ADAPTIVE ENVIRONMENTAL CLASSIFICATION SYSTEM FOR HEARING AIDS

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1. INTRODUCTION

Hearing aids are customized for the user's specific type of hearing loss and are typically programmed to optimize each user's audible range and speech intelligibility. There are many different types of prescription models that may be used for this purpose [1], the most common ones being based on hearing thresholds and discomfort levels. Each prescription method is based on a different set of assumptions and operates differently to find the optimum gain-frequency response of the device for a given user's hearing profile. In practice, the optimum gain response depends on many other factors such as the type of environment, the listening situation and the personal preferences of the user. The optimum adjustment of other components of the hearing aid, such as noise reduction algorithms and directional microphones, also depend on the environment, specific listening situation and user preferences. It is therefore not possible to optimize the listening experience for all environments using a fixed set of parameters for the hearing aid. It is widely agreed that a hearing aid that changes its algorithm or features for different environments would significantly increase the user's satisfaction [2]. Currently this adaptability typically requires the user's interaction through the switching of listening modes.

New hearing aids are now being developed with automatic environmental classification systems which are designed to automatically detect the current environment and adjust their parameters accordingly. This type of classification typically uses supervised learning with predefined classes that are used to guide the learning process. This is because environments can often be classified according to their nature (speech, noise, music, etc.). A drawback is that the classes must be specified a priori and may or may not be relevant to the particular user. Also there is little scope for adapting the system or class set after training or for different individuals.

In this paper, an adaptive environmental classification system is introduced in which classes can be split and merged based on changes in the environment that the hearing aid may encounter. This results in the creation of classes specifically relevant to the user. This process would continue to develop during the use of the hearing aid and therefore adapt to evolving needs of the user.

2. METHOD

2.1 Overall System

Figure 1 shows the block diagram for the adaptive classification system. First, the sound signal received by the hearing aid is sampled and converted into a feature vector via feature extraction. This step is a very crucial stage of classification since the features contain the information that will distinguish the different types of environments [3]. The resulting classification accuracy highly depends on the selection of features. The feature vector is then passed on to the adaptive classifier to be assigned into a class, which in turn will determine the hearing aid settings. However, the system also stores the features in a buffer which is periodically processed to provide a single representative feature vector for the adaptive learning process. Finally, the post processing step acts as a filter, to remove spurious jumps in classifications to yield a smooth class transition. The buffer and adaptive classifier are described in more detail below.

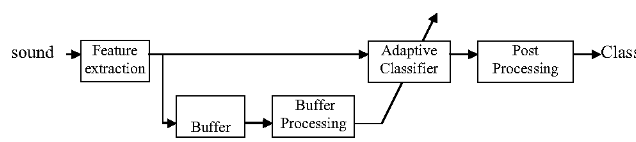

Fig. 1: Adaptive Classification System

2.2 Buffer

The buffer stage consists of an array that store past feature vectors. Typically, the buffer stage can be 15-60 seconds long depending on the rate at which the adaptive classifier needs to be updated. This allows the adaptation of the classifier to run at a much slower rate than the ongoing classification of input feature vectors. The buffer processing stage calculates a single feature vector to represent all of the buffered data, allowing a more accurate assessment of the acoustical characteristics of the current environment for the purpose of adapting the classifier.

2.3 Adaptive Classifier

The adaptive classification system is divided into two phases. The first phase, the initial classification system, is the starting point for the adaptive classification system when the hearing aid is first used. The initial classification system organizes the environments into four classes: speech,

speech in noise, noise, and music. This will allow the user to take home a working automatic classification hearing aid. Since we are training the system to recognize specific initial classes, a supervised learning algorithm is appropriate.

The second phase is the adaptive learning phase which begins as soon as the user turns the hearing aid on following the fitting process, and modifies the initial classification system to adapt to the user-specific environments. The algorithm continuously monitors changes in the feature vectors. As the user enters new and different environments the algorithm continuously checks to determine if a class should split and/or if two classes should merge together. In the case where a new cluster of feature vectors is detected and the algorithm decides to split, an unsupervised learning algorithm is used since we do not have any a priori knowledge about the new class.

3. TEST RESULTS

The following example illustrates the general behavior of the adaptive classifier and the process of splitting and merging environment classes. The initial classifier was trained with two ideal classes, meaning the classes have very defined clusters in the feature space as seen in Figure 2a). The squares in the center of each cluster represent the class centers. These two classes represent the initial classification system. Figure 2b) shows the test data that will be used for testing the adaptive learning phase. As the figure shows, there are four clusters present, two of which are very different than the initial two in the feature space. The task for the algorithm is to detect these two new clusters as being new classes. To demonstrate the merging process, the maximum number of classes is set to three. Therefore two of the classes must merge once the fourth class is detected.

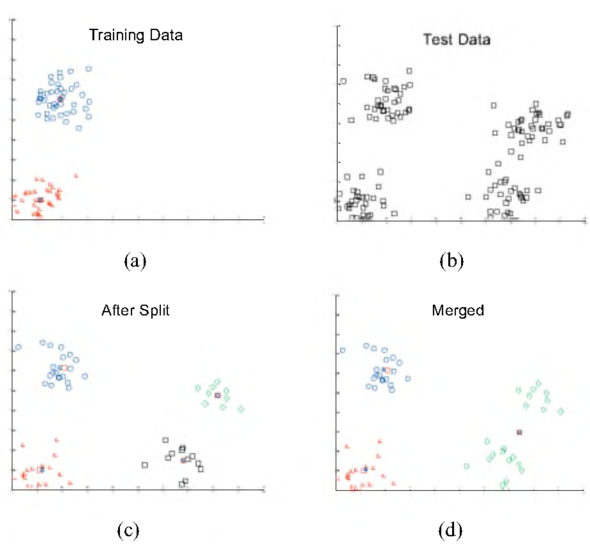

Fig. 2: a) Training data for initial classification; b) Test data for adaptive learning algorithm; c) After splitting two times; d) After merging of two classes

3.1 Splitting

While introducing the test data, a split criterion is continuously monitored and checked until enough data lies outside of the cluster area. This sets a flag that then triggers the algorithm to split the class into two. Figure 2c) shows the data after the algorithm has split and detected the two new classes.

3.2 Merging

Once the fourth cluster is detected and the splitting process occurs, as shown in Figure 2c), the merging process begins where two classes must merge into one. Figure 2d) shows the two closest clusters merging into one, thus resulting with three classes, the maximum set in this example.

4. DISCUSSION

This paper introduced a new adaptive classification system for hearing aids which would allow the device to track and define environmental classes relevant to each user. Once this is accomplished the hearing aid may then aim to learn the user preferences (volume control, directional microphone, noise reduction, etc.) for each individual class. Further work is ongoing to determine the best algorithm for the split and merge process.

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