Modeling and Noninvasive Correction of Auditory Disorders with Inverse Artificial Neural Network

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Abstract—**A framework for noninvasive correction of hearing impairment is demonstrated with an outlined method of developing into a hearing aid type device. A noninvasive auditory brainstem response (ABR) measured from people with normal hearing and hearing loss is utilized to distinguish among individual hearing functions and characteristics. A model of ABR is developed using the modified nonlinear Hopfield neural network and the model inverse to the modified Hopfield is also derived. The method is presented in system scale as well as in analog behavioral modeling. Simulation results on a model of a patient with sensorineural hearing loss are given as an example.**

I. INTRODUCTION

The noninvasive means to correct an auditory disorder effect is investigated in this paper which opens up the new possibility of developing into a hearing aid type device that helps to cancel and correct the hearing loss effects and hypothetically improves the hearing ability of the hearing impaired. Unlike traditional hearing aids whose amplifying gains are adjusted over limited sets of frequency bands according to the hearing thresholds measured with the standard pure tone audiograms we take into account the physical and behavioral characteristics of an individual's hearing mechanism and hearing loss configuration. This correction method originally proposed in [1]-[2] is that we create an ear type system of the human auditory system, particularly the hearing sensitivity and its characteristics for which another ear type system inverse to this system can then be developed. Consequently, cascading these two systems yields the identity result. The hearing aid is composed of the connection of the ear type system with normal characteristics and the system inverse to the aid user's ear type system so that damaged parts or hearing loss effects are potentially cancelled and corrected. The stimulated acoustical emission signal detected in the human ears known as transiently evoked oto-acoustic emission (TEOAE) or also named as Kemp echo [3] was utilized to model the cochlea which is useful and accepted worldwide as a reliable method for hearing loss diagnosis in hospitals today due to its inexpensive, fast, effective and especially noninvasive properties. It is used as an assessment tool to gain access into the functioning of the cochlea, hearing sensitivity, threshold evaluation and hearing loss up to the section of the outer hair cells inside the inner ear.

Here we would like to extend the hearing function beyond that, so the use of the auditory brainstem response (ABR) is investigated. The ABR is an electrical signal measured on the scalp in response to the acoustical stimulation in the ear, Fig. 1. It reflects the synchronous activity of neurons within the human auditory system and the functions of the cochlea, auditory nerve and brainstem pathway. Its waveform lasts about ten milliseconds and consists of five to seven major peaks which are believed to generate from the cochlea, the auditory nerves, the cochlear nucleus, and the brainstem pathway up until the first part of the lateral lemniscus [4]. Evaluated by major peak latencies (I, III and V), inter-peak latencies (I-III, III-V and I-V), inter-aural peak V latencies, waveform morphology, and amplitudes, these criteria are quite consistent among normal hearing individuals. Also, ABR is highly affected by cochlear and retrocochlear pathologies, so hearing function disorders and tumors can be diagnosed by comparing measured responses with established normative values [5]-[6]. The ABR is a useful noninvasive method for testing the integrity of the auditory nerve and brainstem in addition to that of the cochlea. Moreover, it has an advantage over others when dealing with newborns or anyone having a difficulty responding to a conventional pure tone audiogram since it is an objective measurement.

In this paper, first the modified nonlinear Hopfield neural network is introduced to model the ABR. Parameter estimation is performed using the MATLAB system identification toolbox with signals measured from people with normal hearing and hearing impairment so that each model is individualized. Second, the model inverse to the modified Hopfield neural network is derived whose output is equivalent to the input of the original network. The way to

inverse the Hopfield network was motivated by [7]-[8]. However, higher order equations are needed making it more complicated, extra different steps are required. Third, the method for correction of hearing loss and the PSPICE analog behavioral modeling of the device are discussed. Finally, simulations and results are illustrated on the model of a hearing impaired patient.

II. NEURAL NETWORK AND ITS INVERSE SYSTEM

The correction method requires modeling of the auditory system via ABR for which the Hopfield neural network is utilized.

A. The Modified Hopfiled Network

The Hopfield artificial neural network [9] has been of interest in system identification with its simple structure suitable for a hardware realization. Here the Hopfield neural network with structure of a dynamical semistate system and an added external input is derived as adapted for ABR modeling. The Hopfield neural network continuous time semistate system for single input and single output has two layers, n neurons in the first layer with nonlinear activation functions, n×n weight matrix, and n-vector bias and one neuron in the second layer with linear activation function and a bias value. Mathematically in semistate form

$$\mathbf{E}(d\mathbf{x}(t)/dt) = \mathbf{A}\mathbf{v}(t) + \mathbf{G} + \mathbf{B}u(t), \ \mathbf{x}(0) = \mathbf{x}_0 \quad (1)$$

$$\mathbf{v}(t) = f(\mathbf{x}(t)) \quad (2)$$

$$y(t) = \mathbf{C}\mathbf{v}(t) + d \quad (3)$$

where $\mathbf{x}(t)$ is an internal state-type n-column vector with initial value $\mathbf{x}_0$, $u(t)$ is a scalar input signal, $y(t)$ is a scalar output signal, $\mathbf{v}(t)$ is a nonlinear n-column vector, $\mathbf{E}_{[n×n]}$ is a constant matrix equal to e×$\mathbf{I}$ ($\mathbf{I}$ = Identity matrix) for which a possibly singular matrix could also be applied taking a semistate system into account, $\mathbf{A}_{[n×n]}$ is a constant weight matrix, $\mathbf{G}_{[n×1]}$, $\mathbf{B}_{[n×1]}$, and $\mathbf{C}_{[1×n]}$ are constant vectors, and $d_{[1×1]}$ is a scalar output bias. The nonlinear activation function, $f(.)$, can be any nonlinear function that is monotonically increasing and differentiable such as a sigmoid function which is favorably

used in system identification using neural networks. Here a hyperbolic tangent is selected since it has a large output range; moreover, it coincidentally matches the mechanical motion with saturation of hair cells.

B. The Inverse Network

The above Hopfield type system is a nonlinear n[th] order semistate equation with scalar input and scalar output so we can neither directly calculate the reciprocal of its transfer characteristics nor invert the activation function. To find the system inverse to it, we apply the concepts from linear system theory. The inverse and converse systems [10] and the approach of using the differential value of the output from the forward system as the input to the inverse system to avoid the need for vector or matrix inversions are applied to the nonlinear case [11] with our network. From (3), the output y(t) is differentiated

$$y^{(1)}(t) = dy(t)/dt = \mathbf{C}(d\mathbf{v}(t)/dt)$$

$$= \mathbf{C}(df_x\mathbf{I})(d\mathbf{x}(t)/dt) \quad (4)$$

where df_x stands for $df(.)/dx$. Substitute $dx(t)/dt$ from (1) in (4) and rearrange to get $u(t)$,

$$u(t) = (\mathbf{C}(df_x\mathbf{I}) \mathbf{B})^{-1}\{e(y^{(1)}(t)) - \mathbf{C}(df_x\mathbf{I})(\mathbf{A}\mathbf{v}(t) + \mathbf{G})\} \quad (5)$$

which returns the scalar value. Substituting (5) in (1) yields (6). The system inverse to the original system of (1)-(3) is achieved as $u(t) = y_{inv}(t)$ and $y^{(1)}(t) = u_{inv}(t)$. The equations

$$\mathbf{E}dx_{inv}(t)/dt = \{\mathbf{A} - \mathbf{B}(\mathbf{C}(df_x\mathbf{I}) \mathbf{B})^{-1} \mathbf{C}(df_x\mathbf{I})\mathbf{A}\}\mathbf{v}_{inv}(t)$$

$$+ \mathbf{G} - \mathbf{B}(\mathbf{C}(df_x\mathbf{I}) \mathbf{B})^{-1} \mathbf{C}(df_x\mathbf{I})\mathbf{G}$$

$$+ \{\mathbf{B}(\mathbf{C}(df_x\mathbf{I}) \mathbf{B})^{-1}e\}u_{inv}(t),$$

$$\mathbf{x}_{inv}(0) = \mathbf{x}_0 \quad (6)$$

$$\mathbf{v}_{inv}(t) = f(\mathbf{x}_{inv}(t)) \quad (7)$$

$$y_{inv}(t) = - (\mathbf{C}(df_x\mathbf{I}) \mathbf{B})^{-1}\mathbf{C}(df_x\mathbf{I})\mathbf{A}\mathbf{v}_{inv}(t)$$

$$- (\mathbf{C}(df_x\mathbf{I}) \mathbf{B})^{-1}\mathbf{C}(df_x\mathbf{I})\mathbf{G}$$

$$+ (\mathbf{C}(df_x\mathbf{I}) \mathbf{B})^{-1}eu_{inv}(t) \quad (8)$$

act as the inverse of (1)-(3). Given the input u(t) to the

- The left ear is tested and fed with the click sound thru the head phone.
- Positive electrode is at the forehead, negative electrode at the ipsilateral(left) mastoid, and ground is at the contralateral(right) temple.
- To test the right ear, negative electrode is switched to the right mastoid and ground is at the left temple.

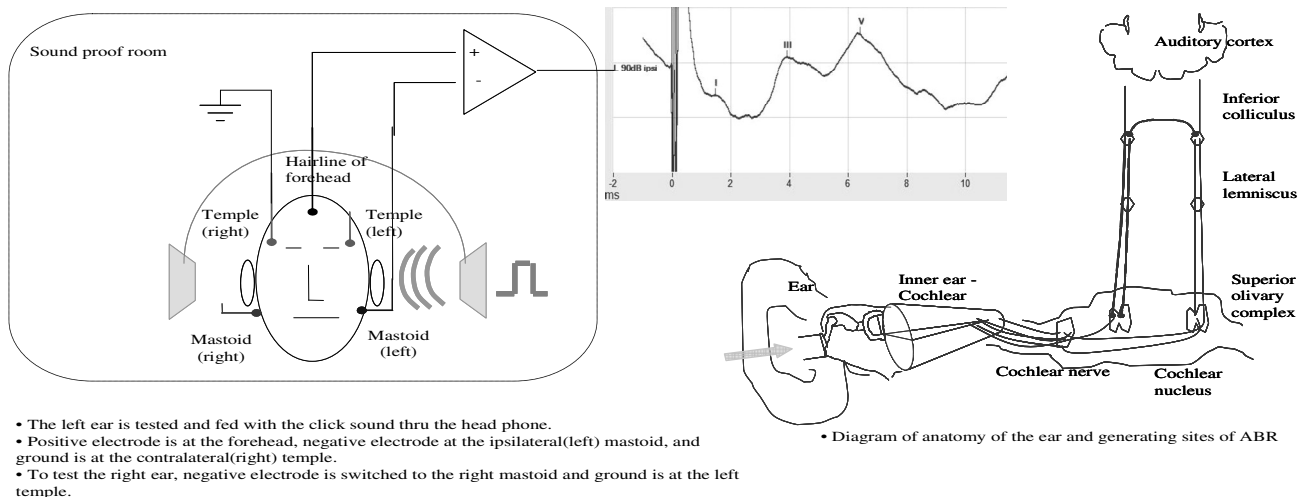- Diagram of anatomy of the ear and generating sites of ABR

Figure 1.   ABR measurement diagram (adapted from [12])

Hopfield network, we can achieve the output from the inverse network which returns u(t) as well, so the inverse is completed.

III.   The System for Noninvasive Correction

In the case of hearing disorders detectable with the change of the click evoked - auditory brainstem response this correction method is applied. Once we achieve the modified Hopfield network and its inverse, system identification is then performed aiming to characterize the normal or damaged characteristics which are later developed into the hearing aid type device. By using the combination of the model inverse to the impaired ear and the model with normal behavior, for which normal can be defined by using established normative values of ABR characteristics or by using the signal measured from the opposite ear if the patient suffers a loss only in one ear. The block diagram of the device via ABR is shown in Fig. 2.
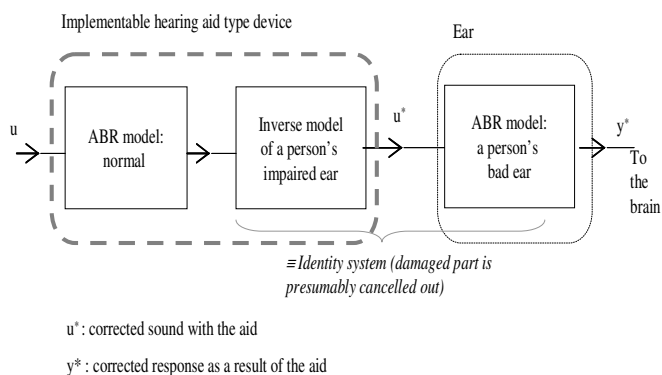

Figure 2.   The hearing aid used with the impaired ear

IV.   Simulation Results And Disscussions

The ABR test of one patient coming in with suspected hearing loss was performed at the King Chulalongkorn Memorial hospital, Bangkok, Thailand as shown in Fig. 3. The air and bone conduction pure tone audiograms suggested high frequency sensorineural hearing loss (SNHL) in the left ear which was later confirmed with the ABR. The ABR of the left ear shows a delay of wave V latency (6.40 ms) as normally resulted from a high tone loss. The reason [4]-[6], [13] is that evoked potential from a click stimulus whose broad frequency spectrum is mainly in the high region is consequently dominated by the activities from the high frequency region of the cochlea (basal part) and high frequency sensitive neurons. Since he has a high frequency SNHL, activities from lower frequency section (apical part) become dominant. Additionally there is no cancellation activity from the high frequency region resulting in longer wave latencies than those measured from normal ears. System identification is done on input and output signals where the number of states used is first found by trial and error search and compared intensively to get as small size as possible with reasonably good fit which was found to be six states. The Hopfield network (1)-(3) is implemented for the left ear as the impaired model. The mean square error between measured and modeled data, $(1/N)\varSigma(y_{measured}(t)-y_{modeled}(t))^2$ where N is the total data size, is
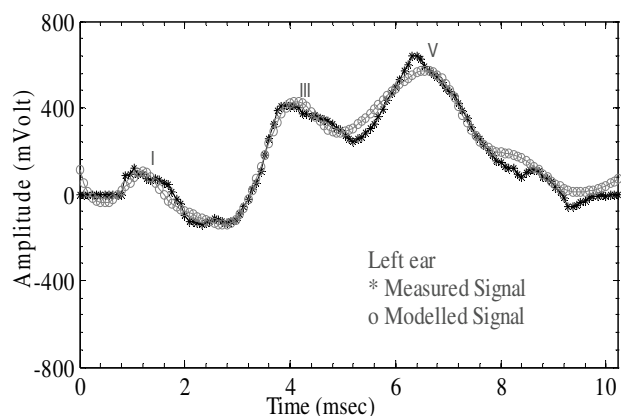

Figure 3. Comparison of measured (*) and modeled (o) ABRs of the impaired left ear
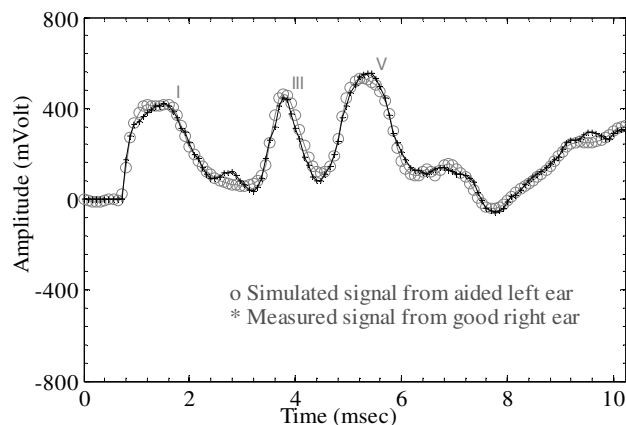

Figure 4. Corrected responses from the impaired left ear with the aid   (from simulation)

minimized returning the model with the best fit. The MATLAB simulation result from the left ear model is also shown in Fig. 3 showing a response in good agreement with the measured one with the 83% fit.

The correction method is applied by deriving the system inverse to this impaired left ear system using (4)-(8). To construct the aid, the normal ear system is required which in this case can be implemented by using the data from the right ear. The response from the aided impaired ear is simulated and shown in Fig. 4 where the correction is applied and the normal type response is achieved. Circuit realization of the device of Fig. 2 is initially designed with the analog behavioral modeling which will be later developed into an analog VLSI chip. A simple circuit of one state of the Hopfield system can be realized as in Fig. 5. The transistorized circuit using basic differential pairs and current mirrors [14] is also given but some scaling is needed before final hardware implementation. The desired ABR response as shown in Fig 6 is retrieved confirming the validity of the method. The preliminary works presented in this paper give a promising first step toward the alternative noninvasive correction. Future works will include the performance evaluations. Some examples of ABR measurement with the aids [15] and in cochlear implant
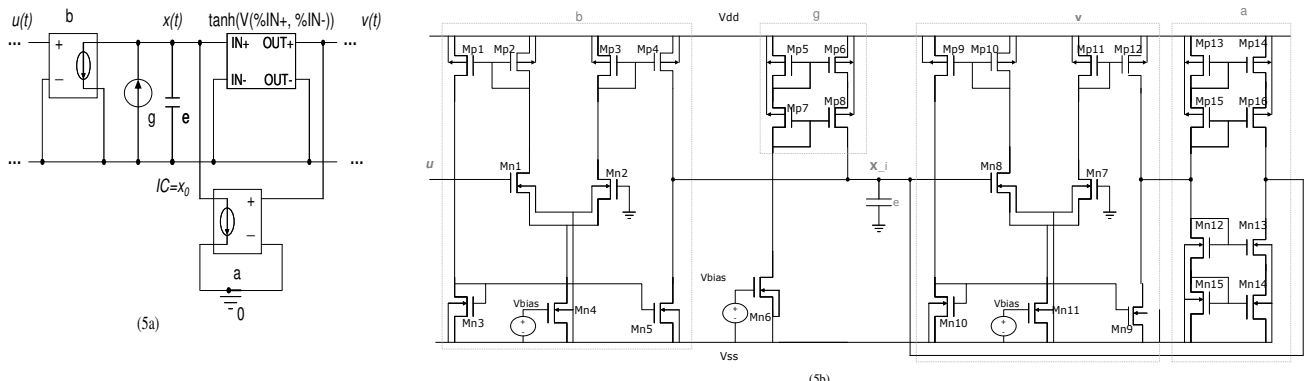
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Figure 5. Circuit realization of a one state Hopfield network (1)-(2) with Fig. 5a) the analog behavioral modeling and Fig. 5b) its transistorized couterpart
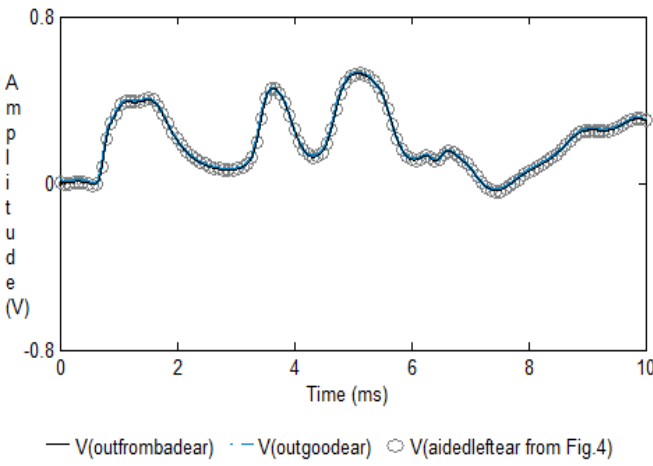

Figure 6. Signal from PSPICE of the impaired ear model with the aid compaired with simulated signal from Fig. 4

patients [6] show the potential of improved sound perception by using the correction of responses investigated here.

V. CONCLUSIONS

A noninvasive correction method of auditory disorder is presented using the modified Hopfield neural network and its derived inverse network. With the help of the auditory brainstem response, a hearing aid type device is developed based on the correction method and potentially compensates the hearing loss effect. Simulation result of the model with the device shows the desired response. The method presented could be found useful in other applications as well, for example, in a control design where the correction method using the inverse neural network can be applied to achieve a desired controlled response or in a speech signal application where the ability to achieve back a certain input from a known output is possible. It provides the alternate noninvasive way to help with the hearing impaired aiming toward patients with mild to moderate hearing loss.

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