Parameterisation Of Transient Evoked Otoacoustic Emissions

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In this paper we compare the application of the discrete wavelet transform (DWT) and wavelet packets (WP) to transient evoked otoacoustic emissions (TEOAE) to conduct a differential diagnosis of frequency-specific hearing loss. By parameterising the TEOAE with WP, we aim to improve the separation of groups with different hearing ability compared to a DWT parameterisation.

1. Introduction

Transient evoked otoacoustic emissions (TEOAE) are low-level sounds produced by the inner ear as a response to an external acoustic stimulus, which are measured in the outer ear canal by sensitive microphones. An open question is how reliable TEOAE can be employed to clinically evaluate and characterise a potential cochlear hearing loss (HL), particularly in newborns and infants.

Due to the transient nature of the signals, previous work on the qualitative analysis of TEOAE has focused mostly on time-frequency (TF) methods, such as filter banks [1], Wigner transforms [2], matching pursuit [3], or discrete wavelet transforms [4, 5]. A quantitative study w.r.t. the achievable distinction of frequency-specific HL has been performed in [6], based on the discrete wavelet transform (DWT).

In this paper, we aim to improve TF parameterisations in [6] by minimising the entropy using a wavelet packet (WP) parameterisation and comparing the results with a DWT. The obtained parameterised data can be used for further investigation of the TEOAE, e.g. for detecting and distinguishing different forms of HL.

2. Parameterisation by Discrete Wavelet Transform and Wavelet Packets

The DWT is a fixed transform based on a "mother wavelet" from which the transformation coefficients are derived by scaling, translation and sampling. Here, we have chosen the Mallat wavelet for which good results have been reported in similar studies [6]. The transform coefficients approximately cover TF tiles as illustrated in Fig. 1 a).

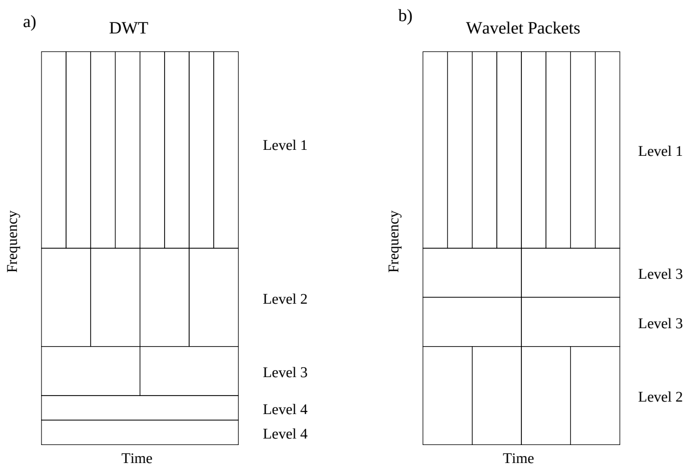


Fig. 1: TF tiling comparison between a) a DWT and b) a sample WP decomposition.

The WP transform is an adaptive transformation similar to the DWT but with a flexible partitioning of the TF plane. The advantage of this approach compared to the DWT is that the entropy of the transformed data shall be minimised through variable levels of decomposition such that the energy is concentrated in as few coefficients as possible. That minimisation is achieved by the reduction of the concentration according to Shannon's entropy [7]. Fig. 1 b) shows a sample WP decomposition.

3. Results and Discussion

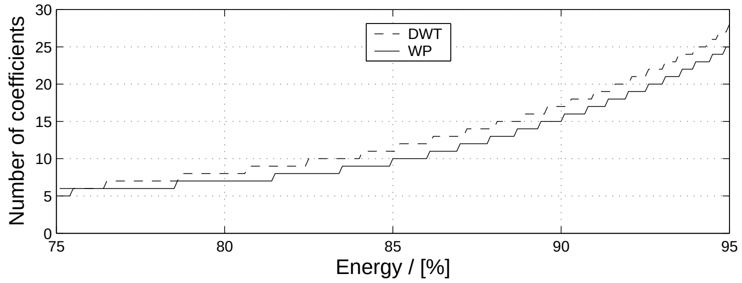
The exemplarily analysed TEOAE data consists of 3 different hearing ability groups, namely patients with normal hearing, high-frequency HL and pantonal HL referred to as groups NH, HF and PT, respectively. The data is discrete with a length of 512 samples. In Fig. 2, the number of coefficients versus reduction of the energy from 95% to 75% for the parameterised data is illustrated. It was found that the WP parameterisation leads to a reduction of coefficients containing the stated energy of approximately 10% for all hearing ability groups. These results were confirmed by an analysis of a control data group. By the reduction of the coefficients, the quantity of coefficients that contain information that can be used to detect HL is reduced. Therefore, separability methods, such as derived for example in [8], become numerically less costly and more efficient. Furthermore, the separability between the groups can be improved by calculating a specially adapted WP decomposition for each distinction case. Tab. 1 shows the resulting separability values based on the receiver-operating characteristic [9] for the distinction of the 3 groups with different hearing ability based on the DWT and WP. The stated values are the areas under the ROC curve. It indicates an improvement in separability, which also holds for the control data for the majority of the cases. To illustrate the results more clearly, Fig. 3 indicates the ROC curves for the adjustment data, where the specificity and the sensitivity can be observed. However, it can be noted that the WP parameterisation is slightly adapted to the data used for the adjustment. The generalisation is ensured by the results for the control data group which are not as good for NH vs HF and NH vs PT, but still acceptable to confirm the WP parameterisation approach. The adaptation to the adjustment data results from applying the entropy reduction method to find the WP decomposition to each differentiation case separately yielding three specially adapted WP decompositions for each case. One could suggest using a Karhunen-Loeve transform (KLT, [10]) for parameterisation. However, the findings that a WP decomposition already shows a slightly adaptation to the data used for adjustment lead to the expectation, that the KLT would not yield good results for the control data for confirming generalisation.

4. Conclusions

By a parameterisation of TEOAE data by a WP transform which is based on a entropy reduction, the number of coefficients possibly containing information to detect HL, is reduced by 10% compared

	separability results by WP parameterisation		separability results according to [6] for DWT	
group distinction	data used for adjustment	control data	data used for adjustment	control data
NH — HF	0.932	0.773	0.878	0.853
NH — PT	0.990	0.967	0.918	0.963
HF — PT	0.821	0.837	0.768	0.847

Tab. 1: Comparison: Separability (area under ROC curve) between the 3 hearing ability groups for the adjustment and control data for the WP and DWT.



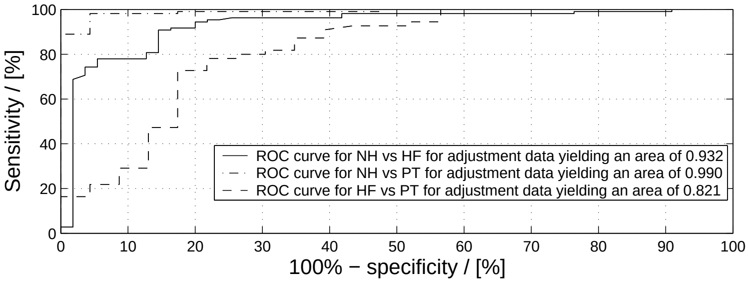


Fig. 2: (top) number of transform coefficients required for representing a TEOAE (512 coefficients equal 100% of TEOAE energy).

Fig. 3: (bottom) ROC curves for WP parameterisation for the 3 hearing ability differentiation cases for the adjustment data.

to a DWT. This leads to better separability results for patients with different hearing ability.

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