid systems which averages posterior likelihoods of context-dependent HMM states produced by a finite set of feature samples. As main innovation, we introduce a weighted (instead of arithmetic) posterior-likelihood averaging based on a minimum classification error criterion and apply it to a new probabilistic distortion model for spatial diffuseness features. The experimental results for the 8-channel REVERB challenge task show that incorporating uncertainty decoding improves the recognition accuracy of a DNN-HMM hybrid with multichannel front-end signal enhancement and that the proposed weighted DNN-output averaging further reduces the word error rate scores.

7. Acknowledgements

The authors would like to thank the Deutsche Forschungsgemeinschaft (contract number KE 890/4-2) and the Foundation for Science and Technology (project UID/CEC/50021/2013 and grant SFRH/BPD/68428/2010) for supporting this work.

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