

# TEXT-FREE NON-PARALLEL MANY-TO-MANY VOICE CONVERSION USING NORMALISING FLOWS

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## ABSTRACT

Non-parallel voice conversion (VC) is typically achieved using lossy representations of the source speech. However, ensuring only speaker identity information is dropped whilst all other information from the source speech is retained is a large challenge. This is particularly challenging in the scenario where at inference-time we have no knowledge of the text being read, i.e., text-free VC. To mitigate this, we investigate information-preserving VC approaches.

Normalising flows have gained attention for text-to-speech synthesis, however have been under-explored for VC. Flows utilize invertible functions to learn the likelihood of the data, thus provide a lossless encoding of speech. We investigate normalising flows for VC in both text-conditioned and text-free scenarios. Furthermore, for text-free VC we compare pre-trained and jointly-learned priors. Flow-based VC evaluations show no degradation between text-free and text-conditioned VC, resulting in improvements over the state-of-the-art. Also, joint-training of the prior is found to negatively impact text-free VC quality.

**Index Terms**— voice conversion, Flow-TTS, Glow-TTS, Copy-Cat, AutoVC

## 1. INTRODUCTION

Voice conversion (VC) is the process of taking speech from a source speaker and changing the perceived speaker identity to match that of a target speaker [1, 2]. The result is that we are able to change source speech to sound as though it was read by the target speaker. There are two major families of training paradigms for VC: parallel and non-parallel [3]. Parallel VC relies on the same text being read by source and target speakers, therefore allowing to train the model directly on the VC task (i.e., having ground truth paired source and target speech for training). However, such datasets are expensive to record and challenging to enrol speakers. Therefore, more commonly non-parallel methods are applied, which have no such data requirements. Non-parallel VC approaches allow for much easier enrolment of speakers as the only requirement is transcribed speech. This work focuses on the non-parallel VC scenario.

Typical non-parallel VC approaches in literature learn lossy representations of the source speech to achieve successful conversion [4, 5, 6, 7, 8, 9]. These models are encouraged to drop information that we wish to change (i.e., speaker identity) whilst retaining all other aspects of the source speech (i.e., the text being read and prosody). This makes the approach challenging to train to ensure that the balance between retaining and losing information from the source speech is achieved. Therefore, in this investigation we explore information-preserving approaches to VC.

Whilst there has been numerous previous works investigating the application of normalising flows for speech, these have typically focused on text-to-speech (TTS) [10, 11, 12, 13] or neural vocoding [14, 15] rather than VC [16]. Normalising flows, learn an invertible mapping of the input data to a latent vector [17, 18, 19]. During training the latent vector is trained to maximise the likelihood of a prior distribution. Typically, conditioning features are passed to the flow steps to help the model to better maximise this likelihood [16, 11, 12, 13]. The motivation for this is that the network can learn to remove the contributions of these conditioning features from the latent vector, hence removing the level of noise to the prior. The invertible nature of the flow ensures that the network is information-preserving, meaning that the latent vector is a lossless representation of the input data. Given the challenges described above with designing models using lossy speech representations for VC, the application of normalised flows for VC is of clear interest. Provided that the prior distribution is disentangled from the speech attribute we wish to convert, the network should be capable of converting the speech attribute from the source speech, as long as it has successfully learnt its contribution. This allows for a paradigm to perform disentangled conversion of multiple speech attributes (for example speaker identity, accent and speaking style). Here the focus of the investigation is conversion of speaker identity (i.e., VC), however we leave exploration of further speech attributes within this paradigm as future work.

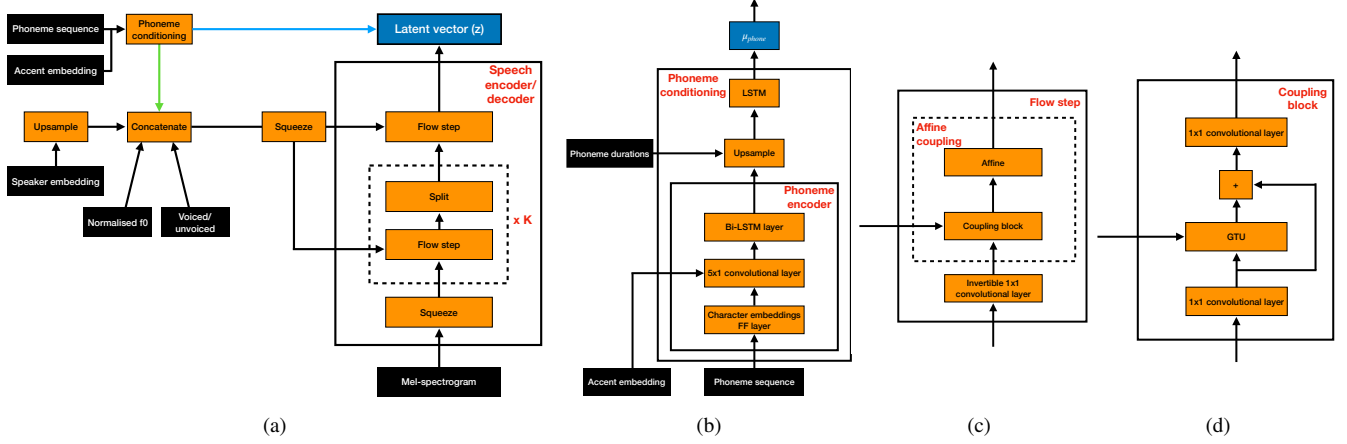
A similar application of normalised flow for VC was explored in [16]. However, this was conducted on raw audio input, a noisy representation of speech, resulting in conversion being more challenging. Mel-spectrograms are a more stable speech representation, hence is used in the majority of recent work in TTS and VC literature [20, 5]. Therefore, this investigation focuses on mel-spectrograms instead of raw waveforms. In addition, the investigation in [16] did not explore the use of alternative priors. These are explored in this investigation. Using Glow-TTS for voice conversion is mentioned in [10, 13] however was not formally evaluated.

The contributions of this paper are: 1) formal investigation into normalising flows for the problems of both text-conditioned and text-free VC, resulting in significant improvements over state-of-the-art text-free VC, 2) for text-free VC using normalising flows we investigate whether it is better to use a pre-trained “expert” prior or whether joint-training of prior and flow are beneficial. This finds that joint-training of prior and flow negatively impacts the convergence of the model, indicating that improvements to training schedule will likely improve the state-of-the-art for both TTS and VC.

## 2. PROPOSED FLOW-BASED VC APPROACHES

Flow-TTS has demonstrated state-of-the-art quality for TTS [11] so was selected as the basis for the model topology of the proposed

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**Fig. 1:** Overview of our VC approach using normalised flows (a) followed by phoneme conditioning component (b), Flow step (c) and Coupling block (d). Green line denotes phoneme conditioning for text-conditioned VC models. Blue line denotes the phoneme-based prior used for text-free VC models.

VC approach. Two variants of VC with this topology are investigated: 1) text-conditioned VC, where text information is provided to the model at both training-time and inference-time, 2) text-free VC, where text information is only required at training-time.

### 2.1. Text-conditioned VC: fixed prior

Text-conditioned VC is most similar to the original Flow-TTS implementation [11]. The model topology is shown in Figure 1, with arrows arranged according to training-time. During training-time the model ‘encodes’ input mel-spectrograms ( $x$ ) into the latent vector  $z$ , as shown in Equation 1:

$$z = f(x; ph_{source}, spk_{source}, f0_{source}, vuv_{source}) \quad (1)$$

where  $ph_{source}$  denotes phoneme conditioning coming from the phoneme encoder (the green arrow in Figure 1a,  $ph_{source} = \mu_{phone}$  from Figure 1b for the source phoneme sequence),  $spk_{source}$  is a pre-trained utterance-level speaker embedding [21],  $f0_{source}$  is normalised interpolated log-f0 and  $vuv_{source}$  is a binary ‘voiced or unvoiced’ flag denoting whether a frame is voiced or unvoiced. Sentence-level mean normalisation is applied to interpolated f0 to disentangle speaker identity (i.e., relating to the speaker’s average f0) from sentence prosody, thus separating f0 conditioning from speaker embedding conditioning. Providing this conditioning information allows the network to learn to remove these factors from  $z$  in order to better maximise the likelihood of the prior distribution (c) during training:

$$\log P_X(x|c) = \log P_Z(z|c) + \log \left| \det \frac{\partial z}{\partial x} \right| \quad (2)$$

where:

$$c \sim N(\mu_{prior}, \sigma_{prior}) \quad (3)$$

For text-conditioned VC a uniform prior of  $\mu_{prior} = 0, \sigma_{prior} = 1$  is applied for all frames regardless of the speech content. To perform VC, source speech is encoded according to Equation 1, and then converted to the target speaker using Equation 4:

$$x_{converted} = f^{-1}(z; ph_{source}, spk_{target}, f0_{source}, vuv_{source}) \quad (4)$$

where  $spk_{target}$  denotes the speaker embedding of the target speaker. This is similar to the conversion approach in [16].

In previous work on Flow-TTS and Glow-TTS, the phoneme alignment is learnt during training using either attention [11] or monotonic alignment search (MAS) [10]. However, here pre-trained phoneme alignments are instead used to label the data, as was done in [22] for attention-free TTS, simplifying the training process.

### 2.2. Text-free VC: context-dependent prior

This approach is more similar to that of Glow-TTS [10, 13]. The model is shown in Figure 1, with the blue line in Figure 1a used instead of the green line. Unlike the text-conditioned approach, text-free VC does not pass information relating to the phonetic context to the flow steps. Instead, a phoneme-dependent prior distribution (c) is used in Equation 2 to train the speech encoder. As a result, the model learns to represent phonetic context within  $z$ , meaning no prior knowledge of the text being read is required to perform VC. Therefore Equations 1 and 4 for this scenario become:

$$z = f(x; spk_{source}, f0_{source}, vuv_{source}) \quad (5)$$

and

$$x_{converted} = f^{-1}(z; spk_{target}, f0_{source}, vuv_{source}) \quad (6)$$

We explore two options to train the text-free VC approach: 1) use a pre-trained phonetic prior, 2) jointly-train the prior alongside the flow. Following informal listening, we observed that for both of these approaches fixing  $\sigma_{prior} = 1$  for the model prior, alongside the predicted context-dependent  $\mu_{prior}$ , led to better convergence of the model for VC.

#### 2.2.1. Pre-trained phoneme prior

The contextual phoneme prior is pre-trained using an attention-free TTS model. This is based on the model presented in [22] and is shown in Figure 2. The only change to this topology from the previously published work is that the phoneme encoder output was adapted to be a variational encoder. Therefore, the vector output by the phoneme encoder is of size 160 (80-dimensional mean vector plus 80-dimensional log standard deviation vector). The training schedule to apply a phoneme encoder KLD loss during training matches that used to train the prosody encoder VAE (see [22] for further details). For this investigation  $\mu_{phone}$  from this pre-trained model is used as the prior mean ( $\mu_{prior}$ ) to train the flow.

#### 2.2.2. Jointly-trained phoneme prior

This method is closest to the Glow-TTS and SC-Glow-TTS approaches [10, 13]. Here, the flow-based speech encoder is trained together with the phoneme encoder that determines the mean of the prior ( $\mu_{prior}$ ). The structure of the phoneme encoder is shown in Figure 1b ( $\mu_{prior} = \mu_{phone}$ ). There is no additional loss that constrains the phoneme encoder output in any way, instead relying fully on Equation 2.

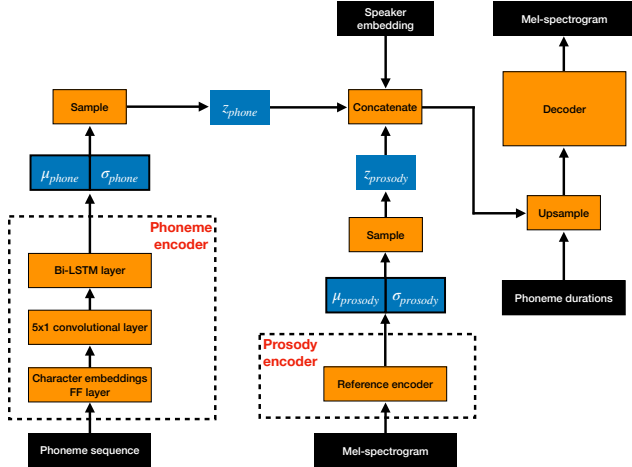


Fig. 2: Overview of model used to pre-train context-dependent prior for flow-based encoder.  $\mu_{\text{phone}}$  is used for the prior.

### 3. EXPERIMENTAL PROTOCOL

#### 3.1. Data

English recordings of approximately 597k utterances from 3173 speakers were used for training. These came from English speakers from 6 different regional accents: US, GB, Canadian, Welsh, Australian, Indian. The amount of data per speaker ranges from 100 to 20k utterances. Despite the large range, even speakers with the largest amounts of data still only account for around 3% of total data, meaning they do not dominate the dataset. The data also features a range of different recording conditions with some speakers recorded in studio-quality conditions whilst other speakers were recorded in more ambient surroundings using lower quality microphones. A sampling rate of 16kHz was used for all recordings, from which 80 dimensional mel-spectrograms were extracted using a frame shift of 12.5 ms. For generating audio samples for evaluation, a universal neural vocoder was used [23].

To evaluate VC quality we take 6 speakers from the training data. These are: US male, US female, Australian female, Indian male, Canadian female and Welsh male. We evaluate all possible combinations of conversion between these speakers, resulting in 30 conversion combinations. We convert 20 utterances from each speaker to each of the other target speakers, resulting in 600 evaluation screens. For accent similarity evaluations we removed comparisons where the source and target speaker are from the same accent (i.e., US male to US female and vice-versa), resulting in 560 evaluation screens.

#### 3.2. Systems

The flow-based VC approaches investigated are: 1) *flow text-conditioned* (Section 2.1), 2) *flow text-free pre-train* (Section 2.2.1), 3) *flow text-free joint-train* (Section 2.2.2). These models consist of 12 flow steps. The squeeze operator was set to 2. After every 4 flow steps the vector dimensionality is reduced by 16 via the split operation.

We baseline the performance of the flow-based VC models against state-of-the-art text-conditioned and text-free VC approaches. For the text-conditioned baseline we use CopyCat [5]. We applied the small modification to the CopyCat approach introduced in [24] where source speaker embeddings are concatenated to the upsampled phonemes before passing to the phoneme encoder. This was found to reduce occurrences of speaker leakage. For the text-free baseline we use AutoVC [4]. We found that for this system careful tuning of the compression across time and information bottleneck size of the content encoder was required. Time-wise compression

of 16 frames and a bottleneck size in the content encoder of 8 was selected following informal listening.

All evaluated systems used the same pre-trained speaker embeddings. In addition, the same phoneme alignments are used to label the data for all systems. Separate front-ends were used per accent. The one-hot phone-set used for all models is the superset of phonemes returned by these different front-ends. Text-conditioned models used an accent embedding to allow the model to disambiguate phonemes according to the accent being used.

#### 3.3. Evaluation

Subjective evaluations of the models were conducted via MUSHRA tests [25] using the following metrics:

- **Naturalness:** “Please rate the audio samples in terms of their naturalness”. The recording from the target speaker is included among the systems to be rated as an upper-anchor.
- **Speaker similarity:** “Please listen to the speaker in the reference sample first. Then rate how similar the speakers in each system sound compared to the reference speaker”. Two different recordings from the target speaker are included. One as the reference sample and the other as one of the systems to be rated, as an upper-anchor. In addition, the source speech recording is included among the systems to be rated, as a lower-anchor.
- **Accent similarity:** “Please listen to the speaker’s accent in the reference sample first. Then rate how similar the accents in each system sound compared to the reference accent”. Recordings from two different non-source speakers with the source accent are included. One is used for the reference sample and the other is one of the systems to be rated as an upper-anchor. In addition, a non-target speaker with the target speaker’s accent is included among the systems to be rated as a lower-anchor. These evaluations ensure that speaker conversion is achieved without changing the source speaker’s accent to that of the target speaker (i.e., speaker identity is successfully disentangled from accent).

Statistically significant differences between systems were detected using paired t-tests with Holm-Bonferroni correction applied. All reported significant differences are for  $p \leq 0.05$ .

### 4. EXPERIMENTAL RESULTS

#### 4.1. Word Error Rate analysis

To measure the intelligibility of converted speech from the range of models we are investigating, we conduct Word Error Rate (WER) analysis. The AWS Transcribe ASR system was used to transcribe converted speech. The WER is then computed between the sentence text and the transcription. Here we present the WER computed across all 600 test utterances. The US-English ASR model is used to transcribe all utterances. This can introduce some false errors due to the range of English accents being investigated here, however numbers are comparable across different systems.

WER results are shown in Table 1. AutoVC is the obvious outlier here, suffering from significantly increased numbers of intelligibility issues following VC. All other systems have similar performance in terms of intelligibility. This includes the text-free VC approaches using normalised flows, a noticeable improvement over the state-of-the-art.

#### 4.2. Comparison of flow-based approaches

Results from naturalness and speaker similarity evaluations are shown in Table 2. Differences between all systems are found to

System	WER
<i>flow text-conditioned</i>	12.65% $\pm$ 0.78
<i>flow text-free pre-train</i>	12.38% $\pm$ 0.77
<i>flow text-free joint-train</i>	12.75% $\pm$ 0.78
<i>CopyCat (text-conditioned)</i>	11.52% $\pm$ 0.75
<i>AutoVC (text-free)</i>	28.97% $\pm$ 1.06

**Table 1:** Word Error Rate (WER) with 95% confidence intervals computed across the test set for all combinations of test speaker conversions.

be statistically significant except between *flow text-conditioned* and *flow text-free pre-train*. This demonstrates that for VC with flow-based models we do not observe improvements from text conditioning. This is in contrast to VC literature where typically text conditioning is used to achieve improvements over text-free VC (for example CopyCat’s improvements over AutoVC come from such conditioning). In addition, these results demonstrate the challenge of jointly-training the normalising flow’s prior alongside the weights of the flow. By breaking the problem down into pre-training of the prior and then training the flow to maximise the likelihood of this prior, we are able to achieve a significantly better VC model. This is in contrast to Glow-TTS approaches from literature where typically the prior is jointly-trained [10, 13]. This indicates that future work to address the challenges of training normalising flows with moving priors may bring improvements to not only VC, but also the Glow-TTS approach. Exploring pre-trained priors (work started here) further or investigating improved training schedules, are of interest for such future work.

System	Mean rating	Median rating
Naturalness		
<i>target speaker recording</i>	72.36	76
<i>flow text-conditioned</i>	70.88	74
<i>flow text-free pre-train</i>	70.80	75
<i>flow text-free joint-train</i>	70.15	74
Speaker similarity		
<i>target speaker recording</i>	74.98	79
<i>flow text-conditioned</i>	64.47	72
<i>flow text-free pre-train</i>	64.48	73
<i>flow text-free joint-train</i>	62.84	71
<i>source speaker recording</i>	60.06	71

**Table 2:** Mean and median MUSHRA scores for naturalness and speaker similarity evaluations comparing different flow-based VC approaches.

#### 4.3. Comparison to baseline VC approaches

Results from naturalness, speaker similarity and accent similarity evaluations are shown in Table 3. Differences between all systems in naturalness, speaker similarity and accent similarity evaluations are statistically significant except between *CopyCat* and *flow text-free pre-train* in the accent similarity evaluation. These results demonstrate that text-free VC with normalising flows outperforms the state-of-the-art for text-free VC, however is currently below the state-of-the-art for text-conditioned VC.

Further analysis was conducted on the MUSHRA responses to look at listener ‘preferences’ between *flow text-conditioned* and *CopyCat* (i.e., for each MUSHRA screen the scores awarded to the systems are interpreted as a preference for one system over the other). These preference scores are then tested for statistical significance using a binomial test, with Bonferonni correction applied. This analysis found a statistically significant preference for *CopyCat* in terms of naturalness, however the preferences for speaker similarity and accent similarity between these two systems are not significant. Following informal listening we believe that listeners are attending to a larger presence of light audio artefacts introduced by the flow model compared to the *CopyCat* model. As the analysis in Section 4.1 shows, these artefacts are not affecting intelligibility but result in a preference for the *CopyCat* approach.

System	Mean rating	Median rating
Naturalness		
<i>target speaker recording</i>	69.59	73
<i>flow text-free pre-train</i>	63.17	66
<i>CopyCat (text-conditioned)</i>	64.74	68
<i>AutoVC (text-free)</i>	60.93	64
Speaker similarity		
<i>target speaker recording</i>	74.57	80
<i>flow text-free pre-train</i>	54.01	55
<i>CopyCat (text-conditioned)</i>	55.07	56
<i>AutoVC (text-free)</i>	52.79	50
<i>source speaker recording</i>	47.39	50
Accent similarity		
<i>target speaker accent</i>	50.70	50
<i>flow text-free pre-train</i>	62.47	65
<i>CopyCat (text-conditioned)</i>	62.04	65
<i>AutoVC (text-free)</i>	59.94	63
<i>source speaker accent</i>	68.94	74

**Table 3:** Mean and median MUSHRA scores for naturalness, speaker similarity and accent similarity evaluations comparing text-free flow-based VC approach against baseline systems.

However, in terms of speaker similarity it appears as though preferences between the two approaches are much closer with the magnitude being larger in cases where *CopyCat* is preferred. These analyses indicate that whilst normalising flows are able to achieve quality parity between text-conditioned and text-free conversion approaches (within normalising flow-based VC approaches) there is still work required to reduce artefacts.

The MUSHRA screen ‘preference’ analysis was repeated between *AutoVC* and *flow text-free pre-train*. This found significant preferences for *flow text-free pre-train* over *AutoVC* for naturalness and accent similarity, however preferences for speaker similarity between these two systems are not significant. This demonstrates that the improvements from the normalising flow over *AutoVC* are focused around perceived naturalness and the flow being better equipped to address the problem of disentanglement, compared to the more naive compression-based approach of *AutoVC*. The flow was able to preserve the speaker’s accent due to its lossless representation, whereas with *AutoVC* the model appears to have struggled more to disentangle phonemes from speaker identity.

## 5. CONCLUSION

In this investigation we explored the use of normalising flows for VC. Flows learn a lossless representation of speech, in contrast to typical VC models from literature. The investigation found that normalising flows experience no degradation in quality from not having prior knowledge of the text being read, allowing for many more applications of VC technology (for example dynamic voice filtering for entertainment purposes). The proposed approach successfully disentangles speaker identity from speaker accent, allowing for VC without losing the accent of the source speaker. We have demonstrated that the flow-based VC approach brings significant improvements over state-of-the-art text-free VC, however work is still required to reach the state-of-the-art in text-conditioned models. We hypothesise this gap is due to a lack of recurrent connections in the flow decoder, which allow to remove artefacts across time. Investigating the use of auto-regressive flows to provide across-frame awareness is left as future work. Finally, we demonstrated that joint-training of the flow’s prior with the flow weights, the typical approach in Glow-TTS literature, is not optimal and further work into improved training schedules is required. Here we investigated VC with the flow-based models however this framework allows for independent control of multiple speech attributes (for example control of accent and prosody). Investigating these controls is left as future work.

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