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## **A Novel Method of Estimation of DPOAE Signals**

## A. K. Ziarani\* and A. Konrad

*Abstract—***A new method of measurement of distortion product otoacoustic emission (DPOAE) signal level based on a recently introduced nonlinear adaptive method of extraction of nonstationary sinusoids is presented. Essentially, three units of such an algorithm are employed to extract and measure the two stimuli and the DPOAE signal. Each unit has the capability of locking on a specified sinusoidal component of the input signal and tracking its variations over time. Performance of the proposed method is demonstrated with the aid of computer simulations and is verified in laboratory using recorded clinical data. Comparison is made between the proposed technique and existing methods. The proposed method features structural simplicity which renders it particularly attractive for implementation on both software and hardware platforms. It offers a high degree of immunity with regard to background noise and parameter variations. Compared to conventional methods, the proposed method offers a shorter measurement time which is of significant value in clinical examinations.**

*Index Terms—***Adaptive signal processing, otoacoustic emissions.**

## I. INTRODUCTION

Distortion product otoacoustic emissions (DPOAEs) are very low level stimulated acoustic responses to two pure tones presented to the ear canal. DPOAE measurement provides an objective noninvasive measure of peripheral auditory function and is used for hearing assessment especially in newborns [1]. DPOAEs have been recognized for a number years [2], [3]. However, DPOAE measurement is considered an active area of research because of the challenging nature of the signal processing task.

In this type of otoacoustic test, two pure tones with frequencies  $f_1$ and  $f_2$  are presented to the cochlea. For best results,  $f_2$  is usually chosen as  $1.2 f_1$ . Since the ear is a nonlinear structure, a number of very low level distortion products are generated due to the intermodulation process within the cochlea. Among various distortion products, the compon very low level distortion products are generated due to the intermodulation process within the cochlea. Among various distortion products, the level of such a distortion product (commonly referred to as the DPOAE signal) is taken as an index of the functionality of the ear. Estimation of such a weak signal buried under two strong stimuli and other intermodulations in a potentially noisy background is a challenging signal processing problem.

Conventionally, the discrete Fourier transform (DFT) has been used as the main signal processing tool to estimate the level of the DPOAE signals. Application of the DFT to this problem has a number of shortcomings, among which the long measurement time is the most pronounced one [4]. Long measurement time is usually required for the acquisition of a sufficiently large amount of data which, when averaged, will reduce the overall background noise effect. In addition to the need to increase the measurement time, the tests are usually required to be conducted in low noise environments such as sound-proof rooms or other types of sound-proof enclosures.

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Fig. 1. Block diagram representation of the proposed method of DPOAE estimation.

In an attempt to devise high performance DPOAE estimation techniques, adaptive signal processing techniques and maximum-likelihood estimators have been employed. Such techniques generally offer better performance in terms of measurement time which may be interpreted as their higher noise immunity compared to that of the **DFT.** 

This paper presents a method of DPOAE signal measurement which employs, as its main building block, a recently introduced nonlinear adaptive signal processing algorithm. The formulation, mathematical properties and DSP implementation of the employed signal processing algorithm are presented in [5] where detailed discussions on the stability and convergence issues of the algorithm are also presented. Some of the applications of the employed algorithm in diverse areas of engineering are presented in [6], [7].

## II. METHOD

The proposed signal processing method employs three units of the algorithm presented in [5], [6] to construct a high performance DPOAE estimation algorithm. Each unit is capable of focusing on and extracting a prespecified sinusoidal component of its input signal which may contain other components and noise. More importantly, it can effectively follow variations in the amplitude, phase (and frequency) of the extracted sinusoidal component. Although the underlying mathematics ensuring the stability and performance of such an algorithm is very complex, its structure remains extremely simple. It is found to be very robust with respect to variations in the internal settings of the controlling parameters, as well as external conditions such as the presence of noise, and exhibits superior performance over existing linear adaptive and DFT-based algorithms in terms of convergence speed versus accuracy tradeoff [5].

The input DPOAE signal is often assumed to consist of two pure sinusoids with frequencies  $f_1$  and  $f_2$  at a very high level (usually about The state of FSI.<br>The input DPOAE signal is often assumed to consist of two pure si-<br>nusoids with frequencies  $f_1$  and  $f_2$  at a very high level (usually about<br>50 to 70 dB SPL) and a very low level DPOAE  $2 f_1 - f_2$  at a 15 dB SPL. It is contaminated by a noise usually considered to be about 0 to 20 dB SPL. In fact, the noise represents the totality of all undesired signals that may be present in the environment in which the examination is being conducted, the sum of all generated intermodulations as well as the unavoidable background noise. It has been observed that the estimation error increases with the increase of the amount of background noise. This can be compensated by re-adjusting the parameters of the algorithm to reduce the error at the expense of the convergence speed. Because of the excessive degree of the noise, one single unit assigned to extract the DPOAE signal out of the input signal exhibits poor performance in terms of the estimation error, (or the convergence speed).

In the block diagram of Fig. 1, the first two units are assigned to extract the two stimuli. They effectively do so with very small errors. The extracted stimuli are then subtracted from the input signal to produce a signal, of which DPOAE has a higher relative portion. The third unit is then set to extract the DPOAE signal. To further enhance the performance of the DPOAE estimator, some preprocessing, postprocessing as well as intermediary filtering stages have been added.

The stage of preprocessing consists of preliminary normalization and bandpass filtering. The purpose of the normalization process is to amplify the input signal to bring it to a certain level on the basis of which the setting of the parameters of the units may be adjusted. The bandpass filtering is intended to attenuate all components except the DPOAE signal as much as possible to enhance the quality of the input signal. This can be achieved by means of a simple second order bandpass filter, the center frequency of which is set to be that of the DPOAE signal.

The intermediate signal out of which the two stimuli are removed may be directly input to a third unit for the extraction of the DPOAE signal. Since elimination of the two stimuli needs certain convergence time, at the very early initial moments a large portion of the two stimuli exists which will set the initial operational point of the third unit too far away from the true level of the DPOAE signal. To overcome this, a time-gating process may be employed to delay the transfer of the intermediate signal to the third unit. This is accommodated in the midprocessing unit of Fig. 1. The output of this unit is zero and remains zero for a short period of time until a more or less steady state condition for the two units is achieved. The mid-processing may also include some normalization and bandpass filtering just like the preprocessing stage.

The postprocessing unit consists of denormalization of the DPOAE signal and its level to restore the original values as well as some (lowpass) filtering to further smooth out the estimate of the DPOAE signal and its level.

#### *A. Adjustment of Parameters*

An important part of the design of the proposed DPOAE estimation method is the adjustment of the parameters. In each application, one has to roughly define the nature of the input signal and the desired speed (or the tolerable error) to be able to appropriately adjust the parameters. For this matter, the level of the two stimuli are assumed to be about 60 dB SPL, the level of the DPOAE signal 15 dB SPL and the noise floor 10 dB SPL. A convergence time of less than one second for each DPOAE level measurement and an estimation error of less than 15% seem to be sufficient from a practical point of view. This definition of the problem is a rough guideline for the design. However, and thanks to the robust and adaptive nature of the employed algorithm, variations of orders of magnitude in these values are observed to be easily tolerated by the system.

Noise floor at about 28 dB

'n  $0.2$  $0.4$  $0.6$  $0.8$  $1.2$  $1.4$ 1.6  $1.8$  $\overline{2}$ Time (s) Fig. 2. Illustration of the performance of the proposed DPOAE estimator

using simulated data. The conditions in this example are in accordance with

the defined conditions of the problem.

The values of the  $\mu$ -parameters (refer to [5] for details) for the two units assigned to extract the two stimuli are  $\mu_1 = 200$  and  $\mu_2 =$ 20 000. The values of the  $\mu$ -parameters for the third unit assigned to extract the DPOAE signal are  $\mu_1 = 200$  and  $\mu_2 = 20$ .

The mid-processing stage consists of a time-gating (switching at  $t = 100$  ms), a gain (or normalization) of 1000 and a bandpass filter. The estimate of the amplitude by the third unit is transferred to the postprocessing unit. The post processing is a denormalization factor of 1/1000 and a smoothing low-pass filter. The output of this filter is the estimated DPOAE level.

#### III. RESULTS

Performance of the proposed method is demonstrated in this section using both flexibly controlled simulated data and a set of real clinically recorded signal.

#### *A. Simulated Data*

For the simulations presented in this section, the frequency of the first stimulus  $(f_1)$  varies over the range of 500 to 4000 Hz. For each numerical experiment,  $f_1$  is randomly generated within this range. The frequencies of the second stimulus and the DPOAE are then set as  $f_2 = 1.2f_1$  and  $f_d = 2f_1 - f_2$ , respectively. The initial phases of the simulated stimuli and the DPOAE are randomly chosen within 0 to  $2\pi$ . The simulated noise added to the input signal is a zero-mean white Gaussian noise for the first two experiments and is a pinkGaussian noise for the third experiment. The levels of the stimuli, DPOAE and noise floor are specified in each case.

Fig. 2 presents the performance of the proposed DPOAE estimator when the levels of the two stimuli are randomly generated within the range of 0.8 to 1 V (roughly corresponding to a relative 60 dB level) while the DPOAE signal has a level of about 6 mV (corresponding to a relative 15 dB level). The noise floor is at about 10 dB. The conditions in this example are in accordance with the defined conditions of the problem. It is observed that the convergence is achieved well within the desired one second test period with a small estimation error.



Time (s)

 $1.2$ 

 $1.4$ 

 $1.6$ 

 $1.8$ 

2

 $0.8$ 

 $0.6$ 

In another numerical experiment, the level of the noise floor is increased about four times (corresponding to about 28 dB level). Fig. 3 shows the estimation process. The estimation is achieved well within the desired one second test period with a tolerable estimation error. The present parameter setting easily accommodates noise levels of up to 30 dB, which is believed to be an exaggeration of the actual scenarios. However, if the expected noise floor happens to be even higher, one can sacrifice the speed by re-adjusting the parameter settings. Generally, one needs to take into account the following factors when choosing the values of parameter settings: some idea about the potential background noise, the desired speed of convergence and the tolerable error. Experience of the authors as well as that of the collaborators in companies manufacturing DPOAE measurement equipment confirms the suitability of the suggested parameter settings in practical DPOAE measurement tests.

Typical environmental noise experienced during the recording of signals within the acoustic range is pink, in which the power density decreases with increasing frequency over a finite frequency range so that each octave contains the same amount of power. To present a more realistic demonstration of the performance of the proposed method, the experiment of Fig. 3 is repeated using a pink background noise. Fig. 4 illustrates the estimation process where  $f_1$  is about 3500 Hz. It is observed that the performance of the proposed method is better in this case as opposed to the case of the contamination by white noise (Fig. 3). This can be explained by the fact that given the nonuniform distribution of the noise power, less noise exists around the frequencies of interest. This renders the estimation process more accurate. Further experiments show that at lower frequencies of  $f_1$ , the effect of pink noise is more destructive than that of the white noise, as would be expected theoretically.

## *B. Recorded Data*

One set of clinical data recorded at Rotman Research Institute of the University of Toronto is used to verify the functionality of the proposed method. The recording is conducted using specialized otoacoustic probes. About 20 seconds of recording is available. The total length of the recording is used to obtain the frequency spectrum of the signal, which in turn can serve as a means of guessing the true value of



 $7 \frac{\text{X} 10^{-3}}{10^{13}}$ 

6

 $\overline{a}$ 

3

 $\overline{2}$ 

Estimated DPOAE Level (V)



Fig. 4. Illustration of the performance of the proposed DPOAE estimator using simulated data. This is the same experiment as that of Fig. 3, but with pink background noise.



Fig. 5. Illustration of the performance of the proposed DPOAE estimator using the first set of clinically recorded data.

the DPOAE level. The frequencies of the two stimuli and the DPOAE are  $f_1 = 1618$ ,  $f_2 = 1797$ , and  $f_d = 1438$  Hz, respectively. Fig. 5 presents the performance of the proposed method. It is observed that the convergence is achieved within the desired one second test period with a small estimation error.

#### IV. DISCUSSION

One of the recently proposed methods presented by Ma and Zhang in [8] is used in this section for a quantitative comparison with the proposed method. The method presented in [8] is an optimal maximum-likelihood estimator for the extraction of DPOAE signals. Superior performance of the method, especially in cases where DFT exhibits leakage effect is observed. The signal model is assumed to consist of the two stimuli and the DPOAE signal with noise. In [8], simulated



Fig. 6. Comparison of the performance of the proposed method with the method of Ma and Zhang.

data are used for the two stimuli and the DPOAE signal whereas the background noise is a recorded noise.

Simulated data were used for the comparison of the method of Ma and Zhang with the proposed method. Similar results to those presented in [8] were obtained using a simulated noise of zero-mean white Gaussian distribution as the background noise. For both cases, the numerical experiments involve two stimuli of frequencies  $f_1 = 2.454$  kHz and  $f_2 = 3.003$  kHz. The DPOAE signal is, thus, at white Gaussian distribution as the background noise. For both cases, the numerical experiments involve two stimuli of frequencies  $f_1 = 2.454 \text{ kHz}$  and  $f_2 = 3.003 \text{ kHz}$ . The DPOAE signal is, thus, at  $f_d = 2f_1 - f_2 = 1.905$  $f_d = 2f_1 - f_2 = 1.905$  kHz. The sampling frequency is chosen as  $f_s = 10.24$  kHz. The DPOAE signal is at 0 dB level while the two stimuli are at 65 dB. The experiment was repeated several times for different levels of the noise floor. Fig. 6 compares the performance of the two methods for varying levels of the noise floor. The index of the performance is taken to be the normalized mean squares error incurred in the estimation process. In the case of the proposed method, the vector of the estimated level of the DPOAE is formed after the signal is stabilized in the time domain (after about 500-ms delay).

When the incurred error exceeds the signal level, the signal is no longer recoverable. It is observed that the proposed method is less sensitive to the level of the background noise. In fact, as soon as the noise level exceeds the DPOAE level, the signal is totally lost and the estimation process fails. The proposed method of this paper has a very high degree of noise immunity, about 20 dB more than that of Ma and Zhang.

#### V. CONCLUSION

A method of measurement of DPOAE signal level employing a recently introduced nonlinear adaptive signal processing technique is presented. Performance of the proposed method is demonstrated using both simulated and real clinical data, and a comparison of its performance with that of one of the existing methods is presented. The main features of the proposed method of DPOAE signal measurement are its 1) structural simplicity, 2) high noise immunity and robustness, and 3) relatively high speed of convergence. Given the low complexity of the proposed method, it requires low level of computational resources, which in turn translates into less expensive equipment. High noise immunity and robustness of the proposed method render it suitable for practical clinical examinations which may be conducted in highly noisy backgrounds, perhaps without involving sound-proof examination rooms. This again translates into less expensive medical equipment. Also, given that the reduction in the level of the stimuli translates into a higher relative degree of background noise, the high noise immunity feature of the proposed method may be used to reduce the level of the stimuli for a more patient friendly examination. High speed of convergence of the proposed method is useful in reducing the examination time which again results in a more patient friendly and time effective clinical examination.

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# **Interictal Spike Detection Using the Walsh Transform**

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*Abstract—***The objective of this study was to evaluate the feasibility of using the Walsh transformation to detect interictal spikes in electroencephalogram (EEG) data. Walsh operators were designed to formulate characteristics drawn from experimental observation, as provided by medical experts. The merits of the algorithm are: 1) in decorrelating the data to form an orthogonal basis and 2) simplicity of implementation. EEG recordings were obtained at a sampling frequency of 500 Hz using standard 10–20 electrode placements. Independent sets of EEG data recorded on 18 patients with focal epilepsy were used to train and test the algorithm. Twenty to thirty minutes of recordings were obtained with each subject awake, supine, and at rest. Spikes were annotated independently by two EEG experts. On evaluation, the algorithm identified 110 out of 139 spikes identified by either expert** (True Positives = 79**%**) **and missed 29 spikes** (False Negatives = 21**%**)**. Evaluation of the algorithm revealed a Precision (Positive Predictive Value) of 85% and a Sensitivity of 79%. The encouraging preliminary results support its further development for prolonged EEG recordings in ambulatory subjects. With these results, the false detection (FD) rate is estimated at 7.2 FD per hour of continuous EEG recording.**

*Index Terms—***Epileptogenic data, focal epilepsy, interictal spike detection, Walsh transform.**

#### I. INTRODUCTION

Algorithms and methods for the automated detection of interictal spikes in the scalp electroencephalogram (EEG) can be very useful, especially during long-term EEG monitoring sessions, and may serve as a support mechanism to the decisions made by EEG experts. Several earlier studies [1]–[12] have described automated spike detection algorithms. Rule-based detection algorithms have explored two characteristics that are considered as most reliable in the detection of spikes: the fast rise and decay of the spike, and the sharpness of its peak. The spatio-temporal context is taken into account in several studies using different approaches: context-based detection [1], [10]–[12], state-based detection [2], neural networks [3]–[6], wavelet theory [7], [8], and expert systems [9], [10], to cite a few. An implementation example of the Walsh transform to stereo vision is provided in [13].

This study evaluates the feasibility of developing a spike detection algorithmusing the Walshoperator. The input EEG signals are decorrelated into signals with different orders (degree of sharpness) and different dimensions (width of the operator) using the Walsh transformation.

#### II. METHODS

## *A. Subjects*

Eighteen children with focal epileptic seizures served as subjects for this study. All of the procedures followed strict protocols pursuant to

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