Subjective intelligibility of speech sounds enhanced by ideal ratio mask via crowdsourced remote experiments with effective data screening

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Abstract
It is essential to perform speech intelligibility (SI) experiments with human listeners to evaluate the effectiveness of objective intelligibility measures. Recently, crowdsourced remote testing has become popular to collect a massive amount and variety of data with relatively small cost and in short time. However, careful data screening is essential for attaining reliable SI data. We compared the results of laboratory and crowdsourced remote experiments to establish an effective data screening technique. We evaluated the SI of noisy speech sounds enhanced by a single-channel ideal ratio mask (IRM) and multi-channel mask-based beamformers. The results demonstrated that the SI scores were improved by these enhancement methods. In particular, the IRM-enhanced sounds were much better than the unprocessed and other enhanced sounds, indicating IRM enhancement may give the upper limit of speech enhancement performance. Moreover, tone pip tests, for which participants were asked to report the number of audible tone pips, reduced the variability of crowdsourced remote results so that the laboratory results became similar. Tone pip tests could be useful for future crowdsourced experiments because of their simplicity and effectiveness for data screening.

Index Terms: Speech intelligibility, remote testing, crowdsourcing, speech reception threshold, speech enhancement

1. Introduction
It is essential to achieve reliable objective intelligibility measure (OIM) for developing hearing assistive devices. Many OIMs have been proposed for evaluating speech enhancement and noise reduction algorithms [1,2]. It is also essential to perform speech intelligibility (SI) experiments with human listeners to evaluate the effectiveness of OIMs. These tests are usually performed in a soundproof room with well-controlled equipment in a laboratory. However, the novel coronavirus (COVID-19) outbreak has made it difficult to conduct such formal experiments. One solution to this is to perform remote testing with sound presentation and response collection using web pages. There have been several SI experiments using crowdsourcing services [3,4,5,6,7]; however, such reports are much less common than those of speech quality assessments [8,9,10,11,12], probably because it is almost impossible to control sound pressure level (SPL), acoustic environments including ambient noise, and listener’s hearing level, each of which affect SI greatly. On the other hand, crowdsourced remote testing is advantageous for collecting a massive amount of data from the various participants. To overcome the disadvantage, it is essential to establish effective methods to estimate all listeners’ conditions for data screening. One of the purpose of this study is to compare laboratory and crowdsourced remote experiments on SI to establish an effective data screening technique.

We evaluated the SI of noisy speech sounds enhanced by a single-channel ideal ratio mask (IRM) [13] and multi-channel mask-based beamformers [14]. Speech enhancement with the IRM is an “oracle” approach and is believed to give the upper boundary of the performance. However, it remains unclear whether IRM sounds really improve subjective SI sufficiently. Moreover, there have been fewer reports on the subjective SI results for multi-channel enhanced sounds than for single-channel ones; in fact, we have not found any usable data at least, no data in Japanese. Thus, another purpose of this study is to attain reliable data for developing new OIMs.

2. Speech enhancement
2.1. Ideal Ratio Mask (IRM)
As a single-channel speech enhancement, this paper considers an IRM based approach [13] for investigating the upper limit of performance. Let \(x_i(n)\) be an observed noisy speech at \(i\)-th microphone

\[x_i(n) = s_i(n) + v_i(n) = h_i(n) + c(n) + v_i(n),\]

where \(n\) is a time index, and \(c(n), h_i(n),\) and \(v_i(n)\) are a clean speech, an impulse response from the sound source at \(j\)-th position to microphone \(i\), and noise at microphone \(i\), respectively. Its short time Fourier transform (STFT) is

\[x_{itf} = s_{itf} + v_{itf},\]

where \(t\) and \(f\) are time and frequency indices, respectively. The IRM for enhancing the speech signals is given as

\[\hat{y}_{itf} = \left(\frac{|s_{itf}|^2}{|s_{itf}|^2 + |v_{itf}|^2}\right)^{0.5},\]

and the enhanced signal in the STFT domain with the IRM is

\[y_{itf} = M_{itf}x_{itf}.\]

The enhanced speech signal is obtained by applying the inverse STFT and the overlap-add to \(y_{itf}\). We refer to this method as “MASKİR

2.2. MVDR beamformer
As a multi-channel speech enhancement, this paper investigates a mask-based beamformer, recognized as the state-of-the-art front-end for recent automatic speech recognition systems [15,16,17].

Let \(x_{itf} = [x_{1itf}, \ldots, x_{Iitf}]^T\) be the observation vector with multiple microphones \(i = 1, \ldots, I\) (\(I = 2\) in this paper)
in the STFT domain, where $(\cdot)^T$ denotes the transpose. The MVDR beamformer coefficients $w_j = [w_{1j}, \cdots, w_{Tj}]^T$ are given as
\[ w_j = \frac{a_j^* R^{-1} a_j}{a_j^* R^{-1} a_j}, \tag{5} \]
where $a_j$ is the (estimated) steering vector, $r$ is the reference microphone index, and $R_{v_j} = \sum_i (1-M_{ij})x_j x_i^H$ (where $T$ is a number of frames) is the spatial covariance matrix (SCM) of noise. In addition, $(\cdot)^H$ and $(\cdot)^*$ denote the Hermitian transpose and complex conjugate, respectively. The steering vector $a_j$ in Eq. (5) is given using the estimated SCMs for speech $R_{s_j} = \frac{1}{T} \sum_i M_{ij} x_i x_i^H$ and noise $R_{v_j}$ as
\[ a_j = R_{v_j} \text{maxeig} \{ R_{s_j}^{-1} R_{v_j} \}, \tag{6} \]
where maxeig($A$) is the operation for finding the eigenvector corresponding to the largest eigenvalue of matrix $A$.

The enhanced signal in the STFT-domain with the MVDR beamformer is
\[ y_{1j} = w_j^H x_j. \tag{7} \]
To calculate the SCMs for the mask-based MVDR beamformer, we used the following two types of mask
- "MVDR$_{IRM}$" $M_{ij}$ is the IRM in Eq. (4)
- "MVDR$_{EST}$" $M_{ij}$ is determined by the preset noise period $P_t$ (in this paper 288 msec. at both the beginning and end of the noisy speech); i.e.,
\[ M_{ij} = \begin{cases} 0 & \text{for } t \in P_t \\ 1 & \text{(otherwise)} \end{cases} \]

3. Subjective experiments
3.1. Speech material
3.1.1. Recording babble noise and impulse response
We used recorded babble noise for $v_i(n)$ in Eq. (1). Mixed or single-speaker speech was played simultaneously from many loudspeakers on a large office floor, and they were recorded using two microphones with 4 cm spacing in a conference room adjacent to it (reverberation time: approx. 360 ms; door open). We also measured the impulse responses $h_{ij}(n)$ in Eq. (1) to the two microphones from 12 loudspeaker positions (index $j$) including nine positions with three directions ($-30^\circ, 0^\circ, +30^\circ$) $\times$ three distances (70 cm, 100 cm, 130 cm), and three locations with a distance of 90 cm and angles of $90^\circ, -75^\circ$, and $-105^\circ$.

3.1.2. Clean and noisy speech signals
Clean speech $c(n)$ in Eq. (1) used for the subjective listening experiments were Japanese 4-mora words. They were uttered by a male speaker (label ID: mis) and drawn from a database of familiarity-controlled word lists, FW07 [18], which has been used in previous experiments [19, 20]. The dataset contains 400 words for each of four familiarity ranks, and the average duration of a 4-mora word is approximately 700 ms. The source speech sounds were obtained from the word set with the least familiarity to prevent increment to the SI score by guessing commonly used words.

The observed noisy speech $x_j(n)$ was produced by convolving the clean speech $c(n)$ and an impulse response $h_{ij}$ of a source position $j$ and adding babble noise $v_i(n)$ as shown in Eq. (1). The signal-to-noise ratio (SNR) conditions ranged from $-9$ to $+3$ dB in $3$-dB steps. These noisy speech signals were referred to as unprocessed. Three types of speech enhancement algorithms, MASK$_{1ch}$, MVDR$_{IRM}$, and MVDR$_{EST}$, described in Sec. 2 were applied to the unprocessed sounds.

The processing was performed at 16 kHz sampling rate, and the sounds were then upsampled to 48 kHz for playing on a web browser.

3.2. Experimental procedure
We used a set of web pages developed for previous experiments [7]: in addition, we introduced good practices to improve the quality of the experiments [20]. One of these was to measure the listeners’ vocabulary size which may influence SI score, although the results had not yet been analyzed. The effective one was tone pip tests described in Sec. 3.2.1.

In the practice and main experiment sessions, the participants were instructed to write down the words they had heard using hiragana during a 4-second period of silence before the next word was presented. The total number of presented stimuli was 400 words, comprising a combination of the four enhancement conditions, {unprocessed, MASK$_{IRM}$, MVDR$_{IRM}$, MVDR$_{EST}$} and the five SNR conditions with 20 words per condition. Each subject listened to a different word set, which was assigned randomly to avoid bias caused by word difficulty. The experiments were divided into two one-hour tasks to fulfill the crowdsourcing requirement of task duration.

3.2.1. Tone pip test for estimating listening conditions
As described in Sec. 2.2.1 it is essential to evaluate listening conditions for data screening to achieve reliable results. We introduced a web page to estimate how much the sound level was presented above the threshold, which was determined by the listener’s absolute threshold, ambient noise level, and audio device. A sequence of 15 tone pips with -5 dB decreasing steps was presented to the listeners, who were asked to report the number of audible tone pips, $N_{pip}$. The tone frequencies were 500 Hz, 1000 Hz, 2000 Hz, and 4000 Hz, to cover the speech range. Fig. 4 shows the RMS digital level of the sequence of tone pips following a 1-second tone sound. SPL in dB of the tone pip, $L_{pip}$, is calculated from
\[ L_{pip} = L_{ref} - L_{DR} \tag{8} \]
\[ L_{DR} = 5 \cdot (N_{pip} - 1) \tag{9} \]
where $L_{ref}$ is SPL of a calibration tone to normalize speech sounds presented to the listeners and $L_{DR}$ is a dynamic range above the listening threshold. The right y-axis shows SPL when $L_{ref}$ is 64 dB SPL, as an example. Although we could not know the SPLs of sounds presented to participants in the remote experiments, it was possible to use the dynamic range, $L_{DR}$, for data screening effectively, as described in Sec. 3.2.4. The tone pip tests took only a few minutes and could be improved by using an ascending sequence together.

3.3. Laboratory experiments
In the laboratory experiments, the sounds were presented diotically via a DA converter (SONY, NW-A55) over headphones (SONY, MDR-1AM2). The SPL of the stimulus was 63 dB. The processing was performed at 16 kHz sampling rate, and the sounds were then upsampled to 48 kHz for playing on a web browser.

Figure 1: RMS digital level of a sequence of 15 tone pips that decreases at -5 dB steps. The right y-axis shows SPL when the first tone pip is assumed to be 64 dB SPL.
in $L_{Aeq}$, which was calibrated with an artificial ear (Brüel & Kjær, Type 4153) and a sound level meter (Brüel & Kjær, Type 2250-L). Listeners were seated in a sound-attenuated room (YAMAHA, AVITECS) with a background noise level of approximately 26dB in $L_{Aeq}$. Fourteen young Japanese normal hearing listeners (seven males and seven females, 20–24 years) participated in the experiments. The subjects were all naive to our SI experiments and had a hearing level of less than 20 dB between 125 Hz and 8000 Hz.

3.4. Remote experiments

The experimental tasks were outsourced to a crowdsourcing service provided by Lancers Co. Ltd. in Japan [21], as in [7]. Any crowdworker could participate in the experimental task on a first-come-first-served basis. The participants were asked to perform the experiments in a quiet place and to set the volumes of their devices to an easily listenable level. The volume level was recorded and used to maintain consistency between the two experimental tasks, which a total of 39 participants completed. There was a large variety of Japanese participants ages (21 – 64 years) and there were three self-reported HI listeners.

4. Results

We first performed data cleansing of participants’ answers to calculate SI, as described in [7], and then we compared the results of the laboratory and remote experiments.

4.1. Psychometric function of speech intelligibility

Figure 2 shows the word correct rates of the laboratory and remote experiments as a function of the SNR. Circles and error bars represent the mean and standard deviation (SD) across participants. The solid curves represent psychometric functions estimated with the cumulative Gaussian function using psignifit, a Bayesian method [22]. The psychometric functions of both experiments were virtually the same. This implies that the remote experiment results could be usable instead of the reliable laboratory results. Further analysis will be provided later. The psychometric functions of the enhanced conditions (MASK$_{2ch}$, MVDR$_{2ch}$, MVDR$_{EST}$) were located higher than those of the unprocessed condition, implying these algorithms were very effective for speech enhancement. In contrast, spectral subtraction and Wiener filter algorithms did not improve the SI more than the unprocessed condition as observed in the previous studies [7, 19]. Furthermore, the psychometric function of MASK$_{2ch}$ was greater than 50% even in the worst SNR of $-9$ dB and was not much affected by the SNR conditions. This implies that noise components were suppressed sufficiently to reduce masking effect.

It should be noted that Fig. 2 gives the SI of speech sounds enhanced by the IRM and IRM-based beamformer for the first time with respect to a Japanese corpus. The IRM is an “oracle” method that has been recommended for use in a training target of DNN enhancement methods [13]. The results give important information about the upper limit or the goal of the subjective SIs derived by such enhancement methods.

4.2. Speech reception threshold

Speech reception threshold (SRT) was calculated as the SNR value at which the psychometric function reaches a 50% word
The remote experiments. Another reason would be the differences. We surveyed the relationship between the SRTs and age ranges in the same way as in Fig. 3.

As described in Sec. 3.2.1, we introduced tone pip listening screening. Participants ranging from their twenties to their sixties in the remote experiments. Each dashed line shows the individual result. The tendency of the SRT variation across the conditions was similar. However, the variability of the SRTs in the remote experiments was much greater than those in the laboratory experiments, particularly in the MASH\textsuperscript{IRM} condition. One of the reasons for this would be minimal controllability of listening conditions in the remote experiments. Another reason would be the different population of participants: those in the laboratory experiments were in their twenties alone, while there were participants ranging from their twenties to their sixties in the remote experiments. We need to specify the reason for effective data screening.

4.3. Relationship between the number of tone pips and SRT
As described in Sec. 3.2.1, we introduced tone pip listening tests. We surveyed the relationship between \( N_{\text{pip}} \) and the SRT values for the 14 laboratory participants and the 25 remote participants after data screening. There was a similar variance in the distribution of the mean values in these experiments. As a result of multiple comparison tests, there were no significant differences between the same enhancement conditions. Interestingly, there was significant difference between the unprocessed and MVDR\textsuperscript{EST} conditions in the remote experiments but no significance in the laboratory experiments. This is probably because there were more participants in the remote experiments, and therefore the confidence interval was smaller. This result suggests the advantage of data collection using crowdsourcing.

4.4. Data screening
Based on the above discussion, we performed data screening by eliminating points with \( N_{\text{pip}} < 6 \) and \( N_{\text{pip}} > 13 \), and the outlier in Fig. 3(b). There were 25 remaining data points, which are shown as circles in Fig. 3. The magenta line shows the regression line, and there was no correlation \( (r = 0.25; p = 0.22) \). Figure 3(c) shows that the SRT values across the enhancement condition for 25 participants remained after the above data screening. The variability of the SRT values was much lower than those of all 35 participants in Fig. 3(b). The distributions across the enhancement conditions became similar to those in the laboratory experiments in Fig. 3(a). Overall, the procedure using \( N_{\text{pip}} \) was effective for data screening to equalize the remote results to the laboratory results.

Figure 5 shows the mean and SD of the SRT values in the laboratory and crowdsourced remote experiments to evaluate the SI of noisy speech sounds enhanced by a single-channel IRM and multi-channel mask-based beamformers. The results demonstrated that the SI scores were improved by these enhancement methods. The IRM-enhanced sounds seemed to give the upper limit of speech enhancement performance. Moreover, the tone pip test was an effective data screening technique to attain reliable data from crowdsourced remote experiments and could be useful in future studies.

5. Conclusion
In this study, we performed laboratory and crowdsourced remote experiments to evaluate the SI of noisy speech sounds enhanced by a single-channel IRM and multi-channel mask-based beamformers. The results demonstrated that the SI scores were improved by these enhancement methods. The IRM-enhanced sounds seemed to give the upper limit of speech enhancement performance. Moreover, the tone pip test was an effective data screening technique to attain reliable data from crowdsourced remote experiments and could be useful in future studies.

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