I. INTRODUCTION

Communication is an essential tool that people employ to achieve particular goals, from primary needs to higher-level satisfactions (Rubin and Martin, 1998). Verbal communication is among the most efficient means to deliver messages people would like to share. The nature of language acquisition in humans remains fuzzy, but theories from Skinner (1957) and Chomsky (1965) to relatively modern studies (Ambridge and Lieven, 2011; Glenberg and Gallese, 2012; Tomasello, 2003) have touched base to depict the speech production in humans. Using language to communicate, it is easier for people to understand as well as predict others actions. Verbal communication, therefore, becomes a crucial process for people to gain social reward in their everyday life (Roloff, 1981). Most importantly, valid verbal communication makes people feel not alone.

Verbal communication relies on two aspects: being able to generate and recognize the speech. Speech perception in humans involves both the inner brain process and outside environmental conditions. It had been considered that auditory processing dominates the speech perception until McGurk (1976) demonstrated how visual information affects speech recognition. Current research (Giordano et al., 2017; Okada et al., 2013; Shinozaki et al., 2016) regarding speech perception has discovered that the primary auditory cortex also processes visual information and officially claimed that speech perception was no longer merely hearing. A higher audiovisual gain has been found in speech perception and generation in hearing-impaired children (Lachs et al., 2001). This implies that the brain process of audiovisual integrations could be the key for language acquisition and development to support verbal communication.

The surroundings where people receive sound crucially affects speech perception as well. The speech environment which might cause variability in speech perception is defined by the transmission, such as phones or speakers with accents, and noise conditions (Gong, 1995). Challenges to the clarity of the acoustic speech signals increase the cognitive demands for understanding, and types and levels of background noise are crucial elements causing acoustic difficulties (Peelle, 2018). As a result, studies in speech enhancement (SE) steps in the investigation of speech perception. To improve the recognition accuracy under noisy speech environments, the aim is to minimize the mismatching environmental factors interfering with listeners by enhancing the quality and intelligibility of speech as well as reducing the irrelevant background noise.

Distorted or degraded speech signals were used as the experimental tool in previous studies (Dehaan, 1982; Foulke and Sticht, 1969; Heiman et al., 1986) to understand the process of speech recognition in noise. The
so-called unnatural speech signal plays the role in the system of speech perception to increase the mismatch between acoustic information and the environmental factors, and forces listeners to locate the most reliable components at processing to understand the speech. Meanwhile, distorted speech has shown the level of endurance in human audiences when facing changes in speech structure (Altmann and Young, September 22–25, 1993; Remez et al., 1981; Shannon, 2007).

The success of research using distorted speech has been extended from normal hearing (NH) groups to individuals with hearing loss, such as cochlear implant (CI) users. Since speech is a complex representation, speech perception requires higher-level cognitive processing. The feature of noise-vocoding distorted speech (Scott et al., 2000) has allowed researchers destroying the entire intelligibility in the speech to focus on structurally acoustic stimuli and made it a promising tool in studying speech perception. Caldwell et al. (2017) also found that the acoustic challenge caused by spectrally degraded speech could be used to understand the experience of sound quality in CI users and furthermore is able to mitigate relatively poor perception.

People with hearing loss are limited in their communication. According to the World Health Organization (WHO, 2018), hearing loss is the fourth highest cause of disability globally. The current estimated population with hearing loss is 466 million worldwide and the number in 2050 is expected to be greater than 900 million if no further action is taken. To prevent hearing loss requires controlling risk factors. The Centers for Disease Control and Prevention (CDC) highlights three focus areas: early screening and diagnosis for infants and children, protecting of hearing by recognizing harmful sound levels at home and community, and preventing from occupational noise exposure. From the information provided by the WHO and CDC, hearing loss is an undeniable issue and noise reduction could be a convincing strategy to slow the growth of hearing loss.

The SE process consists of two parts: to enhance the intelligibility and quality of speech processing, and to reduce the noises in the background. Previous well-established algorithms have helped improve the SE in CI users (Chen et al., 2015) but there has not yet been studies with a newly developed deep-learning-based algorithm. Traditional SE methods are based on identifying the difference between clean and noisy speech (Boll, 1979; Ephraim and Malah, 1984; Rezayee and Gazor, 2001; Scalart and Filho, May 9–9, 1996). Emerging deep-learning-based models could more accurately match the training and testing conditions to both theoretically and practically optimize the SE performance. For their multi-layered architecture, deep-learning-based models take advantages on extracting representative features with less efforts on classification or regression tasks. Speech recognition has become among the typical processes that would benefit from this model (Fu et al., 2018).

The combination of the developing deep-learning-based algorithm and audiovisual integration seems a breakthrough in the study of SE. Hou et al. (2018) proposed a fusion network using a convolutional neural network (CNN) to link auditory and visual encoder-decoder systems to greatly improve the speech intelligibility than traditional ones could impact. Moreover, children with CI have demonstrated to be better multisensory integrators to incorporate visual and audio information at word recognition in speechreading tasks (Rouger et al., 2007). The greater audiovisual involvement in speech recognition is expected to advance CI users speech perception. Comparing to CI patients, NH participants have demonstrated less variation in characteristics of biological, surgical, and device-related elements at performing the tasks (Waked et al., 2017). Assuming similar auditory encoding and processing for both CI and NH groups, the simulated vocoded result by the NH group is able to get nearer the core of cognitive process beyond the unavoidable individual differences.

This study intended to evaluate how speech intelligibility could be improved under SE technology by simulated vocoded corpus on an NH group. A more efficient deep-learning-based de-noise algorithm was the main SE process using in current research work. As a pilot study, the experiment was expected to test the effectiveness of visual cues in speech reception. In addition, it was anticipated that the cutting-edge deep-learning-based de-noise algorithm targets different background noise to help improve hearing. The task additionally includes two levels of signal-to-noise ratios (SNRs) to understand the threshold level of speech perception in noise for listeners. Furthermore, the results from this study could serve as indicators to predict the possible outcome in a group with hearing loss, particularly for CI users.

II. MATERIAL AND METHODS

Forty participants with gender balance were recruited from the Academia Sinica community to participate in the experiment with the monetary compensation for their time. The group ages were between 20 and 39 with a mean age of 29.38 years old (Standard Deviation, SD, =4.63). All participants were native Mandarin speakers with normal or corrected-to-normal vision as well as normal hearing to perceive the stimuli well during the experiment. Except for one left-handed male participant, all others were right-handed, and all 40 participants did not report a history of neurological diseases or sensational problems. Written informed consent approved by the Academia Sinica Institutional Review Board for this study was obtained from each participant before conducting the experiment.

The stimuli dataset for this study contained video recordings of 120 utterances (100 for the official testing sequence and 20 for pre-experimental training) of Mandarin sentences spoken by a native speaker. The source of recordings was based on the Taiwan Mandarin Hearing in Noise Test (Taiwan MHINT, Wong et al., 2007), and all sentences were specifically designed to have similar phonemic characteristics across the dataset. The full
120 sentences were unique and each consisted of 10 Chinese characters. The length of each utterance was within three to four seconds. The utterances were recorded in a quiet room with sufficient light and the speaker was captured from the front view. Videos were filmed at 30 frames per second (fps) with a resolution of 1920 pixels × 1080 pixels. Stereo audio channels were recorded at 48 kHz which is precisely the same setting as that in Hou et al. (2018). The complete experiment included the training session and which was followed by the official testing period with 20 and 100 sentences, respectively. Both selected numbers of utterances for each session were randomly displayed during its stage.

The experiment employed a tone-vocoder (Figure 1) as the sound generator to present the stimulus for participants with normal hearing. Using vocoder simulations for the NH listeners under various background noise, speech maskers or numbers of electrodes were found in many previous studies as the proven strategy to understand and further predict the speech processing in CI users (Dorman et al., 1997b; Friesen et al., 2001; Lai et al., 2015; MF et al., 1997a; Q.J. et al., 1998; Shannon et al., 1995; Stickney et al., 2004). However, vocoder simulations were not used for estimating the precise level of performance for each single CI user. This strategy was used to access the performance given particular changing parameters and it allows vocoder simulations to be a valuable tool in CI-related research. Therefore, the tone-vocoder simulation was adapted for NH participants in the current study to understand the possible sound processing in CI users.

To understand the intelligibility of sound processing in a noise environment, three different conditions were used during the listening test: without noise maskers (Clean), with noise maskers (Noisy), and the SE upon noise maskers. The fully convolutional neural network (FCN), a deep-learning-based model, was the main algorithm for the SE (Fu et al., 2018) in this study. Except for different conditions, the experiment also covered two types of noise maskers, non-stationary and stationary maskers, implemented as Street and Engine as two example noise maskers. During the experiment, all participants were randomly assigned into two different SNR groups, 1 and 4 dB, with balanced within-group numbers. The interface of the experimental software is shown in Figure 2 and all participants were well instructed to perform the computer-based experiment. Test conditions were labelled in all figures throughout this paper as Clean (without any noise masker), FCN_E (the FCN de-noise algorithm targeting the engine noise masker), FCN_S (the FCN de-noise algorithm targeting the street noise masker), Noisy_E (engine noise masker), and Noisy_S (street noise masker).

FIG. 1. Block diagram of the four-channel tone-vocoder implementation. The first step of speech input was to be processed by the pre-emphasis filter. This operation was followed by the bandpass filters, a full-wave rectifier, a lowpass filter, and finally a compression to generate the vocoded speech.

FIG. 2. Figure 2. Experimental software. The experimental software was run using MATLAB. Figure 2(a) shows the starting interface before the beginning of the experiment while (b) represents the condition with video information. (This experimental software is available via https://github.com/JasonSWFu/VideoAudioTest)
tion with its neighbors to represent the frequency concept. This crucial independency stood out that FCN became a more effective de-noise algorithm than conventional fully-connected deep neural networks (DNNs) for waveform-based SE (Fu et al., December 12–15, 2017; 2018; Long et al., June 7–12, 2015).

Most traditional models have been designed for a frame-wise process; the result would be less accurate for the problem about zero-padding in the frame boundary. However, the FCN could fix this by achieving utterance-based enhancement. Furthermore, an FCN could address not merely fixed-length utterances as all fully connected layers were removed in the FCN. This meant, in the FCN de-noise algorithm, that input features from different lengths would not have to fit in the matrix multiplication. Assuming that the filter length was \( l \) and the length of input signal was \( L \) (without padding), the length of the filtered output would be \( L - l + 1 \). For that FCN contained only convolutional layers, the filters in operation in the convolution could process inputs with different lengths.

The structure of the overall proposed FCN for utterance-based waveform enhancement is shown in Figure 3, where \( \text{Filter}_{m,n} \) denotes the \( n \)th filter in layer \( m \). Each filter coiled together all generated waveforms from the previous layer and then created one further filtered waveform utterance. The goal of SE is to produce one clean utterance, in which the last layer only contains one final filter, \( \text{Filter}_{M,1} \). This completed end-to-end framework indicated again the efficiency of the FCN de-noise algorithm to process the utterance-based enhancement without other redundant pre- or post-processing.

FIG. 3. Architecture of utterance-based raw waveform enhancement by FCN. It provided the progress of SE that how noisy input was filtered by multi-layered FCN de-noise algorithm.

Compared to traditional SE models, FCN provided a better SE result of with reduced model sizes (Fu et al., December 12–15, 2017). Meanwhile, FCN was proven to more effectively enhance speech on non-stationary noises (Tsai and Liao, November 3–5, 2017). Short-time objective intelligibility (STOI) was among the major evaluation methods used in related SE studies (Gao et al., September 8–12, 2016; Taal et al., 2011). The STOI measure for FCN indicated a better result than the Noisy condition, particularly for the non-stationary noise type (Figure 4a). In addition, the normalized covariance measure (NCM) was adopted to understand the performance in processing the speech utterances (Chen, 2012; Lai et al., 2017; Ma et al., 2009). The NCM scores showed consistently higher scores under FCN conditions, especially when targeting a non-stationary noise type (Figure 4b) as STOI did.

FIG. 4. FCN evaluation scores: STOI (a) and NCM (b). Along with the change in SNRs, the FCN received higher scores for both STOI and NCM compared to Noisy conditions, regardless of the types of noise (engine and street); this indicated that the FCN could better facilitate the speech recognition.

Not only were the STOI and NCM scores able to quantitatively specify the enhancement resulting from the FCN de-noise algorithm in the speech intelligibility, but spectrogram plots and amplitude envelopes also qualitatively showed the advantage of the FCN de-noise algorithm. According to Haykin (1995), when studying array processing and signal detection, a time-varying signal could be spectrally represented as a spectrograms. A spectrogram could reveal how noise is reduced to highlight the features of utterances.

As shown in Figure 5, sentences of Clean condition are arranged in the top row of the spectrograms and other four conditions are followed from the second to bottom rows. With the help of the FCN de-noise algorithm, the noise maskers were reduced to represent a similar spectral plots as that of the original utterances (left panel in Figure 5). In addition, the features of each utterance were highlighted under conditions with the FCN de-noise algo-
rithm, particularly in vocoded CI (right panel in Figure 5) compared to Normal ones. The spectrogram results demonstrated that the FCN de-noise algorithm was able to diminish the noise distortion with less noise residual as shown in the plots. This implied more promising improvement of speech intelligibility via FCN modeling.

FIG. 5. Spectrogram of an utterance under different conditions (x axis: time in second, y axis: frequency in kHz). The spectrograms show that the FCN de-noise algorithm helped reconstruct better utterances under two distinguished types of noise, engine and street, for both original and vocoded speech.

From a past research result (American National Standard: Methods for Calculation of the Speech Intelligibility Index, 1997), the middle-frequency band has a crucial position in the speech intelligibility process. In this study, the four-channel tone-vocoded speech was used to generate sentences as the experimental stimuli. As a result, the amplitude envelopes from the second channel were plotted for comparisons of two different SNR tasks, 1 and 4 dBs, under each condition.

The amplitude envelopes provided strong evidence as shown in Figure 6 that after applying FCN de-noise algorithm to the target sentence, the waveform was nearer the original shape (a clean condition; the top row for both SNR tasks). The amplitude of each peak was more similar to the source sentence than sentences of the Noisy conditions. In addition, the smaller amplitude could be more clearly represented while it remained distorted under the Noisy conditions. The results of the amplitude envelopes suggest that better speech intelligibility could be achieved using the FCN de-noise algorithm.

FIG. 6. Amplitude envelopes from the second-channel frequency band (x axis: time in second, y axis: amplitude). The amplitude envelopes from the FCN de-noise algorithm resembled to the original clean target sentence indicating better effectiveness during the speech intelligibility process.
III. RESULTS

According to results of the listening test (Figure 7), the entire performance (mean of 46.91 and SD of 26.34) with the aid of video was better than the audio-only conditions. Participants showed a diverse level at conducting different SNR tasks with an SD of 25.87 and 25.32, respectively. Under working conditions manipulated as video-aided or audio-only, peoples hearing exhibited a relatively smaller variation in SD of 19.38 and 20.18.

![Graph showing performance of different conditions](image)

(a) 1 dB

![Graph showing performance of different conditions](image)

(b) 4 dB

FIG. 7. Listening test results: performance of (a) 1-dB tasks and (b) 4-dB tasks. Conditions with visual aid are marked in a diagonal pattern for both SNRs while solidly filled bars indicate conditions without visual information.

Within the results of lower-SNR tasks shown in Figure 7, the better performance was generally observed in the FCN compared to the Noisy conditions, regardless of noise masker types. Nevertheless, slightly varying degrees were found under conditions with or without video information. Participants best performance fell on the condition of FCN de-noise algorithm targeting the engine noise masker together with visual cues. During audio-only tasks, the result of FCN de-noise algorithm targeting the street noise masker came out to own the highest accuracy rate. FCN conditions ruled the listening test result in the 1-dB tasks, and the visual information helped advance its power.

The performance for higher-SNR tasks unveiled another story toward different conditions. The FCN condition still occupied the first spot at targeting the non-stationary noise masker, street. However, Noisy conditions with the engine noise masker, no matter whether visual cues appeared or not, were slightly ahead of the remaining two conditions. No statistical significance was reported but FCN did not dominate in the 4-dB tasks as it did in the lower-SNR tasks.

The overall performance in different SNR tasks suggested the ease of a higher-SNR to be caught by peoples hearing. In general, for both dBs, the Clean condition without any noise masking took participants the least effort to hear the sounds; however, visual information helping improve hearing was overwhelmingly across every single condition, no matter which SNR tasks were involved. The p-value for the interaction of the Video versus Conditions from the Analysis of Variance (ANOVA) showed the statistically significant value of 0.0126 (Table 1) to confirm the efficiency of visual aid.

| df  | Sum Sq | Mean Sq | F value | Pr(>F) |
|-----|--------|---------|---------|--------|
| dB  | 1      | 16154   | 16154   | <2e-16 |
| Video | 1      | 121104  | 121104  | <2e-16 |
| Condition | 4      | 79604   | 19901   | <2e-16 |
| dB:Video | 1      | 237     | 237     | 1.599  | 0.2068 |
| dB:Condition | 4 | 1006    | 252     | 1.696  | 0.1501 |
| Video:Condition | 4 | 1916    | 479     | 3.229  | 0.0126 |
| dB:Video:Condition | 4 | 493     | 123     | 0.831  | 0.5061 |

TABLE I. ANOVA statistical testing proved that each experimental manipulations (dB, Video, and Condition) functioned in a statistically significant manner in affecting participants performance. In addition, across different conditions, visual aids greatly facilitated to improve the listening test results.

The paired T-Test provided more information regarding how the FCN facilitates humans listening performance compared to the Noisy condition. In Table 2, the T-Test result for the lower-SNR tasks indicated that particularly under the non-stationary noise type, street, the FCN better helped people during the listening test. Notably, when lacking visual aids for peoples hearing, the benefit from FCN became more recognizable as the p-value reached its most practical statistical significance.

The higher- and lower-SNR tasks had resembled results in the paired T-Test. The difference between the
TABLE II. Paired T-Test results for 1 dB. For tasks involving the non-stationary noise type, street, FCN showed better facilitation compared to Noisy conditions, particularly when there were no visual cues to further help peoples hearing.

| Video Noise Condition | Mean  | SD    | t     | df  | p-value |
|-----------------------|-------|-------|-------|-----|---------|
| Yes Street FCN        | 51.90 | 16.28 | 2.3664| 19  | 0.02874 |
| Noisy                 | 44.60 | 12.98 |       |     |         |
| Yes Engine FCN        | 53.95 | 18.02 | 1.2257| 19  | 0.2353  |
| Noisy                 | 50.60 | 16.38 |       |     |         |
| No Street FCN         | 18.50 | 9.74  | 3.8595| 19  | 0.001056|
| Noisy                 | 11.00 | 6.18  |       |     |         |

FCN and Noisy conditions was greater under the non-stationary noise type, street. The performance of FCN targeting engine noise did not surpass that of Noisy conditions while the T-Test results for two different SNR tasks uncovered that there might be some interaction for FCN targeting engine noise. The possible interaction could be noticed by the higher p-value in 4- than in the 1-dB tasks without the visual aid (0.745 vs. 0.2353) and the observed opposite outcome for tasks with the visual aid (0.1708 vs. 0.2353).

TABLE III. Paired T-Test results for 4 dB. The overall tendency was similar to the results for 1 dB but with higher p-values. This confirmed again that the FCN functioned as a reliable facilitator for background noise such as the non-stationary noise type, street, and the lack of other aids such as visual cues.

| Video Noise Condition | Mean  | SD    | t     | df  | p-value |
|-----------------------|-------|-------|-------|-----|---------|
| Yes Street FCN        | 70.10 | 12.68 | 1.7302| 19  | 0.09981 |
| Noisy                 | 64.50 | 12.39 |       |     |         |
| Yes Engine FCN        | 64.10 | 12.29 | -1.4236| 19  | 0.1708  |
| Noisy                 | 67.65 | 12.36 |       |     |         |
| No Street FCN         | 29.70 | 9.71  | 2.4127| 19  | 0.02611 |
| Noisy                 | 24.25 | 11.75 |       |     |         |
| No Engine FCN         | 26.70 | 9.99  | -0.3307| 19  | 0.745   |
| Noisy                 | 27.70 | 13.12 |       |     |         |

Both the ANOVA and paired T-Test results presented no statistically significant indication for the FCN targeting the stationary noise type, engine, but improved performance via the FCN did exist. The interaction plot in Figure 8 displays that during higher-SNR tasks, which were relatively clear for human hearing, the FCN targeting engine noise was merely in the third spot of all the effective conditions. As tasks moved toward lower-SNR, however, the FCN targeting engine noise became the top performer when while the other three conditions remained the same ranking.

FIG. 8. Interaction plot between different SNRs and conditions. FCN targeting engine noise better facilitated human hearing during the lower-SNR tasks while the other three conditions remained the same across the two different SNR tasks.

The listening test scores and statistical results of ANOVA and the paired T-Test all demonstrated that the FCN was able to serve as a better de-noise algorithm and helped enhance the intelligibility of speech recognition. Furthermore, the paired T-Test result and interaction plot provide details regarding how the FCN contributed to human hearing and what conditions might be the best fit for FCN involvement.

IV. DISCUSSION

Consistent with past research (Chen and Massaro, 2008; Desai et al., 2008; Tremblay et al., 2010), visual information is of great help in facilitating peoples hearing. In current listening test results, the performance was improved with the aid of visual cues across various conditions. However, the level of facilitation differs. First, the visual information works well even as background noise appeared and helps particularly well in tasks with specific types of noise maskers. For higher-SNR tasks, with the help of visual information, listeners are able to considerably improve their performance under the non-stationary noise type, street, with the FCN de-noise process. The effectiveness of visual cues shows the most extent compared to other conditions.

The performance of both lower- and higher-SNR tasks reveals that there might be a critical threshold for listeners to detect the sound in noise. In the result of lower-SNR task results, the support from the FCN de-noise is manifest for both types of noise maskers. The possible reason could be that 1 dB is too challenging for listeners to differentiate the background noise from...
the targeting sounds. Both background noise and targeting sounds become homogeneous during sound processing. Visual cues and FCN help sharpen the targeting sounds for listeners to distinguish them from the background noise. Alternatively, the higher SNR allows participants to rather easily hear both the sound and noise; therefore, the boundary of the noise and targeting sound emerges. People with normal hearing can effortlessly process the target-perceiving and de-noising in higher-SNR tasks. The threshold for the NH and CI groups might not be the same but it is an important clue to enhance speech intelligibility.

This study also collected evidence from interaction analysis to reconsider the function of the FCN de-noise algorithm for different SNR tasks. The listening test scores and interaction effect revealed the FCN targeting engine noise was slightly higher than the FCN targeting street noise within lower-SNR tasks. The result implied that though the effect of the FCN targeting engine noise was not universally observed across different conditions, its weighting could become more obvious once people have less cues or more interrupting background noise for them to understand the targeting sounds. As a result, the listening test performance indicates that the FCN de-noise algorithm works differently toward alternative types of noise in higher-SNR tasks but dominates in lower-SNR tasks as participants need the enhancement to detect the comparatively weaker line between targeting sounds and background noises. That is, the FCN de-noise algorithm works particularly well in a chaotic listening environment.

The FCN de-noise algorithm plays a decisive role in improving participants performance in the listening test. Given the noise interference, participants performance under FCN conditions was the best among the test results, for both lower- or higher-SNR tasks. In addition, the accuracy rate of the FCN conditions is generally higher when involving background noise such as street sounds, a non-stationary noise type. This matches the results of Tsai and Liao’s previous study in 2017 that the FCN extracts cleaner speech to achieve an improved listening test result, particularly for a non-stationary noise type. Comparing to purely Noisy conditions, listeners hear better under the stationary noise type which traditional de-noise algorithms used to aim to fix. The listening test results provide more confidence to record the robustness of the FCN de-noise algorithm in enhancing the speech perception.

V. CONCLUSIONS

The FCN algorithm is demonstrated as a better de-noise model for SE as it is similar to a traditional CNN but not limited to process fixed-length inputs (Fu et al., 2018). Given the flexibility that FCN can contribute, the de-noise technology has been leveled up and the listening test results in this study prove its effectiveness in vocoded speech intelligibility. In addition, under different noise maskers, conditions with FCN were able to provide listeners more enhanced speech to obtain higher accuracy scores. Since the preliminary result in CI simulation is positive in verifying the superiority of the FCN, having CI users participate in the future investigation is the most empirical means to demonstrate the real effect on a group with hearing loss.

As a pilot study for enhanced vocoded speech intelligibility, the listening test results have successfully demonstrated the possibility of an updated audiovisual CI system. The performance in the experiment validates the power of audiovisual integration to enhance vocoded speech intelligibility by the much better accuracy rate under conditions with visual aid. Applying audiovisual information on CI processors is a means to better the speech perception for people wearing CI. In addition, given this encouraging listening test results in CI simulation, one can envision an updated fusion system joining deep-learning-based FCN de-noise algorithm and audiovisual integration to further boost the speech intelligibility for a hearing-loss group.

To consolidate the updated fusion system, functional optimization of the FCN de-noise modeling is a necessary future work. The deep structure, however, still requires more computational hardware needs and higher costs than those of old-established models. To properly allocate these resources, developing quantization techniques were used to compress the model (Hsu et al., December 18–21, 2018). With the help of quantized deep-learning-based model, speech intelligibility, including speech recognition and enhancement, would show a more progressive improvement in its reduced processing time (Ko et al., 2017). The fusion of audiovisual integration and SE modeling could be working competently in CI devices as revamped hardware is expanded in the near future.

Speech intelligibility is crucial for both NH and hearing-loss groups to manage the conversations in social status and de-noise technology serves as a tool to improve the interpersonal communication by enhancing the quality of hearing. Beneficial from development of a deep-learning technique, the FCN de-noise algorithm breaks through the limitation of conventional modelings to make progress on a more promising enhancement for speech intelligibility. In addition, the impact of visual cues is clearly proven through the experiment. The listening test results in this CI simulation provide solid evidence that both audiovisual integration and SE technology could greatly facilitate peoples hearing even in a noisy environment. To the final goal to contribute to a hearing-loss group, applying both audiovisual information and FCN in a future investigation involving CI users is a foreseeable process to determine the true value of deep-learning-based modeling for SE and the influence of audiovisual integration.

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