SEQUENCE-TO-SEQUENCE VOICE CONVERSION USING F0 AND TIME CONDITIONING AND ADVERSARIAL LEARNING

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ABSTRACT
This paper presents a sequence-to-sequence voice conversion (S2S-VC) algorithm which allows to preserve some aspects of the source speaker during conversion, typically its prosody, which is useful in many real-life application of voice conversion. In S2S-VC, the decoder is usually conditioned on linguistic and speaker embeddings only, with the consequence that only the linguistic content is actually preserved during conversion. In the proposed S2S-VC architecture, the decoder is conditioned explicitly on the desired F0 sequence so that the converted speech has the same F0 as the one of the source speaker, or any F0 defined arbitrarily. Moreover, an adversarial module is further employed so that the S2S-VC is not only optimized on the available true speech samples, but can also take efficiently advantage of the converted speech samples that can be produced by using various conditioning such as speaker identity, F0, or timing.

Index Terms— Voice conversion, non-parallel voice conversion, F0-preservation, adversarial network

1. INTRODUCTION

1.1. Context and Related works
Voice conversion (VC) consists of digitally altering the voice of an individual - e.g., its identity, accent, or emotion - while maintaining its linguistic content unchanged. Primarily applied to identity conversion, VC has considerably gained in popularity and in quality thanks to the advances accomplished with neural VC (see for instance, [1]). Neural VC is now widely considered as a standard in VC and has reached a highly-realistic rendering of voice identity conversion from a small amount of data of a target voice. Similarly to face manipulation, voice conversion has a wide range of potential applications, such as voice cloning and deep fake [2] in the fields of entertainment and fraud, anonymization of voice identity [3] in the field of security and data privacy, or digital voice prosthesis of impaired speech [4] in the field of digital healthcare. Introduced in the late 2000’s, Neural VC has gradually moved towards many-to-many and non-parallel datasets allowing the scalability of neural VC to large and multiple speakers datasets, with the assumption that the increase of data will induce a substantial increase in terms of quality and naturalness of the VC. In particular, starGAN VC [6,7] has been proposed to extend the paradigm of cycle-GAN to many-to-many and non-parallel VC by proposing a conditional encoder-decoder architecture. As opposed to the cycleGAN VC, starGAN VC is composed of a single encoder-decoder in which the decoder is conditioned on the speaker identity to be reconstructed. A classic GAN discriminator together with an auxiliary speaker classifier is employed as losses to learn the conversion. Many recent neural VC systems formulate the VC problem as a conditional auto-encoder [8,9,10]. Similarly to the starGAN, the architecture is an auto-encoder in which the encoder part encodes the source speaker from the input source speaker’s utterance, and the decoder part reconstructs the target speaker’s utterance from the source encoding and a speaker embedding. The fundamental difference lies in the fact that during training, the source and the target speakers are simply the same. During conversion, one only needs to manipulate the speaker identity in the decoder to convert the input speech to the desired target identity. This breakthrough has opened the way to VC from a very small number of examples of the target speaker (at the extreme from one-shot [9] or zero-shot [10]).

1.2. Limitations and Contributions
In most VC systems the only information which remains from the source speaker during conversion is the linguistic content (e.g., the actual text transcript). This VC paradigm may be too restrictive for a various number of applications in which one can desire to preserve some other aspects from the source speaker. This is typically the case when one wants the source speaker to play the acting which is the one desired for the converted speech, and one needs the converted speech to be lip-synchronized with some audio-visual content. This requires to preserve some aspects of the prosody of the source speaker during conversion, for instance its timing - represented as the sequence of phonemes with corresponding duration - and its fundamental frequency (F0). Some neural VC inherently
preserves the timing as for cycleGAN-VC and starGAN-VC, but this is not the case of S2S-VC. The only research to date proposing to preserve the F0 of the source speaker by conditioning the decoder with the desired sequence of F0 values \[11\]. Moreover the auto-encoder learns to reconstruct a speech signal from its true codes (linguistic content and speaker identity, possibly timing and F0) while one modifies at least one of these codes during the actual conversion. This inconsistency may result into a poorer naturalness and perceived identity of the converted speech.

This paper introduces a hybrid VC framework in which a speech signal is converted to the identity of a target speaker while preserving the timing and the F0 of the original source speaker\[1\]. The main contributions of this paper are: 1) Leveraging on the S2S neural VC as introduced in \[12\], a time-synchronous S2S-VC with F0-preservation is presented. This is achieved by incorporating a F0 encoder module and an explicit F0 loss between the converted speech and the original speech; 2) An adversarial module is added on the converted speech in order to help preserving the naturalness and the identity of the converted speech. This allows to include converted speech samples during training, thus reducing the inconsistency between training and conversion.

### 2. PROPOSED METHOD

#### 2.1. Original S2S Neural VC

The VC framework used in this paper is rooted on a sequence-to-sequence (S2S) auto-encoder, in which linguistic and speaker representation are encoded through dedicated encoders as illustrated in Figure\[1\]. The proposed implementation is a simplified version of the original VC system presented in \[12\] without any substantial loss in quality. The inputs of the system are the speech signal matrix A represented by the Mel-spectrogram computed on T time frames, and the sequence of T phonemes p corresponding to the phonetic transcription of the input text aligned to the corresponding speech signal. Dual encoders \(E^t\) and \(E^s\) are employed to encode linguistic and speaker information. The speaker encoder \(E^s\) converts the speech signal A into a time-independent vector \(h^s\), since it is assumed that the identity of a speaker does not vary within an utterance. A speaker classification loss \(L_{SE}\) is defined between the speaker identity predicted from \(h^s\) and the true speaker identity s. The text encoder \(E^t\) converts the phoneme sequence p into a linguistic embedding \(H^t\) which has the same length \(T\) as the aligned phoneme sequence (and the Mel-spectrogram). A S2S decoder \(G^a\) conditioned on the linguistic embedding \(H^t\) and the speaker embedding \(h^s\) is employed to reconstruct an approximation \(A\) of the original speech signal A. A reconstruction loss \(L_{REC}\) is defined between the reconstructed speech signal \(A\) and the original speech signal \(A\).

During training, the S2S-VC neural network is pre-trained on a multiple-speakers dataset, and then fine-tuned with respect to a given pair of source and target speakers. During conversion, the recognition encoder \(E^r\) computes the linguistic embedding \(H^r_{src}\) corresponding to one utterance A\(_{src}\) of the source speaker; and the speaker encoder \(E^s\) computes the speaker embedding \(h^s_{tgt}\) corresponding the one utterance B\(_{tgt}\) of the target speaker. Then, decoder \(G^a\) is conditioned on the linguistic embedding \(H^r_{src}\) and the speaker embedding \(h^s_{tgt}\) to generate the utterance A\(_{tgt}\) with the identity of the target speaker. Without explicit notification, the architecture and parameters of the S2S-VC are the same as those described in \[12\].

![Fig. 1. Architecture of the proposed S2S-VC system.](http://recherche.irCAM.fr/anasy/n/VC_ICASSP22.html)
learning rate $1e^{-4}$.

2.3. Proposed S2S Neural Voice Conversion

2.3.1. Contribution 1: S2S-VC with time-synchronization and $F0$-conditioning

S2S-VC architecture does not ensure time-synchronicity between the original speech and the converted speech, by definition of the sequence-to-sequence architecture. The S2S-VC is basically composed on a speech-to-text encoding time-compression and a text-to-speech decoding time-decompression with a similar architecture as the Tacotron ([15], [16]). In order to preserve time-synchronization between the original and the reconstructed speech signals, the time dimension of length $T$ is preserved all through the network, from the original speech signal $A$ to the linguistic embedding $H^t$, and to the reconstructed speech signal $\hat{A}$. To do so, the auto-regressive S2S part of the recognition encoder $E^t$ and the decoder $G^t$ are modified accordingly by employing simple recurrent architectures. The recognition encoder $E^t$ is composed of two bidirectional LSTM layers of dimension 128 followed by a fully connected layer (FC) of dimension 128, resulting in a linguistic embedding of dimension (128 $\times$ $T$). The decoder $G^t$ is using two bidirectional LSTMs of dimension 128 each and a Fully Connected layer of dimension 80 which outputs an approximated Mel-spectrogram with the same dimensions as the input Mel-spectrogram, i.e., (80 $\times$ $T$). These simplifications enable time-synchronous conversions and a consequent saving in computational time: approximately 33% of the computational time for training on our server with a single GPU.

In order to preserve the $F0$ of the original speech signal during conversion, a $F0$ encoder $E^{F0}$ is added and a $F0$-loss is explicitly formulated. The $F0$ encoder converts the input Mel-spectrogram into a corresponding sequence of $F0$ values. This value corresponds to the estimated $F0$ value for voiced frames and to 0 for unvoiced frames. This encoding is passed to condition the decoder $G_{a}$ in addition to the linguistic and speaker embeddings to create the Mel-spectrogram. A $F0$ loss is defined as the mean square error between the $F0$ values of the generated speech and the $F0$ values of the original speech, as

$$L_{F0}(h^{F0}, \hat{h}^{F0}) = \frac{1}{T} \sum_{t=1}^{T} (h^{F0}(t) - \hat{h}^{F0}(t))^2$$

(1)

The $F0$ encoder $E^{F0}$ is described in [17], pre-trained on the training set of the VCTK speech database, and then fixed during VC training, i.e. is only used to compute the $F0$ loss $L_{F0}$. Contrary to [11] this loss explicitly constrains the $F0$ to the desired $F0$ by defining a dedicated loss. This ensures that the $F0$ of the converted speech to be effectively preserved during conversion. This loss is added to the reconstruction loss with a weight $\lambda_{F0}$ varying linearly from $10e^{-6}$ to $10e^{-2}$ with the effect of increasing gradually the importance of the $F0$ preservation versus the reconstruction loss during training. Informal experiments revealed that the $F0$ of the converted speech differs by less than 5 Hz in average on a test set, which is not audible in most cases. During conversion, the $F0$ can be transferred from an utterance of a source speaker or fixed arbitrarily (e.g., by applying transposition or setting any arbitrary values).

In this paper, the $F0$ used for conditioning was adapted to the range of the target speaker in order to prevent unnatural converted speech that would be caused by some important difference between the respective ranges of the source and target speakers (typically when converting a male to a female or conversely). This was accomplished by normalizing the $F0$ values corresponding to the sentence of the source speaker with respect to the log($F0$) mean and standard deviation of the target speaker.

2.3.2. Contribution 2: Adversarial Training of S2S-VC

S2S-VC basically relies on an auto-encoder optimizing a reconstruction loss between the original speech signal and the reconstructed one. This is somehow inconsistent with the conversion in which the identity of the speaker is manipulated during conversion (eventually, the $F0$ and timing). In the case of a conversion, one does not have access to the ground truth speech signal and thus one cannot apply the reconstruction loss of the auto-encoder. To overcome this limitation and construct a VC system whose training is more consistent with conversion, we propose to split the training process into two modes: the reconstruction mode corresponding to the classical auto-encoder in which the reconstruction loss can be computed; the adversarial mode, in which we assume that the true speech signal may not be available. This is typically the case in which least one of the codes conditioning the decoder is manipulated. For this mode, we introduce an adversarial module which is similar to the one used in a GAN. A discriminator $D^{adv}$ is optimized to distinguish between the real speech samples and the converted ones, while the decoder $G^a$ is optimized to fool the discriminator. During training, each samples contained in a batch is both passed to the decoder in the reconstruction mode with original unchanged codes and in the conversion mode with unchanged or manipulated codes. In this paper, only the speaker identity is manipulated so that the reconstruction has the right identity and the conversion mode a randomly picked identity. The total loss $L_{GEN}$ including reconstruction and conversion losses can then be expressed as,

$$L_{GEN} = L_{BC} + \lambda_{adv} L_{ADV}$$

(2)

For clarity, the $F0$ loss is not specified in the above loss but is still used as previously described. In this paper, the discriminator $D^{adv}$ is composed of 4 convolution layers with 128 filters of size $(3 \times 3)$ with a stride of $(2 \times 2)$ and $\lambda_{adv} = 1$ was found to provide a good trade-off between the effect of the reconstruction and the conversion on the decoder $G^a$. 

3. EXPERIMENTS

3.1. Speech dataset

The English multi-speaker corpus VCTK [18] is used for training and testing. The VCTK dataset contains speech data uttered by 110 speakers and the corresponding text transcripts. Each speaker read about 400 sentences selected from English newspaper, which represents a total of about 44 hours of speech. Four speakers All speakers are included into the training and validation sets. For each speaker, we split the database in a training set with 90% of the sentences and a validation set with 10% of them. The total duration of the database is around 27 hours after removing silences at the beginning and at the end of each sentence.

3.2. Subjective Experiment Setup

The experiment consisted into the judgment by listeners of: the similarity of the converted speech to the target speaker and the naturalness of the converted speech, using 5-degree MOS scale as commonly used for the experimental evaluation of VC algorithms. Each participant had to judge 15 speech samples which were randomly selected among the total number of speech samples produced for the subjective experiments. The experiment was conducted on-line. Participants were encourage to perform the experiment in a quiet environment and with a headphone. Four speakers were used for the experiment: two males (p232 and p274) and two females (p253 and p300) with eight randomly chosen sentences per speaker in the validation set. Conversion were computed between male speakers and between females speakers, resulting in two male and two female conversion setups. Four configurations were compared: 1) the original audio signal and the converted speech with ; 2) time-synchronous and F0-preserved VC system (referred to as F0 cond.); 3) time-synchronous and F0-preserved VC system with discriminator trained only with the true speaker identity (same identity as the source speech utterance), referred to as F0 cond. w/adv same id; 4) time-synchronous and F0-preserved VC system with discriminator trained only with varying speaker identities (different identities from the one of the source speech utterance), referred to as F0 cond. w/adv. diff id.

3.3. Results and Discussion

25 subjects participated in the experiment. Table 1 presents the mean MOS scores obtained for the compared system configurations. On the one hand, the baseline VC system using time-synchronization and F0 preservation presents fair to good similarity to the target speaker (MOS=3.92 for similarity), even though the timing and the F0 contours is inherited from the source speaker. Also, the naturalness is also rated to the fair range (MOS=3.09). One can observe that the naturalness is degraded with the female speakers (MOS=2.85) as compared to the male speakers (MOS=3.38). These results are consistent with the ones obtained in the literature about S2S-VC, as in [12]. This indicates that the application of a timing and a F0 contour from a different speaker does not degrade consistently neither the similarity nor the naturalness of the converted speech. On the other hand, the proposed VC system with time and F0 preservation together with adversarial loss on varying speaker identities improves the scores in almost all cases compared to the baseline. The overall similarity to the target speaker is good (MOS=4.06) and the naturalness of the conversion is fair (3.18). The improvement in similarity is particularly substantial for the female speakers (MOS=4.23) while in the same time the difference in naturalness between the male and female conversions is much less pronounced (MOS=3.16 for male speakers and MOS=3.21 for female speakers). This indicates that the add of the discriminator not only helps to improve the naturalness of the converted speech (by suppressing perceptible artifacts) but also increases the similarity to the target speaker. Also, the use of varying speaker identities with the adversarial loss improves the scores in all cases compared to using only the true identity of the speaker. This is probably mainly due to the fact that the discriminator is being more efficient when subject to a larger variety of sentence and speaker identities.

| VC system | Male-to-Male Similarity | Male-to-Male Naturalness | Female-to-Female Similarity | Female-to-Female Naturalness | TOTAL Similarity | TOTAL Naturalness |
|-----------|------------------------|-------------------------|-----------------------------|-------------------------------|-----------------|-----------------|
| Orig: target speaker | 4.92 | 4.94 | 4.98 | 4.97 | 4.98 | 4.96 |
| F0 cond | 3.90 | 3.38 | 3.93 | 2.85 | 3.92 | 3.09 |
| F0 cond w/ adv. same id | 3.90 | 3.15 | 3.94 | 2.91 | 3.96 | 3.14 |
| F0 cond w/ adv. diff id | 3.91 | 3.16 | 4.23 | 3.21 | 4.06 | 3.18 |

4. CONCLUSIONS

This paper presented a S2S-VC algorithm which allows to preserve the timing and the F0 of the source speaker during conversion. Moreover, an adversarial module is added so that the S2S-VC can learn both from real speech samples as well as manipulated ones. Experimental evaluation on the VCTK speech database shown that the F0 is effectively preserved during conversion and that the adversarial module clearly helps to reduce the audible artifacts of the conversion as well as improve the perceived identity of the converted speech. Further research will investigate the manipulation of timing and F0 during training, in addition to the speaker identity.
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