Improving GANs for Speech Enhancement

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Abstract—Generative adversarial networks (GAN) have recently been shown to be efficient for speech enhancement. Most, if not all, existing speech enhancement GANs (SEGANs) make use of a single generator to perform one-stage enhancement mapping. In this work, we propose two novel SEGAN frameworks, iterated SEGAN (ISEGAN) and deep SEGAN (DSEGAN). In the two proposed frameworks, the GAN architectures are composed of multiple generators that are chained to accomplish multi-stage enhancement mapping which gradually refines the noisy input signals in stage-wise fashion. On the one hand, ISEGAN’s generators share their parameters to learn an iterative enhancement mapping. On the other hand, DSEGAN’s generators share a common architecture but their parameters are independent; as a result, different enhancement mappings are learned at different stages of the network. We empirically demonstrate favorable results obtained by the proposed ISEGAN and DSEGAN frameworks over the vanilla SEGAN. The source code is available at http://github.com/pquochuy/idsegan.

Index Terms—speech enhancement, generative adversarial networks, SEGAN, ISEGAN, DSEGAN

I. INTRODUCTION

The goal of speech enhancement is to improve the quality and intelligibility of speech which is degraded by background noise [11, 2]. Speech enhancement can serve as a front-end to improve performance of an automatic speech recognition system [3]. It also play an important role in applications like communication systems, hearing aids, and cochlear implants, where contaminated speech needs to be enhanced prior to signal amplification to reduce discomfort [2]. Significant progress on this research topic has been made with the involvement of deep learning paradigms. Deep neural networks (DNNs) [4, 5], convolutional neural networks (CNNs) [6, 7], and recurrent neural networks (RNNs) [5, 8] have been exploited either to produce the enhanced signal directly via a regression form [4, 6] or to estimate the contaminating noise which is subtracted from the noisy signal to obtain the enhanced signal [7]. Significant improvements on speech enhancement performance have been reported by these deep-learning based methods compared to more conventional ones, such as Wiener filtering [9], spectral subtraction [10] or minimum mean square error (MMSE) estimation [11, 12].

There exists a class of generative methods relying on generative adversarial networks (GANs) [13] which have been recently demonstrated to be efficient for speech enhancement [14, 15, 16, 17, 18, 19]. When GANs are used for this task, the enhancement mapping is accomplished by the generator $G$ whereas the discriminator $D$, by discriminating between real and fake signals, transmits information to $G$ so that $G$ can learn to produce output that resembles the realistic distribution of the clean signals. Using GANs, speech enhancement can be done using either magnitude spectrum input [18] or raw waveform input [14, 15] although the latter is more desirable due to being end-to-end in nature.

Existing speech enhancement GAN (SEGAN) systems share a common feature – the enhancement mapping is accomplished via a single stage with a single generator $G$ [14, 15, 18], which may not be optimal. Here we break the entire enhancement mapping into multiple maps in a divide-and-conquer manner. Each of the “simpler” mappings is realized by a generator and the generators are chained to enhance a noisy input signal gradually one after another to yield an enhanced signal. In this way, a generator is tasked to refine or correct the output produced by its predecessor. We hypothesize that it would be better to carry out multi-stage enhancement mapping rather than a single-stage one as in prior works [14, 15, 18]. We then propose two new SEGAN frameworks, namely iterated SEGAN (ISEGAN) and deep SEGAN (DSEGAN) as illustrated in Figure 1 to validate this hypothesis. Similar to [14, 15], ISEGAN and DSEGAN receive raw audio waveform as input. In the former the generators’ parameters are tied. Sharing of parameters constrains ISEGAN’s generators to perform the same enhancement mapping iteratively. In the latter, the generators have independent parameters, and therefore different mappings are expected at different enhancement stages. We will demonstrate that, out of the proposed ISEGAN, DSEGAN, and the vanilla SEGAN [14], DSEGAN obtains the best results on objective evaluation metrics while ISEGAN performs comparably to the vanilla SEGAN. However, subjective evaluation results show that both ISEGAN and DSEGAN outperform their vanilla SEGAN counterpart.

Fig. 1. Illustration of the vanilla SEGAN [14], the proposed ISEGAN with two shared generators $G$, and the proposed DSEGAN with two independent generators $G_1$ and $G_2$. 

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II. VANILLA SEGAN

GAN [13] is a class of generative models that maps a sample \( z \) from some prior distribution \( \mathcal{Z} \) to a sample \( x \) belonging to the training data’s distribution \( \mathcal{X} \). A GAN is composed of two components: a generator \( G \) and a discriminator \( D \). \( G \) is learned to imitate the real training data distribution and to generate novel samples in that distribution by mapping the data distribution characteristics to the manifold defined in the prior \( \mathcal{Z} \). \( G \) is usually a binary classifier and \( G \) and \( D \) are trained via adversarial training. That is, \( D \) has to classify the samples coming from \( \mathcal{X} \) as real and those generated by \( G \) as fake while \( G \) tries to fool \( D \) such that \( D \) classifies its output as real. The objective function of this adversarial learning process is

\[
\min_{G} \max_{D} V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} \log D(x) + \mathbb{E}_{z \sim p_{z}(z)} \log(1 - D(G(z))). \tag{1}
\]

Given a dataset \( \mathcal{X} = \{(x_1, \tilde{x}_1), (x_2, \tilde{x}_2), \ldots, (x_N, \tilde{x}_N)\} \) consisting of \( N \) pairs of raw signals: clean speech signal \( x \) and noisy speech signal \( \tilde{x} \), speech enhancement is to find a mapping \( f(\tilde{x}) : \tilde{x} \mapsto x \) to map the noisy signal \( \tilde{x} \) to the clean signal \( x \). Conforming to GAN’s principle, SEGAN proposed in [14] has its generator \( G \) tasked for the enhancement mapping. Presented with the noisy raw speech signal \( \tilde{x} \) together with the latent representation \( z \), \( G \) produces the enhanced speech signal \( \hat{x} = G(z, \tilde{x}) \). The discriminator \( D \) of SEGAN receives a pair of signal as input and classifies the pair \((\tilde{x}, \hat{x})\) as real whereas the pair \((\tilde{x}, \tilde{x})\) as fake. The objective function of SEGAN is

\[
\min_{G} \max_{D} V(D, G) = \mathbb{E}_{x, \tilde{x} \sim p_{data}(x, \tilde{x})} \log D(x, \tilde{x}) + \mathbb{E}_{z \sim p_{z}(z), \tilde{x} \sim p_{data}(\tilde{x})} \log(1 - D(G(z, \tilde{x}), \tilde{x))). \tag{2}
\]

To improve the stability, SEGAN further employs least-squares GAN (LSGAN) [20] to replace the discriminator \( D \)’s cross-entropy loss by the least-square loss. The least-squares objective functions of \( D \) and \( G \) are explicitly written as

\[
\begin{align*}
\min_{D} V_{LS}(D) &= \frac{1}{2} \mathbb{E}_{x, \tilde{x} \sim p_{data}(x, \tilde{x})} \| D(x, \tilde{x}) - 1 \|^2 \\
&+ \frac{1}{2} \mathbb{E}_{z \sim p_{z}(z), \tilde{x} \sim p_{data}(\tilde{x})} \| D(G(z, \tilde{x}), \tilde{x}) \|^2, \tag{3}
\end{align*}
\]

\[
\begin{align*}
\min_{G} V_{LS}(G) &= \frac{1}{2} \mathbb{E}_{z \sim p_{z}(z), \tilde{x} \sim p_{data}(\tilde{x})} \| D(G(z, \tilde{x}), \tilde{x}) - 1 \|^2 \\
&+ \lambda \| (G(z, \tilde{x}) - x) \|_1, \tag{4}
\end{align*}
\]

respectively. In [4], \( \ell_1 \) distance between the clean sample \( x \) and the generated sample \( G(z, \tilde{x}) \) is included to encourage the generator \( G \) to generate more fine-grained and realistic results [14], [21], [22]. The influence of the \( \ell_1 \)-norm term is regulated by the hyper-parameter \( \lambda \) which was set to \( \lambda = 100 \) in [14].

III. ITERATED SEGAN AND DEEP SEGAN

Quan et al. [23] showed that using an additional generator chained to the generator of a GAN leads to better image-reconstruction performance. In light of this, instead of using the single-stage enhancement mapping with one generator as in the vanilla SEGAN [14], we propose to break the mapping into multiple stages by using a chain of \( N \) (\( N \geq 1 \)) generators \( \Theta = G_1 \rightarrow G_2 \rightarrow \ldots \rightarrow G_N \), as illustrated in Fig. 1 for the case \( N = 2 \). In ISEGAN, the generators share their parameters, i.e. \( G_1 \equiv G_2 \equiv \ldots \equiv G_N \equiv G \), and they can be viewed as an iterated generator with the number of iterations of \( N \). In contrast, DSEGAN’s generators are independent, they can be viewed as a deep generator with the depth of \( N \). Both ISEGAN and DSEGAN reduce to the vanilla SEGAN when \( N = 1 \).

At the enhancement stage \( n, 1 \leq n \leq N \), the generator \( G_n \) receives the output \( \tilde{x}_{n-1} \) of its preceding generator \( G_{n-1} \) together with the latent representation \( z_n \) and is expected to produce a better enhanced signal \( \hat{x}_n \):

\[
\begin{align*}
\tilde{x}_0 &= \tilde{x}, \\
\hat{x}_n &= G_n(z_n, \tilde{x}_{n-1}), \quad 1 \leq n \leq N. \tag{5}
\end{align*}
\]

The output of the last generator \( G_N \) is considered as the final enhanced signal, i.e. \( \hat{x} \equiv \hat{x}_N \), which is expected to be of better quality than all the intermediate enhanced versions. The outputs of the generators can be interpreted as different checkpoints and by forcing the desired ground-truth between the checkpoints, we encourage the chained generators to produce gradually better enhancement results.

To enforce the generators in the chain \( \Theta \) to learn a proper mapping for signal enhancement, the discriminator \( D \) classifies the pair \((x, \tilde{x})\) as real while all \( N \) pairs \((x_1, \tilde{x}_1), (x_2, \tilde{x}_2), \ldots, (x_N, \tilde{x}_N)\) as fake, as illustrated in Fig. 2. The least-squares objective functions of \( D \) and \( \Theta \) are

\[
\begin{align*}
\min_{D} V_{LS}(D) &= \frac{1}{2} \mathbb{E}_{x, \tilde{x} \sim p_{data}(x, \tilde{x})} \| D(x, \tilde{x}) - 1 \|^2 \\
&+ \sum_{n=1}^{N} \frac{1}{2N} \mathbb{E}_{z_n \sim p_{z}(z_n), \tilde{x}_n \sim p_{data}(\tilde{x}_n)} \| D(G_n(z_n, \tilde{x}_{n-1}), \tilde{x}_n) \|^2, \tag{7}
\end{align*}
\]

\[
\begin{align*}
\min_{\Theta} V_{LS}(\Theta) &= \frac{1}{2N} \sum_{n=1}^{N} \mathbb{E}_{z_n \sim p_{z}(z_n), \tilde{x}_n \sim p_{data}(\tilde{x}_n)} \| D(G_n(z_n, \tilde{x}_{n-1}), \tilde{x}_n) - 1 \|^2 \\
&+ \sum_{n=1}^{N} \lambda_n \| G_n(z_n, \tilde{x}_{n-1}) - x \|_1. \tag{8}
\end{align*}
\]

Unlike the vanilla SEGAN [14], the discriminator \( D \) in cases of ISEGAN and DSEGAN needs to handle imbalanced data as there are \( N \) fake examples generated with respect to every real example. Therefore, it is necessary to divide the second term in (7) by \( N \) to balance out penalization for real and fake examples misclassification. In addition, the first term in (8) is also divided by \( N \) to level its magnitude with that of the \( \ell_1 \)-norm term [14]. To regulate the enhancement curriculum in multiple stages, we set \( \lambda_1, \lambda_2, \ldots, \lambda_N \) to \( \{100, 100, 100, 100\} \). That is, \( \lambda_n \) is set to double \( \lambda_{n-1} \) while the last \( \lambda_N \) is fixed to 100 as in case of the vanilla SEGAN [14]. With this curriculum, we expect the enhanced output of a generator to be twice as good as that of its preceding generator in terms of \( \ell_1 \)-norm. As a result, the enhancement mapping learned by a generator in the chain doesn’t need to be perfect as in single-stage enhancement since its output will be refined by its successor.

IV. NETWORK ARCHITECTURE

A. Generators \( G_n \)

The architecture of the generators \( G_n, 1 \leq n \leq N \), of both ISEGAN and DSEGAN is illustrated in Fig. 3. They make use of an encoder-decoder with fully-convolutional layers [24], which is similar to that used in the vanilla SEGAN [14]. Each
generator receives a segment of raw speech signal with length of $L = 16384$ samples (approximately one second at 16 kHz) as input. The generators’ encoder is composed of 11 one-dimensional strided convolutional layers with a common filter width of 31 and a common stride length of 2, followed by parametric rectified linear units (PReLUs) [25]. The number of filters is designed to increase along the encoder’s depth to compensate for the smaller and smaller convolutional output, resulting in output sizes of $8192 \times 16$, $4096 \times 32$, $2048 \times 32$, $1024 \times 64$, $512 \times 64$, $256 \times 128$, $128 \times 128$, $64 \times 256$, $32 \times 256$, $16 \times 512$, $8 \times 1024$ at the 11 convolutional layers, respectively. At the end of the encoder, the encoding vector $c \in \mathbb{R}^{8 \times 1024}$ is concatenated with the noise sample $z \in \mathbb{R}^{8 \times 1024}$ sampled from the normal distribution $\mathcal{N}(0, I)$ and presented to the decoder. The generator encoder mirrors the encoder architecture with the same number of filters and filter width (see Figure 4) to reverse the encoding process by means of deconvolutions (i.e. fractional-strided transposed convolution). Note that each deconvolutional layer is again followed by a PReLU. The skip connections are employed to connect an encoding layer to its corresponding decoding layer to allow the information of the waveform to flow into the decoding stage [14].

B. Discriminator $D$

The discriminator $D$ has similar architecture to the encoder part of the generators described in Section IV-A except that it has two-channel input and use virtual batch-norm [26] before LeakyReLU activation with $\alpha = 0.3$ [14]. In addition, $D$ is topped up with a one-dimensional convolutional layer with one filter of width one (i.e. $1 \times 1$ convolution) to reduce the last convolutional output size from $8 \times 1024$ to 8 features before classification takes place with a softmax layer.

V. EXPERIMENTAL SETUP

A. Dataset

To assess the performance of the proposed ISEGAN and DSEGAN and demonstrate their advantages over the vanilla SEGAN, we carried out experiments on the database in [27] on which the vanilla SEGAN was evaluated [14]. The dataset originated from the Voice Bank corpus [28] and consists of data from 30 speakers out of which 28 and 2 speakers were included in the training and test set, respectively.

A total of 40 noisy conditions was made in the training data by combining 10 types of noises (2 artificial and 8 stemmed from the Demand database [29]) with 4 signal-to-noise ratios (SNRs) each: 15, 10, 5, and 0 dB. For the test set, 20 noisy conditions are considered, combining 5 types of noise from the Demand database with 4 SNRs each: 17.5, 12.5, 7.5, and 2.5 dB. There are about 10 and 20 different utterances in each noisy condition per speaker in the training and test set, respectively. All utterances were downsampling to 16 kHz.

B. Baseline system

The vanilla SEGAN [14] was used as a baseline for comparison. Besides the performance reported in [14], we repeated training the vanilla SEGAN to ensure a similar experimental setting across systems. In addition, the Weiner method based on a priori SNR estimation [1], [30] was used as a second baseline.

C. Network parameters

The implementation was based on Tensorflow framework [31]. The networks were trained for 100 epochs with RMSprop optimizer [32] and a learning rate of 0.0002. The vanilla SEGAN was trained with a minibatch size of 100 while the minibatch size was reduced to 50 to train ISEGAN and DSEGAN to cope with their larger memory footprints. We experimented with different values for $N = \{2, 3, 4\}$ to investigate the influence of the number of iterations of ISEGAN and the depth of DSEGAN.

As in [14], during training, raw speech segments of length 16384 samples were extracted from the training utterances with 50% overlap. A high-frequency preemphasis filter of coefficient 0.95 was applied to each signal segment before presenting to the networks [14]. During testing, raw speech segments were extracted from a test utterance without overlap. They were processed by a trained network, deemphasized, and eventually concatenated to produce the enhanced utterance.


| Metric | Noisy | Weiner SEGAN | SEGAN* | ISEGAN N = 2 | ISEGAN N = 3 | ISEGAN N = 4 | DSEGAN N = 2 | DSEGAN N = 3 | DSEGAN N = 4 |
|--------|-------|--------------|--------|-------------|-------------|-------------|-------------|-------------|-------------|
| PESQ   | 1.97  | 2.22         | 2.16   | 2.19 ± 0.04 | 2.19 ± 0.04 | 2.21 ± 0.06 | 2.35 ± 0.06 | 2.39 ± 0.02 | 2.37 ± 0.05 |
| CSIG   | 3.35  | 3.23         | 3.48   | 3.39 ± 0.03 | 3.23 ± 0.10 | 3.96 ± 0.08 | 3.00 ± 0.14 | 3.55 ± 0.06 | 3.46 ± 0.05 | 3.50 ± 0.01 |
| CBAK   | 2.44  | 2.68         | 2.94   | 2.90 ± 0.07 | 2.95 ± 0.07 | 2.88 ± 0.12 | 2.92 ± 0.06 | 3.10 ± 0.02 | 3.11 ± 0.05 | 3.10 ± 0.04 |
| COVL   | 2.63  | 2.67         | 2.80   | 2.76 ± 0.03 | 2.69 ± 0.05 | 2.52 ± 0.04 | 2.55 ± 0.09 | 2.93 ± 0.05 | 2.90 ± 0.03 | 2.92 ± 0.02 |
| SSNR   | 1.68  | 5.07         | 7.73   | 7.36 ± 0.72 | 8.17 ± 0.69 | 8.11 ± 1.43 | 8.86 ± 0.42 | 8.70 ± 0.34 | 8.72 ± 0.64 | 8.59 ± 0.49 |

Fig. 4. Noisy signals and the enhanced signals of two test utterances produced by the vanilla SEGAN baseline, ISEGAN, and DSEGAN. (a) p237_219.wav and (b) 232_001.wav.

D. Objective evaluation

Following [14], we quantified the quality of the enhanced signals produced by the systems under study based on 5 objective evaluation metrics suggested in [1]:

- PESQ ∈ [−0.5, 4.5]: perceptual evaluation of speech quality.
- CSIG ∈ [1, 5]: mean opinion score (MOS) prediction of the signal distortion attending to the speech signal.
- CBAK ∈ [1, 5]: MOS prediction of the intrusiveness of background noise.
- COVL ∈ [1, 5]: MOS prediction of the overall effect.
- SSNR ∈ [0, ∞]: segmental SNR.

The metrics were computed for each system by averaging over all 824 files of the test set. We experimentally found that the performance may vary with different network checkpoints, so we report the mean and standard deviation of each metric over the 5 latest network checkpoints.

The objective evaluation results obtained by different systems are shown in Table I. First, the results obtained by our re-implementation of the vanilla SEGAN are more or less consistent with those reported in the seminal work [14]. As expected, the enhanced signals obtained by the vanilla SEGAN were of better quality than both the noisy ones and those of the Weiner baseline across most of the metrics. Second, ISEGAN, overall, performs comparably with the vanilla SEGAN. It slightly surpasses the baseline counterpart in PESQ, CBAK, and SSNR (i.e. with N = 2 and N = 4) but marginally underperforms in CSIG and COVL. DSEGAN, however, obtains the best results, outperforming both the vanilla SEGAN and ISEGAN across all the metrics. For example, with N = 2, DSEGAN leads to relative improvements of 7.3%, 4.7%, 6.9%, 6.2%, and 18.2% over the baseline on PESQ, CSIG, CBAK, COVL, and SSNR, respectively. Third, the results in the table suggest marginal impact of ISEGAN’s number of iterations and DSEGAN’s depth larger than N = 2 since no significant changes are seen on the metrics.

E. Subjective evaluation

To validate the objective evaluation, we conducted a small-scale subjective evaluation of four conditions: noisy signals, vanilla SEGAN, ISEGAN, and DSEGAN signals (with N set to two). Twenty volunteers aged 18–52 (F=6, M=14), with self-reported normal hearing, were asked to provide forced binary quality assessments between pairs of 20 randomly presented sentences, balanced in terms of speakers and noise types, i.e. each comparison varied only in the type of system. Following a familiarization session, tests were run individually using MATLAB, with listeners wearing Philips SHM1900 headphones in a low-noise environment. For each pair of utterances, the selected higher quality one was rewarded 1.0 while the lower quality received no reward. A preference score was obtained for each system by dividing its accumulated reward by the count of its occurrences in the test. Due to the small sample size, we assessed statistical significance of results using t-test. Results confirm that the three SEGAN signals are perceived as higher quality than the noisy signals (0.55 to 0.45, with p < 0.05). DSEGAN and ISEGAN together significantly outperform vanilla SEGAN (0.67 to 0.33, p < 0.001). However, DSEGAN and ISEGAN qualities were not significantly different (0.48 to 0.52) in this small test. Results support the detailed objective evaluation in which DSEGAN performs much better than either SEGAN or noise, however we find that ISEGAN also performs well in subjective tests.

VI. Conclusions

This paper presents two novel GAN frameworks named ISEGAN and DSEGAN, for speech enhancement. Improving on the vanilla SEGAN, which has a single generator, ISEGAN and DSEGAN architectures comprise multiple chained generators. ISEGAN and DSEGAN differ in that the generators of the former share their parameters while those of the latter are independent. With multiple generators, ISEGAN and DSEGAN learn multiple mappings, each corresponding to a generator in the chain, to accomplish a multi-stage enhancement process. Unlike from the single-stage mapping of the vanilla SEGAN, the multi-stage mapping allows a generator in the chain to refine the enhanced signal output by its predecessor(s) to produce better versions of the enhanced signal. Objective tests demonstrated that the proposed ISEGAN and DSEGAN perform comparably and are better than vanilla SEGAN. On the other hand, both systems achieve significantly favourable results over the vanilla SEGAN counterpart on the subjective perceptual test.
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