ControlVC: Zero-Shot Voice Conversion with Time-Varying Controls on Pitch and Rhythm

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Abstract

Recent developments in neural speech synthesis and vocoding have sparked a renewed interest in voice conversion (VC). Beyond timbre transfer, achieving controllability on para-linguistic parameters such as pitch and rhythm is critical in deploying VC systems in many application scenarios. Existing studies, however, either only provide utterance-level global control or lack interpretability on the controls. In this paper, we propose ControlVC, the first neural voice conversion system that achieves time-varying controls on pitch and rhythm. ControlVC uses pre-trained encoders to compute pitch embeddings and linguistic embeddings from the source utterance and speaker embeddings from the target utterance. These embeddings are then concatenated and converted to speech using a vocoder. It achieves rhythm control through TD-PSOLA pre-processing on the source utterance, and achieves pitch control by manipulating the pitch contour before feeding it to the pitch encoder. Systematic subjective and objective evaluations are conducted to assess the speech quality and controllability. Results show that, on non-parallel and zero-shot conversion tasks, ControlVC significantly outperforms two other self-constructed baselines on speech quality, and it can successfully achieve time-varying pitch control.

1 Introduction

Voice conversion (VC) is the task of alternating the timbre, style and other para-linguistic features of a speech utterance while maintaining its linguistic content [Sisman et al., 2020]. It is gaining increasing attention from researchers in various domains, thanks to its broad applications in human-computer interaction, virtual human, and multimedia production. Existing VC systems focus on the conversion of timbre and style of the source speaker to those of a target speaker [Sisman et al., 2020, Yi et al., 2020]. The controllability of other para-linguistic features such as pitch and rhythm, however, has not received much attention. In speech communication, para-linguistic features are critical in conveying the emotion, intention and even semantic meaning of the talker [Schuller, 2014]. For example, raising the pitch and slowing down help to emphasize a word [Carlson et al., 1989]; Raising or lowering the pitch at the end of a phrase helps make it a question or statement [Dowhower, 1991]. Therefore, achieving controllability on para-linguistic features such as pitch and speed is a critical step toward making VC techniques useful in many application scenarios.

In general, there are two levels of control on para-linguistic features in voice conversion. Global control refers to controls at the utterance-level, and is often realized under the umbrella of style transfer. For example, when an utterance is converted from a male speaker to a female speaker, the overall pitch range is often raised. Similarly, when an utterance from a slow speaker is converted to a fast speaker, the overall speed is increased. Global control has been well achieved in many modern
Local control refers to time-varying controls of para-linguistic features with examples mentioned in the previous paragraph. Little attention has been paid to it by modern neural-based methods, and it is the concern of this paper.

There are two major categories of VC systems: parametric methods and end-to-end methods. Parametric methods first apply a statistical model (e.g., Gaussian mixture models) or a neural network to estimate speech parameters (e.g., pitch, energy, and voice activity) from the source and target utterances, and then use these parameters to generate converted speech [Chen et al., 2010; Sun et al., 2015]. These methods generally can provide good controllability on para-linguistic parameters such as pitch and rhythm, since such parameters are often explicitly predicted and allowed to be modified by users both globally and locally. However, due to the limited capacity of the parameter predictors and the subsequent vocoder, these methods do not perform well on transferring the target timbre [Nercessian, 2021].

In recent years, end-to-end VC methods have shown significantly better performance on timbre transfer and speech naturalness of the converted utterance [Kameoka et al., 2018; Li et al., 2021]. However, the controllability on para-linguistic features is sacrificed as they are stored in network weights that are difficult to interpret. More recent works try to disentangle different aspects of speech such as content, timbre, pitch and rhythm into separate embeddings to achieve controllability, however, such embeddings, hence the controls of them, are often at the global level [Qian et al., 2021a; Polyak et al., 2021]. Even with frame-level embeddings like those in [Chen and Rudnicky, 2022], time-varying control is still difficult to realize, since the embeddings do not have an explicit mapping to human-interpretable parameters of pitch and rhythm, and the influences of such embeddings on the generation is not clear.

A natural thought is to design a cascade system to achieve time-varying (local) control on pitch and rhythm in voice conversion: First apply a neural-based method for timbre transfer, and then apply signal processing methods such as time-domain pitch synchronous overlap and add (TD-PSOLA) [Charpentier and Stella, 1986] to perform time-stretching and pitch shifting. We tried this, but observed significant artifacts in the converted utterance. We argue that this is because the pitch and speed controls can be hardly designed natural, and there is no following steps in the VC pipeline to fix this unnaturalness. For example, when one speeds up, consonants and vowels are sped up at different rates depending on the context. Similarly, when one raises the pitch, different phonemes are raised at different degrees.

To fill the gap, we propose ControlVC, a voice conversion system that achieves time-varying control on pitch and rhythm. ControlVC performs rhythm control by modifying the speed of the source utterance using TD-PSOLA. It then performs pitch control by modifying the pitch contour of the speed-controlled source utterance, and uses a VQ-VAE pitch encoder to compute discrete pitch embedding. It employs a pre-trained HuBERT model to extract the linguistic embedding from the speed-controlled source utterance, and a pre-trained speaker encoder to extract the speaker embedding from the target utterance. A modified version of the HiFi-GAN vocoder [Kong et al., 2020] is then used to generate the waveform of the converted utterance by integrating the pitch, linguistic and speaker embeddings. It is noted that the pre-trained speaker encoder enables the model to generalize to unseen speakers, and the pre-trained linguistic encoder using vast datasets improves the coverage of diverse linguistic content. They work together to help the system to work in a zero-shot conversion scenario, without the need of additional training data from the source or target speaker.

To our best knowledge, ControlVC is the first neural VC system that achieves time-varying controls on pitch and speed. To validate it, we conduct systematic subjective and objective evaluations and compare it with two self-constructed baselines (as no existing systems could be found). Experimental results show that ControlVC realizes a good level of time-varying controllability on pitch, while achieving significantly better naturalness and timbre similarity than the comparison methods.

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1Demo page with audio samples: https://bit.ly/3PsrKlJ
2 Background

2.1 Zero-Shot Voice Conversion and Controllability

Zero-shot voice conversion (VC), in which both the source and target speakers are unseen in the training dataset, has become a popular research topic. One commonly used strategy is to disentangle the linguistic content and the speaker identity. For speaker identity modeling, speaker embeddings are better than one-hot vectors in terms of the generalization ability to unseen speakers. Some methods employ auto-encoders, e.g., VQ-VAE [Van Den Oord et al., 2017], with a carefully designed bottleneck layer [Ho and Akagi, 2020] [Wu and Lee, 2020] [Ding and Gutierrez-Osuna, 2019], while others borrow pre-trained speaker encoders from automatic speaker recognition systems [Lin et al., 2021a,b]. Some more systems use mutual information [Wang et al., 2021a], or diffusion models with maximum likelihood sample scheme [Popov et al., 2021].

While significant advances have been made on timbre transfer for zero-shot VC, prosody (i.e., pitch and rhythm) transfer remains insufficient due to data scarcity [Wang et al., 2021b]. Some researchers address this issue with explicit pitch modeling [Hayashi et al., 2021], which predicts the pitch contour and uses it to condition the voice generator, and directly regulation of the utterance length for rhythm control [Qian et al., 2021a].

Another approach is using a style embedding as the prosody representation. Style embedding can be obtained using speech disentanglement and self-supervised learning [Qian et al., 2021b] [Wang et al., 2021b]. For example, Chou et al. [2019] applies instance normalization to the feature map of the content embedding to disentangle the style information. The disentangled style embedding of the target utterance is then used to condition a decoder to generate speech that mimics the target speaker’s prosody. Style embedding improves the naturalness of pitch and rhythm generation, but it is entangled with speaker identity, thus making it difficult to control individual aspects independently. In addition, this utterance-level embedding can only be used for global conditioning but not time-varying control.

2.2 Self-Supervised Decomposition and Speech Synthesis

Self-supervised learning has demonstrated its success in speech representation learning. One approach is to learn representations that can predict a certain part of the speech signal from other parts [Liu et al., 2020] [Chung et al., 2019] [Hsu et al., 2021]. Another approach is to learn representations that can reconstruct the signal itself, e.g., auto-encoders, where the input speech is first encoded into low-dimensional representations and then decoded back to speech [Chorowski et al., 2019]. Multi-task learning has also been used in self-supervised learning for speech representations [Ravanelli et al., 2020] [Pascual et al., 2019].

Self-supervised learning has also been used in speech synthesis tasks. In a speech resynthesis system, Polyak et al. [2021] use self-supervised learning and a clustering algorithm to extract discrete units from speech to separate content and speaker information. Choi et al. [2021] also investigate self-supervised decomposition on speech resynthesis with continuous embeddings to mitigate false pronunciation. Similar techniques can be applied to voice conversion systems, where the learned speaker embedding is replaced with the target speaker’s embedding. However, those VC systems only focus on timbre transfer but not the controllability of pitch and rhythm.

3 Proposed ControlVC System

3.1 Overview

ControlVC aims to achieve time-varying control over pitch and rhythm in non-parallel and zero-shot voice conversion using control curves. As shown in Figure 1, the system consists of three stages: pre-processing, analysis and synthesis. The pre-processing stage employs TD-PSOLA to modify the rhythm of the source speech according to the speed control curve. In the analysis stage, the pitch contour of the processed source utterance is estimated and modified by the pitch control curve, before being fed into a VQ-VAE to obtain a pitch embedding. A linguistic embedding is computed from the speed-modified source utterance through a linguistic embedding network. Finally, a speaker embedding is computed from the target utterance. The pitch, linguistic and speaker embeddings are
then up-sampled, concatenated and fed to the synthesis stage, which uses HiFi-GAN neural vocoder \cite{Kong et al., 2020} to synthesize the time-domain waveform of the converted speech utterance. Note that only the HiFi-GAN vocoder is trained from scratch on voice conversion task, while the linguistic, speaker, and pitch encoder are pre-trained on other tasks and fixed. This makes our system end-to-end, with conversion and audio synthesis accomplished by a single vocoder.

### 3.2 TD-PSOLA Prepossessing and Rhythm Control

In the preprocessing stage, we use the time-domain pitch synchronous overlap and add (TD-PSOLA) algorithm to modify the rhythm of the source utterance according to the input speed control curve. TD-PSOLA was originally introduced in \cite{Charpentier and Stella, 1986} to achieve time-varying speed and pitch change of audio signals. We first segment the original utterance and apply time-stretching to each frame using the stretching ratio indicated by the control curve at the corresponding location. The pitch is retained, and so are the timbre and phoneme.

### 3.3 Pitch Control and Pitch Embedding

We employ the YAAPT algorithm \cite{Kasi, 2002} to extract the pitch sequence \((p_1, \cdots, p_T)\) of the rhythm-controlled source utterance with a frame length of 20 ms and a hop size of 5 ms, where \(T\) is the number of frames. This pitch sequence is then multiplied by the input pitch control curve to obtain the modified pitch sequence \((p_1', \cdots, p_T')\).

The modified pitch sequence is fed to a pitch embedding network to obtain the pitch embedding for the converted utterance. This pitch embedding network uses a VQ-VAE architecture which consists of a convolutional encoder, a discrete bottleneck codebook, and a convolutional decoder. Taking the pitch sequence as input, the encoder produces a sequence of 128-d latent vectors \((h_1, \cdots, h_T)\), which are then mapped to their respectively closet codes in the bottleneck codebook to form the pitch embedding sequence. Instead of using the actual code vectors, the embedding sequence takes the indices of the code vectors as values and passes them to the following stages of the system. We denote the pitch embedding sequence as \(z^{(p)} = (z_1^{(p)}, \cdots, z_T^{(p)})\).
This VQ-VAE embedding network is trained on original utterances in the training set without applying speed and pitch controls. To train it, the pitch embedding sequence is computed using the encoder and codebook as stated above, and the decoder is used to reconstruct the pitch sequence from the pitch embedding sequence. A mean-square-error (MSE) loss is used to compare the estimated pitch sequence with the original pitch sequence, and its gradient is propagated back. Following Dhariwal et al. [2020], an exponential moving average update is utilized to learn the codebook, and random restart is employed to prevent unused embeddings.

3.4 Linguistic Embedding

As one goal of voice conversion is to maintain the linguistic content of the source utterance, we need a linguistic encoder to compute the linguistic embedding from the (rhythm-controlled) source utterance. In recent years, self-supervised speech representation had shown to achieve superior performance on content analysis tasks such as speech recognition. In particular, the hidden unit BERT (HuBERT) model [Hsu et al. 2021] learns both acoustic and language models from continuous inputs, and achieves great performance on speech recognition, generation and compression tasks. In this work, we use HuBERT to extract the linguistic embedding from the (rhythm-controlled) source utterance.

We use a publicly available HuBERT model that is pre-trained on 960 hours of LibriSpeech audio. In our system, the input to the linguistic encoder is the source waveform, segmented into the same frames as those fed to the pitch detector. The output of the linguistic encoder are 768-d feature vectors extracted from the 6-th layer, one vector for each frame. As the feature vectors extracted from HuBERT are continuous and may contain speaker information, a K-means clustering procedure is applied on the HuBERT output. We train a mini-batch K-means clustering algorithm on the LibriSpeech-train-clean-100 dataset. During voice conversion model training, new data is assigned to pre-stored clusters based on the distance to the centroids. The final linguistic embedding is the sequence of cluster indices of each frame $z^{(l)} = (z^{(l)}_1, \cdots, z^{(l)}_T)$, where $z^{(l)}_i$ are integers. In our experiment, we set $K$ to 100.

3.5 Speaker Embedding

In order to transfer the timbre information of the target speaker, we need a speaker encoder to compute the speaker embedding from the target utterance. A good speaker encoder is expected to produce consistent embeddings for utterances from the same speaker and unique embeddings for different speakers. The majority of speaker encoders are designed for analysis tasks such as speaker verification, while only a few of them have been used in audio generation systems.

In this paper, we follow the design of Qian et al. [2019]. The speaker encoder consists of a stack of two LSTM layers with 768 cells. It takes mel-spectrogram as input and passes the outputs of the last time step through a fully converted layer. This results in a 256-d speaker embedding vector, which is then copied into an embedding sequence $z^{(s)}$, to match the same frame rate as that of the pitch and linguistic embedding sequences. We use a pre-trained speaker encoder, which is trained using GE2E loss [Wan et al. 2018]VoxCeleb [Nagrani et al. 2017] and Librispeech [Panayotov et al.] datasets. Prior experiments demonstrate that this speaker encoder can be generalized to unseen speakers in generation tasks [Qian et al. 2019].

3.6 HiFi-GAN Neural Vocoder

To construct the encoded discrete representation, the linguistic and pitch embedding are up-sampled, and the utterance-level speaker embedding is copied to match the same frame rate. These three embeddings are then concatenated into the intermediate representation $z = (z^{(p)}, z^{(l)}, z^{(s)})$, which is then fed into a neural vocoder to generate the waveform. We use HiFi-GAN’s vocoder but modify the original implementation so that it directly accepts the discrete and continuous mixed representation $z$ as input. The HiFi-GAN architecture uses a generative adversarial network (GAN) framework.

The generator includes a set of transposed convolution blocks and a residual block with dilated layers. The transposed convolutions increase the sample rate of the discrete representation to match the desired sample rate, while the dilated layers increase the receptive filed.2

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2https://scikit-learn.org/stable/modules/generated/sklearn.cluster.MiniBatchKMeans.html
The discriminator contains two types of sub-discriminators: multi-period discriminators (MPD) and multi-scale discriminators (MSD). There are five MPD sub-discriminators with identical network structures, each of which accepts a resampled and stacked 2-D audio input. This is designed to capture various implicit structures and periodic patterns of the input audio. There are three MSD sub-discriminators operating on different pooling scales, allowing for the exploration of features at different frequency ranges.

We denote the generator as $G$ and the discriminator as $D$, which contains a total of $K = 8$ sub-discriminators as $D_k$, for $k \in 1, \cdots, K$. The objectives for training the generator and the discriminator are:

$$L_G = \sum_{k=1}^{K} \left[ L_{Adv}(G; D_k) + \lambda_{fm} L_{FM}(G; D_k) \right] + \lambda_{mel} L_{Mel}(G),$$

(1)

$$L_D = \sum_{k=1}^{K} L_{Adv}(D_k; G),$$

(2)

where $L_{Adv}$, $L_{FM}$ and $L_{Mel}$ are adversarial loss, feature matching loss and mel-spectrogram loss, respectively. Following [Kong et al., 2020], the tradeoff parameters $\lambda_{fm}$ and $\lambda_{mel}$ are set to 2 and 45, respectively. The feature matching loss $L_{FM}$ and mel-spectrogram loss $L_{Mel}$ are defined as:

$$L_{FM}(G; D) = \mathbb{E}_{x, \hat{x}} \left[ \frac{1}{N_i} \| D^i(x) - D^i(G(x)) \|_1 \right],$$

(3)

$$L_{Mel}(G) = \mathbb{E}_{x, \hat{x}} \left[ \| \phi(x) - \phi(G(x)) \|_1 \right],$$

(4)

where $x$ is the ground-truth audio. $M$ denotes the number of layers in the discriminator. $D^i$ and $N^i$ represent the features and the number of features in the $i$-th layer, respectively. $\phi$ is the function that transforms a waveform into the corresponding mel-spectrogram.

4 Experiments

4.1 Dataset

We evaluate ControlVC on the CSTR VCTK Corpus [Yamagishi et al., 2019]. VCTK includes 44 hours of clean speech uttered by 110 English speakers with various accents. All recordings are downsampled to 16k Hz from their original sample rate of 48k Hz. We randomly select 10 speakers (5 male and 5 female) and use all of their utterances for testing. We use the remaining 100 speakers for training. In total, there are 39,781 utterances in the training set and 3,690 utterances in the test set.

4.2 Baseline Methods

To our best knowledge, ControlVC is the first VC method that achieves time-varying control on pitch and rhythm. We could not find any exiting methods to compare with directly. Therefore, we designed two baseline methods using well-established algorithms in signal processing and voice conversion to achieve time-varying control. Note that both baselines are new controllable voice conversion systems that do not exist in literature.

The first baseline is PSOLA-LPC. In this system, TD-PSOLA is used to modify the pitch and rhythm of the source utterance. Then linear predictive coding (LPC) [Zölzer et al., 2002] is employed to model the timbre of the target speech and transfer it to the converted utterance.

To compare ControlVC with high-fidelity VC techniques, we design the second baseline named PSOLA-AutoVC. It again first uses TD-PSOLA to modify the pitch and rhythm of the source utterance, but then uses AutoVC [Qian et al., 2019] to achieve timbre transfer. AutoVC is a widely-used neural-based VC method that achieves high quality of converted utterances. However, it only performs timbre transfer but has no pitch or rhythm controllability. The combination of TD-PSOLA with AutoVC leverages advantages of both algorithms.
4.3 Training

For the proposed ControlVC method, the pitch encoder is pre-trained on the VCTK dataset for 40k steps. The linguistic embedding is extracted from the 6-th layer of a publicly available pre-trained HuBERT model\(^3\). The speaker encoder is pre-trained on a combination of VoxCeleb [Nagrani et al., 2017] and Librispeech [Panayotov et al.] datasets with a total of 3,549 speakers using GE2E loss\(^4\). Finally, we train the HiFi-GAN vocoder on the VCTK dataset using one RTX 2080Ti with batch size 8 for 350k steps. We use Adam optimizer with an initial learning rate of 0.0002 and a decay rate of 0.999. For the PSOLA-AutoVC baseline, we use the pre-trained AutoVC model available at\(^4\).

4.4 Experimental Setup

The VC experiments are performed among all of 90 pairs of 10 test speakers. Each utterance of one test speaker is converted to each of the other 9 speakers’ voices. Each speaker in the test set reads a different set of sentences that are unseen during training, therefore, the conversion is non-parallel and zero-shot.

In this experiment, we apply control curves for rhythm and pitch, and compare the generated result with the uncontrolled conversions. Four control settings are tested: “No Control” means that a traditional voice conversion is conducted without taking any explicit control; “Pitch Only” and “Rhythm Only” denote pitch or rhythm control but not both; “Rhythm + Pitch” means that both aspects are controlled. We test two curves for pitch control: stressing (i.e., pitch rising abruptly then going down gradually) and rising, and three curves for rhythm control: parabola, speed up and slow down. A more detailed account of control curves is given in the appendix. The four control settings and the control curves are drawn with equal probability for each conversion.

In both subjective and objective evaluation experiments, we assess the controllability and the conversion quality of the proposed system. Controllability refers to how accurately the change of pitch or rhythm between the uncontrolled and controlled conversions follows the user control curve(s). Conversion quality consists of two aspects: naturalness of the converted utterance and timbre similarity with the target utterance.

4.5 Subjective Evaluation

We perform two subjective experiments using a self-designed survey website. The website is publicly available and is shared within the University of XXX and its alumni to recruit study participants without providing monetary incentives. We do not record any demographic information of the participants, but assign a unique ID to each participant-session. A participant who performs the assessments at two different times is hence treated as two participants. Details of subjective evaluation page are given in the appendix.

Audio Quality Test. In the first test, we use mean opinion score (MOS) [Streijl et al., 2016] to assess the naturalness and timbre similarity of the converted speech. Study participants are presented with paired source, target and converted utterances which we refer to as a sample. The converted utterances are outputs of ControlVC and the two baselines, and are presented in a random order in each sample. For each sample, the participants are asked to rate between 1-5 on the naturalness of the converted utterances and the timbre similarity between the target and the converted utterance. Higher scores are better. Each participant is asked to complete at least 6 samples, i.e., 36 ratings for 18 converted utterances from 3 comparison methods. However, they are allowed to continue the assessment after completing the 6 samples. In total, 466 rounds of tests are completed, resulting in 1398 ratings.

Table\(^1\) shows the subjective evaluation results of the first test on naturalness and timbre similarity. It can be seen that ControlVC archives the best MOS score among three comparing methods in all of the three control settings. In addition, comparing the three with control settings with “No Control”, we see that applying controls only slightly decreases the speech quality of the converted speech.

Controllability Test. The second test assesses controllability of the proposed ControlVC method. We do not include the two baselines in this test due to their poor audio quality in the previous test.

\(^3\)https://github.com/facebookresearch/fairseq
\(^4\)https://github.com/auspicious3000/autovc
Table 1: Subjective evaluation results on naturalness of the converted utterance and its timbre similarity with the target utterance of the three comparison methods in four controllability settings. MOS and the 95% confidence interval is reported.

|                  | PSOLA-LPC | PSOLA-AutoVC | ControlVC (proposed) |
|------------------|-----------|--------------|----------------------|
| **No Control**   |           |              |                      |
| Nat.             | 1.20 ± 0.09 | 2.17 ± 0.16  | 4.36 ± 0.18          |
| Sim.             | 1.33 ± 0.11 | 2.68 ± 0.20  | 4.57 ± 0.14          |
| **Rhythm Only**  |           |              |                      |
| Nat.             | 1.54 ± 0.12 | 1.89 ± 0.16  | 4.13 ± 0.16          |
| Sim.             | 1.77 ± 0.15 | 2.08 ± 0.15  | 3.98 ± 0.17          |
| **Pitch Only**   |           |              |                      |
| Nat.             | 1.66 ± 0.14 | 2.18 ± 0.18  | 3.53 ± 0.18          |
| Sim.             | 1.82 ± 0.13 | 2.35 ± 0.17  | 3.34 ± 0.19          |
| **Rhythm + Pitch**|          |              |                      |
| Nat.             | 1.32 ± 0.12 | 2.02 ± 0.21  | 3.83 ± 0.17          |
| Sim.             | 1.52 ± 0.14 | 2.38 ± 0.21  | 3.93 ± 0.17          |

Table 2: MOS results of the controllability subjective test with 95% confidence interval. This table shows pitch OR rhythm control only scenarios.

| Control Method       | Accuracy Rating                  |
|----------------------|----------------------------------|
|                      | Real Curve | Random Curve |
| Pitch Control Only   | 3.38 ± 0.15 | 3.00 ± 0.19 |
| Rhythm Control Only  | 3.37 ± 0.25 | 3.21 ± 0.19 |

The participants are presented with uncontrolled and controlled conversion results, along with a figure of the corresponding control curve(s). The participants are then asked to assess how accurately the curve describes the change of pitch or rhythm between the uncontrolled and controlled conversions on a scale of 1 to 5, with 1 being "not at all accurate", 3 being "moderately accurate" and 5 being "very accurate". Same as the audio quality test, each participant is asked to complete 6 rounds of tests, with each round containing a pitch control, a rhythm control and a pitch+rhythm control of the same source-target reference pair. Participants are allowed to complete more rounds. In total, participants completed 169 rounds of tests, resulting in 676 ratings.

In single-factor control conversions, the presented control curve has a 15% chance of being a randomly generated curve rather than the one actually used in the conversion. This provides us a baseline of no controllability for comparison. Tables 2 and 3 show the assessment results. It can be seen that our proposed method achieves a statistically significantly higher MOS rating than the baseline on pitch control. On rhythm control, the MOS is slightly higher than the baseline, but the difference may not be statistically significant. One possible explanation is that some utterances are short, making it hard to tell the change in rhythm. A t-test on the rating data suggests that the difference between the single-control and double-control accuracy MOS ratings is not statistically significant. This shows that our system is able to control both factors simultaneously without significant quality degradation.

Note that in unseen zero-shot voice conversion, AutoVC achieves a MOS and similarity score of about 3 and 3 in the original paper, MOS of 2.59 in [Choi et al., 2021]. Our PSOLA-AutoVC baseline achieves 2.17 and 2.68 in MOS and similarity. Note that [Choi et al., 2021] is trained on VCTK (44 hours) and LibriTTS (360 hours), while our model is trained on VCTK only. In addition, it is noted that AutoVC is applied after the PSOLA preprocessing, which introduces noticeable degradation.

Table 3: MOS results of the controllability subjective test with 95% confidence interval. Pitch AND rhythm controls are applied.

| Accuracy Rating |
|-----------------|
| Pitch | Rhythm |
| 3.18 ± 0.15 | 3.41 ± 0.14 |
Table 4: Objective evaluation result.

|                  | Verification ↑ | WER (%) ↓ | Distance ↓ |
|------------------|----------------|-----------|------------|
| GT               | 1.00           | 9.82      | 0.0        |
| PSOLA-LPC        |                |           |            |
| No Control       | 0.65           | 89.12     | -          |
| Pitch Only       | 0.66           | 88.56     | 31.54      |
| Rhythm Only      | 0.65           | 88.64     | 98.58      |
| PSOLA-AutoVC     |                |           |            |
| No Control       | 0.66           | 76.51     | -          |
| Pitch Only       | 0.65           | 72.83     | 87.00      |
| Rhythm Only      | 0.65           | 72.59     | 151.89     |
| ControlVC        |                |           |            |
| No Control       | 0.85           | 10.99     | -          |
| Pitch Only       | 0.82           | 12.40     | 75.82      |
| Rhythm Only      | 0.84           | 16.37     | 136.44     |
| Pitch + Rhythm   | 0.83           | 22.46     | -          |

artifacts that are likely to affect the performance of AutoVC. Due to both reasons, we believe that this performance degradation of PSOLA-AutoVC baseline is reasonable.

4.6 Objective Evaluation

We conduct an additional objective evaluation to assess the speech intelligibility and timbre similarity of the converted utterances. For speech intelligibility evaluation, we use IBM speech recognition service [Saon et al., 2015] to transcribe converted speech into text and then calculate the word error rate (WER) [Wang et al., 2003] against the ground-truth transcripts. For timbre similarity, we use a pre-trained speaker encoder Resemblyzer\(^5\) to score the speaker similarity of the converted utterance and the target utterance on a scale of 0 to 5. The higher the score, the more similar they are. In measuring controllability, for either pitch or rhythm, we first use the dynamic time warping on MFCC features to align the source and converted speech utterances and obtain an alignment curve. The alignment curve is then compared with the user input curve using dynamic time warping and euclidean distance for their similarities. The same set of samples generated for subjective evaluation is used for this section.

The objective evaluation results are in Table 4.6. ControlVC has the lowest WER and highest speaker similarity in all test configurations.

5 Conclusions

In this paper, we proposed a controllable voice conversion system named ControlVC, which allows users to impose time-varying controls on pitch and rhythm of the converted utterance. The converted utterance maintains the source utterance’s linguistic content, mimics the target speaker’s timbre, and sounds natural while following the user input pitch and/or rhythm controls. The proposed model utilizes signal processing-based pre-processing and pre-trained self-supervised speech decomposition. We demonstrate the effectiveness of the proposed method by comparing it with two self-constructed baselines in different experimental settings. Both objective and subjective evaluation results suggest that ControlVC is able to perform multi-factor control while producing high-quality conversions.

As the first method to achieve neural voice conversion with time-varying controls, ControlVC still has some limitations. In order to improve speech information disentanglement, we use discrete embedding spaces, which could lead to inaccurate phoneme and pitch generation. Also, ControlVC contains multiple modules that take different input features, making the system somewhat complicated. In the future, we will investigate improved generative features to replace the current ones designed for analytical tasks (e.g., speaker encoder is designed for automatic speaker verification rather than generation). In addition, we plan to adapt ControlVC to take other types of control inputs from other modalities, such as video and natural language.

\(^5\)https://github.com/resemble-ai/Resemblyzer
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A Control Curves

Here we present the plots of control curves used during pitch and rhythm control experiments. We select curves that are representatives of potential user inputs.

B Subjective Evaluation Website

We attach the screenshots of the self-designed survey website built for subjective evaluation. The two tests of subjective evaluation are described in section 4.5.
Figure 2: Rhythm control curves. The converted utterance is expected to generally follow the speed trend specified by the curve. Take the top-left curve as an example, the converted utterance is expected to increase its speed from 0.5x original speed of the source utterance to 1.2x.

Figure 3: Pitch control curves. The converted utterance is expected to have a similar pitch trend as the control curve. Similar to rhythm, the curve indicates the ratio of pitch (in Hz) of the converted utterance and the original utterance. For example, 1.2x pitch rate means that the pitch of the converted utterance is expected to be 1.2 times of the source utterance.
Figure 4: Survey website, test 1 - audio quality test.
Figure 5: Survey website, test 2 - controllability test.