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KAUNAS UNIVERSITY OF TECHNOLOGY

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Non-linear digital filtering of biomedical signals

Doctoral dissertation

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Abstract

The aim of this dissertation is to investigate the benefits of using wavelet based time-frequency analysis in filtering of non-stationary biomedical signals.

Filtering of non-stationary signals is an important issue in biomedical applications for increasing the accuracy of signal detection. One of possible applications of filtering methods is transient evoked otoacoustic emission (TEOAE), which is used to separate hearing impaired and normal hearing subjects in large screening tests of hearing. It is very important to have high sensitivity and specificity of these tests. Linear bandpass filtering was shown useful for increasing the specificity without loss of sensitivity in detection of TEOAE. However, linear filtering gave very limited improvement, since the spectrum of these signals is changing in time and overlaps with the spectrum of the noise.

In this dissertation, we have shown the use of wavelet transform for denoising of TEOAE signals using non-linear filtering and time- frequency filtering. Non- linear filtering, which is using the shrinkage of wavelet coefficients, was shown useful in applications, where spectrum of the signal and of the noise overlap. Very important issue is here to estimate the optimal shrinkage threshold. We developed the procedure to estimate this threshold. The threshold can be found by maximizing some criterion for optimality, e.g. cross correlation coefficient of the two subaverages of the TEOAE. The results of the non-linear filtering using proposed and thresholds found in the literature were compared. New threshold showed advantage over known thresholds. Another contribution of this dissertation is the method for time- frequency filtering of the signal using selection of the relevant signal expansion coefficients in discrete wavelet basis. The relevant coefficients can be determined by using a priori knowledge about the location of the signal components in time- frequency plane or by using statistical analysis, e.g. decomposing large amount of the signals and averaging them in time- frequency plane. Comparison of filtering results with proposed non-linear, time-frequency and known linear methods showed time-frequency filter being the best.

The feature extraction method using discrete orthonormal wavelet transform was investigated. The extracted features were cross correlation coefficients among in frequency and in time limited TEOAE signal components. It was shown how these features could be obtained very efficiently using fast discrete wavelet transform. A neural network was suggested for combining the extracted features. Comparison of the subjects' separation results in large database of TEOAE signals using proposed and known in literature filtering methods and proposed feature extraction methods was made. Receiver operator characteristics were used for comparisons. The highest increase of specificity at the level of 90% of sensitivity was achieved by using neural network for combining the extracted TEOAE features: from 68% to 84%.

Contents

1 Introduction

Most of biomedical signals are non-stationary, very low in amplitude and usually are embedded in noise of various origins: environmental noises, noise of the recording hardware, subject generated noise and other. To remove these noises from the signal it is impossible to use classical filtering because in most of the cases spectra of the signal and of the noise overlap.

Another problem is the detection of biomedical signals. This task we formulate as making the decision whether a recorded waveform consists of "noise alone" or "signal masked by noise". The detection of biomedical signals is more difficult than of radar as the shape of the signal is usually unknown. In addition, the recorded waveforms exhibit high variability among the subjects with similar parameters. Thus, the most salient features that are characteristic to signal class of interest should be established. This problem can be reformulated as feature extraction.

New emerging tool for signal analysis, a wavelet transform, was shown useful in the processing of non-stationary signals. Thus, it was decided to investigate the benefits of moving from time domain to wavelet domain in the processing of biomedical signals: transient evoked otoacoustic emissions.

The aim. The aim of this dissertation is to investigate and to develop new wavelet analysis based methods for denoising and detection of complex, non-stationary biomedical signals and to adopt them to the signals of transient evoked otoacoustic emission.

Novelty. The framework of signal denoising and detection in the discrete wavelet transform domain is established. New threshold estimation method was proposed in wavelet based denoising of signals of transient evoked otoacoustic emission. Novel, wavelet coefficient selection based denoising method, was developed. Time-frequency features and neural network to combine these features were suggested in the problem of transient evoked otoacoustic emission signal detection.

Practical implementation. All the developed methods and algorithms were designed taking in to account speed and practical implementation. They were implemented using scientific computing language Matlab5.3, MathWorks, Inc., which is becoming a standard in computation science and engineering.

Reliability of the results. All the developed new algorithms were tested on the large database consisting of 5213 signals.

The statistical hypothesis test was used to check if the difference between the methods was statistically significant. Although the resulting difference between the two signal classification methods was small, the hypothesis test showed that we could reject the null hypothesis, as the evaluated *P* value was *0.0002.*

With this dissertation author defends the following conclusions:

1. The methods based on time- frequency (time- scale) signal decompositions are more suitable for filtering and detection of non-stationary biomedical signals when comparing with methods based only on time or frequency analysis.

2. The feature of wavelet transform to concentrate the energy of the correlated signal into a few high energy coefficients while scattering the energy of the noise into many low amplitude coefficients can be used for the non-linear filtering. Non-linear filtering of the signal can be accomplished by the non-linear processing of the wavelet coefficients.

3. The results of wavelet based non-linear filtering depend on the used analyzing wavelet. We have formulated the criterion of the optimality of the wavelet for the given signal. It is a measure of the energy concentration expressed as Shannon entropy. In case of otoacoustic emission the best results among orthogonal wavelets with finite time support showed "Symmlet 8" wavelet.

4. The optimal threshold for non-linear wavelet shrinkage can be estimated by solving the problem of the maximization of some optimality criterion. In case of otoacoustic emission, the cross correlation coefficient between subaverages can be used as the criterion of the optimality.

5. The feature of wavelet transform to localize in time and in frequency at the same instant can be used to establish the statistical location of the non-stationary signal components in time- frequency plane and for time-frequency filtering.

6. The cross correlation coefficients calculated among time and frequency limited components of the signal can be used as the features for the TEOAE signal detection. These features can be very efficiently calculated directly in wavelet domain.

7. Wavelet based TEOAE filtering enabled to increase the specificity of the TEAOE signal detection by 16% without any decrease of the sensitivity.

8. The neural network was suggested for combining the extracted features in the application of separation hearing impaired and normal hearing subjects. However, the increase in accuracy of the subject separation is small when comparing with feature combiner, which uses average of the features. This suggests similar weights of the features.

Outline of the dissertation contents

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List of publications by the author of the dissertation

Journal papers:

1. Marozas V., Lukoševičius A., Engdahl B., Svensson O. and Sörnmo L. "*Otoacoustic emissions and pass/fail separation using artificial neural network*". Ultragarsas, 1(34), pp. 7-12, 2000.

2. Marozas V., Janušauskas A., Engdahl B., Svensson O. and Sörnmo L. "*Detection of otoacoustic emission in the wavelet domain*". Medical & Biological Engineering & Computing, Suppl. vol. 37, pp.334-335, 1999.

3. Marozas V. "*Vienmačio nestacionaraus signalo skleidimo laiko ir dažnio plokštumoje metodai ir jų pritaikymas otoakustinės emisijos signalo analizei*". Elektronika ir elektrotechnika, 3(12), pp.18-20, 1997.

4. Janušauskas A., Marozas V., Engdahl B., Svensson O. and Sörnmo L. "*Otoacoustic emissions and improved pass/fail separation using wavelet based de-noising*". Accepted for publication in Medical and Biological Engineering and Computing, 2000.

5. Janušauskas A., Marozas V., Engdahl B., Svensson O. and Sörnmo L. "*Wavelet based denoising of otoacoustic emissions*". Elektronika ir elektrotechnika, 5(18): 38-41, 1998.

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1. Marozas V., Lukoševičius A., Svensson O., Engdahl B. and Sörnmo L. "*Wavelets for feature extraction and neural network for detection of otoacoustic emission*". Biomedical engineering'99, KTU, Kaunas, October 1999.

2. Janušauskas A., Marozas V., Engdahl B., Svensson O. and Sörnmo L. "*Otoacoustic emissions and improved pass/fail separation using wavelet based denoising*". Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Hong Kong, pp. 3129- 3131, 1998.

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5. Marozas V., Janušauskas A., Lukoševičius A., Engdahland B., Svensson O. and Sörnmo L. "*Wavelets and Neural Networks in Detection of Otoacoustic Emission*" Workshop "Advances in Signal and Image Processing for Solving Real Problems of the Real World" Nida, Lithuania, August, 1999.

Technical reports:

6. Marozas V. "*Modeling of the Hearing System*". In the report BK8-11 "Investigation of acoustic medical diagnostic systems and signals" by A.Lukoševičius, D. Jegelevičius, R. Jurkonis, V. Marozas, A Janušauskas, Kaunas, KTU, 1998.

Abbreviations

ANN	Artificial neural network
DFT	Discrete Fourier transform
DWT	Discrete wavelet transform
FN	False negative
FP	False positive
GCV	Generalized cross validation
HI	Hearing impaired subject
HTL	Hearing threshold levels
MAD	Median Absolute Deviation
MHL	Mean hearing level
MLP	Multilayer perceptron
MRA	Multiresolution analysis
MSE	Mean square error
NH	Normal hearing subject
OAE	Otoacoustic emission
PSD	Power spectral density
ROC	Receiver operator characteristic
SNR	Signal-to-noise ratio
SPL	Sound pressure level
STFT	Short time Fourier transform
SURE	Stein's Unbiased Risk Estimate
TEOAE	Transient evoked otoacoustic emission
TN	True negative
TP	True positive

Notation

j	-	Level of the wavelet decomposition
2^j	-	Dyadic scale
$1/2^j$	-	Resolution
J	-	Maximal level of decomposition
L	-	Length of the filter involved in wavelet decomposition
O	-	"Order of ..." (in counting the number of operations)

2 Biomedical signals. Signals of transient evoked otoacoustic emission

2.1 Biomedical signals in general

A signal is a phenomenon, which carries information. Biomedical signals are signals that emanate from living systems. The analysis of these signals gives the information about the living system, which created the signal.

Biomedical signals are used for diagnostic, monitoring and other goals. The process of information extraction can be simple as inspection by experienced eye of physician. However, often in biomedical applications the acquisition of the signal is not enough. It is required to process the signal to get the information, which is hidden in it. This may be because of the noise in the signal. Therefore, information cannot be seen with the "naked eye". The signal must be "cleaned". Different terms are used to describe this process: signal recovering, signal enhancing or signal denoising.

The biomedical signals are classified according to their origin: bioelectric, bioacoustic, bioimpedance, biomechanical, biooptical, biomagnetic, biochemical signals. Further, they can be divided into two main groups: deterministic and stochastic. Deterministic signals can be divided in periodic and non-periodic, while stochastic signals- into stationary and non-stationary. Such a vast variety of biomedical signals do not allow creating the universal methods, suitable for the processing of all the biomedical signals. Thus, it is a very important task today to identify the methods that are suitable for the particular signal classes and in opposite- to define the classes of the signals that can be treated with the particular method. Another important task is to achieve a full success in the particular application and to make a step further by identifying signal specific features and incorporation of all the a priori known information about the signal and system under investigation.

In this investigation we will consider biomedical signal enhancement methods with the application to one of the bioacoustic signals- transient evoked otoacoustic emission (TEOAE), which can be used to extract information about the state of the hearing organ- cochlea.

2.2 TEOAE signal

TEOAE is low-level sound produced by the cochlea as the response to the short acoustical stimulus. TEOAE is present usually in the normal hearing ear but absent, or attenuated, in the dysfunctional cochlea [47].

Gold [32] was the first who hypothesized otoacoustic emission in 1948 and Kemp [47] was the first who recorded it in 1978. There is still no complete theory explaining TEOAE generation, yet. It is believed that the TEOAE is partial product of amplification process, which is present in the cochlea [35].

The main properties that characterize the TEOAE are:

1. Non-linearity. Due to the non-linear nature of cochlear preprocessing of sound, the presentation of different frequencies leads to the generation of several additional combination frequencies. In addition, the physical properties of the basilar membrane mechanics in the cochlea change with stimulus level. This "compressive" non-linearity leads to compressive amplitude growth functions in the TEOAE acquisition. This property is used to separate the linear acoustical stimulus from non-linear response in time with the technique called "non-linear differential averaging" [6]

2. Dispersion. Otoacoustic emissions (OAE) are delayed with respect to the onset of acoustical stimulation. OAE exhibit strong dispersion. The latency of otoacoustic emissions increases from approximately 3 ms at frequencies of about 6 kHz to more than 10 ms at frequencies near 1 kHz. Changing spectral characteristics of TEOAE signal causes it to be non-stationary in time, which causes problems for signal filtering from the noise. Investigation of latencies of different frequency components in TEAOE signal attracted much of attention [40], [91], [92], [94], [58].

3. Reproducibility. Otoacoustic emissions are highly reproducible. The temporal and spectral properties of OAE are unique for each subject and are stable for long time ("fingerprint of the inner ear"). Because of this feature TEOAE signal can be treated as deterministic for the same subject and signal averaging technique can be used in order to increase signal to noise ratio.

PC based systems are used for TEOAE recording. The click stimulus is produced by application of an 80 μs electrical pulse to the speaker in the ear canal probe. Stimuli are presented at a rate of 50 Hz. The stimulus voltage results in click levels of approximately 80 dB SPL in adult ears. The stimuli have flat spectra up to 4-5 kHz in the ear canal. The ear canal sound

pressure is sampled at 25.6 kHz for 20 ms after each stimulus with a 12-bit analog-to-digital converter and alternate samples are stored in separate 512-point waveform buffers, resulting in two waveforms.
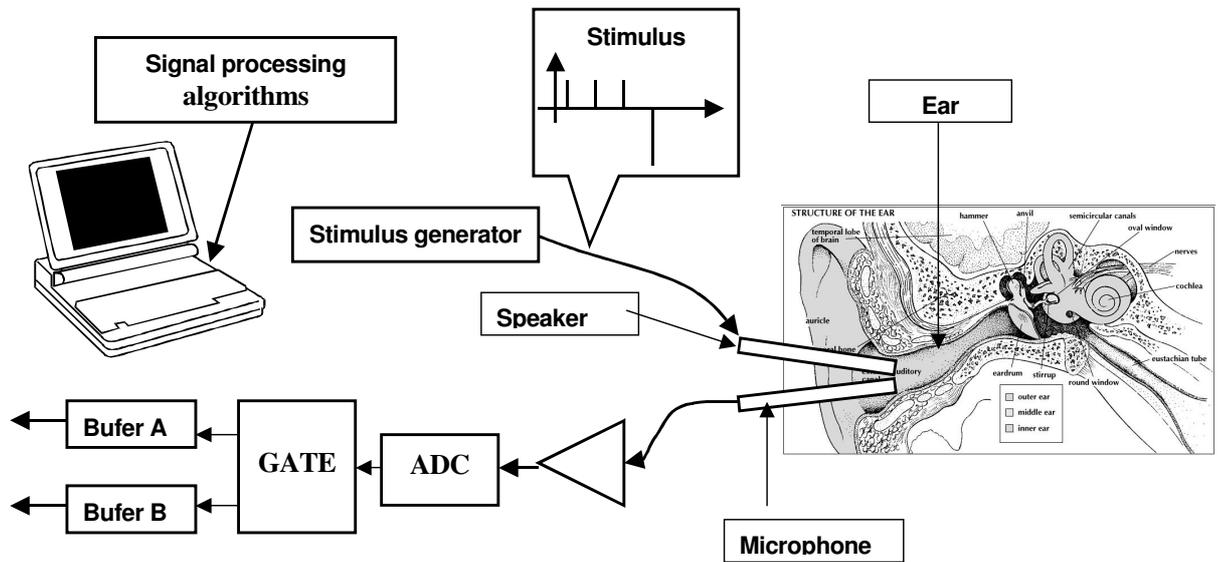
Figure 2.1 System for TEOAE signal acquisition
(ADC- analog to digital converter)

The typical example of two subaveraged TEOAE waveforms is shown in Figure 2.2. Earlier described different features can be identified: both waveforms exhibit shorter periodicities or higher frequencies at shorter post stimulus times and both subaveraged waveforms show very high similarity or reproducibility in this case.
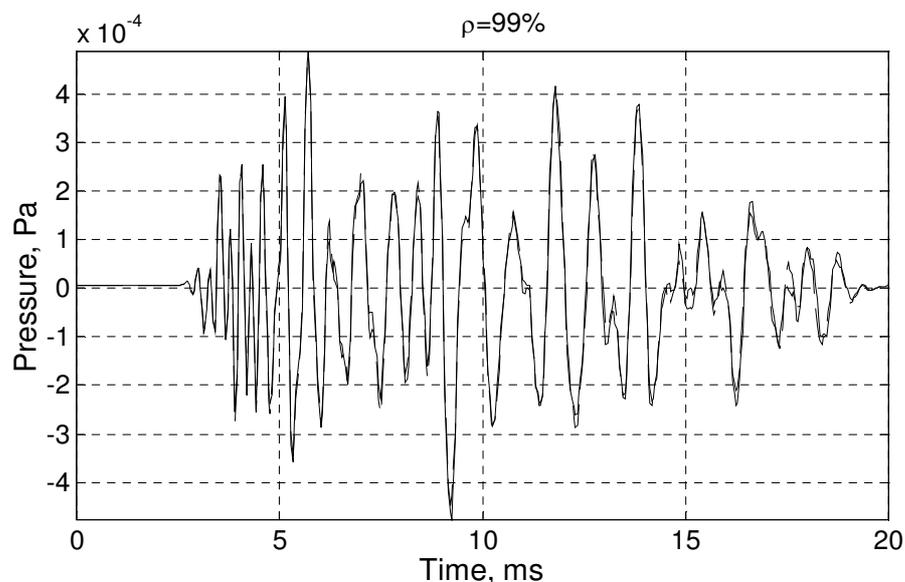
Figure 2.2 Example of TEOAE subaverages as recorded from a normal hearing subject having mean hearing threshold 9dB

Although TEOAE is mainly object of the research yet, applications in clinical practice appear. TEOAE appeared to be useful in screening tests in

neonates [7], in population exposed by noise [8] and to monitor the influence of drugs [9]. The most promising application is hearing screening. Screening can be understood as a sieve separating subjects into hearing impaired and normal hearing. Preliminary large population studies of TEAOE screening in Norway (screening of hearing in population living near the airport) and Australia (monitoring cochlea function of the workers in the coalmine) revealed conveyance, readability and speed of the technique [24], [25].

The most important application of TEAOE test up to date is hearing screening. The purpose of any screening test is to act as a sieve that extracts a smaller set of cases from the screened population. A screening test is said to have 100% "sensitivity" when the extracted set of cases contains all cases to be identified. A "specific" screening test is one that is efficient in keeping down the number of cases reaching follow-up tests. The consequence of lack of specificity is the high cost and increase in the resources required by the follow-up centres, whereas the consequence of lack of sensitivity is that cases go untreated until they are identified by other means.

There is a consensus that ears with hearing threshold levels (HTL) greater than 20 to 30 dB do not demonstrate TEOAE [47], [50]. The studies [42], [53] have shown that in order to have high sensitivity of the TEOAE test, the separation criterion should be high. However, the corresponding specificity is low in that case. The main reason for the poor specificity is noise contamination of the emission responses. For example, an increase of the signal-to-noise ratio by 0.6 dB increased the specificity (the "pass" percentage) from 83 to 86 % [6].

Thus maximizing signal to noise ration is of the most important technical challenges for applied TEAOE measurement.

3 Classical and new solutions of biomedical signal enhancement and detection

We review classical methods of biomedical signal denoising and detection in this section. We formulate the problems associated with these approaches and point out the directions to solve them.

3.1 Averaging

The basic method used for enhancing biomedical signals including TEAOE is to make an average of the recorded signal obtained from several consecutive stimuli [88]. The signal must satisfy the following conditions in order to achieve good results:

1. The signal epochs should contain a deterministic signal component, which does not vary for all the epochs

2. The contaminating noise is a broadband stationary process with zero mean and variance σ^2.

3. Signal *f[n]* and noise *v[n]* are uncorrelated so that the recorded signal *s(t)* at the *i-th* realization can be expressed:

$$s[n]_i = f[n] + v_i[n] \qquad (3.1)$$

After N time averaging it can be written:

$$\frac{1}{N}\sum_{i=1}^{N} s_i[n] = \frac{1}{N}\sum_{i=1}^{N} f_i[n] + \frac{1}{N}\sum_{i=1}^{N} v_i[n] \qquad (3.2)$$

If all the previous conditions are satisfied the averaging result is:

$$\widehat{s}_i[n] = f[n] + \frac{1}{N}\sum_{i=1}^{N} v_i[n] \qquad (3.3)$$

The averaged noise signals variance σ^2 decreases N times and improvement in SNR (rms value) is $\sqrt{N}$.

An example of the TEOAE signal subaverages with different numbers of realizations included in the average is shown in Figure 3.1.

One of main drawbacks of such estimator is long averaging time to achieve signal estimate with suitable SNR for further analysis. In addition, the conditions for background noise normality can be broken during long

averaging time. Thus, in general averaging time is limited and other techniques for further signal enhancement are sought.
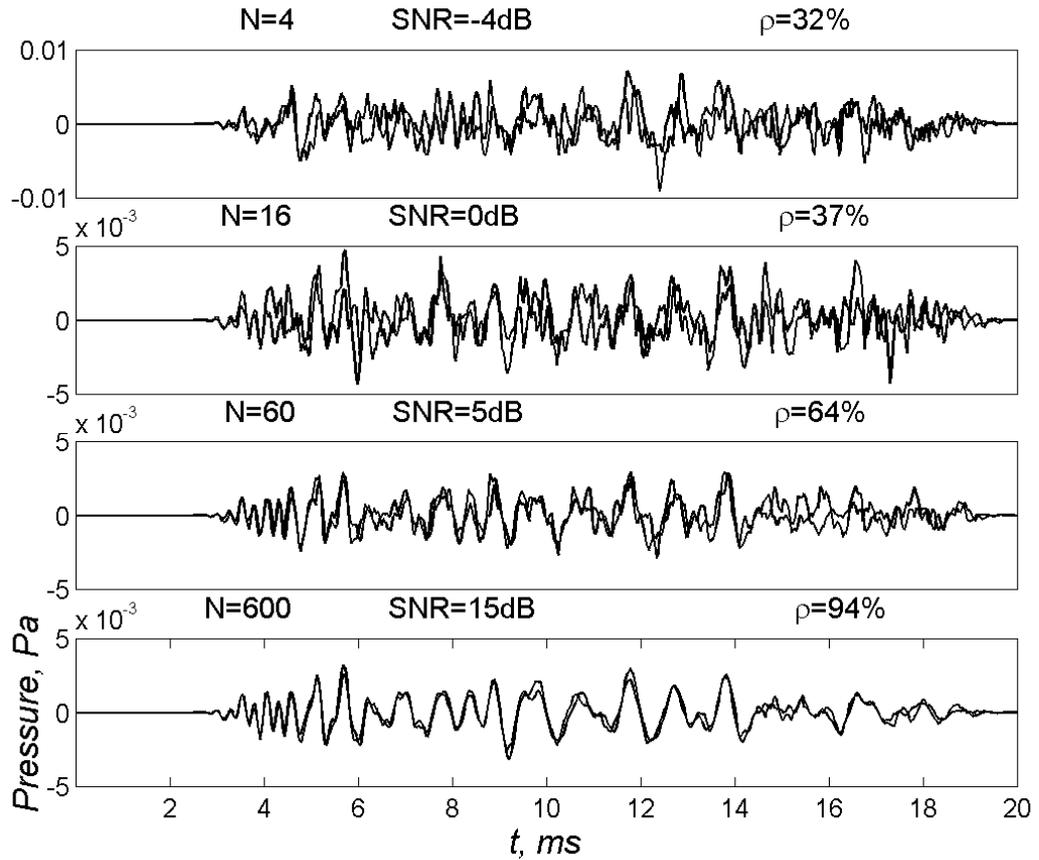
Figure 3.1 Enhancement of TEOAE signal by means of averaging technique. The noise is progressively reduced by increasing number of sweeps N in each subaverage. ρ is the cross correlation coefficient between subaverages.

3.2 Filtering

Averaged signal estimate can be further enhanced with linear filter by exploiting the fact that the spectra of noise and response do not completely coincide. In case of standard TEOAE acquisition procedure two filters are used: low-pass with the cut-off 6.4 kHz to exclude instrumentation noise and high-pass, with the cut-off 0.6 kHz to exclude some of the stimulus artefact and the largest components of ambient and subject generated noise [6].

The performance of a filtering procedure in reducing noise of TEAOE can be improved by optimising the frequency response of the filter. Optimisation of the cut-off frequency of the high pass filter has been performed in study [93]. The criterion for the optimum frequency was maximal reproducibility of the responses with the constrain to the loss of the cross-

spectral energy. The same strategy was used in study [78] with the difference that bandpass filter was used instead of high pass and both cut-off frequencies low and high were optimised. The best results of the optimal filter in terms of increasing the post-filtering reproducibility was obtained when the procedure was applied to recordings whose reproducibility before filtering ranged between 60 and 80 %, i.e. for responses classified as partial pass.

However, when the PSD of signal and noise overlap the highest increase in SNR with lowest distortion to the signal can be obtained by Wiener filtering approach. The Wiener filter is given by the transfer function:

$$H(\omega) = \frac{S_{ss}(\omega)}{S_{ss}(\omega) + S_{nn}(\omega)} \tag{3.4}$$

where $S_{ss}(\omega)$ is power spectrum of the response and $S_{nn}(\omega)$ is power spectrum of the noise.
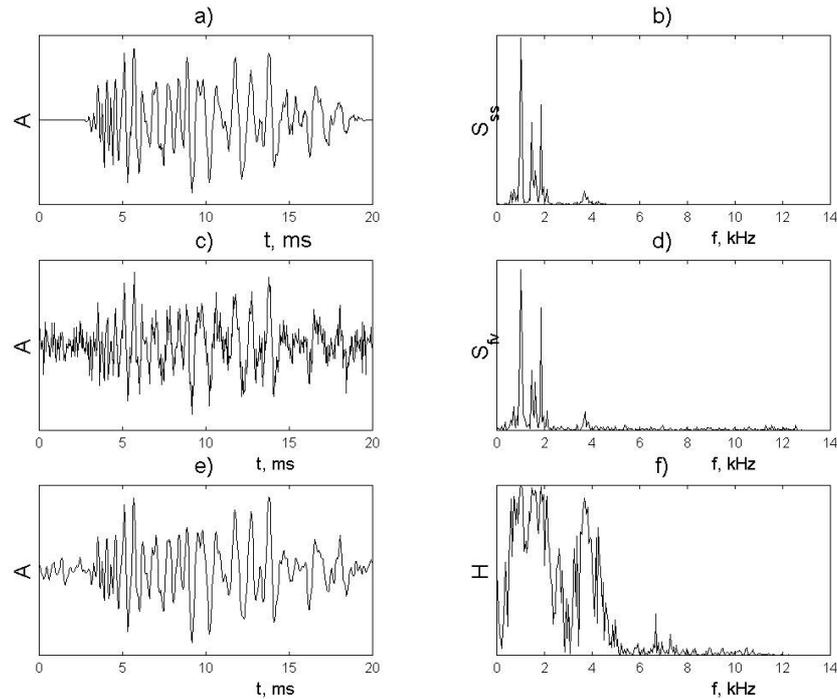
Figure 3.2 Filtering with Wiener filter: a) real TEOAE signal (SNR=∞), b) power spectrum of the clean signal, c) signal contaminated with white Gaussian noise (SNR=0.6dB), d) power spectrum of contaminated signal, e) filtered signal (SNR=8.8) and f) transfer function of the Wiener filter

Since $S_{ss}(\omega)$ and $S_{nn}(\omega)$ are not known in advance they should be estimated from the records [89]. Figure 3.2 shows the experiment where real TEOAE signal (plot *a*) was contaminated with white Gaussian noise (plot c) and the signal after filtering with Wiener filter shown in plot *f*. Plot *b* shows

power spectrum of the clean signal, plot *d* shows power spectrum of contaminated signal. The gain in SNR after filtering is 7 dB. It is idealized situation as in real conditions the quantities $S_{ss}(\omega)$ and $S_{nn}(\omega)$ are not known. They have to be estimated from the recorded signal, thus errors in the estimates will lead to the lower performance.

Another problem that faces Wiener filter, is non-stationary signals. The Fourier transform is used to estimate the transfer function of the filter. However, the Fourier transform is not localized in time space and removing noise at a specific frequency with Wiener filter also involves removing any signal components, which also share the same frequency. Thus, any change made to a Fourier coefficient is a global, effecting both noise and signal.

To overcome the limitations of the Fourier analysis to represent non-stationary signals, Short Time Fourier Transform (STFT) was proposed. It contains the time parameter and the frequency parameter as well. The localization in time is achieved by weighting or windowing previous infinite Fourier basis functions. If the Gaussian function *exp(-t²)* is used as the window function then it is known as the Gabor transform. The time resolution of the STFT is given by the time width of the window function. The spectrum is only captured with finite resolution, too. Here, the spectral resolution is given by the bandwidth of the window function. The product of the bandwidth and the time width of the window function is a constant, which depends only on the shape of the window function. In the case of the STFT, the division of the time-bandwidth product into time duration and bandwidth is the same for all values of frequency and time. Thus, STFT has a constant resolution. However, most of the biomedical signals are multi-component in nature. They consist of high frequency components of shorter duration and low frequency components of longer duration. STFT is not adequate to such kind of signals. There was a need for the transform, which divides the time-bandwidths product differently at different frequencies and different times. This can be attained by the relatively new signal processing tool- wavelet transform [16].

3.3 Detection

The signal detection problem is to decide whether the waveform consists of "noise alone" or signal "masked by noise". Our goal is to use the received data as efficiently as possible in making the decision while being correct most of the time.

More formally detection problem in discrete function domain could be formulated as "having received the signal *s[n]*, form the function of the received data *d{s[n]}* and when make the decision based on its value".

In clinical diagnostic applications, biomedical signals carry information, which is often interpreted as "true negative" (TN) or "true positive" (TP). For example, in TEOAE case, detected signal is interpreted as "negative" result indicating normally functioning cochlea, while response, which shows no TEOAE like activity is interpreted as "positive" result showing problems in the cochlea.
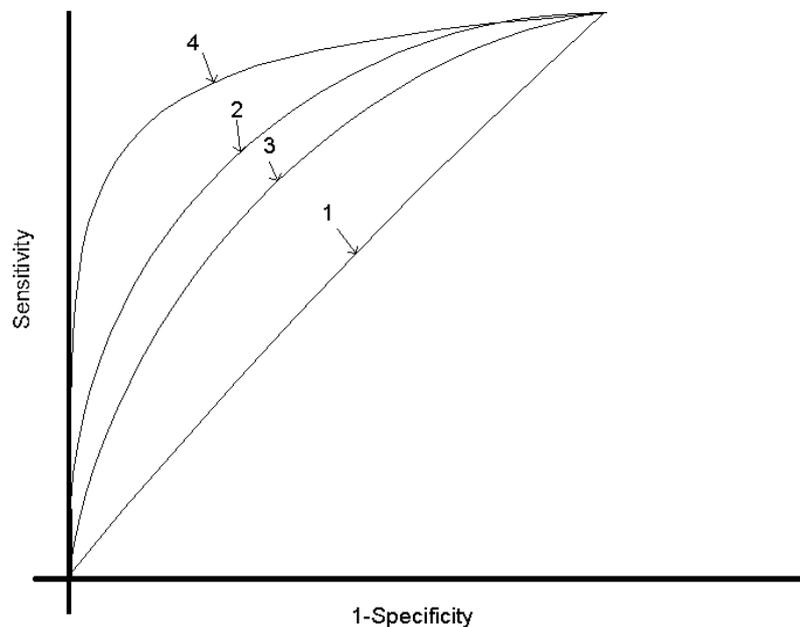
Figure 3.3 Four members of the family of ROC curves. ROC curves are indexed over increasing range of SNR. The curve Nb. 1 indicates detection performance at the lowest SNR, Nb.4- at the highest.

In practice we face with two problems when making the detection: how to form the function *d{s[n]}* and where to set the decision threshold *T* on function *d{s[n]}* so as to ensure that the number of decision errors is small. There are two types of errors possible: the error of missing the signal (decide "noise" when in reality is "signal+noise") and the error of false alarm (decide "signal+noise" when only "noise" is present). In biomedical diagnostic applications these errors are named "false positive" (FP) and "false negative" (FN). In case of TEOAE based hearing test FP result would point to the normally hearing subject as hearing impaired while because of FN result we would miss the hearing impaired subject. The probability to detect correctly normal hearing subject is named "Specificity" of the test. The probability to detect correctly hearing impaired subjects is named "Sensitivity" of the test.

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These probabilities can be varied by choosing different decision threshold T in the output of the detector $d\{s[n]\}$. However, when one of the probabilities is increased, the other is decreased. A function of sensitivity as a function of the variable *1-specificity,* when the decision threshold is varied over all range of the detector $d\{s[n]\}$ values, is called receiver operating characteristic (ROC). Good detector should have ROC curves which have desirable properties such as concavity (negative curvature), monotone increase in sensitivity as specificity decreases, high slope of sensitivity at the point (Sensitivity, 1-Specificity)=(0,0) [38]. Simply stated, the goal of signal processing algorithms is to find ways to test between outcomes Negative and Positive, which push the ROC curve towards the upper left corner of Figure 3.3, where both sensitivity and specificity are high. In practice, one operating point or the threshold T is chosen to meet particular requirements of the application. For example, in TEOAE based hearing test more important parameter is sensitivity than specificity. Thus, it is usually chosen to be high: 90 or 95 %.

Another issue in the signal detection problem is the determination of the function $d\{s[n]\}$. This problem is known as pattern recognition problem [11]. It can be divided into the steps of feature extraction and combination of the features to form the function $d\{s[n]\}$. The stage of feature extraction involves the transformation of the received data *s(n)* in such a way as to reveal key features of a signal that are difficult or impossible to discern in the original domain. For example, Fourier transform reveals the composition of the signal in terms of building blocks, or basis functions of transformed domain: sines and cosines. Fourier transform depends on the one parameter-frequency. Time dependence is lost in the transform. It cannot be seen when exactly the spectral components of the signal appear and this is unsatisfactory for non-stationary signals. Thus, wavelet transform was planed to be used for extraction of the features.

The final issue in the construction of detection function $d\{s[n]\}$ is how to combine the extracted features. The features can be combined linearly and non-linearly. The weights for linear combination of the features can be chosen by doing regression analysis. However, the most exact detector can be achieved by using a artificial neural network as the non-linear feature combiner [37].

4 Wavelets and wavelet transform

In this section, we summarize some relevant aspects of wavelet theory, which was introduced by Yves Meyer and Jean Morlet in 1984. Later in section 4.2, we present some experiments and explorations of the relevant properties of wavelet transform.

4.1 Wavelet theory

Every function can be expanded in such a way:

$$f(t) = \mu(t) + \sum_j w_j \psi_j(t) \qquad (2.1)$$

where $\mu(t)$- the mean of the function $f(t)$, $\psi_j(t)$- system of elementary functions and w_j are expansion coefficients that are defined as:

$$w_j = \int_{-\infty}^{\infty} f(t) \psi_j^*(t) dt \qquad (4.2)$$

The possible examples of systems $\psi_j(t)$ could be: signal dependant Karhunen- Loeve basis of eigen functions [99], complex sines and cosines in Fourier basis $\psi(t) = \exp(j\omega t)$. However, these functions are infinite in time and are not suitable for characterization of non-stationary signals, spectral characteristic of which are changing in time course. Another possibility is to choose the system, which consist of elementary functions that are well localized in time and frequency i.e. have rapid decay in time and frequency. Elementary functions would behave as time- frequency atoms giving possibility to represent the signal into joint time- frequency plane. Such localized systems of elementary functions are short time Fourier transform (STFT) and wavelet transform. The basis functions of STFT are windowed sines and cosines:

$$\psi(t) = w(t - \tau) \exp(j\omega t) \qquad (4.3)$$

Where $w(t)$ is window function, τ- shift in time parameter, ω- radial frequency.

Basis functions of wavelet transform are defined as:

$$\psi_j(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \qquad (4.4)$$

Where $\psi\left(\dfrac{t-b}{a}\right)$ is mother wavelet, b- time shift parameter, a- scaling parameter of the time variable t.

There are many such mother wavelets and many systems of wavelet functions and wavelet transforms, which have different characteristics. Some example analytic expressions and shapes of wavelets are shown below:

Morlet wavelet:

$$\psi(t) = e^{-\frac{t^2}{2}} e^{j\omega_0 t} \qquad (4.1)$$

Wavelet transform with this wavelet is expressed as:

$$CWT(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\left(e^{-\frac{1}{2}\left(\frac{t-\tau}{a}\right)^2} e^{j\omega_0\left(\frac{t-\tau}{a}\right)} \right) dt \qquad (4.2)$$

"Mexican hat" wavelet:

$$\psi(t) = \left(1 - t^2\right) e^{-\frac{t^2}{2}} \qquad (4.3)$$

and wavelet transform:

$$CWT(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\left(\left(1 - \left(\frac{t-\tau}{a}\right)^2\right) e^{-\frac{1}{2}\left(\frac{t-\tau}{a}\right)^2} \right) dt \qquad (4.4)$$

With continuous parameters a and b, wavelet transform is called continuous wavelet transform (CWT) and is highly redundant having minor practical importance.
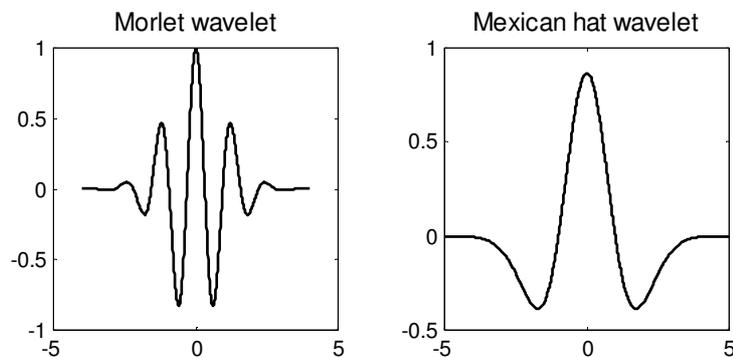
Figure 4.1 "Morlet" and "Mexican hat" wavelets

This redundancy is removed in another type of wavelet transform- the discrete wavelet transform (DWT). Signal transformed into discrete wavelet domain has as many coefficients as it has in original time domain. Another advantage of DWT to CWT is existence of the fast decomposition and reconstruction algorithm based on filter banks and changing of sample rate.

The DWT stems from multiresolutional analysis and filterbank theory [57]. The multiresolutional analysis is a decreasing sequence of closed subspace $\{V_j\}$, which approximate square integrable functions space in $L^2(R)$. A discretized function $f[n]$ is projected at each step j, onto the subset V_j. This projection is defined as the scalar product noted a_j, of $f(n)$ with a scaling function noted $\phi[n]$:

$$a_{jk} = \frac{1}{\sqrt{2^j}} \sum_n f[n] \phi[2^{-j}n - k]$$

(4.5)

Here k is the translation parameter and j is the dilation parameter.

Scaling function $\phi[n]$ has the following property:

$$\frac{1}{2}\phi\left(\frac{n}{2}\right) = \sum_k h(k)\phi(n-k)$$

(4.6)

The sequence $h(k)$ is the impulse response of a low pass filter.

Each step smoothens the signal. The lost information can be restored using the complementary subspace W_{j+1} of V_{j+1} in V_j. This subspace is generated by a wavelet $\psi(n)$ with integer translations and dyadic dilation; the projection of $f(n)$ on W_j is defined as:

$$w_{jk} = \frac{1}{\sqrt{2^j}} \sum_n f[n] \psi[2^{-j}n - k]$$

(4.7)

As the scaling function, the wavelet function has the following property:

$$\frac{1}{2}\psi\left(\frac{n}{2}\right) = \sum_k g(k)\ \phi(n-k)$$

(4.8)

The sequence $g[k]$ is the impulse response of a high-pass filter.

Then the analysis is defined as:

$$a_{j,k} = \frac{1}{2}\sum_{n} h[\,n - 2k\,]a_{j-1,k}$$

$$w_{j,k} = \frac{1}{2}\sum_{n} g[\,n - 2k\,]a_{j-1,k}$$

(4.9)

For orthogonal wavelets, the restoration is performed with:

$$a_{j,k} = 2\sum_{n} h[\,k - 2n\,]a_{j+1,k} +$$

$$2\sum_{n} g[\,k - 2n\,]w_{j+1,k}$$

(4.10)

Thus, the function $f[n]$ can be represented as the finite summation:

$$f[\,n\,] = \sum_{j=1}^{J}\sum_{k} w_{j,k}\psi_{j,k}[\,n\,] + \sum_{k} a_{k}\phi_{J,k}[\,n\,]$$

(4.11)

The wavelet coefficients $w_{j,k}$ and scaling coefficients a_k comprise the wavelet transform. For a wavelet centred at time zero and frequency f, w_{jk} measures the content of the signal around the time $2^j k$ and frequency $2^{-j} f$ (or level j). Wavelet transform of sampled signal can be computed extremely efficiently using two-channel filter banks structure [56] as it is shown in Figure 4.2.
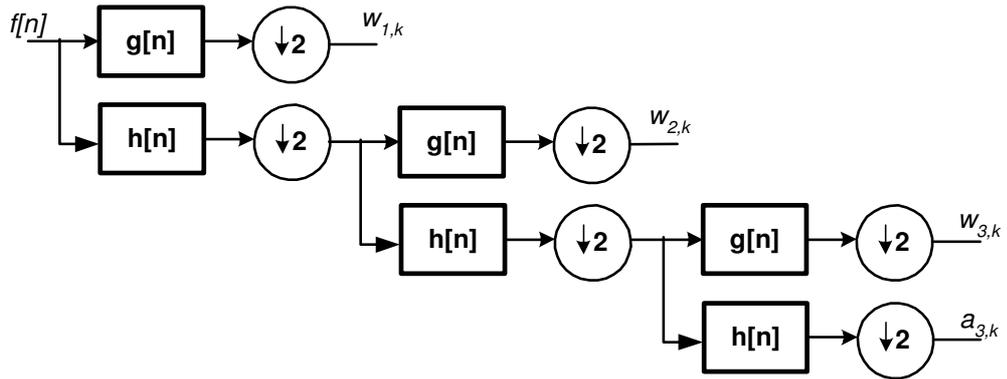
Figure 4.2 The DWT using multirate filterbank algorithm (g[n] is the highpass filter, h[n] is the lowpass filter, ↓2 means down sampling operation). Wavelet coefficients $w_{1,k}$ represent the first level of decomposition (j=1), $w_{2,k}$ represent the second level of decomposition (j=2),

When a signal has n samples, they are ordered in wavelet domain as follows:
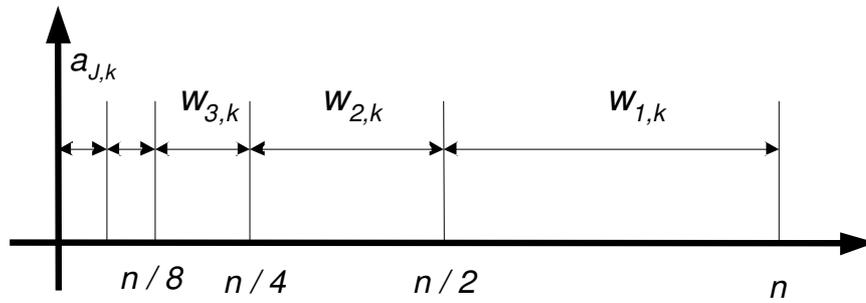
Figure 4.3 The order of the wavelet coefficients from different levels of wavelet decomposition in the vector of coefficients after wavelet transformation. Here n is the number of samples in the signal in the original time domain

For DWT and IDWT structures shown in Figure 4.2 and Figure 4.4 to be valid, the coefficients of the filters *g[n]* and *h[n]* have to be chosen carefully. They have to satisfy three groups of conditions [16]:

1. Conservation of area condition,

2. Accuracy condition,

3. Orthogonality condition.

Thus, it is not easy to find the filters *g[n]* and *h[n]* satisfying all previous conditions and limited amount of wavelets for DWT were found. The most popular are:

- Daubechies filters indexed by their length, Par, which may be one of 4,6,8,10,12,14,16,18, 20;

- Coiflet filters are indexed as 1,2,3,4 or 5;

- Symmlets are wavelets within a minimum size support and as symmetrical as possible, as opposed to the Daubechies filters, which are highly asymmetrical. They are indexed from 4 to 10.

These wavelet families differ in the smoothness and compactness of the basis functions.
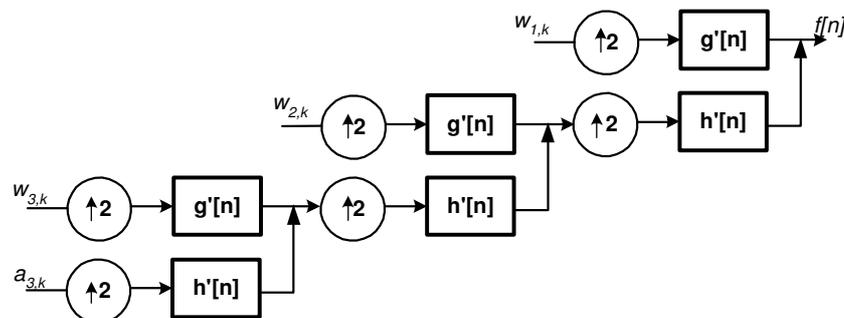
Examples of some typical orthogonal and finite in time wavelets are shown in Figure 4.5.
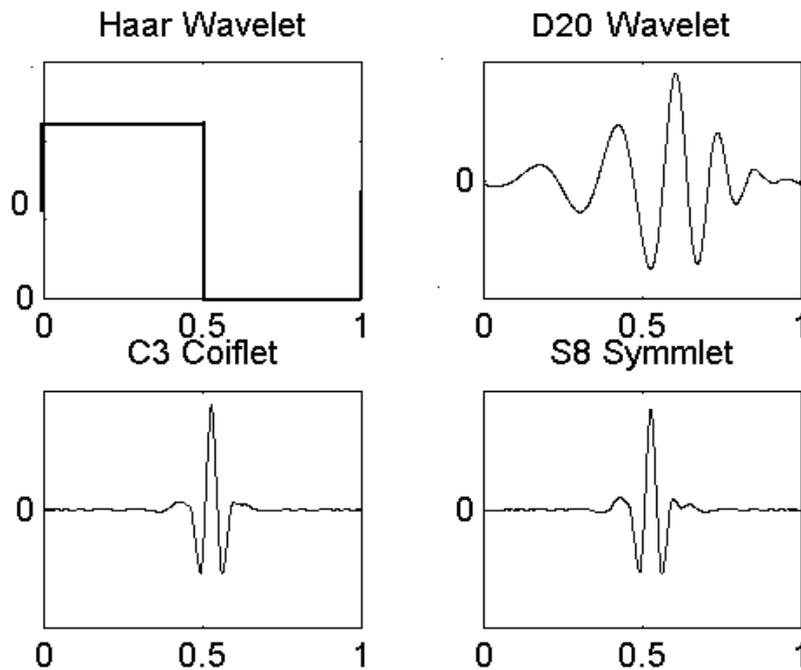
Figure 4.5 Examples of compactly supported orthogonal wavelets

4.2 Properties of wavelet transform

4.2.1 Locality in time- frequency

Wavelet basis functions are localized in time and are scaled versions of one mother function. A wavelet coefficient shows how much of the corresponding wavelet basis function 'is present' in the total signal: a high coefficient means that at the given location and scale there is an important contribution of a singularity. This information is local in time and in frequency (frequency is approximately the inverse of scale).

Figure 4.6 shows six wavelets from the same family Symmlet 8 and corresponding frequency bands. Numbers in the brackets correspond to *j,* which shows the level of decomposition or the location of wavelet in frequency axis, and *k* is interpreted as the location of wavelet in time axis. Figure 4.3 shows that there are n/2 wavelets in the first level i.e. j=1, n/4 wavelets in the level j=2 level there are n/4 wavelets and so on, where n is number of samples in original time domain. Thus, time resolution decreases in time level j or equivalently frequency is increasing. However, frequency resolution is increasing when level increases (the second plot in Figure 4.6).

In conclusion, wavelet coefficient carries local information. Manipulating of the wavelet coefficients causes a local effect, both in time and in frequency.
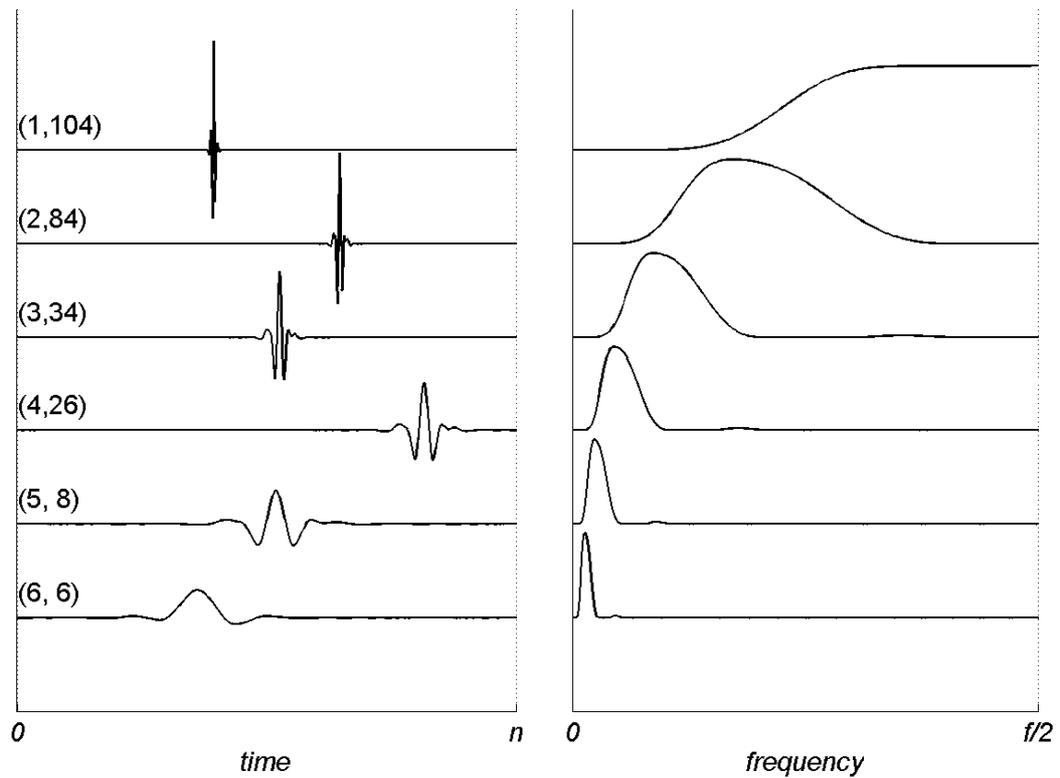
Figure 4.6 Symmlet 8 wavelet examples $\psi_{j,k}$ corresponding to different locations in time k and representing different frequency bands j. Here f is sampling frequency

4.2.2 Energy concentration

Wavelet transform of a smooth signal is concentrated in relatively small number of wavelet coefficients. On the other hand, the transform of a white noise signal spreads out over all coefficients.

For example, signal representations in time domain, frequency domain and wavelet domain were compared in terms of energy concentration in a few large coefficients. Signals, shown in Figure 3.1 and white Gaussian noise were used for the experiments.

Figure 4.7 shows three representations of white Gaussian noise: in time domain, frequency domain and wavelet domain. Coefficients were taken in absolute value, normalized to the range 0-1 and sorted in descending order.

29
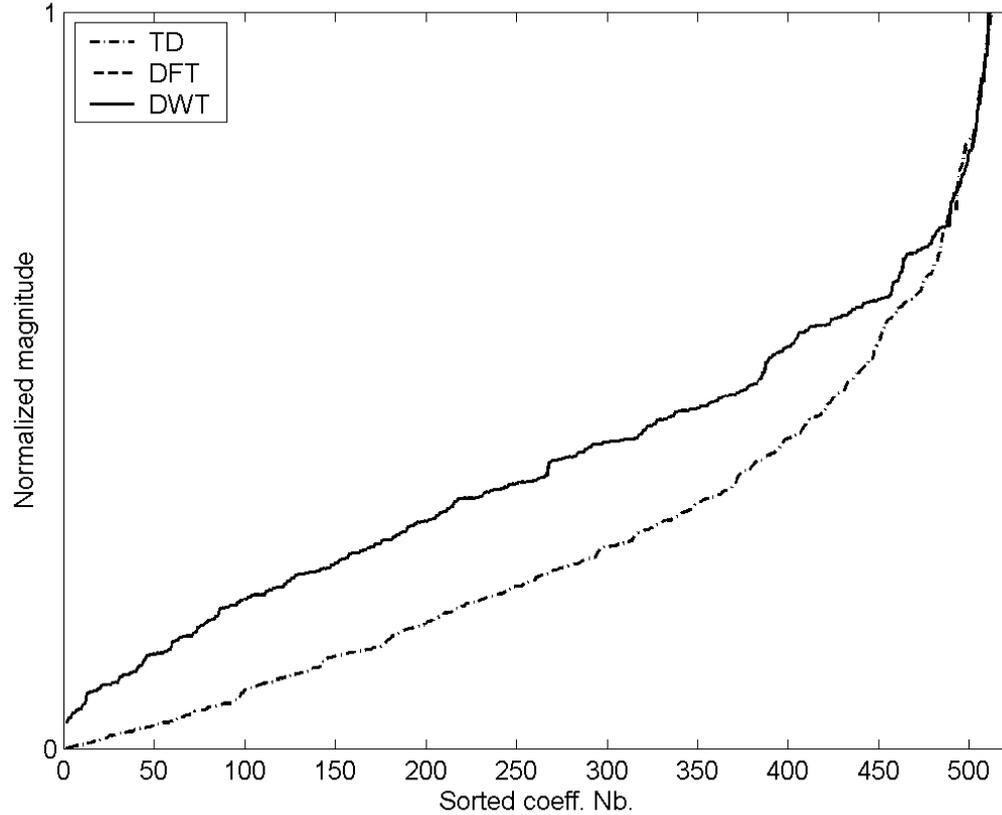
Figure 4.7 Coefficients from different signal representations sorted in ascending order. TD - time domain coefficients, DFT- discrete Fourier transform coefficients, DWT- discrete wavelet transform coefficients. For the DWT Symmlet 8 as mother wavelet was used.

Is obvious that curves of sorted DFT and DWT coefficients coincide, showing that no one is better in compaction of white Gaussian noise. Surprisingly, time domain representation of white Gaussian noise is more compact as it has less large coefficients than other representations.

Figure 4.8 shows experiment with "correlated" signals that are depicted in Figure 3.1. However, in this case, time domain representation of the signal is the most "expensive": representation uses many large coefficients. In frequency domain, signals are more concentrated than in time domain, however wavelet representation shows the highest concentration of signal energy in a few large coefficients. Especially it is noticeable at low SNR (compare 2dB and 15dB plots in Figure 4.8).

The energy concentration ability of wavelet transform depends on the number of vanishing moments m of mother wavelet ψ [95] :

30

$$\int_R x^k \psi(x) = 0, \qquad k = 0,....,m\text{-}1 \tag{4.12}$$

Wavelet transform, which uses mother wavelet with many vanishing moments, is able to concentrate smooth signal very efficiently. However, the number of vanishing moments defines the number of coefficients N used in wavelet filter: $N=2m$. Thus, there is the contradiction between energy concentration ability of wavelet transform and time localization feature as increasing the number of filter coefficients increases time support of the wavelet.
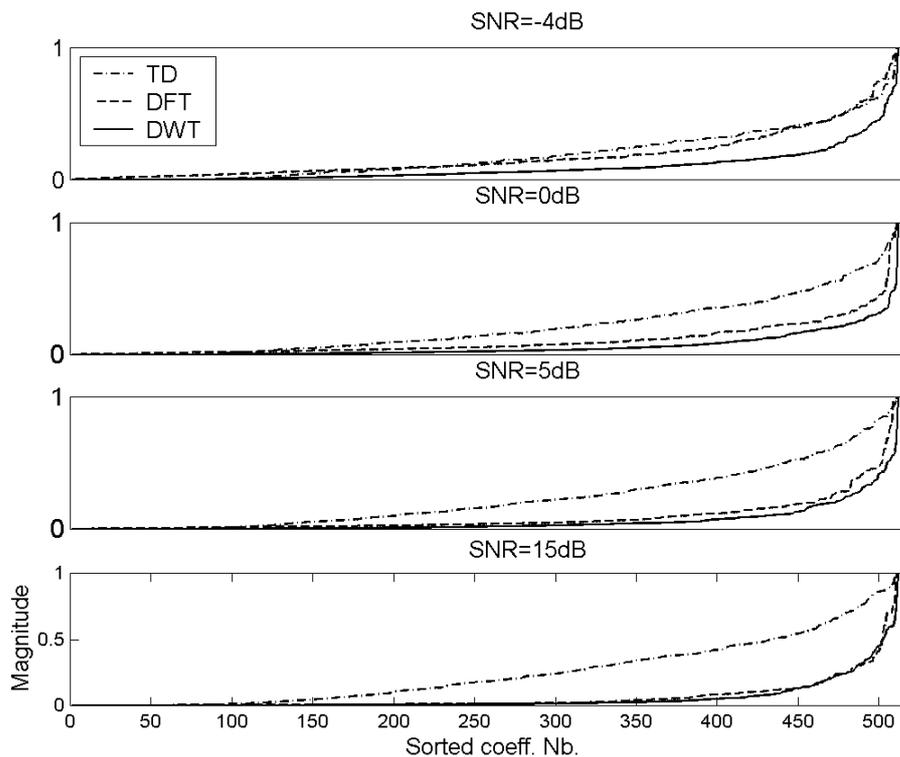
Figure 4.8 Coefficients from different signal representations sorted in ascending order. TD - time domain coefficients, DFT- discrete Fourier transform coefficients, DWT- discrete wavelet transform coefficients. For DWT Symmlet 8 as mother wavelet was used.

The next experiment shows the dependence of energy concentration of the wavelet transform as a function of the type of wavelet used and the number of vanishing moments. In order to evaluate quantitatively concentration of the energy we will use Shannon entropy, which has its roots in information theory [15]:

$$H(w) = -\sum_i w_i^2 \log(w_i^2) \tag{4.13}$$

Here w_i are the wavelet coefficients.

Shannon entropy can be interpreted as energy concentration measure: large H value indicates high entropy and low energy concentration, while smaller H indicates lower entropy and higher energy concentration.

In the energy concentration experiments the same signals as in Figure 3.1 were used. Figure 4.9 shows entropy dependency on the SNR and on vanishing moments (Par) in Symmlet type wavelet. It can be seen that entropy or energy concentration depends on the wavelet and SNR. However, there is an optimal wavelet, which achieves the highest concentration at all SNR ratios. It is Symmlet wavelet with 8 vanishing moments.
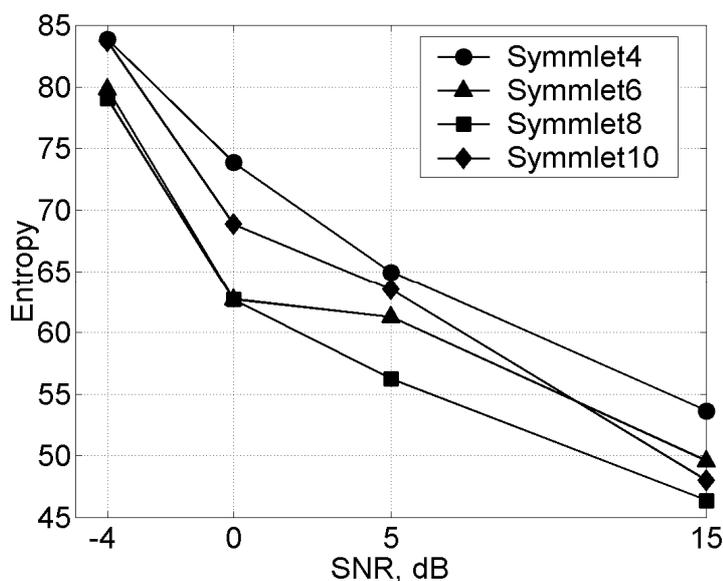
Figure 4.9 Entropy as the function of SNR and the number of vanishing moments (Par) in Symmlet type wavelet

In group of Coiflets there is no optimal wavelet, which would concentrate energy equally well at low SNR and high SNR rates. For example, Coiflet5 concentrates very well at 15 dB SNR, however, at 3 dB concentration is even worse than with Coiflet 3.

Similar situation is in the group of Daubechies wavelets. There is no wavelet, which is optimal in all SNR range and overall concentration ability of these wavelets is somewhat lower than of the wavelets in other groups.
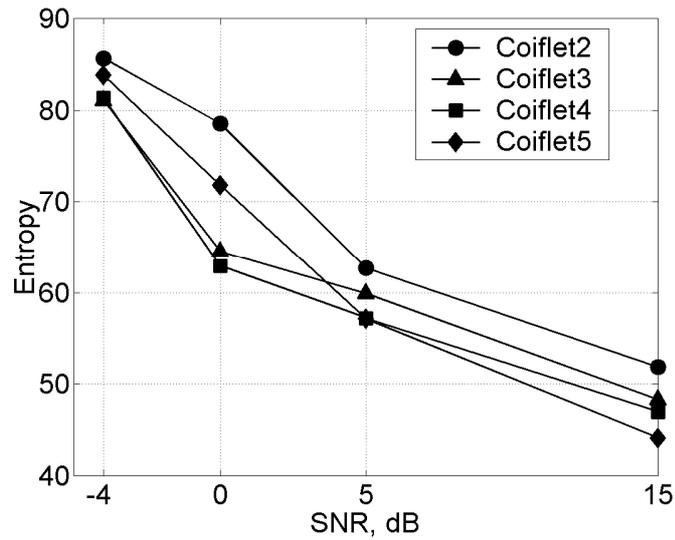
Figure 4.10 Entropy as the function of SNR and the number of vanishing moments (2*Par) in Coiflet type wavelet
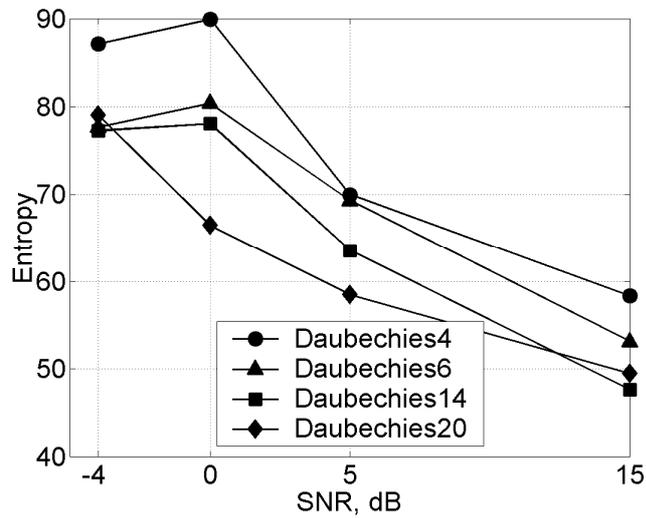
Figure 4.11 Entropy as the function of SNR and the number of vanishing moments (Par/2) in Daubechies type wavelet

4.2.3 Energy preservation

Discrete orthogonal wavelet transform preserves energy of the signal i.e. Perseval's equality admits:

$$\sum_{n=1}^{N}(s[n])^2 = \sum_{k=1}^{2^J}(w[k])^2 \qquad (4.14)$$

4.2.4 Fast implementation

Discrete wavelet transform implemented as a filterbank is efficient and fast. Decomposition of the computation into elementary cells and the

subsampling operations (decimations) that occur at each stage makes the DWT to be fast [95]. The operations required by one elementary cell at the jth octave are counted as follows. There are two filters of equal length L involved. The "wavelet filtering by h(n) directly provides the wavelet coefficients at the considered octave, while filtering by g(n) and decimating is used to enter the next cell. A direct implementation of the filters g(n) and h(n) followed by decimation requires *2L* multiplications and *2(L-1)* additions for every set of two inputs. That is, the complexity per input point for each elementary cell is:

$$L \, mult./point/cell \quad and \quad L\text{-}1 \, adds/point/cell \qquad (\,4.15\,)$$

Since the cell at the jth octave has input subsampled by 2^{j-1} , the total complexity required by a filter bank implementation of the DWT on J octaves is $(1+1/2+1/4+...+1/(2^{J-1}))$ times the complexity (4.15). That is :

$$2L(\,1-2^{-J}\,) \, mult./point \quad and \quad 2(\,L-1\,)(\,1-2^{-J}\,) \, adds/point \quad (\,4.16\,)$$

The DWT is therefore approximately equivalent, to one filter of length *2L* and full decomposition of N point signal would take *O(2LN)* multiplications. However, often we are not interested in a full decomposition until the level J. Thus, actual number of required operations in practice is less and even less than the amount of operations involved in FFT- *N log2(N)*.

5 Non-linear filtering

Conventional linear filters (optimal Wiener filter, Kalman filter, e.t.c.) may smoothen details, they are very poor for impulsive noise removal. While conventional non-linear filters (median filters) may induce false details and they are very poor for white noise removal [89]. Pioneering works of Donoho and Johnstone [20], [18] introduced wavelet based non-linear filtering for non-stationary signals. They named it as "wavelet based denoising".

Wavelet based denoising is motivated by three observations and assumptions:

1. Decorrelating property of wavelet transform creates a sparse signal: most untouched coefficients are zero or close to zero.

2. Noise is spread out equally over all coefficients.

3. The noise level is not too high, so that we can recognize the signal and the signal wavelet coefficients.

The denoising procedure is relatively simple:

1) Transformation of the signal into wavelet domain,

2) Thresholding of small coefficients with well chosen threshold λ and leaving large coefficients that most probably represent the clean signal,

3) Transforming back into time domain via inverse wavelet transform.

We expect that wavelet based denoising should be useful in biomedical applications (for example TEOAE signal estimation problem) to reduce the averaging time and probability of over smoothing the signal to be estimated.

5.1 Wavelet transform of the signal with noise

It can be assumed that the recorded signal *s[n]* is a linear summation of a noise free signal *f[n]* and a noise process *v[n]:*

$$s[n] = f[n] + v[n] \qquad\qquad (5.1)$$

The vector *s[n]* represents the input signal. The noise *v[n]* is a vector of random variables, while the untouched values *f[n]* are a purely deterministic signal.

The aim is to recover the original signal *f[n]* with a small mean-square-error:

$$MSE = \frac{1}{N} \sum_{n=1}^{N} \left(\hat{s}[n] - f[n] \right)^2 \qquad (5.2)$$

Where $\hat{s}[n]$ is the estimated signal after wavelet based denoising.

The linearity of a wavelet transform leaves the additivity of model (5.1) unchanged. We get:

$$w_{jk} = wf_{jk} + wv_{jk} \qquad (5.3)$$

where w_{jk}, wf_{jk}, and wv_{jk} are wavelet coefficients of $s(n)$, $f(n)$ and $v(n)$, respectively, at level j and time index k.

Manipulation with wavelet coefficients influences the signal in time and frequency locally. This feature of filtering makes it non-linear. In the following, we will describe two procedures for the manipulation with wavelet coefficients: wavelet coefficient shrinkage and novel method: wavelet coefficient selection from the region of interest. In addition, we will introduce new method for the estimation of threshold. Finally, we will compare and discuss the ability of different wavelet based denoising methods to reduce the noise in oscillatory signals.

5.2 Wavelet coefficient shrinkage for non-linear filtering

The manipulation of wavelet coefficients based on coefficient shrinking involves selection of shrinking function $\eta(\lambda)$ and threshold λ.

5.2.1 Non-linear shrinkage functions

Hard shrinking function. The policy for hard thresholding is to keep it or "kill". The absolute values of all wavelet coefficients are compared to a fixed threshold λ. If the magnitude of the coefficient is less than λ, it is replaced by zero. Thresholding is described by shrinkage functions. For hard thresholding shrinkage function is:

$$\eta_{hard}(w,\lambda) = \begin{cases} w & |w| \geq \lambda \\ 0 & |w| \leq \lambda \end{cases} \qquad (5.4)$$

Hard thresholding is used when one is interested in the shortest possible wavelet code. Long sequences of zeros that are obtained in thresholded wavelet decomposition vector are coded in efficient way. The graph of the function performing the hard thresholding is shown in Figure 5.1.
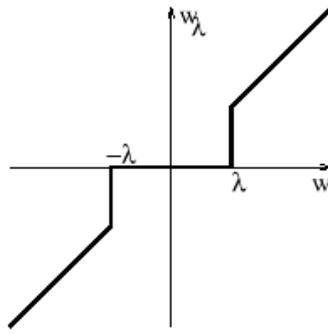
Figure 5.1 Hard shrinkage function

Soft thresholding. This shrinkage function was introduced by Donoho [17]. The soft thresholding shrinks all the coefficients towards the origin:

$$\eta_{soft}(w,\lambda) = \begin{cases} w - \lambda & w \geq \lambda \\ 0 & |w| < \lambda \\ w + \lambda & w \leq -\lambda \end{cases} \qquad (\,5.5\,)$$

Soft shrinking function is more continuous than hard. The graph of the function performing the soft thresholding is given in Figure 5.2.
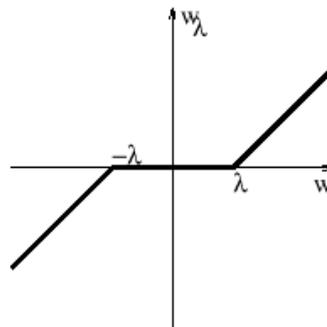
Figure 5.2 Soft shrinkage function

Other functions proposed in [7], [103] are intermediate and have smoother transitions from noisy coefficients to important ones.

5.2.2 Threshold estimation

Another important issue in the procedure of wavelet coefficient shrinkage is the assessment of the threshold λ. It is sought, usually, to fulfil the criterion (5.2), but later we will introduce a new criterion for selection of λ.

We found these threshold estimation methods in the literature:

- Universal. Johnstone and Donoho proposed universal threshold [21]:

$$\lambda = \sigma\sqrt{2\ln N} \qquad (5.6)$$

Here σ is standard deviation of estimated noise level, N is the length of the signal in samples.

Together with soft shrinkage function and Gaussian white noise, this threshold choice produces noise-free reconstruction, but at cost of shrinking genuine features. Hard thresholding preserves features (peak heights), but yields less smooth fit.

The next two methods are based on MSE criterion (5.2).

- SURE (Stein's Unbiased Risk Estimate) shrink. This threshold selection scheme proposed by Johnstone and Donoho [18] is based on the estimation of the MSE function:

$$MSE(\lambda) = SURE(\lambda) = \frac{1}{N}\sum_{i=1}^{N}(w_{\lambda i} - w_i)^2 + 2\sigma^2\frac{N_1}{N} - \sigma^2 \qquad (5.7)$$

Here N_1 is the number of coefficients with magnitude above the threshold, $w_{\lambda I}$ are shrunk wavelet coefficients, w_I are wavelet coefficients before shrinkage. The optimal threshold λ is chosen as:

$$\lambda_{opt} = arg\,min\,SURE(\lambda) \qquad (5.8)$$

In practice, we have to estimate variance of the noise σ^2.

- GCV (Generalized Cross Validation). This scheme of threshold selection was proposed by Weyrich and Warhola [97]. First, the GCV function is formed:

$$MSE(\lambda) \approx GCV(\lambda) = \frac{\frac{1}{N}\sum_{i=1}^{N}(w_{\lambda i} - w_i)^2}{(N_0/N)^2} \qquad (5.9)$$

Here N_0 is the number of coefficients replaced by zero. This is a function of threshold value as in SURE shrink case, however it uses only known parameters. It has approximately the same shape as the MSE. The optimal threshold λ is estimated by minimizing GCV function:

$$\lambda_{opt} = arg\,min\,GCV(\lambda) \qquad (5.10)$$

5.2.3 Alternative method for threshold estimation

This method is derived for comparison with previous threshold estimation methods and is using some heuristics as in [5] together with the step of optimisation as in SURE shrink and GCV methods.

We will estimate the optimal threshold λ_{opt} by defining the function, which is depending on it as it was done in previous methods. This function will be the dependence of cross correlation coefficient ρ between the two noisy signal replicates on the applied threshold:

$$\lambda_{opt} = arg\,max_{\lambda \in [0,\lambda_{60\%}]} \rho(\lambda).$$

$$(5.11)$$

In addition, we introduce a constrain in the maximization problem (5.11) the maximum number of zeroed coefficients should not exceed some fraction of the total number of coefficients. This constrain is motivated by the "fear" of zeroing all the coefficients in seeking the maximum of ρ. An example in Figure 5.3 explains the method.
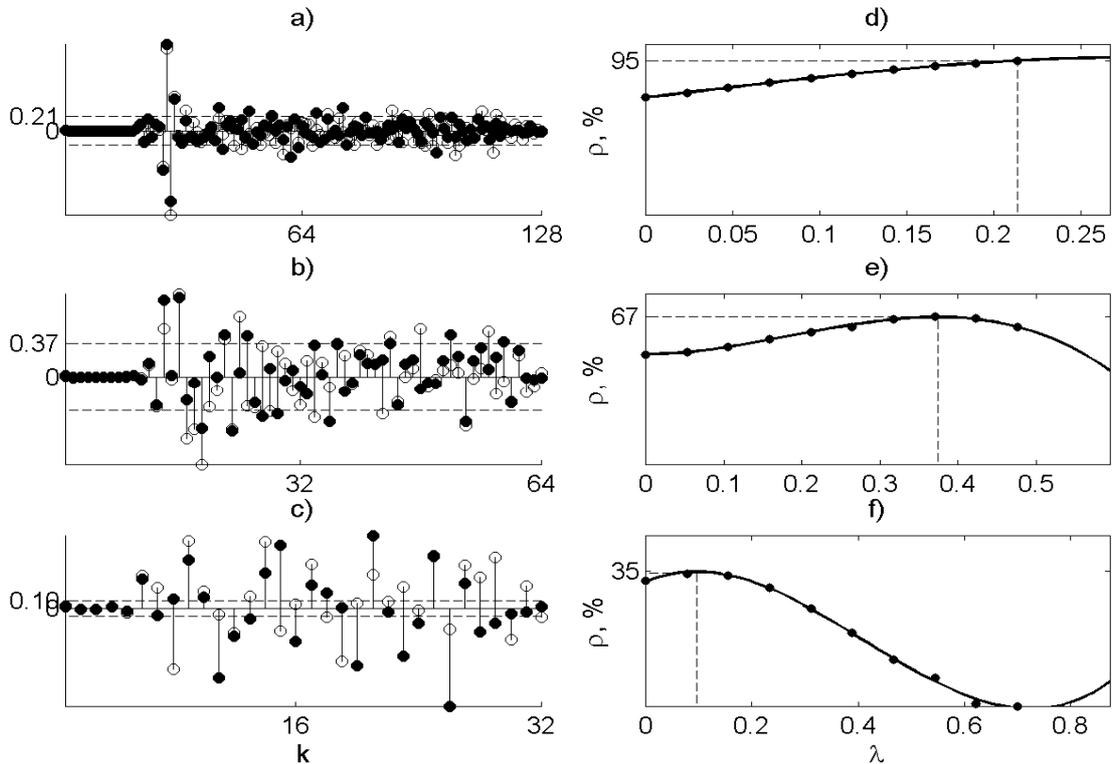
Figure 5.3 Wavelet coefficients of the TEOAE signal decomposition: a) at level 2, b) at level 3, c) at level 4. The dashed horizontal lines show optimal threshold λ_{opt}. The estimation of λ_{opt} is explained in the axes d, e and f. The dots represent the estimates of the function $\rho(\lambda)$ and the lines- the fitted polynomials

Due to inherent smoothness of $\rho(\lambda)$ in case of soft shrinkage, only a few evaluations of the function $\rho(\lambda)$ is needed to fit the model using the third order polynomial. Thus, in practice λ_{opt} can be found very efficiently by finding the maximum of the polynomial e.g. calculating the derivative and equating it to zero.

5.3 Wavelet coefficient selection for time- frequency filtering

Another approach to the wavelet based denoising is time- frequency filtering by using the feature of wavelet transform to localize in time and in frequency.

Many investigations using time- frequency energy distributions and wavelet decompositions have been carried out to establish the location of TEAOE signal components in time- frequency plane [91], [92], [94], [100], [102], [105]. However, the available amounts of the TEOAE records in these investigations were rather small (from 20 to 50 signals). Thus, the achieved accuracy of the general localization was limited. The general time- frequency properties of the non-stationary signals can be determined more accurately by using statistical averaging when available amount of the signals is large. For example, we computed the average of the spectrograms obtained from 2000 TEOAE signals (Figure 5.4).
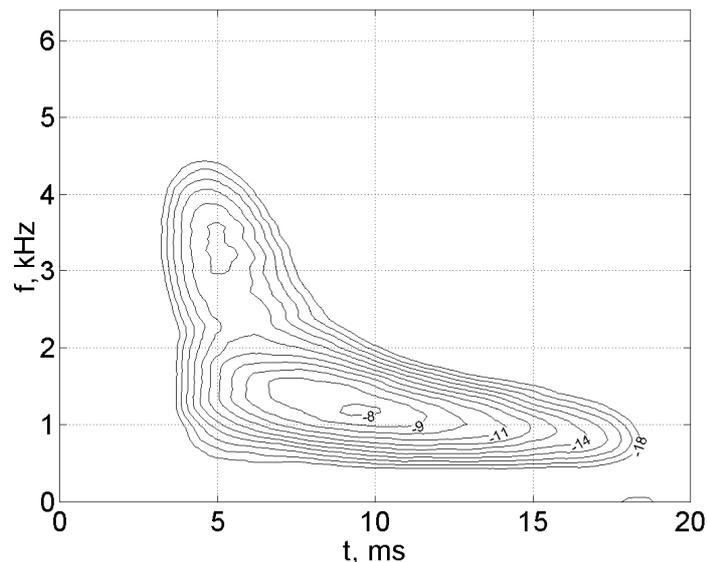
Figure 5.4 Averaged spectrogram of 2000 TEAOE signals

The contour map shows the distribution of the energy of the averaged TEAOE signal simultaneously in time and in frequency. The different latencies and durations of frequency components evidence non-stationary character of these signals. The specific composition of TEAOE signal- higher

frequency components have shorter duration and latencies than the signal components with the lower frequency- conforms very well with the feature of the wavelet transform to analyse the signal with increasing time resolution when frequency increases. Thus, we define the method of non-stationary signal filtering by determining the average location of signal components in wavelet domain and selecting relevant wavelet coefficients by using a mask or indicator function.

An important issue here is the determination of the region of interest in the time frequency plane. The ensemble correlation technique was proposed by Sörnmo and Atarius in study [4] for the enhancement and end point determination of late potentials in high resolution ECG. This technique was successfully adopted by Janušauskas et.al. [40] in TEOAE analysis for the determination of the latency of filtered TEOAE components. Our aim is to define general location of TEOAE signal in wavelet domain.

Generally, the symbolic location of TEOAE in wavelet domain is shown in Figure 5.5. The horizontal rows of rectangles are wavelet coefficients corresponding to octave frequency bands. Wavelet coefficients in the highest raw represent high frequency band, the middle raw represents middle frequency band and the lowest one represents low frequency band. The shaded rectangles symbolically show the location of the typical TEOAE signal in time- frequency plane.
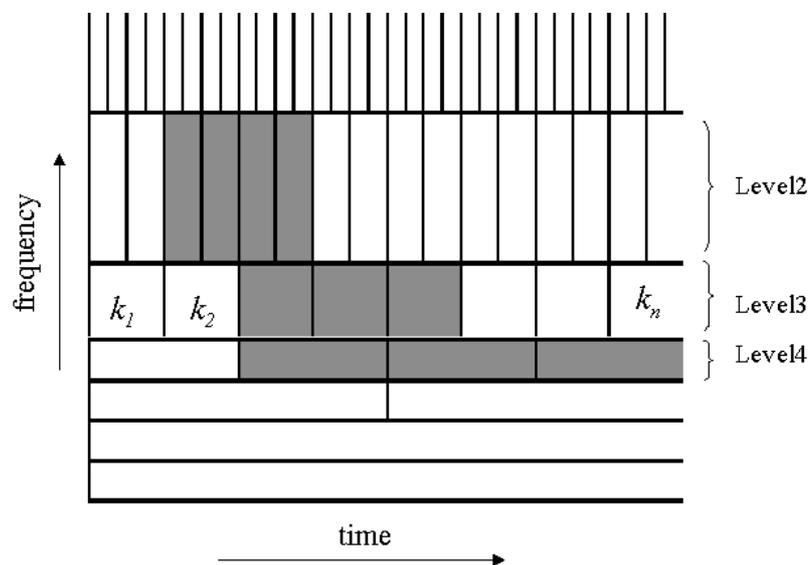
Figure 5.5 Symbolic location of TEOAE signal in the time- frequency plane. Each rectangle represents one wavelet coefficient

In order to identify the levels of wavelet decomposition, in which the energy of the average TEOAE signal resides, we transformed 2000 signals and calculated the average distribution of the energy among all the levels of decomposition. Figure 5.6 shows this distribution. It can be seen, that most

of the energy (>90%) is concentrated in the frequency band 0,8- 6,4kHz, which corresponds to three levels of wavelet decomposition- level 2, level 3 and level 4. Thus, it is acceptable to consider only these levels.
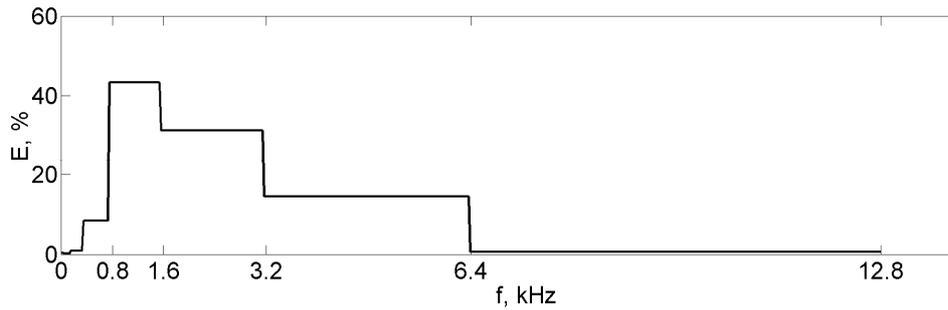
Figure 5.6 The distribution of the energy of averaged 2000 TEAOE signals in the octave frequency bands, which correspond to the levels of wavelet decomposition

The definition of the region interest in different levels of the decomposition is explained in Figure 5.7.
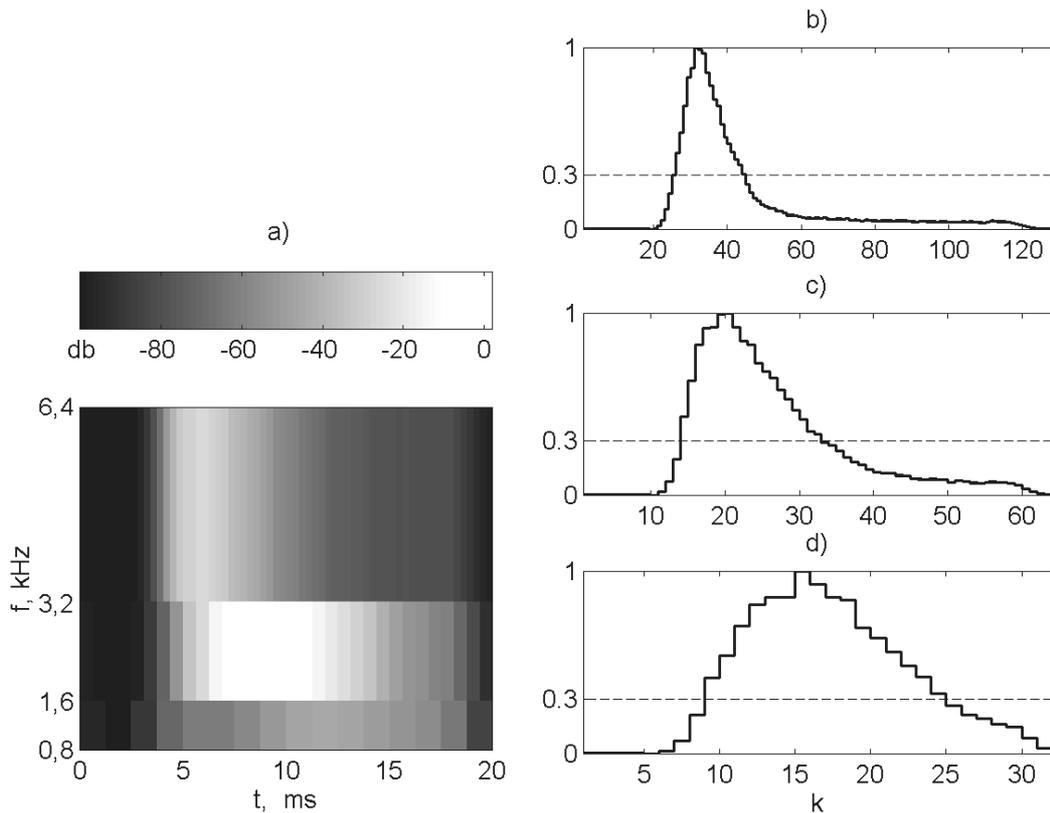
Figure 5.7 a) The average distribution of the energy of TEAOE signal in time- frequency plane, and distribution of the energy among wavelet coefficients in the selected levels of decomposition: b) level 2 (frequency band 3.2-6.4kHz), c) level 3 (frequency band 1.6- 3.2kHz), d) level 4 (frequency band 0.8- 1.6kHz). Here k is the index of wavelet coefficient (corresponds to the time in time domain)

Figure 5.7 shows average distribution of the TEOAE signal energy in each of the selected levels. The time window, in which is higher likelihood to find

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the component of TEOAE signal, can be defined by applying some threshold, as it is shown in axes b, c and d of the Figure 5.7. The determined levels and windows in these levels form the region of interest R in time- frequency plane. The time- frequency filtering of TEOAE signals can be accomplished by the application of the indicator function on the transformed signal in wavelet domain:

$$\hat{w}(\,j,k\,) = w(\,j,k\,)\ I(\,j,k\,). \qquad (\,5.12\,)$$

Here $w(j,k)$ wavelet coefficient at level j and time location k. The indicator function $I(j,k)$ is defined as:

$$I(j,k) = \begin{cases} 1, & if\ (j,k) \in R, \\ 0, & if\ (j,k) \notin R. \end{cases} \qquad (\,5.13\,)$$

In this case, the criterion of the importance is the location of the coefficient in transformed domain and not the magnitude of as it was in previous filtering methods.

5.4 Simulations. Comparison of the different denoising methods

The simulations were performed to evaluate different wavelet based denoising methods described in section 5.

5.4.1 Data set for experiment

An ensemble of TEOAE signal realizations was used in order to compare the performance of different wavelet based denoising methods in case of real biomedical signal and natural noise. Four pairs of subaverages were used:

1. Subaverages of the first pair were averages of the four realizations (N=4) of the TEOAE signal,

2. Subaverages of the second pair were averages of N=16 realizations of the TEOAE signal,

3. Subaverages of the third pair were averages of N=60 realizations of the TEOAE signal,

4. Subaverages of the fourth pair were averages of N=600 realizations of the TEOAE signal.

Each pair represents different quality of the signal and different averaging time needed to record the signal. In order to reduce the probability of taking the sample of the best quality from the ensemble, the procedure was

repeated 300 times, each time randomly mixing the realizations in the ensemble (random permutation of rows of the signal matrix was used). Therefore, the denoising procedure was repeated 4x300 times with each method.

5.4.2 The denoising parameters and measures of performance

The signals were transformed and reconstructed using Symmlet 8 wavelet. This wavelet is the most symmetrical among the finite compactly supported wavelets. The property of symmetry ensured the highest energy concentration in the wavelet domain using this wavelet as it was shown in the example experiments in section 4.2.2. The maximum decomposition level has been set to $J=5$. For reconstruction only $j=2$, $j=3$ and $j=4$ levels were used as it is expected that most of the TEOAE signal energy is concentrated in the frequency band 0.8-6.4kHz.

In the literature, most of the denoising methods study only the case of a white Gaussian noise. Johnstone and Silverman [43] have studied the case of correlated noise. They found that on each scale the noise coefficients follow approximately a Gaussian distribution. From these findings they proposed to use different thresholds for different scales i.e. to make threshold level depended. We used this level dependent strategy as our signal was made colored after bandpass filtering in the recording hardware.

Zero lag cross correlation between subaverages was chosen as the performance measure of the signal estimates:

$$\rho = \frac{\sum_{n=1}^{N} x[n] \cdot y[n]}{\sqrt{\sum_{n=1}^{N} x^2[n]} \cdot \sqrt{\sum_{n=1}^{N} y^2[n]}} \quad (5.14)$$

Here $x[n]$ and $y[n]$ are subaverages, N is length of the signal. The estimate of standard noise deviation $\hat{\sigma}_j$, which is needed for "Universal" and "SURE" threshold estimation methods, was calculated as:

$$\hat{\sigma}_j = \frac{1}{0.6745} MAD(w_j) \quad (5.15)$$

MAD is the median absolute value of wavelet coefficients in the level j and is estimated as:

$$MAD(w_j) = median\left\{w_j\right\} \qquad\qquad (\ 5.16\ )$$

All simulations have been carried out 300 times, and the minimum, median and maximum of the performance measure are presented in the tables.

5.4.3 Simulation results

The results of denoising with different threshold estimation methods using "soft" shrinkage functions are presented in *Table 5.1* and Table 5.2. The "hard" shrinkage function was used only with "Universal" threshold and denoising results are presented in Table 5.3. A visual control of denoising methods at different ensemble sizes (equivalently at different SNR ratios) can be carried out by inspecting the figures Figure 5.8, Figure 5.9, Figure 5.10 and Figure 5.11.

"Hard" thresholding function is not suitable for "GCV", "SURE" and "Alternative" methods. Thus, it was used only with "Universal" threshold estimation method. Preliminary experiments showed that with "Hard" shrinkage, threshold dependant functions are not continuous and proper minimum in "GCV" and "SURE" cannot be attained. Similarly, we met the same problem in maximization of threshold dependant function in the "Alternative" method.

The worst results showed "GCV" method: the median ρ value at all the ensemble sizes is the lowest. It is even lower when comparing with "No denoising". Other denoising methods gave improvement in comparison to unprocessed data. The largest improvement is obtained with method "Selection". If we draw up methods in ascending order according the improvement of median ρ value, we will get "GCV", "SURE", "Universal", "Alternative", "Selection".

However, comparison of the ranges between minimum and maximum of ρ values in *Table 5.1* and Table 5.2 changes previous ordering of the methods. "Selection" method has the largest spread of results at the smallest ensemble sizes. This feature increases the probability to achieve high ρ value only by chance, even when no deterministic signal is present in the recorded ensemble. However, more investigations are needed to validate this method.

Table 5.1 Comparison of different threshold estimation strategies when Soft shrinkage function was used for denoising (N is the number of realizations included in the subaverages)

Soft shrinkage function					
Threshold	**ρ, %**	**N=4**	**N=16**	**N=60**	**N=600**
No denoising	Max ρ	39	63	85	97
	Median ρ	19	47	76	96
	Min ρ	-18	6	58	95
Universal	Max ρ	54	72	89	98
	Median ρ	21	52	79	97
	Min ρ	-23	5	58	95
SURE	Max ρ	46	68	87	98
	Median ρ	20	50	78	97
	Min ρ	-10	14	58	95
GCV	Max ρ	52	71	87	98
	Median ρ	13	37	62	84
	Min ρ	-15	1	18	44
Alternative	Max ρ	50	74	90	98
	Median ρ	23	54	81	97
	Min ρ	-20	15	58	96

Table 5.2 The performance of the denoising method based on wavelet coefficient selection

Method	**ρ**	**N=4**	**N=16**	**N=60**	**N=600**
Wavelet	Max ρ	59	83	94	99
Coefficient	Median ρ	33	65	86	98
Selection	Min ρ	-36	15	62	97

Table 5.3 shows the performance of "Universal" threshold using "hard" shrinkage function. Comparison with the "soft" shrinkage function shows no advantages.

Table 5.3 The performance of the denoising method based on wavelet coefficient thresholding using "Universal" threshold

Hard shrinkage function					
Threshold	ρ, %	**N=4**	**N=16**	**N=60**	**N=600**
Universal	*Max ρ*	50	69	84	97
	Median ρ	20	48	75	96
	Min ρ	-8	7	53	95

Figures from 5.8 to 5.11 are presented for visual indication how the different denoising methods work at different sizes of the ensembles.

Figure 5.8 shows the case when only 4 realizations were used for subaveraging. Thus, the signals appear very noisy. The method of "Selection" shows the cleanest estimate of the signals.
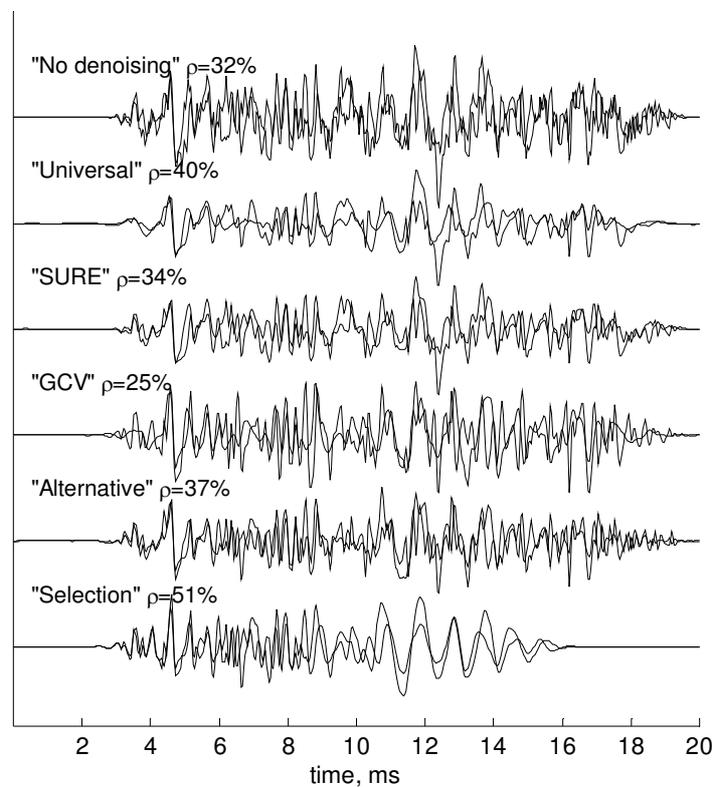
Figure 5.8 Denoising example, when 4 realizations were used for subaveraging

Figure 5.9 presents the denoising example when more realizations (N=16) were used. However, the unprocessed and estimated signals are still noisy. The best results in terms of improved ρ value showed proposed methods: "Alternative" threshold estimation and wavelet coefficient selection. They increased ρ value from 37 % to 44 % and 56 % respectively.
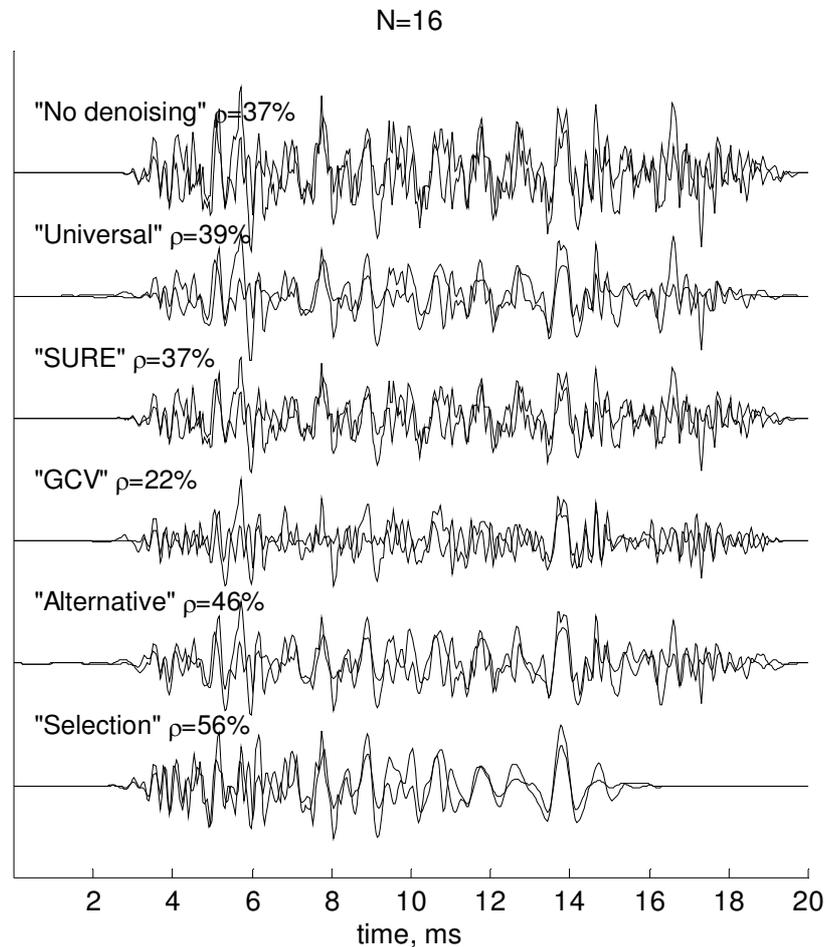
Figure 5.9 Denoising example, when 16 realizations were used for subaveraging

Figure 5.10 shows subsequent improvement in signal estimates when the number of realizations in the subaverages was increased. Again, substantial improvement in ρ value was achieved when using "Selection" method.
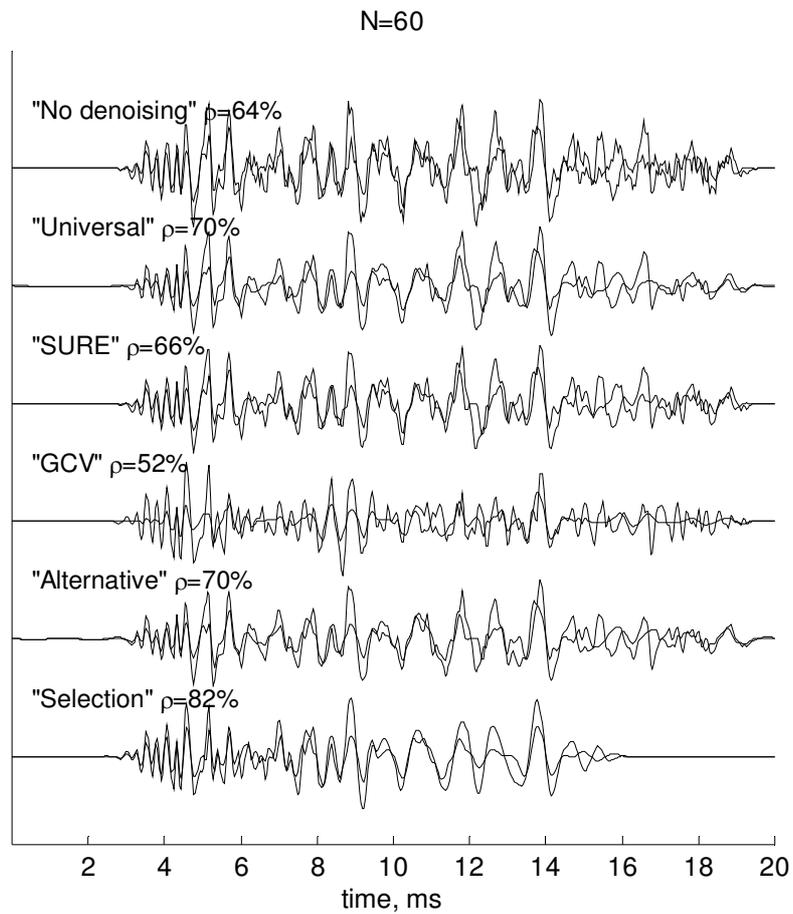
Figure 5.10 Denoising example, when 60 realizations were used for subaveraging

The last Figure 5.11 presents almost noise-free signals as the ensembles of realizations were very large: 600 realizations for each subaverage. The improvements provided by the denoising methods were small as there was nothing to improve: ρ value even in unprocessed signal was very high – 94 %.

N=600

"No denoising" ρ=94%

"Universal" ρ=95%

"SURE" ρ=94%

"GCV" ρ=78%

"Alternative" ρ=96%

"Selection" ρ=96%

time, ms
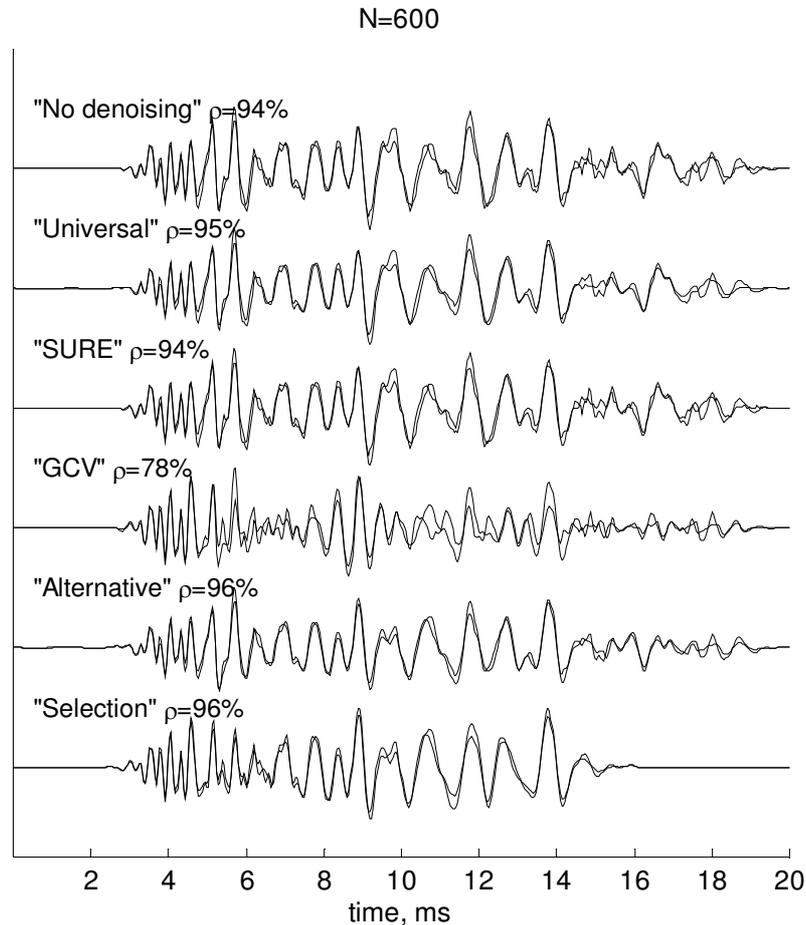
Figure 5.11 Denoising example, when 600 realizations were used for subaveraging

5.4.4 Summary

Different denoising methods were compared in the problem of the TEAOE signal denoising. Two of them were proposed by the author: "Alternative" estimation of the threshold, and denoising based on wavelet coefficient "Selection". The proposed methods showed better results in terms of improvement of cross correlation value ρ between two subaverages of TEOAE signal than other wavelet based denoising methods found in the literature.

In general, simulations showed that wavelet based denoising can be used for subsequent enhancement of the signal after ensemble averaging. For example, the highest panel of Figure 5.10 shows the unprocessed signal,

which is the average of 60 realizations, and is very close in quality with the signal in lowest panel of Figure 5.9 based only on 16 realizations. Thus, wavelet denoising can be used to save time. Especially it is true when using fast DWT based on filterbanks.

When comparing wavelet denoising methods individually, wavelet coefficient "Selection" method was found the best in terms of improved ρ value. However, this was achieved using extensively a priori knowledge about the location of the signal components in time frequency plane. Such knowledge can be acquired very efficiently by using ensemble correlation technique in time- frequency plane as it was shown in [40]. Thus, improvement from 10 to 20 %, when comparing "Selection" method with "No denoising" is encouraging result. Less of a priori knowledge is needed in "Alternative" threshold selection method. The only parameter, which has to be chosen heuristically, is the maximal number of wavelet coefficients allowed to be zeroed after the thresholding operation. However, the maximization of the function $\rho(\lambda)$ when estimating the optimal threshold is still time consuming operation, which can "burn" the time saved from averaging.

Other denoising methods showed smaller improvement than proposed methods. Especially GCV method was not adequate to the problem. One possible reason for the unsatisfactory results of this method might be too short signal length of 512 samples.

6 Time- frequency feature extraction for signal detection

The signal detection problem requires the conversion of patterns to features that are a condensed representation of patterns, ideally containing only salient information. These features are used often in biomedical signal detection problems: amplitude, bias, duration, phase, energy, moments, Karhunen- Loeve eigenvalues [11]. Statistical measures such as cross correlation and cross- spectrum between two replicate recordings of the biomedical signal are used too, for example, for TEAOE detection. However, in case of non-stationary multi component biomedical signals zero-lag cross correlation coefficient, when calculating it for all the length of the signal, may be low because of the high noise level in the recorded signals. One of the possibilities for increasing the detection performance is to use only these time and frequency intervals of the signal in which higher probability is for the presence of the signal components. One problem in this approach is efficient splitting of the signal into time and frequency limited signal components.

In the following, we will show how this task can be accomplished very efficiently in wavelet domain. First, we will prove that calculation of cross correlation coefficient between band limited signals in time domain is equivalent to calculation of cross correlation coefficient between wavelet coefficients from the corresponding levels of discrete orthogonal wavelet decompositions of these signals. The consequence of this equality is savings of time in the calculations, since the signal in wavelet domain is represented by fewer coefficients than in time domain. Second, it will be shown that windowing the signal in time domain has an analog in wavelet domain. By combining these two observations we proposed efficient way to calculate cross correlation coefficients between the time and frequency limited intervals of two signals.

6.1 Correspondence of cross correlation calculations in time domain and in wavelet domain

As we know, reconstructing signal from wavelet coefficients from one level only is equivalent to band pass filtering. Normalized product of two signals x and y reconstructed in such a way will give us their cross correlation in frequency band corresponding to scale 2^j. If denote by x_j and y_j reconstructions of signals x and y, respectively, from their wavelet coefficients at scale 2^j, then:

$$\sum_{n=1}^{N} x_j[n] \cdot y_j[n] = \sum_{n=1}^{N} \left\{ \sum_{k=1}^{2^{J-j}} [w_{j,k}(x)\psi(2^{-j}n-k)] * \sum_{k=1}^{2^{J-j}} [w_{j,s}(y)\psi(2^{-j}n-s)] \right\} =$$
$$= \sum_{k=1}^{2^{J-j}}\sum_{s=1}^{2^{J-j}} \left\{ w_{j,k}(x) w_{j,s}(y) \cdot \sum_{n=1}^{N} \psi(2^{-j}n-k)\psi(2^{-j}n-s) \right\}$$

(6.1)

Orthogonality property of wavelet transform gives:

$$\sum_{n=1}^{N} \psi\left(2^{-j}n-k\right)\psi\left(2^{-j}n-s\right) = \delta_{k,s}$$

(6.2)

Where Kronecer delta δ is:

$$\delta_{k,s} = \begin{cases} 1, & k = s \\ 0, & k \neq s \end{cases}$$

(6.3)

Hence from (6.1) and (6.2):

$$\sum_{n=1}^{N} x_j[n] \cdot y_j[n] = \sum_{k=1}^{2^{J-j}}\sum_{s=1}^{2^{J-j}} \left\{ w_{j,k}(x) w_{j,s}(y) \cdot \delta_{k,s} \right\}$$

(6.4)

Taking into account (6.3) we can write:

$$\sum_{n=1}^{N} x_j[n] \cdot y_j[n] = \sum_{k=1}^{2^{J-j}} w_{j,k}(x) w_{j,k}(y)$$

(6.5)

This shows that correlation coefficient of two signals in a frequency band corresponding to an octave of multi resolution decomposition can be efficiently obtained as scalar product of vectors of wavelet coefficients from a given decomposition level.

As we can see from (6.5) the main advantage in using wavelet transform in comparison with conventional bandpass filtering is gain in speed of calculations: splitting the signal into frequency bands takes as much as wavelet transform until the level J while calculation of cross correlation coefficients takes less time again, because the numbers of coefficients in the levels are reduced from N to 2^{J-j}.

6.2 Time windowing in wavelet domain

The most important property of the wavelets is locality in time and in frequency. Each coefficient in wavelet domain corresponds to small interval in time domain. Thus, weighting of the wavelet coefficients in the particular

scale in wavelet domain is the same as the time windowing of bandpass filtered component of the signal in time domain:

$$s_j[n]\ W_j[n] = \sum_{k=1}^{2^{J-j}} w_{jk} \widehat{W}_{jk} \psi\left(2^{-j}n - k\right) \tag{6.6}$$

Here s_j is the reconstructed signal component at level j, W_j is the time window N samples long for scale j, $\widehat{W}_{jk}$ is the window 2^{J-j} samples long in wavelet domain.

The straightforward way for construction of the weighting window $\widehat{W}_{jk}$ is decimation of original window similarly as it was done, when transforming the signal into wavelet domain. The windowing operation (6.6) can be rewritten as:

$$s_j[n]\ W_j[n] = \sum_{k=1}^{2^{J-j}} w_{jk} W\left(2^{-j}n\right) \psi\left(2^{-j}n - k\right) \tag{6.7}$$

Relevant coefficient selection is another choice to accomplish the windowing in wavelet domain. Particularly it is convenient when no reconstruction is planed and just gross parameter like cross correlation coefficient is to be calculated. In this case the number of coefficients used for calculation is reduced 2^j times in comparison with original time domain calculations. The relation between time t and time index k in the decomposition level j is found as:

$$k = \frac{t}{\Delta t\, 2^j} \tag{6.8}$$

Here Δt is time interval of signal sampling in time domain.

The final band- and time- limited cross correlation coefficient, which can be used as a feature in signal detection problem, can be written as:

$$\rho_j = \frac{\sum_{k=m}^{n} w_{j,k}(x)\cdot w_{j,k}(y)}{\sqrt{\sum_{k=m}^{n} w_{j,k}^2(x)}\cdot \sqrt{\sum_{k=m}^{n} w_{j,k}^2(y)}} \tag{6.9}$$

Where $w_{j,k}$ and $w_{j,k}$ are wavelet coefficients of the signals x and y from the decomposition level j and where m and n are indexes of the first and last coefficient in the respective window.

6.3 Artificial neural network for signal detection

As it was written in section 3.3, artificial neural network can be employed to combine extracted time-frequency features into signal detection function $d\{s(n)\}$. Subsequent decision about the presence of the signal in the record is based on the threshold applied to the $d\{s[n]\}$. Why should we use neural network in combining the features? The reason is that biological non-linearity's are present in production of most biomedical signals as for example in TEOAE, EEG. Thus, the combiner, which could account for any non-linear relationships among extracted features, would perform better than combiner restricted to be only linear in the signal detection problem. Another reason is that probability of signal detection can be maximized by using a priori knowledge in teaching the network from a set of input/output data. The network, which was taught on part of the data, can generalize to another data. This property is equivalent to drawing the optimal detection function $d\{s[n]\}$.

The artificial neural network is represented by a structure, consisting of units called neurons and connections called weights as seen in Figure 6.1. Each neuron is a unit that computes the weighted inputs from neighbouring neurons. The output of a neuron depends on the input values and an activation function. This output can in turn serve as one of the input values for other neurons. The weights are multiplicative coefficients that can change the influence of one neuron's output to another neuron's input. By changing the connection weights during the training procedure a very complex, possibly non-linear, relationship between the network inputs and the output can be established.
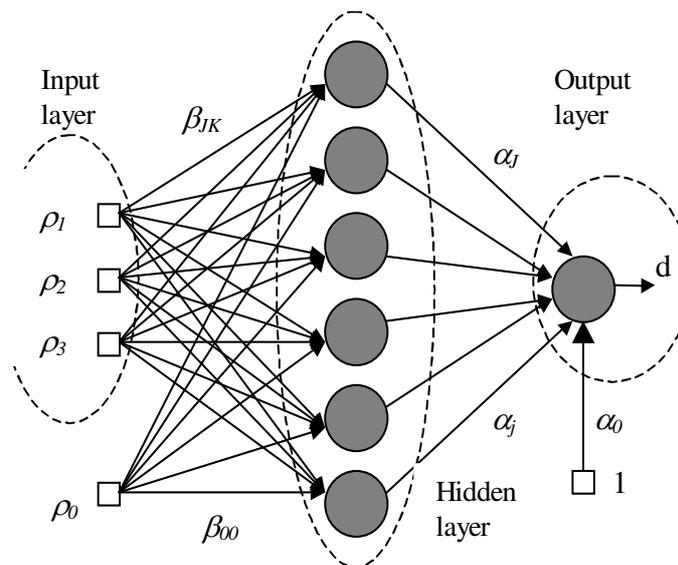
Figure 6.1 Schematic representation of a three layer ANN

The output of this network d can be written as:

$$d(\alpha,\beta,\rho) = tanh\left(\sum_{k=0}^{K}\alpha_k \cdot tanh\left(\sum_{j=0}^{J}\beta_{jk} \cdot \rho_j\right)\right)$$ (6.10)

where ρ_j denotes the feature vector parameters with $\rho_0 = 1$, J is the number of inputs, K is the number of hidden neurons, *tanh* is the non-linear activation function hyperbolic tangent, β_{jk} are the weights between inputs and hidden layer and α_k are the weights between hidden and output layers.

The neural network training procedure is based on adjusting the weight parameters α_k and β_{jk}. The neural network is considered to be trained when it gives small errors when applied on the training set of data but also responds properly to a new testing set not used in the training procedure. When a network is able to perform both on testing and training sets of data, we say that the network generalizes well and the optimal detection function *d{s[n]}* is established.

7 Applications and algorithms

7.1 Wavelet based TEOAE denoising and detection

It is not easy to give the definition of genuine TEOAE response. The large intersubject variability in the shapes of TEAOE responses do not allow to set fixed rules for detection and classification of TEOAE's. For example, we can see in Figure 7.1 typical TEOAE responses from 4 subjects having similar MHL about 0dB in 0.5-6.4 kHz frequency band. If we try to compare them sample by sample, we will not find any similarities among them: at the same time instances different records have very different values. Although the TEOAE responses, like fingerprints, can be very stable during long time from the same ear, but they can be completely different even from the same subject's equally hearing left and right ears. Thus global features that capture similarities in TEOAE responses from similar hearing ears should be extracted.
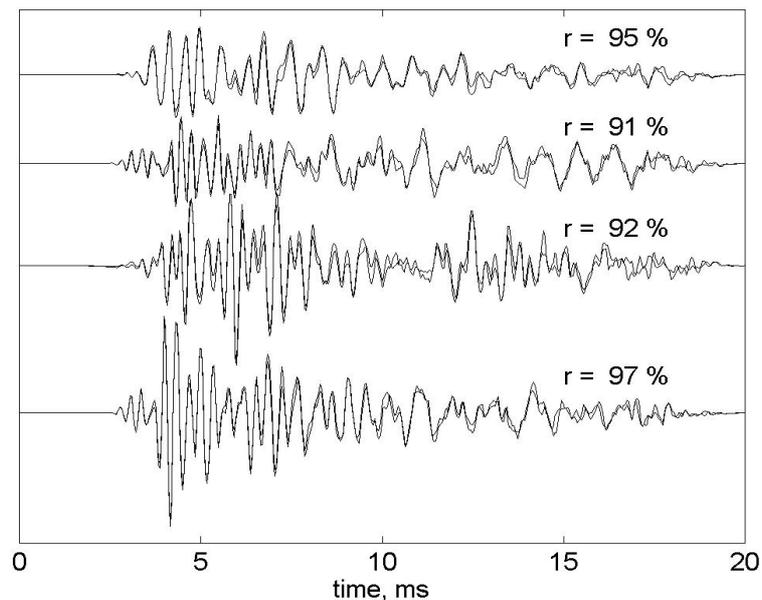
Figure 7.1 Examples of TEOAE subaveraged responses from 4 subjects, having the same MHL ≈ 0dB. Here r indicates cross correlation value between subaverages of the response

We refer to D. Kemp, the first who detected TEOAE in 1978 [47] for definition of the TEOAE. However, he gives very common definition: "release or return of acoustic energy from the cochlea into the ear canal, in response to an acoustic transient". It was already said that TEOAE responses distinguish themselves by the signal shape stability for the same subject during the long time. Thus the most popular criterion for TEOAE detection is the cross correlation coefficient between the two subaverages (we remind

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here that TEOAE response is recorded into two accumulators). If the calculated cross correlation coefficient between the two subaverages exceeds some predetermined threshold, it is considered as an evidence of the presence of deterministic activity in the recorded signal and a conclusion about detected TEOAE is made. The TEOAE responses shown in Figure 7.1 can be clearly distinguished with a high cross correlation value, but this is not always the case. The calculated cross correlation value depends on both initial signal-to-noise ratio and available averaging time (i.e. number of sweeps in the average). Long averaging time is often difficult to maintain in the clinical practice, especially in child investigations. In order to reduce further the influence of the remaining noise in the averaged signal, additional measures can be considered, which use a priori information on TEOAE. Many investigations [13,10,20] have shown that TEOAE exhibit frequency dependant latency: where higher frequencies have shorter post-stimulus time while lower frequencies have longer. This particular feature of TEOAE can also be observed in the example of TEOAE subaverages shown in Figure 7.1, where oscillations of higher frequency, starting 3 ms post-stimulus, precede oscillations with lower frequency. These observations led us to the assumptions that taking into account such time- frequency specific structure of TEOAE can increase the signal-to-noise ratio and detection performance.

As an application of the investigated signal denoising and feature extraction methods here we present the results of denoising the real TEOAE signals and automatic TEOAE detection method. The method was investigated on large database of real TEOAE signals.

7.2 Experimental data

A database consisting of 5213 TEOAE records was collected during the health screening test "Genetic and environmental study of hearing loss in Nord-Trondelag county" Norway [24]. The ILO92 Otodynamics analyzer was used for recording of TEOAE data and air conduction pure tone audiograms were recorded using Interacoustics AD25 automatic audiometers. The audiometric criterion used to separate normal hearing from hearing impaired subjects was chosen as 30 dB of mean hearing level as obtained at the frequencies 0.5, 1, 2 and 4 kHz (MHL). Based on that separation level a total of 4404 subjects were classified as having normal hearing while the remaining 809 were classified as having impaired hearing.

7.3 Wavelet based TEOAE denoising

7.3.1 Algorithms

The denoising algorithms described in Sections 5.2.3 and 5.3 were applied to all the TEOAE records from the database to estimate the efficiency of proposed methods and to compare them with the methods known from the literature.

7.3.2 Other methods for signal-to-noise ration improvement in TEOAE records

Various methods have been presented with the aim to improve the SNR and detection performance of TEOAE, e.g. by time windowing [98] of the subaveraged signals or by bandpass filtering [34].

Optimal time windowing. Time windowing technique is based on the assumption that a shorter analysis time window increases the SNR. The best results were obtained by using the window 2.5-9 ms [98].

Optimal bandpass filtering. In study [34] linear bandpass filtering with four different octave bandpass filters with center frequencies: 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz were considered to improve SNR. The filter with central frequency of 4000 Hz gave the best results.

Before processing. The cross correlation coefficient between two unprocessed subaverages, or "wave reproducibility'", is used as a base for comparisons. This parameter is used for TEOAE detection in conventional clinical TEOAE recording device ILO92 manufactured by Otodynamics Ltd.

7.3.3 TEOAE denoising results with different methods

The example of TEOAE record before any processing, after time windowing, after linear bandpass filtering, after wavelet coefficient shrinkage based denoising and after wavelet coefficient selection based time- frequency filtering is shown in Figure 7.2. The cross correlation values reflect the improvement of the quality of this signal example. Since the mean hearing level for this particular subject was 10 dB, otoacoustic emissions were expected to be present. Figure 7.2 shows that no emission is present in the unprocessed signal (ρ=64 %) as the criterion for the presence of TEOAE is considered ρ=70 %. All the filtering methods improved ρ in this case and indicated TEOAE signal being present in this record.
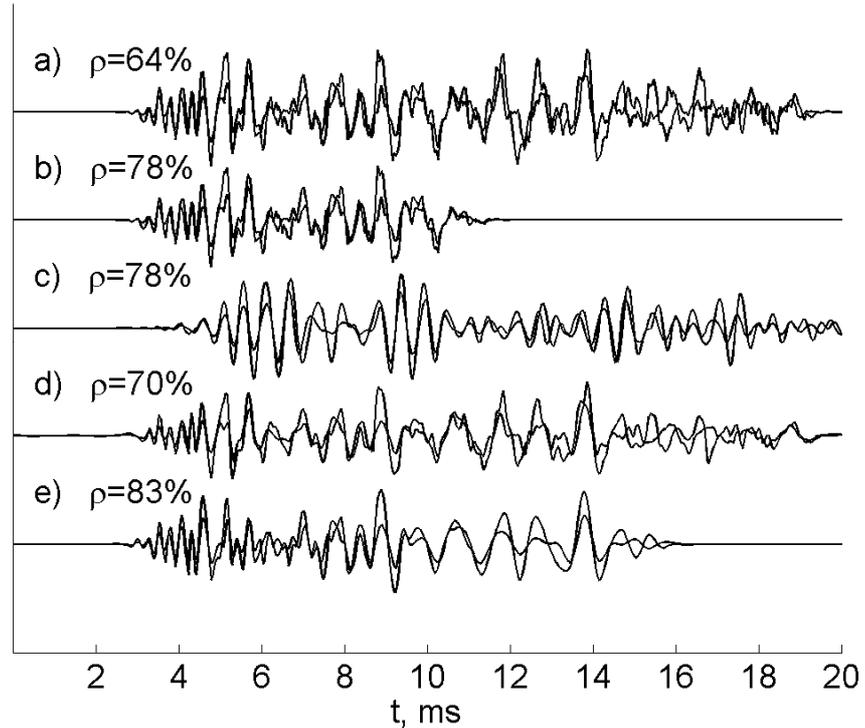
Figure 7.2 The examples of the TEOAE subaverages: a) before any processing, b) after bandpass filtering, c) after time windowing, d) after wavelet coefficient shrinkage based denoising, e) after wavelet coefficient selection based time- frequency filtering

It is important to know the influence of the signal denoising procedures on all the TEOAE records in the database. How differently the different records with different initial signal to noise ratio were effected by the denoising procedures? The cross correlation values of unprocessed database, sorted in ascending order, were chosen as a base for comparison with the data after denoising. Overall influence of all the denoising methods on all the signals in the database is shown in Figure 7.3. In the figure the data, cross correlation values, representing records before denoising are shown as thick line and the dots correspond to the same sorted subjects after influence of denoising. It can be observed that all the recordings were affected by the denoising using time windowing, bandpass filtering, both wavelet based methods and have spread of cross correlation values in both sides of the baseline. This means that, in addition, to increased cross correlation values we get decreased values. The spread of cross correlation values after time windowing and bandpass filtering is much higher than using wavelet coefficient shrinkage or coefficient selection based methods. This indicates less dramatic influence of the last two methods to the signals. Another good feature of the last two methods is mostly positive direction of the affect to the records that had cross correlation above some 50% before processing. The

records that had before processing the cross correlation value below 40% in the average were unchanged. It is very important result as it shows that the denoising procedure will not produce false negatives by discovering TEOAE, where it should not be.
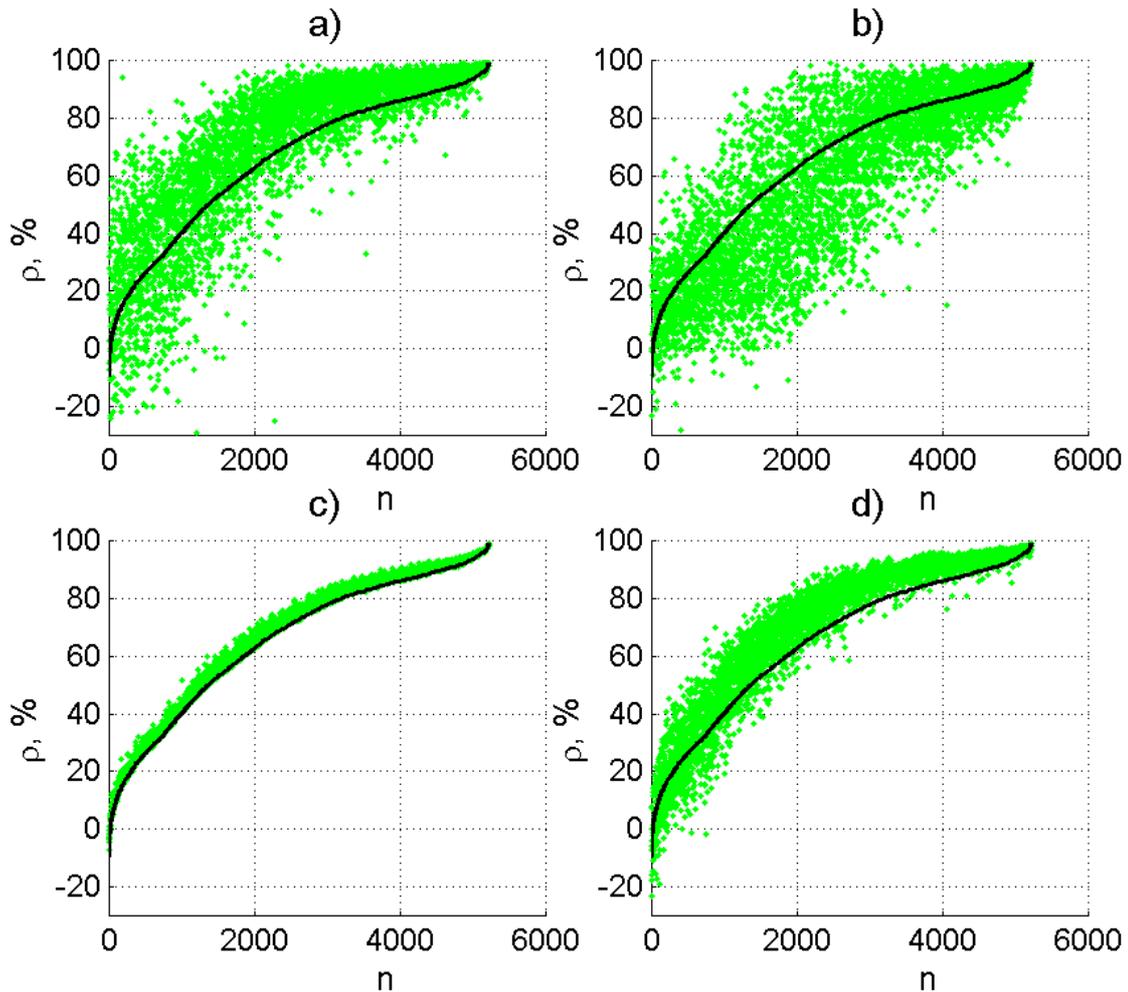
Figure 7.3 Distribution of cross correlation values computed before and after denoising using: a) time windowing, b), bandpass filtering, c) wavelet coefficient shrinkage, d) wavelet coefficient selection. The line represents the sorted in ascending order cross correlation values before denoising. The points represent the same signals in the database, but after denoising with different methods. Here n is the number of the record in the database.

Figure 7.4 gives more insight about the different effect of the denoising methods to the similar records representing various cross correlation intervals. It shows the influence of different SNR improvement techniques in six cross correlation ranges. The recordings were clustered by their cross correlation value into six groups before application of the processing techniques. Then all the techniques were applied to the recordings in the groups and mean cross correlation values calculated. It can be seen that all the methods, except bandpass filtering, increased the cross correlations in

all the selected intervals. The records from the intervals (40-50)%, (50-60)% and (60-70)% experienced the highest positive influence from both wavelet based methods, while records from the interval "<30%" are almost unaffected. Time windowing influenced the records from the all intervals significantly to the positive direction, too. However, it significantly affected the records from the interval "<30%", where with high probability only noise resides. Thus, it is negative feature, since errors (false negatives) can be produced in signal recognition tasks.
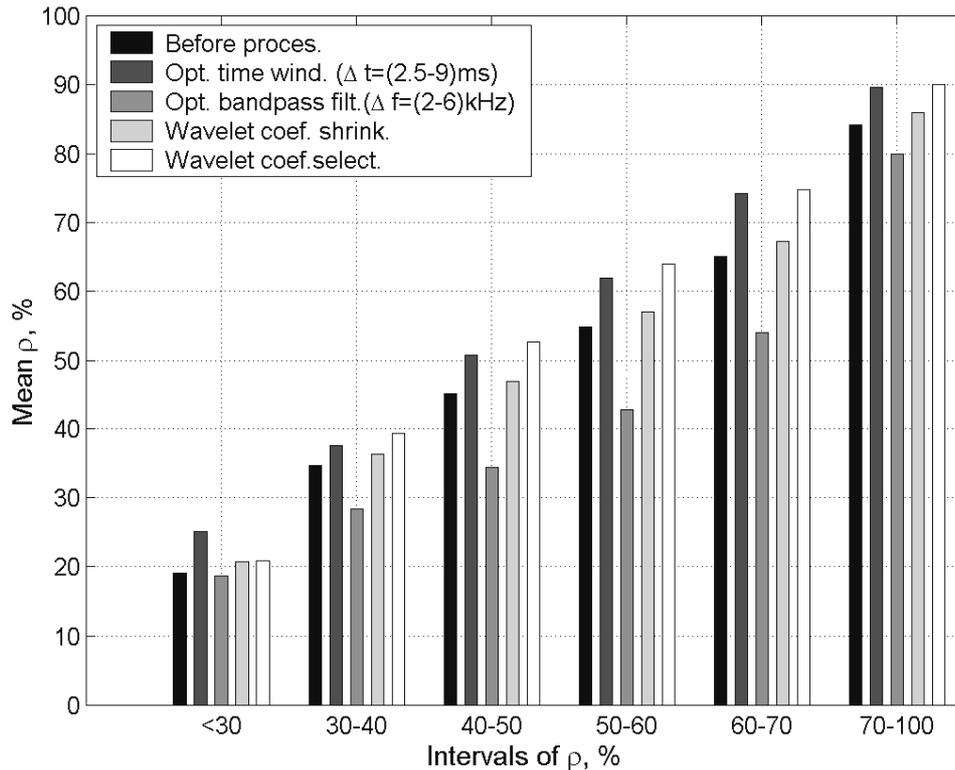
Figure 7.4 Comparison of various SNR improvement techniques in different cross correlation ranges

7.3.4 Discussion

TEOAE signal measurement promises to become a new tool in objective, quick and reliable assessment of the functionality of inner ear. However, many problems have to be solved until TEOAE measurement based tests of hearing will gain the popularity among the clinicians. One of the problems is a noise reduction or enhancement of the acquired TEOAE signal for reliable detection.

We have shown that TEOAE signals could be enhanced by using a knowledge about the time- frequency contents of this kind of signals. The motivation for this approach was earlier investigations made by Whitehead

et.al. [98] and Gorga et.al. [34], where time windowing or bandpass filtering were used. In contrast, we have tried to use both dimensions: time and frequency, in signal enhancement. We employed discrete wavelet transform for mapping the signal into joined time-frequency representation. Discrete wavelet transform decomposes the signal into octave frequency bands with increasing time resolution when frequency increases. This property agrees with time- frequency structure of TEOAE signals, where high frequency components have shorter duration than low frequency components. Other authors: Wit et. al. [100] and Tognola et.al. [92], have used continuous wavelet transform (CWT) for TEOAE analysis. We admit that CWT allows more flexibility in choosing frequency bands and time resolutions, however it is highly redundant and computationally expensive. Wavelet pocket analysis [13] is worth considering. It is an alternative to CWT having some degree of flexibility in time- frequency plane division and fast analysis algorithms.

The analysis of enhancement of TEOAE signals in database showed wavelet based algorithm works. These signals, which had very low cross correlation value (<30 %) before processing, were almost unaffected by the algorithm i.e. TEOAE was not "found" where it was not present. This is correct, because it is very high probability that these records were recorded from impaired ears and contain no TEAOE activity i.e. only noise was recorded. The group of signals, which had cross correlation value in the range 40- 70 %, experienced the highest influence (increase of cross correlation value in the average) by all the signal enhancement methods. Thus, many previously indeterminate cases, where cross correlation values were just below the decision threshold of 70 %, reached the threshold and can be diagnosed as normal hearing. However, these signals may represent either TEOAE signals, which are contaminated by high amplitude subject generated and environmental noises, or pure noise, which has accidentally achieved high cross correlation value. The question arises: which signals were enhanced more in this group? There could be two possible answers to this question: a) just signals having TEOAE activity were enhanced, b) both types of signals with TEOAE activity and without it were enhanced equally. The first possibility is desirable as the number of subjects that were miss classified as hearing impaired would decrease, while the second would bring highly undesirable consequences: hearing impaired subjects might be diagnosed as normal hearing. We will try to answer the former question in the next section where the detection of TEOAE or classification of subjects into normal hearing and hearing impaired will be considered.

7.4 TEOAE feature extraction and detection

As it was written in section 7.1, the features that take into account specific time-frequency properties of TEAOE can be more useful than, for example, gross features like energy or maximum amplitude of the signals. Thus, feature extraction procedure, which was described in section 6 was used in our TEOAE feature extraction problem.

Choosing wavelet coefficients from decomposition level j is equivalent to bandpass filtering of the signal, while choosing wavelet coefficients with indexes from k to l from the given decomposition level is equivalent to time windowing. The fast orthogonal discrete wavelet transform decomposes the signal by definition into octave frequency bands, which cannot be chosen independently. The time windowing in wavelet domain can, however, be accomplished with no restriction in the choice of the indexes k and l.

The choice of time indexes k and l in our TEOAE specific feature extraction problem was based on the data from the section 5.3, where the average location of the bigger part of the TEOAE energy in the selected levels was determined. Our data agrees with data from a study of Janušauskas et. al. [40], where the average time locations of TEOAE in a database of normal hearing subjects was studied by the use of an ensemble correlation technique. The time windowing was thus carried out directly in wavelet domain by selecting or, equivalently, by applying the rectangular windows to the wavelet coefficients from the given level of decomposition (as seen in Figure 7.5). The features, cross correlation coefficients between two windowed frequency components of two TEOAE subaverages A and B in the wavelet domain, are then obtained as:

$$\rho_j = \frac{\sum_{n=k}^{l} w_{A,j}(n) \cdot w_{B,j}(n)}{\sqrt{\sum_{n=k}^{l} w_{A,j}^2(n)} \cdot \sqrt{\sum_{n=k}^{l} w_{B,j}^2(n)}} \qquad (7.1)$$

where $w_{A,j}$ and $w_{B,j}$ are wavelet coefficients of subaverages A and B from level j and where k and l are indexes of the first and last coefficient in the respective window.

An example of TEOAE subaverages transformed into wavelet domain is shown in the Figure 7.5. It can be seen that the highest similarity between the wavelet coefficients and equivalently the highest cross correlation appears in rectangular windows as defined by Janušauskas et. al. The calculated cross correlation values between the TEAOE subaverages with

and without windows, as indicated in the Figure 7.5, exemplify the improvement achieved by windowing.
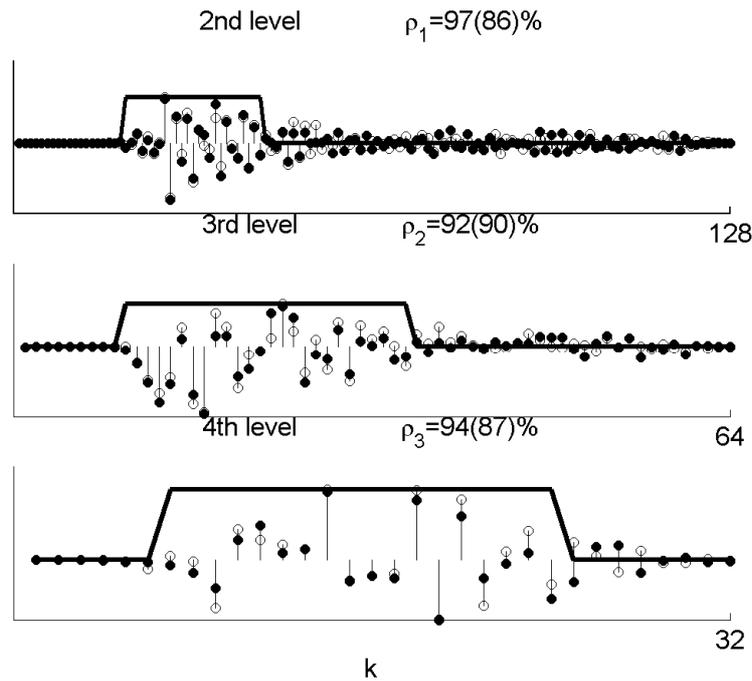
Figure 7.5 Three levels of wavelet decomposition of two subaverages and corresponding time windows. The two subaverages A and B are shown as open and filled circles, respectively. Solid lines indicate corresponding time windows (k is time index). The cross correlation values ρ_j with and without windows (in parentheses) are indicated.

The three cross correlation coefficients ρ_j, which represent each recorded signal consisting of two subaverages with 512 time samples each are in the following used as TEOAE features.

7.4.1 Feature average based detector

In order to establish TEAOE detection criterion, features extracted from recorded signals should be combined in some way to form the detection function $d\{s[n]\}$. The final decision, about the presence of TEAOE in the response can be made by setting the threshold on the value of detection function. Two ways to combine the features in order to form $d\{s[n]\}$ for TEAOE detection were proposed.

The first detection function was constructed as simple feature average. This assumes that extracted features, time and frequency limited cross correlation coefficients, have equal weights in forming discriminatory function to detect TEOAE:

$$d(\rho_1, \rho_2, \rho_3) = \frac{1}{3}\rho_1 + \frac{1}{3}\rho_2 + \frac{1}{3}\rho_3 \qquad (7.2)$$

In addition, we associate the presence of TEOAE with normal hearing (mean hearing threshold less than 30 dB). Thus, separation of subjects belonging to normal hearing or hearing impaired is made according to this rule:

$$d(\rho_1, \rho_2, \rho_3) = \begin{array}{c} NH \\ \geq \\ < \\ IH \end{array} \; T \qquad (7.3)$$

where *NH* represents the normal hearing subjects, *IH* the impaired hearing subjects, *T* is the threshold value.

7.4.2 Neural network based detector

It is well known that TEOE generation is closely related with non-linearities which are present in the cochlea and which are responsible for the high dynamic range of the hearing system. Thus, it would be natural to think about more complex relationship than linear in associating hearing level and time-frequency features extracted from TEOAE. Artificial neural networks are used in applications, where predetermined analytical relationships are difficult to establish because of the lack of knowledge about the phenomenological background, but where rich empirical datasets are available for teaching of the network of the desired relationship. Thus, we were inspired by our large database of TEOAE records to construct the second TEOAE detection and subject separation parameter with the help of artificial neural network.

The multilayer perceptron was chosen due to its ability to model both simple and very complex functional relationships [14]. We restricted, however, ourselves to consider artificial neural network having only one hidden layer and only hyperbolic tangent activation functions. The Bayesian technique of regularization proposed by D. Foresee and F. Hagan [29] to improve generalization was used in training procedure. In addition, this regularization procedure gives the number of weights in the neural network that are effectively used in reducing the error function. This feature can be employed to choose optimal number of network neurons. We can simply add more neurons and retrain. If the larger network has the same final effectively used number of parameters, then the smaller network was large enough. In our case, the final network had 3 inputs, 6 neurons in the hidden layer and

one neuron in the output layer. The weights were adjusted using Levenberg-Marquardt algorithm during the training procedure. This algorithm has the most rapid convergence properties for networks with moderate complexity [37].

The network was trained using supervised learning with a training set of inputs and targets. This procedure is described by:

$$d(\rho_1, \rho_2, \rho_2) = \begin{cases} 1, & if \quad MHL < 30dB \\ -1, & if \quad MHL \geq 30dB \end{cases} \qquad (7.4)$$

where $d(\rho_1, \rho_2, \rho_3)$ is the detection function, which has to be determined by the ANN to minimize the mapping error of the features ρ_1, ρ_2, ρ_3 to the targets, the binary values 1 and −1. These binary values represent the subjects having audiometric MHL in frequency range 500-4000 Hz less than 30 dB and more than 30 dB, respectively. Thus, normal hearing subjects are coded by "1" and hearing impaired subjects by "-1".

The preliminary attempts of the neural network training showed that the network generalized well if the training set consisted of approximately equal number of hearing impaired and normal hearing cases. The training set was therefore made of a database representing 385 hearing impaired and 400 normal hearing subjects. The testing set contained all the subjects: 809 hearing impaired and 4404 normal hearing.

The separation of subjects belonging to one of the groups is made according to the rule in (7.3).

7.4.3 Statistical decision theory for the comparison of the detectors

The principles of statistical decision theory [67] were used for the comparison of the different detectors. The ROC curves (introduced in section 3.3) were used to assess the ability of the detectors to detect TEOAE signals.

In TEOAE detection applications it is important to have high sensitivity of the detector to identify the main part of the hearing impaired subjects. The comparison of the performance of the different detectors was therefore made by keeping the sensitivity at a fixed level of 90 % and comparing the resulting specificity.

7.4.4 Subject separation results when separation parameter is an average of the features extracted from TEOAE

In order to validate the increased complexity of the new denoising methods, comparison with conventional TEOAE detection techniques, which were described in section 7.3.2 as noise reduction techniques, was made. The detection function $d(\rho_i)$ was: the average of the three cross correlation coefficients in case of wavelet based time- frequency feature extraction "Time- frequency feat." method and the simple cross correlation coefficient in the remaining methods.

Figure 7.6 shows fife ROC curves corresponding to different methods of TEOAE signal processing and feature extraction.
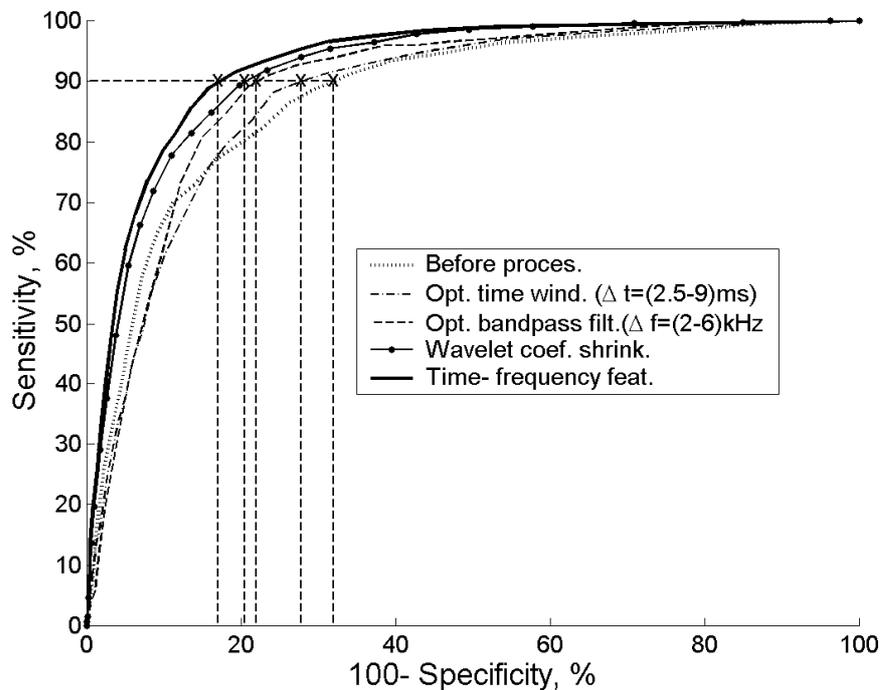
Figure 7.6 ROC curves before any processing of TEAOE signals ("Before process."), after windowing ("Opt. time wind."), after linear bandpass filtering ("Opt. bandpass filt."), after non-linear wavelet based filtering ("Wavelet coef. shrink.") and after wavelet based time- frequency feature extraction ("Time- frequency feat.")

It was shown that wavelet methods and especially wavelet based time-frequency feature extraction method outperform the other methods by achieving a better specificity at all investigated sensitivity value. The specificity values at a sensitivity of 90 % are presented in Table 7.1

Table 7.1 The specificity of different TEOAE detection methods at 90% of sensitivity

Method	Used signal features	Specificity±std, (Sensitivity=90%)
Before processing	ρ	[68,03±0,70] %
Time windowing (Δt=(2.5-12,5)ms).	ρ	[72,31±0,67] %
Bandpass.filt. (Δf=(2-4)kHz)	ρ	[78,12±0,62] %
Wavelet coef. shrinkage	ρ	[79,51±0,61] %
Time frequency features	ρ_1, ρ_2, ρ_3	[82,71±0,57] %

In order to provide further insight into the above results, the sensitivity and the specificity are presented separately as the decision threshold functions[1] in Figure 7.7. Again, it is obvious that time windowing corresponds to a less favourable sensitivity and specificity than do the wavelet methods. Bandpass filtering has a better sensitivity but a worse specificity than the other methods; the sensitivity characteristic is explained by lower noise contamination in the higher frequency region which reduces the likelihood of high cross correlation values due to correlated noise artefacts.

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[1] A sensitivity curve, which is less steep indicates that, for a certain value of the separation parameter, a larger number of cases are mistaken as true OAE as a consequence of residual stimuli or correlated noise artifacts. A specificity curve, which is less steep indicates a larger number of cases where noise is insufficiently reduced or where an OAE was not present because of methodological problems.
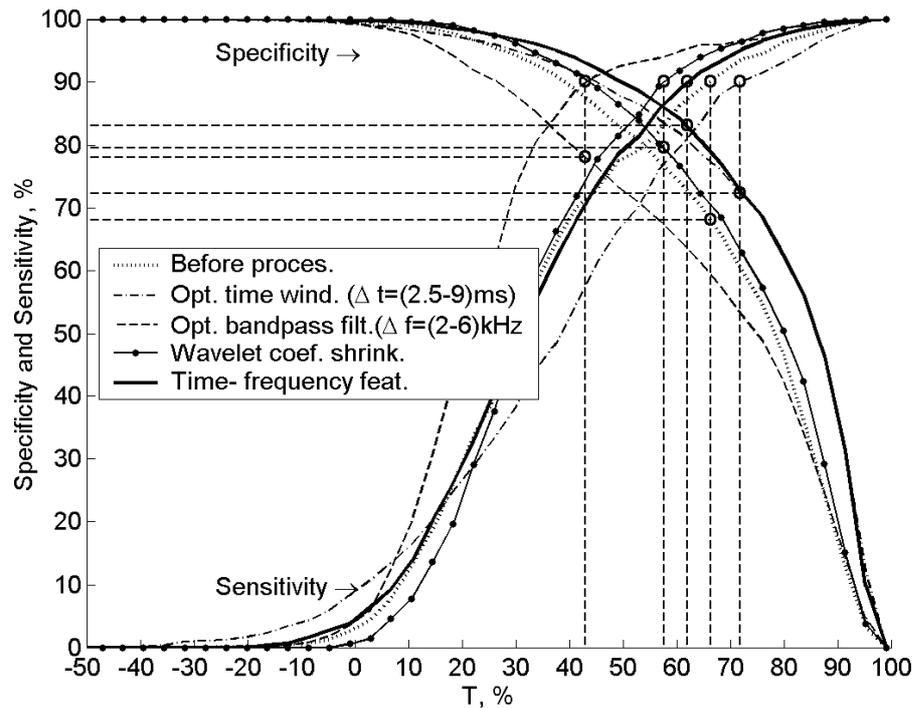
Figure 7.7. Sensitivity and specificity versus threshold.

7.4.5 Comparison of linear and non-linear TEOAE detectors in hearing screening

In order to check if more complex detector than linear can perform better in separation normal hearing subjects from those with hearing loss we compared two detectors. The first used simple average of features as separation parameter and the second neural network, which can combine extracted features, in such a way as the best separation performance could be achieved. Both classifiers, the linear and the non-linear, transformed a vector of three TEOAE features, representing one subject, into one single output. The results of both classifiers are shown in Figure 7.8 and Figure 7.9. Normal hearing subjects are grouped in the left part of the figures (4404 subjects), while hearing impaired are grouped in the right part (809 subjects). The decision threshold (dashed horizontal line) for separation of hearing impaired from normal hearings is selected such that sensitivity of 90 % is obtained. It can be observed that most of normal hearing subjects are above the decision threshold. They constitute the true negatives. The normal hearings below the decision threshold are the false positives. Similarly, hearing impaired subjects (right side of the graphs) below the threshold are true positives and above the threshold are the false negatives. It can be concluded that the linear approach distributes subjects more evenly in comparison with ANN, which seems to separate most of subjects in two distant regions. Although, this looks like an advantage of the non-linear

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approach versus linear, the improvement expressed as a specificity value is a minor showing a difference between the methods of 82.7 % versus 84.1 % for a specificity at a sensitivity of 90 %. The numbers of correctly and not correctly identified subjects and the calculated 95 % confidence intervals of specificity at 90 % of sensitivity for both types of classifiers are presented in Table 7.2.
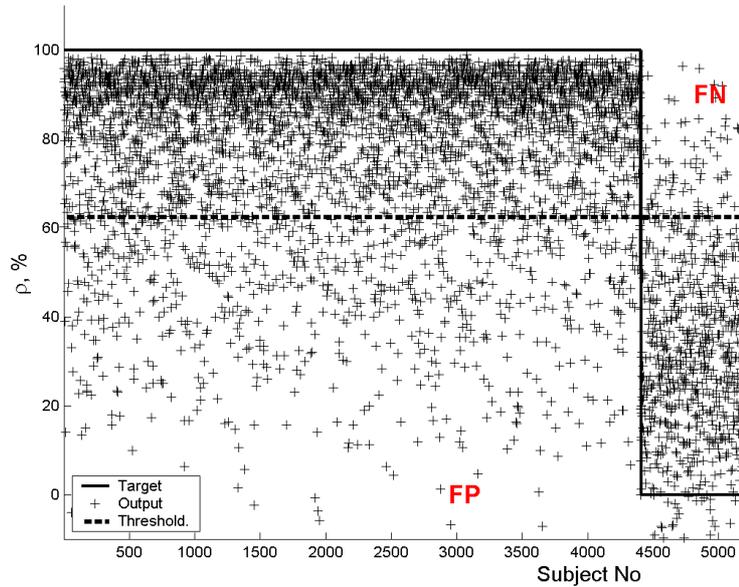
Figure 7.8 Separation of normal hearing and hearing impaired subjects using a linear classifier. Here ρ is the average of the features- ρ₁, ρ₂ and ρ₃
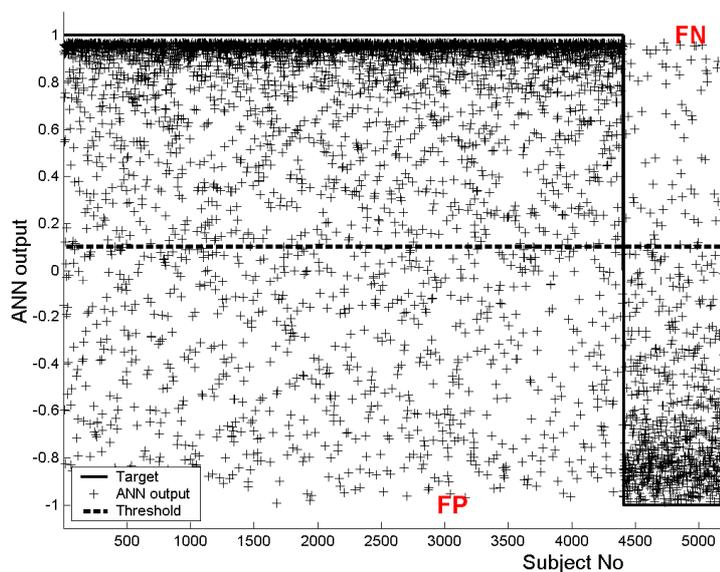
Figure 7.9 Separation of normal hearing and hearing impaired subjects using ANN separation

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A comparison of the numbers of false negatives and false positives shows close similarity between the classifiers with minor improvement for the non-linear classifier, which gives less number of false positives (Table 7.2).

Table 7.2 The separation results at 90% of sensitivity

	NT	TP	FN	FP	Specificity and std.	Confidence interval (0.05%)
Linear classif.	3644	727	82	760	(82.7±0.57) %	[81.6– 83.8]%
Non-linear classif.	3704	726	83	700	(84.1±0.55) %	[83- 85.2]%

It may be assumed that larger differences would appear at other levels of sensitivity. But this is not the case, as can be seen in the ROC curves in Figure 7.10. The curves indicate that the separation methods are very similar, though, non-linear approach exceeds linear at several regions.
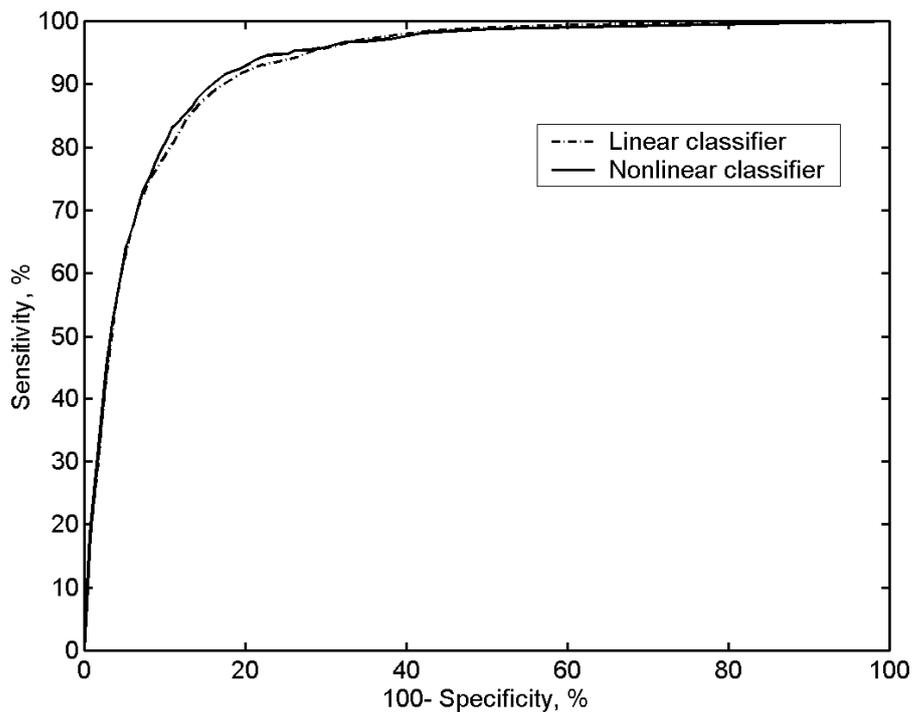
Figure 7.10 ROC curves for both methods

Although the resulting difference between the two methods was small, we could prove that the difference is statistically significant by applying a hypothesis test with the null hypothesis defined, as "no differences among the results from the classifiers". After making the assumption about normal

distribution of the results, the hypothesis test showed that we could reject the null hypothesis, as the evaluated *P* value was *0.0002.*

The dependence of separation accuracy in terms of sensitivity and specificity curves as the functions of decision threshold is shown in Figure 7.11. Before comparison, outputs of the neural network were transformed into the same range as averaged cross correlation values: from 0 to 100 %. The curves show that to achieve the same sensitivity of 90 % different decision thresholds should be applied: 70 % for linear method and 53 % for non-linear. The shapes of the curves from respective method differ considerably for a given decision threshold value; the difference is particularly large between the sensitivity curves. This is due to transformation of distribution of hearing impaired subjects by the non-linear classifier as it shown in Figure 7.8 and Figure 7.9.
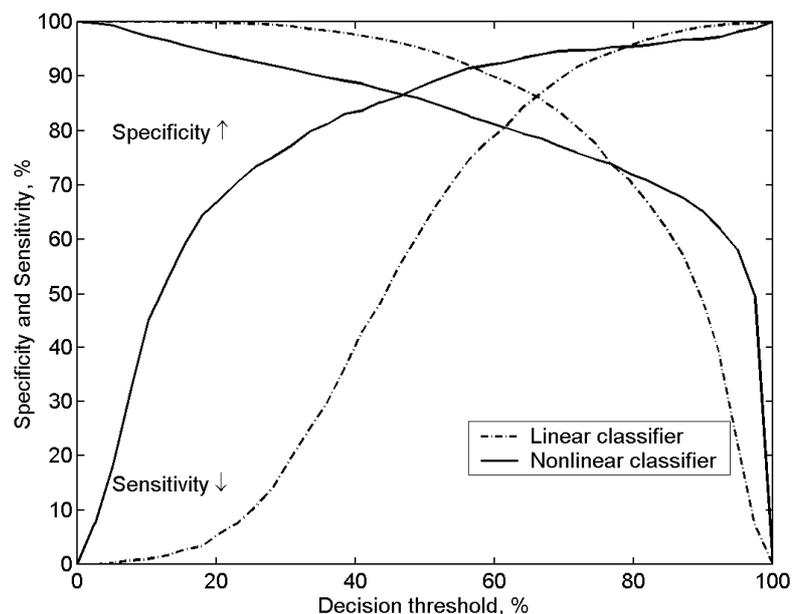
Figure 7.11 Sensitivity and specificity of linear and non-linear classifiers as the functions of the separation threshold.

7.4.6 Discussion

In this section we compared different signal processing methods to increase accuracy of the separation hearing impaired and normal hearing subjects in the database using TEOAE records. The question, which was left from the section 7.3 can be answered. The question was: which signals were enhanced more in the group of signals that have cross correlation value just below the threshold? There were two possible answers to this question: a) just signals having TEOAE activity were enhanced, b) both types of signals with TEOAE activity and without it were enhanced equally. Now we can

answer from Table 7.1 that signals having TEOAE activity were enhanced more, since the accuracy of subject separation was improved.

Further, we compared two classifiers to separate hearing impaired and normal hearing subjects, using TEOAE based features. The first classifier was constituted by the linear average of the set of features, while the second one- based on neural network, which could account for a more complex relationship, possibly non-linear, among the set of features as extracted from TEOAE and the mean hearing level in the frequency range 0.5-4 kHz. Based on the facts about non-linear TEOAE generation mechanism in the cochlea we expect a substantial improvement in subject separation using more complex non-linear classifier as compared to a linear. The results were, however, very similar with a small but still statistically significant advantage of the neural network based classifier.

A possible reason why the neural network did not decrease the number of errors might be due to the fact that the database includes a certain amount of errors caused by deficient measurements of TEOAE or audiograms. The outliers may prevent the neural network from the establishment of the right separation function during the training procedure. We have manually inspected some cases with erroneous behaviour: hearing impaired subjects with a TEAOE like response (false negatives) and normal hearing subjects with a response in which TEOAE cannot be detected (false positives). There are several reasons that may contribute to false positives: a) poor fitting of the probe into the ear canal (loose seal to the ear canal reduces stimulus pressure and TEOAE amplitudes), b) a blockage of the microphone or speaker ports against the ear canal wall or by ear wax, which prevents the recording of the TEOAE response, c) strong ambient noise during the session of recording, d) conductive hearing loss in middle ear from 10 to 20 dB can make emission undetectable. One example of a false positive case is shown in Figure 7.12, where the subject has MHL=4 dB indicating the potential to generate TEAOE and where the ρ value equal to 40 % indicates mainly the random activity. The possible reasons for low ρ value might be a) somewhat low stimulus pressure –72 dB (scaled stimulus is shown in the left-hand side of the figures), while the average pressure is 80 dB in the database and b) strong ambient noise.
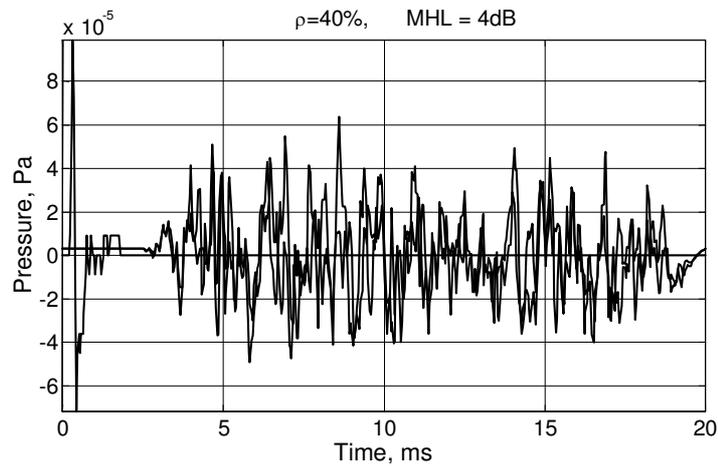
Figure 7.12 The example of TEOAE response in case of false positive subject

False negatives, may also appear due to technical failures: a) bad fitting of the probe into the ear canal may cause prolonged stimulus artefact, which will give increased cross correlation values, b) noise from instrumentation which is synchronized with stimulus may be detected as the TEOAE.
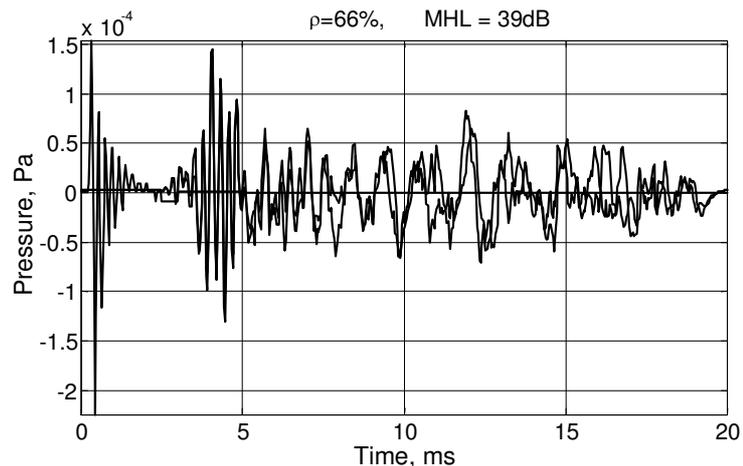
Figure 7.13 An example of prolonged artifact

Figure 7.13 shows an example representing a false negative case, which may have increased cross correlation value due to prolonged stimulus artefact. This subject is classified as normal hearing although the MHL is 39 dB.

It is, however, sometimes difficult to find a simple explanation for the achieved error. Figure 7.14 shows a TEOAE response from a subject, which is hearing impaired according to audiometric data with MHL 53 dB.
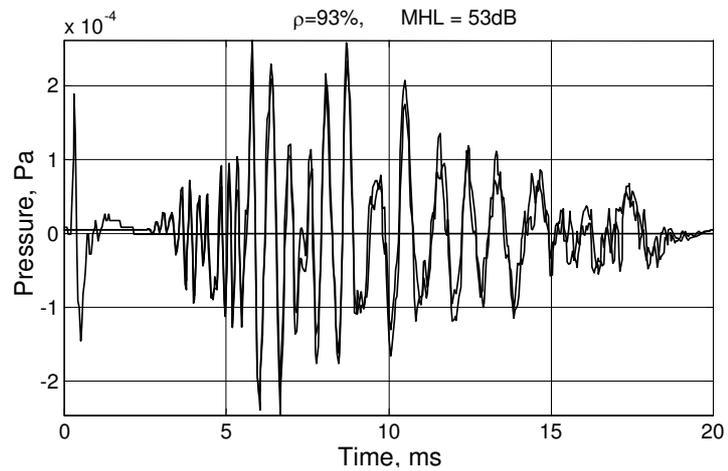
Figure 7.14 The example of false negative case

This response looks like a response from a completely normal hearing subject, where: high, middle and low frequencies easily can be distinguished in the response. One possible explanation for this example is that it may be a retrocochlear hearing loss, which means that the hearing loss is caused by dysfunction the auditory pathway after the cochlea. Such a condition cannot be detected by a TEOAE test, since these cases have a normal cochlea producing a normal TEOAE. Another possible explanation is error in the measurement of the audiogram.

8 Conclusions

The following conclusions can be derived from this study:

1. Signal denoising in the transform domain can be more effective than in the original time domain. We showed that the energy of the non-stationary signal is concentrated better in discrete wavelet domain than in discrete Fourier domain or time domain.

2. We found that among the families of finite in time and orthogonal wavelets: Daubechies2-20, Coiflet1-5, Symmlet2-10, the best performance in terms of energy concentration showed Symmlet 8 wavelet.

3. We proposed two different algorithms to enhance the signal in wavelet domain. One of them is based on wavelet coefficients thresholding and we proposed the method to estimate the threshold, which maximizes the quality of the signal. Other algorithm uses knowledge about average location of signal components in wavelet domain for relevant wavelet coefficients selection. These methods were compared with other wavelet based denoising methods in the problem of TEOAE signal enhancement. The results showed that method based on wavelet coefficient selection is the best among compared methods and could reduce averaging time needed to achieve the signal of sufficient quality. The quality of enhanced signal averaged over 16 realizations was approximately equal to unprocessed signal, which was averaged over 60 realizations.

4. Signal denoising method based on wavelet coefficient selection was validated in the application of denoising 5213 TEAOE signals from large database. The results showed that processing mainly affects these signals, which have average quality in the beginning. This is an important property as no clean signal is produced from noise only.

5. In the problem of signal detection, we proposed the efficient procedure to extract features from the non-stationary signal. We showed that calculation of band limited product of two signals in time is equivalent to the calculation directly in wavelet domain. Furthermore, windowing in time can be replaced with selection of relevant wavelet coefficients. Thus, calculations of cross correlation coefficients between time and frequency limited intervals of two signals can be accomplished very efficiently in wavelet domain.

6. The algorithm for automatic separation of hearing impaired and normal hearing subjects using the features extracted from TEOAE signals was proposed and tested on the database of 5213 signals. By using proposed features, the specificity of separation was increased by 10-15 % in comparison with conventional features.

7. We compared two classifiers in separation of hearing impaired and normal hearing subjects, using TEOAE based features. The first classifier was constituted by the linear average of the set of features. The second classifier was based on neural network, which could account for a more complex relationship, possibly non-linear, among the set of features as extracted from TEOAE and the mean hearing level in the frequency range 0.5-4kHz. We expected, based on the facts about non-linear TEOAE generation mechanism in the cochlea, a substantial improvement in subject separation using more complex non-linear classifier as compared to a linear. The results were, however, very similar with a small but still statistically significant advantage of the neural network based classifier.

Acknowledgements

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Appendix

An attempt to simulate the TEOAE emitting ear and TEOAE acquisition hardware was made in this study. The aim was to build the systems, which generate synthetic TEAOE signal showing resemblance with real TEAOE signal and to understand what kind of transformations experiences the signal in different places of the modelled systems.

1 Simulation of the system "Kemp's hearing faculty tester and TEOAE emitting auditory periphery"

Modeling of auditory periphery, composed of external, middle, and inner ear (cochlea), has a long history and it aims to explain complex processes involved in hearing. The first model of hearing was proposed by Helmholtz in 1863. He suggested a parallel bank of resonators as the mechanism for selectivity in frequency. He directed to basilar membrane as the bank of resonant elements. Many models have contributed to the modern understanding of cochlear mechanics, [2], [45], [46], [69], [70], [84], [95]. Next to the frequency selectivity, cochlea distinguishes as highly non-linear "device". Somehow, the cochlea compresses the large dynamic range of acoustic pressure variations that enter the much smaller dynamic range that can be processed by the sensory hair cells that detect these signals in the cochlea. The dynamic range of the hair cells (between thermal noise and signal saturation) is about 1000, whereas the range of audible sound pressure levels is about 100000. The cochlea is a non-linear signal processing device that, in addition to separating frequency components, is able to compress the dynamic range of input signals without significant degradation of the signal content. Thus non-linear saturating element should be present in more advanced model of the inner ear. It is believed now that outer hair cells provide the compressing mechanism of incoming audio signal. Unlike the inner hair cells, which act as sensory transducers involved in the transmission of information to the brain, the outer hair cells act as tiny muscles, adding energy to the traveling wave.

Cochlea is often modeled as a filter bank in a first approximation. Such filter bank is based on critical bands. It has been experimentally measured that the critical bandwidth increases when the center frequency is raised as it is exemplified in Figure 1.1 and Table 1.1.
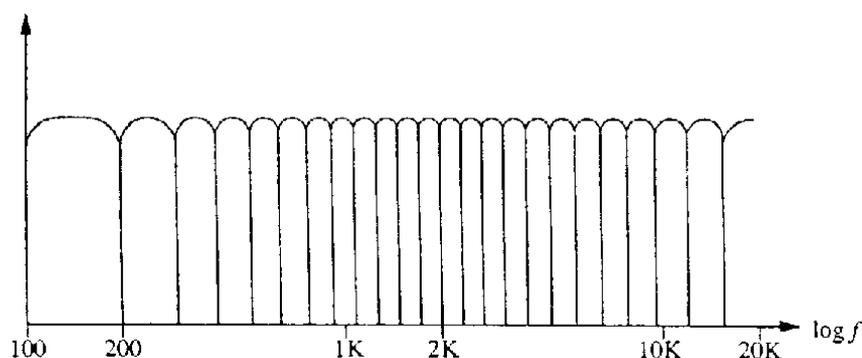
Figure 1.1 Critical bands of the auditory system.

Table 1.1 Critical bands, which are of constant bandwidth at low frequencies (below 500Hz) and of constant relative bandwidth at high frequencies

Band number	Lower edge (Hz)	Center (Hz)	Upper edge (Hz)	BW (Hz)
1	0	50	100	100
2	100	150	200	100
3	200	250	300	100
4	300	350	400	100
5	400	450	510	100
6	510	570	630	120
7	630	700	770	140
8	770	840	920	150
9	920	1000	1080	160
10	1080	1170	1270	190
11	1270	1370	1480	210
12	1480	1600	1720	240
13	1720	1850	2000	280
14	2000	2150	2320	320
15	2320	2500	2700	380
16	2700	2900	3150	450
17	3150	3400	3700	550
18	3700	4000	4400	700
19	4400	4800	5300	900
20	5300	5800	6400	1100
21	6400	7000	7700	1300
22	7700	8500	9500	1800
23	9500	10500	12000	2500
24	12000	13500	15500	3500
25	15500	19500		

Patterson's inner ear model [73] is based on an array of independent bandpass filters. The filters are organized from high frequencies at the base of the cochlea and to low frequencies at the apex. For bandpass filtering Peterson uses gamma-tone filters, that have impulse response:

$$g(t) = A t^{n-1} e^{-2\pi bt} cos(2\pi f_c t + \varphi) \qquad (1.1)$$

where A- gain factor, n- integer order, b- bandwidth, φ- starting phase.

The construction of impulse response of the gamma-tone filter is shown in Figure 1.2.
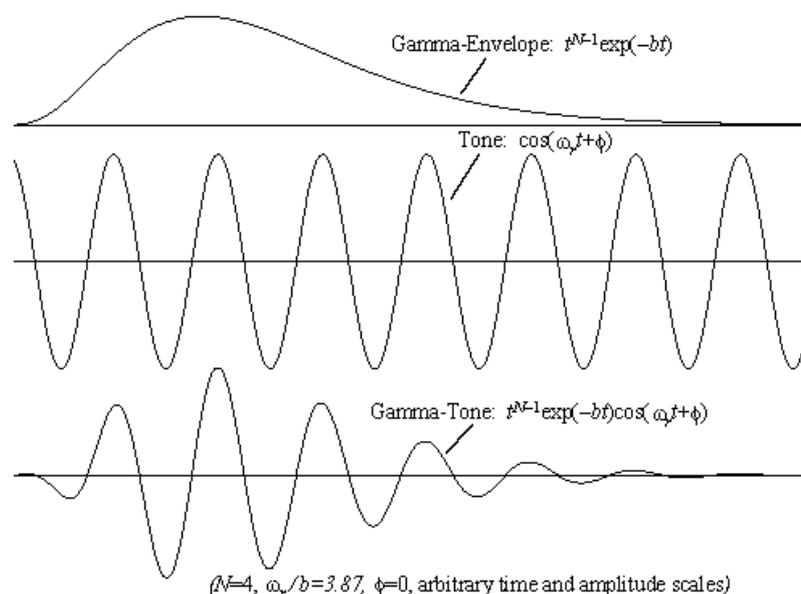
Figure 1.2 The components of a gamma-tone filter impulse response. The gamma- envelope (top), sinusoidal tone, and their product- the gamma-tone (bottom).

The efficient digital filter, which has all-pole gamma-tone impulse response, was introduced by Slaney [83]. The impulse invariance design technique was used to get the transfer function of the digital filter from the continuous space filter impulse response. The frequency response of gamma tone filterbank with 14 filters is shown in Figure 1.3.
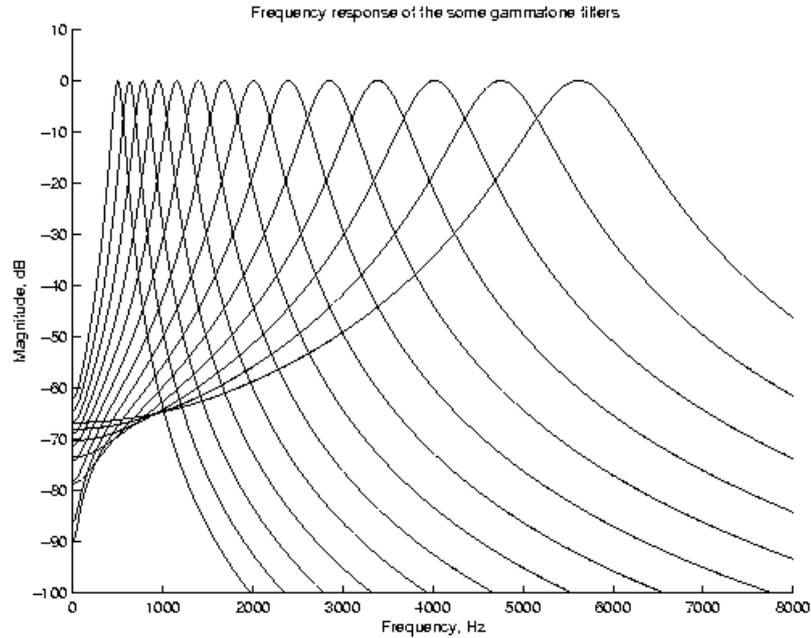
Figure 1.3 Frequency responses of 14 cochlea channels 4th order gamma-tone filters

The resemblance of the TEOAE signal and the sum of the impulse responses of the individual filters in the gamma-tone filter bank were noticed in study [100]. It was suggested to use gamma-tone filter bank to synthesize artificial TEOAE signals. However such model does not account for non-linearity of TEOAE: an amplitude of synthetic TEOAE grows linearly when amplitude of stimulus (short impulse) increases. In order to incorporate the feature of TEOAE to saturate when the stimulus increases, we suggest to use the hyperbolic tangent function in the output of each filter. The synthetic TEOAE signal can be written as:

$$s(t) = \sum_{k=1}^{K} tanh[h_k(t)] \qquad (1.2)$$

where h_k- impulse response of kth gamma-tone filter.

Otoacoustic emissions are fascinating field of auditory and signal processing research since they were first recognized 20 years ago by Kemp. The USA patent "Hearing faculty testing" belongs to him and Peter Bray [48]. The device described in the patent is almost the only one type used by researchers audiologists and physicians in hearing screening for 15 years. It is of interest to study the properties of this device in conjunction with TEOAE emitting model of auditory periphery.

New simulation techniques are now available. Among them are MATLAB and SIMULINK by MathWorks Inc. MATLAB has no substitute in complex

mathematical calculations, while SIMULINK- in interactive system modeling. In the meanwhile MATLAB is relatively more flexible than SIMULINK, since the program consists of raws of commands, also many already written macros are available for MATLAB. SIMULINK model consists of blocs that correspond to various actions in the system. This makes very easy to understand SIMULINK model. The blocks can be taken from arranged libraries. These libraries are not very rich so far, but flexibility can be attained by writing S functions, which is more work consuming than writing m functions for MATLAB. However, visual programming of models with SIMULINK was chosen in this study, because it is near real hardware with its possibility to change interactively various simulation parameters: the power of different additive noise sources, for example, instrumentation and of patient generated noise, the stimulus amplitude and etc.

1.1 Kemp's hearing faculty tester

The block diagram of original device is presented in [48] and it is shown in Figure 1.4.

Linearly balanced set of short impulses, clicks, is used as the stimuli to evoke TEOAE. TEOAE is evoked from a large part of the cochlea simultaneously also including all the byproducts of non-linearity and intermodulation. By using special "non-linear differential" stimulus block, which consists of four 100µs duration with 20ms periodicity and with the fourth impulse inverted and three times greater in amplitude, non- linear components of the response are kept while linear are eliminated. Thus, OAE response, which is very weak by comparison with stimulus, but highly non-linear, remains in the subaverage of four responses while strong stimulus artifact disappears, because it is linear.

The block "Stim.Gen." in Figure 1.4 represents the generator of differential stimulus packets. Stimulus is applied to patient's ear by the probe (miniature phone). In the same probe small microphone (block "Detect.") is placed, which captures small TEOAE responses, primary elements (stimulus artifacts or echoes in the ear canal) and environmental noise. Four responses to stimuli packet are fed to algebraic summator "Sum" after amplification and filtering in the block "Detect". The sum of four responses are applied to an interrogation unit "Interrogate" for comparison with a predetermined threshold and to a "Store" for possible reprocessing. Signals, which were passed through "Interrogate" are applied in alternating sequence under the control of the "Gate" to one or the other signal averagers "Average". Here the synchronous averaging enhances the signal to noise

ratio of OAE waveform. Outputs from the averagers are applied as inputs to a correlator "Correlate". The decision about presence of OAE is made then the achieved cross correlation factor is greater than 60%. Another alternative is to use signals collected in the "Store", reprocess them, for example, by filtering, and compute cross correlation again.
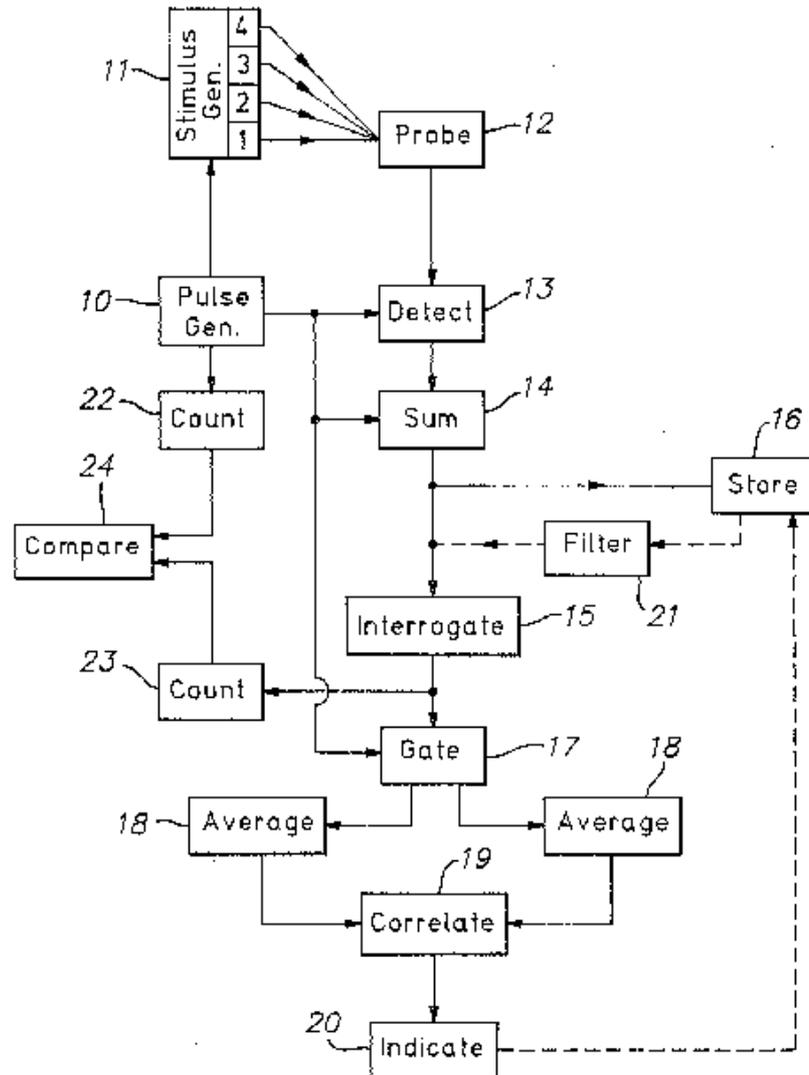
Figure 1.4 Block diagram of Kemp's hearing faculty tester. Adopted from [43]

1.2 SIMULINK model of Kemp's hearing faculty tester

SIMULINK model of complete system- model of the auditory periphery and hearing tester is presented in Figure 1.5.
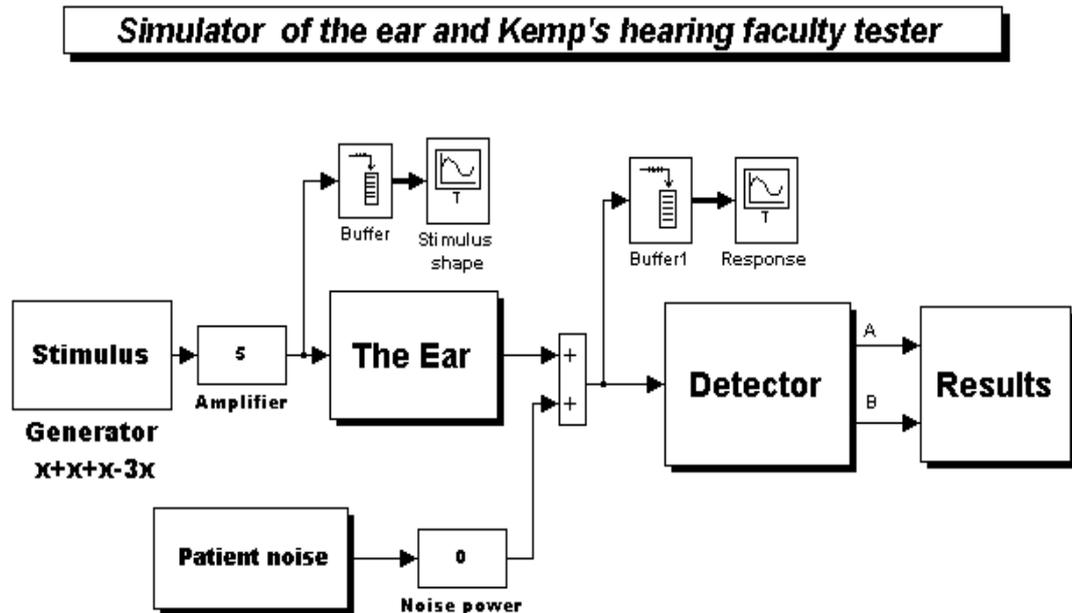
Figure 1.5 SIMULINK model of complete system

Non-linear differential stimulus is generated in the block "Stimulus". Two impulse generators with different frequencies are used to form the sequences of four sound stimuli packets. By the help of block "Amplifier" it is possible to change interactively the amplitude of the stimulus during the simulation. An oscilloscope "Stimulus shape" shows continuously the stimulus.

The train of stimulus clicks are applied to the model of the ear, which is described later.

Tiny OAE like responses from the model of cochlea with strong responses of ear canal are summed with portion of low passed white noise to model the contamination of the signal with patient and instrumentation noise. The response can be monitored during the simulation with oscilloscope "Response" (see Figure 1.5).

The inner content of subsystem "Kemp's detector" is shown in Figure 1.6:
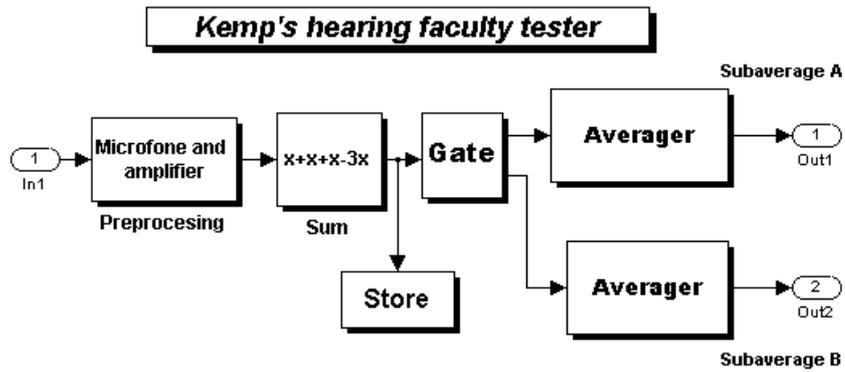
Figure 1.6 Inside of subsystem "Detector"

It consists of 5 smaller subsystems: preprocessing block, where amplification and filtering of the signal takes place (Figure 1.7). Block "Sum" algebraically sums four successive responses to eliminate linear artifacts (Figure 1.8). Block "Store" stores all the responses obtained during simulation time for further analysis, "Gate" block splits responses into two alternating sequences for further comparison, "Averager" calculates the current average according to Figure 1.9.
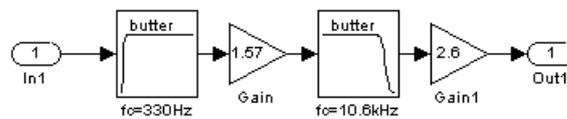
Figure 1.7 Preprocessing subsystem

Summing circuit consists of the buffer, that can hold four responses, and four selectors that help to apply four responses to the summator at the same time. Gain factor 2 restores the amplitude of OAE component. The oscilloscope helps to monitor the outgoing response.
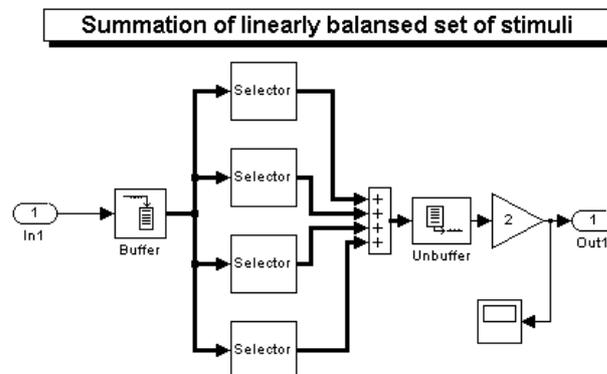
Figure 1.8 Summing circuit

Averager averages the current response with the current average.
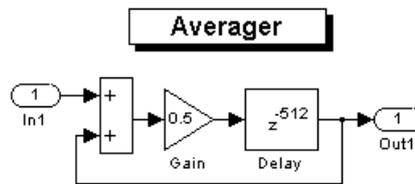
Figure 1.9 Calculation of the current average

Decision making block about presence of OAE is the subsystem "Results" in Figure 1.10. Here the subaverages of A and B can be monitored during simulation time and also spectrum analysis is possible.
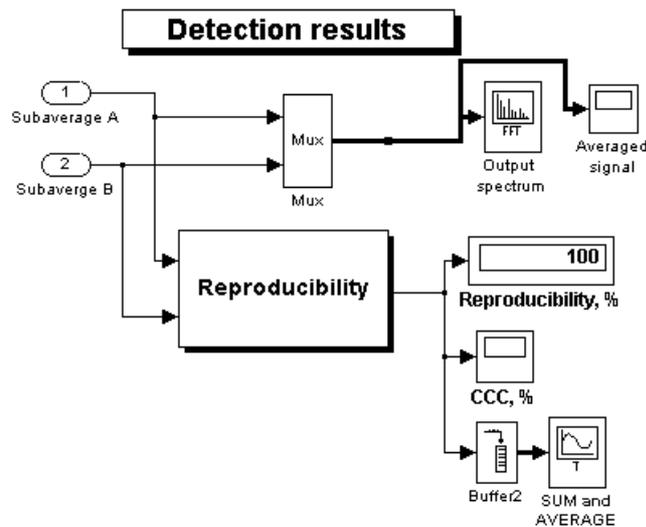
Figure 1.10 Subsystem "Results"

The main parameter for decision making is cross correlation coefficient or reproducibility of subaverages of the responses A and B. It is thought that reproducibility greater than 60% indicates the presence of OAE. The block diagram of reproducibility calculation is showed in Figure 1.11. At first, the subaverages A and B are buffered. The lengths of buffers are 512 samples, which is equal to 20ms, then calculation of cross correlation takes place. New value of cross correlation coefficient appears every 20ms in the display and, in addition, the history of changes of this coefficient can be monitored in indicator- oscilloscope.
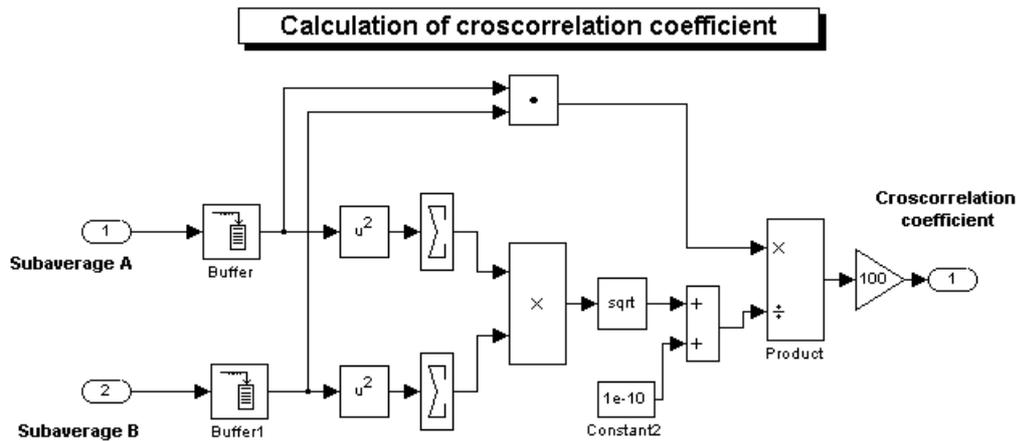
Figure 1.11 Calculation of cross correlation by means of SIMULINK

1.3 SIMULINK model of TEOAE producing ear

Our ear model consists of two blocks: 1) outer and middle ears, 2) cochlea. Sound entering the outer ear acts to the tympanic membrane. This pressure gain is maximal in the region between 2 and 5kHz [60]. The middle ear also has bandpass transfer function, but the peak is about 1kHz and has much steeper slope at low frequencies. Two bandpass transfer functions were combined to the one and modeled with bandpass filter, which has the cut off frequencies 800Hz and 6000Hz.
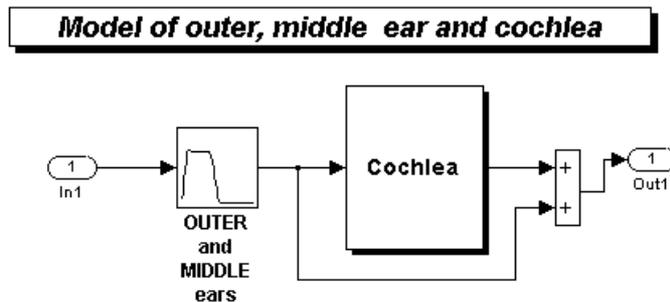
Figure 1.12 The subsystem "The ear" in Figure 1.7

Entering to the middle ear sound is transformed to the mechanical motion of middle ear osciles, entering to the cochlea sound experiences another transformation to the fluid pressure wave traveling from the base to the apex. Fluid pressure wave travels with limited speed and stimulates inner and outer hair cells along the basilar membrane. Inner hair cells are responsible for transformation of pressure to electrical neuronal impulses, which go further to the brain. While outer hair cells generate mechanical feedback forces at a given place of basilar membrane to increase motion of

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that place. The influence of outer hair cells is limited (non- linear), because the ability to become longer of these cells is limited- 10% of the length. It is believed that otoacoustic emissions are generated by the activity of outer hair cells.

The traveling fluid pressure wave is modeled by the delay line with taps going to the models of "outer hair cells" (Figure 1.13). The delays of each section depends on the section's central frequency and are calculated according to [80]:

$$\tau[s] = \frac{1}{4f_c}\left(1 + tanh\frac{log(600/f_c)}{1.4}\right)$$ (1.3)

The central frequencies f_c were chosen from the range 600-6400Hz, where main energy of TEOAE is concentrated.
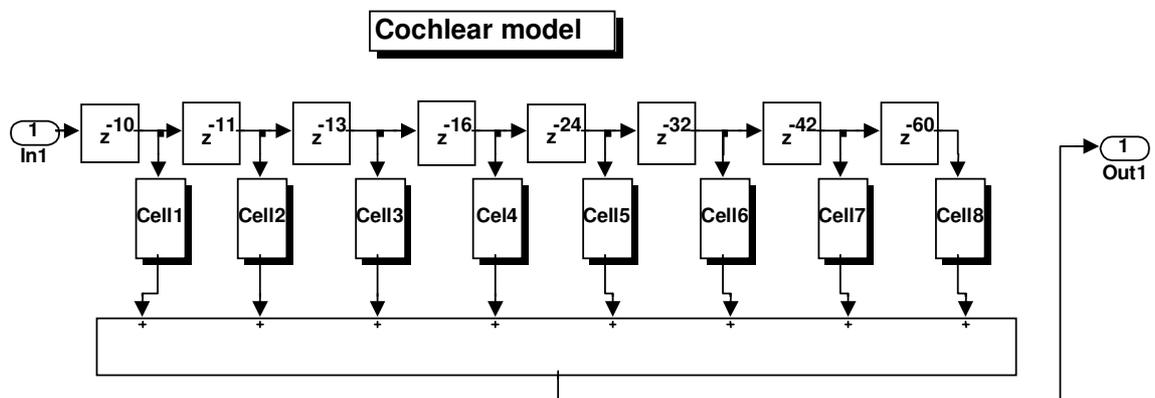
Figure 1.13 SIMULINK version of the cochlea

The models of outer hair cells (Figure 1.14) consist of bandpass filters, which correspond to critical bands. Parameters for filters are taken from Table 1.1middle frequency region 600- 6000Hz. Saturating non-linearity is modeled with hyperbolic tangent function.
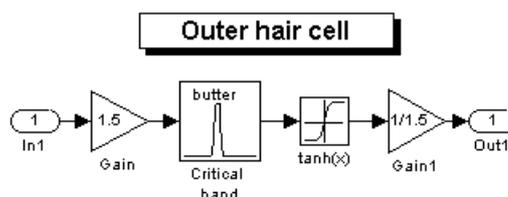
Figure 1.14 SIMULINK version of outer hair cell

TEOAE is generated as the response to the short impulse- click. In our SIMULINK model, TEOAE like response is obtained by summing all the

impulse responses of the models of outer hair cells- non-linear bandpass filters.

1.4 Results of the system simulation

Figure 1.15 shows the generated stimulus sequence. There are shown three differential packets, though, there is no restriction for simulation time.
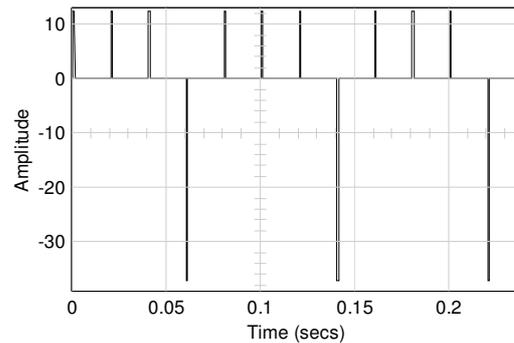
Figure 1.15 Stimulus sequence: three differential packets

Figure 1.16 shows the response to differential stimulus package from model of TEOAE emitting ear.
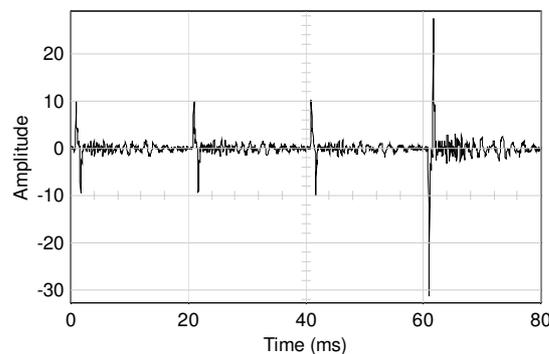
Figure 1.16 Responses of outer and middle ears (large impulses) and of the cochlea (small amplitude long duration signal) to three positive and one negative clicks with portion of noise added

Figure 1.17 shows the result of arithmetical summation of four responses in Figure 1.16.
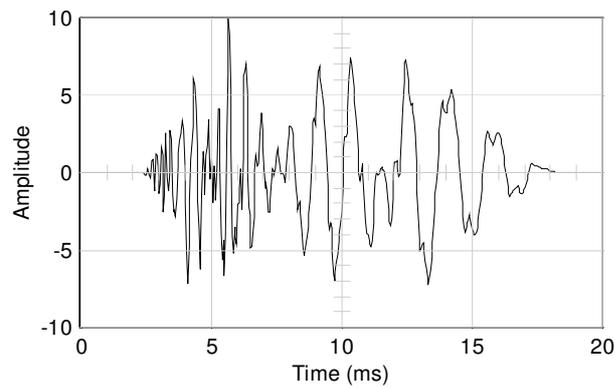
Figure 1.17 Non-linear cochlear response with no noise added (linear artifacts completely removed)

It was checked the influence of the noise to the mechanism of linear components removing. It was confirmed that noise is increased after application of "Summing circuit".
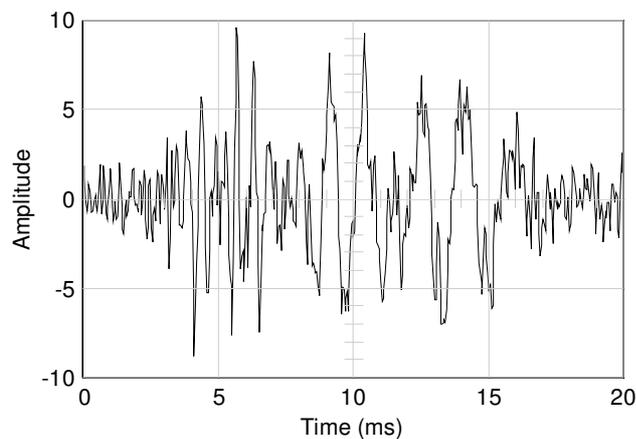
Figure 1.18 Non-linear cochlear response with noise (linear artifact-stimulus- completely removed)

Our SIMULINK model is the first approximation of the outer ear, the middle ear, the cochlea and Kemp's hearing faculty tester. Even at this stage of approximation, it is useful in the exploration the effects of non-linear differential stimulus block for reduction of linear artefacts in OAE response.