Vocoder-free End-to-End Voice Conversion with Transformer Network

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Abstract—Mel-frequency filter bank (MFB) based approaches have the advantage of learning speech compared to raw spectrum since MFB has less feature size. However, speech generator with MFB approaches require additional vocoder that needs a huge amount of computation expense for training process. The additional pre/post processing such as MFB and vocoder is not essential to convert real human speech to others. It is possible to only use the raw spectrum along with the phase to generate different style of voices with clear pronunciation. In this regard, we propose a fast and effective approach to convert realistic voices using raw spectrum in a parallel manner. Our transformer-based model architecture which does not have any CNN or RNN layers has shown the advantage of learning fast and solved the limitation of sequential computation of conventional RNN. In this paper, we introduce a vocoder-free end-to-end voice conversion method using transformer network. The presented conversion model can also be used in speaker adaptation for speech recognition. Our approach can convert the source voice to a target voice without using MFB and vocoder. We can get an adapted MFB for speech recognition by multiplying the converted magnitude with phase. We perform our voice conversion experiments on TIDIGITS dataset using the metrics such as naturalness, similarity, and clarity with mean opinion score, respectively.

Index Terms—voice conversion, vocoder-free, transformer, spectrum, phase

I. INTRODUCTION

Voice conversion has gained considerable attention in various industrial areas. In recently, encoder-decoder models built with recurrent neural networks (RNNs), such as long short-term memory (LSTM) [1], bidirectional long-short term memory (BiLSTM) [2], and gated recurrent unit (GRU) [3] have been widely utilized for sequence modelling. There are lots of neural network models based on RNN encoder-decoder structure also known as sequence-to-sequence (Seq2Seq) [4] and they achieved good results for voice conversion tasks.

RNNs, however, process words one by one for each sequence. This sequential property of RNNs can be an obstacle for parallel computation of GPUs and make training slow. On top of that, if these temporal information gets longer, the model tends to forget the contents of distant locations or mixes it with the contents of the next location. The transformer [5] network partially solved these problems of RNNs by using an attention mechanism to derive global dependency between input and output, which reached state-of-the-art performance in many fields. Transformer which does not have any convolutional neural network (CNN) [6] or RNN layers has shown the advantage of learning fast and solved the limitation of sequential computation of conventional RNN.

Given the waveform speech as the model input for voice conversion, the short-time Fourier transform (STFT) converts it into raw spectrum in time-frequency domain form. This spectrum computed with STFT can provide useful information than waveform speech. In particular, the conventional approaches used in text-to-speech (TTS), voice conversion, and speech recognition pass Mel filter banks through raw spectrum to generate Mel-frequency filter bank (MFB, also called Mel-spectrogram). In MFB, the frequency components of the spectrum are obtained after STFT. After that, it is compressed according to the Mel curve [7] reflecting the characteristics of the Cochlea in the human ear. In MFB, phase information is removed when it is compressed.

MFB, which consist of 40 to 80 feature dimensions per time step, has the advantage of learning speed compared to raw spectrum since MFB has less feature size. However, it can’t be converted directly to waveform speech because of losing phase information. Thus, speech generator with MFB approaches require additional vocoder that needs a huge amount of computation expense for training process. In other words, MFB fed into the Seq2Seq should be synthesized for natural speech through phase estimation with the help of vocoder, which synthesizes the linear scale spectrum. Then, it can get the final output of the model into waveform speech.

Thus, speech generator with MFB approach requires additional vocoder that demands a heavy training computation process. Using the vocoder such as Griffin-Lim [8] and WaveNet [9], it is possible to get better quality of voice with the synthesis. On the contrary, it is inevitable to avoid problem with complexity due to the extra computation.

However, to avoid additional pre/post processing such as MFB and vocoder, we propose a fast and effective approach to convert realistic voices using raw spectrum in a parallel manner to generate different style of voices with clear pronunciation. In this paper, we introduce a vocoder-free end-to-end voice conversion method using transformer network. We focus on the converting the raw spectrum obtained by the
STFT without help of the vocoder which requires iterative synthesis. In addition, it is possible to use phase information to restore the waveform speech through inverse STFT.

Our presented conversion model can also be used in speaker adaptation for speech recognition. Our approach can convert the source voice to a target voice without using MFB and vocoder. We can get an adapted MFB for speech recognition by multiplying the converted magnitude with phase. Furthermore, it is also possible to convert voices of minorities (elderly, children, dialects, speaker with disabilities) with poor speech recognition performance to those of common adults. It is possible to achieve better speech recognition performance through speaker adaptation which replaces the features of minorities and common adults. We perform our voice conversion experiments on TIDIGITS dataset using the metrics such as naturalness, similarity, and clarity with Mean Opinion Score (MOS), respectively.

II. RELATED WORK

In this section, we first introduce the prior research on vocoder, voice conversion, and the transformer network that we used in this paper.

A. Vocoder

Vocoder is used to synthesize linear scale spectrum into speech signals, synthesizing natural speech through phase estimation. In Griffin-Lim algorithm [8], the STFT of the speech signal output in the previous step is calculated and the amplitude is replaced by the modified-STFT magnitude given as input. This algorithm recovers speech signals with the STFT magnitude which is the most similar to a given modified-STFT through an iterative process of restoring the original signal to minimize the squared error of the amplitude of the new STFT and the input modified STFT.

WaveNet [9] is an autoregressive model that uses sequential features between speech samples and has succeeded in synthesizing high quality speech by predicting the next sample using previous samples. However, the speed of the generation rate is slow because the next sample is generated one by one from the previous samples. Parallel WaveNet [10] is designed to solve the WaveNet’s slow sample generation speed, which uses inverse autoregressive flow to synthesize voices. Since inverse autoregressive flow does not know the distribution of the target voice data set during learning, the learning is performed by extracting the distribution information of the target data set using a well-trained WaveNet (teacher network) and comparing it with the result of inverse autoregressive flow. It has the advantage of faster speech synthesis than WaveNet, but the quality of synthesized speech is lower. Unlike [10], WaveGlow [11] is not required for a pre-trained teacher network and has the advantage of fast voice synthesis. However, since WaveGlow uses a distribution based loss function, the quality of synthesized speech is poor. Furthermore, when combined with TTS, poses the problem that the quality of synthesized speech depends on the quality of the predicted MFB from the text.

B. Voice Conversion

In [12], the voices of speaker with a disability are converted into general voices. The encoder consists of CNN and three BiLSTMs, and the decoder consists of two LSTMs. Attention between encoder-decoder is used. In order to solve the problem of signal-to-signal conversion, the speech recognition decoder is connected to the encoder output for the multitask learning [13] and it used only in the training task.

To translate between voices of different languages and synthesize the translated output as speech, usually it had to go through speech recognition, translation, and TTS tasks. In this paper [14], however, they convert the speech of different languages into an end-to-end attention-based Seq2Seq network. Without going through other steps, it can directly translate the speech of another language into one. Encoder is composed of 8 BiLSTMs, and the encoder output is used to predict the phoneme temporal information of input and target through auxiliary tasks. Likewise [12], these auxiliary decoders were used only for learning. In addition, the decoder can be optionally adjusted according to the input speaker. Thus, voice can be converted to the desired speaker’s voice by using pre-trained speaker encoder. They consider to use WaveRNN vocoder [15] rather than Griffin-Lim because it dramatically improves voice quality.

C. Transformer network

RNN is widely used method for sequence modeling tasks such as neural translation and language modeling. However, because the RNNs process words one by one for each sequence, this sequential process can be an obstacle with parallelization and slow learning. On top of that, if these temporal information get longer, the model tends to forget the contents of distant locations in order or to mix with the contents of the next location. The transformer network in [5], is the model architecture that relies entirely on attention mechanisms to derive global dependencies between inputs and outputs. As Fig.1 shows, the transformer model architecture without CNN and RNN have shown the advantage of fast learning time. The shortcomings of traditional RNN due to poor performance in temporal information, have been solved with self-attention. BERT [16], which is evolved from transformer, is used in many natural language processing (NLP) fields such as not only translation but also summary and prediction of sentence relevance, etc. BERT is widely used in other fields along with NLP. VideoBERT [17] learned two-way joint distribution of visual and linguistic token sequences derived from vector bidirectional and speech recognition with output of video data. This has led to the research in a variety of tasks, including action classification and video captions. In [18], combination transformer network with TTS model which is called Tacotron2 [19], used to present the results of speech synthesis. In [20], which performs voice conversion based on the transformer network, uses pre-trained TTS. They perform voice transformation with pre-trained model parameters using vocoder based synthesis.
Consequently, vocoder helps to improve the quality of speech synthesis, but it takes time to synthesize. We use transformer network due to its generalization performance through self-attention as well as fast and effective parallel learning techniques. In addition, we perform our experiments by focusing on the conversion of raw spectrum stage without adopting the voice synthesis method through the vocoder. More details are given in section 3.

III. METHOD

This section introduces using raw spectrum rather than MFB for end-to-end voice conversion without the help of vocoder.

A. Raw spectrum

Fig. 2 shows a flowchart that converts waveform speech into spectrum, MFB, and back to waveform speech. Given a continuous audio signal \( x[n] \), this can be expressed as:

\[
x[n] = A \cos(\omega n T + \phi) = A \cos(2\pi f n T + \phi)
\]

where \( A \) is amplitude, \( \omega \) is angular frequency in radians/seconds, \( f \) is \( \omega / 2\pi \), \( \phi \) is initial phase in radians, \( n \) is time index, and \( T \) is \( 1/f \), respectively. Next process is applying a pre-emphasis filter on the \( x \) to amplify the high-frequency.

Pre-emphasis filter is useful in several ways. High-frequency is generally smaller than low-frequency. Thus, using pre-emphasis filter helps to avoid numerical problems during STFT and improves signal-to-ratio.

As the frequency of the signal changes over time, after pre-emphasis, the signal is split into short time frames. Because of the frequency contour of the signal is lost over time, the Fourier transform is performed assuming that the frequency of the signal is stationary for a very short period of time, not over the entire signal. The typical frame size for speech processing is 20ms to 40ms, with 50% overlap. Usually 25ms is used for frame size and 10ms (15ms overlap) for stride overlap size.

The next step is to cut the signal into frames and apply the hamming, hanning window function to each frame. The spectrum can be calculated by performing an N-point FFT (NFFT) on each frame. Here, NFFT generally uses 256 (16ms) or 512 (32ms). Finally, the spectrum that is obtained through STFT can be expressed with magnitude and phase by the following equation:

\[
D = S \ast P
\]

where \( D \) is complex-valued spectrum, \( S \) is magnitude and \( P \) is phase, respectively.

In summary, raw spectrum can be recovered from speech waveform directly as shown in Fig. 2. Thus, we use spectrum to perform voice transformation in an effective way with out any post-processing.

B. Proposed model structure

1) Model flow: The vocoders mentioned in section 2 are complex and computationally expensive which require a lot of repetitive works to restore the audio waveforms. To solve this problem, we focus on the conversion at the spectrum level. Fig. 3 shows the conventional method of using MFB in the upper part, and the proposed transformer network in the lower part. Conventional method uses the output of MFB expressed as \( M_1, M_2, ..., M_n \) as input to Seq2Seq and the output is obtained through the vocoder. The encoder input in the Seq2Seq considers all the temporal information. It’s no different from our model. However, the decoder predicts

\[
\text{Output Probability} = \begin{bmatrix} 0.16 & 0.12 & 0.01 \\ 0.02 & 0.91 & 0.02 \\ 0.10 & 0.04 & 0.91 \end{bmatrix}
\]
We used zero-padding for all the spectrum. The reason for using zero-padding is that the transformer network considers the whole sequence and learns in parallel. Even if the voice scripts are the same, the length of each speaker’s characteristics is different. For this reason we used zero-padding.

In order to avoid attention between the zero value and the real vector, we multiplied $-1e^{-9}$ when there is a zero value on dimension in each time step. Zero-padding is described in the next section.

3) Transformer-based model architecture: Fig. 4 shows our transformer-based model architecture. Firstly, we obtain a spectrum that depends on the $NFFT$ coefficients and then separate $S$ and $P$ by Eq. (2). After that, $S$ is used as the encoder input. In this case, we don’t use word embedding because the $S$ is a time-frequency domain that consists of sampling the frequency along the time axis. The final input is $S$ plus the position vector passed through PE. Then multi-head attention is performed through $N$-encoders. The multi-head attention results pass through two-layers feed-forward network that contain rectified linear units (ReLU) to reconstruct information which are not cleaned up. The process up to now is to make a new context information by combining the entire temporal information for each time step. Then we perform a residual connection [24] that adds input data to the values which are obtained until now. This means that context information which are not included in the input temporal information are processed by the input and added. The encoder looks at the entire given temporal information and encodes each time step information into a better representation.

Decoder uses only $S$ which passed through STFT from spectrum signal of target $y$ like the encoder method, and creates new information based on the known information. However, the decoder is different that it uses masked multi-head attention when performing self-attention. The reason for using masked multi-head attention is to prevent self-attention by covering features after its time step during self-attention. This shows the transformer network is autoregressive model. After that, attention is concatenated between the encoder outputs and decoder outputs. This process determines how much
Fig. 4. Our transformer-based model architecture. The input of the encoder is magnitude of raw spectrum and the output of decoder is converted magnitude. Predicted \( \hat{x} \) perform element-wise multiplication with source phase. Word embedding, output linear, and softmax function are not needed, respectively. The decoder uses \( x \) of input spectrum temporal information to express \( y_i \). The results of encoder-decoder attention are added to the masked multi-head attention results of the decoder. Then they are put into the feed forward network. The outputs finally come out. So far, the outputs \( \hat{x} \) have the same dimension \( d_{\text{model}} \) as inputs \( x \) and targets \( y \), only the magnitude temporal lengths are different. Finally, \( \hat{x} \) currently only have magnitude that converted from source \( x \) to target \( y \). Then we multiply this values by \( P \) to make a spectrum containing complex numbers. Finally, it can be restored to waveform speech using inverse STFT.

The transformer has fewer parameter numbers than other models, and because it uses feed forward network, parallelism is easy and fast operation is possible. Nevertheless, accurate modeling is possible because information between distant temporal information are directly linked.

IV. EXPERIMENTAL SETUP

In this section, we introduce the dataset, pre-processing, and hyperparameters.

A. Database and feature extraction

We use the TIDIGITS [25] dataset which consists of 326 speakers (111 men, 114 women, 50 boys, 51 girls) pronouncing numbers. Among them we experiment with independent numeric units (e.g., "one", "two", ..., "oh", "zero"). Our experiments require the pair of source and target dataset from each different speakers. Therefore, we train a paired dataset of 55 men, 57 woman, 25 boys and 26 girls. There are two numerical data of each train dataset. Because of TIDIGITS test dataset was separated, we use as it is. The sampling rate of the corpus is 20 kHZ and dataset was collected with an Electro-Voice RE-16 Dynamic Cardiod microphone in a quiet space.

We downsampled 20 kHZ to 16 kHZ for reducing the computation. We pre-processed the dataset such as \( NFFT \) is 512 (32ms) and \( \text{hop_length} \) is 256 (16ms) to get raw spectrum. The dimension of the obtained spectrum is \((257, T)\). However, since the transformer \( d_{\text{model}} \) is \( 2^n \), we intentionally remove the last imaginary part of the spectrum.

B. Data pre-processing

1) Voice Activity Detection: Voice Activity Detection (VAD) is a technology applied to voice processing that detects the presence or absence of human voice. As shown in Fig. 5, VAD is an algorithm that determines the threshold criteria which is used to distinguishes background noise from real speech mainly used in speech recognition. We use VAD to reduce the maximum sequence length of the dataset by removing the front and back silence sections based on threshold to speed up computation. Through the pre-processing, this technique not only make our model accelerate learning but also prevent the learning to be difficult as the magnitude temporal information get longer.

2) SOS token, EOS token, Padding: In natural language processing, the first token of a sentence is start-of-sentence (SOS), and the end token is end-of-sentence (EOS). Usually, EOS is used because let model to know the input sentence is over. In addition, SOS token is utilized in inference phase as decoder input. Thus, we create SOS and EOS token corresponding to the \((256, 1)\) dimension which are randomly uniform distribution between 0 and 1. We concatenate the SOS token in front of the decoder inputs in all train dataset. Moreover, we use zero-padding at the end after concatenating the EOS token with target dataset. In the test phase, we put SOS token into the decoder and our model inference prediction using greedy search.

Fig. 5. Original wav (left), VAD (middle), trimmed (right).
In the last part of pre-processing is padding. We find the maximum sequence lengths in the train dataset. In order to match the same magnitude temporal information, we use zero-padding with all train dataset to maximum sequence lengths. In model training, $-1e - 9$ values are used to prevent multi-head attention from occurring in the zero-padding part.

C. Hyperparameter

We use the Adam optimizer [26] with $\beta_1 = 0.9$, $\beta_2 = 0.98$, and $\epsilon = 1e - 9$, respectively. Since the number of train dataset is small, we cannot adopt the original learning rate in [5]. On the other hand, our initial learning rate is at $1e - 4$ with proceeds to decay_step is 4000 and decay_rate is 0.96.

We implement our model with Tensorflow 2.0 and train with one Titan RTX GPU. However, since we have small paired dataset and no post-processing, it’s enough to use one 1080TI GPU in our experiments. In inference phase, the testing GPU memory that we only used is around 500 to 550MiB.

| TABLE I | MODEL HYPERPARAMETERS |
|----------|-----------------------|
| Hyperparameters | Value |
| $N_{encoder}$ | 6 |
| $N_{decoder}$ | 6 |
| $N_{heads}$ | 8 |
| $d_{model}$ | 256 |
| $d_{ff}$ | 1024 |
| $d_{rate}$ | 0.1 |

Table I shows the hyperparameters. Six encoders and decoders, eight multi-head attentions were used in our model. The model size $d_{model}$ is 256 and the dimension size used for feed forward network $d_{ff}$ is 1024. Dropout [27] selected 0.1 and it was used for training only. We adopt two losses.

$$L_1 = \sum_{i=1}^{n} |y_{true} - y_{predicted}|$$  \hspace{1cm} (3)

$$L_{MSE} = \frac{1}{2} \sum_{i=1}^{n} (y_{true} - y_{predicted})^2$$  \hspace{1cm} (4)

$$L_{final} = L_1 * 0.5 + L_{MSE} * 0.5$$  \hspace{1cm} (5)

Eq. (4) has the advantage of minimizing the difference between variance and bias quickly, and Eq. (3) tends to ignore the outlier, which is disadvantage of Eq. (4). Therefore, we use half of these equations under the hypothesis that they could complement each other.

V. RESULTS

In this section, we perform our voice conversion experiments on the TIDIGITS dataset using the metrics such as naturalness, similarity, and clarity with MOS.

Fig. 6 shows the speech conversion results of our proposed model. The figures in the first row are the result of conversion from man to boy. The left figure in first row is the input of man, and the converted output is middle, and the source of boy is right in the figure, respectively. From the frequency in Fig.6 on upper side, $\hat{x}$ period got wider than $x$ in 0 to 2 kHz frequencies. In addition, part from 2 kHz to 5 kHz of $x$ does not have high dB, but the result of $\hat{x}$ is similar to $y$. Likewise, the input frequencies of second row of $x$ is converted similarly to $y$.

Fig. 7 shows more accurate analysis of our conversion results. Each figure on the first row is the frequency with analyzed spectrum of man, result which is converted from man to boy, and spectrum of boy, respectively. The maximum y-axis in $man_x$ is near 1.3, in $boy_y$ is near 0.9, and in $\hat{x}$ which is our converted result is near 0.9. Frequency of $man_x$ in low-frequency cell is more higher than the frequency of $boy_y$. Through these analysis, it shows that low-frequencies from magnitude of $man_x$ are densely distributed and more higher than magnitude of $boy_y$. From the performance of model, the highest magnitude value in low-frequencies from $\hat{x}$ is near 0.8. This shows very close to the $boy_y$, and the $\hat{x}$ frequency distribution also similar to $boy_y$.

Likewise, each figure on the second row is the frequency which analyzed spectrum of woman, result which is converted from woman to man, and spectrum of man. The maximum y-axis in $woman_x$ is around 7.0, in $man_y$ is around 2.4, and
our conversion result ̂x is around 2.4. Before conversion, the highest magnitude in low-frequency cell is 7.0. However, the highest magnitude in ̂x is around 2.4. Moreover, magnitude on ̂x2 between 50 to 100 cell is cutting and closer to target man2 target. In addition, the highest magnitude value on woman2 is near the seventh around 20th frequency cell. After the conversion, however, the highest magnitude value on ̂x2 is under 2.5 around 20th frequency cell. Therefore the results, as shown in Fig. 7 indicate that our proposed model successfully performed the conversion.

To get quantitative performance, we randomly gather 38 adults from 20 to 30 ages. We measure our proposed model results using the metrics such as naturalness, similarity, and clarity with MOS, respectively. Sample of voices are randomly selected and same batches of samples are given to participants. Four sources, targets, and result samples of our model are extracted. Totally, 144 samples are evaluated. Source speakers and target speakers are different.

**TABLE II**

| Source | Target | Man | Woman | Boy | Girl |
|--------|--------|-----|-------|-----|------|
| Man    |        | 3.8 ± 0.39 | 3.78 ± 0.27 | 3.72 ± 0.34 | 3.72 ± 0.34 |
| Woman  | 3.22 ± 0.29 | 4.29 ± 0.34 | 3.78 ± 0.27 | 3.78 ± 0.27 |
| Boy    | 3.01 ± 0.29 | 3.56 ± 0.25 | 3.53 ± 0.32 | - |
| Girl   | 3.01 ± 0.29 | 3.56 ± 0.25 | 3.53 ± 0.32 | - |

Table II is an evaluation about how natural the converted voice is as human. We got the highest score (4.20 ± 0.53) from conversion tasks from man to boy and the lowest score (2.82 ± 0.29) from conversion tasks from woman to man. Table

**TABLE III**

| Source | Target | Man | Woman | Boy | Girl |
|--------|--------|-----|-------|-----|------|
| Man    |        | 3.40 ± 0.24 | 4.36 ± 0.19 | 4.26 ± 0.22 | 4.26 ± 0.22 |
| Woman  | 3.09 ± 0.34 | 3.09 ± 0.34 | 3.09 ± 0.34 | 3.09 ± 0.34 |
| Boy    | 3.30 ± 0.30 | 3.30 ± 0.29 | 3.30 ± 0.29 | - |
| Girl   | 3.39 ± 0.30 | 4.04 ± 0.29 | 4.13 ± 0.24 | - |

Table III is an evaluation about how similar the converted voice is to the target voice. Source speakers and target speakers are different. We got the highest similarity (4.20 ± 0.22) from conversion tasks from man to boy and the lowest similarity (3.09 ± 0.31) from conversion tasks from woman to man.

Table IV is an evaluation about how clear the pronunciation of converted voice to given script is. We get the highest clarity (4.31 ± 0.19) from conversion tasks from man to boy and the lowest clarity (3.47 ± 0.26) from conversion tasks from boy to man. The score of converting to children is high when they are targeted.

In the overall speaker average MOS, the scores of our experiment results are 3.40 ± 0.31 in naturalness, 3.82 ± 0.25 in similarity, and 3.93 ± 0.25 in clarity, respectively. Our results show that the proposed method transforms voice with good clarity while maintaining appropriate naturalness and similarity.

**VI. CONCLUSION**

**A. Summary**

We proposed a voice transform with self-attention mechanism in a raw spectrum level, while conventional methods use a vocoder in MFB level. MFB-based approaches had the advantage of computational learning convenience compared to raw spectrum. However, speech generator with MFB approaches require vocoder that needs a huge amount of computation expense for training process. With vocoder, it is possible to get better quality of the voice with the synthesis. On the contrary, the problem of complexity due to the extra computation is inevitable. The additional pre/post processing such as MFB and vocoder is not essential to convert real human speech to others. In this paper, we proposed a vocoder-free end-to-end voice conversion method using a fast and efficient transformer network that can convert spectrum in parallel manner. Obtaining the conversion results with raw spectrum without the help of repetitive vocoder had the advantage of using an original phase information to provide the result. We gathered 38 participants and conducted MOS evaluation on the naturalness, similarity and clarity of the converted speech. In the overall speaker average MOS, the scores of our experiment results got 3.40 ± 0.31 in naturalness, 3.82 ± 0.25 in similarity, and 3.93 ± 0.25 in clarity, respectively. Our results showed that the proposed method is possible to transform with good clarity while it is maintaining appropriateness of naturalness and similarity.

**B. Future Work**

In the evaluation phase, there was an unnatural converted part of ̂x. It seems to be caused by misalignments since the lengths of ̂x and phase ̂x deviate significantly. This is a feature of the transformer-based model which is converting to the maximum length. In other words, the length of all dataset are same because of zero-padding. However, if the actual vector length of phase ̂x is less than the ̂x, it causes a serious problem that make misalignment. In the above case, the quality of the recovered waveform can be poor. Thus, the pitch is broken and the naturalness is weakened. Therefore, Our model need

1Audio samples are available at https://kaen2891.github.io/e2e_vc/transformer_results/

**TABLE IV**

| Source | Target | Man | Woman | Boy | Girl |
|--------|--------|-----|-------|-----|------|
| Man    | 3.78 ± 0.27 | 4.31 ± 0.19 | 4.22 ± 0.21 | 4.22 ± 0.21 |
| Woman  | 3.83 ± 0.26 | 3.80 ± 0.22 | - | 3.80 ± 0.22 |
| Boy    | 4.01 ± 0.25 | 4.24 ± 0.22 | - | - |
| Girl   | 3.84 ± 0.30 | 4.00 ± 0.25 | 4.24 ± 0.22 | - |
to phase transform to solve misalignment problem. The finding is unexpected and it suggests that there is problem related with the input spectrum length.

We found the importance of phase in the study. The problem can be solved if $\phi_x$ and the converted $\hat{x}$ are aligned with each other. To solve the problem, we have to use complex neural network [28] to align the magnitude and phase which are included in the raw spectrum. If the phase could be aligned based on the converted magnitude, the quality of human voice will be improved. It will be possible to convert voices of minorities with poor speech recognition performance to those of common adults. It is available to achieve better voices of minorities with poor speech recognition performance of human voice will be improved. It will be possible to convert using transformer with text-to-speech pretraining which replaces the features of minorities and common adults.

We are going to research phase adaptation and alignment with magnitude as our next task.

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