TOWARDS IDENTITY PRESERVING NORMAL TO DYSARTHRIC VOICE CONVERSION

Wen-Chin Huang\textsuperscript{1}*, Bence Mark Halpern\textsuperscript{2,3,4}*, Lester Phillip Violeta\textsuperscript{1}, Odette Scharenborg\textsuperscript{2}, Tomoki Toda\textsuperscript{1}

\textsuperscript{1}Nagoya University, Japan
\textsuperscript{2}Multimedia Computing Group, Delft University of Technology, Delft, The Netherlands
\textsuperscript{3}University of Amsterdam, Amsterdam, The Netherlands
\textsuperscript{4}Netherlands Cancer Institute, Amsterdam, The Netherlands

ABSTRACT

We present a voice conversion framework that converts normal speech into dysarthric speech while preserving the speaker identity. Such a framework is essential for (1) clinical decision making processes and alleviation of patient stress, (2) data augmentation for dysarthric speech recognition. This is an especially challenging task since the converted samples should capture the severity of dysarthric speech while being highly natural and possessing the speaker identity of the normal speaker. To this end, we adopted a two-stage framework, which consists of a sequence-to-sequence model and a nonparallel frame-wise model. Objective and subjective evaluations were conducted on the UASpeech dataset, and results showed that the method was able to yield reasonable naturalness and capture severity aspects of the pathological speech. On the other hand, the similarity to the normal source speaker’s voice was limited and requires further improvements.

Index Terms— voice conversion, pathological speech, dysarthric speech, sequence-to-sequence modeling, autoencoder

1. INTRODUCTION

Neural voice conversion (VC) has substantially improved the naturalness of synthesized speech in a wide range of tasks, including read speech [1], emotional speech [2] and whispered speech [3]. However, pathological VC (and TTS too) is a largely unexplored area, which has several interesting applications. In this work, we focus on normal-to-dysarthric (N2D) VC, which refers to the task of converting normal speech to dysarthric speech. N2D VC could be applied in informed decision making related to the medical conditions at the root of the speech pathology. For instance, an oral cancer surgery results in changes to a speaker’s voice. The availability of a VC model that can generate how the voice could sound after surgery could help the patients and clinicians make informed decisions about the surgery and alleviate the stress of the patients. Another application is the improvement of automatic speech recognition (ASR) by augmenting the training dataset with additional pathological data. Such augmentation could ease the low-resource constraints of a pathological ASR task.

In addition to the requirements for conventional VC, N2D VC has its own unique requirements, each corresponding to one research question:

RQ1: Do the converted samples sound as natural as real dysarthric samples? Naturalness is a basic requirement in all speech synthesis tasks, but it becomes challenging under the con- text of N2D VC because listeners seem to confuse naturalness and severity [4].

RQ2: Is the VC model able to retain the speaker identity of the source normal speaker? Since it is often impossible to collect ground truth pathological speech data of a normal source speaker, training a VC model that directly maps a normal source speech to its pathological counterpart is infeasible. Thus, specific techniques need to be developed to tackle this issue. In addition, evaluation of similarity is hard because listeners have to determine the similarity of a converted pathological speech to the source speaker while having access to only a normal speech of him/her.

RQ3: Is the VC model able to model severity characteristics in a linear way, so that expert listeners perceive more severe samples as more severe? As the condition of patients deteriorates, the severity of the patient’s voice will increase. To capture the progress, it is essential to correctly model the severity of the converted speech. This requires modifying specific attributes of speech, such as speaking rate and insertion of pauses.

In this work, we aim to create an identity preserving N2D VC system. The key advantage of this approach is that it allows arbitrary inputs from the source normal speaker, while preserving its identity. The aim of this work is to evaluate the model in a more practical setting than [4] by taking normal speech as input, which alleviates the need of maintaining a pathological voice bank described there. Inspired by [5], the proposed method is a two-stage approach, as depicted in Figure 1. In the first stage, to capture the unique temporal structure of dysarthric speech, we adopt the Voice Transformer Network (VTN) [1,7], a sequence-to-sequence (seq2seq) VC model based on the Transformer [8] architecture. The converted speech at
this stage has the characteristics of dysarthric speech, with an un-
wanted speaker identity of the reference dysarthric speaker. Then,
the normal source speaker identity is restored through a frame-by-
frame autoencoder-based VC model [9], which is assumed to be able
to preserve local speech attributes related to dysarthria. We evaluated
the proposed method on UASpeech [10], and the method achieves
good naturalness results, is able to mimic the severity of pathologi-
cal speech according to three speech language pathologists, while
having limited ability to preserve the source speaker’s characteris-
tics.

2. RELATED WORKS

2.1. Normal-to-dysarthric VC for data augmentation in ASR

Previous research on data augmentation for dysarthric speech has
shown promising improvements in ASR word error rates. The main-
stream is to use frame-wise models such as deep convolutional gen-
eral adversarial networks (DCGANs) [11] or Transformer Encoders
[12] to convert the speech timbre. As these models do not change
the length, extra procedures are needed to change the speaking rate,
including speed perturbation [11] or dynamic time warping [12].

There are several downsides to this line of work. As ASR only
requires the various dysarthric features to be modeled, the speaker
identity of the normal speaker is not retained after conversion. Also,
no evaluation methods were conducted to measure the severity of
the samples, which means that it was not verified whether the pro-
posed methods were truly able to model the dysarthric features well.
In this work, we use a seq2seq model to jointly convert the timbre
and speaking rate, which was shown to be more effective than con-
verting them separately in conventional VC [13]. We also address
the identity preservation issue with the proposed two-stage approach
and conduct subjective evaluations to verify if the severity is indeed
modeled.

2.2. Normal-to-dysarthric VC for clinical usage

There are two previous works that focus on VC for clinical usage.
The diagram on the left of Figure 1a depicts an N2D VC system
presented in [5], which was a combination of a CycleGAN-based
frame-wise VC model and a PSOLA-based speech rate modification
process. This method suffers from the same issues as those in
Section 2.1 including audible vocoder artifacts brought by the extra
PSOLA operation, and the inability to preserve the speaker identity
of the control speaker.

A different work [4] is depicted on the righthand side of Figure
1a. The authors focused on dysarthric-to-dysarthric VC, by us-
ing a frame-wise VC model called HL-VQ-VAE [14]. However, the
setup was not flexible in that (1) a severity-matched VC setup was
required to avoid the need of varying speech rates, and (2) the method
required a pathological source utterance, wherein real-world applica-
tions we might want to synthesize an arbitrary utterance from the
normal source speaker.

3. PROPOSED FRAMEWORK

Given a speech sample from a normal speaker, N2D VC aims to
change the characteristics into that of a dysarthric speech, while pre-
serving the speaker identity of the source normal speaker. In the
following subsections, we describe the two components, the parallel
seq2seq model and the nonparallel frame-wise model, of our pro-
posed two-stage approach for N2D VC in detail.

3.1. Many-to-one seq2seq modeling

The goal in the first stage is to completely capture the characteris-
tics of the dysarthric speech. Following [6], we adopted the VTN [1]
[7], a Transformer-based [8] seq2seq model tailored for VC. When a
parallel corpus is available, seq2seq modeling is considered state-of-
the-art due to its ability to convert the prosodic structures in speech,
which is critical in N2D VC. However, collecting a parallel corpus is
especially difficult in our case since it is impractical (almost not feasible)
to collect a large amount of data from dysarthric patients. To solve the
data scarcity problem, we applied two techniques, as described below.

First, a TTS pretraining technique is applied which facilitates the
core ability of a seq2seq VC model, i.e., encode linguistic-rich hid-
den representations by pretraining using a large-scale TTS dataset [11]
[7]. This technique is flexible in that the VC corpus and the pretrain-
ing TTS dataset can be completely different in terms of speaker and
content, even when trained between normal and dysarthric speakers.
In [6], it was shown that training using only 15 minutes of speech
from each speaker can yield good results.

Second, we trained the VTN in a many-to-one (referred to as
M2O) fashion. Considering that it is easier to collect data from nor-
mal speakers rather than patients, we assume that apart from the data
of the source normal speaker, we also have access to a set of parallel
training set from multiple normal speakers. Given a training utter-
ance from any of the normal speakers, the VTN model is trained to
convert to the predefined target dysarthric speaker. M2O training
was also used in [14], except they used an auxiliary phoneme
recognition regularization loss.

3.2. Nonparallel frame-wise model

In the second stage, given the converted dysarthric speech, the goal
is to restore the identity of the source normal speaker while pre-
serving the dysarthric attributes. We adopted the same assumption
as in [6]: a nonparallel frame-wise VC model changes only time-
variant characteristics such as the speaker identity, while preserv-
ing time-invariant characteristics, such as the pronunciation. As in [6],
we used crank [9], an open-source VC software that combines re-
cent advances in VQVAE [15]-based VC methods, including the use
of hierarchical architectures, cyclic loss and adversarial training,
to carry out the conversion of the speaker identity step. For the remain-
der of this paper, we refer to this model as VAE for short.

4. EXPERIMENTAL SETUP

4.1. Dataset

We used the UASpeech dataset [10], which contains parallel word
recordings of 15 dysarthric speakers and 13 normal control speakers.
The training and test set consist of 510 and 255 utterances, respec-
tively. Each dysarthric speaker is categorized to one of three intelli-
gibility groups: low, mid, and high, which correspond to 0 – 25%,
25 – 75%, and 75 – 100% subjective human transcription error rate
(STER). The intelligibility of each speaker was judged by 5 non-
expert American English native speakers. We chose two dysarthric
speakers from each intelligibility group (high: M08, M10; mid:
M05, M11; low: M04, M12) as test speakers for VC. For each
dysarthric speaker, a separate VTN was trained using the data of that
speaker and all control speakers. For the VAE model, in our prelimi-
nary experiments, we found that it was crucial to train with only the
normal data rather than training with a mix of dysarthric and normal
datasets. We thus used data from the 13 control speakers only.
4.2. Implementation

The implementation of the VTN (the left rounded rectangle in Figure 4.2) was based on the open-source toolkit ESPNet [17][18]. The detailed configuration can be found online[3]. The TTS pretraining was conducted with M-AILABS judy [19], which was 31 hr long. Parallel WaveGAN (PWG) [20] was used as the neural vocoder. We followed an open-source implementation[4]. The training data of PWG contained the audio recordings of all control speakers in UASpeech.

4.3. Objective evaluation metrics

The speech sample outputs of the two stages (VTN, VTN-VAE) are separately evaluated using the metrics described in this section, whenever the evaluation does not require ground truth. In this evaluation, we considered conversion pairs between all 13 normal source speakers and the 6 dysarthric speakers mentioned in Section 4.1.

4.3.1. P-ESTOI/P-STOI

P-ESTOI/P-STOI were previously demonstrated to work well for the objective evaluation of dysarthric speech [21]. These methods focus on quantifying distortion in the time-frequency structure of the speech signal, which is related to severity and naturalness (RQ1 and RQ3). In short, we used multiple gender-specific ground truth control utterances to form a reference utterance. By calculating the frame-level cross-correlation of each pathological utterance with the reference utterance, we obtain an utterance-level P-ESTOI/P-STOI score. Taking the mean of each utterance-level score, we obtain a speaker-level score, which is correlated with the STER scores for the six speakers to obtain $T_{GT}$. This is repeated with the ground truth speakers to obtain $T_{GT}$.

4.3.2. Phoneme error rate

The phoneme error rate (PER) calculated with a phoneme recognizer evaluates the intelligibility, which is also related to severity and naturalness (RQ1 and RQ3). We use a pre-trained Kaldi ASR model with the same specifications as the one used in [22] for phoneme recognition. The ASR was trained with the TIMIT dataset and used an HMM acoustic model. The TIMIT corpus is an English read speech corpus specifically designed for acoustic-phonetic studies [23]. To measure the PER, we require phonemic transcriptions of the UASpeech utterances (reference). We used g2p-e[5] for grapheme-to-phoneme conversion. The reference is compared to the VC utterances transcribed by the trained ASR.

4.4. Subjective evaluation protocols

Subjective evaluation was carried out by naive listeners to assess the naturalness and similarity of samples (RQ1, RQ2). An additional evaluation was done by expert listeners to assess severity (RQ3). Contrary to the objective evaluations, we did not consider all conversion pairs (due to constraints in time and budget). Audio samples can be found online[6].

4.4.1. Severity

We designed an AB evaluation study for evaluating severity (RQ3). In the study, 3 trained speech-language pathologists (SLPs) were asked to listen to two different synthesized utterances from two unknown speakers whom have different speech severity and select the synthesized speech sample that they perceived as being more pathological. We used four speaker pairs (see Table 4), two for each severity level. For each speaker pair, 20 utterances were rated. After rating the synthesized pathological speech samples, the experiment was repeated with the ground truth samples – as a control for cases where we observe a reversal in the expected severity judgment in the VC speech samples. So, in total, each SLP was asked to rate 80 utterances. A binomial test is performed to calculate significance.

4.4.2. Naturalness

In order to evaluate naturalness (RQ1), we followed the setup in [4] with a few modifications based on our previous findings. In our previous study, listeners rated the severity of the speech samples (instead of the naturalness) on a 5-point mean opinion score (MOS) scale. The results showed a flooring effect. Therefore, in this experiment, we increase the resolution of the MOS-scale to have increments of 0.5. The questionnaire starts with an explanation of what we mean with naturalness, followed by an example of natural, normal and pathological (low severity) speech. The respondents were instructed to rate these both as 5 (highly natural). The stimuli consisted of 13 utterances for both pathological speakers of each severity (low, high, mid), leading to a total of 78 utterances. Subsequently, the experiment was repeated with the ground truth samples. The utterances were rated by 30 native American English listeners. A Wilcoxon signed-rank test is performed to calculate significance.

4.4.3. Similarity of the voice with the source normal speaker

For the similarity (RQ2) evaluation, we follow the protocol in [4]. Listeners are presented a converted sample and a reference sample, and are asked to judge whether the two samples are uttered by the same speaker. In short, the evaluation is AB similarity study where the source speaker is a pathological speaker, the target speaker is the control speaker. The reference speech is either from the source (Similarity to source) or the target (Similarity to target). We selected three pathological speakers (M04, M11, M10) which have deemed to have recognisable characteristics in our previous study [4]. Furthermore, we randomly sampled (without replacement) two control speakers for each pathological speaker. The test were done by 5 naive American English listeners. A binomial test is performed to calculate significance.

5. EVALUATION RESULTS

5.1. Objective evaluations

5.1.1. P-ESTOI/P-ESTOI

The second block of Table[7] summarizes the results of the P-ESTOI/P-ESTOI analyses. In the VTN stage, the obtained correlation between the P-ESTOI/P-ESTOI and the STER are similar to the ones
Table 1: Objective evaluation results.

|        | High       | Mid       | Low       | r_{GT}     |
|--------|------------|-----------|-----------|------------|
| P-STOI VTN | 0.73 ± 0.05 | 0.62 ± 0.06 | 0.58 ± 0.04 | 0.45 ± 0.08 |
| P-ESTOI VTN | 0.37 ± 0.05 | 0.20 ± 0.06 | 0.09 ± 0.04 | 0.08 ± 0.06 |
| P-STOI VTN-VAE | 0.73 ± 0.05 | 0.62 ± 0.06 | 0.63 ± 0.06 | 0.45 ± 0.08 |
| P-ESTOI VTN-VAE | 0.37 ± 0.05 | 0.21 ± 0.09 | 0.12 ± 0.04 | 0.06 ± 0.06 |
| PER VTN | 0.73 ± 0.05 | 0.62 ± 0.06 | 0.63 ± 0.06 | 0.45 ± 0.08 |
| PER VTN-VAE | 0.37 ± 0.05 | 0.21 ± 0.09 | 0.12 ± 0.04 | 0.06 ± 0.06 |
| STER | 0.73 ± 0.05 | 0.62 ± 0.06 | 0.63 ± 0.06 | 0.45 ± 0.08 |

Table 2: Mean opinion score results of the naturalness test with 95% confidence intervals. Columns correspond to the intelligibility level, and rows correspond to ground truth (GT) and synthetic (VC) results. Higher is better.

| Normal | High | Mid | Low | |
|--------|------|-----|-----|---|
| GT     | 3.93 ± .54 | 3.92 ± .54 | 2.86 ± .89 | 2.32 ± 1.16 |
| VC     | 2.70 ± .95  | 2.28 ± 1.03 | 1.94 ± 1.21 | |

One would obtain with the GT (r_{GT}). Therefore, in the VTN stage the severity is well captured. In the VTN-VAE stage, the P-STOI correlation decreases from 0.88 to 0.84, while the P-ESTOI slightly increases from 0.93 to 0.94, which is a bit higher than (r_{GT}). This latter change can be explained as follows: the frame-based VAE model does not change the temporal aspects of the signal but rather the spectral aspects, for which the P-ESTOI has a higher sensitivity.

5.1.2. Phoneme error rate

The VTN PER results in Table 1 show higher correlation with the STER than the GT, which indicates that we can mimic the severity aspects of the pathological speech in the first stage. However, PER VTN-VAE results are decreased compared to the PER VTN. This is probably because the VAE stage causes a naturalness degradation.

5.2. Subjective evaluations

5.2.1. Naturalness

Table 2 shows the MOS results. First, similar to our previous study, we observe that with decreasing intelligibility, naive listeners perceive the heard speech increasingly unnatural – even in the case of ground truth samples. Second, the ground truth samples are consistently rated as more natural than the converted ones (p < 0.001). Although, these results are not directly comparable to [4], we note that we’ve observed overall higher MOS values. We suggest that the use of seq2seq models contributed to this improvement, and such quality is sufficient for further investigation.

5.2.2. Similarity

Table 3 describes the identity preservation ability of the VC framework. We can see that the Similarity to source column has less than 50% similarity for all speaker pairs, therefore we can conclude that the VC can successfully ignore the pathological source speaker’s characteristics. However, we can also see from the Similarity to Target column that (except from the M10→CF03) none of the VC samples have more than 50% similarity to the target. Such results emphasize the “unobtainable ground truth” difficulty faced by the model, as described in Section 4. Meanwhile, this also points out that improving speaker similarity is an important future work, as this problem was also present in [6].

5.2.3. Severity

Table 4 lists the percentage of “correct” answers in the AB severity tests for the ground truth samples and the different stages of the architecture. *** is p < 0.001; * p < 0.05.

6. CONCLUSIONS

In this paper, we proposed a novel two-stage framework for N2D VC. We evaluated the proposed method on UASpeech and the method achieved good naturalness results, was able to mimic the severity characteristics in a linear way according to three speech language pathologists, while being able to convert away from the pathological source speaker’s characteristic. In the future, we will focus on improving the preservation of the normal source speaker identity.

Acknowledgements

We would like to thank Lisette van der Molen, Klaske van Sluis, and Marise Neijman for participating in the severity experiment. All questionnaire participants were remunerated justly (7.50GBP/hour) in each experiment. B.M.H. is funded through the EU’s H2020 research and innovation programme under MSC grant agreement No 766287. The Department of Head and Neck Oncology and Surgery of the Netherlands Cancer Institute receives a research grant from Atos Medical (Hörby, Sweden), which contributes to the existing infrastructure for quality of life research. This work was partly supported by JSPS KAKENHI Grant Number 21J20920, JST CREST Grant Number JPMJCR19A3, and AMED under Grant Number JP21dk0310114, Japan.
7. REFERENCES

[1] W.-C. Huang, T. Hayashi, Y.-C. Wu, H. Kameoka, and T. Toda, “Voice transformer network: Sequence-to-sequence voice conversion using transformer with text-to-speech pretraining,” in Proc. Interspeech, 2020, pp. 4676–4680.

[2] K. Zhou, B. Sisman, and H. Li, “Transforming Spectrum and Prosody for Emotional Voice Conversion with Non-Parallel Training Data,” in Proc. Odyssey, 2020, pp. 230–237.

[3] M. Cotescu, T. Drugman, G. Huybrechts, J. Lorenzo-Trueba, and A. Moinet, “Voice conversion for whispered speech synthesis,” IEEE Signal Processing Letters, vol. 27, pp. 186–190, 2019.

[4] M. Illa, B. M. Halpern, R. van Son, L. Moro-Velazquez, and O. Scharenborg, “Pathological voice adaptation with autoencoder-based voice conversion,” in Proc. SSW11, 2021, pp. 19–24.

[5] B. M. Halpern, J. Fritsch, E. Hermann, R. van Son, O. Scharenborg, and M. M. Doss, “An objective evaluation framework for pathological speech synthesis,” arXiv preprint arXiv:2107.00308, 2021.

[6] W.-C. Huang, K. Kobayashi, Y.-H. Peng, C.-F. Liu, Y. Tsao, H.-M. Wang, and T. Toda, “A Preliminary Study of a Two-Stage Paradigm for Preserving Speaker Identity in Dysarthric Voice Conversion,” in Proc. Interspeech, 2021, pp. 1329–1333.

[7] W. C. Huang, T. Hayashi, Y. C. Wu, H. Kameoka, and T. Toda, “Pretraining techniques for sequence-to-sequence voice conversion,” IEEE/ACM TASLP, vol. 29, pp. 745–755, 2021.

[8] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N Gomez, L. Kaiser, and I. Polosukhin, “Attention is All you Need,” in Proc. NIPS, pp. 5998–6008. 2017.

[9] K. Kobayashi, W.-C. Huang, Y.-C. Wu, P. L. Tobing, T. Hayashi, and T. Toda, “crank: An open-source software for nonparallel voice conversion based on vector-quantized variational autoencoder,” in Proc. ICASSP, 2021, pp. 5934–5938.

[10] H. Kim, M. Hasegawa-Johnson, A. Perlmutter, J. Gunderson, T. S. Huang, K. Watkin, and S. Frame, “Dysarthric speech database for universal access research,” in Proc. Interspeech, 2008, pp. 1741–1744.

[11] Z. Jin, M. Geng, X. Xie, J. Yu, S. Liu, X. Liu, and H. Meng, “Adversarial Data Augmentation for Disordered Speech Recognition,” in Proc. Interspeech 2021, 2021, pp. 4803–4807.

[12] J. Harvill, D. Issa, M. Hasegawa-Johnson, and C. Yoo, “Synthesis of New Words for Improved Dysarthric Speech Recognition on an Expanded Vocabulary,” in Proc. ICASSP, 2021, pp. 6428–6432.

[13] J. Zhang, Z. Ling, L. Liu, Y. Jiang, and L. Dai, “Sequence-to-Sequence Acoustic Modeling for Voice Conversion,” IEEE/ACM TASLP, vol. 27, no. 3, pp. 631–644, 2019.

[14] Tuan V. H. and Masato A., “Non-parallel Voice Conversion based on Hierarchical Latent Embedding Vector Quantized Variational Autoencoder,” in Proc. Joint Workshop for the Blizzard Challenge and Voice Conversion Challenge 2020, 2020, pp. 140–144.

[15] F. Biadsy, R. J. Weiss, P. J. Moreno, D. Kanvesky, and Y. Jia, “Parrottron: An End-to-End Speech-to-Speech Conversion Model and its Applications to Hearing-Impaired Speech and Speech Separation,” in Proc. Interspeech, 2019, pp. 4115–4119.

[16] A. van den Oord, O. Vinyals, and K. Kavukcuoglu, “Neural Discrete Representation Learning,” in Proc. NIPS, 2017, pp. 6309–6318.

[17] S. Watanabe, T. Hori, S. Karita, T. Hayashi, J. Nishitoba, Y. Unno, N. E. Y. Soplin, J. Heymann, M. Wiesner, N. Chen, A. Renduchintala, and T. Ochiai, “ESPnet: End-to-End Speech Processing Toolkit,” in Proc. Interspeech, 2018, pp. 2207–2211.

[18] S. Watanabe, F. Boyer, X. Chang, P. Guo, T. Hayashi, Y. Higuchi, T. Hori, W.-C. Huang, H. Inaguma, N. Kamo, S. Karita, C. Li, J. Shi, A. S. Subramanian, and W. Zhang, “The 2020 ESPnet Update: New Features, Broadened Applications, Performance Improvements, and Future Plans,” in Proc. IEEE Data Science and Learning Workshop (DSLW), 2021, pp. 1–6.

[19] Munich Artificial Intelligence Laboratories GmbH, “The MAILABS speech dataset,” 2019, accessed 30 November 2019.

[20] R. Yamamoto, E. Song, and J. Kim, “Parallel WaveGAN: A fast waveform generation model based on generative adversarial networks with multi-resolution spectrogram,” in Proc. ICASSP, 2020, pp. 6199–6203.

[21] P. Janbakhshi, I. Kodrasi, and H. Bourlard, “Pathological speech intelligibility assessment based on the short-time objective intelligibility measure,” in Proc. ICASSP, 2019, pp. 6405–6409.

[22] M. Purohit, M. Patel, H. Malaviya, A. Patil, M. Parmar, N. Shah, S. Doshi, and H. A Patil, “Intelligibility improvement of dysarthric speech using mnmse discogan,” in International Conference on Signal Processing and Communications (SPCOM), 2020, pp. 1–5.

[23] J. S Garofolo, L. F Lamel, W. M Fisher, Jo. G Fiscus, and D. S Pallett, “DARPA TIMIT acoustic-phonetic continuous speech corpus CD-ROM. NIST speech disc 1-1.1,” NASA STI/Recon technical report n, vol. 93, pp. 27403, 1993.