Chapter book

“Wavelet Transforms for Macro Fiber Composites Transducers”

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Chapter 1

Wavelet Transforms for Macro Fiber Composites Transducers

Raúl Ruiz de la Hermosa González-Carrato, Fausto Pedro García Márquez
and Vichaar Dimlaye

Abstract This paper presents a novel pattern recognition approach for a Non Destructive Test (NDT) for pipes. NDT is based on Macro Fibre Composites Transducers (MFC). The signals are analysed employing Wavelet Transforms (WT). WT is an optimum methodology for the detection and diagnosis of particular behaviors that is very effective for maintenance management in NDT of pipes. WT analysis is a windowing technique that allows the use of time intervals when more precise information is required. It leads to WT to be a powerful tool that can reveal characteristics of the signals as trends, breakdown points or self-similarities. In this paper a real case study is presented, where all possible combinations between signals are considered in order to find pattern recognitions. To achieve the results, signals are broken down by mathematical software based on wavelets principles. Similarities are found with an associated energy percentage for each decomposed signal exchanging the waveforms, levels of decomposition and border distortions.

Keywords transforms · macro fibre composites transducers · pattern recognition · maintenance management

1.1 Introduction

A Macro Fibre Composite (MFC) has been used to detect temperature effects in a pipe. An AC voltage signal was used in the MFC transducers. The signal is transferred along the surface of the pipe. The input voltage signal is in high frequency excitation (30 kHz). Experiments were done using 4 MFC transducers attached at 3

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m from the nearest beginning (Fig. 1.1). The transducers are arranged at 45 degrees around the pipe of 8. The pulse-echo data from each transducer and the sum of them where collected. The sensor and actuator are located at the same place on the pipe. The discontinuities of the structure will lead the change of the wave that is read by the sensor. The signal will represent changes of the structure as geometry (edges of the pipe, extremeness, etc.), faults (corrosion, cracks, defects), environment conditions, etc. The main objective in this paper is to study the environment temperature in the pipe. The authors have not found a previous study about this topic.

Fig. 1.1 shows the allocation of the MFC sensors and the pipe geometry. The pipe has a diameter of 20.32 cm and a length of 9 meters. The MCF sensors are set at 6 m of the end and at 45° between them. Fig. 1.2 present the sum of the 4 MFC transducers signals. The main shapes of the signal are associated to the geometry of the pipe. The pulses are basically longitudinal wave modes with a velocity $V = 5400\text{m/s}$.

The movement of the pulse-echo from along the surface of the pipe is described in Fig. 1.2. Fig. 1.3 shows the movement from the transducers to the beginning of

Fig. 1.1 MFC transducers set on a 8 pipe

Fig. 1.2 MFC signal (mV) vs. samples

the pipe and its return to the transducers. The distance covered is denoted by d_1 , being 3 m and the velocity of $V = 5400\text{m/s}$, therefore $t_1 = 3/5400 = 555\mu\text{s}$. This time corresponds to the near end reflection as shown in Fig. 1.2. Fig. 1.4 shows second part of the pulse-echo movement from the transducers to the end of the pipe (d_2) and vice versa, being $d_2 = 6\text{m}$, $V = 5400\text{m/s}$, $t_2 = 6/5400 = 111\mu\text{s}$. The data from R1A, R1B, R1C and R1D (mV) are plotted in Fig. 1.5.

The correlation coefficients are showed in Table 1.1, where the correlation is calculated between the signal of the column i and row j .

Table 1.1 Correlation coefficients of the signals R1A, R1B, R1C and R1D

	R1A	R1B	R1C	R1D	Total
R1A	1.0000	0.4925	0.2987	0.5094	0.6419
R1B	0.4925	1.0000	0.6393	0.8121	0.9237
R1C	0.2987	0.6393	1.0000	0.4834	0.7835
R1D	0.5094	0.8121	0.4834	1.0000	0.8722
Total	0.6419	0.9237	0.7835	0.8722	1.0000

The correlation coefficients range is from -1 to 1 , where values close to 1 , e.g. principal diagonal, indicate that there high correlation. Every signals and the sum of them, called “total” except R1A, and R1B-R1D, have a positive linear relationship. Values close to -1 would indicate that the data from an experiment has a negative linear relationship to another (anti-correlation), but there is not any case. Finally values close to 0 would indicate that there is no linear relationship between the signals. In this work has been analyzed the signal given by the sum of the signals (called total).

The objective of this project is to detect changes in the structure according to the temperature. The wavelet transform is proposed in order to detect the temperature.

Fig. 1.3 First part of the pulse-echo movement and d_1

Fig. 1.4 Second part of the pulse-echo movement and d_2

1.2 Signal Processing: Wavelet Transform Approach

The transformation of a signal to the frequency domain by the Fast Fourier Transform (FFT) can lead to lose part of the information in time domain, and it can be difficult to determine when a behavior occurs or a certain frequency appears [1]. Wavelet transforms analysis is an excellent method in order to solve this problem, and it leads to work with high and low frequencies. The principle of the Wavelet decomposition is splitting the original signal into different components, as the sum of all corresponds to the original signal, but at different frequency bands. Usually the most important information appears at low frequencies, while the particular features are found at higher frequencies [2].

This paper presents a novel pattern recognition approach for MFC transducer signals related to 8 conditions of environment temperatures $[t_1, \dots, t_8]$. Every signal has 11321 data. The main objective is to develop a pattern recognition method that can identify every pair of signals. The use of the Wavelet transforms stems from the need to find a methodology that suits the type of signal. It is discarded the use of FFT failing to fulfill the expected requirements when working with a data type that does not follow any set pattern [1].

The Wavelet transform is a mathematical approach that has many applications in signal processing, process control and detection of anomalies. It associates every finite energy signal with a particular function that represents the main or mother wavelet. It enables to analyze the signal structures that depend on time and scale, being an useful tool to detect, characterize and identify signals with spectral features, unusual temporary files and other properties related to the lack of stationary.

Fig. 1.5 Signals R1A, R1B, R1C and R1D (mV) versus samples

In general terms, the Wavelet transform of a function $f(t)$ is the decomposition of $f(t)$ in a set of functions and $\psi_{s,\tau}(t)$, forming a base. The Wavelet transform is defined as [4, 5]:

$$\omega_f(s, \tau) = \int f(t) \psi_{s,\tau}^*(t) dt \quad (1.1)$$

Wavelets transforms are generated from the translation and scale change from a same wavelet function $\psi(t)$, called mother wavelet, which is given by Equation 1.2:

$$\psi_{s,\tau}^*(t) = \frac{1}{\sqrt{s} \psi(\frac{t-\tau}{s})} \quad (1.2)$$

where s is the scale factor, t is the translational factor and t the time ...

The wavelets $\psi_{s,\tau}(t)$ generated from the same mother wavelet function $\psi(t)$ have different scale s and location t , but the same shape. Scale factors are always $s > 0$. The wavelets are dilated when the scale $s > 1$ and contracted when $s < 1$. Thus, the changing of the value s can cover different ranges of frequencies. Large values for the parameter s correspond to lower frequencies ranges or a large scale for $\psi_{s,\tau}(t)$. Small values of s correspond to lower frequencies ranges or very small scales.

This study will focuses on finding similar patterns for all the possible combinations between every pair of signals.

Every signal has been transformed in 5 new ones named a_4, d_4, d_3, d_2 and d_1 , where each of them has an energy rate associated from the original signal. Functions in the time domain can be represented as a linear combination of all frequency components present in a signal where the coefficients are the amount of energy provided by each frequency component to the original signal. The main decomposition is associated with a_4 that usually has the highest energy, though not always necessary. It has a similar pattern to the original signal. The first (d_4), second (d_3), third (d_2) and fourth (d_1) transformed signals have decreasing energy rates. Signal s will be the signal to be analyzed. Usually, a_4 is the low frequency component of the original signal while d_i is the high frequency component, having d_1 the biggest value. Fig. 1.6 shows the different signals considered.

1.3 Pattern Recognition Approach

Table 1.1 shows the decomposition level used. Table 1.2 identifies the pattern recognition nomenclature. There are 3 options: Y means that both signals are similar but one of them with amplitude higher than the other one; N is for cases where pattern recognition does not exist and; E implies that signals overlapping themselves with a high degree of accuracy. Table 1.3 complements the Y option in Table 1.2, stating what the signal with the higher amplitude is. Finally, Table 1.4 explains if the behavior is total or partial in the study section. The signal was analysed in three segments in order to consider the different parts that present the signal (Fig. 1.2).

Fig. 1.6 Example of decomposition in 4 levels (t1)

All signals show similar characteristics: an abrupt first phase, a second stabilization phase, where it is supposed to find the conditions of interest, and a third part with a shape irregular. The main conclusion for these experiments was that the pattern recognition for different temperatures was found in the second third.

Table 1.2 Decomposition levels

Energy signal decomposition (4 levels)	a4	Main decomposition
	d4	First decomposition
	d3	Second decomposition
	d2	Third decomposition
	d1	Third decomposition
original signal (s) = main decomposition ($a4$) + $d4$ + $d3$ + $d2$ + $d1$		

Table 1.3 Pattern recognition

Pattern recognition	Y	Yes
	N	No
	E	Signals are(nearly) equal

Table 1.4 Amplitude

Signal amplitude	>	$Amplitude_i > Amplitude_j$
	<	$Amplitude_i < Amplitude_j$

Table 1.5 Pattern recognition, partial or complete

Signal	C	Complete pattern similitude for pair i, j in the section
	P	Partial pattern similitude for pair i, j in the section

1.4 Results

Table 1.6 shows the main conclusions found in the experiment results presented in Fig. 1.7. The nomenclature employed has been:

N means there is no pattern recognition.

- $Y, <, P$ means that there is a partial pattern recognition where signal i is smaller than signal j .

- $Y, >, P$ means that there is a partial pattern recognition where signal i is bigger than signal j .

- $Y, <, C$ means that there is a complete pattern recognition where signal i is smaller than signal j .

- $Y, >, C$ means that there is a complete pattern recognition where signal i is bigger than signal j .

- E, P means that both signals are almost identical but with minor differences.

- E, C means that both signals are identical.

Fig. 1.8 presents the results given in Table 1.5. It can be seen that employing d1 most of the temperatures at the structure, 96,43 %, can be detected, where only 1 case was not detected (Table 1.7). Studying other signals, the percentages of the temperatures detected decreased.

Fig. 1.7 Simplified statistics

Fig. 7. Statistics with all the possibilities studied.

Fig. 1.8 Statistics with all the possibilities studied**Table 1.6** Statistics with all the possibilities studied

	N	$Y, >, P$		$Y, <, C$		$Y, >, C$		$Y, <, C$		E, P		E, C		Total		
	Cases	%	Cases	%	Cases	%	Cases	%	Cases	%	Cases	%	Cases	%	Cases	%
a4	20	71,43	0	0,00	0	0,00	0	0,00	0	0,00	3	10,71	5	17,86	28	100
d4	22	78,57	0	0,00	0	0,00	0	0,00	0	0,00	3	10,71	3	10,71	28	100
d3	21	75,00	0	0,00	0	0,00	0	0,00	0	0,00	4	14,29	3	10,71	28	100
d2	13	46,43	0	0,00	3	10,71	0	0,00	0	0,00	5	17,86	7	25,00	28	100
d1	1	3,57	2	7,14	12	42,86	0	0,00	1	3,57	3	10,71	9	32,14	28	100

Table 1.7 Simplified statistics

	N		Y		Total	
	Cases	%	Cases	%	Cases	%
a4	20	71,43	8	28,57	28	100
d4	22	78,57	6	21,43	28	100
d3	21	75,00	7	25,00	28	100
d2	13	46,43	15	53,57	28	100
d1	1	3,57	27	96,43	28	100

1.5 Conclusions

The main conclusions are:

- (1) The second third, around the sample interval [5500, 8000], is the section of major interest for the environment temperature.

- (2) The best results have been found using the signal d_1 . Signal d_1 has lower percentages of energy. It is the high frequency component and provides more signs of identity.
- (3) Cases $Y,<, P$; $Y,>, P$; $Y,<, C$ and $Y,>,C$ have more interest. They are over 55 presented employing d_1 .
- (4) Mathematically, it is impossible to draw conclusions with signals 5 and 6 because they provide several errors, but in visually terms they report good behaviors, especially of the form $Y,>,P$.

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