

# A NOVEL APPROACH TO DETECT FREQUENCY-SPECIFIC COCHLEAR HEARING LOSS

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**Abstract - The aim of this paper is to evaluate the application of time-frequency (TF) transforms and support vector machines (SVM) to transient evoked otoacoustic emissions (TEOAE) in order to achieve a detection of frequency-specific hearing loss. We introduce a system to determine detection rates between groups of persons with normal hearing, high frequency hearing loss, and pantonal hearing loss. The validity and use of our approach is verified on a different patient group.**

## I. INTRODUCTION

Transient evoked otoacoustic emissions (TEOAE) are used as a clinical standard procedure to detect cochlear hearing loss [1], and measurement equipment [2] is widely available in hospitals. The analysis of TEOAE is usually performed by an human expert. Recently, signal processing detection systems aiming at an automated detection of cochlear hearing loss have been motivated to assist or replace the human expert. These studies aiming at detection of TEOAE apply discrete wavelet transform and neural networks [3],[4]. Here, we introduce a system applying various time-frequency (TF) transforms for feature extraction, a signal-to-noise (SNR)-like criterion for feature selection and support vector machines for classification.

Fig. 1 gives an overview of our system. For the feature extraction, TF transforms, namely the discrete wavelet transform (DWT), wavelet packets (WP) and Gabor frames transform (GF) are applied. To select the features of the data, an SNR-like criterion is applied to the transformed data resulting in a reduction of coefficients to be used for classification and aiming at a reduction of noisy coefficients. This approach will be outlined in more detail in Sec. III, following a description of TEOAE data and TF transforms in Sec. II. The classification of the data is conducted by a support vector machine (SVM) classifier explained in Sec. VI more explicitly. In Sec. V, based on the training data, a support vector classification network

is found and applied to the test data group yielding detection rates which describe the performance of the system and can be compared with other studies. Finally, Sec. VI draws the conclusions.

## II. TEOAE AND TF TRANSFORMS

The patient data consists of two sets measured at the Universities of Homburg and Heidelberg, with each consisting of an evaluation of more than 200 ears. The Homburg data represents the training data, the Heidelberg data is addressed as test data. Both sets are classified to one of the three groups of normal hearing (NH), pantonal (PT), or high frequency (HF) hearing loss, as defined in Fig. 2. For each ear, the TEOAE equipment measured a total of 520 responses, each for a period of 20.48 ms, and calculated two partial averages (labelled A and B) alternatingly over 260 responses each.

Due to the transient nature of the signals, previous work on the qualitative analysis of TEOAE has focused on time-frequency (TF) methods, such as filter banks [5], matching pursuit [6], or the DWT [3], whereby a quantitative study w.r.t. the achievable distinction of frequency-specific hearing loss has been performed in [3], based on the DWT. Here, we aim to broaden and improve these methods by considering a range of transformation methods, namely the DWT, WP and GF.

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 [3]. The transform coefficients approximately cover TF tiles as illustrated in Fig. 2 (left).

The WP transform is an adaptive transformation similar to the DWT but with a flexible partitioning of the TF plane which therefore can be seen as a more general transform compared to the DWT. 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

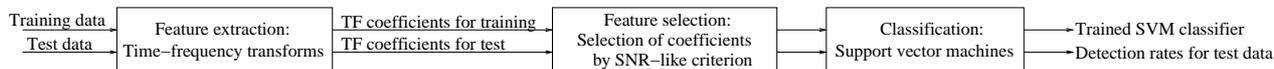


Fig. 1. Overview of the detection system for cochlear hearing loss.

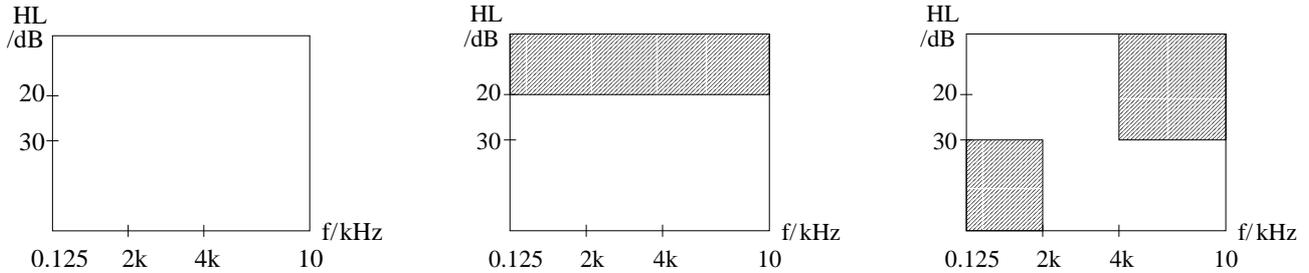


Fig. 2. Characterisation of hearing loss (HL) for (left) normal hearing, (middle) pantonal HL, and (right) high frequency HL.

in as few coefficients as possible. That minimisation is achieved by the reduction of the concentration according to Shannon's entropy [7]. Fig. 2 (middle) shows a sample WP decomposition.

The GF decomposition yields a uniform tiling of the TF plane and hence can provide a desired resolution in a specific TF segment, see e.g. Fig. 2 (right). It is based on an oversampled filter bank with a flexible number of channels constructed according to [8], whereby the channel number is again selected in order to minimise the transform coefficients' entropy when applied to TEOAE data. All transformations are operating on finite length EEG segments and are implemented with symmetric boundary extensions [9].

Based on a parameterisation of the data by the TF transforms, representing the feature extraction of the data, the application of an SNR-like criterion for the feature selection is conducted which will be described next.

### III. FEATURE SELECTION

To quantify and exploit differences in the TEOAE TF coefficients of the three groups of hearing ability within the Homburg data, a signal-to-noise-ratio (SNR) based criterion is invoked. First, the SNR is estimated for each of the 512 parameters in the TF-plane based on the TF transforms of the two partial averages,  $C_{A,i}(n)$  and  $C_{B,i}(n)$ ,  $n = 1, \dots, 512$ ,  $i = \{\text{DWT, WP, GF}\}$ . The SNR of the  $n$ th coefficient is (coarsely) estimated by comparing the sum and the difference obtained from the partial averages

A and B:

$$\text{SNR}(n) = 20 \log_{10} \frac{|C_{A,i}(n) + C_{B,i}(n)|}{|C_{A,i}(n) - C_{B,i}(n)| + \epsilon} \quad (1)$$

with  $\epsilon$  being a small constant. This SNR is calculated for all measurements, and for each of the 512 TF coefficients within each of the three hearing ability groups, the distribution is recorded. The SNR value of a TF coefficient is used to evaluate the separability of any two groups with different hearing status. The separability can be assessed independent of the selection of a specific threshold by means of a so-called receiver operating characteristic (ROC) curve. The area underneath the ROC is a measure for the separability of both groups, and independent of the definition of SNR-thresholds [10].

As single WP coefficients yield a poor separability between any two groups, we pick the coefficient that gives the best separable SNR according to (1) as a starting value and iteratively grow a coefficient set  $\mathcal{G}$  to improve separability. Further coefficients are added to  $\mathcal{G}$  from the neighbourhood of surrounding coefficients. Adjacency is defined by edge and corner connections in the TF plane. The iteration is stopped when the ROC does not further improve for the SNR of the coefficients contained in  $\mathcal{G}$ . To broaden the search algorithm, also the second largest coefficient is selected as a starting value for the search procedure; moreover, the neighbourhood search is broadened by including the adjacent coefficients to the ones described previously. The reason is that by this generalisation an improvement of the separability results is ex-

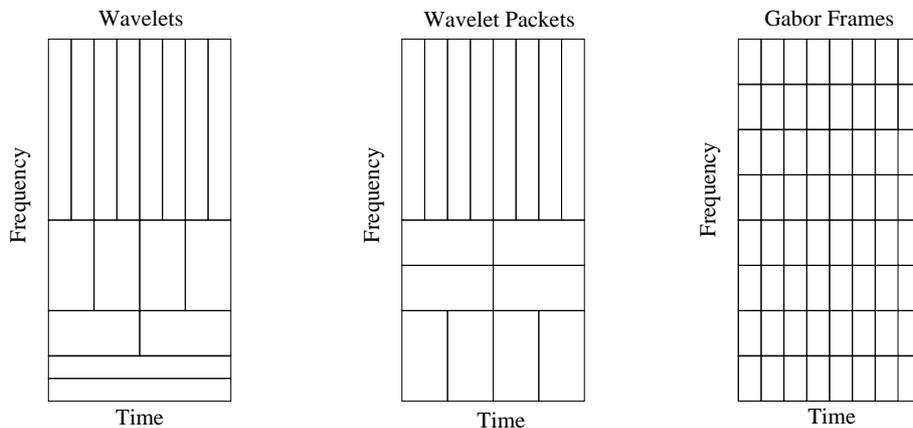


Fig. 3. TF tiling comparison between a DWT (left), a sample WP (middle) and a sample GF (right) decomposition.

pected.

#### IV. SVM CLASSIFICATION

In the following, we briefly explain SVM, [11],[12]. We consider a three class classification problem for the classes defined by the groups NH, HF and PT, starting with an explanation for a two class classification. The training data originates from the Homburg data, while the test data comprises the Heidelberg measurements.

The training data is described as a set of training vectors  $\{\mathbf{p}_i\}_{i=1 \dots M}$  with corresponding binary labels  $S_i = 1$  for the one class, e.g. NH, and  $S_i = -1$  for the second class, e.g. HF. The SVM conducts a classification of a test vector  $\mathbf{t}$  by assigning a label  $\hat{S}$  by calculating

$$\hat{S} = \text{sign}(f(\mathbf{t})) \quad \text{with} \quad f(\mathbf{t}) = \sum_i \alpha_i S_i K(\mathbf{t}, \mathbf{p}_i) + b. \quad (2)$$

The  $\alpha_i$  are called weights and  $b$  is the bias, which are SVM parameters and adopted during training by maximising

$$L_D = \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j S_i S_j K(\mathbf{p}_i, \mathbf{p}_j) \quad (3)$$

under the constraints

$$0 \leq \alpha_i \leq C \quad \text{and} \quad \sum_i \alpha_i S_i = 0 \quad (4)$$

with  $C$  being a positive constant which weighs the influence of training errors.  $K(\cdot, \cdot)$  is called kernel of the SVM. If there is a solution for  $\alpha_i$ , a value for  $b$  is determined. Usually  $\alpha_i = 0$  for the majority of  $i$  and thus the summation in (2) is limited to a subnet of the  $\mathbf{p}_i$ , which therefore is called the set of support vectors. There are several commonly used kernels for SVM, which give some flexibility for the underlying application. Many implementations of kernels can be found in literature, whereby two popular ones are Gaussian and polynomial kernels. If  $K(\cdot, \cdot)$  is positive definite, (3) and (4) is a convex quadratic optimisation problem, which converges towards the global optimum assuringly. This optimisation can be quite demanding in terms of computation time for real-world problems, and therefore, sophisticated algorithms like sequential minimal optimisation (SMO) [11] are used for the solution.

To find a significant value for the training error  $C$ , a leave-one-out (l-o-o) estimation of the error rate is applied as follows: From the training samples, remove the first example. Train the SVM on the remaining samples. Then test the removed example. If the example is classified incorrectly, it is said to produce a leave-one-out error. In [11], an approach to estimate the maximum l-o-o error is shown avoiding training the SVM more than once, which is also used for our study. By changing the value for  $C$  stepwise, the minimum for the l-o-o error is found determining the SVM classification network. For our application, a Gaussian kernel was used.

So far, we have described the SVM for only two classes. As we aim at distinguishing 3, we need to define a multi-class method. In [13] a decision directed acyclic graph

(DAG) for multi-class SVM is introduced. It is based on an 1-vs-1 classification where the training is conducted for all possible combinations of the classes. Based on a trained SVM classifier for each possible class combination, a binary acyclic graph is used for testing. Fig. 4 shows the decision DAGSVM for our application to the three classes with different hearing ability.

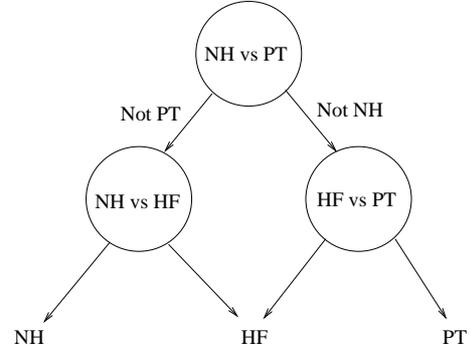


Fig. 4. DAGSVM for TEOAE.

#### V. RESULTS AND DISCUSSION

Having described the detection methods and the data used for our system, we present the results in the following. For each transform method and based on the selected coefficient sets, a SVM classification is conducted for each distinction case using the training data. The test data is analysed by the determined classifiers according to the decision DAG in Fig. 4 yielding the detection rates in Tab. 1 for each class for each parameterisation method.

group	detection rates for test data		
	DWT	WP	GF
NH	79.7%	68.1%	91.3%
HF	63.2%	74.7%	63.2%
PT	69.3%	56.4%	53.9%

Tab. 1. Detection rates yielded by DAGSVM.

The table shows that the DWT yields the best overall results. The HF can be detected most significantly with the WP. The PT group is the most difficult to determine, just above half of the patients can be allocated correctly for the WP and GF. These results may not seem to be encouraging. However, when only considering the the case NH vs PT, the following results are obtained:

- DWT: NH 91.3%, PT 89.7%,
- WP: NH 89.9%, PT 84.6%
- GF: NH 99%, PT 84.6%,

which is well in the range of other studies.

E.g in [14], a group of normal hearing is defined by no hearing loss up to 30 dB and a hearing impaired group with a hearing loss over 30 dB. A separation method based on wavelet transforms, ensemble correlation, time window design and mean cross-correlation is introduced. The

study concludes that by standard analysis 90% of the normal hearing persons and 65% of the hearing impaired patients can be allocated correctly. By applying the various methods, the value for the hearing impaired group is increased by approximately 17% to 83% in that study. Compared to our study we achieve slightly better results when only considering the case NH vs PT, which can be seen as equivalent to the case shown in [14]. One could also argue, that our methods lead to a better separation of hearing loss as our threshold for defining the difference between NH and PT was 20 dB, and the worse the hearing loss gets, the weaker the TEOAE appear and therefore the easier it should be to separate them. On the other hand, we achieve the lowest value of 53.9% for the PT group, which shows that it is easier to separate when clear TEOAE are present, which is more likely the case for a threshold of hearing loss of 20 dB than for 30 dB. Recapitulating it can be said that our approach yields separation results than can well compete with other studies so far.

## VI. CONCLUSIONS

We have presented a TF analysis of TEOAE that aims at the detection of frequency specific hearing loss. We have motivated the use of TF methods, and proposed a method to optimise a set of distinctive TF coefficients. This maximisation represents the input to a SVM classifier for the detection. We used two data sets for training and testing. The validity of the results was verified by a test group. Moreover, the obtained results proved to be competitive when they were compared to similar study which also aims at the detection of TEOAE. Therefore, the results appear reasonably robust and encourage frequency specific hearing loss detection via signal processing of TEOAE.

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