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COMPARISON OF DNN-BASED AND TRADITIONAL HEARING-AID ALGORITHMS FOR SENSORINEURAL HEARING-LOSS

Marjoleen Wouters[1*] **Chuan Wen**[1] **Attila Fráter**[1]
Sarah Verhulst[1]
[1] Hearing Technology@WAVES, Dept. of Information Technology, Ghent University, Belgium

ABSTRACT

Traditional hearing aid (HA) algorithms, based on computational and non-differentiable auditory models, are unable to compensate for cochlear synaptopathy (CS). In order to provide hearing solutions for sensorineural hearing-loss (SNHL), deep-neural-network- (DNN) based HAs have recently been developed. We trained several DNN-based HA models using an optimized version of our differentiable DNN-based auditory model $dCoNNear$ to compensate for outer-hair-cell (OHC) loss and/or CS. The HA models were trained using backpropagation to minimize the difference in hearing-impaired and normal-hearing auditory nerve (AN) responses. On the basis of transfer functions, simulated auditory model responses to standard auditory stimuli and speech, and the normalized-root-mean-square-error (NRMSE) of the AN population response, we compare our own DNN-based HAs to the NAL-NL2 reference HA to offer an objective assessment of DNN-based HA processing as a compensation strategy for SNHL. We will objectively assess the effect of the HA processing on the sound quality and speech intelligibility in future clinical experiments.

Keywords: *hearing-aid processing, machine-learning, cochlear synaptopathy*

**Corresponding author*: *marjoleen.wouters@ugent.be.*

1. INTRODUCTION

Noise exposure, ototoxic drugs, and aging can cause sensorineural hearing-loss (SNHL) by damaging the outer-hair-cells (OHCs) or synapses to the auditory nerve (AN), the latter is a condition known as cochlear synaptopathy (CS) [1–3]. CS often leads to difficulties understanding speech in noisy environments, even when pure tone audiometric thresholds remain normal, therefore CS is called 'hidden hearing loss'. Traditional hearing aids primarily address OHC loss by amplifying sounds based on audiometric thresholds. However, they do not specifically compensate for the auditory processing challenges associated with CS. Recent advancements in auditory modeling and machine learning (ML) offer promising approaches. By employing differentiable descriptions of biophysical models of hearing impairment, ML-based audio signal processing algorithms can be developed to compensate for various aspects of SNHL, including both OHC loss and CS [4–7]. These models facilitate non-linear compensation without relying on pre-defined gain tables, allowing for more personalized and effective hearing assistance.

2. MATERIALS AND METHODS

Here, we present a couple of DNN-HAs that were trained in a closed-loop system consisting of a normal-hearing (NH) and hearing-impaired (HI) $dCoNNear$ auditory periphery model, visualized in Figure 1. They were trained using backpropagation, such that the DNN-HA processes the input speech x into the processed speech $\hat{x}$ in order to result into a HA-compensated AN response $\hat{r}$ that is restored as close as possible to the NH AN response r, by minimizing the difference between the HI and NH AN response using different sets of loss functions [4, 4–10, 10–12].

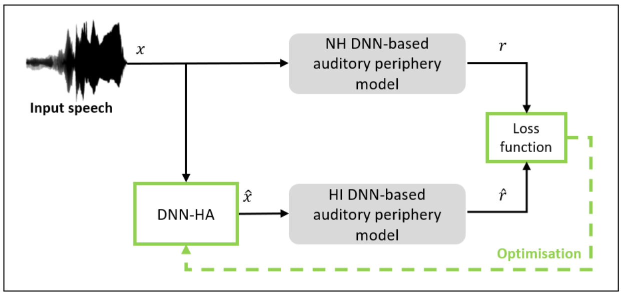

Figure 1. Overview of the backpropagation loop used to train the DNN-based HA models.

2.1 dCoNNear auditory model

We developed $dCoNNear$, an improved neural network model of the auditory periphery, building upon the previously used biophysically-inspired $CoNNear$ model [8, 11–13]. $dCoNNear$ offers a fast, differentiable simulation of human auditory processing: basilar membrane (BM) vibrations, inner hair cell (IHC) potentials and AN firing across 201 cochlear locations (center frequencies ranging from 112 Hz to 12 kHz). Since the previous $CoNNear$ model, which used an auto-encoder convolutional-neural-network (CNN) architecture, caused artifacts such as aliasing and tonal distortions, we designed a new architecture for $dCoNNear$, inspired by temporal-convolutional-networks (TCN) and deep feed-forward sequential memory networks (DFSMN) [4–7, 14]. In order to model OHC loss in the $dCoNNear$ auditory periphery, we use transfer learning to retrain the cochlear stage of $dCoNNear$ [15], based on the measured audiogram [16]. To model CS in $dCoNNear$, we modify the number of auditory nerve fibers (ANFs) to include a different number of high-, medium- and low-spontaneous rate (HSR, MSR and LSR) ANFs per characteristic frequency (CF). For the NH auditory periphery, the model uses 13 HSR, 3 MSR and 3 LSR ANFs per CF [13]. In case of CS, high-frequency ANFs are progressively reduced, starting with LSR and MSR ANFs, leading to more severe CS profiles where even HSR ANFs are lost [16].

2.2 DNN-based HA models

In this work, we present five different DNN-HAs, trained in a closed-loop system to compensate for different combinations of OHC loss and/or CS, using the same $dCoNNear$ architecture, but different loss functions to minimize the difference between different aspects of the NH and HI auditory responses [4–9, 11, 12]. The training dataset consisted of 2310 randomly selected recordings from the TIMIT speech corpus [17], calibrated to 70 dB SPL rms, with reference $p_0 = 2 \cdot 10^{-5} Pa$.

2.3 HA model evaluation

To evaluate the capabilities of the different DNN-HAs in compensating for selected SNHL profiles, we will investigate the HA processing performance for speech stimuli and standard auditory stimuli such as clicks, steps and sinusoidally amplitude modulated pure tones. We will examine the transfer function of each of the DNN-HAs, to observe the frequency- and level- dependent gain applied in each SNHL condition. The DNN-HA processed stimuli were given to the HI $dCoNNear$ model with the considered degree of OHC loss and CS profile, to investigate the difference in simulated responses between the NH and HI models, and see how the HA processing affects the output for the HI case, aiming to restore the AN responses to the NH level. The normalized root-mean-square-error (NRMSE) of the AN population response shows how well each of the DNN-HAs performed at restoring the AN population response to the NH level for each phoneme category of the TIMIT core test set. We will compare the outcomes of the DNN-HAs to the reference NAL-NL2 HA prescription procedure from The National Acoustic Laboratories (NAL) which applies dynamic compression, using the openMHA toolbox [18, 19].

3. RESULTS

At the conference, we will present the processing outcomes for the different auditory stimuli to investigate which auditory features the different HA processing algorithms focused on to compensate for CS and/or OHC loss, and compare this with the reference NAL-NL2 processing.

4. ACKNOWLEDGMENTS

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