Robust auditory profiling: Improved data-driven method and profile definitions for better hearing rehabilitation

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Currently, the clinical characterization of hearing deficits for hearing-aid fitting is based on the pure-tone audiogram only. This relies on the assumption that the audiogram can predict performance in complex, supra-threshold tasks. Sanchez-Lopez *et al.* (2018) hypothesized that the hearing deficits of a given listener, both at threshold and supra-threshold levels, result from two independent types of auditory distortions. The authors performed a data-driven analysis of two large datasets with results from several tests, which led to the identification of four auditory profiles. However, the definition of the two types of distortion was challenged by differences between the two datasets in terms of the tests and listeners considered. In the Better hEAring Rehabilitation (BEAR) project, a new dataset was generated with the aim of overcoming these limitations. A heterogeneous group of listeners was tested using measures of speech intelligibility, loudness perception, binaural processing abilities and spectro-temporal resolution. As a consequence, the auditory profiles of Sanchez-Lopez *et al.* (2018) were refined. The updated auditory profiles, together with the investigation of optimal hearing-aid compensation strategies, are expected to form a solid basis for improved hearing-aid fitting.

INTRODUCTION

Hearing deficits are typically characterized by hearing loss severity as defined by the World Health Organization. The severity and shape are assessed based on the individual's sensitivity to pure tones, i.e., the audiogram. However, while the audiogram describes hearing thresholds, it does not reflect supra-threshold deficits. In general, such deficits are not addressed systematically in clinical practice. Nowadays, profiling has gained broad attention as a tool for typifying groups of observations (e.g., users, recordings or patients) that follow similar patterns. Data-driven profiling allows for uncovering complex and hidden structures in the data and has been used

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in psychology and audiology, for example in connection to hearing-aid features (Lansbergen *et al.*, 2020). Data-driven auditory profiling might thus help to identify groups of listeners that are defined by specific hearing deficits, as a basis for rehabilitative precision audiology.

Recently, Sanchez-Lopez *et al.* (2018) proposed a method for auditory profiling that was tested and verified by analyzing two datasets from previous studies. Their method is tailored to the hypothesis that a listener's hearing deficits can be characterized along two independent auditory distortion types, type-I and type-II. A normal-hearing listener is placed at the origin whereas other listeners, with a hearing loss that differs in the degree of the two types of distortion, are placed at different points in the two-dimensional space. While profile C represents a high degree of both distortions, profile B and D reflect hearing deficits dominated by one of the two distortions. Profile A, the group with a low degree of distortions, represents near-normal hearing. Each type of distortion would then covary with specific deficits observed in behavioral tasks, such as temporal processing or modulation sensitivity, that define a given auditory profile.

In Sanchez-Lopez *et al.* (2018), it was hypothesized that distortion type-I covaries with the audiometric thresholds, whereas distortion type-II is not related to audibility. However, the results of the analysis of two different datasets did not confirm this hypothesis. Distortion type-I was found to be connected to high-frequency hearing loss and reduced speech intelligibility in the analysis of both datasets. In contrast, distortion type-II was found to be linked to reduced binaural processing abilities in the case of one dataset (Thorup *et al.*, 2016) and to a low-frequency hearing loss in the case of the other dataset (Johannesen *et al.*, 2016). These mixed results were attributed to differences between the two datasets in terms of listeners and behavioral tests. It was concluded that there was a need for a new dataset that included listeners with more heterogeneous audiograms to better define the distortions and, thus, the auditory profiles. Furthermore, the tests should investigate several aspects of auditory processing while being clinically feasible. In the Better hEAring Rehabilitation (BEAR) project, a new dataset was therefore generated with the aim of overcoming these limitations. The considered tests were chosen based on a literature review.

The resulting dataset includes a large and heterogeneous group of seventy-five listeners that were tested in a clinical environment in several behavioral tasks divided into five domains: audibility, loudness perception, binaural processing abilities, speech perception and spectro-temporal processing. In the present study, the analysis of the new dataset did not aim to disentangle the effects of audibility and supra-threshold deficits but to identify four clinically relevant patient subpopulations by refining the definition of the auditory profiles and the two types of distortions.

METHOD

Description of the dataset

Seventy-five listeners participated in the study. Seventy participants presented various degrees and shapes of symmetrical sensorineural hearing loss and five had near-normal audiometric thresholds. The participants were recruited from clinical databases at Odense University Hospital (OUH) and Bispebjerg Hospital (BBH). All listeners completed the BEAR test battery described in Sanchez-Lopez *et al.* (2019). The selected tests have shown potential for auditory profiling and their outcomes[†] may be informative for hearing-aid fitting. Table 1 summarizes the chosen tests.

Name of the test	Category	Variables[†]
A. Pure-tone audiometry	Audibility	AUD_xF
B. Fixed level frequency threshold		FLFT
C. Word recognition scores	Speech	SRT_Q, maxDS
D. Hearing in noise test	Perception	SRT_N, SS^{4dB}
E. Maximum frequency for IPD detection	Binaural	IPD_{fmax}
F. Binaural pitch	processing	BP20
G. Extended binaural audiometry in noise	abilities	BMR
H. Adaptive categorical loudness scaling	Loudness	HTL_{xF}, MCL_{xF}
	perception	$DynR_{xF}$, $Slope_{xF}$
I. Fast spectro-temporal modulation sensitivity	Spectro- temporal	$sSTM_8$, $fSTM_8$
		TiN_{xF}
J. Extended audiometry in noise	processing	SMR_{xF}, TMR_{xF}.

Table 1: Overview of the tests used for the collection of the BEAR dataset. The tests are divided by categories, and the outcome variables are presented in the right column. When a variable is frequency specific, the sufix $_{xF}$ follows the variable. It can be LF for lower frequencies or HF for higher frequencies.

The results of the tests were processed in a similar fashion as in Sanchez-Lopez *et al.* (2018). First, for each of the tests, the outcome measures of interest were extracted from the raw results. When the tests had frequency specific values, the results were grouped into low (≤ 1 kHz) and high (> 1 kHz) frequency averages. In case of monaural examination, the mean of the two ears was used. The variables with more than 12 missing data points were excluded as well as listeners with more than two missing outcome measures. The data were then normalized between the 25th and 75th percentiles. In total, 26 variables were selected from the outcome measures, as shown in Table 1.

Unsupervised learning

The data-driven analysis used here is based on the unsupervised learning stage of the method described in Sanchez-Lopez *et al.* (2018). This is divided into three

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[†]The outcome variables are further explained in Sanchez-Lopez *et al.* (2019)

steps: I) Dimensionality reduction: based on principal component analysis (PCA), a subset of variables highly correlated with the principal components PC1 and PC2 was kept for the following steps; II) Archetypal analysis: the data were decomposed into two matrices, the test matrix, which contained the extreme patterns of the data (archetypes), and the subject matrix, which contained the weights of each archetype. A given subject can then be represented as a convex combination of the archetypes. The analysis was limited to four archetypes; III) Profile identification: the subject matrix was used to estimate the distance between observations and the four archetypes. Each listener was then assigned to an auditory profile based on the nearest archetype.

In the present study, the method for profile identification was refined according to the following modifications: 1) Iterative bagging: Since a data-driven analysis can be highly influenced by the data themselves, here, the data were decimated randomly in terms of listeners and tests. Then, one thousand iterations of the steps I, II and III were performed with only 83% of the data (69 listeners and 24 variables); 2) Dimensionality reduction: Since the use of several correlated variables in PCA can bias the results, the dimensionality reduction was refined by removing highly correlated variables. If two variables resulting from step I were highly correlated (Pearson's $r > 0.85$), one of them was dropped and this step repeated. The number of selected variables (6, 8 or 10) was also randomly chosen in each iteration; 3) Profile identification: Instead of using the criterion of the nearest archetype, listeners with a weight larger than 0.5 for one of the four archetypes were identified as belonging to that auditory profile. Otherwise, they were left "unidentified".
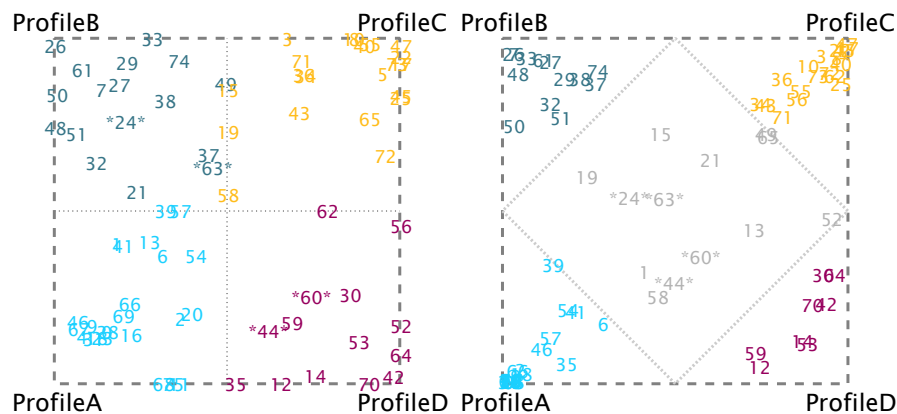

Fig. 1: Square representation result of the data-driven method. Left panel: results from the Sanchez-Lopez *et al.* (2018) method where the listeners are represented based on the subject matrix of the archetypal analysis. Right panel: results from the refined method where the listeners' representation is based on the probabilities. The listeners indicated by grey squares show a low probability of belonging to any of the four profiles ($P < 0.5$) and listeners labelled as ∗*Number*∗ show a high probability ($P > 0.5$) of being "unidentified".

The final output of the refined method is the probability of being identified as belonging to an auditory profile. This was estimated by the fraction of times a listener was assigned to a profile after the 1000 iterations. The probability of being "unidentified" was also calculated.

RESULTS

The left panel in Figure 1 shows the results of the data-driven auditory profiling as used in Sanchez-Lopez *et al.* (2018). Listeners are located in the square representation based on the results of the archetypal analysis. The representation does not show clear clusters and the listeners identified as belonging to an auditory profile may have been wrongly identified. The right panel shows the results of the refined method where the listeners are located in the two-dimensional space based on the probability of belonging to any of the four auditory profiles. Listeners located close to a corner exhibited a high probability of belonging to that profile and four clear clusters can now be observed. The "unidentified" listeners are placed in between the four quadrants.
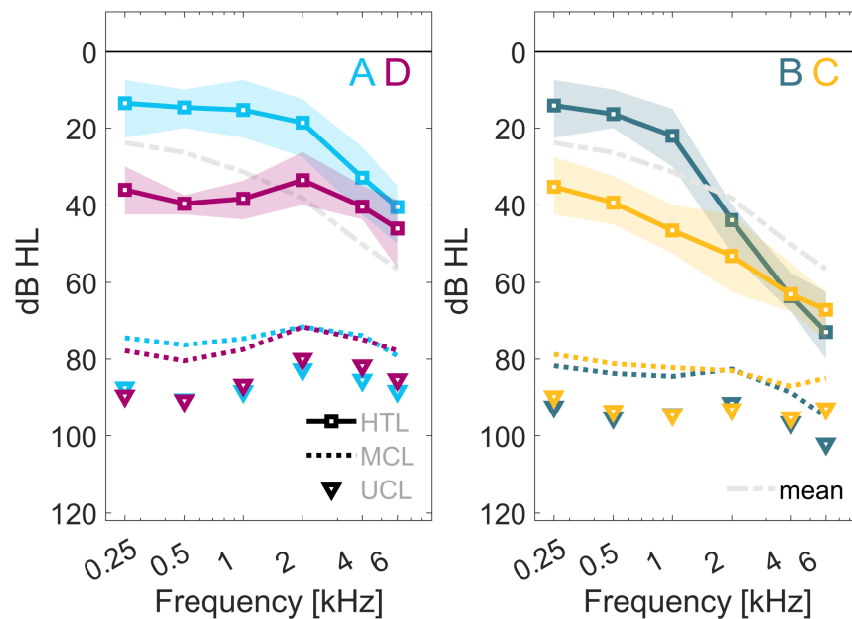

Fig. 2: Results of the ACALOS measurements presented in terms of hearing thresholds (HTL), most comfortable level (MCL) and uncomfortable levels (UCL). Results are divided by profiles (solid lines) and averaged across the whole dataset (dashed line).

Figure 2 shows average hearing threshold levels (HTL) as well as the corresponding interquartile ranges, most comfortable levels (MCL) and uncomfortable levels (UCL) (▽). Profiles A and D (left panel) exhibit a mild-to-moderate high-frequency hearing loss with hearing levels below the average high-frequency hearing loss (dashed line). The difference between profiles A and D is at low frequencies where profile D exhibits

thresholds that are more elevated than the average values ($\gtrsim 30$ dB HL). Profiles B and C (right panel) also exhibit a high-frequency hearing loss but with values above the average ($\gtrsim 45$ dB HL). The difference between profiles B and C is mainly in terms of the low-frequency hearing thresholds where profile C exhibits a low-frequency hearing loss that is above the average values.
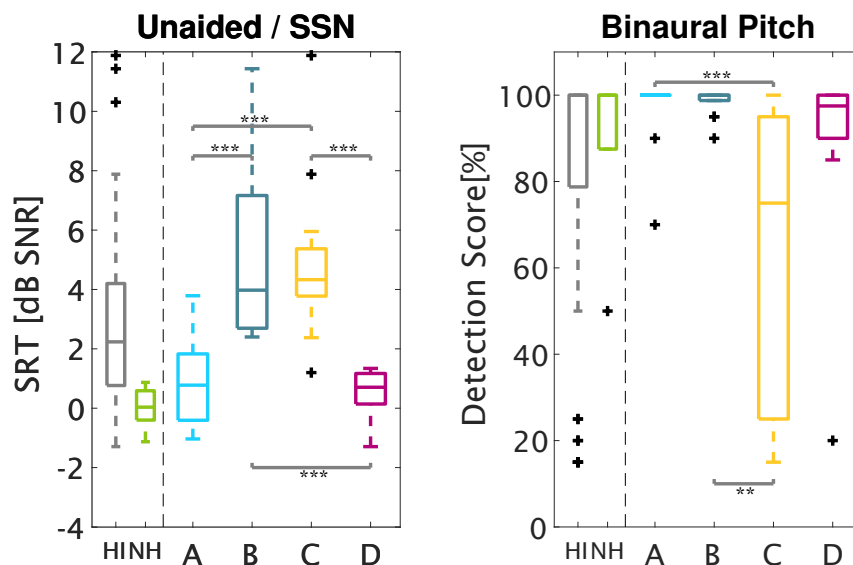

Fig. 3: Boxplots of the results from suprathreshold measures. Left: Unaided speech intelligibility in speech-shaped noise (SSN). Right: Binaural pitch detection. In each panel, the average data of the whole group of the hearing-impaired (HI) listeners and the normal-hearing (NH) listeners are shown on the left, whereas the results for the sub-populations according to the profiles are shown on the right.

Figure 3 (left panel) shows unaided speech reception thresholds (SRT) measured for sentences presented in speech-shaped noise. The median SRT for the hearing-impaired (HI) listeners data was at about 2.5 dB signal-to-noise ratio (SNR). Profiles A and D showed a better performance (median: ≈ 1 dB SNR) than profiles B and C (median: ≈ 4-5 dB SNR).

The right panel of Figure 3 shows the results from the binaural pitch detection test. The detection scores for listeners with profiles A, B and D were significantly higher (better performance) than for the listeners with profile C. Some profile C listeners were not able to detect the dichotic pitch percept, whereas they could detect the diotic pitch.

DISCUSSION

The refined method showed four clusters of listeners with significant differences in terms of several supra-threshold tasks. In the previous study of Sanchez-Lopez *et al.* (2018) the data-driven analysis of the Thorup *et al.* (2016) data set showed that distortion type-II was associated with binaural processing abilities in listeners with near-normal or mild-moderate high-frequency hearing loss. The binaural pitch test was found to be the most relevant prediction in that study and the listeners in profiles D_T^* and C_T showed scores lower than 95 %. In the present study, only listeners with profile C showed such a behaviour. In contrast, the analysis of the Johannesen *et al.* (2016) data set in Sanchez-Lopez *et al.* (2018) showed that distortion type-II was associated with outer hair cell loss at low frequencies and their participants had moderate-to-severe hearing loss. Profiles $D_J^\dagger$ and C_J showed higher audiometric thresholds and a loss of cochlear non-linearity at low frequencies. In the present study, the results are in better agreement with the analysis performed on the Johannesen *et al.* (2016) data set than on the Thorup *et al.* (2016) data set. This suggests that the use of data from a representative sample of different degrees of hearing loss and a normal hearing reference was crucial for a robust profile-based hearing-loss characterization.

The audiometric thresholds corresponding to the four robust auditory profiles were significantly different in terms of the degree and shape of the hearing loss. Interestingly, the four audiometric profiles look similar to the audiometric phenotypes of Dubno *et al.* (2013). According to this view, the flat "attenuation" observed in profile D may be ascribed to a metabolic hearing loss (endocochlear potential loss) and the sloping hearing loss observed in profile B may be associated with a sensory loss. Metabolic hearing loss yields flat elevated thresholds but does not affect speech-intelligibility in noise (Pauler *et al.*, 1986), which is consistent with the results of the present study. Furthermore, according to Plomp's model, profiles B and C exhibited a distortion component because of their elevated speech reception thresholds in noise (Plomp, 1978). (Wu *et al.*, 2020) carried out an accompanying study assessing aided speech-in-noise performance with the same test participants. Their results also showed elevated SRT_N for the listeners with profiles B and C suggesting that amplification did not fully compensate for their hearing deficits.

CONCLUSION

Based on a refined data-driven method and a new dataset, a solid definition of the auditory profiles was obtained. The different profiles showed significant differences in terms of low- and high-frequency hearing loss, speech-in-noise intelligibility, binaural processing abilities and spectro-temporal modulation sensitivity. Overall, the results of the present study suggest that the shape and degree of sensitivity loss can be

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*The subindex T refers to the profiles from the analysis of Thorup *et al.* (2016)

†The subindex J refers to the profiles from the analysis of Johannesen *et al.* (2016)

a consequence of specific impairment mechanisms with associated supra-threshold deficits. Moreover, stratifying the listeners in clinically relevant subgroups has potential for further investigating the independence of sensitivity vs supra-threshold deficits as well as physiological correlates of the perceptual auditory distortions.

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REFERENCES

Dubno, J. R., Eckert, M. A., Lee, F. S., Matthews, L. J., and Schmiedt, R. A. (**2013**). "Classifying human audiometric phenotypes of age-related hearing loss from animal models," J. Assoc. Res. Oto., **14**(5), 687-701. doi: 10.1007/s10162-013-0396-x.

Johannesen, P. T., Pérez-González, P., Kalluri, S., Blanco, J. L., and Lopez-Poveda, E. A. (**2016**). "The influence of cochlear mechanical dysfunction, temporal processing deficits, and age on the intelligibility of audible speech in noise for hearing-impaired listeners," Trends Hear., **20**(0). doi: 10.1177/2331216516641055.

Lansbergen, S. and Dreschler, W. A. (**2020**). "Hearing aid feature profiles: the success of rehabilitation," Proc. ISAAR, **7**, 229-236.

Pauler, M., Schuknecht, H. F., and Thornton, A. R. (**1986**). "Correlative studies of cochlear neuronal loss with speech discrimination and pure-tone thresholds," Arch. Otorhinolaryngol., **243**(3), 200-206. doi: 10.1007/bf00470622.

Plomp, R. (**1978**). "Auditory handicap of hearing impairment and the limited benefit of hearing aids," J. Acoust. Soc. Am., **63**(2), 533-549. doi: 10.1121/1.381753.

Sanchez-Lopez, R., Bianchi, F., Fereczkowski, M., Santurette, S., and Dau, T. (**2018**) "Data-Driven Approach for Auditory Profiling and Characterization of Individual Hearing Loss," Trends Hear., **22**. doi: 10.1177/2331216518807400.

Sanchez-Lopez, R., Nielsen, S. G. ,..., and Santurette, S. (**2019**). "Data for: "Auditory tests for characterizing hearing deficits: The BEAR test battery"," (Version v1.0). Zenodo. doi: 10.5281/zenodo.3459580.

Thorup, N., Santurette, S., Jørgensen, S., Kjærbøl, E., Dau, T., and Friis, M. (**2016**). "Auditory profiling and hearing-aid satisfaction in hearing-aid candidates," Dan. Med. J., **63**(10), A5275.

Wu, M., Sanchez-Lopez, R., ..., and Neher, T. (**2020**). "Perceptual evaluation of six hearing-aid processing strategies from the perspective of auditory profiling: Insights from the BEAR project," Proc. ISAAR, **7**, 265-272.