AUTOMATIC VOLUME SETTINGS FOR ENVIRONMENT SENSITIVE HEARING AIDS

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1. INTRODUCTION

The development of intelligent devices is becoming a popular trend in the hearing aid industry. Such devices aim at making the user's listening experience more natural and at improving customer satisfaction. One focus of interest in this paper is the automatic adjustment of the hearing aid control settings to minimize the need for manual user interventions. The proposed system is based on computational intelligence tools, namely artificial neural networks and neurofuzzy systems, which have the ability to learn the dynamics of highly nonlinear systems without the need for the explicit knowledge of their mathematical models. Such techniques are adopted here to map the acoustic features (input space) to the desired volume setting (output space) of the hearing aid user. Eventually the proposed system would be integrated into a trainable self-learning hearing aid, such as [1] and [2].

In this paper, two computational intelligence tools, a multi-layer perceptron (MLP) and an adaptive network-based fuzzy inference system (ANFIS) were analyzed on three simulated users with moderate, severe, and profound hearing losses. A hearing aid simulation system provided target volume settings to train and test the learning networks, selected to optimize the speech intelligibility index (SII) in each acoustic situation [3]. The performances of both soft computing models obtained from over 2000 recordings demonstrated a high efficiency of the adopted approach in automatically optimizing volume settings for the three simulated users. The framework of the system is presented in the following section.

2. METHOD

The objective of this paper is to develop an automatic volume control system to optimally match the volume gain preferences of the hearing aid user in different acoustic situations. The automatic volume control system proposed contains the followings stages: a large data set of environmental audio files, feature extraction, selection of the influential features and mapping of features to their optimal volume setting (computational intelligence tool). The system's layout is depicted in Figure 1.

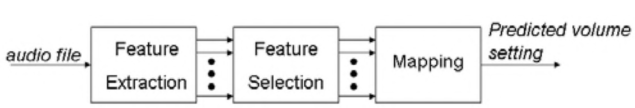

Fig. 1. System's Layout.

2.1 Experimental Data

Audio Files

A virtual environment simulator was used to generate environmental noises. The virtual environment simulator can emulate speech distortion in real environments, thus creating realistic training and testing data for the network. The sound database used for experiments consisted of a total of two thousand noisy speech files, which mimics typical environmental conditions.

Target Volume Settings

Target volume settings are obtained through a simulated hearing aid user assumed to adjust its hearing aid to optimize intelligibility at all times. This set of targets, defined as the volume settings for maximum SII in all environment conditions, is required to train the networks to map features into optimal volume settings. Users with moderate, severe and profound hearing loss (HL) and different uncomfortable listening levels were simulated.

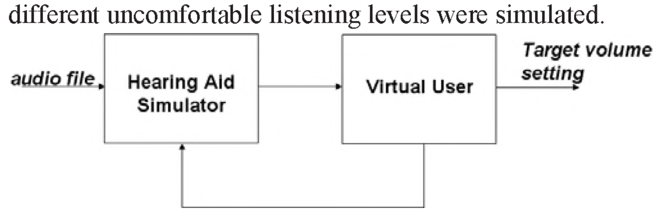

Fig. 2. Generation of target volume settings.

2.2 Feature Extraction

To perform mapping of the feature input space to the output space, it is desirable to extract a set of feature vectors which preserves information that is highly correlated to the output space. Doing so will improve the performance of the network and decrease processing time. Twenty-four real valued features were considered, including a number of frequency-domain and time-domain features. Features were extracted from frames of a sampled audio signal, with no overlap between frames.

2.3 Feature Selection

Feature selection can provide a sub-optimized set of features and reduce the dimensionality of the feature vector. The selection criteria typically involves the minimization of a measured error from models with different inputs. A starting set of 24 features is considered, and then a subset of highly correlated features is selected by using a feature selection method known as the sequential forward search (SFS) [4]. The SFS method was used to select three sets of influential features. Each set corresponds to a certain simulated user (moderate, severe and profound) and includes six influential features.

2.4. Mapping

Two computational intelligence tools were considered to perform the mapping, the MLP and ANFIS models [5], which were analyzed on the three simulated users.

Learning Process

The learning process for both the MLP and ANFIS models is divided into three phases: training, validation and testing. The training process requires a set of network inputs and target outputs for the models to learn (shown in Figure 2). Training allows the models to become familiar with every possible situation. Validation improves the models' generalization during testing and avoids the models from "overfitting" the training data. Finally, the testing stage provides the models with unfamiliar data and will determine the models' robustness and ability to make generalizations on unfamiliar data.

3. RESULTS

For cross-validation, the data set is partitioned into three groups, 1200 files (60%) for training, 400 files (20%) for validation and 400 (20%) for testing. The performance of the models is measured by determining how accurate the predicted outputs of the models are, after training and testing. The predicted output of the model is compared against the target signal and when the mean square error between the two is minimized, the performance of the model is maximized. The performance measure is evaluated by the volume error (VE) and the absolute value of the speech intelligibility index error (SIIE), presented in the following equations:

$$VE(i)=V_{opt}(i) - V_{pred}(i) \quad (1)$$

$$SIIE(i) = |SII_{opt}(i) - SII_{pred}(i)| \quad (2)$$

where i refers to each pattern, the subscript *opt* and *pred* refer to the target and the quantity predicted by the network, respectively.

Figure 3 presents the MLP's testing performance. The plot is the volume error (equation 1) for each testing pattern for the moderate HL user. At first glance, there are a number of volume errors greater than 20 dB. However, this may not necessarily result in a high SII error. Indeed, Figure 4 demonstrates that the great majority of the audio files resulted in a low SII error (equation 2).

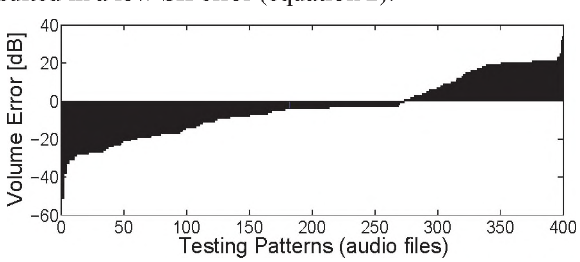

Fig. 3. Volume error plot. MLP's testing performance for the moderate HL user.

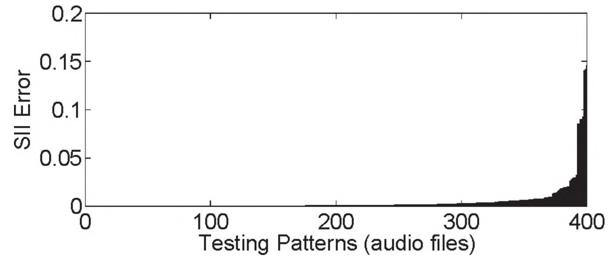

Fig. 4. SII error plot. MLP's testing performance for the moderate HL user.

Figure 5 compares the testing performances of the MLP and ANFIS models for the moderate user. For 95% of the testing patterns, the MLP's performance obtained an SII error of less than 0.02 and ANFIS obtained an SII error of less than 0.005. This demonstrates ANFIS's ability in optimizing the moderate HL user's speech intelligibility more effectively.

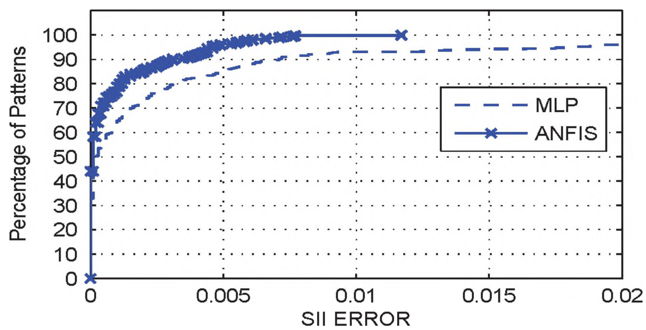

Fig. 5. SII error plot of MLP versus ANFIS testing performances for the moderate HL user.

4. DISCUSSION

From the plots presented in the results, the MLP optimized the volume setting for the majority of the testing patterns for the moderate HL user. As a result the speech intelligibility index for the moderate HL user was optimized as well. In conclusion, both the MLP and the ANFIS showed high accuracy in automatically optimizing the SII for a simulated user. ANFIS performance in terms of SII error is slightly advantageous compared to the MLP's performance. A future direction of this research is to test the proposed system on real human subjects.

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