REDDUCING ONE-TO-MANY PROBLEM IN VOICE CONVERSION BY EQUALIZING THE FORMANT LOCATIONS USING DYNAMIC FREQUENCY WARPING

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ABSTRACT

In this study, we investigate a solution to reduce the effect of one-to-many problem in voice conversion. One-to-many problem in VC happens when two very similar speech segments in source speaker have corresponding speech segments in target speaker that are not similar to each other. As a result, the mapper function usually over-smoothes the generated features in order to be similar to both target speech segments. In this study, we propose to equalize the formant location of source-target frame pairs using dynamic frequency warping in order to reduce the complexity. After the conversion, another dynamic frequency warping is further applied to reverse the effect of formant location equalization during the training. The subjective experiments showed that the proposed approach improves the speech quality significantly.

Index Terms: voice conversion, dynamic frequency warping, formant equalization

1. INTRODUCTION

The task of Voice Conversion (VC) is to convert speech from a source speaker to sound similar to that of a target speaker’s. Various approaches have been proposed; most commonly, a generative approach analyzes speech frame-by-frame and then maps extracted source speaker features towards target speaker features, with a subsequent synthesis procedure. The mapping is achieved using a non-linear regression function, which must be trained on aligned source-target frame pairs. Helander et. al. [2] extensively study the impact of frame alignment on VC performance. They compare various approaches to aligning speech such as hand-labeling, Dynamic Time Warping (DTW), and using Automatic Speech Recognition (ASR) output. They conclude that with using variations of DTW, they could achieve the performance of hand-labeling alignment. The alignment can be updated after one or several iterations of training [1]. The output of this stage is the source-target frame pairs that are supposed the same speech content as each other. The mapping function is usually trained on these aligned speech segments.

One inherent problem in VC is one-to-many problem [1]. For two or more similar aligned speech segments, there is no guarantee that there exist corresponding target speech segments that are similar. In other words, the mapping problem that VC is trying to solve is not a function. This makes the learning the mapping function a challenging task. With such frame pairs present, some methods such as Gaussian Mixture Models (GMMs) [4, 5] or Neural Networks [6, 7] might result in over-smoothing or a muffling effect in the converted speech. The reason is that the mapper is trying to learn a mapping that does not have a function property. Since these mappers usually try to find a solution with most similarity to the target speech typically by trying to find a minimum mean squared error (MMSE) solution, the one-to-many problem causes these mappers to converge to a solution that is most similar to all the dissimilar target segments. This will ultimately contribute to producing average speech segments that have over-smoothing or muffling property.

Some approaches try to reduce the muffling property by applying a post-processing to match the variance of the converted speech features to the original target features [8], but it does not address this inherent problem in VC. The effect of one-to-many problem might be different in other VC approaches. For example, in approaches such as codebook [9, 10] or dictionary mapping [11, 12], it might result in discontinuous speech, since the similar source segments are used for finding target speech segments which are dissimilar. Concatenating these dissimilar segments results in audible discontinuities in converted speech.

Various factors might be the cause of the one-to-many problem. One reason might be that people utter certain speech segments different from each other because they pronounce words in the same context different from each other. As a result, the source speaker might say a word in two different sentences similarly, but the target speaker pronounces the word differently. Another reason for the one-to-many problem might be due to the rendition differences. When one person utters a certain sentence multiple times, there is difference between the multiple renditions of the sentence. This has been shown by objective measure differences between the sentences uttered by the same speaker [13]. This is another contribution to the one-to-many problem.

Mouchatris et. al. [3] have studied one-to-many problem by extending the vector quantization (VQ) VC technique to conditional VQ, which can capture one-to-many relationships. It uses hard clustering on source frames independently from target frames. Godoy et. al. [4] proposed to solve this problem by considering context-dependent information. They consider phonetic information in GMM framework. They also studied the effect of training only on source versus training on the joint source-target space and isolating one-to-many mappings from training using a threshold. Turk et. al. [15] also proposes to filter out some source-target pairs that are unreliable based on some type of confidence measure.
In this study, we posit that one cause of the one-to-many problem is the difference in formant locations. The formant difference in target speech segments is a major factor that causes widening in synthesized formants, since the mapping tries to be as similar to the two different target speech segments. We propose to equalize the formant locations of the source and target speech by warping the target speech spectra to match the source formant locations. The mapping function is trained on the formant equalized speech. At conversion time, the source is converted to formant normalized target. The synthesized speech is then warped using a DFW VC approach to match the formants of the target speaker. The overall proposed framework is described in Figure 1.

The formant equalization is described in Section 2. The mapping function is described in Section 3. We then detail our voice conversion experiments, including system configurations and their objective and subjective evaluation, in Section 4. Finally, we conclude in Section 5.

**2. FORMANT EQUALIZATION**

An example of a one-to-many problem is depicted in Figure 3. As can be seen, two similar source spectra correspond to two dissimilar target spectra. Various factors might contribute to this one-to-many problem. One reason might be different contexts that different people say a certain speech segments. For example, they might put different stress on a specific word, or have different accents, or other high-level reasons. Another reason that seems to might cause this one-to-many problem might be due to differences in renditions. Even if one person says the same sentence twice, there is a difference between the two renditions of the sentence [13].

We posit that one difference between the two spectra might be due to different formant locations. This seems to be the most common symptom of the one-to-many problem, and it is evident in Figure 3. We propose to normalize these effects by equalizing formant locations.

We use a method similar to DFW to equalize formants [16][17][18][19]. First, the formant location and bandwidths are extracted from all of the utterances using a signal processing algorithm. The utterances are time-aligned using DTW. The aligned source-target formant information is used as cues in DFW algorithm. Let the aligned feature sequence be represented by $M = [m_1, m_2, \ldots, m_N]$, the corresponding log-spectrum by $S = [s_1, s_2, \ldots, s_N]$, the formant locations by $F = [f_1, f_2, \ldots, f_N]$ and the formant bandwidth by $B = [b_1, b_2, \ldots, b_N]$. The spectra are formant-equalized frame-by-frame. The formant of the target spectrum is equalized to the source spectrum using

$$\bar{s}_y = dfw(s_y, W(f_y, b_y, f_x, b_x))$$

The normalized spectrum $\bar{s}_y$ is converted back to the feature domain $\bar{m}_y$. The warping function $W(.)$ is constructed from both source and target estimated formant location and bandwidth [19]. A sample warping function is shown in Figure 2 where the warping points are determined from source and target formant location and...
bandwidth. If the warping causes the the target spectra to be more different to source compared to no warping, we consider this a sign of formant error and remove those frames.

3. MAPPING FUNCTION

In this section, we briefly overview the GMM mapping function [4]. Let $Z = [M^x, M^y]$ be the joint source-target spectral vector. A GMM represents the distribution using $Q$ multivariate Gaussian

$$P(z) = \sum_{q=1}^{Q} \alpha_q N(z; \mu_q, \Sigma_q)$$

(2)

where $N(\cdot)$ is a normal distribution with $\alpha_q, \mu_q$ and $\Sigma_q$ as prior probability, mean and covariance of component $q$, respectively. Each component would ideally represent an acoustic class. The parameters of the GMM are calculated using the Expectation Maximization (EM) algorithm on the joint vector $Z$. During conversion, for each component, we estimate the MMSE of the target vector given the source vector for each component

$$\hat{m}_q^y = E[M^y|M^x = m_q^x] = \mu_q^y - \Sigma_q^{xy}\Sigma_q^{xx}^{-1}(m_q^x - \mu_q^x)$$

(3)

where each conversion in each component is weighted using the probability that the frame $x_i$ belongs to the acoustic class described by the component $q$

$$\hat{m}_q^y = \sum_{q=1}^{Q} \frac{\alpha_q N(m_q^x; \mu_q^y, \Sigma_q^{xy})}{\sum_{k=1}^{Q} \alpha_k N(m_k^x; \mu_k^y, \Sigma_k^{xy})} \hat{m}_q^y$$

(4)

4. EXPERIMENT

4.1. Configurations

We use two male speakers from the CMU-arctic speech corpus [20]. We select RMS as source and BDL as target speaker. We use 50 training sentences and 20 testing sentences from each speaker. For analysis/synthesis, we use Ahocoder [21], which has shown good quality for parametric speech synthesis. We represent spectrum using $39th$-order MCEPs with $\alpha = 0.42$ and $5\text{msec}$ frame shifts, which are the recommended configurations for $16\text{kHz}$ waveforms. We convert MCEP to log-spectrum and back for performing frequency-domain warpings [21]. We extract 4 formant location and bandwidth using Snack 2.2 with LPC order 14 [22]. We train a GMM with $Q = 32$ components for transforming MCEPs. We also train a separate GMM with $Q = 8$ to map source and target formants from source MCEPs.

4.2. Objective Evaluation

This pre-processing step aims to make the mapping space less complex. We compare the complexity map of the equalized and non-equalized formants in Figure 4. The approach to compute the complexity map is to use a consistency measure based on the hypervolume of the relative vectors in a certain region as represented by the determinant of the data’s covariance matrix [23]. When vectors are mostly parallel in one region, the measure will have a lower value (indicating relative consistency) than when relative vectors are pointing in different directions (indicating relative inconsistency). The weighted covariance for the region around $x'$ is given by

$$\text{WeightedCov}_{x'} = \frac{1}{\sum w_{i,x'}} \sum_{i=1}^{N} w_{i,x'}(y_i - \bar{y})(y_i - \bar{y})$$

(5)

where the weights $w$ can be represented by any function that decreases with the distance between $x$ and $x'$. We chose the Gaussian function

$$w_{i,x'} = \exp\left(\frac{-\|x_i - x'\|^2}{2\sigma^2}\right)$$

(6)

with $\sigma = 0.1$. The final consistency measure was computed by taking the determinant of the weighted covariance in Equation 5. For visualization purposes, the logarithm of the consistency value is computed. As it is evident, the mapping shows less complexity when the formants are equalized. This means for each source feature, there are less dissimilar target features present. The 2-dimensional maps are visualized by taking principal component analysis (PCA) in Figure 4. The raw speech feature pairs have a mel-cepstral distortion (melCD) of 9.23dB and the the formant equalized version have a melCD of 8.38dB.

4.3. Subjective Evaluation

To subjectively evaluate voice conversion performance, we performed two perceptual tests: the first test measured speech quality and the second test measured conversion accuracy (also referred to as speaker similarity between conversion and target). The listening experiments were carried out using Amazon Mechanical Turk, with participants who had approval ratings of at least 90% and were
located in North America. Both perceptual tests used three trivial-to-judge sentence pairs, added to the experiment to filter out any unreliable listeners. The statistical tests in this section were performed using the Mann-Whitney test [24].

4.3.1. Speech Quality Test

To evaluate the speech quality of the converted utterances, we conducted a Comparative Mean Opinion Score (CMOS) test. In this test, listeners heard two utterances A and B with the same content and the same speaker but in two different conditions, and are then asked to indicate whether they thought B was better or worse than A, using a five-point scale comprised of +2 (much better), +1 (somewhat better), 0 (same), −1 (somewhat worse), −2 (much worse). It is worthy to note that the two conditions to be compared differed in exactly one aspect (either different mapping methods or different number of training utterances). The experiment was administered to 20 listeners with each listener judging 20 sentence pairs.

Listeners’ preference scores are shown in Figure 5. FREQ (formant equalized) represents the proposed approach and ORIG represents the baseline. The listeners preferred the speech quality of the proposed framework. The improvement was shown to be significant. The generated speech had less muffling effect which might be the reason listeners judged those as higher quality.

4.3.2. Conversion Accuracy Test

To evaluate the conversion accuracy of the converted utterances, we conducted a same-different speaker similarity test [25]. In this test, listeners heard two stimuli A and B with different content, and were then asked to indicate whether they thought that A and B were spoken by the same, or by two different speakers, using a five-point scale comprised of +2 (definitely same), +1 (probably same), 0 (unsure), −1 (probably different), and −2 (definitely different). One of the stimuli in each pair was created by one of the four mapping methods, and the other stimulus was a purely vocoded condition, used as the reference speaker. The experiment was administered to 20 listeners, with each listener judging 20 sentence pairs.

Listeners’ average response scores are shown in Figure 5. The difference between the two systems were not significant. This was shown using a significance test. One reason might be using the DFW directly on the log-spectrum domain, and also the formant estimation mismatches that are inevitable. For controlling for the first problem, using other warping approaches such as pole-shifting might be helpful. For the second problem, hand-corrected formant values can be used to see the effect of the proposed approach with the ground truth information available to us.

5. CONCLUSION

In this study, we investigated a solution to reduce the effect of one-to-many problem in voice conversion. We proposed to equalize the formant location of source-target frame pairs using dynamic frequency warping in order to reduce the complexity. Finally, a dynamic frequency warping is further applied after the conversion to reverse the effect of formant location equalization. We were able to show a significant gain in speech quality. Two issues present themselves here. The issue is using DFW directly on the log-spectrum domain, which might cause distorted-looking spectra, specially if there is a formant error. For controlling for this problem, using other warping approaches such as pole-shifting might be helpful. The other more important problem is the formant estimation mismatches that are inevitable. For solving this problem, hand-corrected formant values can be used for experimentation purposes to see the real effect of the proposed approach with the ground truth formant information.
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