Proof-of-Concept of a Smart Hearing Protector for Auditory Sensitivities in Individuals with Autism Spectrum Disorder

Danielle Benesch*[1,2,3], Stefanie Blain-Moraes†[1,3], Jérémie Voix‡[2,3]

[1]Biosignal Interaction and Personhood Technology Lab, McGill University, Montréal, Canada
[2]NSERC-EERS Industrial Research Chair in In-Ear Technologies, Université du Québec (ÉTS), Montréal, Canada
[3]Centre for Interdisciplinary Research in Music Media and Technology, McGill University, Montréal, Canada

When conventional hearing protection is worn to manage auditory sensitivities, over-attenuation can prevent the wearer from fully engaging with their surrounding environment. A "smart" hearing protector could overcome this limitation by attenuating distressing sounds while relaying sounds that are useful for the wearer to hear. This project envisions a hearing protector that can selectively filter out the sounds each individual wearer is sensitive to, learning these sounds in real-time using biosignals captured from within the ear as indicators of distress. Prior to development, the device requirements will be characterized. The comfort and attenuation of an existing in-ear technology will be assessed in a group of students with auditory sensitivities. The auditory classroom environment will be recorded, and distressing as well as useful sounds will be identified. Multiple methods of real-time audio filtering will be considered, including those based on the detection of sound events in the signal in addition to classical signal processing techniques. The filtering scheme(s) ultimately selected will depend on the properties of the identified sounds. Once the device is developed, it will be evaluated with individuals on the autism spectrum. If successful, this project will serve as a proof-of-concept of smart hearing protection as an intervention to address auditory sensitivities.

Introduction

Auditory sensitivities are common among individuals with Autism Spectrum Disorder (ASD) [25]. Several studies have explored the effectiveness of hearing protection as an intervention to address sensitivities of children with ASD, with some promising results [20, 21, 8]. However, conventional passive hearing protection devices (HPDs) attenuate all ambient sounds and do not distinguish between sounds causing distress and those conveying information. Conventional passive HPDs used to block out distressing sounds may therefore attenuate too much sound for the wearer, which can prevent children with ASD from being fully engaged with their environment [20].

A possible solution to the problem of over-attenuation is a “smart” HPD [12] that incorporates an external microphone, an internal miniature loudspeaker and a digital signal processor (DSP) in between, enabling the transmission of "useful" signals while blocking the ears from unwanted sounds. One research focus of the NSERC-EERS Industrial Research Chair in In-Ear Technologies (CRITIAS) is precisely the development of such smart HPDs for noisy industrial workplaces. This existing technology could be adapted to address auditory sensitivities by filtering out distressing sounds while retaining those that are relevant for participation in everyday activities. Recent advances in machine learning have offered promise for automatic environmental sound classification, with accuracy exceeding that of humans in some cases [23]. If machine learning techniques can effectively detect the sounds that children with ASD experience as distressing, a smart HPD incorporating these techniques could suppress the signal only when the distressing sounds are present.

Individuals with ASD may become distressed by different sets of sounds [25]; therefore, a device designed to address auditory sensitivities would preferably be customized to the needs of each wearer. A smart HPD could conceivably adapt to the idiosyncratic sensitivities of individual wearers by incorporating biosignal processing to detect distress. The ear canal may be an ideal place to collect such biosignals [27]. HPDs that acoustically seal the ear create a so-called occlusion effect, amplifying bone-conducted sounds within the ear canal [2]. These amplified sounds can be recorded with an in-ear microphone and classified automatically [4]. Heartbeat and respiratory signals are among the audio events that can be extracted from in-ear microphone data [15]. These biosignals are widely used in emotion recognition [24, 7]. A smart HPD measuring distress with in-ear biosignals has the potential to automatically learn the unique set of sounds each individual is sensitive to and attenuate when these sounds occur.

A current limitation of developing a smart HPD for individuals with ASD is the scarcity of data to inform how such a device could fit their needs. This paper outlines the methodology of a research project aiming to identify the constraints for developing a smart HPD for students with ASD and auditory sensitivities, to develop a device given these constraints, and to pilot this device as a proof-of-concept. The next section presents the proposed device in more detail. Section 3 describes the plans and goals for each phase of the project. The paper concludes with the expected contributions of the project.

Envisioned Device

The Auditory Research Platform

The Auditory Research Platform (ARP) is an in-ear wearable technology developed within the NSERC-EERS Industrial Research Chair in In-Ear Technologies (CRITIAS) consisting of two earpieces and a small, portable computer (mini-PC), pictured in Fig. 1. Each earpiece, illustrated in Fig. 2, contains an outer-ear microphone (OEM), an in-ear microphone (IEM), and an internal miniature loudspeaker (SPK). External sound is recorded by the OEM and can be processed by the embed-

*danielle.benesch.1@ens.etsmtl.ca
†stefanie.blain-moraes@mcgill.ca
‡jeremie.voix@etsmtl.ca

ded DSP. The processed sounds can then be played in the wearer's ear through the internal loudspeaker.

Figure 1: Overview of the Auditory Research Platform (ARP) used, featuring 2 wired earpieces, one high-precision audio acquisition card, one micro-PC, one touch screen and stylus, and one extra battery pack. Source: Ref. [17] with permission.

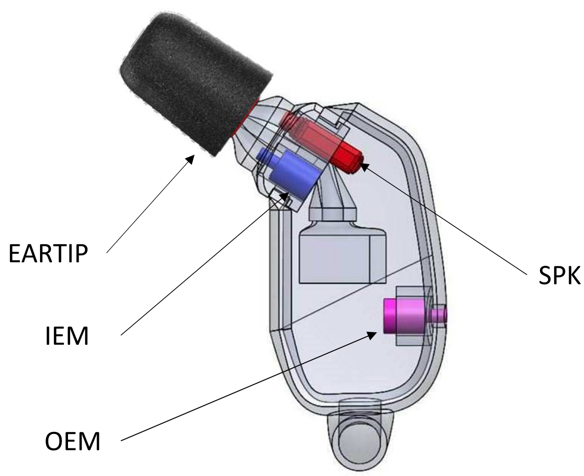

Figure 2: Detailed view of one ARP earpiece, featuring an outer-ear microphone (OEM), an in-ear microphone (IEM), and an internal miniature loudspeaker (SPK). External sound is picked-up by the OEM and can be processed by the micro-PC before being played back on SPK. The disposable eartip is a conformable roll-down foam tip. Source: Ref. [3] with permission.

Proposed features

Acoustically transparent mode. Conventional passive HPDs used to block out distressing sounds may attenuate too much ambient sound and isolate the wearer. Such over-attenuation has been identified as a potential barrier of children with ASD using HPDs during everyday activities [20], and with time, over-avoidance of noise may maintain sensitization to sounds [10]. The ARP could be used to prevent over-attenuation and over-avoidance by picking up external sounds through the outer-ear microphones and playing these back through the internal speakers. This proposed "transparent mode" could be implemented as a linear audio amplifier with a gain of 0 dB, enabling acoustical path-through. The architecture of this implementation is shown in Fig. 3. This setting could be manually controlled (e.g. with switch control "A"), allowing the wearer to choose between "isolation" and "transparency" modes without removing the device, and the ARP could be programmed to automatically record the timestamps of each change in setting. These timestamps coupled with the microphone recordings could yield a trove of data for evaluating how transparent mode is used among individuals with ASD, which is needed to understand the potential benefits of such a setting [21].

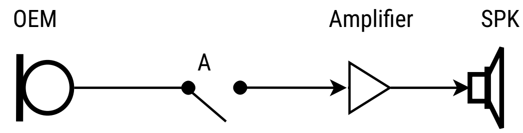

Figure 3: Possible architecture of the acoustically transparent and isolation modes: if the wearer turns on "transparency" mode (A), the signal from the outer-ear microphone (OEM) is transmitted to the amplifier and internal loudspeaker (SPK). Otherwise, the earpiece is in "isolation" mode.

Level-dependent audio filtering. In order to maximize the ability to participate in the classroom while minimizing sound-induced distress, basic signal processing techniques may be used to attenuate only certain sounds and not others, resulting in an automated switching between transparency and isolation modes. One way that distressing sounds might be identified is by their magnitude or level (i.e. the associated sound pressure level) and a whole category of level-dependent audio filtering can be utilized: A "blocker" could block the playback of sounds above a certain level threshold, in the case that loud sounds are identified as distressing or even as a safety feature to prevent hearing loss. Clipping or dynamic range compression could also be used to attenuate louder sounds [6] without completely removing them from the signal transmitted to the internal loudspeaker. Some individuals with ASD have reported sensitivities to quiet noises in addition to loud ones [11]. In this case, a noise gate could be used to remove sounds below a certain level threshold [30]. These basic level-dependent filtering schemes are illustrated in Fig. 4. However, these level-dependent audio filters solely rely on the level of the ambient sound and are only effective when the level of the distressing sounds is distinguishably above or below the level of sounds considered to be "useful". In practice, sounds identified as distressing for individuals with ASD may not reach either of these high or low level extremes but rather carry a time and frequency content that is specifically distressing.

Content-dependent audio filtering. As some distressing sounds may not be removed solely by the level-dependent audio filters, a new class of audio filter, referred to as "content-dependent", should be used to enable attenuation of these distressing sounds in real-time. A first approach could be to consider that all sounds but voice are distressing and to only let speech get through the smart hearing protector. Voice Activity Detectors (VAD) are standard algorithms in telecommunication used to detect the presence of speech [13]. They have already been proposed as an intervention for auditory sensitivities [12]. This first content-dependent approach would be rather drastic as all sounds other than speech would be removed (see Fig. 4), likely resulting in over-protection and over-avoidance issues.

A possible alternative is to detect the distressing sounds using machine learning techniques for sound event classification (as illustrated in Fig. 6). Audio classification has been accomplished with traditional classifiers, e.g. with Gaussian Mixture Models [16], and more recently, deep learning, e.g. with Deep Convolutional Neural Networks [23, 1].

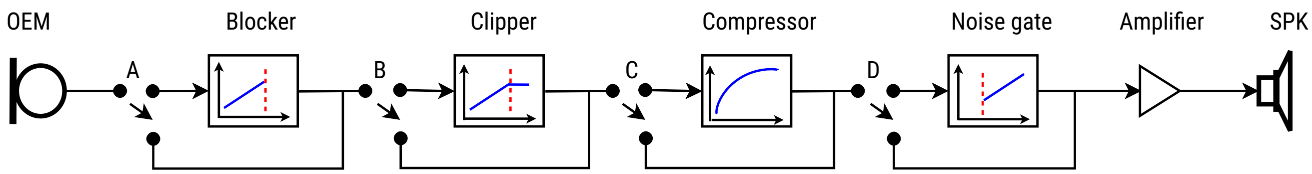

Figure 4: Possible architecture of level-dependent audio filters: a signal from the outer-ear microphone (OEM) could be processed by a blocker (A), clipper (B), compressor (C), and noise gate (D) before being transmitted to the audio amplifier and internal loudspeaker (SPK). They can be used individually or in any combination, thanks to the switch controls A-D.

Some methods extract features such as Mel-Frequency Cepstral Coefficients [23, 16, 4], while others learn directly from the raw waveform [1]. The method ultimately used will depend on constraints created by the acoustic properties of the sounds to be classified, the dataset size, and the computational power of the ARP.

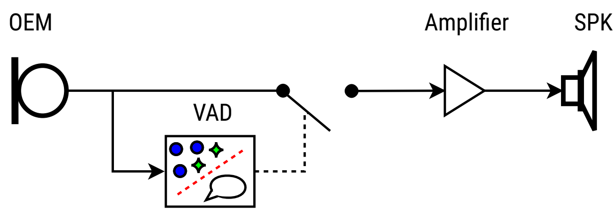

Figure 5: Possible architecture of a first content-dependent audio filtering approach: a signal from the outer-ear microphone (OEM) could be processed by the Voice Activity Detector (VAD). If - and only if - speech is detected, the ambient signal is transmitted to the amplifier and played back by the internal loudspeaker (SPK).

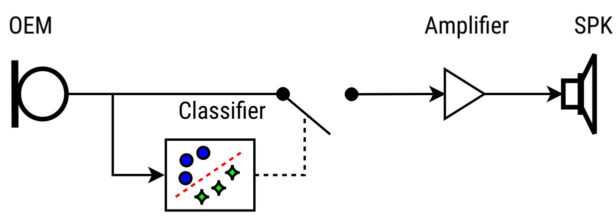

Figure 6: Possible architecture of the second content-dependent audio filtering approach: a signal from the outer-ear microphone (OEM) could be processed by the classifier. If the classifier detects a distressing sound, the signal is suppressed. Otherwise, the ambient signal is transmitted to the amplifier and played back by the internal loudspeaker (SPK).

Customized content-dependent audio filtering with biosignal processing. Children with ASD may be sensitive to different constellations of sounds, as ASD is a complex condition that affects individuals differently [25]. This complexity calls for technology supporting customization [14]. One conceivable way of customizing HPDs for children with ASD would be to automatically learn an individual's unique set of distressing sounds using biosignal data (as illustrated in Fig. **??**). Heart and respiratory rates can be extracted from the ARP's in-ear microphone recordings [15]. These biosignals could be used as input in a multi-modal classification algorithm to detect the sounds that distress the individual wearer. Given training data containing a complete set of sounds that a wearer may be sensitive to, a smart HPD could, over time, learn the subset of sounds that cause distress in the wearer. This learning would be based on how changes in the biosignals correlate to the occurrence of potentially distressing sounds. Once a set decision threshold for classifying the sounds as distressing is reached, the HPD could begin attenuating when these identified sounds are present in the signal.

ANTICIPATED LIMITATIONS

Smart HPD Comfort Sensory sensitivities in ASD are not limited to the auditory domain [22]. HPDs and specifically in-ear devices (often referred to as earplugs, earpieces or intra-aural devices) may be too uncomfortable for some children with ASD: a study exploring the barriers and benefits of HPDs among children with ASD indeed identified discomfort as a barrier of an in-ear device [20]. However, using around-the-ear (often referred to as earmuffs or circum-aural devices) devices would block localization cues that are key for situational awareness: the distance of any outer-ear microphone from the ear itself would distort interaural time (ITD) and level (ILD) differences, and any device covering the outer ear would block access to any cues resulting from the resonances and anti-resonances of the pinna [2]. As perceiving changes in the environment is crucial for interacting with it, reduced situational awareness caused by an around-ear device would already constitute an obstacle to participating in everyday activities. Therefore, only an in-ear device will be considered for this project. Nevertheless, great attention to the earpiece material and structure will aim to maximize comfort, and participants' tolerance of the smart HPD will be assessed before use.

Smart HPD Processing Power Another limitation of the smart HPD results from the computational power constraints of the ARP. These constraints must be accounted for while determining how to implement the filtering features, as real-time filtering requires low latency in order to be effective and comfortable. If the audio filter processing time is too long, the synchronization of audio and visual information could be disrupted, in particular lip synchronization with speech. It has been found that latency between video and audio begins to be perceptible above 25 ms [29]. For children with ASD, the effect of latency on the perception of audiovisual asynchronies may be more complex [19].

A further issue arises from the - necessarily limited - attenuation provided by the HPD. While the attenuation of ambient sounds can be expected to range between 20 to 35 dB (with the exact amount of attenuation depending on the frequency content of the sound as well as the proper fit of the device), the residual level of very loud sounds will remain sufficient to be perceptible. If the latency of the audio processing is too high, sounds that are still perceptible will be heard first, with the processed sound played through the internal loudspeakers perceived as an echo. Research (with neurotypical adult participants) on the shortest delay needed to produce such an echo effect, referred to as the "echo threshold" or the delay of the "just noticeable difference", has found a threshold of 26 ms for clean speech given a deeply fitted HPD [18]. While this short latency may be quite easily achievable with the "level-dependent" filtering approach, it may require substantial optimization of the real-time "content-dependent" algorithms.

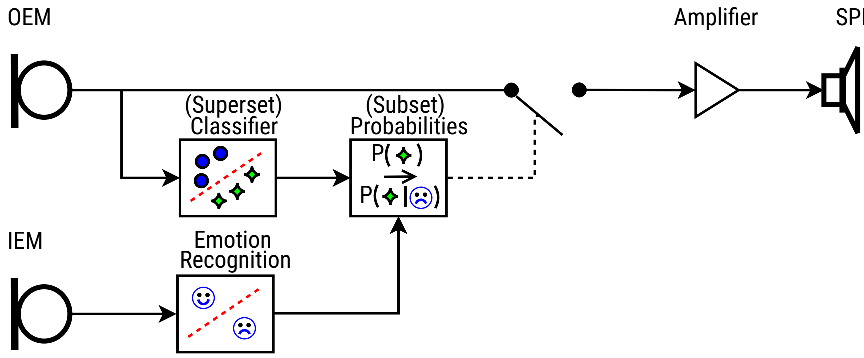

Figure 7: Possible architecture of the third content-dependent audio filtering approach: a signal from the outer-ear microphone (OEM) could be processed by the "superset" classifier. If the classifier detects a sound that is a member of the superset (potentially distressing sounds), the probability of this sound being a member of the wearer subset (sounds that are distressing for the individual wearer) is updated given the output of the emotion recognition algorithm. The emotion recognition is based on biosignals extracted from the in-ear microphone (IEM) signal. If the updated probability is above a set threshold, the signal from the OEM is suppressed. Otherwise, the ambient signal is transmitted from the OEM to the amplifier and played back by internal loudspeaker (SPK).

Research Plan

Characterization

To inform the development of the envisioned device, the needs of the target population and any resulting constraints should be identified. To this end, there are several steps to be taken:

Evaluating the ARP in the target population. In collaboration with a local school for children with disabilities, the comfort and attenuation of the ARP will be characterized in a group of students. Slow-recovery foam eartips of various sizes will be available for fitting the ARP, and at least two configurations of the earpiece will be available. The in-ear and outer-ear microphones in the ARP enable field-microphone-in-real-ear (FMIRE) fit-testing [28], an objective measurement of individual attenuation that does not rely on participant reports. With the assistance of the research team, participants will report their comfort on a seven-point Likert scale. For the participants that can tolerate wearing an in-ear device, the most comfortable combination of ear tip and earpiece that is deemed to sufficiently attenuate will be selected.

Anticipating the needs of the target population. To develop the optimal audio filtering scheme, it must be determined which sounds need to be attenuated, as well as which sounds need to be heard by the students. At the school, teachers will be requested to complete questionnaires about the sounds that are disruptive for their students. The classroom environment will be observed with the aim of identifying distressing sounds as well as sounds that are relevant for students' participation in the classroom (e.g. the teacher's voice). Several students and teachers will be interviewed about the disruptive sounds in more detail. Those interviewed will also be asked about the perceived benefits and challenges of a smart HPD.

Estimating the expected detector performance. At the school, the classroom environment will be recorded. These recordings will be annotated according to the sounds that are identified as distressing, as well as those that are determined to be relevant for students' participation in the classroom. In addition to the recordings of the natural classroom environment, at least 50 samples of 3 commonly distressing sounds will be recorded separately. A dataset including distressing and relevant sounds will be created and used to train multiple machine learning algorithms for sound event detection. Multiple methods of feature extraction will also be considered. The classification speed and performance will be compared, aiming to select an algorithm that achieves a good balance of low latency and high performance.

Examining the relationship between emotional states and in-ear biosignals. In order to estimate the feasibility of classifying distressing sounds with in-ear biosignals, it must be determined whether such biosignals are reliable indicators of distress. This could, for example, be determined by assessing whether changes in in-ear biosignals are associated with certain experimentally-induced emotional states. When the smart HPD is evaluated in the classroom environment, the relationship between in-ear biosignals and the occurrence of distressing sounds in the outer-ear microphone data could be studied to validate whether such biosignals reliably indicate noise-induced distress specifically.

Development

Once the device requirements have been defined, algorithms for filtering out the identified distressing sounds will be implemented on the ARP:

Implementing a level- or content-dependent audio filter. Which signal processing techniques are implemented will depend on the acoustic features of classroom sounds as well as the anticipated consequences of modifying the signal. For example, if it is determined that students are distressed by sounds that are of level considerably higher than any sounds that are relevant for their participation in the classroom, any sounds above a specified sound pressure level could be attenuated. However, the techniques used in order to achieve this attenuation must be carefully considered in order to avoid causing more discomfort. Clipping is known to distort the signal [6, 30]. There are many parameters to consider while implementing dynamic range compression, including the attack time, the release time, the compression threshold, the compression rate, and whether the compression is single-band or multi-band. Depending on the implementation, a compressor can cause a number of undesirable effects such as audio feedback, disruption of intensity cues, and distortion of speech [6]. Multiple techniques will be tested with the aim of ultimately selecting a combination that minimizes latency, distortion of relevant sounds such as speech, discomfort resulting from digital artifacts, and discomfort resulting from the identified distressing sounds. Based on these factors, a VAD-based filter may also be included.

Implementing a customized content-dependent audio filter. If it is determined during the characterization phase that in-ear biosignals are reliable indicators of distress, the generic content-dependent filter will be extended to learn the sounds that distress individual wearers rather than filtering all of the sounds in a predefined set. To this end, biosignal data extracted from in-ear microphone recordings will be labeled for distress and used to train a classifier in order to incorporate emotion detection into the filter. A threshold for classifying the sounds as distressing will be defined, and the filter will use the classification to determine a user-specific set of distressing sounds in the predefined superset of potentially distressing sounds.

Evaluation

After the envisioned device has been developed using the ARP platform, it will be evaluated with individuals from the target population, using the setup illustrated in Fig. 8:

Analyzing the use of features. The smart HPD can be programmed to automatically record the timestamps of when certain audio filtering features were used. This data could be used to study the statistical correlation between the use of these features and the other measured variables, such as the occurrence of a distressing sound and changes in the biosignal data. Interviews or questionnaires could supplement the data collected by the the smart HPD to gain insight on the utility of each feature.

Pilot testing the overall usability. The overall usability of the device will also be evaluated in a pilot study. This evaluation could include a qualification questionnaire to find participants that are likely to benefit most from the smart HPD, followed by interviews and a product evaluation questionnaire. While the purpose of this evaluation is to gather preliminary data on the smart HPD's usability and may be limited in the number of participants, this pilot testing could provide proof-of-concept that a smart HPD can be used as an intervention to address auditory sensitivities among individuals with ASD.

Figure 8: Overview of the the ARP platform placed in fanny pack worn by the participants. Only the two wired earpieces are accessible during field evaluation. Adapted from [Nadon, 2020] with permission.

Expected Contributions

This work envisions a device that can learn which sounds distress individual users and filter out these sounds in real-time. A characterization phase will inform the development and evaluation of this device. To assess the feasibility of customizing the audio filter, the relationship between distress and fluctuations in biosignals extracted from in-ear microphone data will be examined. The findings of this part of the project will provide insight on the potential of in-ear biosignals for emotion recognition. The feasibility of developing an in-ear wearable technology to address auditory sensitivities in the target population will also be assessed: The attenuation and comfort of an existing technology will be evaluated in a group of students with ASD, and the impact of specific sounds on these students will be explored. A dataset of classroom sounds will be created and used to identify the limitations of developing a filter for these sounds. Through these aims, the project could improve understandings of the needs of students with ASD, in particular concerning the nature of the sounds that they are sensitive to.

If the development and evaluation are successful, this work could yield a device enabling students with auditory sensitivities to engage with their environment with reduced distress. Customization of the device with emotion recognition would allow the device to adapt to individual wearers. Future studies could extend this work and evaluate the utility of smart HPDs in other populations. A device developed for students with ASD could potentially be adapted to address sensory sensitivities across multiple conditions (misophonia [5], migraine [9], etc.). Such a device may also prove useful to anyone who would like to avoid undesirable sounds, even without hypersensitivity. Another avenue for future research could study how incorporating other indicators of distress affects the accuracy of the emotion recognition. Such indicators could be included with extensions of the hardware, e.g. embedding in-ear electroencephalography (EEG) electrodes [7, 26] or could be obtained using the existing technology, e.g. vocal characteristics extracted from the microphone data [7]. Future work could also focus on improving the content-dependent filters. The scope of the current project is limited to suppressing the entire signal for the duration of speech or distressing sounds, but the wearer's experience may be enhanced by filtering out detected distressing sounds from the signal.

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