Speak Like a Dog: Human to Non-human creature Voice Conversion

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Abstract

This paper proposes a new voice conversion (VC) task from human speech to dog-like speech while preserving linguistic information as an example of human to non-human creature voice conversion (H2NH-VC) tasks. Although most VC studies deal with human to human VC, H2NH-VC aims to convert human speech into non-human creature-like speech. Non-parallel VC allows us to develop H2NH-VC, because we cannot collect a parallel dataset that non-human creatures speak human language. In this study, we propose to use dogs as an example of a non-human creature target domain and define the “speak like a dog” task. To clarify the possibilities and characteristics of the “speak like a dog” task, we conducted a comparative experiment using existing representative non-parallel VC methods in acoustic features (Mel-cepstral coefficients and Mel-spectrograms), network architectures (five different kernel-size settings), and training criteria (variational autoencoder (VAE)-based and generative adversarial network-based). Finally, the converted voices were evaluated using mean opinion scores: dog-likeness, sound quality and intelligibility, and character error rate (CER). The experiment showed that the employment of the Mel-spectrogram improved the dog-likeness of the converted speech, while it is challenging to preserve linguistic information. Challenges and limitations of the current VC methods for H2NH-VC are highlighted.

Index Terms: Human to Non-human Creature Voice Conversion, non-parallel Voice Conversion, Dog voice, StarGAN-VC, ACAE-VC

1. Introduction

Voice conversion (VC) is a technology that converts the speech waveform of the source speaker into a speech waveform with the characteristics of the target speaker while preserving linguistic information [1]. Specifically, in many VC methods, acoustic features are first extracted from the source speaker’s speech waveform using speech analysis and then converted to acoustic features similar to those of the target speaker. Finally, a speech waveform is synthesized using the converted acoustic features. Most VC studies have focused on human to human VC. In this study, we consider human to non-human creature VC (H2NH-VC). H2NH-VC converts human voice into non-human creature-like voice while preserving linguistic information. Non-human creature-like voice refers to voices with certain non-human creature elements such as animals and monsters speaking in a fantasy world. We expect technologies that can efficiently generate non-human creature-like voice to extend the possibility of creative works in cinema production, game playing, etc. In this study, we focus on dogs as a representative example of the non-human creature target domain because dog voices are relatively easy to collect and are familiar and prevalent in our daily lives. We define an H2NH-VC task called “speak like a dog,” task and investigate the plausibility and challenges of applying existing non-parallel VC methods in this study. Figure 1 illustrates an overview of the human to dog VC.

Notably, the recent development of non-parallel VC methods [2] has made H2NH-VC a possibility. In studies on H2NH-VC, the collection of ground truth speech signals has been a critical barrier to conducting the study. Since “there is no dog in this world that speaks human languages,” the ground-truth utterance output from the VC system corresponding to the input utterance cannot be obtained. Therefore, conventional VC methods that require parallel data for training, parallel VC methods [6,8], cannot be used. For more examples and details of parallel VC methods, readers are referred to a recent review article [9].

The parallel data consists of source and target speech pairs used to express the same sentence. In contrast, non-parallel VC methods do not require parallel data. This means that non-parallel VC methods have theoretically overcome the barrier of H2NH-VC. Recent deep learning-based, non-parallel VC methods have achieved a VC that is comparable to the ground truth speech in a mean opinion score (MOS) test [10,11]. The baseline methods in Voice Conversion Challenge [12] are based on generative adversarial networks (GAN) or variational autoencoders (VAE). One example of a GAN-based method is StarGAN-VC [13,14], and one example of a VAE-based method is the auxiliary classifier VAE-based VC (ACVAE-VC) [15]. However, the applicability of these non-parallel VC methods to H2NH-VC tasks has not been explored.

To this end, in this paper, we propose a task called “speak
like a dog,” which is a new task for VC from human voice into dog-like voice while preserving linguistic information. We construct datasets and evaluation criteria for this task. In addition, we investigated how much VC could be achieved using existing non-parallel VC methods. We experimented with comparing acoustic features, network architectures, and training criteria as baseline methods.

The main contributions of this paper are twofold:

- We propose the “speak like a dog” task as an example of H2NH-VC tasks and construct a dataset and evaluation criteria.
- We investigated the possibilities and characteristics of “speak like a dog” task by conducting an experiment comparing existing representative non-parallel VC methods in acoustic features, network architectures, and training criteria.

The remainder of this paper is organized as follows. Section 2 defines the speech task as a dog task. Section 3 describes the methods used in the experiment. Section 4 describes comparative experiments. Finally, Section 5 concludes the paper.

2. Speak Like a Dog Task

2.1. Problem definition

The proposed “speak like a dog” task is one of the H2NH-VC tasks that converts human voice into dog-like voice while preserving linguistic information and representing a dog-like element of the target domain. Thus, the VC method should preserve linguistic information and represent dog-like elements. It is not enough to satisfy only one or the other. In particular, it is important to preserve linguistic information, that is, uttered sentences are recognized correctly by listeners, while ensuring dog-likeness, sound quality, and intelligibility of speech.

2.2. Dataset

A dataset can be non-parallel but should contain human speech signals and dog voices. We constructed an example dataset for the “speak like a dog” task. Details of the dataset can be found on our website.

ATR digital sound database. We use the ATR digital sound database for human speech signals. This is a database of speech recordings of sentences, single words, and other standardized content uttered by two male (MMY and MTK) and two female (FKN and FTK) professional announcers. The number of each domain’s sounds is 503.

Dog dataset. The dog dataset was constructed from several studies, Freesound project, freesoundslibrary, and Youtube. Because there is no dog dataset created for VC, we removed extremely soft, loud, and noisy sounds from our collected data. We also divided them into two datasets based on pitch, adult dog and puppy. The number of adult dog and puppy sounds is 792 and 288, respectively. The dataset is available under the terms of the Creative Commons Attribution-NonCommercial license.

2.3. Evaluation criteria

Mean Opinion Score (MOS). We defined three MOSs for the “speak like a dog” task. They can be obtained by asking subjects to rate the following three MOS tests on a scale of 1 to 5:

1. **Dog-likeness**: How much of the dog-like element is included?
   - 1 indicates completely not dog-like, and 5 indicates completely dog-like.
2. **Sound quality**: How good is the sound quality?
   - 1 indicates completely low quality, and 5 indicates completely high quality.
3. **Clarity**: How intelligibly were you able to hear the spoken utterance given a written text of the content of the spoken utterance?
   - 1 indicates complete vagueness, and 5 indicates complete intelligibility.

**Character Error Rate (CER).** To evaluate how H2NH-VC preserves linguistic information, we use the character error rate (CER), which represents the error rate between the transcribed sentences of converted speech by the listener and the correct sentences. The CER is defined as

\[
\text{CER} = \frac{D + S + I}{N},
\]

where \(D, S, I, \) and \(N\) are the number of deletion errors, substitution errors, insertion errors, and characters in the reference, respectively.

3. Method

In this section, we introduce the methods for the experiment. The key elements involved in VC are acoustic features, network architectures, and the methods of learning the conversion model. Each element has multiple options, but it is not clear what combination is appropriate for converting human voice to dog-like voice.

3.1. Acoustic features

The main acoustic features transformed by VC are MCC sequences and the mel-spectrogram. MCC is an acoustic feature that corresponds to the spectral envelope (shape of the human vocal tract), and the mel-spectrogram is an acoustic feature that includes a harmonic structure (close to the raw acoustic spectrum). Therefore, it is not clear whether MCC is appropriate for representing a dog’s spectral envelope. We predict that the mel-spectrogram works better than MCC in the “speak like a dog” task. We then compared the results of the experiments.

3.2. Network architecture

Network architectures is another element to investigate. In recent years, both convolutional neural network(CNN)-based and recurrent neural network(RNN)-based network architectures have been employed in VC studies. For example, StarGAN-VC is based on three networks, a generator, discriminator, and domain classifier, with CNN architectures.

This study focuses on a CNN-based network architecture that can be easily investigated by changing the kernel size. We want to investigate how much time range the VC system needs to capture in the “speak like a dog” task. In the experiment, we focus on the kernel size \(k\) because it is not obvious how wide a range of time dependencies must be captured in acquiring a model for converting human voice to dog-like voice.

Notably, unlike humans, dogs’ voice is short. Therefore, reducing the kernel size of the discriminator and the domain

1 https://github.com/suzuki256/dog-dataset
classifier reduces the receptive field of the CNN. That may potentially results in more dog-like voice. However, increasing the
kernel size increases the amount of information the CNN receives and may allow for a conversion that comes closer to
human voice, preserving linguistic information.

3.3. Training criterion
A VAE-based VC method and a GAN-based VC method have
been proposed to enable non-parallel VC. In this study, we used
StarGAN-VC and ACAE-VC because they are known to function
in standard VC tasks as benchmark models and a type of
major generative model.

ACAEE-VC. Figure 3 illustrates an overview of ACAE-VC.
ACAEE-VC is a VC method that applies the regularization concept
of InfoGAN [28] to conditional VAE (CVAE) [29]. One of
the strengths of this method is its fast learning convergence and
stable acquisition of high-performance conversion models.

StarGAN-VC. Figure 3 illustrates an overview of StarGAN-
VC. StarGAN-VC is a VC method that can train many-to-many
conversion models on non-parallel data based on StarGAN’s
[30] learning method. One of the strengths of this method is the
possibility of obtaining a conversion model that performs as well as or better than ACAE-VC, if hyperparameters that
allow for good learning convergence can be found.

4. Experiment
4.1. Conditions
The speaker information used for training the VC models were
("FKN," "MMY," "people (FKN, FTK, MMY, and MTK),"
adult dog," "puppy," and "dogs (adult dog and puppy)"). Ten
recording samples were randomly selected from each domain
as evaluation data. The remaining data of each domain were
used as the training data. The sounds used in the evaluation is
sounds that converted from FKN to adult dog, original sounds
of FKN and adult dog before the conversion, and white noise.
In this experiment, we generated a speech waveform using
WORLD [31] (D4C edition [32]) and parallel WaveGAN [33],
and the acoustic features input to the VC model were the MCC
sequences and mel-spectrogram, respectively. We trained Par-
nal WaveGAN with the same dataset as the VC method.

Experiment 1: comparing acoustic features and learning
methods. We performed VC using StarGAN-VC with MCC
and the mel-spectrogram and ACAE-VC with MCC and the
mel-spectrogram using default kernel sizes in original paper.

Experiment 2: comparing the kernel size k of the conver-
sion model (CNN). We define the kernel size kd of the discrimi-

ator and domain classifier described in the original paper as
default values. The kernel size kd − 2, kd − 1, kd, kd + 1,
and kd + 2 in the time direction were compared. Figure 4 illus-
trate the original paper’s architectures for the discriminator and
domain classifier, respectively. Bold letters indicate the default
kernel size kd for each layer. The value kd was changed in this
experiment.

4.2. Result
Tables 1 and 2 show the results of the MOS and CER tests in
Experiment 1. In all Tables, “mel-spec” and “original” denote
the mel-spectrogram and the unconverted test data, respectively.
The bold and underlined numbers in all the tables also denote
In this study, we proposed the “speak like a dog” task as an example of a human to non-human creature VC task. Although we could convert human voices into dog-like voices in a fragmented manner, we found that it is challenging to preserve linguistic information. It was clear that VC methods that worked well for standard VC tasks did not work sufficiently well here. We also found that using a mel-spectrogram instead of an MCC is important in this task.

4.3. Discussion

In the results of the MOS test in Experiment 1, the mel-spectrogram may have a better representation of dog-like voice than the MCC, as predicted by Section 3.1. There was no significant difference for dog-like elements between StarGAN-VC and ACV AE-VC using the mel-spectrogram in quantitative evaluation. However, when we listened to the converted sounds, we found qualitative differences subjectively. Sounds produced by ACV AE-VC had a tendency to preserve language-like expressions. The converted sounds can be listened to on our website.

From the MOS values for clarity in Table 1 and the CER values in Table 2, ACV AE-VC with the mel-spectrogram preserves less clarity and linguistic information than ACV AE-VC with the MCC. This may be because the source filter model on which the vocoder is based imitates the human voice production process.

In the results of the CER test of Experiment 1, the high value of CER with existing methods indicates the difficulty of preserving linguistic information in the “speak like a dog” task.

In Experiment 2, unlike what was predicted in Section 4.1, increasing the kernel size from the default value did not improve the preservation of linguistic information. This may be because the discriminator and the domain classifier were trained to include the dog’s voice and silent intervals by increasing the kernel size. We found that relatively small kernel size, e.g., $k_d - 1$ or $k_d - 2$, had a better performance in the “speak like a dog” task, generally.

5. Conclusions

In this study, we proposed the “speak like a dog” task as an example of a human to non-human creature VC task. Although we could convert human voices into dog-like voices in a fragmented manner, we found that it is challenging to preserve linguistic information. It was clear that VC methods that worked well for standard VC tasks did not work sufficiently well here. We also found that using a mel-spectrogram instead of an MCC is important in this task.

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The highest numerical value of conversion human voice to dog-like voice and the value of voice expected to obtain the highest numerical value in each MOS evaluation, respectively. The notation inside parentheses next to each VC method in Table 1 denotes the input acoustic features.

Table 1 shows that the method using the mel-spectrogram produces a more dog-like voice than the method using the MCC. Regarding sound quality, StarGAN-VC with a mel-spectrogram produced the best results. It is clear that StarGAN-VC with a mel-spectrogram also has the highest clarity of spoken utterances. In contrast, for ACV AE-VC, we observed that the use of MCC as an acoustic feature synthesizes clearer voice than the use of a mel-spectrogram.

Table 2 indicates that there is no significant improvement in CER while the ACV AE-VC with MCC has the smallest error. This shows that the non-parallel VC methods did not successfully achieve the “speak like a dog” task preserving linguistic information satisfactorily. However, we can notice some language-like sentences were made from converted voice when listening to the sound generated by ACV AE-VC (MCC). That can be listened to on our website.

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