On-the-fly Feature Based Speaker Adaptation for Dysarthric and Elderly Speech Recognition

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Abstract

Automatic recognition of dysarthric and elderly speech highly challenging tasks to date. Speaker-level heterogeneity attributed to accent or gender commonly found in normal speech, when aggregated with age and speech impairment severity, create large diversity among speakers. Speaker adaptation techniques play a crucial role in personalization of ASR systems for such users. Their mobility issues limit the amount of speaker-level data available for model based adaptation. To this end, this paper investigates two novel forms of feature based on-the-fly rapid speaker adaptation approaches. The first is based on speaker-level variance regularized spectral basis embedding (SBEVR) features, while the other uses on-the-fly learning hidden unit contributions (LHUC) transforms conditioned on speaker-level spectral features. Experiments conducted on the UASpeech dysarthric and DementiaBank Pitt elderly speech datasets suggest the proposed SBEVR features based adaptation statistically significantly outperform both the baseline on-the-fly i-Vector adapted hybrid TDNN/DNN systems by up to 2.48% absolute (7.92% relative) reduction in word error rate (WER), and offline batch mode model based LHUC adaptation using all speaker-level data by 0.78% absolute (2.41% relative) in WER reduction.

Index Terms: Speaker Adaptation, Online Recognition, Disordered Speech Recognition, Elderly Speech Recognition

1. Introduction

Despite the recent breakthroughs in automatic speech recognition (ASR) technologies targeting normal speech [1-2], accurate recognition of dysarthric and elderly speech remains highly challenging tasks to date [3-4]. Causes of Dysarthria include cerebral palsy, amyotrophic lateral sclerosis, stroke and traumatic brain injuries [5], while speech and language impairments are also commonly found among the elderly experiencing natural ageing and neurocognitive disorders such as Alzheimer’s disease [21]. The accompanying physical disabilities and mobility limitations makes voice based assistive technologies more natural alternatives [22] for people suffering from speech disordered and the elderly.

Dysarthric and elderly speech presents a prominent challenge to current deep learning based ASR technologies primarily targeting normal speech in many aspects. Heterogeneity commonly found in normal speech sourcing from accent or gender, when further combined with that over age and speech impairment severity, create large diversity among dysarthric and elderly speakers [23-24]. Such diversity is further aggregated when spectral or temporal perturbation based data augmentation techniques [13-15, 26] are used. To this end, speaker adaptation techniques play a crucial role in personalization of ASR systems for impaired and elderly speakers.

Speaker adaptation techniques widely used in modern deep neural networks (DNNs) based ASR systems targeting normal speech can be segmented into three broad categories: 1) auxiliary speaker embedding feature based approaches that represent speaker dependent (SD) features using compact vectors including speaker codes [27], i-Vectors [28] and bottleneck features [29, 2] feature transformation based approaches that generate speaker independent (SI) canonical features at the acoustic front-ends [30, 32] and 3) model based approaches that handle the speaker-level variability by often applying extra SD transformations to DNN parameters or hidden layer outputs [33-37].

In contrast, these has been limited research on speaker adaptation techniques targeting dysarthric and elderly speech. Earlier works were mainly conducted in the context of traditional hidden Markov models (HMMs) with Gaussian mixture model (GMM) state density distributions, with a focus on feature transformation based adaptation. These include maximum likelihood linear regression (MLLR) and maximum a posteriori (MAP) adaptation [38-40] and their combination with speaker adaptive training [8], feature-space maximum likelihood linear regression (f-MLLR) based SAT [31] and regularized speaker adaptation via Kullback-Leibler (KL) divergence [42]. More recent researches applied model based adaptation techniques to a series of state-of-the-art DNN based dysarthric and elderly ASR systems, including direct parameter fine-tuning based adaptation in both lattice-free maximum mutual information (LF-MMI) trained time delay neural networks (TDNNs) [11,13] and end-to-end recurrent neural network transducers (RNN-Ts) [11,15], learning hidden unit contributions (LHUC) based adaptation [9,13,15,18] and Bayesian learning inspired domain and speaker adaptation [46]. Auxiliary speaker embedding feature based adaptation was investigated in our previous work [47] where spectro-temporal deep embedding features pooled and averaged over time were used.

One major issue associated with the above prior researches is the lack of suitable rapid, on-the-fly dysarthric and elderly adaptation techniques. Such methods serve as dual-purpose solutions to handle not only the difficulty in collecting large quantities of data from such speakers with mobility issues that essential for model based adaptation approaches, but also their latency issue due to the use of multi-pass decoding and speaker dependent parameter estimation. Our prior research on Bayesian model based adaptation using very limited speaker...
data [18] [48] [49] only addressed the above data scarcity issue, but the latency problem remains unvisited. Similarly, the spectro-temporal deep embedding features [47] that were computed and averaged over all speaker-level data also lead to latency and precludes the use of on-the-fly adaptation.

In order to address this issue, two novel forms of feature based on-the-fly rapid speaker adaptation approaches are proposed in this paper. The first is based on speaker-level variance regularized spectral basis embedding (SBEVR) features. An additional variance regularization term was used when training spectral basis embedding DNNs [47] [49] to ensure speaker-level homogeneity of the resulting embedding features, and thus allow them to be applied on-the-fly during test time feature based adaptation. The second approach uses on-the-fly LHUC transforms conditioned on speaker-level spectral features. Specially designed regression TDNN [50] predicting speaker-level LHUC transforms are used to directly generate and apply such parameters in test adaptation thus resolve the latency due to multi-pass decoding. Experiments were conducted on the largest available and most widely used UASpeech [51] dysarthric and DimentiaBank Pitt [52] elderly speech datasets.

The main contributions of the paper are summarized below:

1) As far as we know, this paper presents the first work of on-the-fly feature based fast speaker adaptation targeting dysarthric and elderly speech. In contrast, previous researches on feature based adaptation required all data for a specific to be available [47] while those on the model based adaptation required multiple decoding passes and explicit parameter estimation in test time and leads to further latency [9] [13] [15] [18] [46].

2) The speaker-level variance regularized spectral basis embedding (SBEVR) features are inspired and intuitively related to the underlying variability of dysarthric and elderly speech associated with speech impairment severity and age. Experiments conducted on the UASpeech dysarthric and DimentiaBank Pitt elderly speech datasets suggest the proposed SBEVR features based adaptation statistically significantly outperform both the baseline on-the-fly i-Vector feature adapted hybrid TDNN/DNN systems by up to 2.48% absolute (7.92% relative) reduction in word error rate (WER), and offline batch mode model based LHUC adaptation using all speaker-level data by 0.78% absolute (2.41% relative) in WER reduction.

The rest of this paper is organized as follows. The estimation of speaker-level variance regularized spectral basis embedding features is presented in Sec. 2. The derivation of on-the-fly spectral feature conditioned LHUC transforms is proposed in Sec. 3. Sec. 4 presents the experimental results and analysis on the UASpeech and DimentiaBank Pitt corpora. Sec. 5 draws the conclusion and discusses possible future works.

2. Variance Regularized Spectral Embed

To model the spectro-temporal diversity in dysarthric and elderly speech, singular value decomposition (SVD) is performed on Mel-filterbank log amplitude spectrum $S_r$ [53] as:

$$S_r = U_r \Sigma_r V_r^T$$

where the top-$d$ principal spectral basis vectors are retrieved from the column vectors of the $U_r$ matrix. Further supervised learning of deep spectral embedding features is performed via constructing deep neural network (DNN) based speech intelligibility or age classifier following the settings of [47] [49] shown in the upper part of Fig. 1 the inputs of which is the selected principal spectral basis vectors. For the UASpeech dysarthric speech corpus the targets include both the speech intelligibility groups and the speaker IDs, while for the DimentiaBank Pitt elderly speech corpus the targets include the binary aged vs. non-aged annotation only.

To ensure the speaker-level homogeneity of the spectral basis embedding (SBE) features, a pair of such DNN classifiers are constructed as shown in Fig. 1 Speaker-level average of the 25-dimensional SBE features is taken from the bottleneck layer of the upper classifier before serving as the regression targets of the lower DNN classifier. A multitask learning (MTL) [54] style cost function is used to train the lower classifier using an interpolation between the cross-entropy (CE) error computed over speech intelligibility/age labels, optionally plus that computed over speaker IDs, and the mean squared error (MSE) computed between the lower DNN bottleneck features and the corresponding speaker-level average SBE features produced by the upper DNN classifier, given as:

$$L_{MTL} = \omega_1 L_{MSE} + \omega_2 L_{CE_{group}} + \omega_3 L_{CE_{intel/age}}$$

(2)

![Figure 1: A pair of DNN based speech intelligibility or age classifiers containing a bottleneck layer to extract speaker-level variance regularized spectral basis embedding (SBEVR) features for speaker adaptation. “spkrID” denotes speaker ID and “intel.” stands for speech intelligibility.](image)

The 25-dimensional speaker-level variance regularized spectral basis embedding (SBEVR) features are then taken from the bottleneck layer of the lower classifier in Fig. 1 and concatenated to the acoustic features at the front-end of hybrid DNN/TDNN systems as shown in Fig. 5 to facilitate on-the-fly test time feature based adaptation.

3. On-the-fly F-LHUC Transforms

In feature-based learning hidden unit contributions (f-LHUC) based adaptation approaches [50], LHUC transforms are directly predicted from the acoustic features on the fly. Supervised estimation of LHUC transforms on the training data is first conducted via standard speaker adaptive training (SAT) procedure, on which principal component analysis (PCA) is further applied to produce compressed, low-dimensional LHUC vectors (from 2000 projected down to 29) encoding the most distinctive speaker level features. These serve as the output targets for the TDNN based LHUC transform regression network.

$$\omega_1 = \omega_2 = \omega_3 = \frac{1}{3}$$ while for the DimentiaBank Pitt corpus, $$\omega_1 = \omega_2 = \frac{1}{2}, \omega_3 = 0.$$
shown in Fig. 2 with a specially designed online averaging layer constructed following \([59]\) given as:

\[
G_s^{(i)} = \sum_{t=1}^{T_s} h_s^{(i)} + \alpha \cdot G_s^{i-1} \tag{3}
\]

\[
N_s^{(i)} = T_s + \alpha \cdot N_s^{i-1} \tag{4}
\]

\[
m_s^{(i)} = G_s^{(i)}/N_s^{(i)} \tag{5}
\]

![Figure 2: TDNN based LHUC regression network with an especially designed online averaging layer \([59]\).](image)

where \(G_s\), \(N_s\) and \(m_s\), denote the accumulated hidden vector, frame count and averaged hidden vector till the \(i^{th}\) segment of speaker \(s\). The \(i^{th}\) audio segment contains \(T_s\) frames with the hidden vector of the \(i^{th}\) frame to be \(h_s^{(i)}\) and \(\alpha \in [0, 1]\) is the history interpolation weight. Mel filter-bank (FBK) plus variance regularized spectral basis embedding (SBEVR) features serve as the inputs of the LHUC regression network as shown in Fig. 2. Once such regression network is trained, an additional affine transformation is further trained to map the predicted low-dimensional LHUC features for any training speaker’s data to the corresponding full size LHUC transforms. During test time on-the-fly adaptation, the LHUC regression network and the affine transformation (circled in green in Fig. 2) are applied in turn to generate test speaker level LHUC transforms using FBK plus SBEVR features, as shown in Fig. 2.

![Figure 3: Incorporation of variance regularized spectral basis embedding (SBEVR) features at the front-end of hybrid DNN ASR system \([18]\). Selecting path (i) leads to systems with auxiliary feature based adaptation only, while selecting (ii) leads to systems with additional feature-based LHUC adaptation.](image)

4. Experiments and Results

4.1. Experiments on the UASpeech Dataset

**Task Description:** The UASpeech dataset is the largest publicly available and widely used dysarthric speech dataset \([51]\). It is designed as an isolated word recognition task containing approximately 103 hours of speech recorded from 16 dysarthric and 13 control healthy speakers. For each speaker the data is split into 3 blocks B1, B2 and B3, each with the same set of 155 common words and a different set of 100 uncommon words. The training set includes the data from B1 and B3 of all 29 speakers (60.1 hours of audio) while the test set includes the data from B2 of all 16 dysarthric speakers (22.6 hours of audio, excluding speech from control healthy speakers). After removing excessive silence at both ends of the audio segments using a HTK \([55]\) trained GMM-HMM system \([9]\), the training set contains a total of 30.6 hours of speech from B1 and B3 (99195 utterances) while the test set contains 9 hours of speech from B2 (26520 utterances). Data augmentation featuring speaker independent and dependent speed perturbation \([13]\) was further conducted to produce a 130.1h augmented training set (399110 utterances, perturbing both healthy and dysarthric speech) while perturbing dysarthric speech only produced a 65.9h augmented training set (204765 utterances).

**Experiment Setup:** The settings of the 7-layer hybrid DNN acoustic models implemented via an extension to the Kaldi toolkit \([56]\) follow our previous work \([13, 18]\) with the inputs to be 80-dimensional filter-bank (FBK) plus 25-dimensional speaker-level variance regularized spectral basis embedding (SBEVR) features or 100-dimensional on-the-fly i-Vectors \([3]\). Top 2 principal spectral basis vectors served as the inputs of the DNN speech intelligibility classifier. The history interpolation weight \(\alpha\) of the LHUC regression network was set to 0.9 while the slicing indices for the four context slicing layers were set as \([-2, 2], [-2, 0, 2], [-3, 0, 3]\) and \([-4, 0, 4]\). A uniform language model was used in decoding \([6]\).

**Table 1: Performance comparison of the proposed speaker-level variance regularized spectral basis embedding (SBEVR) based adaptation, i-Vector adaptation and LHUC adaptation on the UASpeech test set of 16 dysarthric speakers. “DYS” and “CTL” in “Data Aug.” column denote perturbing the dysarthric and the healthy speech respectively for data augmentation. “SBE” denote spectral basis embedding features. “VLM/MH” refer to intelligibility subgroups. “On Fly” column indicates using on-the-fly or offline adaptation. \(^{\dagger}\) denotes a statistically significant improvement (\(\alpha = 0.05\)) is obtained over the comparable on-the-fly i-Vector adapted systems (Sxs.2.9, 20).**

| Sys. | Model | Data Aug. | VLM | M | H | Avg |
|------|-------|-----------|-----|---|---|-----|
| 2    | Vector |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 3    | SBE   |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 4    | SBEVR |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 5    | Hybrid DNN (FBK) |       | 68.4 | 28.1 | 19.1 | 9.67 |
| 6    | Vector |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 7    | SBE   |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 8    | SBEVR |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 9    | Hybrid DNN (SBEVR) |       | 68.4 | 28.1 | 19.1 | 9.67 |
| 10   | Vector |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 11   | SBE   |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 12   | SBEVR |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 13   | Hybrid DNN (FBK) |       | 68.4 | 28.1 | 19.1 | 9.67 |
| 14   | Vector |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 15   | SBE   |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 16   | SBEVR |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 17   | Hybrid DNN (SBEVR) |       | 68.4 | 28.1 | 19.1 | 9.67 |
| 18   | Vector |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 19   | SBE   |           | 68.4 | 28.1 | 19.1 | 9.67 |
| 20   | SBEVR |           | 68.4 | 28.1 | 19.1 | 9.67 |

**Result Analysis:** Table 1 shows the performance comparison \([3,\dagger]\).
between our proposed speaker-level variance regularized spectral basis embedding (SBEVR) feature based adaptation, spectral feature driven f-LHUC based adaptation, on-the-fly i-Vector based adaptation and offline batch mode model based LHUC-SAT adaptation on the UASpeech test set containing all 16 dysarthric speakers. Several trends can be observed: 1) Our proposed SBEVR feature adapted systems consistently and statistically significantly outperform the comparable on-the-fly iVector adapted systems across most speech intelligibility groups with various amounts of training data (Sys.5 vs. Sys.2, Sys.14 vs. Sys.11, Sys.23 vs. Sys.20) by up to 2.48% absolute (7.92% relative) reduction in overall WER (Sys.5 vs. Sys.2). 2) Compared with the comparable offline batch mode model based LHUC-SAT adaptation using all speaker-level data (Sys.6,15,24), our proposed SBEVR feature adapted systems (Sys.5,14,23) retain up to 82.28% of the improvements over their comparable SI systems (Sys.5-6 vs. Sys.1). 3) Compared with our previous offline averaged (Avg) SBE feature \[47\] adapted systems (Sys.4,13,22), the proposed SBEVR feature adapted systems (Sys.5,14,23) retain up to 76.47% of the improvements over their comparable SI systems (Sys.4-5 vs. Sys.1). 4) The proposed spectral feature (FBK+SBEVR) driven f-LHUC adapted systems outperform the comparable FBK driven f-LHUC adapted systems (Sys.9 vs. Sys.8 and Sys.18 vs. Sys.17) while also outperforming the SBEVR feature online adaptation on the 30.6h and 65.9h training sets (Sys.9 vs. Sys.5, Sys.18 vs. Sys.14). 5) Frame-level log-likelihood score combination between SBEVR feature online adaptation and spectral feature driven f-LHUC online adaptation leads to further improvement (Sys.5+9, Sys.14+18, Sys.23+27).

### 4.2. Experiments on the DimentiaBank Pitt Dataset

**Task Description:** The DimentiaBank Pitt \[52\] dataset contains approximately 33 hours of speech recorded over interviews between the 292 elderly participants and the clinical investigators. After split of data and removal of excessive silence \[15\], the training set contains 15.7 hours of audio data from 244 elderly and 444 investigators (29682 utterances) while the development and evaluation sets contain 2.5 hours from 43 elderly and 76 investigators (2103 utterances) and 0.6 hours from 43 elderly and 76 investigators (925 utterances) of audio data respectively\[4\]. Data augmentation featuring speaker independent and dependent speed perturbation \[15\] produced an 58.9h augmented training set (11280/30 utterances).

**Experiment Setup:** The hybrid TDNN systems with 14 context slicing layers and a 3-frame context follow the Kaldi \[56\] chain setup, with the inputs to be 40-dimensional FBK plus 25-dimensional SBEVR features or 100-dimensional on-the-fly i-Vectors. Top 3 principal spectral basis vectors served as the inputs to the DNN age classifier. A word level 4-gram LM was trained \[15\] and a 3.8k word recognition vocabulary covering all words in DementiaBank Pitt corpus was used in recognition.

**Result Analysis:** Table 2 shows the performance comparison between our proposed speaker-level variance regularized spectral basis embedding (SBEVR) feature based adaptation, on-the-fly i-Vector based adaptation and offline batch mode model based LHUC adaptation on the DimentiaBank Pitt dataset. Trends similar to those found on the UASpeech task in Table 1 can be observed. 1) Our proposed SBEVR feature adapted systems statistically significantly outperform the comparable on-the-fly iVector adapted systems (Sys.5 vs. Sys.2) by 1.82% absolute (5.45% relative) overall WER reduction. 2) Our proposed SBEVR feature adapted system outperforms the comparable offline batch mode model based LHUC adaptation using all speaker-level data (Sys.5 vs. Sys.6) by 0.78% absolute (2.41% relative) overall WER reduction. 3) The proposed SBEVR feature adapted system retains 83.96% of the improvement of our previous offline averaged (Avg) SBE feature \[49\] adapted system over the SI system (Sys.4-5 vs. Sys.1).

### 5. Conclusions

This paper proposes two novel forms of feature based on-the-fly fast speech adaptation approaches, the first based on speaker-level variance regularized spectral embedding (SBEVR) features and the other using speaker-level spectral feature driven LHUC transforms. Experiments conducted on the UASpeech dysarthric and DimentiaBank Pitt Elderly datasets suggest our proposed SBEVR feature adapted systems outperform both on-the-fly i-Vector adapted systems and batch mode model based LHUC adaptation. Future research will focus on implementing spectral feature drive LHUC adaptation for elderly speech.

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