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A novel approach for estimating initial sound level for speech reception threshold test

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Abstract.
BACKGROUND: The speech reception threshold (SRT), synonymous with the speech recognition threshold, denotes the minimum hearing level required for an individual to discern 50% of presented speech material. This threshold is measured independently in each ear with a repetitive up-down adjustment of stimulus level starting from the initial SRT value derived from pure tone thresholds (PTTs), measured via pure-tone audiometry (PTA). However, repetitive adjustments in the test contributes to increased fatigue for both patients and audiologists, compromising the reliability of the hearing tests.
OBJECTIVE: Determining the first (initial) sound level closer to the finally determined SRT value, is important to reduce the number of repetitions. The existing method to determine the initial sound level is to average the PTTs called pure tone average (PTAv).
METHODS: We propose a novel method using a machine learning approach to estimate a more optimal initial sound level for the SRT test. Specifically, a convolutional neural network with 1-dimensional filters (1D CNN) was implemented to predict a superior initial level than the conventional methods.
RESULTS: Our approach produced a reduction of 37.92% in the difference between the initial stimulus level and the final SRT value.
CONCLUSIONS: This outcome substantiates that our approach can reduce the repetitions for finding the final SRT, and, as the result, the hearing test time can be reduced.

Keywords: Hearing test, speech audiometry, pure tone threshold, speech reception threshold, convolutional neural network

1. Introduction

Hearing loss is associated with critical health issues, including heart conditions, cognitive decline, dementia, and various chronic diseases [1,2]. Hearing tests evaluate the auditory ability of a patient, with several types of hearing tests. Among them, along with the bone-conduction test, pure tone audiometry (PTA) performed by air-conduction is the most common test to find the quietest volume the patient can hear at some frequencies [3]. The lowest volume levels are termed pure tone thresholds (PTTs). Speech audiometry (SA) is important for assessing the applicability of hearing aids and includes sub-tests such as the speech reception threshold (SRT) test [4].

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The SRT test often validates PTA results [5], measuring the lowest hearing level required for recognizing language or speech through a "listen and repeat" process [6] for a set of words with sound level adjustment. The repetition continues until 50% of the words are successfully repeated, defining the sound level as SRT [5]. In the current method, the starting sound level for the repetitive process is determined by the pure tone average (PTAv), an average of PTTs at specified frequency components [4].

However, repetitive adjustment in the test leads to increased fatigue for both patients and the audiologist, causing the hearing test to have low reliability. Determining the first (initial) sound level closer to the finally determined SRT value is important to reduce repetitions.

This study proposes a novel method using a machine-learning approach to estimate a better initial sound level for the SRT test using machine learning approach. A convolutional neural network with 1-dimensional filters (1D CNN) was used to predict a better initial sound level than existing methods determining the initial level by PTAv, a linear combination of PTTs. Our approach produced 37.92% less difference between the initial sound level and the final SRT value, supporting that our approach can reduce repetitions for finding the final SRT and, as a result, the hearing test time can be reduced.

2. Related works and current methods

2.1. Air-conduction audiometry

Audiometry is the gold standard testing method for evaluating hearing availability by sound [7]. Two types of audiometry exist: air conduction (AC) and bone conduction. Pure tone and speech tone are involved in AC audiometry. Pure tone is used to determine the type and degree of hearing loss [8,9], while speech tone is used to examine the applicability of hearing aids [5]. This section introduces detailed descriptions of pure tone and speech audiometry for the AC test.

2.1.1. Pure tone audiometry

PTA aims to find the lowest hearing levels with sine wave sounds, termed pure tones [3]. Using different frequencies of pure tones, the hearing thresholds of patients corresponding to the frequencies, known as PTTs, are measured [6]. The PTA procedure for measuring PTTs is shown in Fig. 1.

First, a patient was instructed to wear an AC headset in a soundproof booth and press a feedback button upon hearing a sound. After that, the pure tone sounds with dB_s at *xHz* was played, where dB_s and *xHz* represent the stimulus sound level and the frequency of pure tone sound, respectively. Usually, dB_s ranged from 0 to 100 dB, and *xHz* was one of six frequencies: 250, 500, 1 K, 2 K, 4 K, and 8 KHz. After playing the pure tone sound of a certain frequency *xHz* at a certain dB_s, the response was inspected to determine whether the feedback button was pressed. Depending upon the response, the sound level dB_s was adjusted by decreasing 10 dB or increasing 5 dB until the audiologist determined the dB_s as the PTT for the *xHz* frequency, represented by PTT_{xHz}.

As the result of the PTA for a patient, two data sets corresponding to the left and the right ears, each with six PTTs, were obtained as described in the Eq. (1).

$$\overrightarrow{PTA_d} = \{PTT^d_{0.5K}, \ldots, PTT^d_{4K}, PTT^d_{8K}\} \tag{1}$$

where d represents either the left or the right ear. This data set was used to find the initial sound level for further processing, as described in the following section.

2.1.2. Pure tone average

The current method for finding the initial sound level for repetitive adjustment in the SRT testing

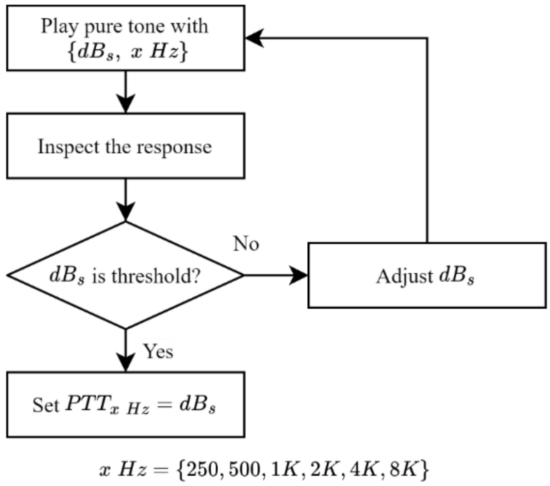


Fig. 1. Procedure of measuring pure tone thresholds.

process, described in the following section, was to compute a PTAv [10]. PTAv is considered an average of PTTs at specified frequency components, typically 0.5 K, 1 K, 2 K, and 4 KHz. The PTAv value measures the average hearing sensitivity of the patient at various frequency sounds in each ear. The outermost frequencies were not included in the PTAv calculation because most information on speech sounds was mainly represented in the mid frequencies. Three PTAv calculations were 3 frequencies average (3FA), weighted 3 frequencies average (W3FA), and weighted 4 frequencies average (W4FA), with equations given in Eqs (2)–(4).

$$\text{3FA} = (PTT_{500} + PTT_{1K} + PTT_{2K})/3 \tag{2}$$

$$\text{W3FA} = (PTT_{500} + 2 * PTT_{1K} + PTT_{2K})/4 \tag{3}$$

$$\text{W4FA} = (PTT_{500} + 2 * PTT_{1K} + 2 * PTT_{2K} + PTT_{4K})/6 \tag{4}$$

Incorporating modified equations representing the average hearing sensitivity for various frequencies, the chosen PTAv, the value is used as the starting sound level for repetitive adjustment in determining find the SRT value. Consequently, with a PTAv closer to the finally determined SRT value, the number of repetitions can be reduced. This is the motivation of this study to find a better initial level for SRT adjustment.

2.1.3. Speech audiometry

In human communication, it is important not only to hear pure tone frequencies, but also to hear words. Given that hearing aids represent a prevalent treatment for hearing loss, evaluating their applicability is essential and accomplished through speech audiometry. Among various tests in SA, the SRT test holds particular significance because it measures the lowest hearing level with speech. The procedure of the SRT test is shown in Fig. 2.

The patient was instructed to do a "*listen and repeat*" which means involving the vocal repetition of heard words [6]. The audiologist initiated the presentation of a word with dB_s determined as the initial sound level using a PTAv equation, and evaluated the accuracy of the patient in repeating the word. The count of correctly repeated words among N was counted during the test with a set of N words. If the number exceeded half of N, the sound level dB_s was adjusted by decreasing 5 dB Conversely, if the

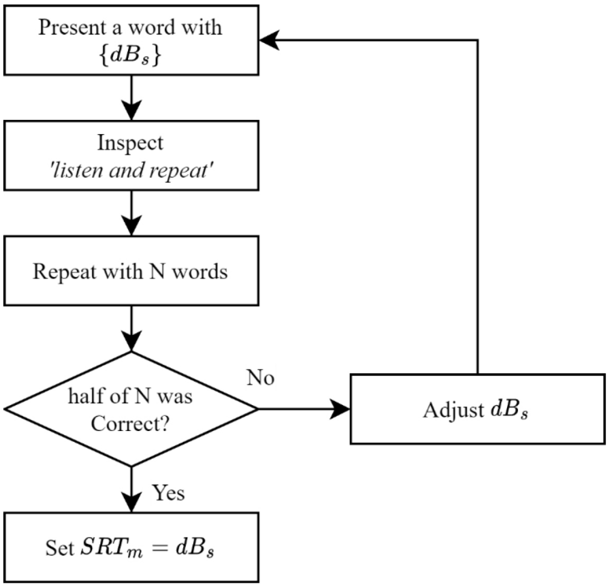


Fig. 2. Procedure of speech reception threshold test.

number fell below half of N, the sound level dB_s was adjusted by increasing 10 dB. This adjustment and "*listen and repeat*" test iterated with a different set of N words until precisely half of N was correctly repeated. The sound level used at that test cycle was set to SRT_t, representing the SRT value for the patient, and the test was terminated [5].

As described in Fig. 2, the "*listen and repeat*" process was time-consuming, and patients, especially those required to discern small sound words, easily experienced fatigue. Minimizing the number of adjustments was imperative to simplify the entire hearing test and reduce patient fatigue. Note that, currently a PTAv [10] is used. This study proposes a machine learning approach to predict a better starting sound level SRT_p using PTTs.

2.2. 1D convolutional neural network

A convolutional neural network (CNN) is a neural network-based machine learning technique [11]. This algorithm integrates a 2-dimensional convolution layer, performing feature extraction through convolutional filtering operations, with a multi-layer feed-forward neural network. Although it is commonly used for image classification and segmentation due to its 2-dimensional operations [12], it is also adaptable to 1-dimensional signal data using a 1D convolution layer, referred to as a 1D CNN [13]. The multi-layer feed-forward neural network, also known as a multi-layer perceptron (MLP), is connected after the convolution layer to produce output values [14]. The activation function for neurons in both layers is typically non-linear, such as ReLU and Sigmoid [11]. Parameters for both layers are learned through the error back-propagation rule [15].

3. Motivation and goal

As detailed in Section 2.1.2, the SRT for a patient SRT_t was obtained through several repetitions of the "*listen and repeat*" test with a set of N words at an adjusted sound level. Numerous repetitions can

Table 1
Components of data

Feature	Dimension	Unit
ID	1	–
Ear	1	"L", "R"
$\overrightarrow{PTA}$	6	dB
SRT_t	1	dB

induce fatigue in both the patient and the audiologist, diminishing the reliability of the test and potentially leading to test refusal. Therefore, reducing the number of repetitions for the SRT test is important.

PTAv such as 3FA, W3FA, or W4FA in SA is assumed to be similar to the SRT_t [5,10]. Hence, an PTAv was used as the starting sound level dB_s. However, there is a lack of solid evidence that PTAv is a superior starting sound level that can reduce the repetitions. Although the PTAv may be considered an appropriate method for selecting the starting sound level, it merely constitutes a simple linear combination of PTTs and overlooks potential non-linear property between them.

Hence, obtaining a more optimal starting sound level one closer to the true or finally determined SRT value SRT_t, could reduce the number of repetitions for the SRT test. The error was defined as the difference between the true value SRT_t and the predicted value SRT_p and Eq. (5) should be minimized.

$$Error_{SRT} = |SRT_t - SRT_p| \tag{5}$$

Note that the existing method used the PTAv for SRT_p, while we proposed a machine learning approach to estimate a more optimal SRT_p.

4. Dataset description

AC audiometry data was obtained from Chonnam National University Hospital in Korea, which were collected from 8,936 patients experiencing hearing difficulties. The data collection followed the procedure outlined in Section 2. The dataset comprised the following components: ID (patient identification number), ear (left or right), $\overrightarrow{PTA}$, and SRT_t. Table 1 shows the dataset components, including "*feature*" – commonly used in the machine learning field, "*dimension*" – representing the number of values, and "*unit*."

The data was treated as independent data in this study because the hearing test was conducted separately on both "L" and "R" ears. Therefore, the total number of original data was 17,872, equivalent to twice the number of patients. However, acknowledging the presence of various human errors during the PTA, a meticulous selection process was undertaken. We carefully cleansed data by addressing issues such as missing values or redundancy. Finally, 10481 data were discerned as non-erroneous and deemed suitable for inclusion in this study.

5. SRT prediction with CNN

5.1. CNN model architecture

In this study, the CNN model showing the state-of-the-art performance in many fields, was used [13, 14]. Alternatively, any other model capable of accurately predicting SRT_t as the output, with $\overrightarrow{PTA}$ as the input vector, can be employed. Specifically, we used 1D CNN which is suitable for 1D signal input data

Table 2
CNN model architecture

	Layer	No	Parameter
Input		1	Input size: (6)
Hidden	Convolution	4	Filter size: (3) No. of filters: 16 Activation: ReLU Padding: zero padding
	Flatten	1	96 output/input (1D)
	Fully connected	2	No. of neurons: 32 Activation: ReLU
Output		1	No. of neurons: 1 Activation: linear

involving 6 PTT values. The input layer obviously had six neurons corresponding to the number of PTTs. The output layer had single neuron with linear activation function to produce the output SRT_p.

The architecture and hyper-parameters of the CNN model are summarized in Table 2. Note that, the architecture can significantly impact performance. However, detailed optimization of architecture and training parameters, such as drop-out, stride, batch normalization, and pooling [12], was not the primary focus because the primary goal was to introduce a novel approach employing machine learning techniques to reduce hearing test time by determining an optimal starting sound level. Further investigation into the ideal architecture for the model is recommended for enhanced performance.

The flatten layer transformed the outputs of 16 filters, each containing six values, into a flattened vector format of 96 values. This flattened vector served as the input to the fully connected layer. The output neuron had linear activation function, representing SRT_p with values ranging from 0 dB to 100 dB, as detailed in Eq. (6). Note that the ReLU can also be applied as the activation function for the output neuron.

$$o = f(net) = net = \sum_{i=1}^{32} w_i o_i + b \tag{6}$$

where i corresponds to neurons in the last hidden layer of the fully connected layer. Note that o denotes the neuron output, w corresponds to the connection weight, and b represents the bias.

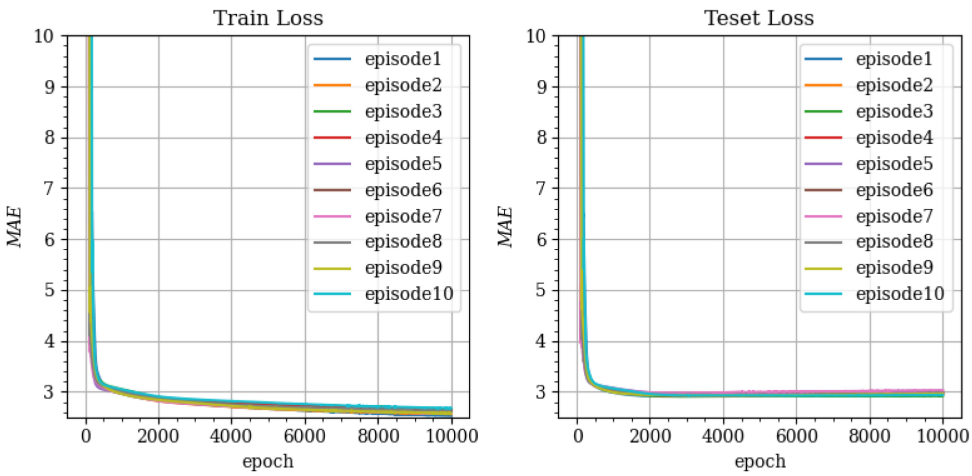
5.2. Training the CNN model

We randomly split the 10,481-sample data into two subsets for training and testing in a 50:50 ratio. The 1D CNN model was trained with the training subset to minimize the mean absolute error (MAE) defined by the Eq. (7):

$$MAE^{CNN} = \frac{1}{n}\sum_{i=1}^{n} |Error^i_{SRT}| = \frac{1}{n}\sum_{i=1}^{n} |SRT^i_t - SRT^i_p| = \frac{1}{n}\sum_{i=1}^{n} |SRT^i_t - o^i| \tag{7}$$

where n denotes the number of data samples, $Error^i_{SRT}$ corresponds to the prediction errors for the i-th sample, SRT^i_t represents the final *SRT* value determined by the test procedure depicted in Fig. 2, and SRT^i_p corresponds to the *SRT* value predicted by the output neuron of the proposed model for the i-th sample. *MAE* can be substituted with alternative error functions, such as mean squared error (MSE) related to the least square approach.

The proposed 1D CNN model was trained using a learning rate of 0.0001, using the ADAM algorithm as the optimization method, which is widely used in deep learning fields. The maximum training epoch was set at 10,000, and the MAE on the test subset was evaluated at each epoch to select the model with the best performance on the test subset. We again note that the primary focus was not on fine-tuning the architecture and training parameters.



(a) (b)

Fig. 3. Error curves for training data (a) and testing data (b).

The training and testing episode was iterated ten times to eliminate dependencies on data separation and parameter initialization, each time employing new data separation and initial parameters. Subsequently, we computed assessments for each episode, including the best, worst, and average outcomes. Further details are explained in the subsequent section.

6. Result and analysis

6.1. Result of model train

The training progress is visualized in Fig. 3 through the MAE^{CNN} curves for the training subset (left) and the test subset (right). The curves depict that the training process was effective across all ten trials, exhibiting a continuous decrease in both training and testing curves without signs of overfitting or memorization issues. The training curves decreased despite halting the training process at 10,000 epochs. This suggests that further training could yield even better results with lower *MAEs*.

MAE^{CNN} values for the ten experimental trials are reported in Table 3. Although not explicitly presented in this table, the ranking of the training results did not necessarily match the ranking of the test results.

6.2. Prediction comparison

MAE values were computed for the conventional approaches 3FA, W3FA, and W4FA, employing the following equation to facilitate a comparison with conventional approaches elucidated in Section 2:

$$MAE^{xFA} = \frac{1}{n}\sum_{i=1}^{n}(|xFA^{i} - SRT_{t}^{i}|) \quad (8)$$

where xFA^{i}. represents the PTAv computed by any 3FA, W3FA, or W4FA approaches for the i-th sample. For example, W4FA$^{i}(x = W4)$ was computed by the Eq. (4) in Section 2. Table 4 presents the MAE^{xFA}

Table 3
Average result of ten repetition

Dataset		MAE^{CNN}
Training	Average	2.64 dB
	Best	2.57 dB
	Worst	2.71 dB
Testing	Average	2.96 dB
	Best	2.91 dB
	Worst	3.01 dB

Table 4
Comparison of SRT prediction

Conventional method	MAE^{xFA}	$(MAE^{xFA} - MAE^{CNN})/MAE^{xFA}$
3FA	4.76 dB	37.92%
W3FA	4.74 dB	37.59%
W4FA	3.86 dB	23.35%

values and the ratio between MAE^{CNN} and MAE^{xFA} for the testing set. Note that the MAE^{CNN} value for the testing set, obtained by our method, was 2.96 dB on average, as indicated in Table 3.

As observed in Table 4, our machine learning approach reduced the SRT test time because of lower MAE^{CNN} implied a smaller number of adjustments and repetitions to reach the SRT_t^i value. All MAE^{xFA} values were larger than MAE^{CNN}, even for the worst result (3.01 dB). Although the ratio may not precisely exactly reflect the number of repetitions, we claimed that our method reduced the time for the SRT test by up to 37.92% compared to the 3FA approach.

6.3. Discussion

In hearing tests, the most time-consuming aspect is the SRT test, involving the repetitive "*listen and repeat*" process with continuous adjustments of sound levels based on the responses of the patient. Prolonged test durations pose significant challenges because the monotonous nature of the "*listen-and-repeat*" process may lead to patient non-cooperative, resulting in unreliable test outcomes and inaccurate designs for hearing aids. Additionally, extended test times can inconvenience other patients who must wait for their turn. Therefore, our proposed approach is a promising solution to reduce the overall testing time by accurately predicting the SRT closer to its final value.

We did not focus on finding the optimal machine learning model and its parameters, while this study empirically demonstrates the successful application of machine learning techniques to reduce hearing test times. Hence, those implementing our approach for enhanced results should conduct further investigations to find a superior model and its associated parameters. Moreover, all experiments were performed using a dataset not specifically collected for our approach, limiting the comparison with conventional methods solely to *MAE* values. However, the number of repetitions for adjusting the sound level for the "*listen and repeat*" process should be compared.

7. Conclusion

In hearing tests, measuring SRT requires repeating the "*listen and repeat*" process with iterative adjustments to the sound level. This repetitive testing procedure makes the test inefficient, causes fatigue for both the audiologist and the patient, thereby compromising the reliability of the test. The starting sound level should be closer to the finally determined SRT value to address the challenge of reducing repetitions in the SRT test. The conventional method has traditionally employed PTAv as the starting value.

While the PTAv has been deemed appropriate for initiating the SRT test, it represents a simple linear combination of PTTs and lacks consideration for the non-linear properties between PTTs. This study proposed a machine learning approach to estimate a more accurate starting sound level for the SRT test. Our proposed approach used a 1D CNN model with 1D convolution filters to predict the optimal starting sound level. The model was trained to accurately predict SRT values as outputs based on the PTTs as input values.

The CNN prediction model reduced MAE by up to 37.92% compared with the conventional method. Therefore, our approach has the potential to streamline hearing test times by estimating a more precise starting sound value, resulting in fewer repetitions of the SRT test. While this study experimentally proved the applicability of machine learning techniques in reducing hearing test times, we did not focus on finding an optimal machine learning model and its parameters. Hence, those implementing our approach for improved results should investigate to ascertain a superior model and its associated parameters.

Furthermore, this study exclusively used the dataset of pure tone AC audiometry, and the applicability of bone-conduction audiometry warrants consideration. Additionally, our machine learning approach holds promise for enhancing other tests assessing hearing abilities, such as most comfortable level (MCL) and word recognition score (WRS).

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Conflict of interest

None to report.

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