# Two-stage model and optimal SI-SNR for monaural multi-speaker speech separation in noisy environment

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#### **Abstract**

In daily listening environments, speech is always distorted by background noise, room reverberation and interference speakers. With the developing of deep learning approaches, much progress has been performed on monaural multi-speaker speech separation. Nevertheless, most studies in this area focus on a simple problem setup of laboratory environment, which background noises and room reverberations are not considered. In this paper, we propose a two-stage model based on conv-TasNet to deal with the notable effects of noises and interference speakers separately, where enhancement and separation are conducted sequentially using deep dilated temporal convolutional networks (TCN). In addition, we develop a new objective function named optimal scaleinvariant signal-noise ratio (OSI-SNR), which are better than original SI-SNR at any circumstances. By jointly training the two-stage model with OSI-SNR, our algorithm outperforms one-stage separation baselines substantially.

**Index Terms**: conv-TasNet, multi-speaker speech separation, noisy environment, SI-SNR

## 1. Introduction

In real world environments, speech is always corrupted by background noise, room reverberation and interference speakers. The presence of such noise, interference and reverberation has a corrupting negative effect on speech intelligibility and speech quality. Many applications, such as speaker identification and automatic speech recognition, become much more challenging in such severe environments, as well as normal hearing and hearing-impaired listeners [1], [2], [3], [4]. Therefore, better enhancement, dereverberation and separation have a significant benefit to not only human listeners but also many speech processing missions.

Over the past few decades, significant efforts have been, and still are being devoted to speech enhancement and speech dereverberation [5], [6], [7], [8]. However, only limited breakthrough has been made in single-channel speaker-independent multi-speaker speech separation task. The most severe difficulties we faced, label permutation problem, are not solved until last ten years.

More recently, several particular approaches have been proposed to deal with the label permutation problem. In [9], [10], Permutation Invariant Training (PIT) and utterance-level PIT choose the speaker arrangement on the basis of thee lowest separation error within all possible permutations. In [11], [12], Deep Clustering (DPCL) algorithm achieves label assignment using the clustering methods in a deep embedding space. In [13], Deep Attractor Network (DANet) produces attractors in deep embedding space to achieves label assignment. In [14], a time-domain audio separation network

(TasNet) is proposed. In TasNet, traditional short-time Fourier transform (STFT) is replaced with a convolutional encoder-decoder architecture. In [15], the fully-convolutional TasNet (conv-TasNet) is proposed. The use of stacked dilated 1-D convolutional blocks to replace the deep LSTM networks for the separation step not only significantly reduces the model size, but also has a better performance, even surpasses the performance of ideal time-frequency magnitude masks. In [16], a source-aware context network is designed to address the label permutation problem by exploiting temporal dependencies and continuity of the same speech source.

With the astonishing achievements on monaural multispeaker speech separation, only several works considered the robustness of speech separation algorithms [17], [18], [19]. In this paper, we build a baseline of speech separation in the noisy environment. Inspired by [20], we also propose a two-stage model to perform the enhancement and separation stage separately. Furthermore, an optimal scale-invariant SNR is proposed. We show that this OSI-SNR is better than other two SI-SNRs in any circumstances.

# 2. Algorithm description

#### 2.1. Problem formulation.

Let  $x_i(t)$  and n(t) denote speech from speaker i and background noise, respectively. The noisy multi-speaker speech y(t) is modeled by

$$y(t) = \sum_{i=1}^{N} x_i(t) + n(t)$$
 (1)

The goal of monaural robust speech separation is to estimate the individual speech signals from a given noisy mixture of speech signals and noises. In this work the number of target signals is assumed to be known and set to 2.

#### 2.2. baselines settings.

The baselines are based on conv-TasNet [15]. Fig.1 shows the diagram of the monaural speech separation baseline systems. The systems consist of three modules: an encoder module, a separation module and a decoder module.

The first baseline system is exactly same as conv-TasNet. The noisy mixture y(t) is input to the 1-D convolutional encoder module and embedded to a spectral space. At this paper, we will call this embedded space matrix as spectral, because we considered and confirmed that this embedded space matrix is quite similar to traditional spectral. The temporal convolutional network (TCN) separation module estimates the masks based on the encoder output. The dilate factors in the separation module increase exponentially, which guarantee an enough reception field to take advantage of the long-range dependencies of the speech signal. The output of the separation module multiplied with the output of encoder is

passed to the decoder module and transferred to clean separated speech signal.

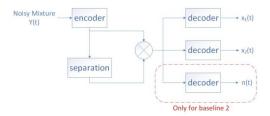


Figure 1: System diagram of the proposed baselines

Since the output of the network are the waveforms of the estimated clean signals, here the scale-invariant source-to-noise ratio is used and Permutation invariant training (PIT) is applied during training to settle the permutation problem. Consequently, the loss function of baseline-1 is:

$$L_{PIT} = \min_{\pi \in P} \sum_{c} -SISNR(x_c(t), \widehat{x_{\pi(c)}}(t))$$
 (2)

Where P is the set of all possible permutations over the set of sources  $\{1, ..., C\}$ ,  $x_c(t)$  denotes the recovery separated speech,  $\widehat{x_{\pi(c)}}(t)$  denotes the original clean speech. and the definition and improvement of SI-SNR will be explained in section 2.4.

The baseline-2 is also shown in Fig.1. Contrasting to baseline-1, baseline-2 added an extra decoder and output the noise in noisy mixture. Let n(t) be the original noise and  $\hat{n}(t)$  be the recovered noise, the loss function of this three-output system is defined as shown below:

$$L_{3-outputs} = L_{PIT} - SISNR(n(t), \hat{n}(t))$$
 (3)

We will compare the proposed system with these two baselines.

## 2.3. two-stage model.

Inspired by [20], we proposed a two-stage system to perform the enhancement and separation stage separately.

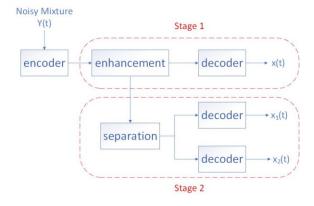


Figure 2: System diagram of the proposed two-stage model

Fig.2 shows the system diagram of the proposed two-stage monaural speech separation system. The proposed model has two stages: enhancement stage and separation stage. To simplify the system, we use spectral mapping methods as a

replacement of masking methods, the enhancement stage and separation stage output the processed spectral directly.

The noisy mixture speech is input to the encoder as same as baselines. Then the enhancement module uses the noisy mixture spectral to generates the clean mixture spectral. After a decoder module, we can get a clean mixture speech signal  $\hat{x}(t)$  as a reconstruction of  $x_1(t) + x_2(t)$ . The enhancement stage output will contribute to the whole loss function. The output of enhancement stage will be sent to separation stage simultaneously. After PIT training and two decoder modules, we can get two separated reconstruction speech signals. The total loss function is:

$$L_{2-stages} = L_{PIT} - \alpha SISNR(x_1(t) + x_2(t), \hat{x}(t))$$
 (4)

In this paper,  $\alpha$  was set to 0.1.

It should be noted that, the enhancement of two mixed speech signal is not as simple as the enhancement of one single speech signal, so the module complexity is as same as the separation module. If we decrease the complexity of module and layers of convolutions to 1/4 of original module, the performance of single speech signal enhancement is still good as before, whereas the performance of mixed speech signal enhancement decreases to a very low level.

## 2.4. optimal SI-SNR.

The use of Scale-Invariant Source-to-noise ratio (SI-SNR) is a remarkable improvement against SNR [21]. The definition of frequently used SI-SNR is given as:

$$s_{target} = \frac{\langle s, s \rangle s}{\|s\|^2} \tag{5}$$

$$e_{noise} = \hat{s} - s_{target} \tag{6}$$

$$SI - SNR := 10log_{10} \frac{\|s_{target}\|^2}{\|e_{noise}\|^2}$$
 (7)

Where *s* represents the original speech signal and *ŝ* represents the reconstructed speech signal. This method adjusts original speech signal to a proper scale, and calculates an adjusted SNR

It is obvious that the length of  $s_{target}$  is not relevant of original signal s. We can calculate that the equal definition of  $s_{target}$  is as below:

$$s_{target} = |\hat{s}| cos\theta \vec{s} \tag{8}$$

Where  $\vec{s}$  is the unit vector at same direction of s,  $\theta$  is the angle between  $s_{target}$  and s.

While the length of  $s_{target}$  and length of s are proportional, the SNR after adjusted is not relevant of length of  $s_{target}$  or s, but only relevant of angle  $\theta$ . The equal definition of SI-SNR is as below:

$$SI - SNR = 10log_{10} \frac{1}{\tan^2 \theta}$$
 (9)

As [21] explained, we get this formula by finding a point in s which is closest to  $\hat{s}$ , i.e.  $\alpha s \perp (\alpha s - \hat{s})$ . The orange parentheses in Fig.3. illustrates this definition of SI-SNR. However, there is no strong reason to do so. If we adjust s to be closest to  $\hat{s}$ , that will lead to a different result.

In other words, the definition of scale-invariant is not unique. A calculating method can be called a scale-invariant

SNR as long as the scale of  $s_{target}$  is not relevant to the scale of original speech signal.

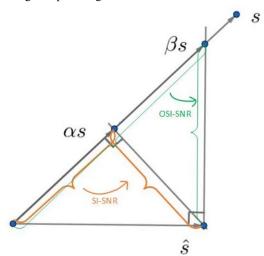


Figure 3: Illustration of the definitions of SI-SNR and OSI-SNR

Table.1 shows three different definitions of SI-SNR. But which one is best? If we can compute a maximum SI-SNR with a fixed s and ŝ, then this calculating method is easier to optimize and less likely to fall into a local best while training.

$$SI - SNR(\lambda) = 10log_{10}(\frac{\|\lambda s\|^2}{\|\lambda s - \hat{s}\|^2})$$
 (10)

$$\lambda = \underset{\lambda}{\operatorname{argmax}} SI - SNR(\lambda) \tag{11}$$

Where  $\lambda$  indicates the scale adjust factor.

Therefore, let's find the maximum SI-SNR. The derivative of this SI-SNR is calculated below.

$$F(\lambda) = \frac{\|\lambda s\|^2}{\|\lambda s - s\|^2} \tag{12}$$

$$F'(\lambda) = \frac{2ks^2(s^2 - kss)}{|ks - s|^4} = 0$$
 (13)

$$\lambda = \frac{|\hat{s}|^2}{\langle s, \hat{s} \rangle} \tag{14}$$

This maximum SI-SNR will be called optimal SI-SNR (OSI-SNR) in this paper. The performance of OSI-SNR will be demonstrated in chapter 4.

Table 1: The definitions and equal definitions of different SI-SNRs.

SI-SNR-1	SI-SNR-2	OSI-SNR
$s_{target} = \frac{\langle s, \hat{s} \rangle s}{ s ^2}$	$s_{target} = \frac{ \hat{s} s}{ s }$	$s_{target} = \frac{ \hat{s} ^2 s}{\langle s, \hat{s} \rangle}$
$s_{target} =  \hat{s}  cos\theta \vec{s}$	$s_{target} =  \hat{s} \vec{s}$	$s_{target} = \frac{ \hat{s} \vec{s}}{cos\theta}$
$SNR = 10log_{10} \frac{1}{\tan^2 \theta}$	$SNR = 10log_{10} \frac{1}{4\sin^2 \frac{\theta}{2}}$	$SNR = 10log_{10} \frac{1}{\sin^2 \theta}$

Table.1 shows three definitions of different SI-SNRs. SI-SNR-1 is the commonly used SI-SNR. If we compare the SI-SNR-1 and OSI-SNR, we will find they are opposite in many ways. The green parentheses in Fig.3 also demonstrates the differences between SI-SNR-1 and OSI-SNR.

SI-SNR-2 is an SI-SNR definition which is easy to think of. The scale-invariant-ness of SI-SNR-2 is obvious and no need to prove. One weakness of SI-SNR-2 is we need to calculate square root of *s* and *ŝ*, which may increases calculation consumption while training but does not affects performance.

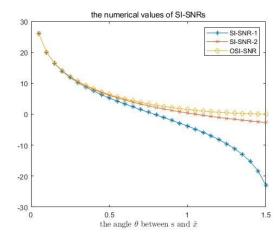


Figure 4: The illustration of three different SI-SNRs.

Fig.4 shows the numerical values of different SI-SNRs. The boundaries of different SI-SNRs is easy to observe from Fig.4 and calculate from the equal definitions in Table.1. When  $\theta$  ranges from 0 to  $\frac{\pi}{2}$ , the value of SI-SNR-1 ranges from  $-\infty$  to  $+\infty$ , while the values of SI-SNR-2 and OSI-SNR range from 0 to  $+\infty$ .

As we proved before, while the values of OSI-SNR is the maximum among all possible SI-SNRs, it will be easier to optimize and faster to converge. The OSI-SNR is the ridge in high dimension space.

## 3. Experimental settings

The 2-speaker speech separation dataset we evaluated our system on is based on wsj0-2mix [11], which contains 30 hours of training data, 10 hours of validation data and 5 hours of evaluation data. When generating mixtures, the way of randomly choosing speakers and utterances, the SNR adjustment between two speakers and other settings are exactly same as wsj0-2mix. However, we add some noise after mixing the utterances. The noise file is from NoiseX [25] noise sets. The chosen noise type is babble, destroyer engine, destroyer ops and factory1. The SNR between clean mixture and noise is normally distributed in -5dB to 5dB, i.e. for most noisy speech,  $20*log_{10}\frac{|x_1(t)+x_2(t)|}{|n(t)|}\approx 0$ .

We also compared and evaluated three different SI-SNRs in clean speech separation systems. When we test them in clean speech separation system, the wsj0-2mix dataset is used.

The networks are trained for 100 epochs on 4-seconds long segments. Adam optimizer [22] is used. The learning rate is initialed to 1e-3 and halved if the accuracy of validation set is not improved in three epochs. The hyperparameters of the network are same as conv-TasNet [15].

We use signal-to-distortion ratio improvement (SDRi) as objective measures of separation accuracy. The scale-invariant signal-to-noise ratio improvement (SI-SNRi) and the optimal scale-invariant signal-to-noise ratio improvement (OSI-SNRi)

is also compared afterwards. In addition, we also evaluated the quality of the separated speech using both the perceptual evaluation of subjective quality (PESQ [23]) and the short-time objective intelligibility (STOI [24]). The PESQ scores is between [-0.5, 4.5], while the STOI scores range from 0 to 1. Higher values in PESQ and STOI are reflection of better speech quality.

#### 4. Evaluation results

In this study, three objective metrics, source-to-distortion ratio improvement (SDRi), perceptual evaluation of speech quality (PESQ) and short-time objective intelligibility (STOI) are employed to evaluate the performance of separation systems.

Table 2: model and training target comparison in terms of SDRi, PESO and STOI.

		Before processing	SI- SNR 1	SI- SNR 2	OSI- SNR
Baseline -1	SDRi	-	9.895	10.291	10.010
	PESQ	1.575	2.215	2.265	2.249
	STOI	0.586	0.800	0.814	0.811
Baseline -2	SDRi	-	9.533	9.558	10.163
	PESQ	1.575	2.265	2.280	2.306
	STOI	0.586	0.814	0.815	0.820
2-stage model	SDRi	-	10.421	10.680	10.581
	PESQ	1.575	2.222	2.233	2.285
	STOI	0.586	0.814	0.820	0.820

Table.2 shows performance of three different systems trained by three different SI-SNRs. First of all, we compare three systems with same loss functions. Clearly, each system improves SDRi, PESQ and STOI substantially. By using our proposed 2-stage system, we find a large performance improvement in terms of SDRi and STOI. As for PESQ, baseline-2 always performs best.

Secondly, we compare three SI-SNRs with same separation systems. This time we can find that more performance gains are obtained by employing OSI-SNR in terms of all three metrics: SDRi, PESQ and STOI.

We also can see that SI-SNR 2 is roughly the same as OSI-SNR from both Fig.4 and Table.1 when  $\theta$  converges near 0.5. The original SI-SNR is probably the worst SI-SNR in some ways, or it's maybe the misuse of the OSI-SNR.

Table 3: different measures of 2-stage model trained with SI-SNR-1 and OSI-SNR

		Before proc	After proc	Improve
2-stage model trained with SI-SNR-1	SDR	-2.553	7.868	10.421
	SI-SNR1	-5.681	6.695	12.376
	OSI-SNR	1.770	8.110	9.880
2-stage model trained with OSI-SNR	SDR	-2.553	8.028	10.581
	SI-SNR1	-5.681	6.799	12.480
	OSI-SNR	1.770	8.381	10.151

Table.3 shows the difference when we use SI-SNR-1 and OSI-SNR as objective measures. Of course, they are different, and the values of OSI-SNR is always the maximum and the values of SI-SNR-1 is usually minimum. However, we don't

judge the usefulness of SI-SNR-1 as a measurement. This paper only confirmed that OSI-SNR is doubtlessly better than SI-SNR-1 when they are used as the training targets.

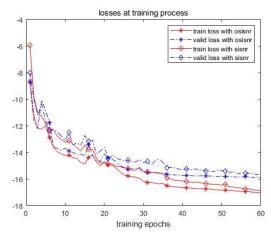


Figure 5: losses comparison between different SI-SNRs while trained in noise-free separation system

Fig.4 shows the curve that SI-SNRs change with difference of angles  $\theta$  between original signal and reconstructed signal. They are quite the same when  $\theta$  is extremely low. That's why even the original SI-SNR have a remarkable performance when you deal with the noise-free monaural speech separation task. Still, we trained the multispeaker monaural speech separation system with SI-SNR-1 and OSI-SNR. Like Fig.5 shows, although they all converge to same point and have a same performance eventually, training process using OSI-SNR converges more rapidly. Both the training losses and validation losses decrease faster. The lines with \* markers is usually below the lines with diamond markers.

As Fig.4 demonstrated, when  $\theta$  becomes bigger, the difference among three SI-SNRs also grows. So, the adoption of OSI-SNR becomes important when we deal with noisy monaural speech separation task.

#### 5. Conclusion

In this paper, we have proposed a two-stage system aiming to enhance the noisy mixture before we separate them. Two TCN modules are utilized to perform enhancement and separation separately, and them form a two-stage system by joint optimization. In addition, we have developed a new objective function for speech separation systems, which probably is the best among all the possible SI-SNRs. Systematic evaluation demonstrated that our two-stage system combined with OSI-SNR improves separation performance substantially in terms of all three metrics, SDRi, PESQ and STOI.

#### 6. Acknowledgement

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## 7. References

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