Towards Developing a Brain-computer Interface for Automatic Hearing Aid Fitting based on the Speech-evoked Frequency Following Response

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1 OBJECTIVES

One of the problems related to the use of hearing aids (HAs) is the difficulty in obtaining a best fit by adjusting different settings, such as those related to the gain and compression in different frequency bands. To help guide the process of fitting, some studies have proposed the use of neural responses to different sounds to give objective measures of hearing aid performance (e.g. Billings et al., 2011, Dajani et al., 2013).

In this work, we propose taking this approach one step further and use the information extracted from the brain's frequency following response (FFR) to speech sounds to automatically adjust the settings of HAs via a brain-computer interface (BCI) (Fig. 1).

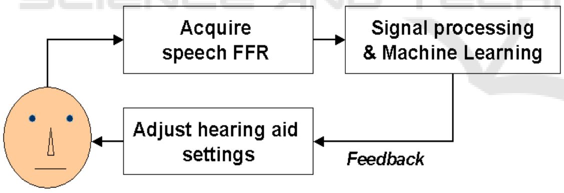

Figure 1: Schematic showing how a brain-computer interface (BCI) would use the speech-evoked frequency following response to automatically adjust hearing aids.

2 METHODS

2.1 Proposed BCI based on the Speech FFR

The speech FFR is particularly interesting because it reflects auditory processing by several nuclei, but unlike cortical responses which are highly abstracted, it is still recognizable as a "speech-like" signal that contains a fundamental frequency (F0) that follows that of the stimulus, as well as higher frequency components that follow those in the stimulus up to the upper limit of neural phase-locking. In fact, if played back as an audio recording, the speech FFR can be intelligible.

The question then becomes how to use the rich spectro-temporal information present in the speech FFR to improve the experience of the impaired listener who wears a HA. Some possibilities include adjusting the settings of the HA so that:

1) The FFR returns to a more "normal-hearing" pattern. However, this may not be possible in principle due to the nonlinear properties of the cochlea (Giguère and Smoorenburg, 1999).

2) The correlation between spectral content of the FFR and stimulus is maximized (Kraus and Anderson, 2012). However, this may not be a desirable target since the FFR reflects transformations in different nuclei of the auditory pathway (Dajani et al., 2013).

3) A normal balance is restored between the envelope FFR (eFFR), which follows the envelope at F0 and its low frequency harmonics, and the spectral FFR (sFFR) which primarily follows the harmonics around the first or second formants (Anderson et al., 2013). However, although it has been suggested that imbalance between these two responses occurs in hearing impairment, the extent and implication of this imbalance is not yet fully understood.

4) The separation between neural responses to different phonetic classes is maximized in tasks of automatic classification. The hypothesis is that this would allow the hearing aid user, particularly if suffering from profound hearing impairment, to discriminate better between the different phonetic classes. Our goal is to develop and test this approach.

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2.2 Data Collection

The speech FFRs of 22 (11F, 11M) normal-hearing adult subjects (20-35 years) to four 100ms synthetic English vowel stimuli with F0=100Hz (F1:/a/=700Hz, /ɔ/=600Hz, /U/=500Hz, /u/=300Hz) at four levels (55, 65, 75, 85 dBA) were recorded. Repeated-measures ANOVAs were performed on the RMS-amplitude of the spectral data for F0 and then for the combination of its next five harmonics (H2 to H6) in the eFFR, and for F1 and then for the combination of F1 and one harmonic on either side of it in the sFFR. Post-hoc pairwise comparisons with Holm-Bonferonni corrections were also performed.

This baseline dataset will be used with an automatic classification task before proceeding to speech FFRs collected from hearing impaired subjects and implementing the full BCI.

3 RESULTS

Significant effects of level were found at F0 in the eFFR and at F1 in the sFFR ($p<0.01$ in all cases). The combined harmonics show effects of level ($p<0.001$ in all cases), as well as significant pairwise comparisons between most levels. Interestingly, although F0 exhibits change in the eFFR across all four of the vowel stimuli, its amplitude does not grow consistently with increasing level, and it in fact appears to saturate at 65 dBA and then decrease in amplitude in all of the vowel stimuli except for /u/, which exhibits strictly increasing growth.

The trend that emerges is one of increasing spectral richness with increasing level via the growth of the harmonics of F0 in the eFFR and via the growth of the first formant and its related harmonics in the sFFR.

Initial machine learning models aimed at exploiting these trends appear promising. Using a 10-fold cross-validation technique, a support-vector machine was trained and tested on a mix of features from both the eFFR and sFFR. A mean vowel classification accuracy of 80.5% was achieved when the model was restricted to the 85dBA case, which is comparable to the result reported by Sadeghian et al. (2015). Additionally, a correlative algorithm that was used to predict sound level across all vowel categories yielded a 2.2-fold increase in accuracy versus the null model, and a 79% reduction in misclassifications of levels greater than 10dB from the target. Since the spectra of within-subject test-retest trials are highly correlated (ranging from $r=0.79$ to $r=0.96$ across all vowels), we would expect much higher classification accuracy on models trained solely on individual subjects, provided that enough individual data is recorded.

4 DISCUSSION

These findings suggest that effects of sound level can be observed in the speech FFR of normal hearing adults, both with respect to the neural encoding of the envelope and the spectral fine structure of the speech signal. Machine learning techniques can be used to automatically classify vowels and sound level, particularly in individual subjects. This approach will be used to tune hearing aids to maximize the separation between the responses to different vowels and levels, with the aim of improving perceptual discrimination and loudness control in hearing aid users.

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