SIGNAL CONDITIONING OF ACOUSTIC EMISSIONS AND ULTRASOUND SIGNALS – MIND THE TRAPS

SIGNAL KONDITIONIERUNG VON SCHALLEMISSIONEN UND ULTRASCHALL SIGNALEN – VORSICHT STOLPERFALLEN

ATTENTION AUX CONDITIONER DES SIGNALS EMISSIONS ACOUSTIQUES ET DES SIGNALS ULTRA-SON

Jochen H. Kurz

SUMMARY

Acoustic emissions and ultrasound signals do not always have a high signal to noise ratio. Furthermore, signal and noise are often in the same frequency range. Due to the application of filters, the signal to noise ration can be improved. As an introduction example of a causal filter the envelope determination of an acoustic emission signal is discussed. Signal conditioning using a FIR filters with a linear phase shift and an anti-causal, zero-phase IIR filters is then discussed. The discrete wavelet-transform and the continuous wavelet-transform are introduced as a further possibility for signal conditioning. The different FIR and IIR filters are compared. This is verified for several applications. The results of the wavelet denoising are also compared to the ones gained by classical filtering. It can be stated that FIR and IIR filters are a stable and reliable tool for signal conditioning of acoustic emissions and ultrasound signals. Wavelet denoising can be of equal quality as classical filters and offers a variety of further applications. However, wavelets should be applied carefully due to the fact that significant artefacts can be created during denoising.

ZUSAMMENFASSUNG

Schallemissonen und Ultraschall Signale haben nicht immer ein hohes Signal-Rausch Verhältnis. Darüber hinaus liegen Signal und Rauschen häufig im selben Frequenzbereich. Mit Hilfe von Filtern ist eine Verbesserung des Signal-Rausch Verhältnisses möglich. Als Einführungsbeispiel zu kausalen Filterfunktionen wird die Berechnung der Envelope eines Schallemissionssignals vorgestellt. Danach werden FIR Filter mit einer linearen Phasenverschiebung und anti-kausale IIR Filter ohne Phasenverschiebung zur Signalkonditionierung vorgestellt. Neben diesen klassischen Filtern wird noch auf die diskrete und die kontinuierliche Wavelet-Transformation als weitere Möglichkeiten zur Signalkonditionierung eingegangen. Anhand von ausgewählten Signalbeispielen werden die Ergebnisse der verschiedenen Filterfunktionen miteinander verglichen. Dabei hat sich gezeigt, dass FIR und IIR Filter stabile und zuverlässige Ergebnisse bei der Signalkonditionierung von Schallemissionen und Ultraschall Signalen liefern. Eine Entrauschung mittels Wavelets kann mindestens gleichwertige Ergebnisse produzieren wie der Einsatz klassischer Filter und ermöglichst zudem eine Reihe weiterer Anwendungen. Dennoch sollte vorsichtig mit Wavelets gearbeitet werden, denn sehr leicht können besonders beim Entrauschen Artefakte im Signal generiert werden.

RESUME

Des emissions acoustiques et des signals ultra-son n'ont pas toujour une relation haute entre le signal et le bruit. Signal et bruit sont recurrents en meme gamme de frequence. A cause d'utiliser des filtres de frequences on peut ameliorer la relation entre le signal et le bruit. Pour introduir le principe des filtres de frequences l'enveloppe d'un emission acoustique est calcule. Apres, des filtres de frequences FIR avec dephasage lineaire et des filtres de frequences anti-causal sans dephasage ont presente. La transformation wavelet, discrete et continue et aussi presente. Les filtres de frequences et la transformation wavelet ont compare aux resultats d'appliquation a des signals. On peut dire que les filtres FIR et IIR sont stable et digne de confiance en application a des emissions acoustiques et des signals ultra-sons. Filtrer avec la transformation wavelet peut gagner les meme resultats que filtrer avec des filtres de frequences classique et offre des applications supplementaires. Mais, on doit user la transformation wavelet avec prudence parce qu'on peut generer des artefacts tres vite.

KEYWORDS: Acoustic emission, ultrasound, filter function, wavelet-transform

1. INTRODUCTION

Acoustic emissions are defined as the spontaneous release of localized strain energy in stressed material. Due to micro cracking in the material this energy release can be recorded by transducers on the material's surface [Grosse, 2002]. Acoustic emission analysis is capable of revealing damage processes in materials during the entire load history.

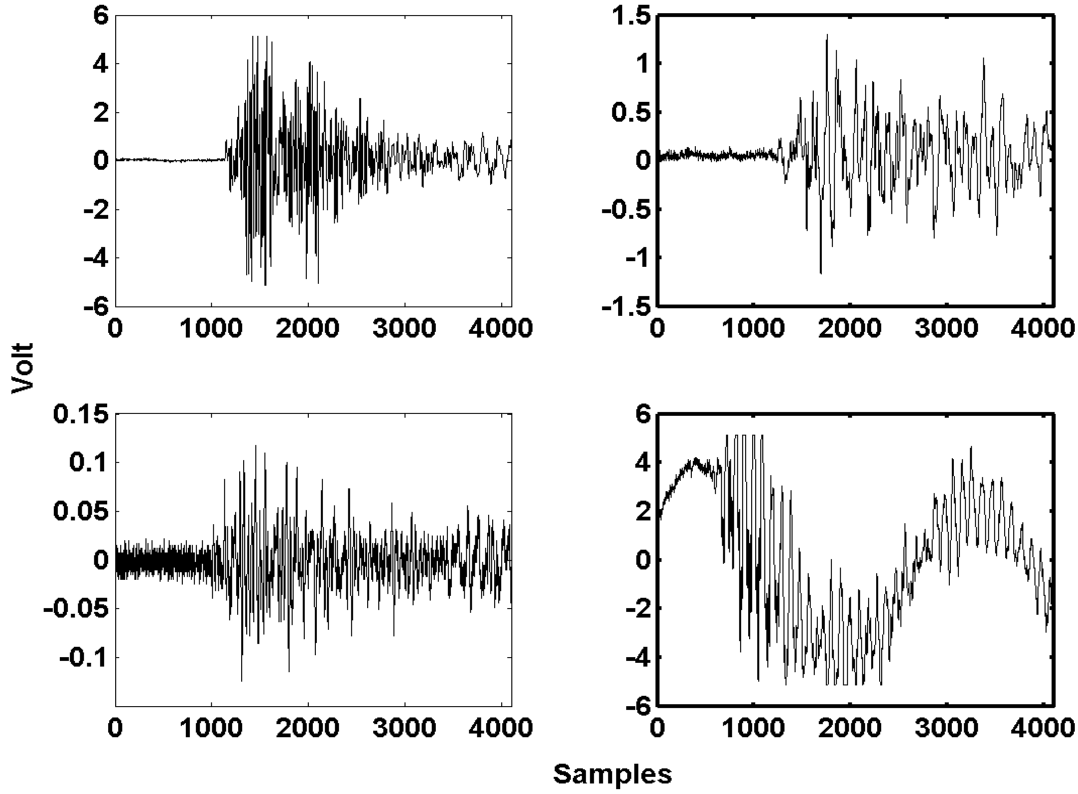

Fig. 1: Top left: acoustic emission example with a high signal to noise ratio and a clear onset. Top right: acoustic emission example with a medium signal to noise ratio and disturbances. Bottom left: acoustic emission example with a low signal to noise ratio. The high frequency noise hides the onset. Bottom right: acoustic emission example disturbed by a low frequent sinusoidal signal.

One severe problem in acoustic emission analysis is that huge data sets (often more than 1000 acoustic emission events) with a low signal to noise ratio are detected. Acoustic emission data, e. g. from concrete, normally contains a lot of high frequency noise, mainly caused by the measurement equipment (preamplifier etc.) and the surrounding. Due to the testing process itself a low frequent signal, caused by the testing device (loading machine), may often superimpose the acoustic emission signal additionally. Fig. 1 shows four examples of possible acoustic emission of concrete including different kinds of noise. The signals also differ in frequency content from each other.

Ultrasound signals emitted by an actuator and recorded by a transducer have generally a better signal to noise ratio than acoustic emissions. However, in certain cases, e.g. at the beginning of setting and hardening tests of concrete where concrete is like a fluid paste with solid particles [Reinhardt and Grosse, 2004], the signal to noise ratio of ultrasound signals is low. I.e. if the ultrasound signal is damped and scattered the signal to noise ratio decreases. Fig. 2 shows two ultrasound signals of a setting and hardening test of concrete, one from the beginning with a low signal to noise ratio and one from a later stage where the concrete is already hardened.

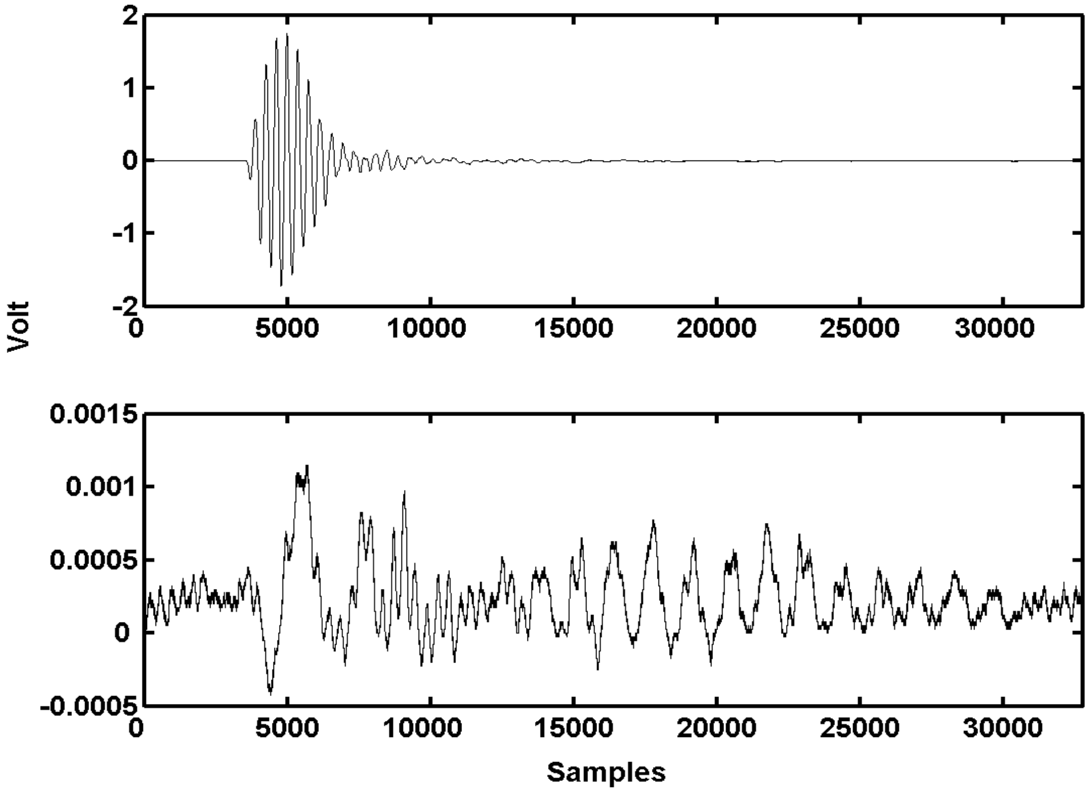

Fig. 2: Top: ultrasound signal transmitted through hardened concrete with a high signal to noise ratio. Bottom: ultrasound signal transmitted through fresh concrete. Notice the low amplitude due to damping of the material.

Concerning further analysis steps, the better the signal to noise ratio the better the results. Therefore, to enhance the signal to noise ratio, filters in a general sense are used. A variety of tools exist. The ones used most frequently are IIR (Infinite Impulse Response) and FIR (Finite Impulse Response) filters [Mathworks, 2000], the wavelet-transform [Percival and Walden, 2002; Misiti et al., 2000] or methods of statistical signal processing [Buttkus, 1991; Mathworks, 2000]. Filters are used in different fields of application where transient signals similar to acoustic emissions and ultrasound signals occur e.g. seismology, acoustics and optics. However, concening acoustic emissions signal and noise are often in the same frequency range [Grosse, 1996]. This has to be taken into consideration if filters are applied to such signals.

Furthermore, filters can easily modify a signal in a way which may lead to wrong results, e.g. due to phase shifts and amplitude distortions. The experiences gained about the application of filters on acoustic emission data and on ultrasound signals will be discussed in the following. The influences of the different signal processing procedures will be shown on several examples.

2. APPLICATION OF FILTER FUNCTIONS TO ACOUSTIC EMISSIONS AND ULTRASOUND SIGNALS

Filters are, in the most general sense, devices or algorithms which act on some input signal to produce a output signal [Scherbaum, 1996]. The mathematical foundation of filtering is convolution. I.e. concerning digital signal processing, a filter's output is related to its input by convolution with its impulse response. Applications of this principle in different forms will be shown in the following.

2.1 The envelope of the signal

A relative simple form of signal conditioning is the calculation of the signal's envelope by the Hilbert transform.

The Hilbert transform Ř of a real time dependent function R(t) is defined as [Buttkus, 1991]:

$$\check{R}(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{R(t)}{\omega - u}\, du = \mathcal{H}\{R(t)\} \qquad (1)$$

The Hilbert transform is represented by a convolution integral, i.e the Hilbert transform is a causal transfer function which behaves like a filter. Transforming a time series by the Hilbert transform, a phase shift of $\pi/2$ is generated. Thus, the envelope time function E(t) can be calculated [Buttkus, 1991]:

$$E(t) = \sqrt{R(t)^2 + \check{R}(t)^2} \qquad (2)$$

Squaring and norming of the envelope of the signal leads to a suppression of noise of lower amplitude and to an increase of the signal content of higher amplitude (Fig. 3). The high frequency noise is suppressed and the signal is accented. Then, the envelope can be used to estimate the onset of the signal or for signal detection in general. Calculating the signal's envelope is a fast and simple way and therefore often applied to signal conditioning.

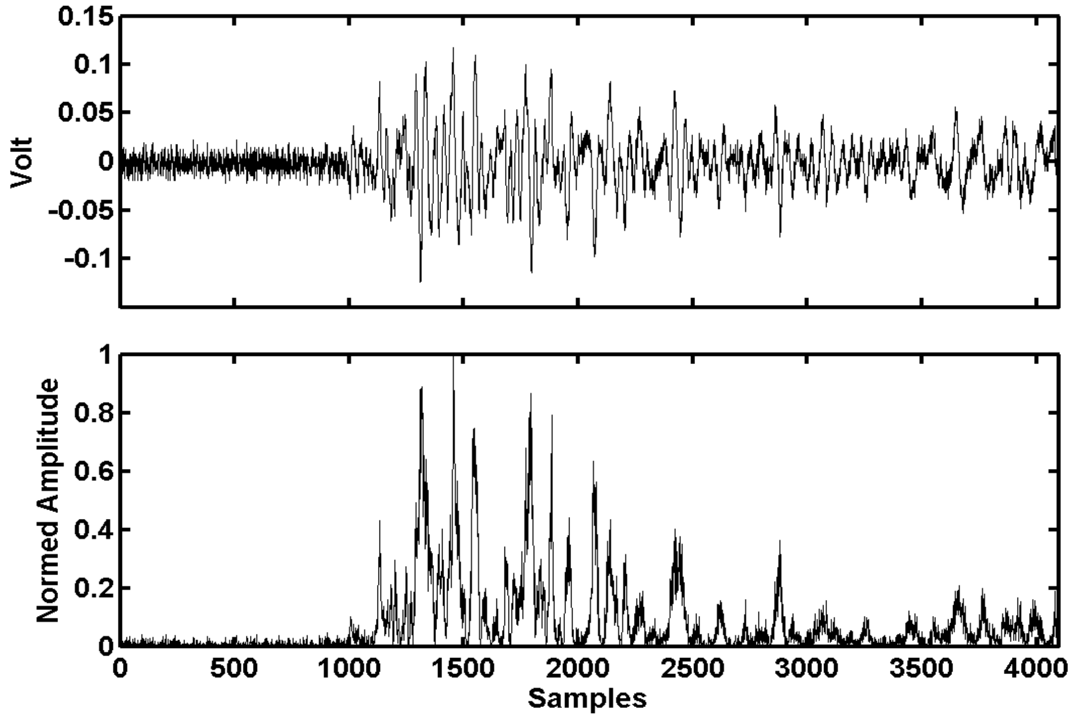

Fig. 3: Top: Acoustic emission signal from Fig. 1 (bottom left). Bottom: Squared and normed envelope of the signal calculated by the Hilbert transform.

However, if there are further disturbances on the signal other signal conditioning approaches should be used. Calculating the envelope the way described above is normally free of any errors of mistreating the signal. This cannot be guaranteed for the methods described in the following.

2.2 Application of IIR and FIR filters

IIR and FIR filters can be used to erase high frequent noise and/or low frequent disturbances in form of a low-, a high-, a bandpass or a bandstop filter. Such filter functions are the main computational workhorses for classical digital signal processing [MathWorks, 2000]. Before digital signal processing became possible, such filters were already used as analog filters.

The mathematical tool to calculate the discrete transfer function of a discrete system is the z-transform. The z-transform Y(z) of a digital filter's output y(n) is related to the z-transform X(z) of the input by [MathWorks, 2000]:

$$Y(z) = H(z)X(z) = \frac{b(1) + b(2)z^{-1} + \cdots + b(nb+1)z^{-nb}}{a(1) + a(2)z^{-1} + \cdots + a(na+1)z^{-na}}X(z) \qquad (3)$$

where H(z) is the filter transfer function and z is a continuous complex variable. The constants b(i) and a(i) are the filter coefficients. The order of the filter is the maximum of na and nb. Even if there are several exceptions as a rough guideline it can be said:

- nb=0 means, that the filter is an IIR, all-pole, recursive filter
- na=0 means, that the filter is a FIR, all-zero, nonrecursive filter
- na > 0 and nb > 0 means, that the filter is an IIR, pole-zero, recursive filter

Scherbaum [1996] summarized the main characteristics of FIR and IIR filters as follows:

- FIR filters are always stable. However concerning steep filters many coefficients are needed. Filters with given specifications such as linear phase or even zero phase can easy be implemented.
- Steep IIR filters can easiliy be implemented with a few coefficients. Therefore, filtering is very fast. However IIR filters are potentially unstable and given specifications such as zero phase are difficult to implement.

Concerning digital signal processing a variety of tools e.g. in Matlab [MathWorks, 2000], LabVIEW [National Instruments, 2004] or for free in the world wide web [Mathtools, 2004; MathWorks, 2004] are available. Furthermore, the Numerical Recipes [Numerical Recipes, 2004] for different programming languages and the DSP group [DSP group, 2004] provide free filter algorithms. The corresponding adresses in the world wide web can be found in the references. This list is not exhaustive. This is only a compilation of resources which I frequently use for solving problems in digital signal processing of acoustic emissions and ultrasound signals. Several of these sources of information about filter functions also contain descriptions and algorithms of the wavelet-transform which will be discussed in section 2.3.

The signals shown in Fig. 1 were used for demonstrating the capabilities of the different filter functions. The software tool used here was Matlab. FIR filters with a linear phase shift and anti-causal, zero-phase IIR filters (in the following called IIR filter) were used an compared.

The FIR filter is a causal filter and produces therefore a linear phase shift of n/2 where n denotes the filter order, e.g. n=100 means a shift of 50 samples. The anti-causal, zero-phase IIR filter produces no phase shift. However, in general the amplitude is smaller than the one of an FIR filtered signal. Fig. 4 (middle) shows the already phase corrected FIR filtered section of the signal around the onset (dotted line) of Fig. 1 (top right) and the the same section of the original section (solid line). The non-filtered signal is shifted 0.1 V upwards to allow a better comparison of the two waveforms. The FIR filter does not distort the original waveform. The shape and the amplitude of the signal are kept. The curve is smoothed according to the filter characteristics.

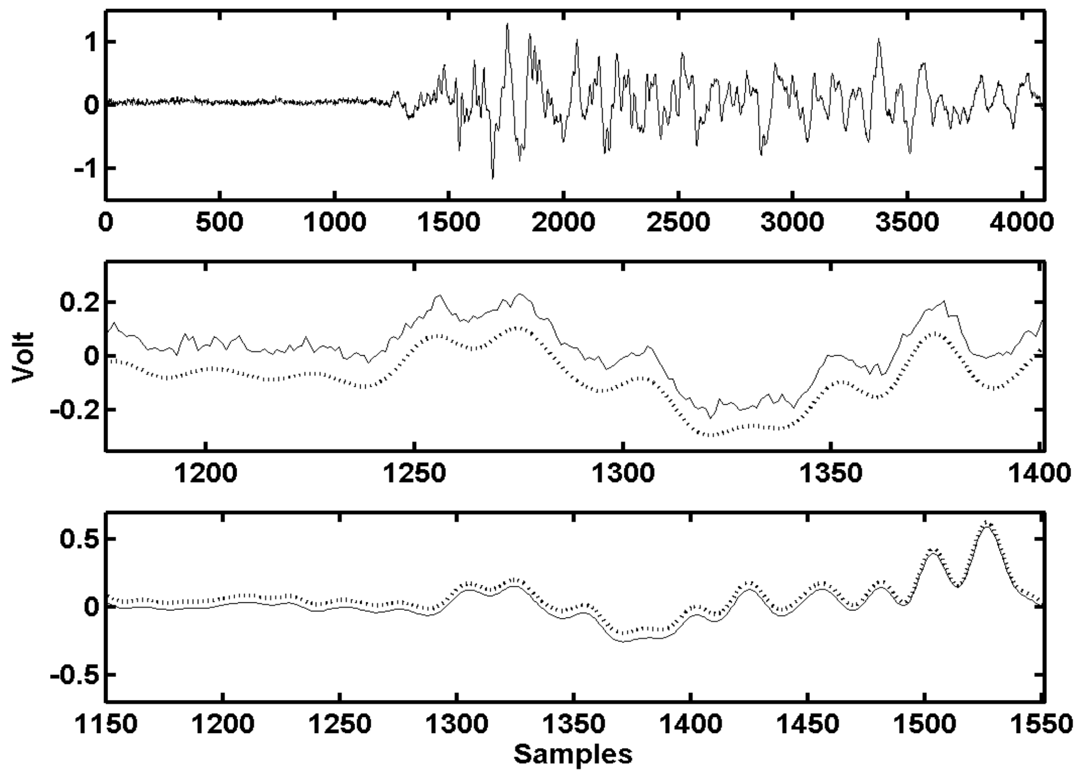

Fig. 4: Top: acoustic emission signal from Fig. 1 (top right). Middle: Kaiser window FIR bandpass filtered signal (corner frequencies: 5 kHz and 300 kHz) Bottom: Comparison of onset region filtered by the FIR bandpass filter (dotted line) and an anti-causal, zero-phase IIR bandpass filter with the same corner frequencies (solid line). The IIR filtered signal was artificially shifted by 0.1 V to allow a better comparison of the filtered signals.

The comparison of the FIR and the IIR filtered signal (Fig. 4, bottom) shows that both filters are equal in quality. I.e. none of them produces a non-linear phase shift and the amplitude damping of the IIR is low compared to the FIR.

The capabilities of the FIR and the IIR bandpass filter are confirmed by results of the FIR and IIR lowpass filter (Fig. 5). The amplitude differences between the FIR filtered signal and the IIR filtered one are very small (Fig. 5, middle and Fig. 5, bottom). Again non-linear phase shift is not observable.

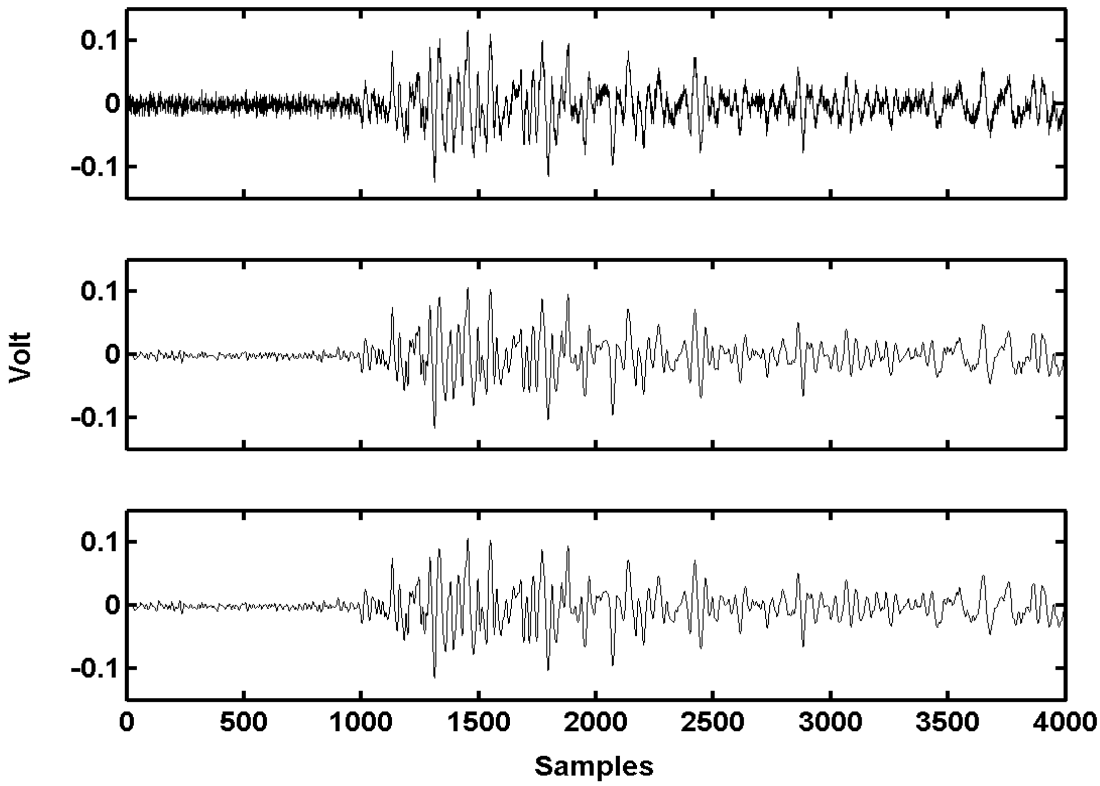

Fig. 5: Top: Acoustic emission signal (see also Fig. 1, bottom left) with a low signal to noise ratio. Note the low amplitude. Middle: lowpass (corner frequency: 150 kHz) filtered signal using a Kaiser window FIR filter. Bottom: lowpass (corner frequency: 150 kHz) filtered signal using a Butterworth IIR filter.

Filtering the Signal shown in Fig. 1 (bottom right) with a FIR and an IIR highpass filter shows differences in the amplitudes of the FIR and the IIR filtered signal (Fig. 6). This highpass filtered signal is an example for possible effects of an IIR filter compared to a FIR filter. Especially the coda of the IIR filtered waveform in Fig. 6 (bottom) shows significant lower amplitudes than the coda of the FIR filtered waveform (Fig. 6, middle). A detailed look at the main part of the signal also shows this effect. However, again no nonlinear phase shift could be verified.

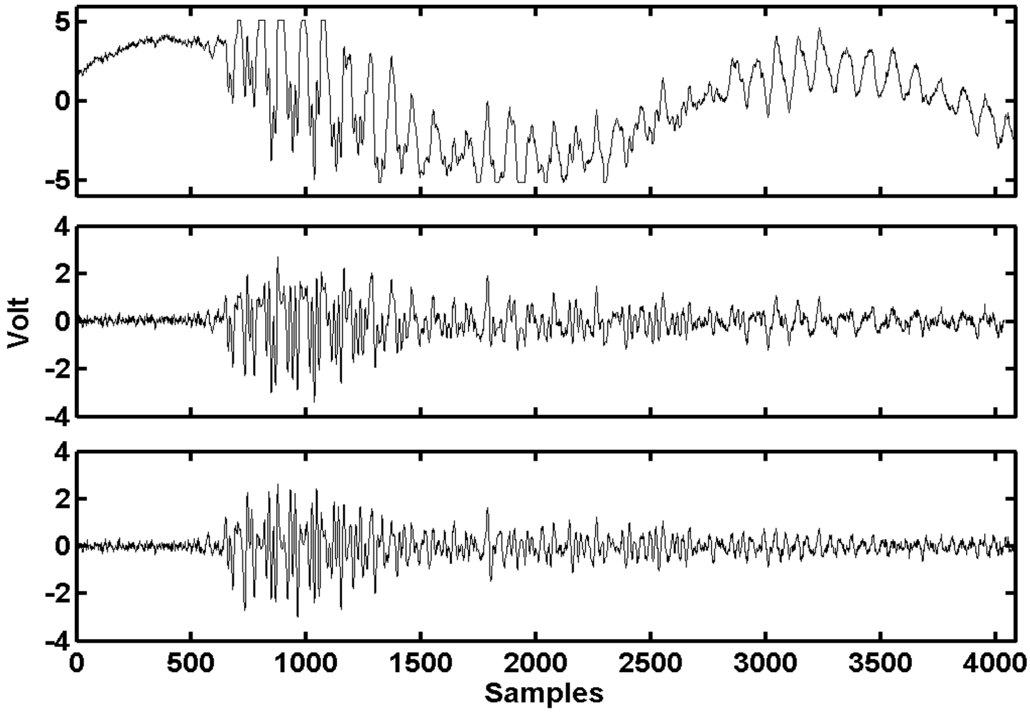

Fig. 6: Top: Acoustic emission signal disturbed by relative low frequent noise (see also Fig. 1, bottom right). Middle: highpass (corner frequency: 15 kHz) filtered signal using a Kaiser window FIR filter. Bottom: highpass (corner frequency: 15 kHz) filtered signal using a Butterworth IIR filter.

2.3 The Discrete wavelet-transform

Wavelets are mathematical functions that have to be well localized (other requirements are of technical matter). The mathematical steps used for the wavelet transform can be summarized as follows:

i. a fully scalable modulated window solves the signal cutting problem

ii. this window is shifted along the signal and for every position the spectrum is calculated

iii. the process is repeated many times with a slightly shorter or longer window for every new cycle

iv. this results in a collection of time-scale representations (scale is proportional to frequency) of the signal, all with a different solution

These four points represent the principle of the wavelet transform. General concepts known from Fourier analysis form the application base. Therefore, the basic concepts of convolution and filtering of finite sequences and some basics about orthonormal functions are needed. The mathematical concept presented in the following is adopted from Percival and Walden [2002].

The DWT is an orthonormal transform of the form:

$$\mathbf{W} = \mathcal{W}\mathbf{X} \qquad (4)$$

The first two points of the above enumeration show that a periodized filter is needed which is indeed the wavelet. The N x N matrix *W* consists of these periodized filters. The third point indicates that the filter is rescaled for every new cycle. That means the matrix *W* consists of the wavelet and the scaling filter. The wavelet filter is a high pass filter with a nominal pass-band while the scaling filter is a low pass filter with a different nominal pass-band. Applying them on the time series **X**, the Wavelet coefficients **W** are gained which are a collection of time-scale representations of the signal, all with a different solution. In other words: the wavelet is scaled and shifted and then moved along the time series. Therefore, the wavelet-transform is essentially a bandpass filter of uniform shape and varying location and width [Torrence and Compo, 1998].

The main difference between the discrete and the continuous wavelet transform (CWT) is that due to redundancies in the CWT the DWT can be thought of as a subsampling of the wavelet coefficients with dyadic scales. That means each vector of **W** contains 2^j elements, j = 1,...,J. Each element is one wavelet coefficient. The rows of *W* that produce the wavelet coefficients (the wavelet filter) for a particular scale are circularly shifted versions of each other. The amount of the shift between adjacent rows is 2^j for j = 1, ..., J. Furthermore, changes concerning the wavelet scale (the scaling filter) are also of dyadic order in the same range as for the wavelet filter. The DWT is computed using the Mallat algorithm that is faster than the fast Fourier transform. Nevertheless, a time series can be perfectly reconstructed from its DWT coefficients. This is an advantage of the DWT compared to the CWT.

A detailed description of the wavelet theory can be found in Percival and Walden [2002]. A broad compilation of articles, tutorials and links can be found in the world wide web at the homepage of Amara Graps [2004]. Beside the commercial wavelet tools of Matlab and LabVIEW there is also a free wavelet toolbox available: Wavelab 802 [2004].

Using the wavelet-transform for denoising requires an adopted model for the current noise of the dataset. Concerning the example shown in Fig. 7 a biorthogonal wavelet of the order 4.4 was wavelet-transformed using a level 8 DWT. The applied denoising algorithm was Stein's Unbiased Risk Estimator with hard thresholding for an unscaled white noise model. Furthermore, the approximation coefficient of level 8 was set to zero to erase the offset of the signal (Fig. 7, middle). The wavelet denoised signal in Fig. 7 (bottom) was artificially shifted by 0.2 V to allow a better comparison. The direct comparison of the wavelet denoised signal and the FIR filtered signal (Fig. 7, bottom) shows only slight differences in amplitude smoothing. I.e. the FIR filter produces a smoother curve. Furthermore, the comparison shows that no phase shift is observable. This is guaranteed due the use of biorthogonal wavelets.

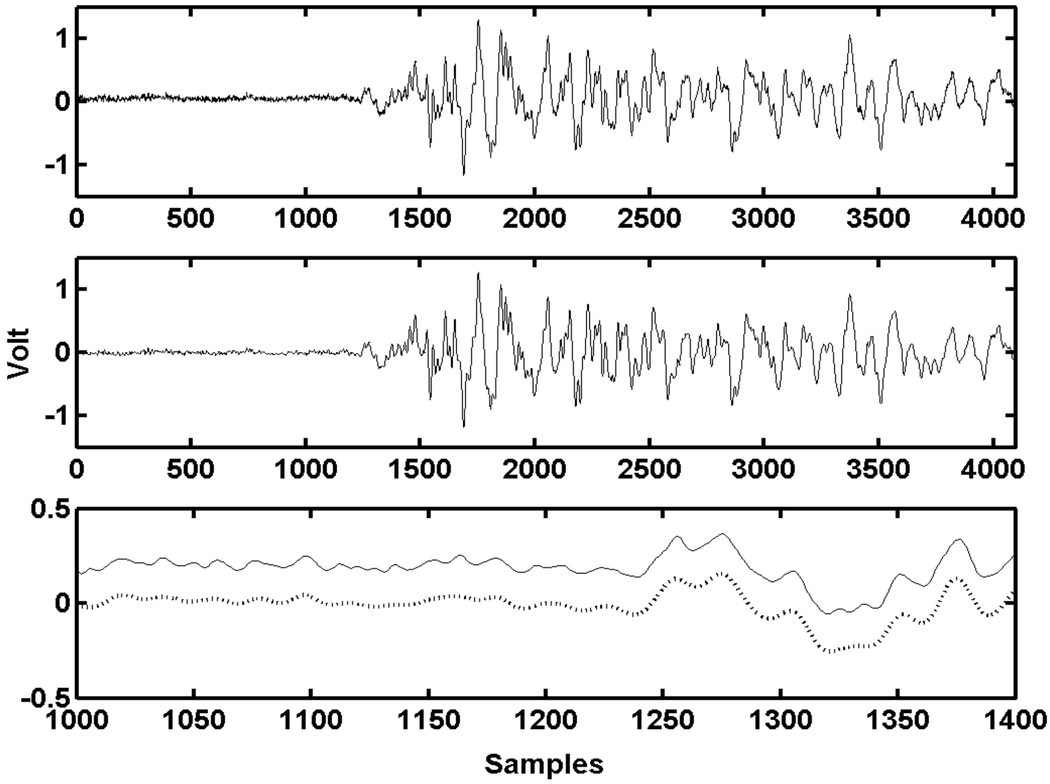

Fig. 7: Top: acoustic emission signal from Fig. 1 (top right). Middle: wavelet denoised signal using a biorthogonal wavelet of the order 4.4. Bottom: Comparison of the wavelet denoised signal (solid line) to the FIR filtered signal already shown in Fig. 4. Only the region around the onset of the signal is shown. The wavelet denoised signal was artificially shifted by 0.2 V to allow a better comparison of both signals.

Choosing a different noise model for wavelet denoising can lead to significant different results. Fig. 8 shows a comparison of the bandpass FIR filtered signal (dotted line) already used for comparison in Fig. 7 (bottom) and the corresponding wavelet denoised version of the signal differing only in the choosen noise model from the wavelet procedure described above. Instead of using unscaled white noise for thesholding non-white noise was used. The result differs significant from the one shown in Fig. 7. The similarity between the FIR band-pass filtered signal and the wavelet denoised signal from Fig. 7 (bottom) could not be maintained with the non-white noise theshold. The amplitude of the wavelet denoised signal is damped and distorted. Due to the non-white noise thresholding, several artefacts also occured in the shape of the signal. E.g. the area right in front of the onset of the signal changed completely its shape. Furthermore, the structure of the noise is completely different. This makes clear that if choosong the wrong model of noise for thresholding the important characteristics of the signal can be conditioned badly. Then, e.g. a wrong onset time of the signal will be determined.

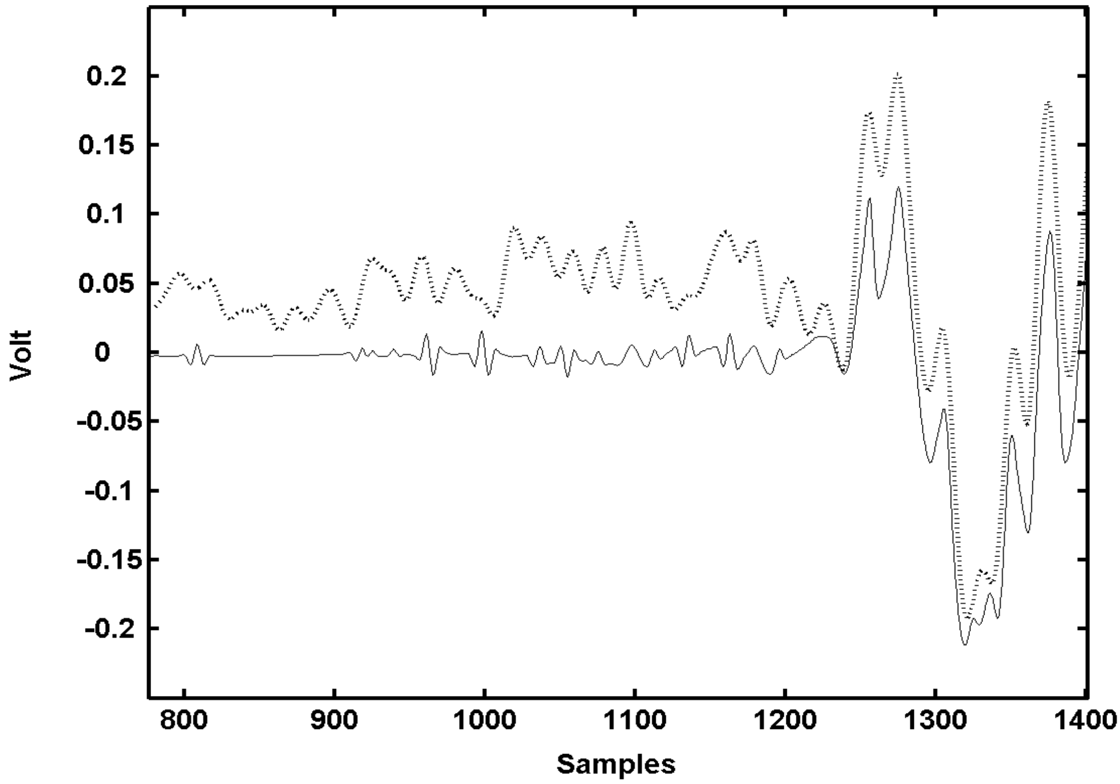

Fig. 8: Comparison of the FIR filtered signal already shown in Fig. 4 (dotted line) and the corresponding wavelet denoised signal. The area around the onset of the signal is displayed. The change compared to the denoising shown in Fig. 7 is that the noise was modelled as non white noise.

2.4 The Continuous wavelet-transform

The principal ideas behind the DWT and CWT are identical. Therefore, the possibilities and the procedures concerning filtering and denoising of acoustic emissions and ultrasound signals do not differ from each other. The continuous wavelet-transform of a discrete sequence R(t) is defined as the convolution of R(t) with a scaled and translated version of the wavelet function $\psi_{\lambda,\nu}$ [Torrence and Compo, 1998]:

$$W(\lambda,\nu)=\int_{-\infty}^{\infty}\psi_{\lambda,\nu}(t)R(t)\,dt,\ where\ \psi_{\lambda,\nu}(t)=\frac{1}{\sqrt{\lambda}}\left(\frac{t-\nu}{\lambda}\right) \qquad (5)$$

The continuous wavelet-transform also means continuously shifting a continuously scalable function $\psi_{\lambda,\nu}$ over the signal and calculating the correlation between the two. The discrete sequence R(t) is decomposed into a set of basis functions $\psi_{\lambda,\nu}$, called the wavelets. Thus, λ denotes the scale (scale is proportional to frequency) and ν the translation. The discrete sequence R(t) is decomposed into a set of basis functions with the new dimensions λ and ν. Thus, all scales are accounted for the transform. The CWT gives an high resolution image of the frequency distribution over time. Therefore, it is much slower than the DWT or a short-time Fourier transform. However, if there is no idea about the frequency distribution over time of the important parts within the investigated signal the CWT is a helpful tool to make clear the frequency changes over time.

Examples of application concerning filtering and denoising of acoustic emissions and ultrasound signals with the CWT can be found in Ruck and Reinhardt [2002, 2003].

The CWT offers the possibility to apply a complex tranform using complex wavelets. One possible application will be given in the following.

Since the complex continuous wavelet transform is a complex valued orthonormal transform represented by a convolution integral, the modulus of one scale of the complex continuous wavelet transform represents the envelope of a signal at one certain frequency.

$$|W(\lambda,\nu)|=\sqrt{x^2+y^2}\ where,\ W(\lambda,\nu)=x+iy \qquad (6)$$

The envelope calculated by the complex continuous wavelet-transform (Fig. 9) could also be calculated by filtering the original signal with a bandpass filter and then calculating the envelope using the Hilbert transform. However, the advantage of the complex continuous wavelet transform is that the filter bonds do not need to be known in advance. The corresponding scale can be chosen instead.

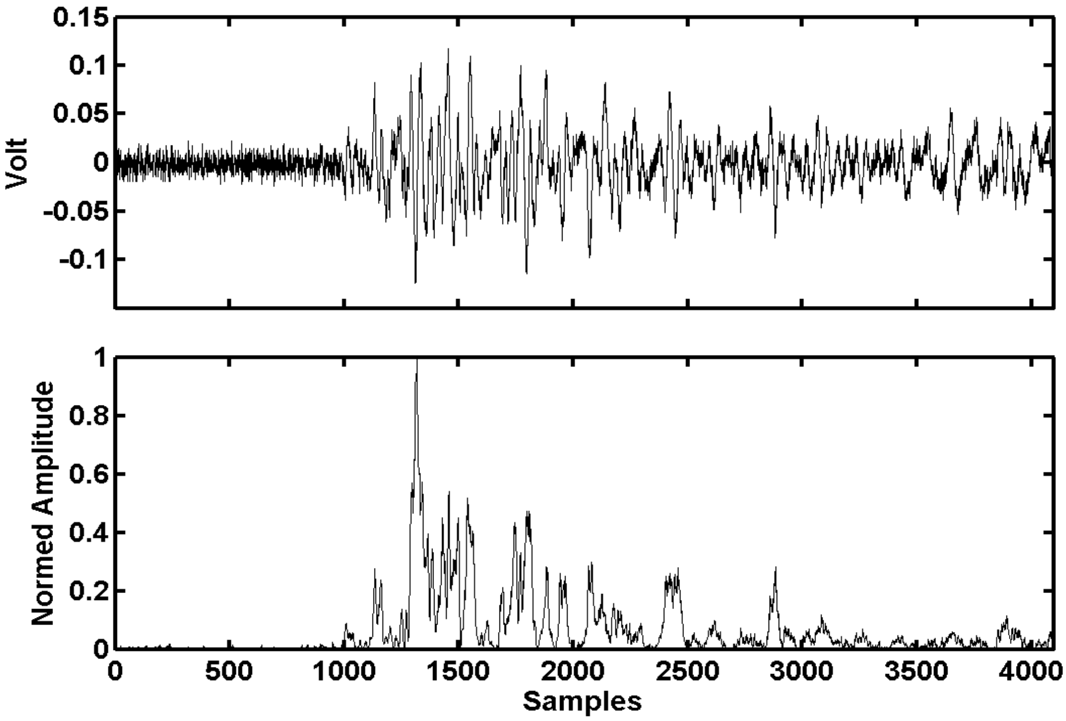

Fig. 9: Top: Acoustic emission signal from Fig. 1 (bottom left). Bottom: Squared and normed envelope of the signal calculated from one scale of the complex continuous wavelet-transform.

3. CONCLUSION

Signal conditioning is a crucial part during data analysis, due to the fact that mistakes there have got a severe impact on the results gained during the further analysis. Furthermore, concerning acoustic emissions or ultrasound signals signal and noise are often in the same frequency range [Grosse, 1996]. These facts require stable and reliable algorithms for signal conditioning.

Calculating the envelope using the Hilbert transform is a descriptive form of filtering due to the fact that the Hilbert transform is a causal transfer function which behaves like a filter and produces a phase shift of $\pi/2$. Squaring and norming of the envelope suppresses low amplitude noise. Using the complex continuous wavelet-transform leads also to the envelope, however only of a certain frequency.

The applied FIR filters are also causal filters and produce a linear phase shift of half the filter order, i.e. if the filter order is 100 the signal is shifted 50 samples. The filtered sequence has to be corrected by this number of samples.

FIR filters from the used Matlab package [MathWorks, 2000] do not cause any non-linear phase shift or amplitude distortion. Therefore, they are a reliable tool for signal conditioning. IIR filters normally cause highly nonlinear phase distortions. However, using an anti-causal, zero-phase filter implementation of an IIR filter the nonlinear phase distortions are corrected. This cannot be guaranteed for all cases. Regarding the examples shown in Fig. 4 to 6 no nonlinear behaviour of the anti-causal, zero-phase IIR filter could be verified. A further requirement for the successful use of such IIR filters is that the filtered signal has a length of at least three times the filter order and tapers to zero on both edges [MathWorks, 2000]. Nevertheless, the anti-causal, zero-phase IIR filter can cause amplitude damping. This could only be verified for the highpass filter (Fig. 6).

The wavelet-transform is essentially a bandpass filter of uniform shape and varying location width [Torrence and Compo, 1998]. Denoising by thesholding can produce as good results as a bandpass filter (Fig. 7) if the correct noise model was chosen. Furthermore, the denoising technique has the advantage over traditional filtering in that it removes noise at all frequencies and can be used to isolate single events that have a broad power spectrum or multiple events that have varying frequency [Torrence and Compo, 1998]. However, if the noise was classified wrong, i.e. if the the wrong noise model was chosen the denoising procedure can produce significant artefact. E.g. artificial signal onsets are created. The Stein's Unbiased Risk Estimator algorithm is able to chose the thresholds for every level adaptively. The selection rules are more conservative and are more convenient when small details of signal lie in the noise range. However, if the wrong noise classification was chosen wavelet denoising will produce significant artefacts which will lead to wrong results.

Finally it has to be stated that signal conditioning is not able to improve the signal to noise ratio of all signals. Fig. 2 (bottom) is an example for the case where signal conditioning would not be successful. It is not not possible to valuate the results of signal conditionig if the signal has got such a low amplitude and is heavily distorted in a way that makes the separation of signal and noise impossible. In such cases an improved recording procedure is recommended.

ACKNOWLEDGEMENTS

This work was carried out in the collaborative research centre SFB 381 at the University Stuttgart whose financial support by the Deutsche Forschungsgemeinschaft is gratefully acknowledged.

REFERENCES

[1] Amara Graps, 2004. http://www.amara.com/current/wavelet.html

[2] Buttkus, B., 1991. Spektralanalyse und Filtertheorie in der angewandten Geophysik. Springer Verlag, Berlin Heidelberg.

[3] DSP group, 2004. http://www-dsp.rice.edu

[4] Grosse, C.U., 1996. Quantitative zerstörungsfreie Prüfung von Baustoffen mittels Schallemissionsanalyse und Ultraschall. Ph.D. thesi, University of Stuttgart.

[5] Mathtools, 2004. http://www.mathtools.net

[6] MathWorks,2004. http://www.mathworks.com/matlabcentral/filechange/loadCategory.do

[7] MathWorks, 2000. Signal Procesing Toolbox. The MathWorks, Inc., Natic MA, USA.

[8] Misiti, M. Misiti, Y. Oppenheim, G. Poggi, J.-M., 2000. Wavelet Toolbox User's Guide. The MathWorks, Inc., Natic MA, USA.

[9] National Instruments, 2004. LabVIEW Analysis Concepts Handbook. March 2004 Edition.

[10] Numerical Recipes, 2004. http://www.nr.com

[11] Percival, D., Walden, A., 2002. Wavelet Methods for Time Series Analysis. Cambridge University Press, Cambridge, United Kingdom.

[12] Reinhardt, H.-W., Grosse, C.U., 2004. Continuous monitoring of setting and hardening of mortar and concrete. Construction and Building Materials 18 (3), 145 – 154.

[13] Ruck, H.-J., Reinhardt, H.-W., 2002. Anwednung der Wavelet-Transformation in der Signalanalyse. Hüthig, 92 – 97.

[14] Ruck, H.-J., Reinhardt, H.-W., 2003. Anwednung der Wavelet-Transformation – Analyse von Schallemissionssignalen. MP Materialprüfung 45 (9), 382 – 386.

[15] Scherbaum, F., 1996. Of Poles and Zeros. Vol. 15 of Modern Approaches in Geophysics. Kluwer Academic Publishers, Dordrecht, The Netherlands.

[16] Torrence, C., Compo, G., 1998. A Practical Guide to Wavelet Analysis. Bulletin of the American Meteorological Society 79 (1), 61 – 78.

[17] Wavelab 802, 2004. http://www-stat.stanford.edu/~wavelab