WHALETRANS: E2E WHIsper to nAturaL spEech conversion using modified TRANSFormer network

Abhishek Niranjan, Mukesh Sharma, Sai Bharath Chandra Gutha, M Ali Basha Shaik

Abstract—In this article, we investigate whispered-to natural-speech conversion method using sequence to sequence generation approach by proposing modified transformer architecture. We investigate different kinds of features such as mel frequency cepstral coefficients (MFCCs) and smoothed spectral features. The network is trained end-to-end (E2E) using supervised approach. We investigate the effectiveness of embedded auxiliary decoder used after N encoder sub-layers, and is trained with the frame level objective function for identifying source phoneme labels. We predict target audio features and generate audio using these for testing. We test on standard wTIMIT dataset and CHAINS dataset. We report results as word-error-rate (WER) generated by using automatic speech recognition (ASR) system and also BLEU scores. In addition, we measure spectral shape of an output speech signal by measuring formant distributions w.r.t the reference speech signal, at frame level. In relation to this aspect, we also found that the whispered-to-natural converted speech formants probability distribution is closer to ground truth distribution. To the authors’ best knowledge, this is the first time transformer with auxiliary decoder has been applied for whispered-to-natural speech conversion. [This pdf is TASLP submission draft version 1.0, 14th April 2020.]

Index Terms—whisper-to-natural speech conversion, whispered speech recognition, sequence-to-sequence framework, transformer.

I. INTRODUCTION

WHISPERED speech is a low-energy pronunciation which does not involve vocal cord vibration. In general, natural speech is not appropriate form of communication in places like libraries, meeting rooms and hence people usually rely on whispered speech for human-human dialogue or human-computer interactions. Mainly, because of privacy and confidential reasons, people sometimes prefer whispered speech for communication in public places as well. In addition to this, whispering is the only form of communication for patients suffering from chronic disease related to larynx structures [1], [2]. In principle, whispered speech is a low-energy signal as there is no vocal cord vibration involved in its production process. Because the signal does not contain the fundamental frequency (F0), whispered speech signals display noise-like characteristics [3]. The energy intensity of a whisper signal is generally 20 dB lower than voiced speech signals and thus the possibility of noise interference is also higher which makes the whisper speech recognition a very challenging problem. In addition, formants are highly displaced (i.e. formant shifts) compared to its corresponding natural speech signal.

Recent times have seen a surge in research on whisper speech communications. Whisper speech recognition have been an area of focus since the visible prominence of voice assistants like Samsung’s Bixby, Google, Amazon’s Alexa etc. In the literature, [4] proposed the usefulness of spectrum sparse-based approach to obtain features for HMM speech recognizer model. [5] adopted deep neural networks to produce robust cepstral features to improve whispered speech recognition. Reference [6] investigated alternative feature extraction algorithm for natural/whisper speaker identification problem. Article [7] exploited phrase length based features for whispered speech emotion recognition task. For the purpose of augmenting the limited transcribed data-set for whispered speech recognition, [8] studied the inverted problem of generating synthetic whisper utterances from natural speech signals. In recent times, whisper-to-natural speech conversion task has gathered the attention of many researchers. The motive behind this research domain is to improve the intelligibility and recognition quality of whispered speech utterances.

Two methods were addressed in [9] for whispered speech conversion. First being the rule-based whisper conversion in which, mixed excitation linear prediction (MELP), linear prediction coding (LPC), and code excited linear prediction (CELP) parameters of the source-filter model are modified on the basis of statistical differences between acoustic features of whispered and natural speech [10], [11], [12], [13], [14], [15]. It is based on simple transformation rules in combination of fundamental statistical modeling, and thereby the whisper converted speech lacks high level of intelligibility and naturalness, compared to natural speech. The other method for whisper-to-natural speech conversion includes supervised learning framework. Gaussian mixture model (GMM) [10] and neural networks [17] have been explored by researchers to train a learning model using parallel training data. [16] built a GMM model to learn the joint spectral feature space for parallel
whisper and natural speech signals. However, [18] showed that the speech signals learned by basic GMM models display discontinuity and over-smoothing. Recently, neural networks have emerged as a boon to supervised learning problems as they can learn complex nonlinear functions fairly easily. [17] proposed restricted Boltzmann machine (RBM) to model joint feature space composed of whispered and parallel natural speech. [19] proposed a deep bidirectional long short term memory (DBLSTM) network for speech conversion which was trained on frame-aligned parallel data and produced results which were more natural and similar to natural speech. A very recent article [9] proposed a sequence-to-sequence framework with fundamental network consisting of LSTM units and two separate LSTM networks to learn F0 and aperiodic component of the target natural speech. Their approach eliminated the requirement for time aligned data since the proposed sequence-to-sequence framework is built over a LSTM (recurrent) network.

Alternatively, researchers have found the effectiveness of sequence-to-sequence architectures for other speech-to-speech problems [20], [21], [22], [23]. In [22] attention-based voice conversion network to produce spectrograms in target voice based on spectra features from the source voice is proposed. [20] proposed Translatotron, an end-to-end direct speech-to-speech translation (S2ST) model. They incorporated a speaker characteristics encoder to enable the model produce target speech using the voice of source speaker. The author emphasized that the paper shows a proof of concept that a direct model can be trained for S2ST, though it slightly under-performed with respect to the baseline cascade system in their evaluation. Recently, transformer [24] was a major breakthrough in sequence-to-sequence frameworks. The deep networks based on transformer architecture have proven to be the state-of-the-art solutions for a number of sequence-to-sequence tasks such as machine translation [25], grammatical error correction [26], end-to-end automatic speech recognition [27], etc. Transformer architecture eschews recurrence and instead relies entirely on attention mechanisms to draw global dependencies between input and output sequences. As it does not rely on recurrent structured units, transformer architecture can be trained relatively faster than RNNs and achieve better or at par performance on majority of the tasks.

To exploit these advantages, we propose a novel whisper-to-natural speech conversion framework using modified transformer architecture for matching time-aligned parallel data. The network takes frame level spectral features of whispered speech as input and generates corresponding spectral features for the target natural speech. We modify the conventional transformer network and add an auxiliary decoder after N sub-layers at the encoder side which is trained with the objective of identifying the triphone unit per frame during training. The model learns to map a contiguous segment of k input frames to the corresponding contiguous segment of k frames in output audio. Thereby an entire source audio frame sequence as input to predict the entire target audio frame sequence as output is avoided [20]. Finally, we also provide evidence on the model’s ability to learn formant distribution without explicitly defining an objective function for the same. In all our experiments, we select k = 3 as empirically tuned parameter. In this work, we propose two approaches for whisper-to-natural speech conversion and vice-versa. In the first method, we use MFCC features to train our end-to-end framework. In the second method we use smoothed spectral features for the learning problem. In both the cases the auxiliary decoder is also pre-trained on LibriSpeech corpus’ features and corresponding triphone units. Similarly, we also investigate natural speech to whisper conversion with our proposed architectures, as additional experiment. In theory, synthetic whisper signal can be generated by removing F0 from speech signal. However, it differs from actual whisper signal with respect to whisper shift, although perceptually, it sounds as one.

The remainder of this paper is organized as follows: In section II the detailed neural network architecture of modified Transformer model is described, section III details the datasets used for the training and testing purposes. Section IV lists down training model configurations, experimental results and observations. Section V is devoted to conclusions and future plans. To the best of the author’s knowledge, the proposed approaches haven’t been used in the literature for whisper-to-natural speech conversion problem.

II. Network Architecture

We modify the conventional transformer architecture [24] as our sequence-to-sequence modeling pytorch framework. In our version, the encoder stack maps an input sequence of \( (\vec{x}_1, \vec{x}_2, \vec{x}_3) \) to a continuous representation \( z = (\vec{z}_1, \vec{z}_2, \vec{z}_3) \). Given \( z \), the decoder stack then generates output sequence \( y = (\vec{y}_1, \vec{y}_2, \vec{y}_3) \); where \( \vec{x}_i \) and \( \vec{y}_i \) are \( X_n \) dimensional input feature for \( x_{th} \) frames of time-aligned parallel whispered and natural audio signals. Since we are converting three frames of \( Y_n = X_n \) dimensional input feature values from source to target side, the embedding layer is redundant in both encoder and decoder stacks. We’ve also removed positional encoding layer since the sequence length for both source and target is fixed to three frames. The network architecture is shown in Fig 2.

A. Encoder

Encoder is composed of a stack of \( N = 6 \) identical layers like in the conventional transformer. Each layer is made of two sub-layers; Multi-head self-attention layer followed by fully connected feed-forward network as shown in Fig. 2. Each sublayer has a residual connection and undergo layer normalization operation. All sub-layers in the model generate \( Y_n \) dimensional outputs to resonate with the residual connections. For a batch size = \( B \), the encoder takes input \( x \) of shape \( (B, k, X_n) \) and generates \( z \) of same shape.
B. Decoder

Just like the encoder, decoder is also composed of N = 6 identical layers. Decoder layer is comprised of three sub-layers: Multi-head self-attention layer, encoder-decoder multi-head attention layer and feed-forward layer. Encoder-decoder sub-layer performs attention operation over the representation $z$ as shown in Fig. 2. The sub-layer connections are exactly similar to the encoder ones. However, we removed the softmax layer and the linear layer sits as the ultimate layer. The decoder generates $y$ of shape same as the input $x$, i.e $(B, k, Y_n)$. 

C. Auxiliary Decoder

We add an auxiliary decoder to our network architecture which takes input, $h$, after three layers of encoder as shown in Fig. 2 which is of shape $(B, k, X_n)$. Layers in auxiliary decoder are stacked in the similar fashion as main decoder with number of identical layers fixed $N = 3$. The purpose of auxiliary decoder is to predict tri-phone unit per source frame input. For the source speech signal, tri-phones are generated using Kaldi based ASR system generated forced alignments. On top of the librospeech lexicon, all the words contained in the training data are included in the lexicon. Similarly text is also included in the count based backoff n-gram language model. We used scripts provided by Kaldi’s standard s5 recipe. Thus, for input $x$ of shape $(B, k, X_n)$, the tensor used to calculate cross-entropy loss over is $p$ of shape $(B, k, P)$ where $P$ is unique tri-phone vocabulary.

The attention mechanism used is "Scaled Dot-Product Attention" described in [20].

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}}) V$$  (1)

(2)

Where $Q$, $K$ and $V$ are query, key and value vectors respectively, $d_k$ is the dimension of key vector. We fixed the number of heads = 8, empirically selected, in the Self and Multi-head attention layers in the each of encoder, decoder and auxiliary decoder.

III. Datasets and Feature Extraction

A. Transformer Model Training

We train our network on combined dataset of SpeechOcean (King-ASR-066 American English Speech Recognition Corpus, subset 100h) and Whispered TIMIT (wTIMIT) corpus. We selected a subset of SpeechOcean data comprising of 100 hours. We professionally recorded 100hrs of American English whisper speech for the corresponding speech corpus from SpeechOcean\(^1\) and we refer both King-ASR-066 speech corpus and recorded whisper corpus jointly as SWPC-066 (i.e. Speech-Whisper parallel corpus-066). The data-set comprises of 84K parallel natural and whisper speech utterances having a total of 198 speakers. It has 84K phonetically balanced sentences. Whisper speech signal and it’s natural counterpart were sampled at 44kHz and 16kHz respectively, with 16-bit resolution storage. The vocabulary file generated from the transcriptions contain 23.5K unique tokens. Thereby, each utterance has an average of 8 words and time duration of 4.27 seconds.

TIMIT is a well-known corpus often used as a benchmark for phoneme recognition task. The wTIMIT corpus has two accents, i.e Singaporean-English and North American, with 20 and 28 speakers from each accent group respectively. The speaker recorded natural utterance and the whispered counterpart from 450 phonetically balanced sentences of the TIMIT prompt set, resulting in 18620 parallel speech utterances (15 hours). The vocabulary contains 3588 unique tokens and each utterance, on average, has 7 words. Each source-target utterance pair was sampled at 44kHz, with 16-bit resolution.

As our training data has audio files of different sample rates, we down-sample natural-speech audio files from 44kHz to 16kHz. Since the proposed architecture requires time aligned parallel data, we did fundamental preprocessing for source and target audio pairs. Initial and final silences are trimmed. The duration of the audio pairs differ marginally to few milliseconds. Time stretching operation is performed on the audio file which is of lower duration to make time-duration matched source-target pair. As transformer network is not based on recurrent architecture,

\(^1\)This whispered data is licensed and not currently public
Vocoder signal.

produce MFCC features for corresponding natural speech groups, i.e. Singaporean-English and North American, to consisting recorded audios from speakers of the two accent parallel whisper audio files from WITIMIT test corpus.

C. Testing Model Performance

vocoder features are described in the next section.

speech conversion, but F0. Model configurations using 3x513. Similar procedure is followed for natural to whisper dimensions are 3x24 with corresponding output dimension sions 3x1 and for aperiodicity prediction model input parameters and generate natural audio. For F0 prediction features (24) to corresponding F0 (1) and aperiodic (513).

B. World Vocoder based Feature Extraction

We used World Vocoder [31] to extract F0 (1-dimensional), Smoothed spectrogram features (24-dimensional) and Aperiodic parameters (513-dimensional) by passing input audio waveform. Initially F0 values per frame are extracted using algorithms described in [31], followed by F0 adaptive extraction of Smoothed spectrogram features & Aperiodic parameters. In the synthesis part, the waveform synthesizer takes these extracted features (F0,spectrogram,aperiodic parameters) as input to generate back the audio waveform. In their paper, the authors described world vocoder as an effective one in terms of Synthesized Audio quality as well as in real-time processing compared to other conventional vocoders. An overview is depicted in Fig. 3 showing feature extraction and synthesis. A more detailed explanation about the algorithms & the effectiveness of the vocoder can be found in the paper. We use transformer model to map smoothed spectrogram features of whispered speech to those of corresponding natural speech. We use two separate transformer models to map the predicted natural speech’s spectrogram features (24) to corresponding F0 (1) and aperiodic (513) parameters and generate natural audio. For F0 prediction model, input dimensions are 3x24 with output dimensions 3x1 and for aperiodicity prediction model input dimensions are 3x24 with corresponding output dimension 3x513. Similar procedure is followed for natural to whisper speech conversion, but F0. Model configurations using vocoder features are described in the next section.

C. Testing Model Performance

To test the performance of our model, we used 70 parallel whisper audio files from WITIMIT test corpus, consisting recorded audios from speakers of the two accent groups, i.e. Singaporean-English and North American, to produce MFCC features for corresponding natural speech signal.

2https://github.com/JeremyCCHsu/Python-Wrapper-for-World-Vocoder

In addition, we have used complete CHAINS [32] corpus as well for evaluation. The corpus features approximately 36 speakers (16 male, 16 female) recorded under a variety of speaking conditions. In order to cover good phonetic coverage, the corpus consists of 4 fables and 33 sentences. Both fable and sentences were recorded in natural speech and whisper condition, generating 1332 parallel audios. All audio recordings are sampled at 44.1 kHz and 16 bit PCM. For both test corpus we used Librosa vocoder and World vocoder to generate natural audio signals from the output MFCC and Spectral features respectively.

We used following metrics to measure the quality of our generated speech signals. We used word error rate as a meaningful metric to measure ASR [33] system performance on the generated natural speech and whisper signals. In addition, we computed BLEU scores as well as formant distributions based K L divergence metric w.r.t the ground truth. We compared how an ASR system performed on original WITIMIT whispered speech signals versus corresponding model converted whispered-to-natural speech signals. The ASR systems adopted and trained are described in the Section IV-C. For simplicity, we’ve used the open-sourced recipe in reference to [33] without using the language model for fair comparison. The training data used for training such ASR systems have been described in Table II.

IV. Experiments

A. Training Model Variations

We train our modified transformer architecture with two different input-output feature characteristics as shown in Table II

- MFCC Features: We generate 80 dimensional features for source and target speech frames using Librosa toolkit.
- Smoothed Spectral Features: We generate 24 dimensional features for source and target speech frames using world vocoder toolkit. Increasing the input feature dimension didn’t show noticeable improvements in the model performance.

3https://github.com/rwth-i6/returnn-experiments/tree/master/2018-asr-attention/librispeech/full-setup-attention
The variation W1 and V1 are conventional transformer systems trained to use as baseline results. The objective function used is root mean square loss. The loss per input-target pair can be formulated as follows:

\[
L_1 = \left( \sum_{i=1}^k \left( \frac{1}{n} \sum_{j=1}^n (t_i - y_i')^2 \right) \right)^{1/2}
\]

where \(y_i\) and \(t_i\) represents the output vector generated for frame \(i\) and the corresponding ground truth vector. \(k\) = number of frames which is empirically set to 3 for both the models and \(n\) is the dimension of output vectors, 80 for W1 and 24 for V1, respectively. Models W2 and V2 are modified transformer architecture, with the addition of auxiliary decoder, and are trained for whisper-to-natural speech conversion. To warm up the encoder and auxiliary decoder parameters, we pre-train the auxiliary decoder with 30 hours of librispeech\(^4\), selected randomly from the corpus. The auxiliary decoder is trained by keeping a cross-entropy objective function to correctly identify tri-phone unit per frame. This loss value per input-triphone pair can be formulated as Eq 4.

\[
L_2 = \left( \sum_{i=1}^k \left( -\frac{1}{n} \sum_{j=1}^n (d_i' \log(p_i')) \right) \right)
\]

Where \(d_i\) is one hot vector of dimension \(P\), representing the tri-phone unit of frame \(i\), \(p_i\) is the softmax vector generated by auxiliary decoder corresponding to the frame \(i\). The total loss propagated through the network is described in Eq. 5 for W2 and V2 models. In addition to these systems, we also train W3 and V3, which follow the same architecture as W2 and V2 respectively, for natural-to-whisper speech conversion.

**B. Model Parameters**

We’ve kept the exactly same hyper-parameter settings as [24]. Adam optimizer values are set with \(\beta_1 = 0.9\), \(\beta_2 = 0.98\) and \(\epsilon = 10^{-9}\). The learning rate was varied according to the formula:

\[
lrate = a_{\text{model}}^{-0.5} \cdot \Gamma
\]

where

\[
\Gamma = \min(\text{step\_num}^{-0.5}, \text{step\_num} \cdot \text{warmup\_steps}^{-1.5})
\]

The residual dropout was applied to the output of each sub-layer before it is added to the residual connection and normalized. The dropout probability was set to \(P_{\text{drop}} = 0.1\). The batch size is set to 128 and the each of the model variation listed in Table I was trained for 80 epochs. For the network parameters, the number of layers in encoder and decoder is set to 6. Auxiliary decoder contains a total of 3 layers. Outputs of each sub-layer are either 80 or 24 dimensional vectors corresponding to MFCC or Smoothed spectral feature inputs respectively. The number of heads used to split before applying the attention mechanism is empirically set to 8.

Finally, we trained our models on one machine with 8 NVIDIA P40 GPUs. Each training step took about an average of 4200 seconds for our trained models.

**C. Results and Analysis**

To determine the performance of our whisper-to-natural speech conversion models, we trained multiple ASR systems \(^4\) without language model using the returnn toolkit. Table II lists down the details of such systems along with their performance on LibriSpeech Corpus.

| Model Name | Input-Output Feature (Dimension) | Source | Target | Auxiliary Decoder (Yes/No) |
|------------|---------------------------------|--------|--------|---------------------------|
| W1         | MFCC (80)                       | Whisper| Natural| No                         |
| W2         | MFCC (80)                       | Whisper| Natural| Yes                       |
| W3         | MFCC (80)                       | Natural| Whisper| Yes                       |
| V1         | Smoothed Spectral Features (24)  | Whisper| Natural| No                         |
| V2         | Smoothed Spectral Features (24)  | Whisper| Natural| Yes                       |
| V3         | Smoothed Spectral Features (24)  | Natural| Whisper| Yes                       |

\(d\) = 80, \(k\) = \(3\) for both the models and \(n\) is the dimension of output vectors, 80 for W1 and 24 for V1, respectively. Models W2 and V2 are modified transformer architecture, with the addition of auxiliary decoder, and are trained for whisper-to-natural speech conversion. To warm up the encoder and auxiliary decoder parameters, we pre-train the auxiliary decoder with 30 hours of librispeech\(^4\), selected randomly from the corpus. The auxiliary decoder is trained by keeping a cross-entropy objective function to correctly identify tri-phone unit per frame. This loss value per input-triphone pair can be formulated as Eq 4.

\[
L_2 = \left( \sum_{i=1}^k \left( -\frac{1}{n} \sum_{j=1}^n (d_i' \log(p_i')) \right) \right)
\]

Where \(d_i\) is one hot vector of dimension \(P\), representing the tri-phone unit of frame \(i\), \(p_i\) is the softmax vector generated by auxiliary decoder corresponding to the frame \(i\). The total loss propagated through the network is described in Eq. 5 for W2 and V2 models. In addition to these systems, we also train W3 and V3, which follow the same architecture as W2 and V2 respectively, for natural-to-whisper speech conversion.

\[
L = L_1 + L_2
\]

**Table II**

| ASR System | Training Data | dev-clean (WER) | dev-other (WER) | test-clean (WER) | test-other (WER) |
|------------|---------------|-----------------|-----------------|------------------|-----------------|
| S1         | LibriSpeech   | 4.87            | 14.37           | 4.87             | 13.39           |
| S2         | LibriSpeech + wTimit + SWPC-066 (100h speech only) | 4.48 | 14.07 | 4.63 | 14.49 |
| S3         | LibriSpeech + wTimit + SWPC-066 (100h speech, 100h whisper) | 4.53 | 13.90 | 4.67 | 14.40 |
| S4         | SWPC-066 (100h speech only) | 79 | 81.83 | 79.03 | 82.54 |
| S5         | SWPC-066 (100h whisper only) | 85.83 | 90.98 | 85.22 | 90.18 |

The ASR systems listed in Table II were trained for 250 epochs except for S1. We picked the opensource pretrained encoder-decoder ASR model\(^4\) described in [33].

\(^4\)https://github.com/rwth-i6/returnn-experiments/tree/master/2018-asr-attention/librispeech/full-setup-attention
which was trained for 238 epochs. We observe S2 and S3 systems generated lower word error rates, compared to baseline S1, for standard LibriSpeech test corpus. Thus, whisper data augmentation is found to be beneficial. The poor performance of S4 and S5 systems can be explained with the limited training data. S2 and S3 systems performed better than S1 as shown in Table III. We used W1, W2, V1 and V2 models to generate natural speech counterparts of testing data as mentioned in Section III. The ASR performance on these datasets is shown in following tables (i.e. Table III, Table IV).

### Table III

| ASR System | wTimit (original whisper) | wTimit (whisper-to-natural by W1) | wTimit (whisper-to-natural by W2) | Chains (original whisper) | Chains (whisper-to-natural by W1) | Chains (whisper-to-natural by W2) |
|------------|---------------------------|---------------------------------|---------------------------------|---------------------------|---------------------------------|---------------------------------|
| S1         | 109.14                    | 90.86                           | 80.19                           | 66.35                     | 43.59                           | 43.32                           |
| S2         | 106.48                    | 31.43                           | 18.48                           | 60.07                     | 37.64                           | 37.69                           |
| S3         | 104.76                    | 22.10                           | 13.33                           | 46.29                     | 31.59                           | 32.00                           |
| S4         | 107.62                    | 111.05                          | 84.00                           | 89.56                     | 87.21                           | 87.33                           |
| S5         | 108.00                    | 109.33                          | 96.00                           | 92.74                     | 92.79                           |

### Table IV

| ASR System | wTimit (original whisper) | wTimit (whisper-to-natural by V1) | wTimit (whisper-to-natural by V2) | Chains (original whisper) | Chains (whisper-to-natural by V1) | Chains (whisper-to-natural by V2) |
|------------|---------------------------|---------------------------------|---------------------------------|---------------------------|---------------------------------|---------------------------------|
| S1         | 109.14                    | 112.38                          | 92.00                           | 66.35                     | 165.74                          | 160.28                          |
| S2         | 106.48                    | 22.29                           | 23.31                           | 106.48                    | 154.54                          | 150.14                          |
| S3         | 104.76                    | 33.71                           | 34.67                           | 104.76                    | 175.46                          | 182.79                          |
| S4         | 107.62                    | 89.52                           | 88.95                           | 107.62                    | 101.68                          | 101.65                          |
| S5         | 108.00                    | 99.05                           | 99.24                           | 108.00                    | 131.07                          |

### Table V

| Model      | wTimit (naturalS) (whisper-to-naturalS) | Chains (naturalS) (whisper-to-naturalS) |
|------------|----------------------------------------|----------------------------------------|
| W2         | 85.36                                  | 62.68                                  |
| V2         | 68.60                                  | 33.00                                  |

We also plot spectrograms for whispered speech generated by W3,V3 system along with their corresponding ground truth whispered speech, similarly for natural speech generated by W2,V2 system along with the corresponding ground truth natural speech depicting the model’s ability in generating audio similar to the reference audios. These whispered and natural speech audios belong to wTimit dataset and are spoken by the same speaker with same transcription (“publicity and notoriety go hand in hand”).

![Ground Truth Spectrogram](image1)

![Hypothesis Spectrogram](image2)

![Ground Truth Spectrogram](image3)

![Hypothesis Spectrogram](image4)

Experimental results show that ASR systems can recognize whisper-to-natural converted speech better than the whisper utterance. We observe that MFCC features performed better compared to Smoothed spectral features on both wTIMIT and CHAINS datasets, as shown in Table III and Table IV also in Table V (BLEU score). It is also observed from Table V that, although most of the words are correctly recognized, higher number of
insertion errors has decreased the overall accuracy of the ASR system on CHAINS corpus compared to wTIMIT dataset. Whisper-to-Natural converted speech by W2 and V2 attain the lowest word error rates (WERs) for all the ASR systems. This can be supported with the loss inclusion from phoneme classification by auxiliary decoder during the training phase.

D. Formant Analysis and Observations

The vocal cords are basic elements of speech production in humans. They generally produce well-defined pitch under naturally spoken conditions. A formant is the spectral shaping resulting from an acoustic resonance caused by the geometry of the physiological tubular system of the speaker’s vocal tract. As we speak, the cavities of our vocal tract changes in the shape and volume, so the formant frequencies will be constantly changing. The effects of formants are visible in spectrogram of a speech, because the spectrum is affected by the resonance of vocal tract. In this paper we study first four formant frequencies (F1,F2,F3,F4) and fundamental frequency (F0). Fundamental frequency or F0 is the frequency at which vocal chords vibrate in voiced sound. F0 measurements were made because F0 is known to affect formant measurements [35]. The frequency location of F1 and F2 are primarily based on the shape of the vocal tract as tongue, jaws, lips move to generate sound. The frequency of third formant F3 is related to few specific speech sounds. The fourth (F4) and higher formants remains almost constant in frequency location regardless of changes in articulation. As the formant frequency locations depends on three factors i.e (1) length of the pharyngeal-oral tract (2) the location of constriction in the tract (3) the degree of narrowness of the constriction, we consider only dominant formants F1-F4.

Generally, F0 range is 75-300Hz for a male, 100-600Hz for a female. In the vowel category, F1 can vary from 300Hz to 1000Hz. The lower value suggest the tongue is closer to the roof of the mouth. F2 varies from 850Hz to 2500 HZ; it’s proportional to the frontness or backness of the highest part of the tongue during the production of vowel. F3 is usually considered to determine phonemic quality and F4 is significant in determining voice quality of speech sound.

We used standard Burg (1967) linear prediction coefficients (LPC) algorithm for formant frequency estimation (F1-F4) [36]. In order to examine the audios generated by our model, we have analysed the behavior of fundamental frequency (F0) and first four formants (F1-F4) and compared with the reference audio formants. As shown in the formants graph (i.e Fig 8) we fit a k-component Gaussian Mixture Model (GMM) on the reference audio formants (i.e. Ref GMM), where, k is a hyper parameter determined by Expectation-Maximization algorithm. Using the same number of components we try to fit a GMM model on the formants value extracted from audios generated by our model W1 and W2 (i.e. Hyp_GMM_W1 and Hyp_GMM_W2). As we can observe in the Fig 8 that GMM fit on the formants of the generated audios has a marginal shift from the Reference GMM but follows the same pattern. It’s evident from the Fig 8 that GMM of model W2 is similar to the reference GMM as compared to the GMM of model W1. We approximated KL-Divergence between Ref_GMM and Hyp_GMM_W1, Hyp_GMM_W2 using Monte Carlo method [37]. KL divergence values are shown in Table VI for comparison W1 and W2 systems. Corresponding formant graphs are shown in Fig 8. Lower values towards zero are always preferred. We observe KL divergence values for all formants F1-F4 for W2 is better than W1, except F0. Similarly, KL divergence values are shown in Table VII for comparison.
Fig. 8. Comparison of GMMs of F0-F4 for W1 and W2.

Fig. 9. Comparison of GMMs of F0-F4 for V1 and V2.
of V1 and V2 systems. Corresponding formant graphs are shown in Fig. We observe KL divergence values for all formants F1-F4 for V2 is better than V1, including F0. Thereby, W2/V2 systems outperformed baseline systems W1/V1, respectively. Simply put, the formants generated by the W2’s output speech are more precise w.r.t the target speech. On the other hand, we also observe KL divergence values generated using W3 are better than V3 system (ie. Natural-speech to whisper, cf. Table VIII).

| TABLE VI | KL-DIVERGENCE BETWEEN REFERENCE GMM AND GMM OF W1 AND W2. |
|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| F1 | F2 | F3 | F4 |
|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| W1 | 0.0950 | 0.1543 | 0.2620 | 0.3868 | 0.0675 |
| W2 | 0.1297 | 0.1034 | 0.2344 | 0.1945 | 0.0474 |

| TABLE VII | KL-DIVERGENCE BETWEEN REFERENCE GMM AND GMM OF V1 AND V2. |
|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| F1 | F2 | F3 | F4 |
|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| V1 | 0.1066 | 0.1060 | 0.0395 | 0.1627 | 0.0697 |
| V2 | 0.0808 | 0.0703 | 0.0308 | 0.4404 | 0.0655 |

| TABLE VIII | KL-DIVERGENCE BETWEEN REFERENCE GMM AND GMM OF W3 AND V3. |
|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| F1 | F2 | F3 | F4 |
|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| W3 | 0.1210 | 0.0835 | 0.1089 | 0.1600 | 0.1451 |
| V3 | 1.2497 | 0.4185 | 0.5115 | 0.1157 | 0.4552 |

V. Conclusion

In this article, we’ve proposed a sequence-to-sequence framework for whispered-to-natural speech conversion built on top of conventional transformer architecture. To quantify the performance of our framework, we passed the whisper-to-natural converted speech through various end-to-end ASR systems trained on different datasets. Experimental results shows that natural speech generated from whisper speech using our proposed architecture is more recognizable and intelligible compare to original whisper speech. Our proposed models are capable of generating natural speech without taking explicit speaker dependent information as input. As our motivation is mainly to improve the ASR accuracy under whisper conditions, output speech quality is of higher importance compared to speaker related information. Word error rate (WERs) drop by ≈ 65% when a whisper utterance is converted to natural speech signal by our best sequence-to-sequence model which adds an auxiliary decoder to the fundamental encoder-decoder stacks. MFCC features performs better than smoothed spectrum features in terms of over all performance. We also showed that the synthesised natural speech from whisper signals follows the same pattern of formant distribution as the original natural speech counterpart. We plan to make our source code, used features, and pytorch model checkpoints publicly available in the near future.

VI. Future Plans

Our proposed transformer models only maps a short chunk of input frames to output frames. As a future work, we plan to explicitly introduce context using CNN/RNN Autoencoder framework similar to [35] to embed a variable length sequence of input frames (source speech) into a fixed dimensional vector. We plan to study the performance of the proposed whispered-to-natural speech model by passing the context vector along with the current input structure to generate k contiguous frames for target speech signal. We also plan to study the utility of auxiliary decoder for target side tri-phones in the proposed architecture. The availability of translations for both source and target side in the tasks such as speech-to-speech translation (S2ST), multilingual speech-to-text translation, etc. is the major motivation behind it.

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