LEARNING USER VOLUME CONTROL PREFERENCES IN HEARING AIDS

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1. INTRODUCTION

It has been reported that many users are not satisfied with their hearing aids and would rather not wear them. Some reasons given are the presence of background noise, no perceived added benefit, discomfort, and the difficulty and frequency in which the volume control of the hearing aid has to be adjusted [1]. This paper focuses on advancements in the learning of user control preferences in order to minimize the amount of adjustments being made to the hearing aids over time. Reducing the need for frequent adjustments would create a better listening experience and draw less attention to the fact that an assistive hearing device is being worn. The gains prescribed during the hearing aid fitting process are a good starting point to compensate an individual's hearing loss. However, these gains still need to be adjusted during follow up visits to the audiologist after being worn in real life situations. This process can be tedious and long for both the patient and clinician. Moreover, optimal gain and other control setting requirements may differ according to the specific environments and listening situations encountered by the user, and it is difficult to resolve these needs in the clinic.

The concept of self-learning hearing aids addresses the issues of fine tuning and optimal adjustment by learning what settings the user prefers in environments that are presented on a daily basis. The device has memory and remembers previous settings. At specified points in time, it adjusts the present settings to some combination of the previous settings. Some research has already gone into this and a few devices with self-learning features are currently on the market. The SAVIA© hearing aid from Phonak has a datalogging component that analyzes and stores the volume changes made by the user as they go about their day-to-day activities in each environment. Based on the analysis a volume setting is suggested [2]. The clinician makes a decision on whether or not to include this suggestion at next follow up visits as the device does not automatically update the volume. The CENTRA hearing aid by Siemens is able to learn user preferences for volume in different listening environments. Each time the hearing is turned on it calculates the weighted average of past volume preferences and sets the volume accordingly. The device is typically able to learn the volume preferences for a specific environment on average by the end of the first week [3]. Another hearing aid manufacturer, GN Resound, approaches this issue in a slightly different way. The gain function of the device is adjusted after each volume control change. Features are extracted from the input signal and used in the Automatic Volume Control (AVC) module to calculate a gain. The gain is applied to the input to produce the output that will be heard by the user. The system absorbs changes in the volume control register every time into the AVC module [4]. The parameters of the AVC are adjusted so that the gains applied will put the input at a level preferred by the user.

Currently, a fixed time constant or weighted average is typically used to learn or memorize past user control settings. This should suffice if all users had the same behavior and if this behavior would be identical in all situations or environments. This, however, is not generally the case, and it would be expected that the optimum time constant for learning should be dependent on the user's behavior and environment. In this research, the use of a fixed time constant was tested in different behavioral scenarios for learning volume control preferences; then three adaptive exponential smoothing algorithms were analyzed. The task was to learn what volume control settings the user prefers in different environments with the goal of being able to predict what the user would like when they re-enter the same environments again. Over the course of the day the user switches between different environments. The device should be able to recommend the best initial setting when the user goes into a specific environment.

2. METHOD

The learning algorithm should be robust enough to learn different user behaviors. In order to test the fixed and adaptive methods, it is necessary to have data and performance measures with which to make comparisons. Real volume control preferences selected by users over time are difficult to obtain; therefore, different user behaviors were simulated in this research to supplement any real data to be collected in the future. A user is assumed to have a desired mean volume control setting and a standard deviation around the mean to generate more or less variability in the user's decisions. The basic behaviors generated are fairly constant, fairly fluctuating and fluctuating user. More complex behaviors were generated as combination of these basic behaviors. The volume control setting profile for each user behavior was made up of several phases, where the start and end of a phase signify entering and leaving an environment. These behaviors varied in the amount of time the user spends in an environment, the frequency of changing the volume control, the amount of change and variations in the desired mean within a user profile.

The goal of the learning algorithms is to minimize user intervention when entering a new phase in a given environment. A good learning algorithm should reduce the number of times that the user changes the settings. Even if this calculated value is not exactly what the user wants, it should be as close as possible. In the process of learning, the algorithm should adjust according to the data being used in the analysis and should not give one-sided estimates that are consistently lower or higher than the first initial setting by the user. It is with these considerations in mind that four performance error measures were identified. The first error is the average over all phases in a user profile of the difference between the learned value for a phase and what the user actually sets the device to. The second error measures the average bias of the learned value over all phases of the user profile. The third error is the average root mean squared error between the learned volume setting and the actual user settings for a phase. The last error measure is the percentage of phases in a profile for which the learned value and the initial setting by the user differ by more than 3dB.

In analyzing the fixed method, the optimum time constant for each profile was found. This was to investigate if the best time constant would be the same for each user behavior. This also allowed establishing a baseline reference from which to compare the adaptive algorithms. These were modified from their original implementation to update the time constants at the end of each phase and not on each sample point. Also, the update is based on the value of one of the four errors discussed above.

Firstly, it important to confirm that the adaptive algorithms could indeed perform as well the optimum time constant for a given profile. In doing the comparison for a given profile, the parameters for each of the three adaptive algorithms were tuned to the best values for the profile and the four error measures were calculated. This was then compared to the optimum fixed time constant for the profile.

The performance of the adaptive algorithms was also analyzed over a wide range of profiles. The best adaptive parameters on average were used for these tests since, in practice, the clinician might not able to tune the adaptive algorithms for each user. This was compared to the optimum fixed time constant on average over all user profiles.

3. RESULTS AND DISCUSSION

In finding the best fixed constant for the different profiles generated, it was found that the value of this optimum varied, as expected. The range of time constant that performed best was different for the different profiles. No single time constant would be able to minimize the errors for all the profiles. When the optimum parameters for the Taylor and Chow adaptive methods are used, they are able to perform as good as the best fixed time constant on a profile-by-profile basis. Figure 1 below shows the values obtained for error 1 for a given user profile using some fixed time constants (including the optimum one for the profile) and three adaptive methods. The best average parameter values are used in the adaptive methods.

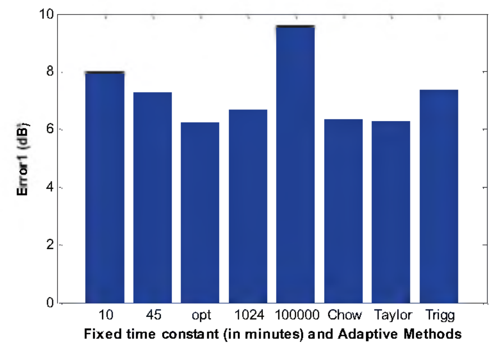

Fig.1. Comparisons of fixed methods and adaptive algorithms using best average parameter values.

It can be seen that very short time constants give a higher error value than the optimum one (about 2 dB). The methods by Chow and Taylor perform as good as the optimum. The simulations carried out show that without having prior knowledge of a person's behavior, using an adaptive algorithm with a good initialization, hearing aid volume control preferences can be learned as well as if the optimum time constant was used for a particular user.

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