PHASE RECONSTRUCTION BASED ON RECURRENT PHASE UNWRAPPING WITH DEEP NEURAL NETWORKS

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ABSTRACT
Phase reconstruction, which estimates phase from a given amplitude spectrogram, is an active research field in acoustical signal processing with many applications including audio synthesis. To take advantage of rich knowledge from data, several studies presented deep neural network (DNN)-based phase reconstruction methods. However, the training of a DNN for phase reconstruction is not an easy task because phase is sensitive to the shift of a waveform. To overcome this problem, we propose a DNN-based two-stage phase reconstruction method. In the proposed method, DNNs estimate phase derivatives instead of phase itself, which allows us to avoid the sensitivity problem. Then, phase is recursively estimated based on the estimated derivatives, which is named recurrent phase unwrapping (RPU). The experimental results confirm that the proposed method outperformed the direct phase estimation by a DNN.

Index Terms— Spectrogram inversion, group delay, instantaneous frequency, time-frequency analysis, recurrent neural network

1. INTRODUCTION
Phase reconstruction has been widely used in many acoustical signal processing, including speech enhancement [12] and synthesis [3, 7]. While phase reconstruction with observed noisy phase has been applied to speech enhancement successfully [8, 10], phase reconstruction solely from a given amplitude spectrogram is still a challenging problem. To address this problem, various approaches have been studied including the consistency-based approach [14, 15] and model-based approach [16]. While the former approach is based on the model of the short-time Fourier transform (STFT) [15], the latter one explicitly uses a model of the target signal. By taking the property of the target signal into account, the model-based approach has achieved better performance than the consistency-based one in many applications [14, 16, 17].

To take advantage of more knowledge about the target signal, deep neural network (DNN)-based phase reconstruction [18–23] has gained increasing attention. Although DNNs have strong modeling capability and learn rich knowledge from training data, DNN-based phase reconstruction has the following two problems: the wrapping effect and sensitivity to a waveform shift. Since phase is wrapped in [−π, π], it is discontinuous at ±π even when phase rotates smoothly. Hence, conventional loss functions for regression problems including the mean-squared error (MSE) are not suitable for phase reconstruction because they do not take the periodic nature of phase into account. Instead of estimating phase directly, one approach estimates complex-valued spectrogram [19, 20], and another approach treats phase reconstruction as a classification problem by discretizing phase [21, 22]. To estimate continuous phase directly, [23] proposed a loss function based on the distribution of a periodic variable called the von Mises distribution.

While those previous studies effectively dealt with the wrapping effect, the sensitivity of phase to a waveform shift has not been considered explicitly. Considering the Fourier transform, its phase is sensitive to the shift in the time-domain while its amplitude is shift-invariant. In other words, an infinite number of Fourier phases can exist for one Fourier amplitude. This is also approximately true for STFT, i.e., the STFT phase changes with the small shift in the time-domain while the STFT amplitude does not (see Fig. 2.1). That is, DNN-based direct phase estimation needs to learn an unstable map that converts a small changes in the input STFT amplitude to a large changes in the output STFT phase. However, it is not an easy task to train a DNN as such an unstable map.

In this paper, we propose a two-stage phase reconstruction method as illustrated in Fig. 1. To avoid the sensitivity problem, DNNs estimate phase derivatives instead of phase itself since phase derivatives have a relation to the amplitude spectrogram [24, 26]. Then, the proposed method recursively reconstructs phase from the estimated phase derivatives, which is named RPU. RPU solves a least-squares problem for estimating phase, which resembles a 2D phase unwrapping technique [27]. Experimental results indicate the proposed method is more effective than the direct phase estimation.

2. PHASE RECONSTRUCTION VIA DNN
Motivated by the recent advance in deep learning, several DNN-based phase reconstruction methods have been presented [18–23]. However, phase reconstruction from a given amplitude spectrogram is not an easy task for DNNs due to the following two problems:
the wrapping effect and sensitivity to a shift of a waveform. In the next subsections, we describe these problems and introduce the von Mises DNN proposed for handling wrapped phase \[23\].

2.1. Difficulty of DNN-based phase reconstruction

The first problem is the wrapping effect of phase. Phase is given by the complex argument of a complex-valued spectrogram, and it is wrapped in \([-\pi, \pi]\) even when it rotates smoothly. Training of a DNN for phase reconstruction should take this wrapping effect into account, but ordinary loss functions for regression problems, including MSE, do not consider such periodic nature of phase.

The second problem is the sensitivity to a shift of a waveform. Considering the Fourier transform, its amplitude is shift-invariant, i.e., the amplitude does not change by shifting a waveform. In contrast, its phase is sensitive to the shift, and thus an infinite number of Fourier phases can be considered for an amplitude spectrum. Here, we experimentally show the same tendency of STFT amplitude and phase. As an example, we consider an utterance from JSUT corpus \[28\] and that shifted 0.5 ms (8 samples). Their STFT amplitude, phase, and time-directional phase derivative, i.e., instantaneous frequency, were shown in Fig. 2. While their amplitudes look similar, phase, and instantaneous frequency were different as observed in the rightmost column of Fig. 2.

2.2. Related works

To address the first problem, \[23\] proposed a loss function based on the von Mises distribution. The von Mises distribution is a distribution of a continuous periodic variable given by \( p(\phi) = e^\kappa \cos(\phi - \mu)/2\pi I_0(\kappa) \), where \( \mu \) is a circular mean, \( \kappa \) is a concentration, and \( I_0(\kappa) \) is the modified Bessel function of the first kind of order 0. Its negative log-likelihood is given by

\[
-\log p(\phi) = -\kappa \cos(\phi - \mu) + C(\kappa),
\]

where \( C(\kappa) \) is independent of \( \mu \). Derived from Eq. \[1\], the loss function proposed in \[23\] is formulated by

\[
L(\theta) = -\sum_{\omega, \tau} \cos(\Phi_{u, \tau}^\omega - \Phi_{v, \tau}^\omega, \theta),
\]

where \( \Phi_{u, \tau}^\omega \in [\pi, \pi] \) is the clean phase, and \( \tau = 0, \ldots, T - 1 \) and \( \omega = 0, \ldots, K - 1 \) are the time and frequency indices, respectively. \( \Phi_{v, \tau}^\omega \) is a DNN for direct phase estimation, \( \theta \) is a set of parameters of the DNN, and \( \Phi_{v, \tau}^\omega \) is the input feature calculated from an amplitude spectrogram for estimating phase at the \( \tau \)th time-frame. This loss function is insensitive to the ambiguity of \( 2\pi \) of the estimated phase.

In addition, \[23\] also proposed the group delay loss, evaluating the group delay calculated from the estimated phase, because group delay has a strong relation to amplitude spectrogram. Recently, some studies for DNN-based audio synthesis focused on phase derivatives \[29, 30\].

To learn a generative model of complex-valued spectrograms, \[29\] uses both instantaneous frequency and group delay in its loss functions as an extension of the group delay loss. On the other hand, \[30\] reconstructs phase by integrating the estimated instantaneous frequency along with the time-direction.

3. PROPOSED PHASE RECONSTRUCTION

In the previous section, we describe the sensitivity of the phase to a waveform shift which makes the map for direct phase estimation unstable. To overcome this problem, we propose a two-stage phase reconstruction method which uses the phase derivatives estimated by DNNs. The overall procedure of the proposed phase reconstruction is illustrated in Fig. 3. In the proposed method, two DNNs estimate the instantaneous frequency and group delay to avoid the sensitivity problem. Then, phase is recursively reconstructed by solving the least squares problem from its derivatives.

3.1. Estimation of phase derivatives

In our proposed method, the instantaneous frequency and group delay at the \( \tau \)th time-frame are estimated by DNNs as follows:

\[
v_\tau = \mathcal{F}_W(\psi_\tau, \theta_W),
\]

\[
u_\tau = \mathcal{F}_D(\psi_\tau, \theta_D),
\]

where \( v_\tau = [v_{0, \tau}, \ldots, v_{K-1, \tau}]^T \) is the estimated instantaneous frequency, and \( u_\tau = [u_{0, \tau}, \ldots, u_{K-2, \tau}]^T \) is the estimated group delay. DNNs are trained to minimize following loss functions:

\[
L_W(\theta_W) = -\sum_{\omega, \tau} \cos(V_{\omega, \tau}^u - \mathcal{F}_W(\psi_\tau, \theta_W)_\omega),
\]

\[
L_D(\theta_D) = -\sum_{\omega, \tau} \cos(U_{\omega, \tau}^u - \mathcal{F}_D(\psi_\tau, \theta_D)_\omega),
\]

where \( V_{\omega, \tau}^u = \Phi_{0, \tau+1}^\omega - \Phi_{0, \tau}^\omega \) and \( U_{\omega, \tau}^u = -\Phi_{0, \tau+1}^\omega + \Phi_{0, \tau}^\omega \) are the instantaneous frequency and group delay defined by the numerical difference of the clean phase \( \Phi^\omega \). Phase derivatives are treated as periodic variables because they are approximated by the difference of wrapped phase. Hence, estimated phase derivatives also have the ambiguity of \( 2\pi \), which is dealt in the next subsection.

\[1\] We call the time- and negative frequency-directional phase derivatives as the instantaneous frequency and group delay for intuitiveness.
### Estimated phase derivatives

As $D$, then the group delay is also calculated from the estimated phase in the target time-frame is temporally estimated by Eq. (10). Then, the group delay is also calculated from the estimated phase as $D_u(\hat{\phi}_r)$.

The rightmost figure solves the ambiguity of the group delay estimated by the DNN as in Eq. (11).

### Recurrent phase unwrapping (RPU)

In this subsection, we explain the later part of the proposed phase reconstruction, i.e., recursive phase estimation from its derivatives, which is named as RPU. We first explain a popular 2D phase unwrapping algorithm because RPU borrows an idea from it. The estimation of unwrapped 2D phase from its derivatives is not obvious because the unwrapped phase should be consistent in both directions. Let $V$ and $U$ be given phase derivatives in each direction. One of the famous methods for 2D phase unwrapping is formulated by the following least squares problem \(^2\):

$$\text{Find } \Phi \in \arg \min_{\Phi} \|D_r(\Phi) - V\|^2_F + \|D_u(\Phi) - U\|^2_F, \quad (7)$$

where $\Phi$ is the unwrapped phase, $\| \cdot \|_F$ is the Frobenius norm, $[D_r(\Phi)]_{\omega,\tau} = \Phi_{\omega+1,\tau} - \Phi_{\omega,\tau}$ is the time-directional difference operator, and $[D_u(\Phi)]_{\omega,\tau} = -\Phi_{\omega+1,\tau} + \Phi_{\omega,\tau}$ is the frequency-directional difference operators. This method can be applied to phase reconstruction of a spectrogram by considering phase reconstruction as the estimation of unwrapped 2D phase. However, this approach has the following two problems. It requires huge computation for calculating the inverse of $KT \times KT$ matrix. Second, the phase derivatives estimated the NNs have the ambiguity of $2\pi$, which should be properly solved to maintain spatial consistency.

For avoiding the first problem, we propose RPU that recursively solves the following small least squares problem:

$$\phi_r = \arg \min_{\phi} \|\phi - \phi^{W}_{r-1} - v_{r-1}\|^2_2 + \|D_u(\phi) - u_r\|^2_2, \quad (8)$$

where $\phi^{W}_{r-1} = VW(\phi_{r-1})$ is the estimated wrapped phase in the $(\tau - 1)$th time-frame, $\| \cdot \|_2$ is the Euclidean norm, and $W(\cdot) = :+\pi|\mod 2\pi - \pi$ is the wrapping operator\(^3\). This least squares problem aims to estimate the phase which is consistent with the phase derivatives estimated by DNNs. The least squares problem given in Eq. (8) is solved as

$$\phi_r = (I + D_u^T D_u)^{-1}(\phi^{W}_{r-1} + v_{r-1} + D_u^T u_r), \quad (9)$$

where $I$ is the identity matrix. In Eq. (9), the required computation is reduced to only $K \times K$ matrix inversion. This is because RPU focuses on phase in the successive time frames and treats the phase in the previous time-frame as a fixed value while Eq. (7) considers all time frames at the same time.

The second problem is the ambiguity of the phase derivatives estimated by DNNs. The estimated instantaneous frequency and group delay have the ambiguity of $2\pi$ as discussed in the previous subsection, and we must solve this ambiguity appropriately. For this goal, we fix the instantaneous frequency, and select the appropriate group delay, which is consistent with the instantaneous frequency, from the set $\{u_{\omega,\tau} \pm 2n\pi\}$, where $n \in N$. The proposed group delay modification is conducted by

$$\hat{\phi}_r = \phi^{W}_{r-1} + v_{r-1}, \quad (10)$$

$$\hat{u}_r = D_u(\hat{\phi}_r) + W(u_r - D_u(\phi_r)). \quad (11)$$

This modification process is illustrated in Fig. 3. In Eq. (10), phase in the target time-frame is temporally estimated as shown in the second left figure. Then, the appropriate group delay, which is the nearest to $D_u(\phi_r)$, is selected from the set $\{u_{\omega,\tau} \pm 2n\pi\}$ by Eq. (11) as shown in the rightmost figure. After solving the ambiguity, $\hat{u}_r$ is substituted to $u_r$ in Eq. (8).

### Summary of the proposed phase reconstruction

In the training, pairs of clean amplitude spectrogram and phase are calculated from utterances by STFT, and the instantaneous frequency and group delay are calculated by the numerical difference of the phase. Two DNNs for estimating the phase derivatives are trained by the loss functions given in Eqs. (5) and (6). Then, the proposed phase reconstruction method is summarized as follows:

1. Estimate the instantaneous frequency in the previous time-frame $v_{r-1}$ and group delay in the target time-frame $u_r$, as in Eqs. (3) and (4), respectively.
2. Reconstruct phase by RPU:
   2.1 Modify the estimated group delay as in Eqs. (10) and (11).
   2.2 Estimate phase in the next time-frame by Eq. (9).
   2.3 Repeat 2.1 and 2.2 for all time-frames.

After reconstructing phase in all time-frames, we can obtain the complex-valued spectrogram and convert it to the time-domain.

### EXPERIMENTS

To validate the effectiveness of the proposed method, the quality of reconstructed speeches from given amplitude spectrograms was evaluated. It was compared with the direct phase estimation by the von Mises DNN\(^23\). In addition, we also investigated the performance of the phase reconstruction by integrating the estimated instantaneous frequency as in \(^3\).

### 4.1. Experimental condition

Evaluations were performed using the subsets of JSUT corpus\(^28\) (BASIC5000 and ONOMATOPE300) which is a Japanese speech corpus uttered by one female speaker. Utterances from BASIC5000 were used as a training set where all utterances were resampled at 16 kHz. STFT was implemented with the Hann window, whose duration was 32 ms with 8 ms shift. During the training, the utterances were divided into about 2-second-long segments. In this experiment, \(^3\) This method corresponds to reconstruct phase by Eq. (10), which does not consider the group delay. In contrast, the proposed method uses not only the instantaneous frequency but also group delay in RPU.
Table 1. Accuracy of the DNN estimations. Range of the accuracy is from –1 to 1, and higher is better.

|        | Phase | Instantaneous frequency | Group delay |
|--------|-------|-------------------------|-------------|
| Training | 0.238 | 0.675                   | 0.702       |
| Testing  | 0.003 | 0.644                   | 0.646       |

Fig. 4. Examples of the estimated phase and its derivatives.

The DNNs were trained by the Adam optimizer for 10,000 epochs where the learning rate was decayed every 1,000 epoch by multiplying 1/2. The initial learning rate was set to 0.01. In the testing, 300 utterances from ONOMATOPE300 were used.

The input feature $\psi_t$ was the vector which consists of the log-amplitude spectrogram at current and $\pm 2$ frames with a normalization. Fully connected DNNs with 4 layers were used where each layer had 1024 units, and gated tanh nonlinearity [31] was used for the activation except the last layer.

4.2. Experimental results

We first evaluated the prediction accuracy of phase and its derivatives by DNNs. Table 1 shows the accuracy of the estimation defined by $\sum_{i \in, r} \cos(\phi_{i, r} - \phi_{i, r}) / KT$ which takes a value in $[-1, 1]$. The accuracy of the phase derivatives was higher than that of the phase itself in both training and testing. This indicates that the estimation of phase derivatives is easier than that of phase itself as our expectation. Considering phase derivatives, the difference between the accuracy in training and testing are relatively small, but the accuracy of phase estimation significantly decreased in testing. That is, the DNN for direct phase estimation caused overfitting in our experimental condition. We also trained the same DNN for direct phase estimation using the testing dataset (ONOMATOPE300). Its accuracy was 0.557 which was higher than the accuracy in the training, because the DNN overfitted to the small testing dataset. However, it was still lower than the accuracy of the phase derivatives in Table 1.

Figure 4 shows examples of the phase and its derivatives estimated by DNNs. We can observe the same structure in both clean and estimated phase derivatives. On the other hand, there exists a large estimation error in phase, which is consistent with the quantitative evaluation in Table 1.

The boxplots of STOI [32] and PESQ [33] of the reconstructed signals are illustrated in Fig. 5 where the direct phase estimation [23] and the numerical integration of the instantaneous frequency [30] are abbreviated as “Ph” and “IF”, respectively. Since the direct phase estimation caused overfitting as shown in Table 1, we also evaluated the direct phase estimation trained by the testing dataset (ONOMATOPE300) as “Ph (test)” to approximately evaluate its best possible performance on the testing dataset. We evaluated the zero-phase, i.e., without phase reconstruction, as “Amp.” In addition, we applied the Griffin–Lim algorithm (GLA) to each estimation [11]. The proposed method outperformed the direct phase estimation by the von Mises DNNs and the numerical integration of the estimated instantaneous frequency with and without GLA. Comparing to those conventional methods, the effectiveness of the proposed method was confirmed by comparing the zero-phase, i.e., without phase reconstruction, as “Amp.” In addition, we applied the Griffin–Lim algorithm (GLA) to each estimation [11]. The proposed method outperformed the direct phase estimation by the von Mises DNNs and the numerical integration of the estimated instantaneous frequency with and without GLA. Comparing to those conventional methods, the effectiveness of the proposed method was confirmed by comparing the zero-phase, i.e., without phase reconstruction, as “Amp.” In addition, we applied the Griffin–Lim algorithm (GLA) to each estimation [11]. The proposed method outperformed the direct phase estimation by the von Mises DNNs and the numerical integration of the estimated instantaneous frequency with and without GLA. Comparing to those conventional methods, the effectiveness of the proposed method was confirmed by comparing the zero-phase, i.e., without phase reconstruction, as “Amp.” In addition, we applied the Griffin–Lim algorithm (GLA) to each estimation [11]. The proposed method outperformed the direct phase estimation by the von Mises DNNs and the numerical integration of the estimated instantaneous frequency with and without GLA. Comparing to those conventional methods, the effectiveness of the proposed method was confirmed by comparing the zero-phase, i.e., without phase reconstruction, as “Amp.” In addition, we applied the Griffin–Lim algorithm (GLA) to each estimation [11].

Fig. 5. Boxplots of STOI and PESQ for 300 reconstructed utterances from amplitude spectrograms. The boxes indicate the first and third quartiles. The top row shows the measures of the reconstructed speech by each method. In the center and bottom rows, GLA was applied as post-processing 10 and 100 times, respectively.
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