**Personalized Adversarial Data Augmentation for Dysarthric and Elderly Speech Recognition**

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**Abstract**—Despite the rapid progress of automatic speech recognition (ASR) technologies targeting normal speech, accurate recognition of dysarthric and elderly speech remains highly challenging tasks to date. It is difficult to collect large quantities of such data for ASR system development due to the mobility issues often found among these users. To this end, data augmentation techniques play a vital role. In contrast to existing data augmentation techniques only modifying the speaking rate or overall shape of spectral contour, fine-grained spectro-temporal differences between dysarthric, elderly and normal speech are modelled using a novel set of speaker dependent (SD) generative adversarial networks (GAN) based data augmentation approaches in this paper. These flexibly allow both: a) temporal or speed perturbed normal speech spectra to be modified and closer to those of an impaired speaker when parallel speech data is available; and b) for non-parallel data, the SVD decomposed normal speech spectral basis features to be transformed into those of a target elderly speaker before being re-composed with the temporal bases to produce the augmented data for state-of-the-art TDNN and Conformer ASR system training. Experiments are conducted on four tasks: the English UASpeech and TORGO dysarthric speech corpora; the English DementiaBank Pitt and Cantonese JCCOCC MoCA elderly speech datasets. The proposed GAN based data augmentation approaches consistently outperform the baseline speed perturbation method by up to 0.91% and based data augmentation approaches consistently outperform the baseline speed perturbation method by up to 0.91% and 3.0% absolute (9.61% and 6.4% relative) WER reduction on the TORGO and DementiaBank data respectively. Consistent performance improvements are retained after applying LHUC based speaker adaptation.

**Index Terms**—Dysarthric Speech; Elderly Speech; Speech Recognition; Data Augmentation; GAN; hybrid TDNN; end-to-end Conformer

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**I. INTRODUCTION**

Despite the rapid progress of automatic speech recognition (ASR) technologies targeting normal speech in recent decades [1]–[7], accurate recognition of pathological and elderly speech remains highly challenging tasks to date [8]–[15]. Dysarthria is a common form of speech disorder caused by a range of motor control conditions including cerebral palsy, amyotrophic lateral sclerosis, stroke and traumatic brain injuries [16]–[20]. In a wider context, speech and language impairments are also commonly found among older adults experiencing natural ageing and neurocognitive disorders, for example, Alzheimer’s disease [21], [22]. People with speech disorders often experience co-occurring physical disabilities and mobility limitations. Their difficulty in using keyboard, mouse and touch screen based user interfaces makes voice based assistive technologies more natural alternatives [23], [24] even though speech quality is degraded. To this end, in recent years there has been increasing interest in developing ASR technologies that are suitable for dysarthric [9], [25]–[40] and elderly speech [14], [41]–[46].

Dysarthric and elderly speech bring challenges on all fronts to current deep learning based automatic speech recognition technologies predominantly targeting normal speech recorded from healthy, non-aged users. First, a large mismatch between such data and healthy, normal voice is often observed. Such difference manifests itself on many fronts including articulatory imprecision, decreased volume and clarity, changes in pitch, increased dysfluencies and slower speaking rate. Second, the co-occurring disabilities and mobility limitations often found among impaired and elderly speakers lead to the difficulty in collecting large quantities of such data that are essential for current data intensive deep learning based ASR system development. Prior researches on dysarthric and elderly speech corpus development are mainly conducted for English [59], [47]–[50]. A set of publicly available disordered and elderly speech corpora are shown in Tab. 1.

Among these, the Nemours [47] corpus contains less than 3 hours of speech from 11 speakers, while the 15-hour TORGO [50] dataset is moderately larger. By far, the largest available and widely used dysarthric speech database, the English UASpeech [48] corpus, contains 102.7 hours of speech recorded from 29 speakers among whom 16 are dysarthric speakers while the remaining 13 are healthy speakers. As the largest publicly available elderly speech dataset designed for neurocognitive disorder screening, the DementiaBank Pitt [51] corpus contains approximately 33 hours of audio data recorded over interviews between the 292 elderly participants and the clinical investigators. Compared with more widely available normal speech corpora, such as Switchboard and Fisher conversational telephone speech [52] or LibriSpeech [53] containing from hundreds to thousands of hours of audio data, existing dysarthric and elderly speech corpora are much smaller in size. Similar data scarcity is also found not only among dysarthric speech datasets collected for non-English languages such as Dutch [54], Italian [55], Cantonese [56] and Korean [49], but also in elderly speech corpora.

In addition, sources of variability commonly found in normal speech including accent or gender, when further compounded with those over age as well as speech and language pathology severity, create large diversity among dysarthric and elderly speakers [57], [58]. Their mobility issues further limit the amount of speaker-level data available for fine-grained model based adaptation to facilitate user personalization of
Prior research on GAN based data augmentation for ASR applications targeting normal speech include synthesizing noisy speech to enhance the environmental robustness [90]–[93]; generating data for whisper recognition [94], speech translation [95], far-field recognition [96] and voice search [97]. GAN based data augmentation approaches have also been studied in the context of speech emotion recognition [83], [98]–[102] and speaker verification [103]–[108].

In contrast, only a few prior researches on applying GAN to dysarthric speech processing tasks, represented by dysarthric speech augmentation [109]–[112] and dysarthric speech reconstruction [113], [114] have been conducted to date. To the best of our knowledge, no previous study on GAN based data augmentation approaches designed for elderly speech lies in the precise nature of the underlying task specific data collection protocol. The majority of the disordered speech datasets [39], [47]–[50], [54]–[56] are constructed using a different protocol that is based on non-parallel, spontaneous conversational speech recorded during neurocognitive assessment interviews between elderly participants and clinical investigators. In order to address the above issues, a novel set of generative adversarial networks (GAN) based speaker dependent, personalized data augmentation approaches rendering for the detailed characteristics of dysarthric and elderly speech recognition tasks discussed above are proposed in this paper.

First, for dysarthric speech data where the underlying spoken contents are constrained to be parallel but the speech duration is allowed to vary, speaker dependent deep convolutional GANs (DCGANs) are trained to transform tempo or speed perturbed healthy speech spectra into those of individual target dysarthric speakers. The resulting data augmentation process not only allows the overall change in speaking rate, speech volume and spectral envelope to be simulated as in classic front-end level tempo or speed perturbation, but also ensures further fine-grained spectro-temporal characteristics associated with impaired speech including articulatory imprecision, decreased clarity, breathy and hoarse voice as well as increased dysfluencies and pauses to be injected into the augmented data.

Second, to account for the non-parallel nature of elderly or dysarthric speech datasets, SVD based speech spectrum decomposition is used to derive structured speech representations: a) time invariant spectral basis features more closely related to speaker characteristics, for example, an average description of speech volume and energy distribution over frequency components; and b) time variant temporal basis features more closely related to the precise nature of the underlying task specific data collection protocol.
features more related to spoken contents. The resulting spectral basis matrix of a healthy, non-aged source speaker is then transformed using speaker dependent spectral basis perturbation GANs into those of a target elderly or dysarthric speaker, before being re-composed with the source speaker's temporal basis to produce the final personalized augmented data for state-of-the-art hybrid TDNN [3] and end-to-end (E2E) Conformer [7] ASR system training.

Experiments are conducted on four tasks across two languages: the English UA-Speech [48] and TORG0 [50] dysarthric speech corpora, the English DementiaBank Pitt [51] and Cantonese JCCOCC MoCA [59] elderly speech datasets. Among these, the UA-Speech and DementiaBank Pitt corpora are the largest publicly available datasets on dysarthric speech and elderly speech respectively. The proposed parallel and non-parallel GAN based dysarthric and elderly data augmentation approaches consistently outperform the baseline speed perturbation [63] and SpecAugment [65] methods by up to 0.91% and 3.0% absolute (9.61% and 6.4% relative) reduction in word error rate (WER). Consistent performance improvements are retained after model based speaker adaptation using learning hidden unit contribution (LHUC) is further applied.

The main contributions of this paper are summarized below:

1. To the best of our knowledge, this paper presents the first work to systematically investigate adversarial learning based data augmentation for dysarthric and elderly speech recognition tasks. In contrast, existing data augmentation studies for dysarthric and elderly speech mainly focus on using signal-level tempo or speed perturbation based methods [14], [15], [33], [69], [70]. The only previous research on GAN based dysarthric speech augmentation required the explicit use of parallel speed speech data of the UA-Speech corpus [109], [110]. The non-parallel GAN based normal to pathological voice conversion approach studied in [111] is evaluated on naturalness and severity, but not measured in terms of the performance of ASR systems constructed using the generated data. No GAN based data augmentation approaches designed for spontaneous and conversational elderly speech recognition tasks using non-parallel data have been published to date.

2. The proposed spectral basis GAN model benefits from a distinct advantage of disentangling the time invariant speaker specific spectral characteristics from time variant temporal features that are more related to spoken contents. This novel approach broadens the application scope of GAN based data augmentation, and allows them to be flexibly performed on both parallel and non-parallel dysarthric or elderly speech data for ASR system development.

3. The proposed adversarial data augmentation approaches achieved statistically significant performance improvements over the baseline hybrid TDNN and E2E Conformer systems using state-of-the-art data augmentation techniques including speaker independent and speaker dependent speed perturbation as well as SpecAugment, by up to 0.91% and 3.0% absolute (9.61% and 6.4% relative) word error rate (WER) reduction on four dysarthric or elderly speech recognition tasks across two languages. These findings serve to demonstrate the efficacy and generality of our proposed GAN based data augmentation methods for dysarthric and elderly speech recognition.

The rest of the paper is organized as follows. Traditional data augmentation approaches are presented in Sec. [II]. Adversarial data augmentation methods for parallel and non-parallel corpora are proposed in Sec. [III] and [IV] respectively. Sec. [V] presents the experimental results of using augmented data for training hybrid TDNN and E2E Conformer based ASR systems and analysis. Sec. [VI] draws the conclusion and discusses possible future works.

II. SIGNAL BASED DYSAHRIC AND ELDERLY SPEECH DATA AUGMENTATION

In this section, we present two traditional front-end signal level data augmentation methods, tempo and speed perturbation for dysarthric and elderly speech recognition. These serve as the baseline augmentation approaches to modify the overall speaking rate, volume and spectral shape, and the necessary tempo alignment between normal speed and dysarthric, or elderly speech utterances to facilitate GAN based augmentation model training in Sec. [III].

A. Tempo Perturbation

Tempo perturbation modifies the duration of the input time-domain signal \( x(t) \), while keeping its overall contour the same [60], [61]. This is often implemented using the waveform overlap-add (WSOLA) algorithm [60] that includes three processing stages: signal decomposition, frame relocation and adaptation and signal reconstruction.

After decomposing input audio signal \( x(t) \) into analysis blocks \( \tilde{x}_m(r) \) that are equally distributed along time axis by analysis hopsize \( H_a \), the blocks are relocated based on a method named overlap-add (OLA) [115]. OLA relocates analysis blocks \( \tilde{y}(r) \) along time axis based on the following equation and a given perturbation factor \( \alpha \),

\[
H_s = \alpha \times H_a \tag{1}
\]

where \( H_s \) stands for synthesis hopsize.

In the next frame relocation stage, to ensure the perturbed output \( y(t) \) has the maximal similarity with \( x(t) \), WSOLA uses an iterative approach to update the positions of analysis blocks. For an analysis block \( \tilde{x}_m(r) \), its center is shifted by \( \Delta_m \in [-\Delta_{\max}, \Delta_{\max}] \) along the time axis, where the optimal value of \( \Delta_{\max} \) is obtained by maximizing the cross-correlation between \( \tilde{x}_m(r) \) and \( \tilde{x}_{m-1}(r) \). This ensures that the periodic structures of the adjusted analysis block are optimally aligned with the one of the previously copied synthesis block in the overlapping region while both blocks use \( H_s \). The Hann window function \( w(r) \) is then applied to the adjusted analysis block to compute the synthesis block \( \tilde{y}_m(r) \).

In the final stage, after finishing all iterations, the synthesis frames are processed in order to reconstruct the actual time-scale modified output signal \( y(t) \) in a similar manner as conventional OLA [115]. The perturbed signal \( y(t) \) has a different duration, for example, representing a slower speaking rate of an impaired speaker, but keeps the overall spectral shape the same as \( x(t) \).
B. Speed Perturbation

Speed perturbation \[63\] modifies the input time domain speech signal \(x(t)\) by scaling the sampling resolution via a perturbation factor \(\alpha\). The resulting speed perturbed signal output \(y(t)\) is given as: \(y(t) = x(\alpha t)\). The above time-domain signal modification is equivalent to the following performing in the frequency domain:

\[
X(f) \rightarrow \frac{1}{\alpha} X\left(\frac{1}{\alpha} f\right)
\]

where \(X(f)\) and \(\frac{1}{\alpha} X\left(\frac{1}{\alpha} f\right)\) denote the Fourier transform of \(x(t)\) and \(y(t)\) respectively. Speed perturbation changes both audio duration and overall spectral shape \[63\]. This serves to emulate, for example, slower speaking rates, changes in speech volume and formant positions of impaired or elderly speakers.

C. Speaker Dependent Perturbation Factor Estimation

Speed or tempo perturbation based data augmentation \[63\] are widely used in current ASR systems. During the data augmentation process, a group of speaker independent (SI) speed perturbation factors based on, for example, \{0.9, 1.0, 1.1\}, are applied at the front-end level to produce a three-fold expansion of the original training data. Prior researches further suggest that additional use of speaker dependent (SD) perturbation of normal, healthy speech to expand the limited training data for each target dysarthric \[15\], \[33\], \[69\], \[70\] or elderly speaker \[14\] during data augmentation produced better ASR performances over using the speaker independent perturbation approach only. More detailed analyses on such combined use of speaker independent and dependent speed perturbation for dysarthric speech recognition can be found in \[15\], \[33\].

Without the loss of genericity, for any target dysarthric or elderly speaker, the associated SD perturbation factor is calculated as the average phoneme duration ratio between their respective speech obtained using phoneme alignment analysis \[70\]. Force alignment using a HTK \[116\] trained GMM-HMM system is first performed. The resulting frame-level phoneme alignments are then used to compute the SD perturbation factor \(\alpha_j\) for the \(j^{th}\) target dysarthric or elderly speaker as \(\alpha_j = \frac{d_{j}}{d_{C}}\), where \(d_{C}\) denotes the average time duration of all healthy, control speakers and \(d_{j}\) is the average phoneme duration of the target \(j^{th}\) dysarthric or elderly speaker.

III. Adversarial Augmentation Using Parallel Data

As discussed in Sec. II conventional data augmentation methods based on tempo or speed perturbation in Sec. II only characterize an overall decrease in speaking rate, speech volume and changes in spectral envelope of dysarthric and elderly speech. In this section, for dysarthric speech corpora where the underlying spoken contents are designed to be parallel but the speech duration is allowed to vary, speaker dependent deep convolutional GANs (DCGANs) are utilized to learn the relation between tempo or speed perturbed healthy speech spectra and those of individual target impaired speakers.

A. DCGAN Model Architecture

The overall architecture configurations of the proposed DCGAN model follow our previous work \[110\], also again shown in Fig. 1: The architectures of the proposed adversarial neural network models designed for impaired or elderly speaker dependent data augmentation using (a) parallel normal and dysarthric speech utterances of identical contents shown in Fig. 3a-3b; and (b) non-parallel normal, non-aged and elderly speech data shown in Fig. 3c-3d.
in Fig. 3a. The Generator component contains 4 convolutional layers, the first three of which have 8 kernels while the last one has 1 kernel only. All of these kernels in the Generator have a kernel size of $3 \times 3$ and stride of $1 \times 1$. Each of the first three convolutional layers is also immediately connected to ReLU activations. We use Replicate Padding to replicate the edges of the feature map to ensure the output and input dimensions are the same. The Discriminator component contains 4 convolutional layers of 8, 16, 32 and 64 kernels respectively, all of which use a kernel size of $2 \times 2$ and stride of $2 \times 2$. A flattening operation is applied to concatenate the outputs of convolutional layers, resulting in a 3000-dimensional vector. A fully connected (FC) layer with Sigmoid activation is used for binary classification in the Discriminator.

**B. DCGAN Model Training**

Prior to DCGAN training, pairs of normal and dysarthric speech utterances of identical word contents but often different duration need to be formed. In order to facilitate a frame-by-frame comparison between the GAN transformed normal speech spectrogram against that of the target impaired speech, each normal speech segment is either tempo or speed perturbed to produce a modified duration that matches against that of a target dysarthric speech utterance, as shown in Fig. 3a. This requires a scaling factor to be estimated for each normal and dysarthric speech segment pair using phonetic analysis similar to the procedure described in Sec. II-C for speaker level speed or tempo perturbation. The resulting pairs of normal and dysarthric speech utterances that now have the same duration are further zero mean and unit variance normalized at speaker level, before being used in DCGAN training.

The DCGAN training objective function both maximizes the binary classification accuracy on the target dysarthric speech spectrum and minimizes that obtained on the GAN transformed normal speech. This is given by

$$\min_{G_j} \max_{D_j} \ V(D_j, G_j)$$

$$= \mathbb{E}_{f_b \sim p_{D_j}} \log (D_j(f_b)) + \mathbb{E}_{f_c \sim p_{C}} \log (1 - D_j(G_j(f_c)))$$

where $j$ represents the index for target dysarthric speaker, $G_j$ and $D_j$ are Generator and Discriminator associate with dysarthric speaker $j$, $f_c$ and $f_b$ stand for the Mel-scale filter-bank (FBank) features of paired control and dysarthric utterances. During DCGAN training for each target impaired speaker, the learning rate for both the Generator and Discriminator is halved every 2500 iterations until convergence.

**C. Dysarthric Speech Spectrum Generation**

During DCGAN based data augmentation, as shown in Fig. 3b, the target impaired speaker level tempo or speed perturbed 40-dimensional Mel-scale filter-bank features obtained from normal speech using the baseline tempo or speed perturbation approaches described in Sec. II are fed into the corresponding Generator components to produce the comparable speaker level “tempo-GAN” or “speed-GAN” augmented data for each target impaired speaker, before being further zero mean and unit variance normalized for ASR system training.
The resulting data augmentation process not only allows an overall change in speaking rate, speech volume and spectral shape to be produced as in conventional signal level tempo or speed perturbation, but also injects further detailed spectro-temporal characteristics associated with impaired speech including articulatory imprecision, decreased clarity as well as breathy and hoarse voice into the final augmented filter-bank data for each target impaired speaker.

For instance, in contrast to an example control speech segment’s spectrogram of the word “Some” in Fig. 2a, the comparable dysarthric speech spectrogram in Fig. 2b contains not only weakened formants that indicates articulatory imprecision, but also additional energy distributed over higher frequency components at both the start and end of the utterance due to the difficulty in breath control when speaking. Such additional energy is more clearly captured in the speed-GAN generated spectrogram shown in Fig. 2c than that derived using speed perturbation only shown in Fig. 2d.

IV. ADVERSARIAL AUGMENTATION USING NON-PARALLEL DATA

The adversarial data augmentation approach introduced in Sec. III requires the use of parallel control and dysarthric or elderly speech recordings of identical spoken contents. In this section, SVD based speech spectrum decomposition is used to derive spectral and temporal subspace representations. Among these, the spectral basis features of a healthy, non-aged source speaker considered to be more closely related to time invariant speaker characteristics, are transformed via SD spectral basis columns to produce the augmented data.

A. SPEECH SPECTRUM SUBSPACE DECOMPOSITION

Spectro-temporal subspace spectrum decomposition techniques provide simple and intuitive solutions to decouple the time invariant spectral components of speech signals from their time variant temporal components by modelling the combination between these two using a linear system \[ \mathbf{U}_r \mathbf{\Sigma}_r \mathbf{V}_r^T \] (4) where the set of column vectors of the \( C \times C \) dimensional left singular \( \mathbf{U}_r \) and the row vectors of the \( T \times T \) dimensional right singular \( \mathbf{V}_r^T \) stands for time invariant spectral basis vector and time variant temporal basis vector respectively. Here \( \mathbf{\Sigma}_r \) is a \( C \times T \) rectangular diagonal matrix containing the singular values sorted in descending order.

Two examples of SVD decomposition of Mel-scale filter-bank based log amplitude spectra associated with (a) an Cantonese speech utterance containing the same word “果 (apple)” of the JCCOCC MoCa corpus [59], and (b) another English pair containing the word “okay” of the DementiaBank Pitt [51] dataset, are shown in Fig. 3 and 4 respectively. The resulting spectral and temporal basis matrices intuitively represent the following two sources of information: 1) Time-invariant spectral subspaces: that can be associated with an average utterance-level description of elderly speakers’ characteristics such as an overall reduction of speech volume, weakened formants due to articulation imprecision as well as hoarseness and energy distribution anomaly across frequencies due to difficulty in breath control. For example, the comparison between the spectral basis vectors extracted from a pair of Cantonese elderly and normal speech utterances of the same word “果 (apple)” in Fig. 4 (bottom, left) shows that the elderly spectral basis matrix exhibits a sparser energy distribution pattern than those obtained from the comparable normal, non-aged speech spectral bases in Fig. 4 (top, right). Similar
trends can be found between the spectral basis vectors of the non-aged and elderly speech utterances of the same English word content “okay” shown in Fig. 4 and 2) time-variant temporal subspaces: that are considered more related to time content dependent features such as duration and pauses, for example, shown in the contrast between the temporal basis vectors separately extracted from non-aged and elderly speech in Fig. 4a and Fig. 4b. The dimensionality of the temporal bases captures the duration.

B. Spectral Basis GAN Model Architecture

The overall architecture of the proposed spectral basis GAN model is shown in Fig. 1b. Compared with the DCGAN of Sec. III designed for parallel data shown in Fig. 1a, several changes are made. First, SVD decomposed spectral bases are now used as the GAN inputs instead of filter-bank features. Hence, the convolutional layers adopted in the DCGAN model of Fig. 1a tailored for filter-bank input features are replaced by fully connected layers (FC) layers. More specifically, the Generator (Fig. 1b, top) contains three fully connected layers of 512, 512 and 1600 dimensions. The first two FC layers are both followed by a Leaky ReLU function with a negative slope value set to 0.2, while the third FC layer is followed by a Tanh activation function before producing the final outputs. The Discriminator (Fig. 1b, bottom) also contains 3 FC layers of 256, 512 and 256 dimensions each.

Second, the output targets of the GAN model serve as a perturbation vector, ∆U, to be added to the spectral bases that are derived from the input normal, non-aged speech spectrogram, U. During GAN training, many-to-many mapping exists between multiple normal, non-aged speech utterances and a given set of target elderly speech segments. To this end, three forms of pairing between these two groups of data are considered in the training stage. The first adopts a random pairing between a normal, non-aged speech utterance and any randomly selected elderly speech segment of a target speaker. The second utilizes a pairing between a normal speech utterance and the average, mean spectral bases computed over all the elderly speech utterances of a target speaker. The third approach considers a more expensive and exhaustive, full permutation over all possible pairing between a normal speech utterance and each elderly speech utterance of a target speaker. In practice, these three normal and elderly speech data pairing strategies produced comparable performance, as will be shown later in the experimental results of Sec. V.

Finally, for the speaker dependent spectral basis GAN model considered here, it is vital to ensure speaker level homogeneity, for example, an overall reduced speech volume, to be consistently encoded in resulting spectral basis perturbation output vectors. To this end, in addition to the binary non-aged versus elderly classification task, a second auxiliary task based on elderly speaker ID prediction is also used in the Discriminator training, akin to the Auxiliary Classifier GAN (AC-GAN) introduced in [122]. As shown in the bottom right corner of Fig. 1b, for each of these two tasks, a separate 256-dimensional FC layer followed by a Sigmoid activation is used. Additional speaker ID one-hot encoding features are fed into the Generator as shown in the top left corner of Fig. 1b.

C. Spectral Basis GAN Model Training

An example illustration of spectral basis GAN model training is shown in Fig. 3c on a pair of spectral basis matrices separately derived from SVD decomposition of non-parallel non-aged (top left, U in light blue, Fig. 3c) and elderly (bottom left, U in light green, Fig. 3c) speech spectrograms. The GAN Generator synthesized elderly speech spectral basis matrix, U' = U + ∆U, adds the GAN output perturbation vector to the non-aged speech spectral bases (centre, Fig. 3c), before being fed into the Discriminator to perform binary classification over the non-aged versus aged labels and speaker ID prediction in the second auxiliary task introduced above in Sec. IV-B and Fig. 1b. The spectral basis GAN model training loss function is given by:

$$\min_{G_j} \max_{D_j} V(D_j, G_j)$$

$$= \mathbb{E}_{U \sim U'}[\log(D_j(U))] + \mathbb{E}_{U \sim U_{id}}[\log(1 - D_j(U_C + ∆U))]$$

where $j$, $G_j$ and $D_j$ are the Generator and Discriminator modules associated with a target elderly speaker $j$. $U_{C}$ and $U_j$ denote the spectral bases that are separately derived from SVD decomposition of non-parallel non-aged and elderly speech utterance spectrograms. $∆U = λG_j(U_C)$ represents the generated spectral bases perturbation vector. $λ$ is a scaling factor used to control and moderate the perturbation added to the non-aged speech spectral basis vectors, and empirically set as 0.1 and 0.2 for dysarthric and elderly speech datasets respectively. Further ablation study on the setting of $λ$ and its impact on ASR system performance is provided later in the experiment section of this paper (in Tab. VI).

For the two output tasks, their respective error cost functions are:

$$L_{c} = \mathbb{E}[\log P(\text{Cond.} = E | U_j)] + \mathbb{E}[\log P(\text{Cond.} = C | U_{C} + ∆U)]$$

$$L_{sid} = \mathbb{E}[\log P(\text{Sid} = j | U_j)] + \mathbb{E}[\log P(\text{Sid} = j | U_{C} + ∆U)]$$

where $U_j$ stands for the spectral bases extracted from the spectrogram of an utterance of a target elderly or dysarthric speaker $j$. The above classification cost $L_c$ is formulated such that $\text{Cond.} = E$ and $\text{Cond.} = C$ state whether the real spectral bases, $U_j$, or a synthesized one, $U_{C} + ∆U$, are produced by an elderly speaker or a control, non-aged speaker respectively. The speaker ID prediction cost $L_{sid}$ ensures both the original and synthesized spectral bases share the same target speaker specific characteristics. The Discriminator is trained to maximize $L_{sid} + L_{c}$ while the Generator is trained to maximize $L_{sid} - L_{c}$. For both Generator and Discriminator components, the learning rate is halved for every 2500 iterations until convergence.

D. Elderly Speech Spectrum Generation

An example illustration of spectral basis GAN based speaker dependent elderly speech spectrogram generation is shown in Fig. 3d. This is implemented by re-composition of the
TABLE II: Performance of GAN data augmentation approaches on various sizes of expanded training data before and after LHUC-SAT speaker adaptation on the UASpeech [48] test set of 16 dysarthric speakers. “6M” and “19M” refer to the number of model parameters. “CTRL” in the “Data Augmentation” column stand for dysarthric speaker dependent transformation of control speech during data augmentation using from left to right: temporal or speed perturbation in “T” and “S”; “TG” and “SG” denote the tempo-GAN and speed-GAN models of Sec. III “SBG” stands for the spectral basis GAN of Sec. IV and “SBG+SG” denotes spectral basis GAN perturbed normal speech being further transformed using speed-GAN. “VL/JM/H” refers to intelligibility subgroups (Very Low / Low / Medium / High). “DYS” column denotes speaker independent speed perturbation of dysarthric speech. † and * denote statistically significant improvements ($\alpha = 0.05$) are obtained over the comparable baseline systems with tempo perturbation (Sys. 2, 8, 14, 21) or speed perturbation (Sys. 3, 9, 15, 22) respectively.

| Sys | Model (Parameter) | Data Augmentation | # Has | WER % (Unadapted) | WER % (LHUC-SAT Adapted) |
|-----|------------------|-------------------|-------|-------------------|------------------------|
|     |                  |                   |       | VL M H Avg        | VL M H Avg             |
| 1   |                  |                   | 30.6  | 70.78 42.82 36.47 | 25.86 41.81            |
| 2   | 1x               |                   | 50.2  | 64.50 32.11 23.06 | 13.13 30.77            |
| 3   | 1x               |                   |       | 63.80 32.61 25.16 | 16.35 31.25            |
| 4   | 1x               |                   |       | 62.89 32.61 22.67 | 13.88 30.62            |
| 5   | 1x               |                   |       | 64.37 31.78 23.88 | 13.64 31.03            |
| 6   | 1x               |                   |       | 63.30 32.20 23.90 | 13.03 30.73            |
| 7   | 1x               |                   |       | 66.26 30.25 23.84 | 13.68 30.28            |
| 8   | 1x               |                   | 87.5  | 60.77 30.57 23.45 | 13.86 29.91            |
| 9   | 1x               |                   |       | 60.86 30.81 22.86 | 13.14 29.65            |
| 10  | 1x               |                   |       | 63.01 31.05 23.10 | 13.19 30.26            |
| 11  | 1x               |                   |       | 61.35 30.73 22.14 | 12.78 29.49            |
| 12  | 1x               |                   |       | 60.50 29.82 24.31 | 13.27 28.41            |
| 13  | 1x               |                   |       | 57.84 29.66 24.05 | 13.28 28.09            |
| 14  | 1x               |                   |       | 60.72 29.69 24.10 | 13.24 27.84            |
| 15  | 1x               |                   |       | 58.76 29.74 23.53 | 13.19 27.63            |
| 16  | 2x               |                   | 130.1 | 79.26 33.97 23.12 | 13.13 30.56            |
| 17  | 2x               |                   |       | 66.77 49.39 46.47 | 42.02 50.03            |
| 18  | 2x               |                   |       | 84.81 46.56 24.39 | 42.26 49.70            |
| 19  | 2x               |                   |       | 65.16 48.30 46.64 | 44.61 49.53            |
| 20  |                  |                   | 30.6  | 65.34 47.87 46.54 | 41.98 49.33            |
| 21  | 2x               |                   | 130.1 | 79.26 33.97 23.12 | 13.13 30.56            |
| 22  | 2x               |                   |       | 66.77 49.39 46.47 | 42.02 50.03            |
| 23  | 2x               |                   |       | 84.81 46.56 24.39 | 42.26 49.70            |
| 24  | 2x               |                   |       | 65.16 48.30 46.64 | 44.61 49.53            |
| 25  | 2x               |                   |       | 65.34 47.87 46.54 | 41.98 49.33            |
| 26  |                  |                   |       | 65.34 47.87 46.54 | 41.98 49.33            |

TABLE III: A comparison between published systems on UASpeech and our system. “DA” stands for data augmentation. “L”, “VL” and “Avg” represent WER (%) for low, very low intelligibility group and average WER.

| Systems | WER VL | WER VL | Avg |
|---------|--------|--------|-----|
| CUHK-2018 DNN System Combination [11] | 30.60 |
| Sheffield-2019 Kaldi DNN + DA [70] | 67.83 |
| Sheffield-2020 Fine-tuning CNN-TDNN speaker adaptation [32] | 68.24 |
| CUHK-2020 DNN + DA + LHUC-SAT [15] | 62.44 |
| CUHK-2021 LAS + CTC + Meta Learning + SAT [37] | 60.70 |
| CUHK-2021 QuartzNet + CTC + Meta Learning + SAT [37] | 69.30 |
| CUHK-2021 DNN + DCGAN + LHUC-SAT [110] | 61.42 |
| CUHK-2021 DA + SBE Adapt + LHUC-SAT [125] | 59.83 |
| TDNN + spectral basis GAN + LHUC-SAT (Sys. III) [11] | 59.18 |

V. EXPERIMENTS

In this experiment section, the performance of the proposed adversarial data augmentation approaches of Sec. III and Sec. IV are investigated on four tasks: the English UASpeech [48] and TORG0 [50] dysarthric speech corpora as well as the English DementiaBank Pitt [51] and Cantonese JCCOCC MoCA [59] elderly speech datasets. The baseline data augmentation method features both the standard speaker independent speed perturbation [63] of dysarthric or elderly speech and speaker dependent speed perturbation of control healthy or non-aged speech following our previous works [14], [15], [33], for all four tasks. A range of acoustic models that give state-of-the-art performance on these tasks are chosen as the baseline speech recognition systems, including hybrid lattice-free maximum mutual information (LF-MMI) trained time delay neural network (TDNN) [8], [4] and end-to-end (E2E) Conformer [7] models using additional online data augmentation via SpecAugment [65]. Model based speaker adaptation using learning hidden unit contribution (LHUC) [124] is further applied. Sec. V-A presents the experiments on the two dysarthric speech corpora while Sec. V-B introduces experiments on the two elderly speech datasets. For all the speech recognition results measured in word error rate (WER) presented in this paper, matched pairs sentence-segment word error (MAPSSWE) based statistical significance test [125] is performed at a significance level $\alpha = 0.05$.

A. Experiments on Dysarthric Speech

1) the UASpeech Corpus: The UASpeech corpus is the largest publicly available and widely used dysarthric speech...
dataset [43]. It is an isolated word recognition task containing approximately 103 hours of speech recorded from 29 speakers, among whom 16 are dysarthric speakers and 13 are control healthy speakers. It is further divided into 3 blocks Block 1 (B1), Block 2 (B2) and Block 3 (B3) per speaker, each containing the same set of 155 common words and a different set of 100 uncommon words. The data from B1 and B3 of all the 29 speakers are treated as the training set which contains 69.1 hours of audio and 99195 utterances in total, while the data from B2 collected of all the 16 dysarthric speakers (excluding speech from control healthy speakers) are used as the test set containing 22.6 hours of audio and 26520 utterances in total.

After removing excessive silence at both ends of the speech audio segments using an HTK [116] trained GMM-HMM system, a combined total of 30.6 hours of audio data from B1 and B3 (99195 utterances) are used as the training set, while 9 hours of speech from B2 (26520 utterances) are used for performance evaluation. Data augmentation featuring speed perturbation of both the dysarthric speech in a speaker independent manner [63], and the control healthy speech in a dysarthric speaker dependent fashion is further conducted [15] to produce a 130.1 hours augmented training set (399110 utterances, perturbing both healthy and dysarthric speech). If perturbing dysarthric data only, the resulting augmented training set contains 65.9 hours of speech (204765 utterances).

2) the TORGO Corpus: The TORGO [50] corpus is a dysarthric speech dataset containing 8 dysarthric and 7 control healthy speakers with a total of approximately 13.5 hours of audio data (16394 utterances). It consists of two parts: 5.8 hours of short sentence based utterances and 7.7 hours of single word based utterances. Similar to the setting of the UASpeech corpus, a speaker-level data partition is conducted by combining all 7 control healthy speakers’ data and two-thirds of the 8 dysarthric speakers’ data into the training set (11.7 hours). The remaining one-third of the dysarthric speech is used for evaluation (1.8 hours). After removal of excessive silence, the training and test set contain 6.5 hours (14541 utterances) and 1 hour (1892 utterances) of speech respectively. After data augmentation with both speaker dependent and speaker independent speed perturbation [15], [126], the augmented training set contains 34.1 hours of data (61813 utterances).

3) Baseline ASR System Description: For the UASpeech dataset, hybrid LF-MMI factored time delay neural network (TDNN) systems [3, 4] containing 7 context slicing layers are trained following the Kaldi [127] chain system setup, except that i-Vector features are not incorporated. The end-to-end (E2E) Conformer systems are implemented using the ESPnet toolkit [128] to directly model grapheme (letter) sequence outputs. 80-dimensional Mel-scale filter-bank input features are used in the E2E Conformer systems, while 40-dimensional Mel-scale filter-bank input features and a 3-frame context window is used in the hybrid TDNN system. Following the configurations given in [8, 11], a uniform language model with a word grammar network is used in decoding.

| Sys. | Model (# Parameters) | Data Aug. | # Hrs. | LHUC-SAT | WER % |
|------|---------------------|-----------|--------|----------|-------|
| 1    | (18M)               | CTRL      | 6.5    | 16.22    | 3.87  |
| 2    | Hybrid TDNN (10M)   | S         |        | 12.80    | 8.78  |
| 3    |                     | SG        |        | 13.90    | 5.31  |
| 4    |                     | SBG       |        | 13.29    | 5.82  |
| 5    |                     | SBG+SG    | ✓      | 12.93    | 2.86  |
| 6    |                     | S         |        | 12.52    | 8.27  |
| 7    |                     | SG        |        | 13.90    | 5.00  |
| 8    |                     | SBG       | ✓      | 13.66    | 4.90  |
| 9    |                     | SBG+SG    | ✓      | 12.97    | 5.00  |
| 10   | Conformer           | S         |        | 21.66    | 6.22  |
| 11   | sSpec/Augment (18M) | S         |        | 20.04    | 6.63  |
| 12   |                     | SG        |        | 20.00    | 6.32  |
| 13   |                     | SBG+SG    | ✓      | 20.44    | 5.81  |

Table IV: Performance of GAN data augmentation approaches on expanded training data before and after LHUC-SAT speaker adaptation on the TORGO [50] test set. “SE./MOD./Mild” refers to the speech impairment severity levels: severe, moderate and mild. † denotes a statistically significant improvement ($\alpha = 0.05$) obtained over the comparable baseline systems (Sys. 2, 6, 10). Other naming conventions are the same as those in Tab. II for UASpeech.

8 encoder layers + 4 decoder layers, feed-forward layer dim = 1024, attention heads = 4, dim of attention heads = 256, interpolated CTC+AED cost.
B. Experiments on Elderly Speech

1) The DementiaBank Pitt Corpus: The DementiaBank Pitt corpus contains approximately 33 hours of audio data recorded over interviews between the 292 elderly participants and the clinical investigators. It is further split into a 27.2h training set, a 4.8h development and a 1.1h evaluation set for ASR system development. The evaluation set is based on exactly the same 48 speakers’ Cookie (picture description) task recordings as those in the ADReSS test set, while the development set contains the remaining recordings of these speakers in other tasks if available. The training set contains 688 speakers (244 elderly participants and 444 investigators), while the development set includes 119 speakers (43 elderly participants and 76 investigators) and the evaluation set contains 95 speakers (48 elderly participants and 47 investigators). Different sets of speakers are used in the training, development and evaluation sets. After removal of excessive silence, the training set contains 15.7 hours of audio data (29682 utterances) while the development and evaluation sets contain 2.5 hours (5103 utterances) and 0.6 hours (928 utterances) of audio data respectively. Data augmentation featuring speaker independent speed perturbation of elderly speech and elderly speaker dependent speed perturbation of non-aged investigators’ speech produced a 58.9h augmented training set (112830 utterances).

2) The JCCOCC MoCA Corpus: The Cantonese JCCOCC MoCA corpus contains conversations recorded from cognitive impairment assessment interviews between 256 elderly participants and the clinical investigators. The training set contains 369 speakers (158 elderly participants and 211 investigators) with a duration of 32.4 hours. The development and evaluation sets each contains speech recorded from two different sets of 49 elderly speakers that are not covered by the training set. After removal of excessive silence, the training set contains 32.1 hours of speech (95448 utterances) while the development and evaluation sets contain 3.5 hours (13675 utterances) and 3.4 hours (13414 utterances) of speech respectively. After applying the same baseline speaker independent and dependent speed perturbation based data augmentation adopted above for the DementiaBank Pitt corpus, the expanded training set consists of 156.9 hours of speech (389409 utterances). Different sets of speakers are used in the training, development and evaluation sets.

3) Baseline ASR System Description: The hybrid LF-MMI TDNN and E2E graphemic Conformer systems use the same configurations as those adopted above for the UASpeech data, except that 40-dimensional Mel-scale filter-bank input features are used. On the English DementiaBank data, for both the hybrid TDNN and E2E graphemic Conformer systems, a word level 4-gram LM with Kneser-Ney smoothing is trained using the SRILM toolkit following the settings of our previous work and a 3.8k word recognition vocabulary covering all the words in the DementiaBank Pitt corpus is used in recognition. On the Cantonese JCCOCC MoCA data, the Conformer model training used Cantonese Characters as the output targets. A word level 4-gram language model with Kneser-Ney smoothing is trained on the acoustic transcription.
TABLE V: Performance of spectral basis GAN based data augmentation approaches on the expanded training data before and after LHUC-SAT speaker adaptation on the DementiaBank Pitt corpus [51] development (Dev) and evaluating (Eval) set. “INV” and “PAR” in the “Data Augmentation” column refer to non-aged clinical investigator and elderly participant respectively. In the “INV” column, “S” denotes speed perturbation and “SBG” stands for spectral basis GAN. “rand”, “avg” and “exhaustive” stand for the three spectral basis vectors pairing schemes between investigator and elderly speech in GAN training described in Sec. IV-B. Speaker independent speed perturbation is applied to elderly speech. † denotes a statistically significant improvement (α = 0.05) obtained over the comparable baseline systems (Sys. 3, 7, 11).

| Sys. | Model (# Parameters) | Data Augmentation | # Hrs. | LHUC SAT | WER % |
|------|---------------------|-------------------|--------|----------|-------|
|      |                     | INV | PAR |       | Dev. | Eval | INV | PAR | INV | PAR | Avg. |
| 1    |                     | -   | -   | 15.8  | 21.45 | 51.38 | 21.09 | 39.49 | 36.31 |
| 2    | Hybrid TDNN (18M)   | -   | -   | 15.8  | 21.03 | 50.28 | 21.75 | 38.46 | 35.55 |
| 3    |                     |      |     |       | 19.91 | 47.93 | 19.76 | 36.66 | 33.80 |
| 4    | SBG (rand)          |      |     |       | 19.27±0.16 | 45.28±0.55 | 18.95±0.55 | 34.20±0.30 | 32.16±0.20 |
| 5    | SBG (avg)           |      |     |       | 19.25 | 44.93 | 19.09 | 34.31 | 31.93†|
| 6    | SBG (exhaustive)    | ✓   |     | 58.9  | 19.41 | 46.13 | 19.42 | 35.02 | 32.60†|
| 7    |                     | ✓   |     | 58.9  | 18.66±0.01 | 45.14±0.00 | 19.31±0.04 | 34.12±0.01 | 31.75±0.00 |
| 8    |                     | ✓   |     | 58.9  | 18.62 | 44.88 | 18.65 | 34.08 | 31.60†|
| 9    |                     | ✓   |     | 58.9  | 18.68 | 45.33 | 19.20 | 34.22 | 31.85†|
| 10   |                     |      |     |       | 22.88 | 47.64 | 19.87 | 36.22 | 34.80 |
| 11   | Conformer           |      |     |       | 20.80 | 47.85 | 19.96 | 36.09 | 34.00 |
| 12   | +SpecAugment (52M)  | S   |     |       | 22.23±0.06 | 45.22±0.02 | 20.05±0.04 | 35.06±0.01 | 33.42±0.03 |
| 13   |                     |      |     |       | 21.85 | 46.29† | 19.42 | 34.97 | 33.65 |
| 14   | SBG (exhaustive)    |      |     |       | 22.83 | 47.64 | 19.87 | 36.22 | 34.80 |

TABLE VI: Ablation study on the effect of using different settings of the spectral basis GAN output perturbation scaling parameter λ of Sec. IV-C on the DementiaBank Pitt corpus [51] with 58.9h augmented training data. Naming conventions are the same as those in Tab. V.

| λ    | Dev. | Eval | Avg. |
|------|------|------|------|
| 0.001| 19.75 | 46.84 | 19.64 | 34.85 | 33.00 |
| 0.01 | 19.35 | 45.78 | 18.20 | 34.34 | 32.27 |
| 0.1  | 19.52 | 46.58 | 19.87 | 34.71 | 32.79 |
| 0.2  | 19.25 | 44.93 | 19.09 | 34.31 | 31.93†|
| 1    | 19.10 | 45.70 | 18.76 | 33.49 | 32.03 |
| 2    | 19.23 | 45.67 | 18.87 | 34.20 | 32.19 |
| 5    | 19.71 | 45.99 | 17.87 | 34.39 | 32.51 |

(610k words) and a 5.2k recognition vocabulary covering all the words in the JCCOCC MoCA corpus is also used.

4) Performance of Data Augmentation on Elderly Speech: The performance of various spectral basis GAN (SBG) based augmentation approaches proposed in Sec. IV for non-parallel data are evaluated on the DementiaBank Pitt test set is shown in Tab. V. First, the following trends can be found from Tab. V on the hybrid TDNN systems:

i) Before LHUC-SAT speaker adaptation is applied, all the three SBD based data augmentation approaches with three different spectral bases pairing schemes between non-aged investigator and elderly participant speech described in Sec. III-A consistently outperform the comparable baseline TDNN system using both speaker independent and dependent speed perturbation (Sys. 4, 5, 6 vs. 3). Among these three pairing schemes, using the average, mean spectral bases computed over all the target elderly speaker’s utterances (Sys. 5, “SBG (avg)” as the GAN training targets gives the largest improvement by up to 1.87% absolute (5.53% relative) average WER reduction (Sys. 5 vs. 3, last col.). More specifically, on the two elderly speech “PAR” subsets statistically significant WER reductions of 2.35%-3.0% absolute (6.3%-6.4% relative) are obtained over the baseline speed perturbation (Sys. 5 vs. 3, col. 8 & 10). For the SGB systems using a random pairing (Sys. 4, 8, “SBG (rand)”), a total of 10 TDNN systems are trained using 10 different investigator-participant utterance spectral bases pairing before computing both the WER mean and standard deviation (shown after “±”).

ii) When further combined with LHUC-SAT speaker adaptation, the three systems trained with spectral basis GAN based augmentation again consistently outperform the baseline with speed perturbation only (Sys. 8, 9, 10 vs. 7) by up to 0.73% absolute (2.26% relative) average WER reduction (Sys. 9 vs. 7, last col.). The reduced performance gap between the baseline system using speed perturbation and those using spectral basis GANs after LHUC-SAT adaptation suggest the GAN augmented data produced better coverage of speaker level heterogeneity in the speaker independent TDNN system training before adaptation to unseen speakers in the test data, but not covered in the DementiaBank Pitt training data set.

iii) A further ablation study on the effect of using different settings of the spectral basis GAN output perturbation scaling parameter λ of Sec. III-B is then conducted using the “SBG (avg)” augmented TDNN systems and their performance are shown in Tab. VI. An optimal setting of λ = 0.2 is used in all the experiments of Tab. V and the following Cantonese elderly speech experiments of Tab. VII.

Second, on the Conformer systems, the proposed spectral basis GAN trained using the randomly paired spectral bases “SBG (rand)” and mean spectral bases “SBG (mean)” outperform the baseline speed perturbation method (Sys. 12, 13 vs. 11) by up to 0.58% absolute (1.7% relative) CER deduction (Sys. 12 vs. 11). Among the two GAN augmented Conformer systems (Sys. 12 & 13), the spectral basis GAN trained using the randomly paired spectral bases of target elderly speaker (Sys. 12, “SBG (rand)”) as the GAN training targets produces the lowest average CER of 33.42%.

A similar set of experiments are then conducted using the
TABLE VII: Performance of spectral basis GAN based data augmentation approaches on the expanded training data before and after LHUC-SAT speaker adaptation on the JCCOCC MoCa corpus \(^5\) development (Dev.) and evaluation (Eval) sets containing elderly speakers only; \(\dagger\) denotes a statistically significant improvement (\(\alpha = 0.05\)) obtained over the comparable baseline systems (Sys. 3, 6, 9). Other naming conventions are the same as those in Tab. 7 for the DementiaBank Pitt data.

| Sys. | Model (# Parameters) | Data Aug. | Hrs. | LHUC SAT | CER % | Eval | Avg |
|------|----------------------|-----------|------|---------|-------|------|-----|
| 1    | -                    | INV       | 32.1 | 30.80   | 27.85 | 29.36 |     |
| 2    | -                    | INV       | 32.1 | 30.05   | 27.34 | 28.69 |     |
| 3    | -                    | INV       | 32.1 | 24.71   | 22.86 | 24.00 |     |
| 4    | Hybrid TDNN (16M)    | S         | 156.9| 26.98\(\dagger\) | 22.86\(\dagger\) | 24.00\(\dagger\) |     |
| 5    | SBG (rand)           | SBG (avg) | 156.9| 25.71   | 22.94 | 24.35 |     |
| 6    | SBG (rand)           | SBG (avg) | 156.9| 24.69\(\dagger\) | 22.06\(\dagger\) | 23.44\(\dagger\) |     |
| 7    | SBG (avg)            |           |      | 24.69\(\dagger\) |       |       |     |
| 8    | SBG (avg)            |           |      | 22.05\(\dagger\) |       |       |     |
| 9    | Conformer            | S         | 156.9| 33.08   | 31.24 | 32.15 |     |
| 10   | SpecAugment (53M)    | SBG (rand) |      | 32.18\(\dagger\) | 30.28\(\dagger\) | 31.27\(\dagger\) |     |
| 11   | Conformer            | SBG (avg) |      | 31.78\(\dagger\) | 30.35\(\dagger\) | 31.06\(\dagger\) |     |

Cantonese JCCOCC MoCa data and are shown in Tab. VII. Several trends similar to those observed on the DementiaBank Pitt data of Tab. VII can be found.

**i)** The SBG based data augmentation approaches using either the mean of, or randomly selected, target elderly speaker’s utterance level spectral bases in training consistently outperform the baseline TDNN system using speed perturbation (Sys. 4, 5 vs. 3) by up to 0.92% absolute (3.64% relative) average character error rate (CER) reduction (Sys. 5 vs. 3, last col.);  
**ii)** When further applying LHUC-SAT speaker adaptation, the same two systems trained with SBG augmentation again outperform the baseline system with speed perturbation (Sys. 7, 8 vs. 6) by up to 0.95% absolute (3.90% relative) average CER reduction (Sys. 8 vs. 6, last col.);  
**iii)** The proposed spectral basis GAN augmentation also outperform the speed perturbation method on the Conformer systems (Sys. 10, 11 vs. 9) by up to 1.0% absolute (3.39% relative) statistically significant CER reduction (Sys. 11 vs. 9, last col.). Among the two GAN augmented Conformer systems, the spectral basis GAN trained using the mean spectral bases of each elderly speaker (Sys. 11, “SBG (avg)”) produces the lowest CER of 31.06%.

**VI. CONCLUSION**

This paper presents a set of speaker dependent generative adversarial networks (GAN) based data augmentation approaches for dysarthric and elderly speech recognition tasks. These personalized adversarial data augmentation approaches can flexibly expand the limited amounts of dysarthric or elderly training data that traditionally hinders ASR system development for these atypical speech domains with or without the use of parallel audio recordings. Experimental results obtained on state-of-the-art hybrid TDNN and end-to-end Conformer ASR systems evaluated across four dysarthric or elderly speech datasets of two languages suggest improved coverage in the resulting augmented data and model generalisation are obtained over the baseline systems using conventional methods based on tempo or speed perturbation and SpecAug.

Future research will focus on improving adversarial data augmentation techniques to inject richer spectral and temporal characteristics of dysarthric and elderly speech.

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