Application of Fuzzy Logic to Signal Processing of Ultrasound Measurements

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Abstract

In the presented paper a digital filter based on Fuzzy Logic is applied to ultrasound data from through transmission and acoustic emission measurements from timber and glued laminated timber (glulam) specimens of structural dimensions. It could be shown that the adopted filtering technique was able to reduce random noise efficiently and the level of interfering artefacts or phase shifts could be kept very low. For transmission measurements a significant reduction of repetitions has been achieved, which are necessary to reach reasonably high signal-to-noise ratios. For acoustic emission (AE) measurements the noise reduction worked most efficiently in the high frequency domain. From the preliminary AE results one can expect that the fuzzy filter can increase the ratio of events suitable for evaluation of source locations.

Introduction

Non-destructive Testing (NDT) of wood presents a unique opportunity to examine the material or its constitution in ways that do not impair future usefulness and serviceability [1]. While the integration of NDT methods is already standardised for steel and concrete, its implementation for timber products is still limited due to the special properties of timber and engineered wood products (e.g. growth bound defects, anisotropy, porosity, creep behaviour etc.).

In case of application of ultrasound based NDT methods to glued laminated timber (glulam) of structural dimensions three main fields of research needs can be identified, namely:

- adaptation of the ultrasound equipment to particular requirements of the material, the coupling conditions and the dimensions
- improved comprehension / modelling of wave propagation in timber in the presence / absence of damage or significant defects
- advanced signal processing for derivation of characteristic values from the raw ultrasound signal data

This paper is a contribution to the latter research need of improving signal processing by means of digital de-nosing.

In the following sections it shall be outlined why the problem of signal de-noising is particularly essential in the case of glued laminated timber and large (structural) dimensions.

Due to the strong attenuation of high frequencies in timber, usually low frequency ultrasound is used for transmission measurements. In order to realise transmission measurements of (glulam) members with structural dimensions, the excitation energy is maximised by application of e.g. burst generators and resonant transducers/sensors and the transmitted signals have to be amplified by factors of up to 100 dB. Highly amplified signals of low frequency resonant transducers transmitted through an anisotropic material with limited dimensions may bring about serious problems for signal interpretation and evaluation of characteristic parameters. The shape of the signals usually shows a long tail dominated by multiple reflections caused by the interaction of the (refracted) wave and the boundaries of the examined specimen. Not only compression (p)-waves but also transversal (s-) waves and plate or beam wave modes are hidden in the received signal. Therefore in the analysis of ultrasound transmission signals of highly attenuating materials, the beginning (on-set) of the signal containing the fastest (i.e. non-reflected, p-wave) part yields the most reliable information of ultrasound transmission (see e.g. [2]). However the noise mainly generated through the amplification process interferes considerably with the signal on-set. Therefore the evaluation of ultrasound signals measured obtained from timber or glulam members of structural dimensions is often restricted due to a low signal-to-noise ratio (SNR).

The most common method of noise reduction is the averaging of repeated measurements. For active ultrasound measurements such as pulse through transmission or pulse echo however, this averaging method is limited due to its high requirements either for the pulse repetition rate or for the measuring time. Moreover, in some situations, e.g. acoustic emission (AE) testing, the averaging method cannot be used at all, as each acoustic emission signal is unique and cannot be repeated. As a result digital filters are used in order to reduce noise for each single ultrasound signal.

Five conventional methods, i.e. averaging of repetitive measurements, a moving average filter and two finite impulse response filters are applied and their results compared to those of a fuzzy based filter. In this particular case ultrasound signals taken from through transmission and acoustic emission (AE) measurements from a glulam beam are used.

Ultrasound data from through transmission and acoustic emission measurements

Test configurations

The selected sample of ultrasound data used in this work as raw data for the various signal processing methods were recorded within the framework of two studies:

- The first study considered detection and characterisation of longitudinal cracks in glulam beams by means of ultrasonic pulse transmission measurements. The tests were performed as line (B-) scans in the longitudinal direction and pulse transmission perpendicular to the grain. The glulam beam depth (= distance between transmitter and receiver) varied between 440 mm and 1230 mm. Details of the test set-up and measurement results for the smaller depth please consult [3]. Particularly in the case of large beam depths and in the case of pulse transmission through the cracked area signals with low SNRs had to be evaluated, see. Fig.1b for a signal with low SNR.

- The second study considered monitoring of damage evolution in timber specimens subjected to tensile loading parallel to the grain by means of acoustic emission measurements. In the test section of the tapered specimens (width: 120 mm, length: 600 mm, thickness 20 mm) of the tension specimens, six acoustic emission sensors were fixed to the narrow sides in order to record and locate acoustic emission signals caused by micro-fracture events near natural defects (knots). For details of test set-up and first results please consult [4]. Depending on the distance between the respective ultrasonic sensors and the source location of the micro-fracture event, signals with highly variable SNRs had to be evaluated.

Noise and evaluation of ultrasound signals

Experimental data always contain a portion of "noise" which can be defined as unwanted components interfering with the sought-after "signal" i.e. the pure response of the tested system. Important sources of noise are the components of the measurement system itself and external sources such as electromagnetic radiation disturbances. The main source of noise in the case of the studied ultrasonic signal data stems from the amplification system located between the ultrasound sensors and the transient recording unit. The noise in the ultrasound signals may consist of three different parts:

- generic random ("white") noise without any phase correlation between two deliberate data samples within one recorded signal (typical for amplifier noise)

- recurring disturbances from external sources (e.g. testing machine vibrations, fluctuations in the mains supply etc.) with some phase correlation within one recorded signal

- nonrecurring disturbances from external sources

Generic random noise can be compensated for in the case of active ultrasound measurements by repetition and averaging. However in the case of recurring disturbances, the averaging technique may work well, as the phase of the interfering disturbance usually varies randomly for the repeated measurements. It is nevertheless important to emphasize that recurring disturbance noise shows no random characteristic within the recorded signal. Nonrecurring disturbances are distinct events and as such can not be compensated by averaging techniques.

In order to illustrate the problem of noise occurrence in signal two ultrasound signals from through transmission measurements at a cracked glulam beam (first study as described above) are depicted in Fig. 1. Figure 1a shows an ultrasound signal in the crack free zone with relatively low attenuation and thereby high signal-to-noise ratio of about 10:1. The shape and the on-set of the signal are clearly visible and can easily be evaluated quantitatively. Figure 1b shows an ultrasound signal obtained from the cracked section of the same specimen. The signal is highly attenuated resulting in a low SNR of about 3:1. The shape of the signal is difficult to discern and the quantitative evaluation of the signal on-set is associated with a high error margin. In order to use a consistent algorithm for the evaluation of signals with both high and low SNRs, digital filter techniques have to be applied.

Fig. 1 Signals obtained by the ultrasound through-transmission on a glulam specimen with a thickness of 44 cm

a. signal in the crack free zone

b. signal in the crack zone

c. spectrum analysis of the signal in the crack zone

Conventional filtering techniques

As mentioned in the previous section, the random components and recurring disturbances can be removed by summing up a number of signal measurements. A particular advantage in ultrasound transmission measurement is that in many cases, the repetitive signals can be averaged to significantly improve the signal-to-noise ratio (SNR) [5]. Unfortunately this is not the case for the AE signals since AE events are unique and not repeatable.

A symmetrical moving average filter (SMAF) can be applied as an alternative to the simple averaging technique. The moving average filter is optimal for reducing random noise while retaining a sharp step response [6]. However, it is the worst filter for frequency domain encoded signals, with little ability to separate one band of frequencies from the other [7].

Finite impulse response filters are well-know for their band separation ability. They can be designed to remove noise with high frequency, low frequency or a certain band of frequency and classified accordingly as low-pass, high-pass and band-pass filters. These filters do not perform well in the time domain with respect to their unavoidable amplitude distortion such as excessive ripple and overshoot in the step response [7].

Traditional means of minimising the effects of noise such as frequency domain filtering and averaging are not without their disadvantages [8]. Their shortcoming revolves around the amount of time required to effect repetitive measurements and the large storage space required to save them and the signal evaluation associated with simple averaging filter; Applying symmetrical moving average filters and finite impulse response filters results in far from satisfactory de-noising performance in industrial ultrasound NDT application and additionally artefacts can be introduced.

Other available de-noising solutions are being tested in current NDT research. One of them is the wavelet-transform, which is essentially a band-pass filter [9]. It has shown its advantages over many traditional Fourier based filtering techniques in that it uses more appropriate functions than the sines and cosines which form the bases of the Fourier analysis approach to approximate choppy signals [10]. However, wavelets analysis should be applied carefully due to the fact that significant artefacts can be created during de-noising [11].

In an attempt to avoid these aforementioned shortcomings, a fuzzy logic based filter is implemented in this study.

Fuzzy based filtering technique

Fuzzy based filters adopt a whole new perspective based on human reasoning and logic. Fuzzy logic (FL) was first presented by Lofti Zadeh [12] as a way of processing ambiguous, imprecise, noisy information or linguistic variables rather than crisp values. FL is a superset of Boolean logic dealing with, for example, a situation where a statement and its opposite may both be true to a certain degree [13]. Most natural and/or man-made systems can hardly be holistically described using only crisps variables. Computers and electronic devices, for example are designed to manipulate precise or crisp values. FL was invented to allow for the representation of values between 0 and 1, shades of grey, and maybe; it allows partial membership in a set. Adaptive Network Fuzzy Inference System (ANFIS) is an extension of the application of FL combined with the idea of Artificial Neural Network (ANN) (see e.g. [14]). The first in-depth description of ANFIS was presented by Jyh-Shing Roger Jang [15]. Since then, ANFIS has found its application in various fields such as controller design, online parameter identification for control systems, time series prediction and inference [16].

The proposed approach is a custom-designed ANFIS model hereinafter referred to as 'Y-ANFIS'. It uses first-order Takagi-Sugeno fuzzy rules [17]. The input to the fuzzy model and number of fuzzy rules are determined by the number of training data pairs and the required accuracy. In this study, both signal and noise are functions of time (t) and that they are independent of each other. Signal information is an unknown function of (t). Noise information is a random function of (t) and/or the history of (t). In this work, the input to the fuzzy model is (t) and output is the amplitude (v). To describe the model, a system with two fuzzy rules is used.

The fuzzy rules are constructed as the following:

If t is D_1, then $v_1=P_1\, t + C_1$

If t is D_2, then $v_2 = P_2\, t + C_2$

P_1, P_2, C_1 and C_2 are model parameters to be solved. D_1 and D_2 are fuzzy numbers given by a generalized bell function

$$\mu_{D_i}(t) = \frac{1}{1 + \left[(\frac{t - c_i}{a_i})^2 \right]^{b_i}} \quad (1)$$

where, a_i, b_i and c_i are function parameters (see figure 2).

Figure 2 Generalized bell membership function

The outputs of the two fuzzy rules are combined by taking an arithmetic mean of each output taking into consideration of the value of their weights w_i. which is equivalent to $\mu_D(t_i)$, see fig 2.

$$v = \frac{w_1}{w_1 + w_2} \cdot (P_1 \cdot t + C_1) + \frac{w_2}{w_1 + w_2} \cdot (P_2 \cdot t + C_2) \quad (2)$$

Equations (2) can be formed for each signal sample (v_i, t_i). The function parameters, a_i, b_i, and c_i are given initial values, thus w_i can be obtained. Usually a signal has more than four samples which means there are more data pairs than the parameters to be fitted. The Least Square Estimation (LSE) optimization algorithm can be applied to solve the four model parameters, P_1, P_2, C_1 and C_2. After obtaining optimal model parameters, the function parameters are then optimized by the Gradient Descent (GD) method (using the derivative of the model error). LSE and GD optimization procedures are repeated until they produce an acceptable error defined a priori by the modeller. Up to this point, both the model parameters and the function parameters are optimized accordingly and the overall output can be computed.

To apply the Y-ANFIS model to noise reduction, the noise components have to be dealt with. A measured signal is composed of a clean signal and noise as expressed by Equation (3).

$$v(t) = x(t) + d(t) \quad (3)$$

where,

$v(t)$	=	measured signal
$x(t)$	=	uncorrupted signal
$d(t)$	=	original noise signal

The error of the model is the difference between the measured signal and the modelled clean signal.

$$\|e(t)\|^2 = \|v(t) - x^{\#}(t)\|^2 = \|x(t) - x^{\#}(t)\|^2 + 2x(t)\cdot d(t) - 2x^{\#}(t)\cdot d(t) + \|d(t)\|^2 \quad (4)$$

where,

$x^{\#}(t)$	=	modelled clean signal by Y-ANFIS

The expected value of $||e(t)||^2$ is derived as Equation (5). The noise being dealt with is Gaussian white noise with zero mean value which leads *E[d(t)]* to zero. The expected values $x(t)\cdot d(t)$ and $x(t)^{\#}\cdot d(t)$ are zero due to the fact that clean signal *x(t)* and noise *d(t)* as well as modelled signal $x(t)^{\#}$ and noise *d(t)* are uncorrelated. First, we consider noise as zero signals, which means clean signals can be obtained and used as input training data in the model to reproduce the signal. However, noise is always present and interfering with the desired signals. Fortunately, the noise is zero-mean, Gauss-Markov theorem still holds to ensure an unbiased LSE. Therefore, to minimize the error is to minimize the squared error between the real signal and the modelled signal.

$$E[e^2] = E[(x(t) - x(t)^{\#})^2] + E[d(t)^2] \quad (5)$$

Results and discussion

The five different filters, namely the averaging filter, symmetrical moving average filter, two finite impulse response filters and Y-ANFIS are applied to the ultrasound through-transmission measurements as previously described.

The five filters are applied to the onset of the signal presented in Fig 1b. A comparison of the performance of them is shown in Figure 3. The original signal shown in figure 3a as a grey line is too noisy for one to discern the actual beginning of the signal. After it is treated with the AF with 10 repetitive measurements, the low frequency disturbances are eliminated, but still the SNR is rather low due to the remaining high frequency noise. This situation can be further improved with more repetitions as shown in Fig. 3e with 26 repetitive measurements here serving as the reference result. The digital filters are applied to ten measurements and the averaged values are presented in Figs. 3b, c, d and f. This was done such that the non-random disturbances with frequency band similar to that of the signal could be overcome. The moving average filter (results shown in Fig. 3b) does remove a lot of noise from the signal but it leaves traces of high-frequency noise behind making evaluation difficult still. Both finite impulse response filters and Blackman window filter (results shown in Figs. 3c and d) introduce some artefacts to the signal which may mislead the reading of the signal parameters. Y-ANFIS produces (results shown in Fig. 3f) unnoticeable level of artefacts and amplitude distortion. It enables a judgement of parameters like on-set time of the signal with a much higher confidence level compared to the conventional filters.

Figure 3 Comparison of filter performance in time domain:

a) Original signal and result of AF (10 repetitions)

b) Symmetrical moving average filter

c) Blackman window filter

d) Finite impulse response filter

e) Averaging filter (26 repetitions)

f) Y-ANFIS filter

Y-ANFIS shows excellent de-noising ability with respect to the glulam specimen with a depth of 440 mm and length of approximately 200 cm. Further testing of the proposed algorithm was done by increasing the dimension (depth=1230 mm) of the same glulam specimen by gluing another undamaged glulam beam on the top of the original beam. The idea was to introduce more noise into the signal in order to further test Y-ANFIS de-noising ability. The signal below shown in figure 4 was obtained at the same location as the signal shown in fig. 1b but with a lower SNR ratio. Figure 4a illustrates the effect of 350 repetitions of the averaging (AF) filtering technique compared to the Y-ANFIS filter applied to the original signal without any repetition measurements. Although the high frequency random part of the noise is compensated completely for both methods, some low frequency noise, i.e. non-random disturbance, is still present in the Y-ANFIS signal. The calculation therefore has been performed also by means of combined application of 10 repetitions with the use of the Y-ANFIS filter. The results are presented in Fig. 4b. From the figure it is obvious that the combined action of averaging by the Y-ANFIS method yields nearly identical results compared to the reference, however the needed repetitions could be reduced by a factor of 35.

Figure 4 Comparison of the onset region of one ultrasound transmission measurement (depth=1230mm) treated by averaging filter and by Y-ANFIS

a. evaluation of one signal by application of Y-ANFIS method only
b. evaluation by averaging 10 signals filtered by Y-ANFIS

When it is technically / practically possible to obtain sufficient numbers of repetitive measurements for a target SNR level, such as for the ultrasound transmission method in case of small specimens, the averaging filter remains the most reliable method since it does not alter the true signal. However, Y-ANFIS shows its significant value over the averaging filter in treating results of transmission measurement from timber specimens in structural dimensions with extremely low SNR, where the number of necessary repetitive measurements is beyond practical limits.

Another example of the application of the Y-ANFIS method is the de-nosing of signals which cannot be measured repeatedly, e.g. in the case of acoustic emission measurements. Figure 5 shows two AE signals from the above mentioned acoustic emission measurements from the timber specimens subjected to tension loading. One signal (Fig. 5a and b) represents an example with SNR, whereas the second signal (Fig. 5c and d) represents a relatively high SNR value. In Fig. 5 a and c the entire signals are shown and Fig. 5b and d show a close-up of the respective signal on-sets. In the close-ups the original signal samples are depicted as '+'-symbols and the results of the Y-ANFIS filter are depicted as solid lines. From the figure it is obvious that the Y-ANFIS filter successfully eliminates random noise in the high frequency range. Furthermore, no artefacts such as overshoots or additional wave cycles can be found. It works well both in the case of low and high SNR values. By applying the Y-ANFIS filter, a clearer and less ambiguous evaluation of the signal on-set is possible. However, a portion of the noise, particularly with frequencies lower than the signal frequency, is not compensated by the Y-ANFIS filter. This is due to the non-random character of the disturbances which are reproduced rather than eliminated by the employed filter algorithm. Besides the successful elimination of high frequency noise, the compensation or at least reduction of the interfering non-random (low frequency) noise would, however, be a prerequisite for a reliable automatic detection of signal on-sets.

Figure 5 AE signals treated by Y-ANFIS

a. AE signal with low SNR (complete signal)
b. AE signal with low SNR (close-up of the signal onset)
c. AE signal with high SNR (complete signal): original signal samples given as ‘+’-symbols, Y-ANFIS result given as solid line
d. AE signal with high SNR (close-up of the signal onset): original signal samples given as ‘+’-symbols, Y-ANFIS result given as solid line

Conclusions

In the presented study it was shown, that the developed “Y-ANFIS” digital filter based on fuzzy logic can be successfully applied to ultrasound signals in order to considerably reduce random noise. The feasibility of de-noising and its advantages with respect to Y-ANFIS have been demonstrated through the successful treatment of signals from ultrasound through transmission and acoustic emission measurements. For both examples, however, also the limitations of the method were also discovered: Non-random disturbances, usually in the low frequency domain, could not be compensated by the “Y-ANFIS” filter algorithm. In the case of transmission measurement a combination of conventional averaging techniques (with a reduced number of repetitions) and the fuzzy approach yielded best results. For further development of signal processing of acoustic emission measurements, a combination of the fuzzy approach with advanced band pass filters e.g. based on digital wavelet transform appears to be promising.

Acknowledgement

The work described in this paper is partially supported by a grant from the German Research Foundation (Deutsche Forschungsgemeinschaft - DFG) under the theme of the Special Research Area (Sonderforschungsbereich - SFB), SFB 381, subproject A8 “Damage characterisation and non-destructive testing of the natural composite wood”. Its contents are solely the responsibility of the authors and do not necessarily represent the official position or policy of the German Research Foundation.

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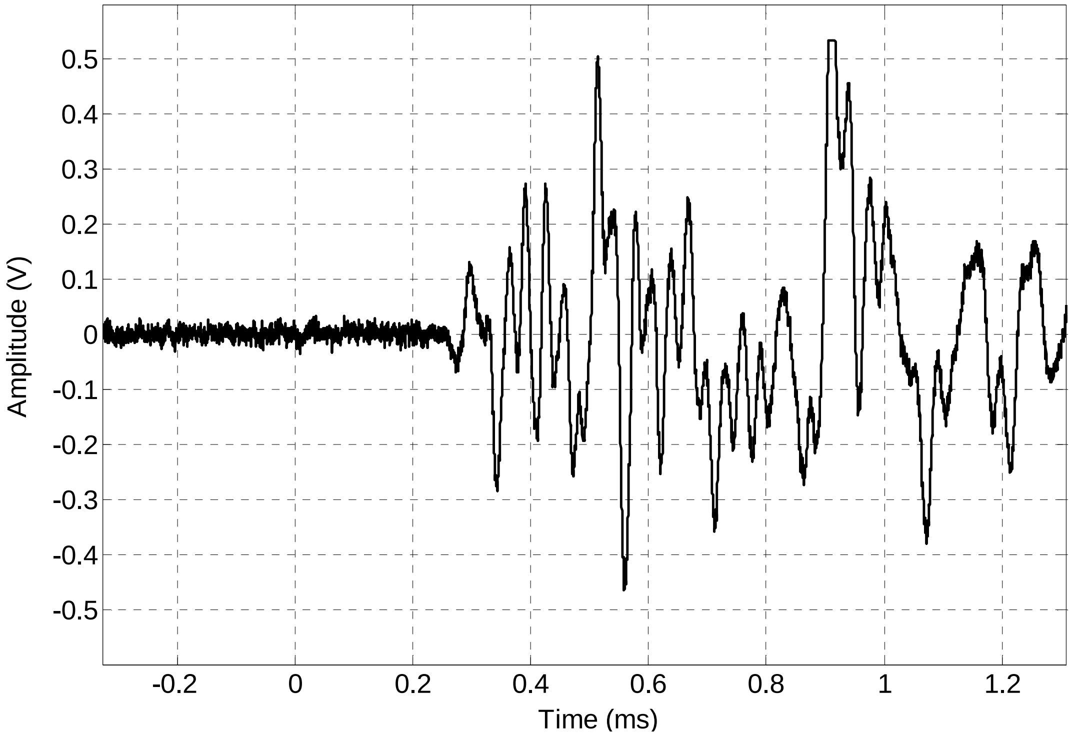
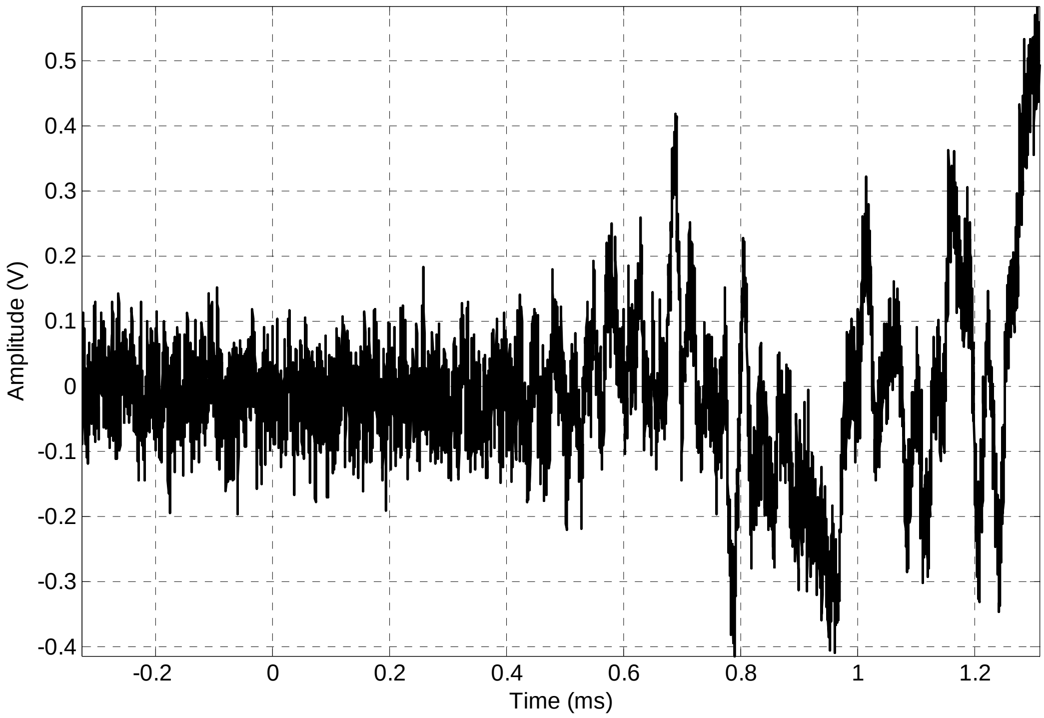


0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
Amplitude (V)
-0.2
0
0.2
0.4
0.6
0.8
1
1.2
Time (ms)

Fig 1a



0.5
0.4
0.3
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0.1
0
-0.1
-0.2
-0.3
-0.4
Amplitude (V)
-0.2
0
0.2
0.4
0.6
0.8
1
1.2
Time (ms)

Fig 1b

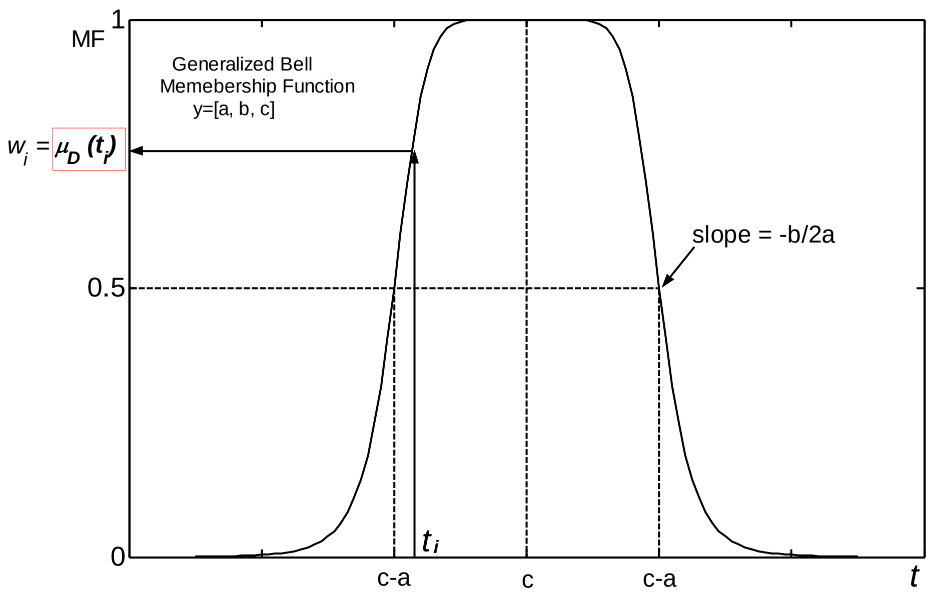

MF
1
0.5
0
Generalized Bell
Memebership Function
y=[a, b, c]
$w_i = \mu_D(t_i)$
slope = -b/2a
t_i
c-a
c
c-a
t

Fig 2

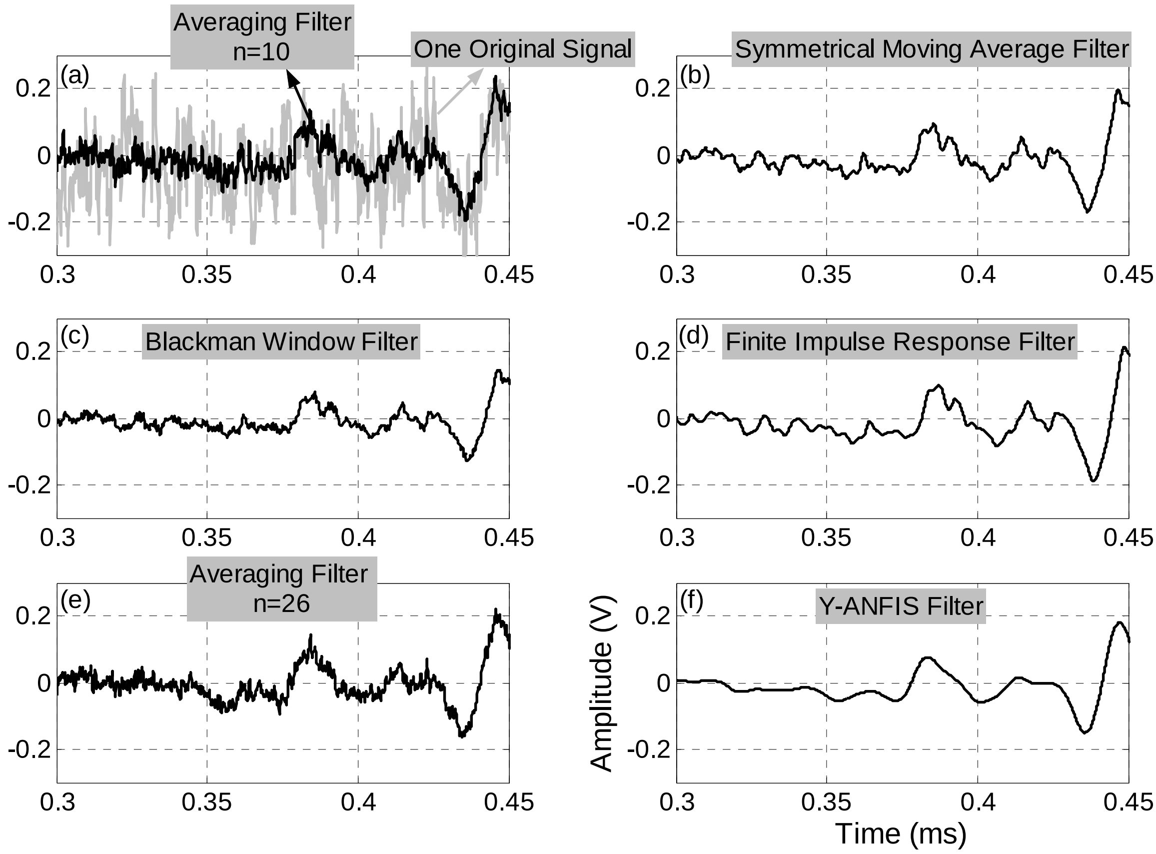

Averaging Filter
n=10
One Original Signal
(a)
Symmetrical Moving Average Filter
(b)
(c)
Blackman Window Filter
(d)
Finite Impulse Response Filter
Averaging Filter
n=26
(e)
(f)
Y-ANFIS Filter
Amplitude (V)
Time (ms)
0.2
0
-0.2
0.3
0.35
0.4
0.45

Fig 3

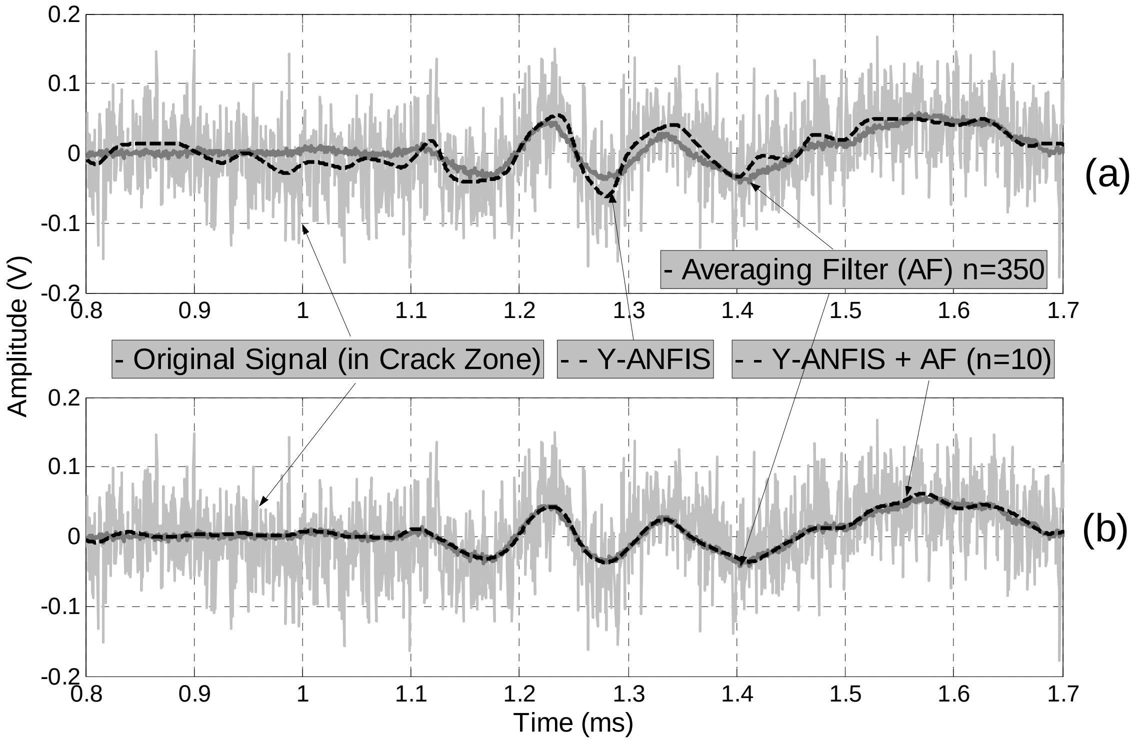
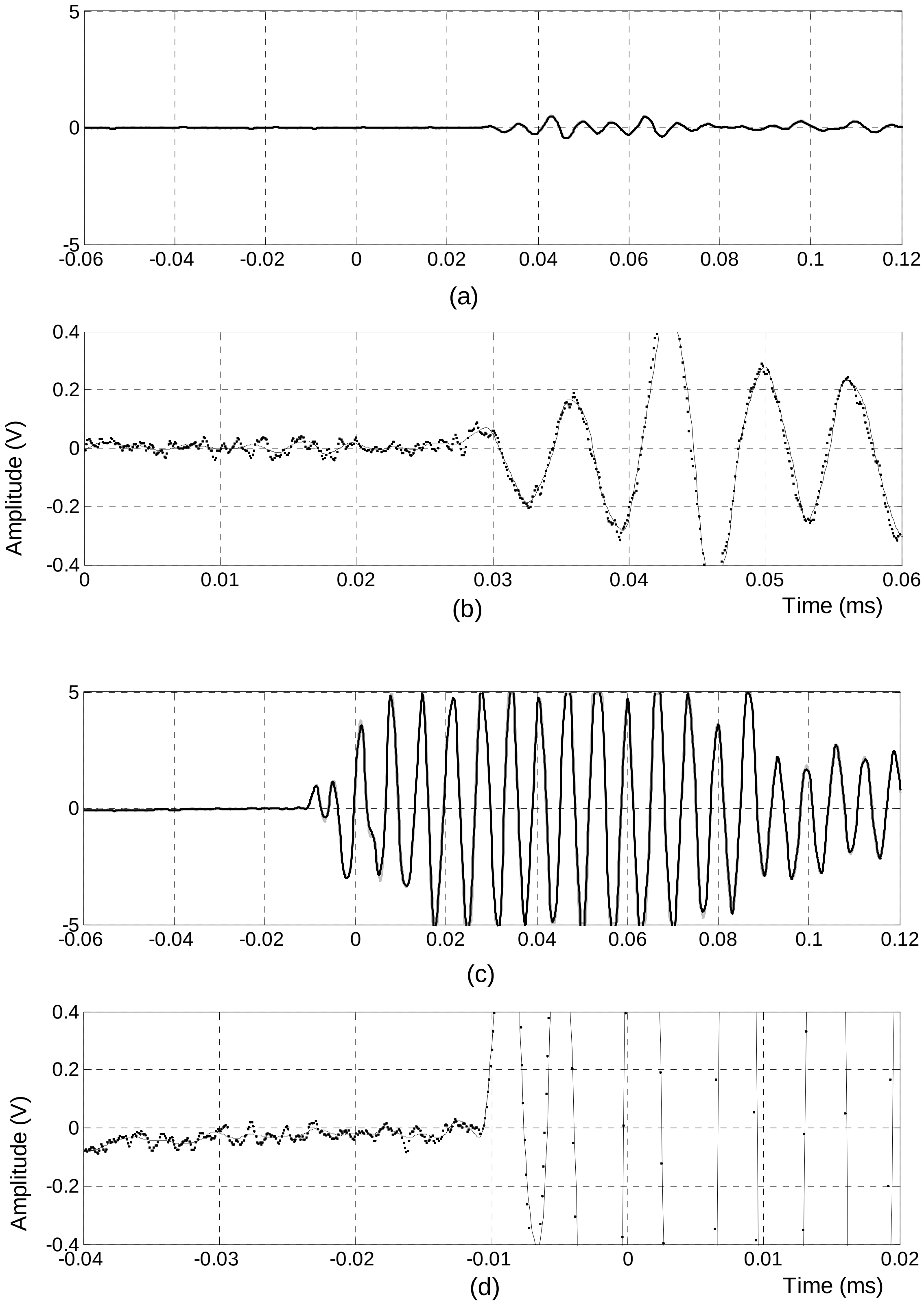

0.2
0.1
0
-0.1
-0.2
(a)
- Averaging Filter (AF) n=350
0.8
0.9
1
1.1
1.2
1.3
1.4
1.5
1.6
1.7
Amplitude (V)
- Original Signal (in Crack Zone)
- - Y-ANFIS
- - Y-ANFIS + AF (n=10)
(b)
Time (ms)

Fig 4



5
0
-5
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
0.08
0.1
0.12
(a)
Amplitude (V)
0.4
0.2
0
-0.2
-0.4
0
0.01
0.02
0.03
0.04
0.05
0.06
Time (ms)
(b)
5
0
-5
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
0.08
0.1
0.12
(c)
Amplitude (V)
0.4
0.2
0
-0.2
-0.4
-0.04
-0.03
-0.02
-0.01
0
0.01
0.02
Time (ms)
(d)

Fig 5