FUZZY LOGIC BASED DE-NOISING OF ULTRASOUND SIGNALS FROM NON-DESTRUCTIVE TESTING

ENTRAUSCHUNG VON ULTRASCHALL-SIGNALEN AUS ZERSTÖRUNGSFREIEN ULTRASCHALLPRÜFUNGEN MITTELS FUZZY LOGIK-BASIERTEN VERFAHREN

DÉBRUITAGE “LOGIQUE FLOUE” DES SIGNALS D’ULTRASONS ORIGINANT D’ UNE APPROCHE D'ESSAI NON DESTRUCTIVE

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SUMMARY

The paper reports on different methods of ultrasound signal de-noising. The reduction of noise is especially important for the evaluation of ultrasound transmission measurements in highly damping materials such as wood and glued laminated timber (glulam). In order to enable a reliable identification of characteristic signal parameters (such as time-of-flight or first amplitude) the poor signal to noise ratios (SNR) of ultrasound signals have to be improved by filtering methods. Conventional methods such as multiple signals averaging are used at the expense of huge data requirement, time consuming measurement procedures and signal processing.

As an alternative approach in this paper a fuzzy logic based adaptive filter is applied for de-nosing in an attempt to use a lower number of experiments, i.e. to minimize data requirements. The results are compared to those of the conventional multiple signal averaging and of a moving average filter. Preliminary results demonstrate the feasibility of the application of the fuzzy filter and clearly illustrate its advantages as well as shortcomings over the conventional approach. The presented approach is one step towards the goal of real-time non-destructive testing (NDT) inspection of glulam beams by means of ultrasound methods.

ZUSAMMENFASSUNG

Der Aufsatz berichtet über verschiedene Methoden der Entrauschung von Ultraschall-Signalen. Die Reduzierung des Rauschens ist insbesondere bei der Auswertung von Signalen aus Ultraschall-Transmissionsmessungen an stark schalldämpfenden Materialien wie Holz oder Brettschichtholz von Bedeutung. Um eine verlässliche Bestimmung charakteristischer Parameter (z.B. die Ermittlung der Ultraschall-Laufzeit oder der Größe der ersten Amplitude) aus den aufgezeichneten Signalen zu ermöglichen, muss das oft schwache Signal-zu Rausch-Verhältnis durch den Einsatz von digitalen Filtern verbessert werden. Konventionelle Methoden wie die Mittelung über mehrere Wiederholungsmessungen werden auf Kosten hoher Anforderungen an die Datenspeicherkapazität, erhöhten Zeitbedarfs bei den Messungen und der Datenauswertung angewandt.

Als alternativer Ansatz zur Entrauschung wird im vorliegenden Aufsatz ein adaptiver Filter eingesetzt, der auf der Methode der Fuzzy Logik beruht. Hierbei werden weniger Wiederholungsmessungen und somit geringere Anforderungen an die Speicherkapazitäten benötigt. Die Ergebnisse werden sowohl den Resultaten der konventionellen Mehrfachmessungs-Methode als auch den Ergebnissen aus dem Einsatz eines „Gleitenden Durchschnitts"-Filters gegenübergestellt. Aus den vorläufigen Ergebnissen der laufenden Forschungsarbeiten ergibt sich der Nachweis der Machbarkeit des Einsatzes von Fuzzy-Logik basierten Filtern zur Entrauschung. Außerdem werden die Vor- und Nachteile gegenüber den üblicherweise verwendeten Verfahren analysiert.

Der vorgestellte Ansatz trägt zur Entwicklung eines ultraschall-basierten , in Echtzeit einsetzbaren Systems zur zerstörungsfreien Untersuchung der Integrität von Brettschichtholzbauteilen bei.

RESUME

L'article rend compte de différentes méthodes de débruitage en ce qui concerne des signaux d'ultrasons. La réduction de bruit est particulièrement importante pour l'évaluation des mesures de transmission d'ultrasons en matériaux fortement atténués tels que le bois et le bois de construction stratifié collé (glulam). Une approche d'essai non destructive est appliquée pour détecter et localiser des fissures longitudinales dans du bois lamellé-collé au moyen d'ultrasons. Une des conditions, capitale et nécessaire, en ce qui concerne l'approche est l'identification des parameters des signaux (tels que le temps-de-vol ou la première amplitude). Les signaux après avoir traversé le faisceau sont reçus et enregistrés pour l'analyse et l'identification des fissures. Après avoir traversé le faisceau, les signaux sont considérablement corrompus par du bruit blanc. Les faisceaux de bois stratifiés par colle, analogue au bois, partagent beaucoup de dispositifs communs avec le bois normal. Ils ont une faible densité et un effet d'atténuation élévé vis-à-vis de leur structure. Les rapports Signal-à-Bruit très faibles rendent les paramètres des signaux reçus moins reconnaissables. La méthode conventionnelle moyenne multiple pour traitement de signal est employée pour améliorer le rapport Signal-à-Bruit au détriment des conditions énormes de données et du traitement prolongé des signaux. Un filtre "logique floue" est appliqué pour la réduction de bruit et l'amélioration de rapports Signal-à-Bruit afin d'essayer d'employer un bas nombre de tentatives expérimentales (c.-à-d. pour réduire au minimum la condition de données). Le filtre proposé est un système adaptatif de neuro-réseau basé sur la théorie du "logique floue". Les résultats sont comparés à ceux de la méthode signal multiple conventionnel faisant la moyenne, et à ceux d'autres filters. Les résultats préliminaires démontrent la praticabilité de l'application du filtre "logique floue" et illustrent clairement ses avantages (aussi bien que ses imperfections) par rapport à l'approche conventionnelle. L'approche réduit les demandes temporelles considérables et la condition de stockage élevée des données requise de l'approche moyenne conventionnelle sans compromettre la résolution des signaux. L'approche présentée est une étape vers le but de l'inspection (NDT) d'essai non destructive en temps réel des faisceaux de glulam au moyen de méthodes d'ultrasons.

KEYWORDS: Non-destructive testing (NDT), fuzzy logic, ultrasound, glued laminated timber (glulam), wood, cracks, Signal-to-Noise Ratio (SNR), filters

1. INTRODUCTION

In the last decades the use of timber and engineered wood products for construction purposes (as e.g. finger jointed timber, glued laminated timber, laminated veneer lumber or oriented strand board) has increased significantly. One decisive aspect for the future performance of timber in the competition with other building materials will be the question of quality assessment. In other words both the quality control of the production process and the survey of existing structures in service are important issues. The integration of non-destructive testing (NDT) methods into improved quality control systems for timber products, as already standardised for steel or concrete, will be a major issue for the future. Due to the special characteristics of timber (e.g. growth bound relatively high variability of material parameters, anisotropy, porosity, creep behaviour etc.) one tends to encounter problems when existing non-destructive testing methods are transferred from other materials to timber.

In the case of ultrasound based methods three main aspects can be identified which are most important for the development of reliable and easy to use NDT inspection procedures for timber structures:

- Adaptation of the usual ultrasound equipment to requirements of the material wood (low frequency, high energy, improved coupling between US transducers and the timber surface)
- Modelling of wave propagation in timber in the presence / absence of damage and significant defects (cylindrical anisotropy of elastic and damping properties, influence of inhomogenities, effects of boundary conditions)
- Improved evaluation of measured ultrasound signals (Correlation methods, filtering, de-noising)

This paper deals with the filtering and de-noising of ultrasound signals from transmission measurements emanating from glued laminated timber beams. After a short description of two conventional methods of de-noising, i.e. the averaging of repeated measurements and the use of a moving averaging filter, a more advanced method based on the application of Fuzzy logic is introduced. The “Fuzzy” concept, i.e. the use of classes with boundaries that are not sharply defined, first introduced by [Zadeh 1963] and the “Fuzzy Logic”, whereby the truth of any statement is a matter of degree (e.g. reviewed in [TAKAGI. T. & SUGENO. 1983]) has found numerous applications in different fields ranging from pattern analysis and system design to damage assessment and industrial process control. The Adaptive Network Fuzzy Inference System (ANFIS) is an extension of the application of Fuzzy Logic combined with the idea of Artificial Neuronal Network. ANFIS has found its application in various fields, e.g. in the field of pattern recognition and signal processing. In this paper the ANFIS method is modified to perform as a special filter.

2. METHODOLOGY

2.1 Averaging Filter

Noise is inherent in any procedure for obtaining signals. One major type of noise is the random type. The effect due to random variation can be cancelled out by summing up a number of signal measurements. The seasonal, cyclic (or non-random) components which are the desired signal are left behind. This approach is not useful when the output signals are not static, or in other words, when the output signals come from a moving object. Equation (1) describes the simple averaging filter (AF).

$$\bar{x}(t) = \frac{1}{n}\sum_{i=1}^{n} x_i(t) \tag{1}$$

where: $\bar{x}(t)$ = mean value of voltage of samples (at one sampling time)

n = number of measurements

$x_i(t)$ = voltage of a sample (at one sampling time)

Its mean squared error (MSE) s is computed by Equation (2).

$$s = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i(t) - \bar{x}(t)\right)^2}{n-1}} \tag{2}$$

The magnitude of s is dependent on the measurements - $x_i(t)$ which in practice is determined by the specimen, measurement device and set up, as well as the number of measurements conducted. Once $x_i(t)$ is fixed, the larger n is, the smaller s becomes. In other words, given a noisy but bounded measurement sequence, we can take a large number of measurements and compute the mean value to give a better estimate of the true signal (assume there is no systematic error or bias in the measurements). It is a conceptually neat approach and often a standard procedure in experimental work. Unlike the other filters, the averaging filter does not remove or change any components of the true signal and hence keeps the original signal information. The averaging filter has good performance both in the time and frequency domains. The unwanted frequency content reduces as the number of averaged signals used increases.

Theoretically, when an unlimited number of measurements are taken, the mean value of all measurements would be the signal without any noise. Naturally the latter is not practical especially in real industrial applications. It is inefficient with respect to its slow convergence rate. Equation (2) demonstrates that the error s is proportional to a factor of $\sqrt{\frac{1}{n-1}}$, which means the amount of effort one puts into the increase of n will not achieve a convergence of s corresponding to the effort invested.

Besides this shortcoming, n times of measurements has to be conducted and the data stored during testing, not terribly suitable for online quality control application. Due to the high damping effect of wood and wood based material, a rather significant number of measurements have to be taken in order to ensure an identifiable signal. Even though relatively high volumes of storage media and high speed microprocessors are currently available at affordable prices, the effort needed for conducting measurements and signal processing can become significant especially when one has to deal with hundreds or perhaps thousands of n. We therefore need to seek more efficient ways of processing and analyzing of signals.

2.2 Moving Averaging Filter

The moving average filter is implemented as an alternative to the averaging filter. It is the simplest filter among all available digital filters. As its name implies, the moving average filter operates by averaging a number of continuous samples from the input signal to produce one sample as the output signal. It is represented by Equation (3).

$$y[t_i] = \frac{1}{M}\sum_{j=0}^{M-1} x[t_i + t_j] \quad (3)$$

where,

$y[t_i]$ = the output signal sample

$x[t_i]$ = the input signal sample

M = the number of continuous samples from the input signal

As an alternative, the group of samples from the input signal can be chosen symmetrically around the output sample. This is called a Symmetrical Moving Averaging Filter (SMAF) and is characterized by Equation (4).

$$y[t_i] = \frac{1}{M}\left(\sum_{j=\frac{1-M}{2}}^{0} x[t_i + t_j] + \sum_{j=1}^{\frac{M-1}{2}} x[t_i + t_j] \right) \tag{4}$$

Equation (4) requires M be an odd number. The moving average filter is optimal for reducing random noise while retaining a sharp step response. However, the moving average filter is the worst filter for frequency domain encoded signals, with little ability to separate one band of frequencies from another (Smith 1999).

2.3 Fuzzy Filter

Fuzzy logic (FL) was first presented by Lofti Zadeh [Zadeh 1965] 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 the concept of partial truth. 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. ANFIS, the tool around which the approach advocated in this undertaking is developed, is based on FL. It implements an artificial neuro-network and provides a computational framework for manipulating and reasoning with respect to imprecise expression of knowledge including complex non-linear functions.

The proposed approach is a custom-designed model hereinafter referred as 'Y-ANFIS'. It uses first-order Takagi-Sugeno fuzzy rule [Takagi & Sugeno, 1983]. The input to the fuzzy model and number of fuzzy rules are determined by the system dependencies, number of training data pairs and the required accuracy. Both signal and noise are functions of time (t), however independent from 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 y. To exemplify the Y-ANFIS model, a system with one input and three fuzzy rules is used.

The fuzzy rules are constructed as the following,

If t is D1, then y1=P1 t + C1,

If t is D2, then y2=P2 t + C2 and

If t is D3, then y3=P3 t + C3.

P1-P3 and C1-C3 are model parameters to be solved. D1-D3 are fuzzy numbers with a generalized bell function. It is shown in Equation (5).

$$\mu_{D_i}(t) = \frac{1}{1 + \left[(\frac{t - c_i}{a_i})^2 \right]^{b_i}} \tag{5}$$

where, a_i, b_i and c_i are function parameters. They are given initial values and will be optimized in the Y-ANFIS model.

The outputs of the three fuzzy rules are combined by taking an arithmetic mean of each output taking into consideration the value of their weights (the degree of fulfilment). The combined response is derived in Equation (6).

$$y = \overline{w_1} t \cdot P_1 + \overline{w_2} t \cdot P_2 + \overline{w_3} t \cdot P_3 + \overline{w_1} C_1 + \overline{w_2} C_2 + \overline{w_3} C_3 = t \sum_{i=1}^{n} \overline{w_{ij}} \cdot P_{ij} + \sum_{i=1}^{n} \overline{w_{ij}} C_{ij} \tag{6}$$

For each *t*, a corresponding y_{ij} can be derived using the above equation. For an entire group of signal time-domain samples, a matrix of y_{ij} can be formed. The function parameters, a_i, b_i and c_i, are given initial values, which implies $\overline{w_{ij}}$ is known. The model parameters, P1-P3 and C1-C3, are left to be solved by means of the Least Square Estimation (LSE) optimization algorithm. After obtaining optimal model parameters, the function parameters are to be optimized by the Gradient Descent (GD) method (using the derivative of the model error). LSE and GD optimization procedures are repeated till they achieve the acceptable error that is previously defined by the modeller. Till here, both the model parameters and the function parameters are optimized accordingly and the overall output can be obtained.

The Y-ANFIS model applied in the signal processing is explained by the following equations. A measured signal is composed of a clean signal and noise as expressed by the addition of noise to signal in Equation (7).

$$y(t) = x(t) + d(t) \tag{7}$$

where,

$y(t)$	=	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.

$$\|e(t)\|^2 = \|y(t) - x^{\#}(t)\|^2 = \|x(t) - x^{\#}(t)\|^2 + 2x(t)\cdot d(t) - 2x^{\#}(t)\cdot d(t) + \|d(t)\|^2 \qquad (8)$$

where,

$x^{\#}(t)$ = the modelled signal

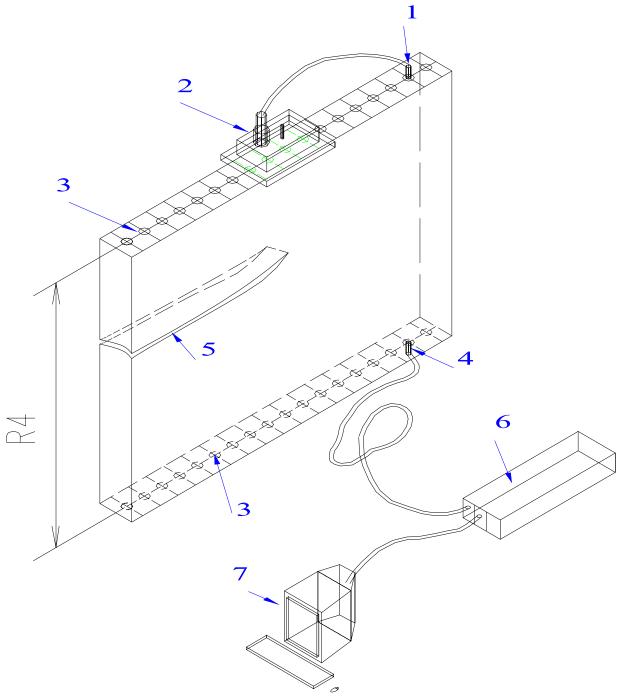
The expected value of $\|e(t)\|^2$ is derived as Equation (9). The noise in the work is Gaussian white noise with zero mean value which leads $E[d(t)]$ to zero. The expected values $x(t)\cdot d(t)$ and $x^{\#}(t)\cdot d(t)$ are zero due to the fact that clean signal $x(t)$ and noise $d(t)$ as well as 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.

$$E[e^2] = E[(x(t) - x(t)^{\#})^2] + E[d(t)^2] \qquad (9)$$

The low-frequency noise is shown as an oscillation and prevents Y-ANFIS from recognizing it as noise. Y-ANFIS is combined with the averaging filter to improve its performance in dealing with the low-frequency noise.

3. RESULTS

The three different filters, namely the averaging filter, moving average filter and Y-ANFIS are applied to the same sets of signals. The data sets for the comparison of the different filters are exemplarily chosen from US transmission measurements at a glulam exhibiting a longitudinal crack. The schematic test set-up is shown in Fig. 1. For the details of the measurements and the evaluation of the (unfiltered) signals see [Aicher *et al.* 2002]. Two sets of signals are evaluated: first, the results of transmission measurement at a location including a crack (measurement I with low SNR) and second, the results of transmission measurements at a location in the crack-free zone (measurement II with relatively high SNR).



1. Transducer
2. Ultrasound Generator
3. Measured Point
4. Receiver
5. Crack
6. Amplifier

Fig. 1 Schematic picture of the test set-up for ultrasound transmission measurements of glulam beams with longitudinal crack

Results from the AF with the original signals are shown in Fig 2 and Fig 3. The AF produces fairly good result as the high frequency noise contained in the averaged signal is removed to a considerable extent. Time required to process 26 measurements using the AF is approximately 24 seconds on an IBM R40e laptop with 2.6GHz processor and 256 MB of RAM.

Results from the SMAF are shown in Fig 4 and Fig 5. Noise corruption is indeed decreased by the SMAF. But compared to the results of the averaging filter, SMAF reduces noise while keeping a residue of high frequency noise. The SNR is also not improved by much. If the signal parameters such as the Time of Flight (TOF) and the first amplitude (Aicher *et al.*, 2002) are to be quantified out of the filtered signal, difficulties occur as they are not easily recognizable. Time required to process a 41-sample SMAF is approximately 28 seconds on the same IBM machine. It is worth to note that unlike the averaging filter, the SMAF achieves a relatively clean signal with only one measurement, which means it saves measurement time and data storage space.

Results from the Y-ANFIS model are shown in Fig 6 and Fig 7. The AF is used after applying the Y-ANFIS model to further remove the low-frequency noise. The mean value of 10 continuous signals treated by the Y-ANFIS is computed as the final output. Results from the AF are included in the analysis of the Y-ANFIS results to facilitate a direct comparison. When one compares the results of the averaging filter, Y-ANFIS reduces high-frequency noise (above 50 kHz) while keeping low-frequency noise (below 10 kHz). Y-ANFIS is not able to recognize low-frequency noise, instead; Y-ANFIS treats it as signal. As this above-mentioned signal is essentially noise composed of random samples, the AF is able to remove the random effect. Time required to do processing using Y-ANFIS with 20 membership functions and 5 iterations is approximately. 22 seconds on the IBM machine. When 10 Y-ANFIS output signals are averaged, additional 75 seconds are consumed on the same machine. It is worth noting that in the application of the Y-ANFIS model, a partial signal that is 3000 samples corresponding to 0.15-0.45 ms is used instead of the complete signal samples. This range covers the part where the signal is about to start and the first few peaks after the commencement of signal. If the complete signal is to be treated by the Y-ANFIS model, more membership functions and iterations would be needed and thus longer computing time.

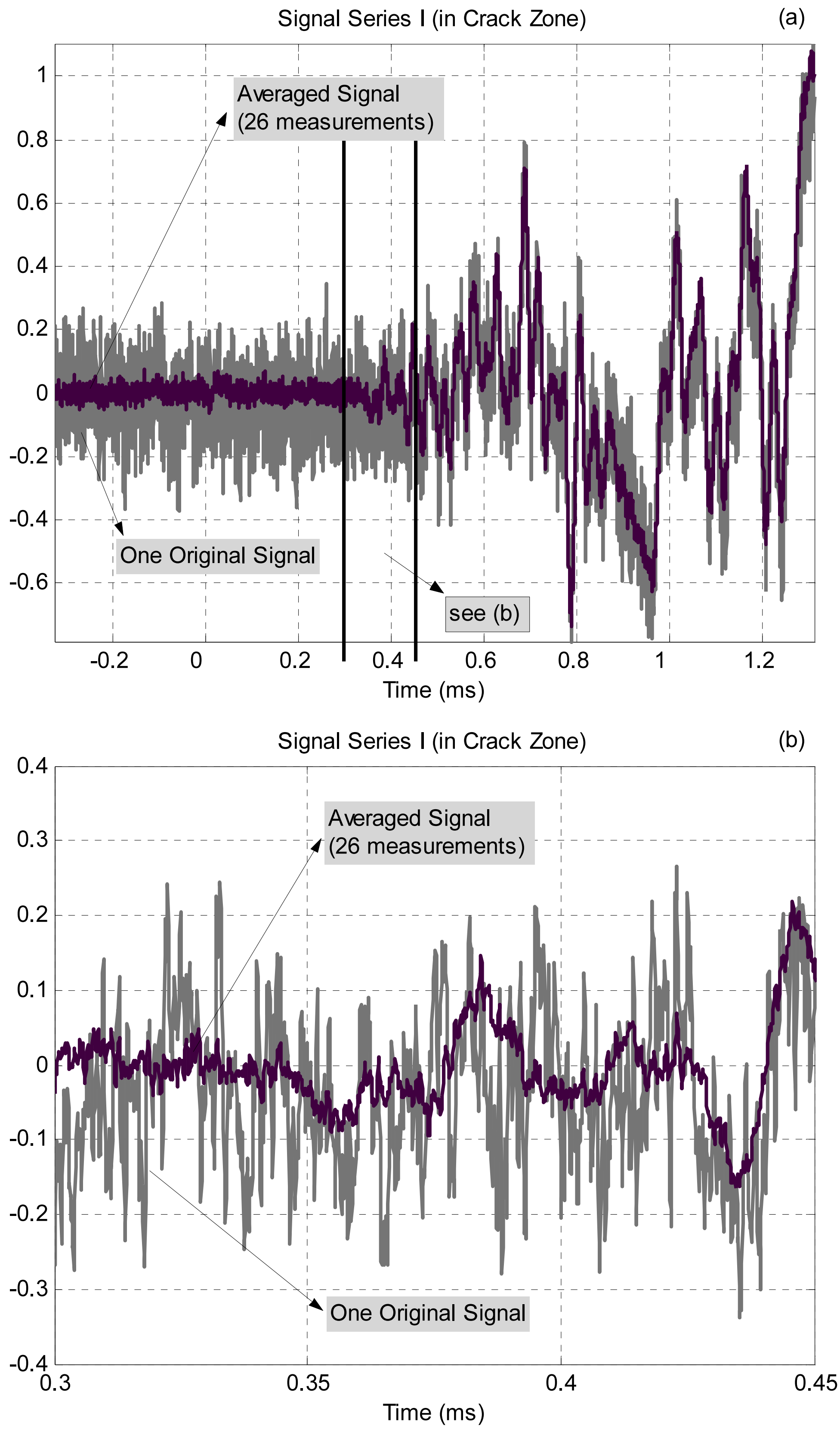


Fig. 2: US transmission signal (measurement I in the crack zone) treated by averaging filter (AF) (a) complete samples, (b) partial samples

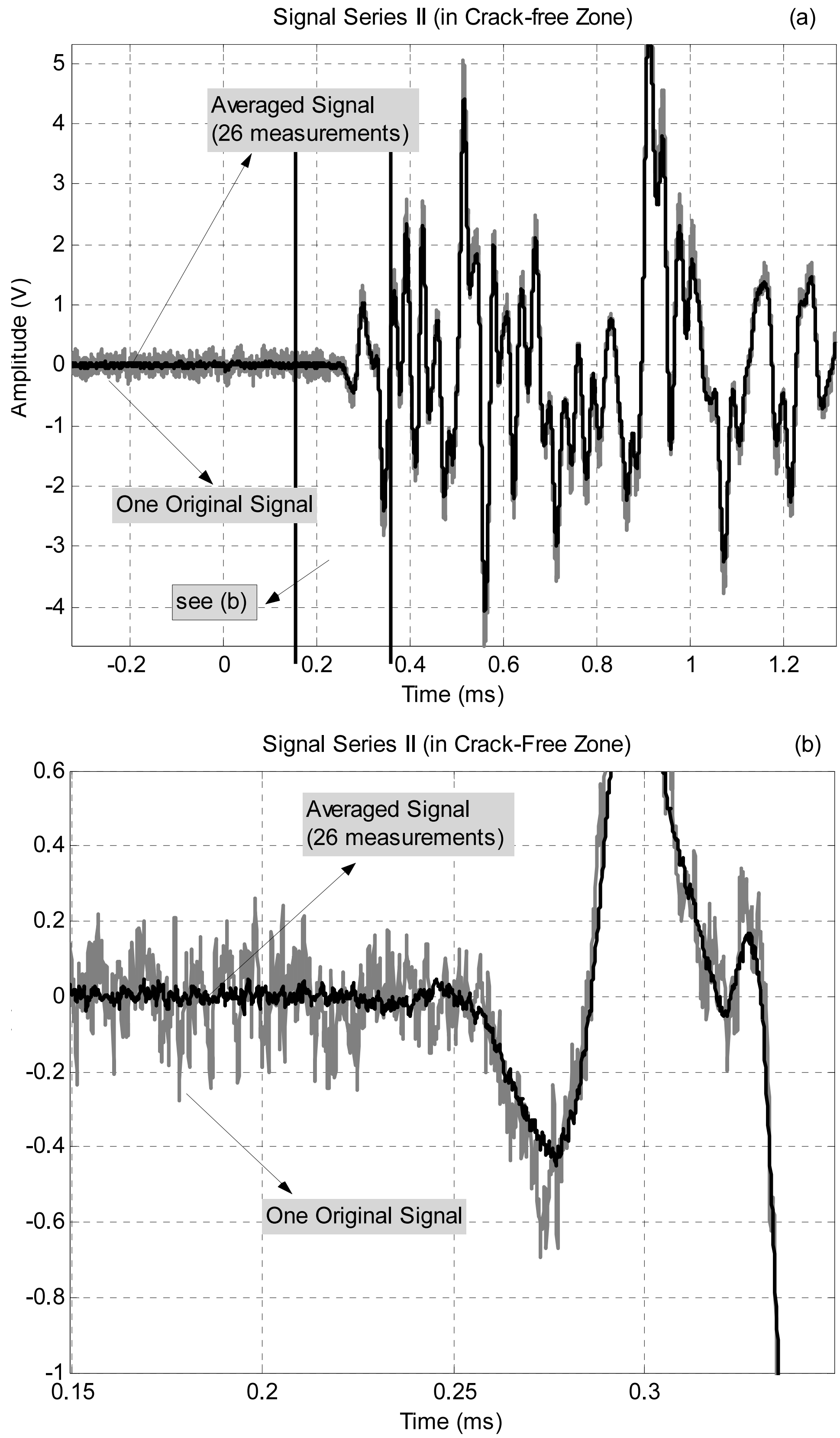


Fig. 3: US transmission signal (measurement II in the crack-free zone) treated by averaging filter (AF) (a) complete samples, (b) partial samples

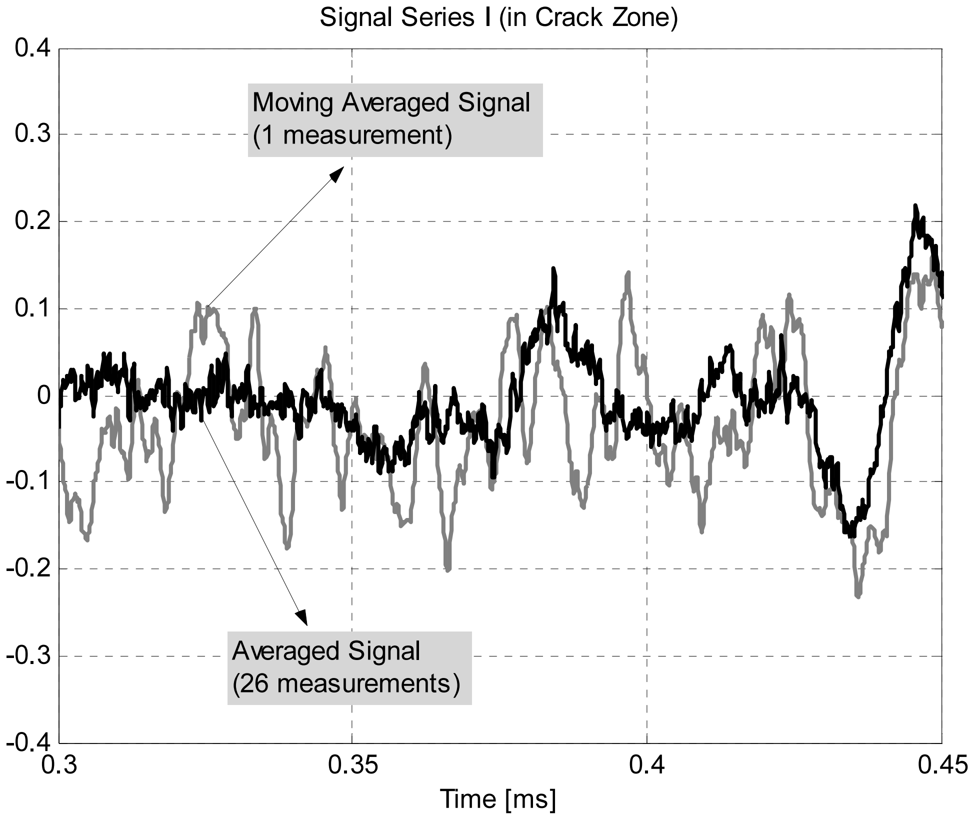


Fig. 4: US transmission signal (measurement I in the crack zone) treated by ***SMAF*** *(partial samples)*

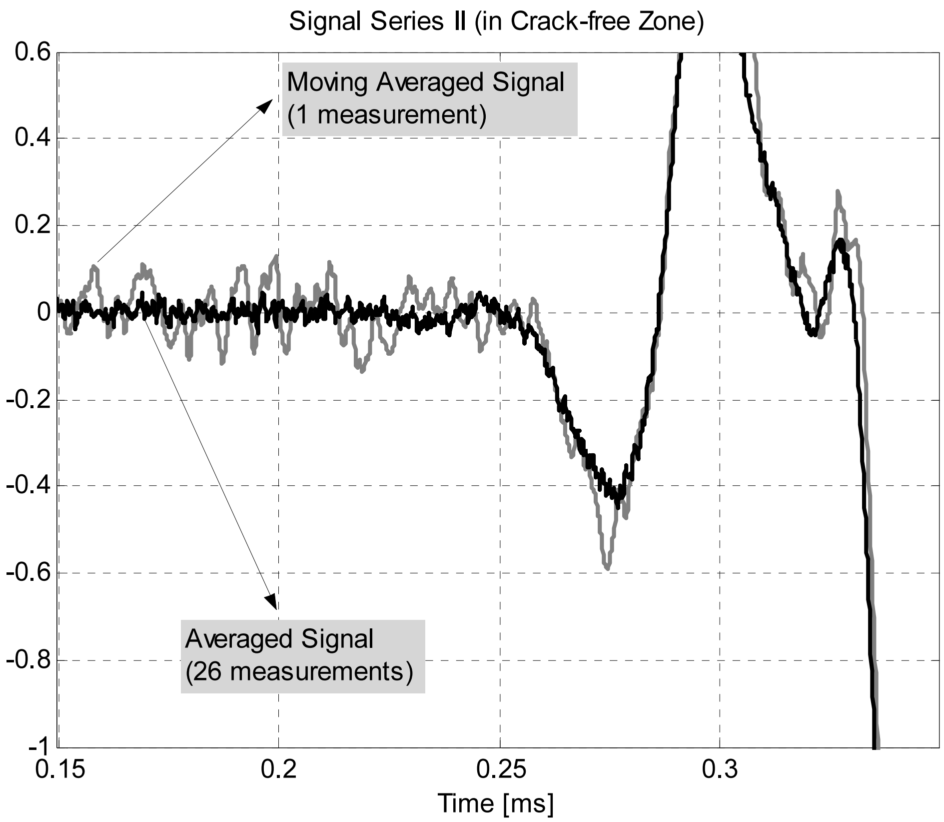


Fig. 5: US transmission signal (measurement II in the crack-free zone) treated by ***SMAF*** *(partial samples)*

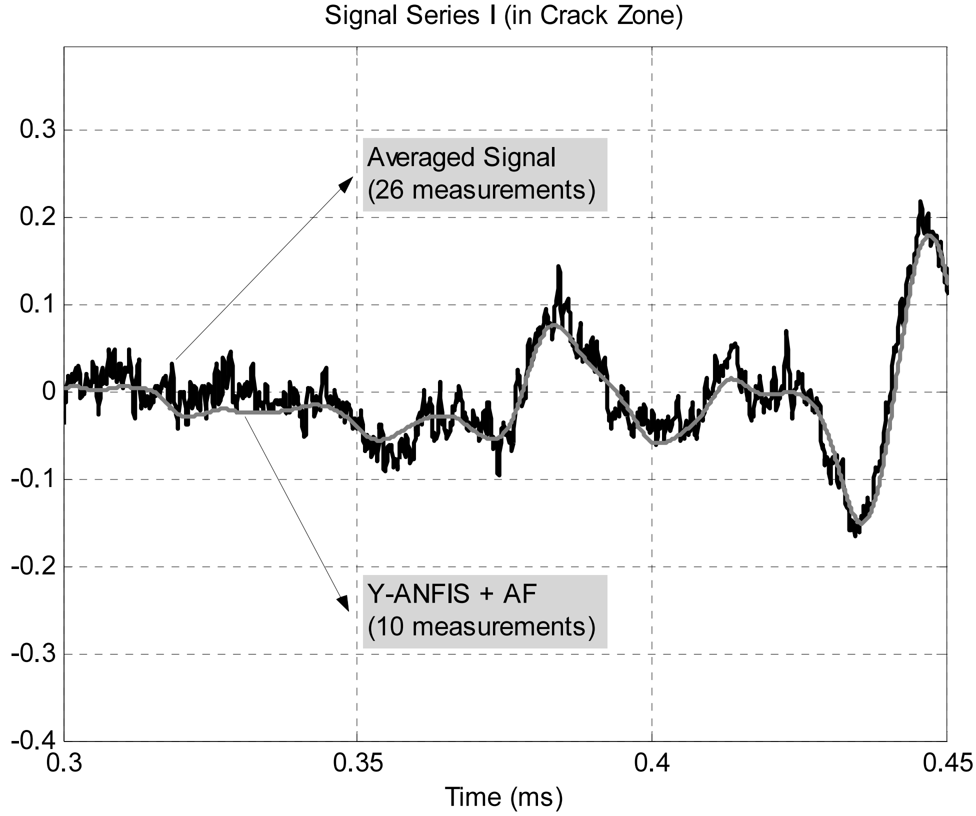


*Fig. 6: US transmission signal (measurement I in the crack zone) treated by **Y-ANFIS + AF** (partial samples)*

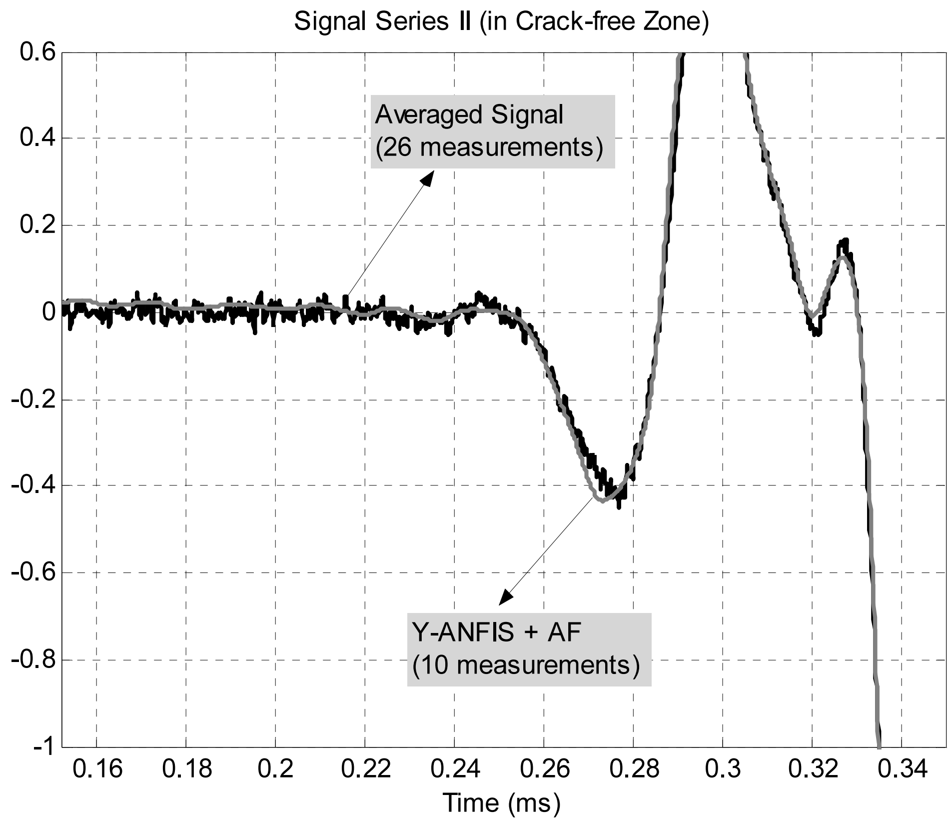


*Fig. 7: US transmission signal (measurement II in the crack-free zone) treated by **Y-ANFIS + AF** (partial samples)*

4. CONCLUSION AND RECOMMENDATION

The averaging filter is the most reliable approach among the methods tested; namely the averaging filter (AF), symmetrical moving averaging filter (SMAF) and fuzzy based adaptive filter (Y-ANFIS). In other words its influence on the original signal is minimal. On the other hand, it is most time-consuming with respect to the NDT signal analysis procedure as well as most demanding in terms of storage space. SMAF shows an acceptable performance with much less time consumed in testing and signal processing. Y-ANFIS + AF show excellent results with regard to noise elimination although a great deal of computational effort is required for the non-linear mapping. Considering the fact that the AF does not alter the content of the true signal, it is the simplest method that can be considered as a reference with which to judge the performance of the other signal processing methods. If the testing device and the specimen under consideration are compatible to allow the registration of measurements with high SNR and within an acceptable time, the AF shall remain the first choice vis-à-vis the other signal processing methods. In the aforementioned situation, Y-ANFIS does not show much superiority over the AF. The AF becomes ineffective when the testing device and the specimen properties lead to signals with low SNR, e.g. in the case of the US transmission testing of real structures with large dimensions. In all cases when repeated measurements are principally not possible, e.g. acoustic emission testing, digital signal processing by means of Y-ANFIS is a reliable approach for noise reduction.

Y-ANFIS + AF could be replaced by a windowed filter (high-pass filter) combined with Y-ANFIS, thus the high-pass filter eliminates low-frequency noise before Y-ANFIS is applied. Windowed filter + Y-ANFIS can further reduce the number of measurements needed for each point under consideration. The latter could be set a research agenda that could be undertaken in a future study. Together with improvements in the measurement device, the real-time application of NDT in the field of timber engineering can be achieved.

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