iMetricGAN: Intelligibility Enhancement for Speech-in-Noise using Generative Adversarial Network-based Metric Learning

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Abstract

The intelligibility of natural speech is seriously degraded when exposed to adverse noisy environments. In this work, we propose a deep learning-based speech modification method to compensate for the intelligibility loss, with the constraint that the root mean square (RMS) level and duration of the speech signal are maintained before and after modifications. Specifically, we utilize an iMetricGAN approach to optimize the speech intelligibility metrics with generative adversarial networks (GANs). Experimental results show that the proposed iMetricGAN outperforms conventional state-of-the-art algorithms in terms of objective measures, i.e., speech intelligibility in bits (SIIB) and extended short-time objective intelligibility (ESTOI), under a Cafeteria noise condition. In addition, formal listening tests reveal significant intelligibility gains when both noise and reverberation exist.

Index Terms: intelligibility, generative adversarial networks, speech modification

1. Introduction

Speech is the main media used by humans to communicate in daily life. However, in speech application systems, the intelligibility of speech messages is inevitably degraded due to background noise and reverberation. Several modification algorithms have been studied to enhance the intelligibility by preprocessing a signal before it is played out \(?\). This task is usually termed near-end listening enhancement (NELE). There are various strategies for NELE tasks, such as spectral tilt flattening \(1, 2\), formant shifting \(2\), and dynamic range compression \(3, 4\). A common idea of the above algorithms is to reallocate the speech energy in the time-frequency (T-F) domain in such a way as to boost the acoustic cues that are perceptually crucial.

In this paper, we utilize deep neural networks (DNNs) to reallocate the speech energy. The output of a DNN acts as scale factor \(\alpha\), which is then multiplied to the T-F bin of the speech. The T-F bin energy is boosted with \(\alpha > 1\) and suppressed otherwise. This framework is very similar to the masking-based speech enhancement approach \(5\), where spectral mask is predicted by NN and applied to the T-F bin as well. Although NELE task shares a similar solution to DNN-based speech enhancement, very few related works have been done so far. One of the biggest challenges with the DNN-based NELE approach is that there is no ground truth label that can be provided for supervised training. Specifically, given an unmodified plain speech, there is no standard that explicitly defines what the perfectly intelligible speech should be, and thus no ground truth label can be prepared. In contrast, in a speech enhancement task, clean speech without noise mixed can be easily prepared and regarded as the training label of corresponding noisy speech.

Experimental results show that the proposed iMetricGAN outperforms conventional state-of-the-art algorithms in terms of objective measures, i.e., speech intelligibility in bits (SIIB) and extended short-time objective intelligibility (ESTOI), under a Cafeteria noise condition. In addition, formal listening tests reveal significant intelligibility gains when both noise and reverberation exist.

2. Problem Formulation and Assumptions

Consider a real scenario of the NELE task, as depicted in Fig.\(^1\). Let \(s(n)\) be the original speech signal. A modification algorithm is applied to \(s(n)\) before it is played out by the loudspeaker and the processed output is denoted as \(\tilde{s}(n)\). The observed signal \(y(n)\) at the listener end is thus given by

\[
y(n) = h(n) * \tilde{s}(n) + w(n)\tag{1}
\]

where \(*\) denotes a convolution operation, \(h(n)\) is the room impulse response (RIR)\(^7\) and \(w(n)\) is the additive background noise. An assumption is made that the RIR \(h(n)\) and the noise \(w(n)\) can be estimated with an acoustic echo cancellation (AEC) technique \(7\). Therefore, the general NELE task is formulated as finding an algorithm to modify the natural speech to improve its intelligibility in known noise and room conditions.

\(^1\)Loudspeaker response is integrated into RIR for simplicity.
In this work, for simplicity, we take only the noise signal \( w(n) \) into account and disregard \( h(n) \), the influence of reverberation. Meanwhile, we do not change the RMS level and the duration of speech before and after modifications. With these assumptions and constraints, the problem can thus be formulated to design a DNN-based mapping function \( \Phi(.) \), as

\[
\tilde{s} = \Phi(s, w) \quad \text{s.t.} \quad \text{RMS}(\tilde{s}) = \text{RMS}(s), \quad \text{Dur}(\tilde{s}) = \text{Dur}(s)
\]  

(2)

where sample index \( n \) is omitted from this point forward and \( \text{Dur}(.) \) denotes the duration of the signal. It takes as input the unprocessed speech \( s \) and the noise signal \( w \). The output \( \tilde{s} \) after modification is more intelligible when masked with noise.

### 3. Proposed iMetricGAN Model

In the field of speech enhancement, MetricGAN [6] has shown a powerful ability to optimize complex and even non-differentiable speech quality metrics, such as PESQ [8]. The proposed iMetricGAN adapts and revises the original MetricGAN for the intelligibility enhancement task, where the target metric to be optimized is the speech intelligibility measure.

#### 3.1. Selecting intelligibility measures

Objective measures are designed to predict the intelligibility score of speech. We select SIIB [9] and ESTOI [10] measures as our optimization targets because they have achieved state-of-the-art performance (i.e., high correlations with listening tests), as demonstrated in [11]. Both of these measures require reference and degraded signals as inputs for assessing relative intelligibility difference. To be specific, the reference is the original speech \( s \), and the degraded signal is \( \tilde{s} + w \). Objective intelligibility scores can thus be rated by the measures. Nevertheless, they cannot be directly set as the training targets for a DNN system, since both measures are quite complex and non-differentiable. Hence, we utilize iMetricGAN to overcome this obstruction.

#### 3.2. Model description and training process

The model framework is depicted in Fig. 2. It consists of a generator (\( G \)) network and a discriminator (\( D \)) network. \( G \) receives speech \( s \) and noise \( w \) and then generates the enhanced speech. An energy normalization layer is inserted to guarantee the energy is maintained after modification. The final processed speech is noted as \( G(s, w) \). The cascading \( D \) is utilized to predict the intelligibility score of the enhanced speech \( G(s, w) \), given \( s \) and \( w \). The output of \( D \) is noted as \( D(G(s, w), s, w) \) and expected to be close to the true intelligibility score calculated by a specific measure. We introduce the function \( Q(.) \) to represent the intelligibility measures to be modeled, i.e., SIIB and ESTOI. With the above notations, the training target of \( D \), shown in Eq. (5), can be represented to minimize the following loss function:

\[
L_D = \mathbb{E}_{s,w}[\{D(G(s, w), s, w) - Q(G(s, w), s, w))^2\}] 
\]  

(3)

Moreover, we introduce \( \hat{s} \), the signal example that is enhanced by reference modification algorithms such as SSDRC [3], in the \( D \) training process. The loss function is thus extended to Equation (4).

\[
L_D = \mathbb{E}_{s,w}[\{D(G(s, w), s, w) - Q(G(s, w), s, w))^2\} + \{D(\hat{s}, s, w) - Q(\hat{s}, s, w))^2\}] 
\]  

(4)

The motivation for introducing \( \hat{s} \) is to improve the generalization of \( D \). By feeding it with not only \( G(s, w) \) but also the signals modified by various other algorithms, \( D \) is encouraged to predict the intelligibility scores in a more accurate way. Thus Equation (4) can be seen as the loss function with auxiliary knowledge, while Equation (3) is the loss function with zero knowledge. Note that \( \hat{s} \) should not be regarded as the ground truth or the training label. In fact, the experimental results in Section 5 demonstrate that iMetricGAN still works well even without introducing \( \hat{s} \).

For the \( G \) training process shown in Fig. 2(b), \( D \)'s parameters are fixed and \( G \) is trained to reach intelligibility scores as high as possible. To achieve this, the target score \( t \) in Equation (5) is assigned to the maximum value of the intelligibility measure.

\[
L_G = \mathbb{E}_{s,w}[(D(G(s, w), s, w) - t)^2] 
\]  

(5)

\( G \) and \( D \) are iteratively trained until convergence. \( G \) acts as an enhancement module and is trained to cheat \( D \) in order to achieve a higher intelligibility score. On the other hand, \( D \) tries to not be cheated and to accurately evaluate the score of the modified speech. This minimax game finally makes both \( G \) and \( D \) effective. Consequently, the input speech can be enhanced to a more intelligible level by \( G \).
with the phase of the input speech.

The generator model $G$ is composed of two BLSTM layers, each with 400 hidden nodes, and two fully connected layers, each with 600 nodes. The activation function for the first fully connected layer is LeakyReLU with slope $= 0.3$, and the last output layer is set as follows:

$$output = \exp (1.5 + 4 \times \tanh(m))$$

where $m$ is the result of the previous layer. This output serves as scale factors, which are point-wise multiplied with the input spectrogram (unmodified speech) to produce an enhanced spectrogram. Scale factors modify the input speech by redistributing its energy: the T-F bin is boosted or declined with the corresponding scale value. The scale range of Equation (6), which is approximately 0.08 to 255, is empirically chosen. We expect such a wide range will facilitate the processing ability of $G$. Once processed by $G$, the enhanced spectrogram is normalized by the energy normalization layer, where the total squared energy of the output spectrogram is normalized to be the same as that of the input. The final processed spectrogram is sequentially passed on to the network $D$.

As shown in Fig. 2, the input features for $D$ are 3-channel spectrograms, i.e., (processed, unprocessed, noise). $D$ consists of five layers of 2-D CNN with the following number of filters and kernel size: $[8 \times (5, 5), 16 \times (7, 7), 32 \times (10, 10), 48 \times (15, 15), \text{ and } [64 (20, 20)]$, each with LeakyReLU activation. Global average pooling is followed by the last CNN layer to produce a fixed 64-dimensional feature. Two fully connected layers are successively added, each with 64 and 10 nodes with LeakyReLU. The last layer of $D$ is also fully connected and its output represents the scores of the intelligibility metrics. Therefore, the number of nodes in the last layer is equal to that of the intelligibility metrics we consider. For example, if we have $D$ predict SIIB and ESTOI scores simultaneously, it should be set to 2. We normalize the SIIB score so that it ranges from 0 to 1, which is consistent with the range of the ESTOI score. Since both metrics of interest are bounded in $[0, 1]$, the sigmoid activation function is used in the last layer. Similar to [6], all the layers in $D$ are constrained to be $1$-Lipschitz continuous by spectral normalization [17] to stabilize the training process.

5. Results

5.1. Notations of different modification methods

As described in Section 3.1, we have different options for learning metrics (SIIB, ESTOI, or both). In addition, two loss functions, Equations (3) and (4), can be chosen in the training process, depending on the use of enhanced examples. Therefore, we built and compared the iMetricGAN model with three different variations. To explain them, we use the following notations.

- **SiibGAN-zs**: Learning target is SIIB, with Equation (3) as the loss function. Since there is no enhanced example provided in this loss function, the model is trained in a zero-short (zs) manner.
- **SiibGAN**: Learning target is SIIB, with Equation (4) as the loss function.
- **MultiGAN**: Learning target includes multiple metrics, SIIB and ESTOI, with Equation (4) as the loss function.

3 Source codes of this work are available at https://github.com/nii-yamagishilab/intelligibility-MetricGAN

Audio samples of the tested systems are available at https://nii-yamagishilab.github.io/samples-iMetricGAN
In this paper, we proposed the iMetricGAN model to enhance the intelligibility of speech-in-noise. Objective results show that our approach outperforms the state-of-the-art SSDRC method in terms of SIIB and ESTOI scores. Large-scale formal listening tests further show its effectiveness in intelligibility enhancement across different languages and background environment conditions.

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6. Conclusion

The results show that our approach outperforms the state-of-the-art SSDRC method in terms of SIIB and ESTOI scores. Large-scale formal listening tests further show its effectiveness in intelligibility enhancement across different languages and background environment conditions.
per computer at the Tokyo Institute of Technology.

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