LEARNING CONTINUOUS REPRESENTATION OF AUDIO FOR ARBITRARY SCALE SUPER RESOLUTION

Jaechang Kim1*, Yunjoo Lee1*, Seunghoon Hong2, Jungseul Ok1

1Graduate School of AI, POSTECH 2School of Computing, KAIST

ABSTRACT

Audio super resolution aims to predict the missing high resolution components of the low resolution audio signals. While audio in nature is a continuous signal, current approaches treat it as discrete data (i.e., input is defined on discrete time domain), and consider the super resolution over a fixed scale factor (i.e., it is required to train a new neural network to change output resolution). To obtain a continuous representation of audio and enable super resolution for arbitrary scale factor, we propose a method of implicit neural representation, coined Local Implicit representation for Super resolution of Arbitrary scale (LISA). Our method locally parameterizes a chunk of audio as a function of continuous time, and represents each chunk with the local latent codes of neighboring chunks so that the function can extrapolate the signal at any time coordinate, i.e., infinite resolution. To learn a continuous representation for audio, we design a self-supervised learning strategy to practice super resolution tasks up to the original resolution by stochastic selection. Our numerical evaluation shows that LISA outperforms the previous fixed-scale methods with a fraction of parameters, but also is capable of arbitrary scale super resolution even beyond the resolution of training data.

Index Terms— audio super resolution, speech super resolution, bandwidth extension, implicit neural networks

1. INTRODUCTION

Audio super resolution is a task to construct the missing high resolution components of given audio in low resolution. The problem is also known as bandwidth extension and sampling rate conversion (SRC), and has been studied extensively in signal processing community. In early works [1, 2], super-resolution of factor \(\frac{L}{M}\) is performed by a sequence of \(L\)-fold upsampling interpolation, low-pass filtering, and then \(M\)-fold downsampling. Note that the output quality of non-integer upsampling interpolation, low-pass filtering, and then output is defined on discrete time domain (i.e., input is defined on discrete time domain), and consider the super resolution over a fixed scale factor (i.e., it is required to train a new neural network to change output resolution). To obtain a continuous representation of audio and enable super resolution for arbitrary scale factor, we propose a method of implicit neural representation, coined Local Implicit representation for Super resolution of Arbitrary scale (LISA). Our method locally parameterizes a chunk of audio as a function of continuous time, and represents each chunk with the local latent codes of neighboring chunks so that the function can extrapolate the signal at any time coordinate, i.e., infinite resolution. To learn a continuous representation for audio, we design a self-supervised learning strategy to practice super resolution tasks up to the original resolution by stochastic selection. Our numerical evaluation shows that LISA outperforms the previous fixed-scale methods with a fraction of parameters, but also is capable of arbitrary scale super resolution even beyond the resolution of training data.

Audio super resolution aims to predict the missing high resolution components of the low resolution audio signals. While audio in nature is a continuous signal, current approaches treat it as discrete data (i.e., input is defined on discrete time domain), and consider the super resolution over a fixed scale factor (i.e., it is required to train a new neural network to change output resolution). To obtain a continuous representation of audio and enable super resolution for arbitrary scale factor, we propose a method of implicit neural representation, coined Local Implicit representation for Super resolution of Arbitrary scale (LISA). Our method locally parameterizes a chunk of audio as a function of continuous time, and represents each chunk with the local latent codes of neighboring chunks so that the function can extrapolate the signal at any time coordinate, i.e., infinite resolution. To learn a continuous representation for audio, we design a self-supervised learning strategy to practice super resolution tasks up to the original resolution by stochastic selection. Our numerical evaluation shows that LISA outperforms the previous fixed-scale methods with a fraction of parameters, but also is capable of arbitrary scale super resolution even beyond the resolution of training data.

We propose Local Implicit representation for Super resolution of Arbitrary scale (LISA) to obtain a continuous representation of audio. LISA consists of a pair of encoder and decoder. The encoder corresponds each chunk of audio to a latent code parameterizing a local input signal around the chunk. The decoder takes a continuous time coordinate and the neighboring set of latent codes around the coordinate, and predicts the value of signal at the coordinate. To train such a continuous representation for audio, we devise a self-supervised learning framework. Specifically, after downsampling the training data to the input resolution, we generate super resolution tasks of random scale factors up to the original resolution. As a training objective, we use a stochastic measure of audio discrepancy between the entire reconstructed and original signals in waveform and spectrogram, in which discrepancy closer to the target chunk receives higher random weight so that the local latent code of a chunk captures a characteristic of the global audio signal, while focuses on the local signal around the chunk.

Thanks to the continuous representation, LISA enables the arbitrary scale super resolution, by requesting the prediction of signal for the set of time coordinates correspond-
Amplitude

The amplitude of \( t \) by the relative distance around a point of interest. (b) A convolutional encoder extracts local continuous representation. (c) An index \( i \) is selected stochastically from \( N(t^*, \delta^*) \). (d) The amplitude of \( t^* \) is predicted by the relative distance around \( t \) and a latent code. \( z_i \) represents a continuous local signal.

Fig. 1: Model architecture. (a) The white circles denote sampled points of the input signal and the red circle denotes the point of interest. (b) A convolutional encoder extracts local continuous representation. (c) An index \( i \) is selected stochastically from \( N(t^*, \delta^*) \). (d) The amplitude of \( t^* \) is predicted by the relative distance around \( t \) and a latent code. \( z_i \) represents a continuous local signal.

2. METHOD

Audio in nature is continuous, denoted by \( F(t) \) for continuous \( t \in \mathbb{R} \), whereas we discretely observe \( F(t) \) for \( t = t_i \)'s in every sampling period \( \frac{1}{R_{in}} \), where \( R_{in} > 0 \) is the input resolution, and \( t_i \) is the \( i \)-th temporal coordinate, i.e., \( t_i - t_{i-1} = \frac{1}{R_{in}} \). Our method, LISA, aims to obtain continuous representation \( \hat{F}(t) \) for continuous \( t \) given a local part of discrete samples \( F(t_i)'s \) only around \( t \) as input so that it provides the arbitrary scale super resolution with low latency. To do so, LISA employs encoder \( g_\phi \) and decoder \( f_\theta \) with neural network parameters \( \phi \) and \( \theta \), respectively. We use encoder \( g_\phi \) to extract local latent code \( z_i \) from \( (2k+1) \) samples around time \( t_i \), i.e.,

\[
z_i := g_\phi(F(t_i-k), ..., F(t_i+k)) .
\]

(1)

Let \( i(t) \) be the closest index to \( t \), i.e., \( i(t) := \arg \min_i |t - t_i| \) where tie breaks with preference to smaller \( i \). We denote by \( z(t) := (z_{i(t)-1}, z_{i(t)}, z_{i(t)+1}) \) the set of local latent codes corresponding to \( t \). Then, LISA represents the signal at any time \( t \in \mathbb{R} \) using decoder \( f_\theta \) as follows:

\[
\hat{F}(t) := f_\theta(t - t_{i(t)}; z(t)) \approx F(t) .
\]

(2)

When we want the super resolution from \( R_{in} \) to \( R_{out} \), the output signal is predicted by putting the sequence of time coordinates every \( \frac{1}{R_{out}} \) to \( F(\cdot) \). We note that ignoring computational cost for encoding and decoding, a theoretical upper bound of latency to predict signal in high resolution around \( t \) is only \( k+\frac{1}{R_{in}} \). A graphical illustration in Fig 1 summarizes LISA.

2.1. Model Architecture

Encoder. To induce the temporal correlation in an audio signal, we use convolutional networks for encoder \( g_\phi \), which produces a latent vector summarizing a few consecutive data points. Our fully convolutional encoder consists of 4 1D-convolution layers with the kernel size of \( \{7, 3, 3, 1\} \) and the channel size of \( \{64, 32, 64, 32\} \). Note that the kernel size of convolutional network determines the range of receptive field of encoder \( g_\phi \) in \( \{1\} \), i.e., in our choice, \( k = 5 = 3 + 1 + 1 + 0 \) as \( 7 = 2 \cdot 3 + 1, 3 = 2 \cdot 1 + 1, \) and \( 1 = 2 \cdot 0 + 1 \). Note that selecting larger \( k \) may force to embed longer pattern inside signal, but it causes longer latency and requires a larger number of parameters.

Decoder. For decoder \( f_\theta \), we use a 5-layer MLP with ReLU activation, of which input to predict signal at \( t \) is the concatenated vector of the relative coordinate \( t - t_{i(t)} \) and the set \( z(t) \)
of local latent codes around \( t \). In \cite{11, 15}, as a part of empowering representation of features in high frequency, periodic activations, such as sine function, have been proposed instead of ReLU. However, according to our experiment, such periodic activations make the training highly sensitive to initialization and hyperparameters. We hence choose to use ReLU for stable training, and small enough \( k \) to express meticulous local representation. The encoder generates the concatenated latent vector \( z(t) = (z_{i(t)-1}, z_{i(t)}, z_{i(t)+1}) \), which adds more information on the signal at a small computational cost.

2.2. Training Strategy

To train encoder \( g_\theta \) and decoder \( f_\theta \), we generate a set of self-supervised learning tasks from a training dataset of resolution \( R_{\text{data}} \). If we aim at super resolution from \( R_{\text{in}} \), dataset resolution \( R_{\text{data}} \) needs to be greater than \( R_{\text{in}} \). Each self-supervised learning task is a super resolution task from \( R_{\text{in}} \) to \( R_{\text{out}} \), where \( R_{\text{out}} \) is drawn uniformly at random from the interval \([R_{\text{out}}^-, R_{\text{out}}^+]\), and the self-supervision can be obtained from downsampling the training dataset at resolution \( R_{\text{in}} \) and \( R_{\text{out}}^+ \) with sinc interpolation \cite{16}. In Section 3, we report experiment results from several choices of \( (R_{\text{in}}, R_{\text{out}}, R_{\text{out}}^+, R_{\text{out}}^+) \). In what follows, we describe the remaining details about training procedure with the generated task.

2.2.1. Loss function

Given the generated super resolution task from \( R_{\text{in}} \) to \( R \), we let \( T \) be the set of time coordinates corresponding to \( R \), and \( x \) be the corresponding signal, i.e., the sequence of \( F(t) \) for \( t \in T \). Using encoder \( g_\theta \) and decoder \( f_\theta \), we generate the sequence of predictions for \( t \in T \), denoted by \( \hat{x} \), with a random perturbation, which will be elaborated in Section 2.2.2. We note that the perturbed prediction \( \hat{x} \) is used only for training and robustifies the prediction, for testing, the prediction is performed as described in 2. Using gradient-based optimizer with back-propagation, we train encoder \( g_\theta \) and decoder \( f_\theta \) to minimize a discrepancy from the perturbed prediction \( \hat{x} \) to the supervision \( x \). To capture the discrepancy both in time and frequency domains, we measure it with L1 loss \( \mathcal{L}_{\text{wave}}(x, \hat{x}) = \|x - \hat{x}\|_1 \), and multi-scale spectrogram loss \( \mathcal{L}_{\text{spec}} \) \cite{17}. Then, the training loss is given as:

\[
\mathcal{L}(x, \hat{x}) = \mathcal{L}_{\text{wave}}(x, \hat{x}) + \lambda \mathcal{L}_{\text{spec}}(x, \hat{x}),
\]

where with balancing hyperparameter \( \lambda > 0 \).

2.2.2. Stochastic selection of a local latent code

We now describe how we generate the perturbed prediction \( \hat{x} \) in 3. The perturbation is designed to reduce the disagreement between two neighboring local predictions at the midway. In order to alleviate this issue, \cite{14} proposes an ensemble method by taking the weighted sum of the predicted signals from different local predictions, where the weights are computed to be inversely proportional to geometric distance in coordinates. If we applied the ensemble method, then the prediction at \( t \) would be \( \frac{1}{(t_{i(t)}-t_{i(t)-1})}f_{\theta}(z_{i(t)-1},t_{i(t)}-t) + \frac{1}{(t_{i(t)+1}-t)}f_{\theta}(z_{i(t)+1},t_{i(t)+1}) \), for \( t \in [t_{i(t)}, t_{i(t)+1}] \). However, we found that as shown in Fig 2 training with the ensemble make considerable errors in the local predictions, although the ensemble has small errors. Hence, we rather choose an input latent vector randomly among a few closest latent vectors around the target coordinate. To do so, we perturb \( t \) and use \( \hat{t} = i(t + \eta) \), for training, where \( \eta \) is zero-mean Gaussian noise with variance \( \delta^2 > 0 \), i.e., \( \eta \sim \mathcal{N}(0, \delta^2) \). \( \delta \) controls the desired covering range of a local signal. We use \( \delta \) as the distance between \( t_i \) and the border \( \frac{t_{i-1}+t_i}{2}, \frac{t_{i+1}+t_i}{2} \). Through the stochastic selection of local latent codes, whichever one is chosen among the closest latent vectors, either one should be able to independently represent high resolution at the target coordinate. Therefore, each latent vector is guided to depict the details of the local signal to predict the high resolution component without referring to predictions from the other closest latent vectors. By sampling the latent vectors, a latent vector \( z_i \) also learns to represent data out of the interval \([\frac{t_{i-1}+t_i}{2}, \frac{t_{i+1}+t_i}{2}] \). Fig 2 shows the local signals are connected to adjacent local signals.

3. EXPERIMENTS

Throughout the experiments, we use CSTR VCTK corpus \cite{18}, a high-quality speech dataset in 48kHz uttered by 109 English speakers. We inherit the same multi-speaker setting used in \cite{7}, where the first 99 speakers are used for training and the rest are served as test set. We compare our method with the existing audio super resolution methods including AudioUNet \cite{7}, AudioTFilm \cite{19}, and WSRGlow \cite{10}. To be as fair as possible, we use the pre-trained models of baselines if available, and we reproduce using the original authors’ official source codes otherwise. We evaluate the performance of super resolution in terms of Signal-to-Noise-Ratio (SNR) and Log-Spectral-Distance (LSD). SNR is defined as

\[
\text{SNR}(x, \hat{x}) = 10 \log \frac{\|x\|^2}{\|x - \hat{x}\|^2},
\]

where \( \hat{x} \) is the predicted signal and \( x \) is the ground truth signal. LSD is defined as

\[
\text{LSD}(x, \hat{x}) = \frac{1}{L} \sum_{l=1}^{L} \frac{1}{K} \sum_{k=1}^{K} \left( X(l, k) - \hat{X}(l, k) \right)^2,
\]

where, using Short-Time Fourier Transform (STFT), \( X(l, k) = \log \text{STFT}^{X(l,k)}(x) \) is log-spectral power magnitudes of \( x \) with index frame \( l \) and frequency \( k \), and \( \hat{X} \) is defined similarly but for \( \hat{x} \). We use Adam optimizer \cite{20} with learning rate of 0.001. We train the model for 50 epochs, and decay the learning rate by half at every 5 epochs. We use gradient clipping with 0.001 max norm for stable training.
Fig. 3: Super resolution results in spectrogram. (a) Ground Truth is 48kHz signal, (b) and (c) are super resolution results of the ×4 (12kHz → 48kHz) setting in Table 1.

Table 1: Objective comparison with other methods.

|               | AudioUNet [7] | AudioTFilm [19] | WSRGlow [10] | LISA (Ours) |
|---------------|---------------|-----------------|--------------|-------------|
| ×2 (8kHz→16k) | SNR↑ 21.68    | SNR↑ 22.23      | SNR↑ 25.29   | SNR↑ 30.7   |
| LSD↓ 1.31     | LSD↓ 1.05     | LSD↓ 0.61       | LSD↓ 0.58    | LSD↓ 0.58   |
| ×4 (12kHz→48k)| SNR↑ 18.55    | SNR↑ 19.51      | SNR↑ 19.41   | SNR↑ 24.16  |
| LSD↓ 2.11     | LSD↓ 2.02     | LSD↓ 1.01       | LSD↓ 0.81    | LSD↓ 0.81   |
| # params      | 71M           | 68M             | 229M         | 89k         |

Table 2: Evaluation of arbitrary scale super resolution and ablation study. The same model is used for 2×, 3×, and 6× super resolution. -sto, -spec denotes models trained without stochastic selection and without multi-scale spectrogram loss.

|               | in-distribution | out-of-distribution |
|---------------|-----------------|---------------------|
| ×2 (8kHz→16k) | LISA 25.66      | LISA 22.17          |
| SNR↑ 0.94     | LSD↓ 24.15      | LSD↓ 1.23           |
| ×3 (8kHz→24k) | LISA -0.18      | LISA -0.08          |
| SNR↑ 1.17     | LSD↓ -0.05      | LSD↓ -0.08          |
| ×6 (8kHz→48k) | LISA -0.08      | LISA -0.08          |
| SNR↑ 1.17     | LSD↓ -0.05      | LSD↓ -0.08          |
| # params      | -0.01           | -0.01               |

3.1. Fixed scale super resolution

We train our model, LISA, on two tasks of fixed scale resolution: i) from 12kHz to 48kHz; and ii) from 24kHz to 48kHz. Table 1 compares LISA to the baselines, in which LISA shows the best performance in terms of both SNR and LSD. It is remarkable that in terms of the number of model parameters, our model is at least 764 times lighter than the others. In Fig 3, LISA captures detailed features in the spectrogram, which are highlighted with red boxes. However, WSRGlow misses the details despite it uses 2,573 times more parameters. The difference is noticeable in listening.

3.2. Arbitrary scale super resolution

To demonstrate the arbitrary scale super resolution using LISA, we obtain a single model with the self-supervised learning tasks from $R_{in} = 8$kHz to the random target resolution drawn from $[R_{out}^l, R_{out}^u] = [8kHz, 24kHz]$, i.e., the training never uses any sound of 48 kHz resolution.

Out-of-distribution. In Table 2, the model is evaluated with 2×, 3×, and 6× super resolution tasks. In the out-of-distribution task, which our model upsamples with a scale of 6, our model even outperforms the results of 4x super resolution task of baselines. Note that the 48kHz data, which is the output resolution of 6× setting, is never seen to the model while training.

Non-integer scale SR. Also, we evaluated our results in non-integer scale. In Fig 4, non-integer scale super resolution performance is no worse than integer scale super resolution, does not show any fluctuation. The test data is generated with sinc interpolation from 48k data.

Ablation Study. In Table 2 we also assess the effect of each component through an ablation study. The perturbed prediction (2.2.2) in training is twice beneficial in terms of SNR gain compared to the spectrogram loss function in (3) in the 2× super resolution. In addition, Fig 2 shows that the discontinuity between the local signals is indeed regulated by the perturbed prediction (2.2.2).

4. CONCLUSION

We propose LISA to obtain a continuous representation of an audio as a neural function, which enables us to perform the arbitrary scale audio super resolution. To train LISA, we devise a sophisticated self-supervised learning strategy, equipped with the perturbed prediction in training and the loss function for audio signal. Our experiment shows that LISA outperforms the other baselines in terms of super resolution performance with a remarkably small size. We expect that our model has a great potential for online audio super resolution applications thanks to the light size compared to other baseline models but also the low latency from the local implicit representation.
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