WSRGlow: A Glow-based Waveform Generative Model for Audio Super-Resolution

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Abstract

Audio super-resolution is the task of constructing a high-resolution (HR) audio from a low-resolution (LR) audio by adding the missing band. Previous methods based on convolutional neural networks and mean squared error training objective have relatively low performance, while adversarial generative models are difficult to train and tune. Recently, normalizing flow has attracted a lot of attention for its high performance, simple training and fast inference. In this paper, we propose WSRGlow, a Glow-based waveform generative model to perform audio super-resolution. Specifically, 1) we integrate WaveNet and Glow to directly maximize the exact likelihood of the target HR audio conditioned on LR information; and 2) to exploit the audio information from low-resolution audio, we propose an LR audio encoder and an STFT encoder, which encode the LR information from the time domain and frequency domain respectively. The experimental results show that the proposed model is easier to train and outperforms the previous works in terms of both objective and perceptual quality. WSRGlow is also the first model to produce 48kHz waveforms from 12kHz LR audio. Audio samples are available at https://zkk06111.github.io/wsrglow/

Index Terms: speech super-resolution, deep learning, generative models

1. Introduction

Audio super-resolution is the task of constructing a high-resolution (HR) audio from a low-resolution (LR) audio by adding the missing band in a coherent manner. Formally, given a LR sequence of audio samples \( x_l = \{x_{l1}/R_l, \ldots, x_{lT}/R_l\} \), we wish to synthesize a high-resolution audio signal \( x_h = (x_{h1}/R_h, \ldots, x_{hT}/R_h) \), where \( R_l \) and \( R_h \) are the sampling rates of the low and high-resolution signals. Audio super-resolution can be used to achieve better speech quality with a limited sampling rate in telecommunications. It can also improve the audio quality of ancient recordings and music, and facilitate TTS applications and methods [16, 24]. The contributions of this work are summarized as follows:

- Our experiments on VCTK [25] dataset show that 1) the proposed model is easier to train and outperforms the previous works both objectively and perceptually; and 2) STFT is capable of efficient realistic-looking synthesis and manipulation of large images [17, 18, 19]. Normalizing flow conditioned on low-resolution images [20] has also improved the performance of image super-resolution, which is similar to speech super-resolution in many ways.

Considering that audio super-resolution is a one-to-many mapping (ill-posed) problem since multiple possible HR audio samples correspond to a given LR one, in this paper, we explore the potential of normalizing flow on modeling the conditional distribution of HR audio samples given an LR one. Specifically, we propose WSRGlow, a novel model for audio super-resolution based on generative flows. WSRGlow generates HR audio by sampling from a simple zero mean spherical Gaussian distribution. The sample taken from the simple distribution is then put through several invertible layers and transformed to the desired output audio. The layers of our model are similar to those in WaveGlow [21] and WaveNet [22]. During training, HR audio is fed to the model as input to obtain the corresponding sample points in the simple distribution, so that we can train our model by directly maximizing the likelihood. During inference, WSRGlow takes a sample from the simple distribution and passes it through several invertible layers to compute the desired output audio.

To better extract the valuable information in LR audio, we propose two encoders: an LR audio encoder and an STFT encoder, which encode LR information from the time and frequency domains, respectively. The LR audio encoder applies \( \mu \)-law transformation to raw low-resolution waveform [23]. The contributions of this work are summarized as follows:

- To the best of our knowledge, WSRGlow is the first model to use normalizing flow structure for audio super-resolution task and proves the potential of normalizing flow for audio super-resolution.
- WSRGlow also explores the potential of normalizing flow on modeling the conditional distribution of LR audio samples in the frequency domain.
- Our experiments on VCTK [25] dataset show that 1) the proposed model is easier to train and outperforms the previous works both objectively and perceptually; and 2) STFT...
encoder improves the model performance significantly and makes the convergence much faster.

2. Model Architecture

Audio super-resolution is an ill-posed problem whose solution is not unique. Various possible solutions exist and form a distribution in the solution space. To capture the probabilistic nature of super-resolution audio, we employ normalizing flow to model the conditional distribution of HR audio given the LR audio. WSRGlow captures the bijection between a zero mean spherical Gaussian distribution and the probability space of audio waveform using invertible layers similar to Glow [17]. To generate high-resolution audio, we encode the low-resolution audio using invertible layers similar to Glow [17]. To model the conditional distribution of HR audio given the LR audio, we employ normalizing flow to capture the probabilistic nature of super-resolution audio, we employ normalizing flow to model the conditional distribution of HR audio given the LR audio.

The invertible layers have a similar structure to those in WaveGlow [21]. Each of the WSRGlow layers consists of an invertible 1x1 convolution $f_{\text{conv}}$ and an affine coupling layer $f_{\text{coupling}}$. The detailed structure of these layers will be described below.

2.1. Glow Layers

To generate high-resolution audio, we take a sample $(z \sim \mathcal{N}(z; 0, I))$ from a simple Gaussian distribution and passes it through several invertible layers $f_i$ that transforms the simple distribution to the desired distribution $x$ in the audio space:

$$ x = f_0 \circ f_1 \circ \cdots \circ f_k(z). $$

During training, high-resolution audio is regarded as a vector and squeezed into groups of 8, as in WaveGlow [21]. This vector is then passed through the invertible layers and transformed into a simple distribution, so that we can optimize the negative loglikelihood directly. The invertibility of the WSRGlow layers ensure that we can calculate the loglikelihood $\log p(x)$ directly using inverted mappings:

$$ \log p(x) = \log p_0(x) + \sum_{i=1}^{k} \log |\text{det}(J(f_i^{-1}(x)))|, $$

where $J$ is the Jacobian of the inverted transformation $f_i^{-1}$.

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2.1.1. Affine Coupling Layer

We use an affine coupling layer $f_{\text{coupling}}$ to make a WSRGlow layer invertible. The channels of the input tensor $x$ is split into two halves $x_a$ and $x_b$. Half of the channels are passed through a transformation $T$ to produce additive term $t$ and multiplicative term $s$ for the other half.

$$ x_a, x_b = \text{split}(x), $$

$$ \log s(t) = T(x_a, \text{concat}(H_{LR}, H_{STFT})), $$

$$ x'_b = s \odot x_b + t, $$

$$ f_{\text{coupling}}^{-1}(x) = \text{concat}(x_a, x'_b), $$

$$ \log |\text{det}(J(f_{\text{coupling}}^{-1}(x)))| = \log |s|. $$

Here $T$ can be any transformation that does not have to be invertible because the coupling layer keeps the invertibility of the network. When inverting the network, since $x_a$ is passed without changing, we can obtain $s$ and $t$ by recomputing $T$ with $x_a$. We can then solve equation (1) for $x_b$ using $s$, $t$, $x'_b$.

In our model, the transformation $T$ is similar to the structure of non-causal WaveNet [22] with dilated convolutions, gated-tanh activations and residual connections. The main difference between $T$ and non-causal WaveNet is that the condition parameter for $T$ is not a mel-spectrogram, but the encoded low-resolution audio signal $\text{concat}(H_{LR}, H_{STFT})$.

2.1.2. 1x1 Invertible Convolution

Following Glow [17], we employ a 1x1 invertible convolution layer $f_{\text{conv}}^{-1} = Wi$ before every affine layer to enable two halves of the channels to modify the one another. The convolution kernel is initialized to be orthonormal to keep its invertibility.

2.2. Conditional Encoder

We propose two encoders to extract information from LR audio for conditioning WSRGlow. One is the LR audio encoder which directly maps raw audio samples to a sequence of embedding vectors. The other is the STFT encoder which encodes LR audio from the frequency domain by encoding its magnitude and phase spectrogram. The size of the group for squeezing LR encoding is chosen to be the same as the time window of STFT, so that the encodings of the two encoders can be concatenated to encode LR audio from both time and frequency domains. The architecture of the two encoders is shown in Figure [2].

2.2.1. LR Audio Encoder

The LR audio encoder $\text{Enc}_{LR}$ maps every sample in the low-resolution signal to an embedding space. For a sample $x_t$, we first apply the $\mu$-law transformation as in WaveNet [23], and then quantize the transformed sample to 256 possible values. We create an embedding vector for each of the 256 possible values. The sequence of embedding vectors is then squeezed into a sequence of groups of vectors $H_{LR}$ to match the dimensionality of $T$.  

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Footnote:

Audio samples are available at [https://zkx06111.github.io/warglow/](https://zkx06111.github.io/warglow/) The codes for this paper is available at [https://github.com/zkx06111/WSRGlow](https://github.com/zkx06111/WSRGlow)
2.2.2. STFT Encoder

The STFT encoder $E_{\text{STFT}}$ encodes the frequency-domain information in LR audio, including magnitude and phase spectrograms. While magnitude spectrogram is a well-known representation, we also introduce phase spectrogram since it has been proven to be of much help in various speech tasks \[26\] including speech enhancement, speech recognition and speech synthesis. Besides, it is also shown that the capacity of human perception due to phase is higher than expected \[27\].

The STFT encoder first applies the short-time Fourier transform (STFT) to the signal. The phases $\phi$ of each time window is quantized and then embedded to $E_\phi$:

$$E_\phi(x) = \text{Embedding}(\text{Quantize}(	ext{imag(STFT}(x)))),$$

while the magnitude spectrogram $S$ is directly taken: $S(x) = \text{real(STFT}(x))$. The two are then concatenated along the channel axis to obtain the STFT encoding $H_{\text{STFT}}$: $H_{\text{STFT}} = \text{concat}(S(x), E_\phi(x))$.

3. Experiments

3.1. Experimental Settings

3.1.1. Dataset

We evaluate our model on the VCTK corpus \[25\], which contains 44 hours of data from 108 different speakers. We generate low-resolution audio signal using the `resample` function with default parameters in Librosa \[28\]. The target sampling rate of HR audio is 48kHz. We randomly split the dataset into training set and test set at utterance level so that the training set also contains the speakers in the test set. The audio file names used in test set are listed in the supplementary materials.

3.1.2. Model Configurations

Four methods for speech super-resolution are implemented for comparison, including two baselines and two proposed WSRGlow models with different LR encodings.

- **AudioUNet**: A deep convolutional model for audio super-resolution proposed in \[12\]. We instantiated the model with 8 down-sampling blocks and 8 up-sampling blocks. We used the same parameters for each block as \[12\] and our PyTorch version of AudioUNet is a reimplementation of the TensorFlow code provided by the author.

- **MUGAN**: A GAN-based model for audio super-resolution proposed in \[15\] \[14\]. We use a similar structure in AudioUNet for the generator and the discriminator. We use MSE Loss for the generator and cross-entropy loss for the discriminator.

- **WSRGlow w/o $E_{\text{STFT}}$**: WSRGlow with only the encoding of LR audio encoder as the condition. We set the embedding dimension to be 256 and the number of glow layers to be 12. Audio encodings are squeezed into groups of 8. The transformation $T$ in the affine coupling layer has 8 layers of dilated convolutions with 256 channels.

- **WSRGlow**: WSRGlow with the concatenated encoding of both LR audio encoder and STFT encoder as the condition. WSRGlow follows the setting of WSRGlow w/o $E_{\text{STFT}}$. We set the embedding size of the phase spectrogram to be 50. The frame size for STFT is set to 8 so that the time dimensionality of phase embeddings and waveform embeddings can be the same.

3.1.3. Training and Evaluation

For all models, we train them on batches of 12 audio waveforms with the maximum number of HR samples being 8192. We train each model for 100k iterations. For AudioUNet, WSRGlow w/o $E_{\text{STFT}}$ and WSRGlow, we use the ADAM \[29\] optimizer with learning rate being 1e-4, $\beta_1 = 0.9$, $\beta_2 = 0.98$. For MUGAN, We set the coefficient for adversarial loss to be 0.001 and start adding the adversarial term to the loss for generator after 40k steps.

Following previous works \[12\] \[14\], on speech super-resolution, we evaluate our experiment results using both objective metrics and perceptual surveys.

We use the Signal to Noise Ratio (SNR) and Log-spectral distance (LSD) \[30\] to measure the quality of generated audio samples by comparing them to the actual high-resolution audio. The SNR is defined as $\text{SNR}(x, y) = 10 \log \frac{||x||^2}{||y-x||^2}$, where $x$ is the reference signal and $y$ is an approximation. The LSD measures the reconstruction quality of individual frequencies, which is defined as $\text{LSD}(x, y) = \frac{1}{L} \sum_{l=1}^{L} \left( X(l,k) - \hat{X}(l,k) \right)^2$, where $X$ and $\hat{X}$ are the log-spectral power magnitudes of $x$ and $y$. They are defined as $X = \log |S|^2$ where $S$ is the short-time Fourier transform of the signal. $l$ is the number of frames and $k$ is the number of frequencies. We use the evaluation setting in \[12\] where the length of frames is 2048.

Following MUGAN \[14\], we perform a randomized, single-blinded A/B test with 10 participants to evaluate the performance of WSRGlow with real listeners. The test presents 10 pairs of audio clips generated by WSRGlow with STFT encoding and the best baseline model MUGAN, and asks participants to select a preferred clip, or “Neutral”.

3.2. Results and Analyses

3.2.1. Subjective Evaluation

We conduct the preference test to compare the perceptual quality of the audio generated by WSRGlow and one of the base-
In this paper, we proposed WSRGlow, a glow-based generative model for audio super-resolution: 1) we use normalizing flow to address the one-to-many problem by modeling the conditional distribution of HR audio; and 2) we proposed an LR encoder and an STFT encoder to exploit the information in LR audio from both time domain and frequency domain, significantly improving model’s ability to synthesize the high-frequency part. Our experiments demonstrated that WSRGlow outperforms previous models in both objective and subjective metrics and converges quickly. The components were verified to be necessary and effective through ablation study.

In the future, we may develop our model to address more generalized audio super-resolution tasks, such as speech in heterogeneous environments and music recordings. We may also

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3.2.2. Objective Evaluation

We also evaluate the objective metrics including SNR and LSD for WSRGlow and baseline methods. The results are shown in Table 2. From the table, we can see that WSRGlow outperforms the baselines and WSRGlow w/o 🎵Enc🎵 significantly, which further demonstrates the superiority of our method. Besides, we remove the STFT encoder 🎵Enc🎵 in WSRGlow and compare it with the original WSRGlow. The results are shown in row 3 (WSRGlow w/o 🎵Enc🎵). We can see that WSRGlow w/o 🎵Enc🎵 outperforms the baseline models in terms of SNR, but performs poorly in LSD. This indicates that WSRGlow w/o 🎵Enc🎵 cannot synthesize the high-frequency part of the signal well. Because SNR is calculated using sample-wise distance, while LSD is calculated using the spectrogram. A low LSD score also suggests unsatisfactory perceptual quality since the LID metric has better correlation with perceptual quality compared to SNR. Besides, we observe that WSRGlow performs much better in LSD score than WSRGlow w/o 🎵Enc🎵. This indicates that encoding the LR audio from frequency domain is of great help in synthesizing the high-frequency part of the audio.

3.2.3. Ablation Study

To verify the effectiveness of our proposed components and analyze our methods, we conduct ablation study in three aspects:

**Convergence speed**: We train WSRGlow on 4x super-resolution task for only 50k iterations (which is half of the iterations run for the baselines) to show that WSRGlow is easy to train. After 50k iterations, WSRGlow achieves SNR = 17.53, LSD = 1.80 on the test set, which is already better than the baseline models. This proves that WSRGlow converges at high speed.

**Necessity of phase and magnitude inputs**: The comparison between WSRGlow and WSRGlow w/o 🎵Enc🎵 in Table 2 already shows that STFT information (phase and magnitude) is crucial in WSRGlow. To examine whether one of the two can be omitted, we train two partial WSRGlow models for 60k iterations. We observe that WSRGlow without phase embeddings results in $SNR = 12.91$, $LSD = 2.35$ while WSRGlow without magnitude embeddings results in $SNR = 5.68$, $LSD = 2.32$. Both results are poor compared to even the baseline models. This proves that both 🎵Enc(long) and 🎵Enc(short) are effective and necessary.

**Temperature in sampling**: We sample the high-frequency audio results using the same WSRGlow model with different temperatures (variance of Gaussian) $T = 0.5, 0.666, 0.8, 1.0, 1.2, 1.5$ to explore the effect on audio quality. We observe that as the temperature becomes lower, SNR score tends to increase while LSD score tends to decrease. Perceptually, we find that the speech quality is the best when $T = 1.0$.

### Table 2: Objective comparison with other methods.

|  | 2x SR | 4x SR |
|---|---|---|
| | SNR↑ | LSD↓ | SNR↑ | LSD↓ |
| AudioUNet | 22.68 | 1.01 | 16% | 20% |
| MUGAN | 24.81 | 0.90 | 17% | 30.84 | 0.68 |
| WSRGlow w/o 🎵Enc🎵 | 25.91 | 1.41 | 16.87 | 2.12 |
| WSRGlow | 30.84 | 0.68 | 18% | 35 |

### Table 1: The preference scores of baselines and WSRGlow.

| Baseline | Baseline wins | Neutral | WSRGlow wins |
|---|---|---|---|
| AudioUNet | 17% | 16% | 67% |
| MUGAN | 18% | 20% | 62% |
model the conditional distribution of HR spectrogram instead of HR waveform.

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