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Improved transient evoked otoacoustic emission screening test using simple regression model and window optimization

Zoran Šarić [a,*], Miško Subotić [a], Ružica Bilibajkić [a], Slobodan Jovičić [b], Marko Barjaktarović [b]

[a] Laboratory of Acoustics, Life Activities Advancement Center, Gospodar Jovanova 35, 11000 Belgrade, Serbia
[b] Faculty of Electrical Engineering, University of Belgrade, Serbia

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ABSTRACT

The underlying problem in detection of transient evoked otoacoustic emission (TEOAE) is its extremely low level which is much under the level of noise that appears in the auditory canal. The algorithms based on wavelet transformation (WT) and frequency (e.g. scale) dependent windows are proved to have higher specificity and sensitivity of TEOAE test in comparison to the FFT-based algorithms using single analysis window. In this paper, a new algorithm for TEOAE screening test with improved performances is proposed. It is based on three improvements. The first one is based on simple linear regression model applied to series of signal-to-noise ratio (SNR) estimates and correction of the reproducibility estimate by mean square error criterion. The second one exploits inter-subjects variability of TEOAE latency by selecting the best window position. The third is based on the use of specific window shape developed from approximate of minimum mean square error criterion. The performance of the proposed TEOAE algorithm was tested on real TEOAE measurements embedded in artificial noise as well as on pure noise extracted from TEOAE measurements. The results provided evidence for the superiority of its performance in comparison with two referential algorithms.

1. Introduction

Analysis of otoacoustic emission (OAE) gives reliable and objective information about the quality of the cochlear function. Transient evoked OAEs (TEOAEs) are especially interesting because measurement of TOAEs elicited by high-level click stimuli can distinguish between normal hearing and impaired hearing and is widely used in the screening programs [1].

A serious problem in OAE signal detection is its extremely low level, between 10 and 20 dB SPL [2]. This is significantly under the level of noise that appears in the auditory canal. In order to provide a favorable signal-to-noise ratio (SNR) and to improve the reliability of OAE detection, different procedures are applied based on improvement of recording conditions, optimization of stimulus signal characteristics, as well as the improvement of the algorithms for processing of OAE signal [3]. Some of the processing algorithms use specific time windowing to overcome the low-frequency noise effect for newborn hearing screening [1]. Contrary to this approach, some of the researchers proposed the use of number of analysis windows in order to increase signal to noise ratio in each of TEOAE sub-bands [4]. This idea is based on dispersion of TEOAE latency for different frequency components [5].

In order to improve signal to noise ratio (SNR), the time-coherent ensemble averaging is commonly used. The omission of the noisy parts from the analysis interval further improves the SNR. This method of "time windowing" has been studied in order to find the exact duration of the analysis interval that provides the best separation between normal hearing and impaired hearing [4].

The wavelet technique, by which the signal is decomposed into a set of frequency components (scales), is well-suited for TEOAE analysis [5]. By computing the reproducibility from various scales, it is possible to improve the pass/fail separation during TEOAE hearing screening [6], as well as to reveal subtle differences that may exist between normal and pathological ears [7].

An advanced technique for time-frequency decomposition of TEOAE signal relies on assumption that TEOAE signal can be considered as a superposition of the resonant modes of characteristic frequencies and latencies [8]. By this approach, decomposition of TEOAE signal is performed by matching pursuit (MP) algorithm which finds a sub-optimal solution in a redundant set (dictionary) of functions [9]. The method has proved to be a reliable tool for

* Corresponding author.
E-mail addresses: sariczoran@yahoo.com (Z. Šarić), ifp2@ikomline.net (M. Subotić), r.bilibajkic@add-for-life.com (R. Bilibajkić), jovicic@etf.rs (S. Jovičić), marko.barjaktarovic@gmail.com (M. Barjaktarović).

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extraction of time-frequency properties of TEOAE components such as amplitude, latency and time span [10].

It was shown that TEOAE latency is inversely proportional to the central frequency of the scale [7]. A considerable increase in reliability of TEOAE detection can be achieved by adjusting the window position and its width in accordance to the latency and click response duration of each scale. The method proposed in [6] combines wavelet signal decomposition, nonlinear denoising, and scale-dependent time windowing. This method is shown to have a much higher specificity in TEOAE signal detection, compared to the previously used procedures. An additional effort has been done in designing the subject specific time window [11]. The windows were designed with reference to a minimum mean square error criterion involving the correlation properties of the ensemble of responses.

The method proposed in [12] was focused on the further reduction of the variance of the calculated cross-correlation caused by noise in TEOAE measurements. Instead of use one pair of buffers, usually denoted as buffers A and B, it uses N paired buffers. The variance of the cross-correlation calculated between buffers A and B is reduced by averaging of the N cross-correlations calculated on N paired buffers.

In this paper, we proposed three improvements of the detection algorithm. The first one is based on a linear regression model applied to series of signal to noise (SNR) estimates. The second exploits inter-subject variability of TEOAE latency by using different windows positions, while the third optimizes the shape of the window using the least squares criterion in signal estimation. The integral algorithm which includes these three proposed improvements is compared with the referent algorithms [6,12] on two test cases. The first test case includes test examples of real TEOAE records artificially noised by method [12]. The aim of this test case is to assess the specificity of tested algorithms. The second test case includes test examples of pure noise extracted from real TEOAE measurements [12]. The aim of the second test case is to assess sensitivity of the tested algorithms. The results are discussed in Section 4.

2. Materials and methods

2.1. TEOAE acquisition

Sixty volunteers participated in this study. Written consent was obtained from all participants prior to testing. The test protocol was reviewed and approved by ethical committee of the Institute for experimental phonetics and speech pathology (Belgrade, Serbia) where all measurements were conducted. Experiments were performed in a quiet room in which SPL of the ambient noise was SPL = 30 dBA. TEOAE recording was performed by our own acquisition system designed for research purpose, also used in [13]. The level of click stimuli was 85 dB SPL. Signal analysis was performed off-line in MATLAB. From sixty normally hearing subjects we selected TEOAE measurements of 46 ears with reproducibility greater than 70%.

According to the derived non-linear response (DNLR) method [1], four evoked responses associated with each set of the four-click stimuli were averaged. The result is referred to as the subaveraged response. Set of 256 packets of stimuli, each consisting of 4 clicks generates 256 subaveraged responses. They were stored in 256 buffers for further processing.

In order to test TEOAE algorithm on TEOAE measurements contaminated with a controlled amount of noise, we used noise generation similar to the method proposed in [12]. The noise was extracted from real TEOAE measurements by subtracting two neighboring subaveraged responses, i.e. buffers 1 and 2, 3 and 4, and so on. To obtain 256 noise buffers, we extended TEOAE measurement until 512 subaveraged responses were recorded. Set of 256 noise buffers was used to generate 20 noise distributions using random permutation generator.

TEOAE responses of 46 ears with artificially generated noise were used to generate two test groups [12]: (*a*) Test group that consisted of 920 TEOAE measurements mixed with artificially generated noise in order to evaluate specificity of tested algorithms; (*b*) The test group that consisted of 920 artificially generated noise measurements in order to evaluate sensitivity of tested algorithms.

2.2. Basic structure of TEOAE detection algorithm

Fig. 1 briefly depicts TEOAE signal processing based on discrete wavelet transformation (DWT), including improvement based on N paired buffers proposed in [12], and a module for reproducibility calculation based on the method proposed in this paper.

During TEOAE measuring session, 256 subaveraged responses of four click stimuli were recorded in 256 buffers for further processing. In commonly used method [1], odd buffers form a set A, while even buffers form a set B. According to the approach [12], any combination of 128 responses of the set of 256 available responses can be used to form buffers A and B. The method [12] proposes the use of N different buffer distributions $P_i = \{A_i, B_i\}$, $i = 1,..,N$, denoted as paired buffers, for which sets A_i and B_i may be defined as $A_1 = \{1,3,5,\ldots,255\}$, $B_1=\{2,4,6,\ldots,256\}$, $A_2=\{1,2,5,6\ldots,254\}$, $B_2=\{3,4,7,8\ldots,256\}$, and so on. A minimal number of paired buffers is one (A_1 and B_1), but for the larger N, the variance of reproducibility estimate becomes lower [12]. In the next processing step, discrete wavelet transformation (DWT) is performed using Coiflet5 [14]. Only scales 5, 6, and 7 with central frequencies 1150, 2200 and 4400 Hz were used [11,12]. These scales were processed by scale dependent windows [6] before reproducibility calculation. The high-frequency scale 7 was windowed from 2.5 to 7.5 ms, middle-frequency scale 6 was windowed from 2.5 to 9 ms, and low-frequency scale 5 from 3.5 to 14 ms.

Cross-correlation coefficient of jth scale of lth paired buffer, usually referred to as "wave reproducibility" is calculated by [15,16] and [17]

$$r(j,l)=\frac{\sum_{t=1}^{T}\bar{x}_{A,l}(t,j)\bar{x}_{B,l}(t,j)}{\sqrt{\sum_{t=1}^{T}\bar{x}^2_{A,l}(t,j)}\sqrt{\sum_{t=1}^{T}\bar{x}^2_{B,l}(t,j)}},\quad j=5,6,7,\quad l=1,\ldots,N, \tag{1}$$

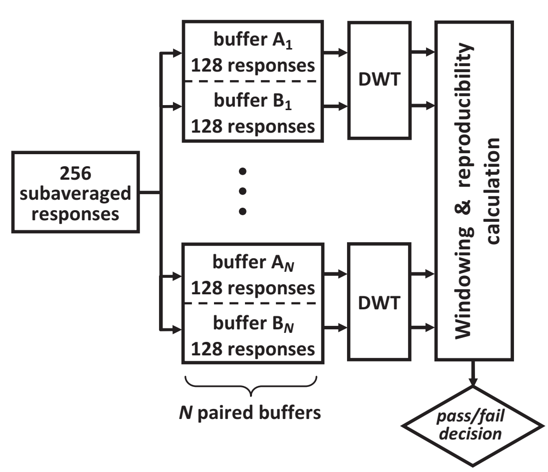

Fig. 1. Block diagram of the proposed wavelet-based algorithm.