Journal Paper

"Pattern recognition by wavelet transforms using macro fibre composites transducers"

Mechanical Systems and Signal Processing

Accepted 1 April 2014

Raúl Ruiz de la Hermosa González-Carrato
CUNEF-Ingenium Research Group, Colegio Universitario de Estudios Financieros, Madrid, Spain
raulruiz@cunef.edu

Fausto Pedro García Márquez
Ingenium Research Group, Universidad de Castilla-La Mancha
FaustoPedro.Garcia@uclm.es

Vichaar Dimlaye
NDT Technology Group, TWI – Technology Engineering, United Kingdom
vichaar.dimlaye@twi.co.uk

Diego Ruiz-Hernández
Ingenium Research Group, Universidad de Castilla-La Mancha
d.ruiz@cunef.edu

Cite as: de la Hermosa González, R. R., Márquez, F. P. G., Dimlaye, V., & Ruiz-Hernández, D. (2014). Pattern recognition by wavelet transforms using macro fibre composites transducers. Mechanical Systems and Signal Processing, 48(1), 339-350.

DOI: 10.1016/j.ymssp.2014.04.002

Pattern recognition by wavelet transforms using macro fibre composites transducers

Raúl Ruiz de la Hermosa González-Carrato [1], *Fausto Pedro García Márquez* [2], *Vichaar Dimlaye* [3] *and Diego Ruiz-Hernández* [1]

raulruiz@cunef.edu;
faustopedro.garcia@uclm.es;
vichaar.dimlaye@twi.co.uk;
d.ruiz@cunef.edu

[1] CUNEF-Ingenium Research Group, Colegio Universitario de Estudios Financieros, Madrid (Spain)
[2] Ingenium Research Group, University of Castilla-La Mancha, Ciudad Real (Spain)
[3] NDT Technology Group, TWI - Technology Engineering (United Kingdom)

Abstract

This paper presents a novel pattern recognition approach for a non-destructive test based on macro fibre composite transducers applied in pipes. A fault detection and diagnosis (FDD) method is employed to extract relevant information from ultrasound signals by wavelet decomposition technique. Wavelet transform is a powerful tool that reveals particular characteristics as trends or breakdown points. The FDD developed for the case study provides information about the temperatures on the surfaces of the pipe, leading to monitor faults associated to cracks, leaks or corrosion. This issue may not be noticeable when temperatures are not subject to sudden changes, but it can cause structural problems in the medium and long-term. Furthermore, the case study is completed by a statistical method based on the coefficient of determination. The main purpose will be to predict future behaviours in order to set alarms levels as part of a structural health monitoring system.

***Key words*:** Wavelet transforms, macro fibre composite transducers, pattern recognition, maintenance management

1. Introduction

The transport technology for gas and liquid elements is rising nowadays. Pipe degradation is induced by corrosion, decreasing the thickness of the pipe wall. Internal (material, shape, age, etc.) and external (temperature, weather or pressure) conditions lead the structural deterioration. The temperature is a key factor that affects to corrosion and erosion (McNeill *et al.*, 2002). Temperature changes are responsible for the detachment of pipe material, e.g. copper (Rushing *et al.*, 2004).

Pipelines require regular inspections to restore the damage and to replace the structure when it is inappropriate for operation (Castanier *et al*, 2006). Fault detection becomes a complicated task when pipelines are located in inaccessible places (Bhalla *et al.*, 2005; Liu *et al*., 2013). Traditional inspection may be accurate, but depends on training and other human factors; and have a detection threshold where corrosion is not measurable (Sahraoui *et al*., 2013). Automated systems have the advantage of reducing the human intervention, and help the worker to make decisions (Iyer *et al.*, 2012). Any maintenance program should include monitoring of pipes among their objectives (Anon., 2003). Erosion, corrosion and leakage may also represent hazards to pumps or valves that are connected to them.

The collection and analysis of data is the first step for a structural health monitoring (SHM) of pipes. Techniques include non-destructive tests (NDT) for condition monitoring. Different types are usually combined to provide more information about the status and characteristics of the structure under consideration (Lim *et al.*, 2013). Some of these methods are widespread e.g. visual inspection, but many others emerge slowly due to the necessity of highly skilled users controlling the equipment (Ogura *et al.*, 1986).

Thus NDT have become an essential tool during the lifecycle of many structures based on, for example, ultrasound signals or self-sensing impedance methods to detect structural damage in joints of pipelines, while Lamb approaches identify cracks and corrosion along the surface (Thien *et al*., 2008). In the field of acoustic emissions (AE), the online monitoring starts to be relevant and this type of NDT is used to detect micro cracks, delamination, fiber breaks in specific structures (Aljets, 2008). Therefore, monitoring pipelines from NDTs is a recurring topic in the literature; but researches tend to relate factors such as corrosion or fractures to stress situations (Elfergani *et al.*, 2013); and not many authors study the performance of the temperature (Lim *et al.*, 2013).

This paper introduces the wavelet methodology for the analysis of temperature using sensors based on macro fibre composites (MFC). There are not case studies using MFC transducers for the pipelines monitoring that link ultrasound and temperature, even when it has been shown that the use of certain transducers (electromagnetic acoustic transducers) is effective on the detection of corrosion and cracks if the results are discussed with the wavelet transform. It is also known that these sensors are sensitive to specific temperatures (Lee *et al.,* 2011); and their strategic placement, assures the monitoring of complex or inaccessible structures.

The case study attempts to verify that the ultrasonic signal provides information about the behaviour of the pipe from temperature and the relation to structural changes. This issue may not be noticeable when the temperature is not subject to sudden changes, but it can cause structural problems in the medium and long-term.

Section 2 provides an overview of the MFC and section 3 introduces the wavelet transform. Section 4 describes the case study, the techniques deployed, the pattern recognition method and the remarkable results. Finally, the last section presents the conclusions.

2. Macro Fibre Composites

There are different types of composites commercially available, e.g. metal matrix composites (Chou *et al.,* 1985), ceramic matrix composites (Naslain, 1998), active fibre composites (Birchmeier *et al.,* 2009) or MFCs. MFC is a polymeric matrix made of piezoceramic fibres (see Figure 1) embedded between phases of adhesive film with electrodes that transfer voltage to ribbon-shaped rods and vice versa (Cook *et al*., 2012). MFC is a composite technology originally developed at the NASA Langley Research Center (United States).

MFCs present a piezoelectric behaviour when there is a transformation of electronic impulses into ultrasonic waves. The impulses can turn into a voltage signal by pressure changes. By applying the voltage difference between the interdigitated electrodes, the piezoceramic fibers contract or expand converting electrical energy into mechanical. This feature enables the use of the MFC to produce movement, vibration or ultrasound.

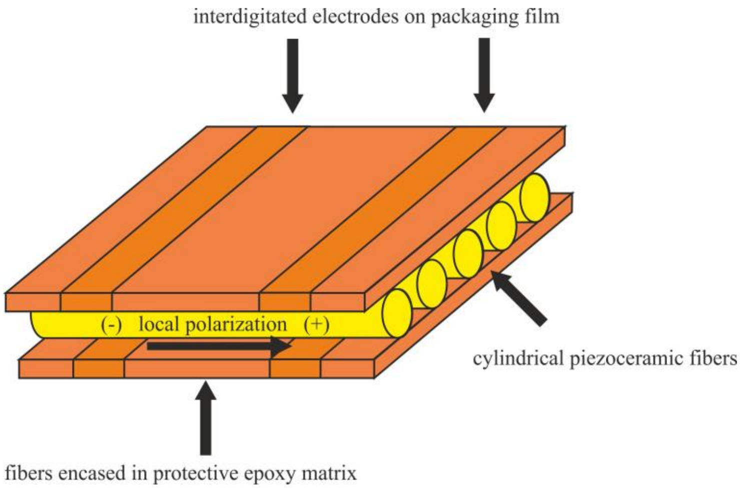


Figure 1. Section of the structure of a generic piezoceramic fibre composite.

They offer excellent qualities in performance and repeatability over traditional materials. The MFC does not introduce significant mass or stiffness when they are incorporated in structures; and the flexible nature of its matrix allows the material to adapt to complex surfaces. In addition, composite materials are a solution for almost all the limitations related to other type of piezoceramic structures (Ivanov, 2011), e.g. the vulnerability to accidental breakage in handling and bonding procedures, their inability to adapt to curved surfaces or the large add-on mass of the lead-based piezoceramic fibers (Sporn *et al*., 1999).

The emergence and establishment of MFCs has become essential in different areas of research and development due to its low cost and the adaptation to the environment. Recent studies analyse MFCs properties using periodic homogenization. The main purpose is to find local details or variations of their poling direction (Deraemaeker *et al*., 2010).

One of the most prominent MFC utilizations is linked to health monitoring systems and the evaluation of damages (Park *et al*., 2006; Hameed *et al*., 2009). MFC sensors are capable of recording AE and detecting damages (Eaton *et al*., 2009). Some vibration tests under optimal running conditions revealed that the monitoring and control can be done with a limited number of actuators, which reduces costs (Sohn *et al*., 2011). A special emphasis has been placed on the use of MFC for smart structures applied to trusses, steel frames or cable-stayed bridges (Song *et al*., 2006). Active controls to remove structural vibration have been developed using configurations from actuators for submarines (Caresta, 2011), aircrafts (Tang *et al.*, 2007), and pressure vessels (Lee *et al.*, 2005).

Besides all the features mentioned above, the choice of MFC for this case study is based on its ability to generate the ultrasonic signal necessary to analyse the performance of the pipe. The easy connection and operation also stand out as positive factors for its selection. Furthermore, its suitable performance has been demonstrated in different case studies related to the SHM. Finally, it must be taken into account that the sensor needs to be adapted to the surface where it is placed, since the placement is definitive due to the inaccessibility of the area to be monitored in many cases.

3. Wavelet transform

The wavelet transform is a tool applied to time and frequency domain analysis, e.g. with the use of a series of decomposition coefficients (Eristi, 2013). It decomposes the original signal into several components at different frequency bands. It leads to work with high and low frequencies, identifying spectral features, unusual temporary files, and lack of stationary and removing random noise (Dong *et al*., 2010). Wavelet transforms are commonly categorized as continuous wavelet transforms (CWT), discrete wavelet transforms (DWT) or wavelet packet transforms (PWT) (Table 1).

Table 1. Categorization of common wavelets.

Mother wavelet	$\Psi_{s,\tau}(t)=\left(\frac{1}{\sqrt{s}}\right)\Psi\left(\frac{t-\tau}{s}\right)$	s = scale factor τ = translational factor
CWT	$W_f(s,\tau)=\int f(t)\psi^*_{s,\tau}(t)dt$	
DWT	$W_f(i,j)=\frac{1}{\sqrt{2^i}}\int f(t)\psi^*\left(\frac{t-j2^i}{2^i}\right)dt$	$s = 2^i$ (scale factor) $\tau = j2^i$ (translational factor)
PWT	More filtering levels from DWT	

The most recurrent families of wavelet transforms are Haar, Daubechies or Symlet transforms. The selection of a particular family can be set by the application where the wavelet is introduced. Haar wavelets are the simplest orthonormal wavelets. They are considered as the Daubechies wavelets in its simplest form (Hariharan *et al.,* 2010). Daubechies wavelets are the most used wavelets, representing the foundations of wavelets signal processing. Daubechies wavelets lead more accurate results in comparison to other families (Patil *et al.*, 2011; Genovese *et al.*, 2008). Symlet wavelet transform is an orthogonal wavelet defined by a low pass filter (Arora *et al.*, 2011).

Wavelet transform has been implemented on pipes for the filtering and signal processing by the technique of ground penetrating radar (GPR). This technique analyses the state of pipes below the ground (Ni *et al.*, 2010). For offshore pipelines, the monitoring is necessary regardless of the technique employed (Peng *et al.*, 2013). Researches for the detection of leaks in plastic pipes from AE signals (Ahadi *et al*., 2010), cracks (Ye *et al*., 2010) or evaluation of the corrosion on non-accessible pipes can be found (Acciani *et al.,* 2010). Crack initiation studies based on temperatures are expected to be helpful for improvements in material design or maintenance issues (Redhead *et al.,* 2013). When the temperatures are high or low, the mechanical characteristics of pipes are modified (Cole *et al.*, 2012). The detection of anomalies is critical to find solutions in earlier stages of deterioration.

Before the selection of an adequate wavelet transform, the choices of the Short-Time Fourier Transform or the Fast Fourier Transform were discarded for the purpose of this study. The signal processing by these transforms implies limitations of resolution in time and frequency; and involves loss of information (Jia *et al*., 2003; Morsi *et al*, 2010).

Among the remaining options, the PWT is also not considered. The PWT is an extension of the DWT with a larger number of filtering levels. Likewise the case of multilevel filters for the DWT, its use is recommended for complex signals, where additional information is obtained per every new level (Aktas *et al*., 2010). However, increasing the number of filters does not entail a significant improvement for the results in this research while the required computational cost is high.

CWT has difficulties to evaluate high amount of integrals. This implies an information redundancy, but on the other hand CWT is enough flexible to adapt to situations where DWT does not give a satisfactory result. The use of the DWT allows direct application to computational processes, being the main advantage for its selection since all the signal processing will be done with computer software focused on discrete analysis.

The family of wavelets chosen was Daubechies in a symmetric mode (Daubechies, 1988). It has been done due to Daubechies is a family of orthogonal and smooth basis wavelets characterized by a maximum number of vanishing moments. It leads to achieve satisfactory results (Balakrishnan *et al*., 2012). Kim and others suggest up to five levels of decomposition in their case study (Kim *et al.*, 2013). These levels are a linear combination of all the frequency components for the original signal and their sum results in the original signal. Nevertheless, different families and levels of decomposition were tested and results did not differ significantly.

4. Fault Detection and Diagnosis using MFCs transducers

4.1. Case study

The use of composites for FDD of pipes will lead to the detection of faults/failures in pipes. The objective of this paper is to extract conclusions related to the temperature using MFC transducers and to develop a FDD method based on wavelet transforms. This method is an efficient alternative to the placement of thermometers due to the sensitivity of composite materials (Konka et al., 2013). As stated in Section 1, this will define the performance of any structural problem in the medium and long-term

22 experiments were recorded at random dates by the NDT Technology Group during 6 months in order to observe the behaviour of the pipe in an extended period of time (Table 2). The measured temperatures are under environmental conditions to ensure a resemblance to the working performance of this type of structures in operation facilities. 17 of the 22 signals were finally selected by the NDT Technology Group for the study. Temperature data was not successfully stored in the rest of cases so that the temperature-behaviour relation was not possible to be determined.

Table 2. Temperatures.

Date (DD/MM)	20/06	22/06	24/06	27/06	29/06	04/07	06/07	15/07	18/07
Temperature (ºC)	22.96	20.10	25.00	31.63	20.96	25.00	20.26	24.36	20.33
Date (DD/MM)	08/08	10/08	16/08	15/09	27/09	14/10	13/12	18/01	
Temperature (ºC)	21.96	24.06	20.50	22.10	13.66	17.73	7.16	10.43	

The data captured by the transducers was an ultrasound signal. Then, they were saved by the monitoring system employing an excitation AC voltage (V) signal at high frequency (30 kHz). The frequency has been set according to the information that is needed, and therefore the samples are obtained. Every signal had 11321 samples with a samling frequency of 10^6 samples/s. The proposed sample selection includes all the important information that is obtained up to 8000 samples for the case study. The signal contains a series of reflections and echoes from that point. A larger signal just adds the attenuation of the ultrasonic pulse, which does not involve the collection of relevant data. This is a standard information that depends on the system monitored (dimensions, material, etc.). The sensors (*R1A*, *R1B*, *R1C* and *R1D*) were located as is shown in Figure 2 and separated 90 degrees. The objective is to analyse the overall performance of the pipeline. The pipe had a diameter of 20.32 cm and a length of 9 m.

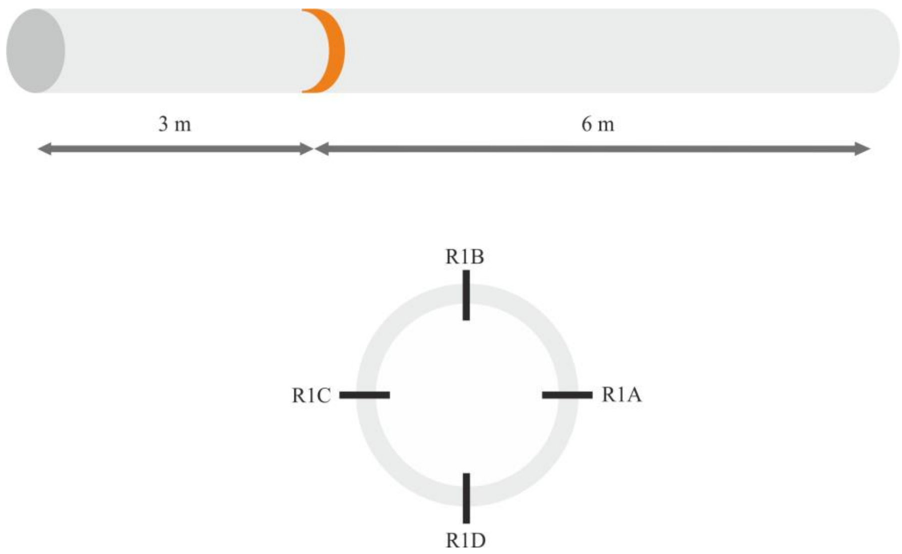


Figure 2. MFC transducers set on a pipe.

Figure 3 represents an example of the sum for the signals stored by the four sensors. A study of correlations shows that the signals collected by the four transducers are highly correlated between them with only uncorrelated noise effect (see an example in Table 3). A matrix of p-values for testing the hypothesis of no correlation is also included. Each p-value is the probability of getting a correlation as large as the observed value by random chance, when the true correlation is zero. It was assumed that if p-value is smaller than 0.05, then the correlation is significant.

Table 3. Correlation of sensors at 25ºC.

	Correlations					p-values			
	S1	S2	S3	S4		S1	S2	S3	S4
S1	1	0.6974	0.8686	0.6761	S1	1	0.0000	0.0000	0.0000
S2	0.6974	1	0.7948	0.8484	S2	0.0000	1	0.0000	0.0000
S3	0.8686	0.7948	1	0.6792	S3	0.0000	0.0000	1	0.0000
S4	0.6761	0.8484	0.6792	1	S4	0.0000	0.0000	0.0000	1

4.2. Pattern recognition approach and results

Ultrasound detects any discontinuity or deformation produced on the surface and shape changes will be associated to structural changes of the pipe. The pulses were basically longitudinal wave modes with a speed of 5400 m/s. The pulse-echo along the surface of the pipe is also shown in Figure 3.

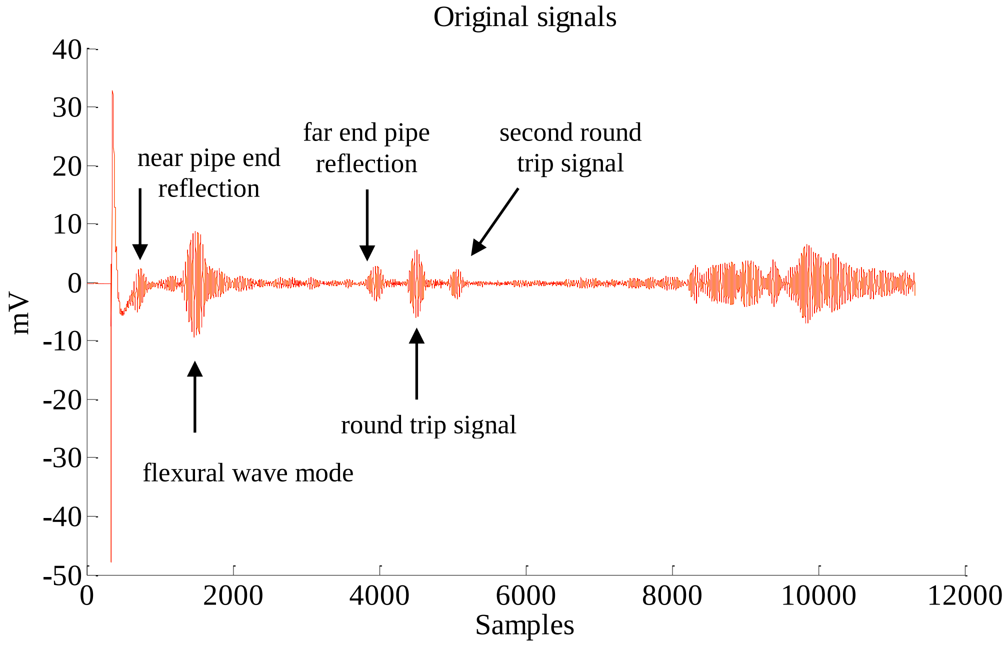


Figure 3. Voltage vs. samples.

Changes on the surface of the pipe lead to changes of the signal shape (Figure 3). Therefore, knowing the speed signal transmission and the sampling frequency, any structural modification can be determined and located. An initial algorithm has been created to compare the signal shapes in order to find these changes. It was proved that the original ultrasonic signals were not sensitive enough to temperature modifications under normal conditions.

A pattern recognition is established from a MATLAB™ code where signals are compared in pairs to take into account the full range of temperatures of the case study. This model works by finding differences in the signal amplitudes for each pair. When these differences in amplitude are constant, then a pattern recognition can be found. This must be understood as a surface modification at a particular temperature (Lee *et al.*, 2008).

Table 4 identifies the occurrence of a pattern, where: *Y* means that the pair of signals is similar in shape but not in amplitude; *N* is for the cases where pattern recognition does not exist (signals are completely different) and; *E* states that signals are similar in shape and amplitude with a high degree of accuracy. Table 5 complements the *Y* option, providing the information of the signal with the biggest amplitude. Finally, Table 6 describes if the pattern recognition is found for the complete signal or just in certain sections. According to the explanation above, cases in the form *Y*,<,*P*, *Y*,>,*P*, *Y*,<,*C* or *Y*,>,*C* will be sought.

Table 4. Pattern recognition.

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

Table 5. Amplitude.

Signal amplitude	>	Amplitude i > Amplitude j
	<	Amplitude i < Amplitude j

Table 6. Degree of similitude.

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

Table 7 shows the possible combinations within the pattern recognition.

Table 7. Pattern recognition.

Heading	Pattern recognition

N	No pattern recognition
Y,<,P	Partial pattern recognition where signal *i* is smaller than signal *j*
Y,>,P	Partial pattern recognition where signal *i* is bigger than signal *j*
Y,<,C	Complete pattern recognition where signal *i* is smaller than signal *j*
Y,>,C	Complete pattern recognition where signal *i* is bigger than signal *j*
E, P	Signals are almost identical but with minor differences in amplitude
E,C	Signals are almost identical in shape and amplitude

Data is divided in three parts to obtain detailed results: the start-up, a stabilised second phase and an irregular third phase. These three parts can be distinguished visually in Figure 4.

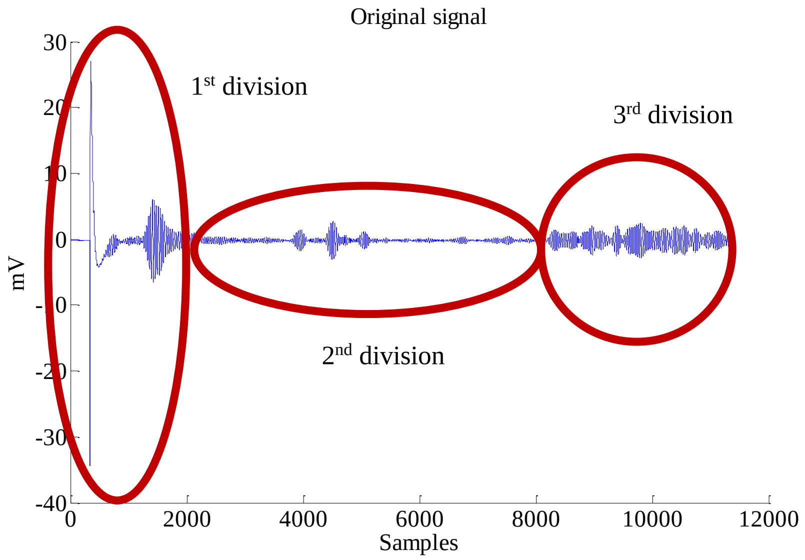


Figure 4. Voltage vs. samples.

Figures 5a, 5b and 5c correspond to three zoomed comparisons of ultrasound. Each graphic compares the contour of two signals. It is observed that the shape is similar but the amplitude differs in 5a (*Y,<, P* or *Y,>,P*). Second graphic is for an *E,C* or *E,P* case because the amplitude and the shape resembles, while there is no similarity in 5c. Figure 5d plots the amplitude differences of signals represented in 5a, 5b and 5c. Amplitude differences are close to zero and constant for 5a and 5b but noticeable where it is not possible to find a pattern recognition (Figure 5d).

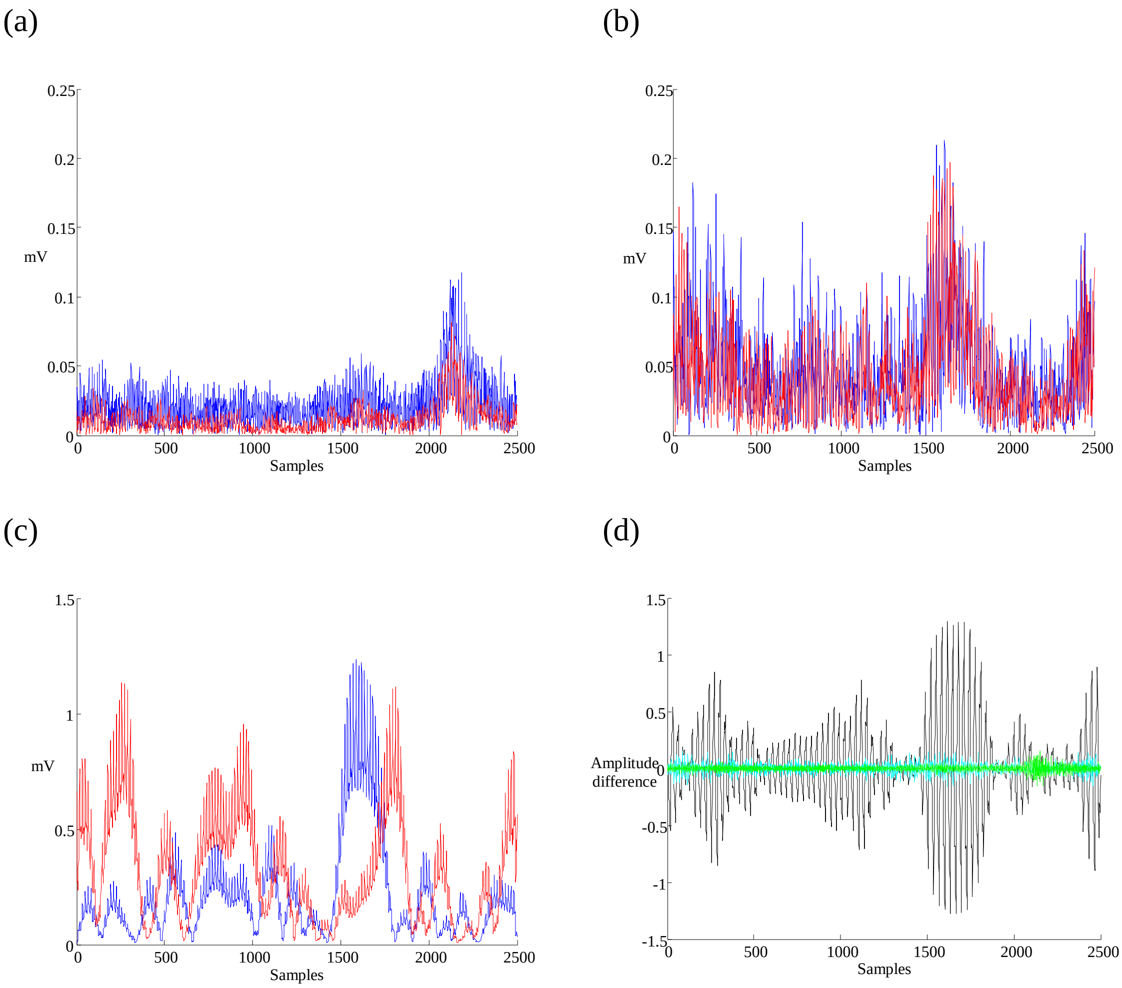


Figure 5. Pattern recognition.

The results of the pattern recognition are shown in Table 8 considering all possible combinations. In summary, the possibility of finding shape changes cannot be determined correctly with the original signals.

Table 8. Results of the initial graphical pattern recognition.

Pattern	**Amount**	**% per specific case**	**% pattern**
E,C	219	31.60	89.47
E,P	401	57.87	
Y,<,C / Y,>,C	0	0	0
Y,<,P / Y,>,P	0	0	
N	73	10.53	10.53
Total of comparisons	693	100	100

Once the similarity has been verified, the next step is to demonstrate that choosing the appropriate frequency range it is possible to draw conclusions from the changes in amplitude and, therefore, there is a relationship with temperature changes.

Signals are decomposed in five levels employing the Daubechies wavelet family (a_4, d_4, d_3, d_2 and d_1) (Figure 6). This choice is determined from several experiments confirming that more than five levels do not provide more accurate information, and computational complications linked to the large amount of data can appear. The approximated decomposition is a_4, and is considered as the low frequency component while d_1 is the high frequency component. The analysis of any signal in levels allows the extraction of detailed features (usually given by d_1 or d_2). All decompositions have an energy rate based on the Parseval's energy theorem (Gaing, 2004) that is presented as in the equation (1):

$$\sum_{t=0}^{N-1} \left| x(t) \right|^2 = \frac{1}{N} \sum_{f=0}^{N-1} \left| A_j(f) \right|^2 + \sum_{j \le J} \left[\frac{1}{N} \sum_{f=0}^{N-1} \left| D_j(f) \right|^2 \right] \quad (1)$$

where $x(t)$ is a signal in the time domain, N is the sampling period and the input signal is defined from approximation a_4 and detailed levels d_4, d_2, d_1 and d_2. This first approach discloses how the energy is split among the divisions (Table 9).

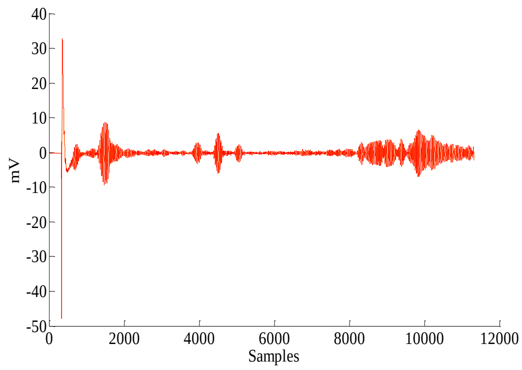
Table 9. Energy rates per signal.

	a_4	d_4	d_3	d_2	d_1
1	28,38	33,19	21,64	9,94	6,85
2	29,81	30,43	23,62	8,19	7,95
3	25,9	35,38	22,65	7,59	8,48
4	29,28	31,76	20,14	10,02	8,8
5	26,12	31,79	26,7	9,25	6,14
6	24,91	32,18	25,03	12,46	5,42
7	25,38	33,49	24,27	9,95	6,91
8	24,29	29,78	24,04	14,1	7,79
9	27,63	27,95	23,09	15,38	5,95
10	25,2	31,06	17,97	19,12	6,65
11	26,09	30,73	23,82	12,33	7,03
12	28,98	29,2	16,01	18,97	6,84
13	31,27	30,44	19,69	11,67	6,93
14	23,95	29,65	21,31	17,42	7,67
15	29,96	30,27	22,95	11,07	5,75

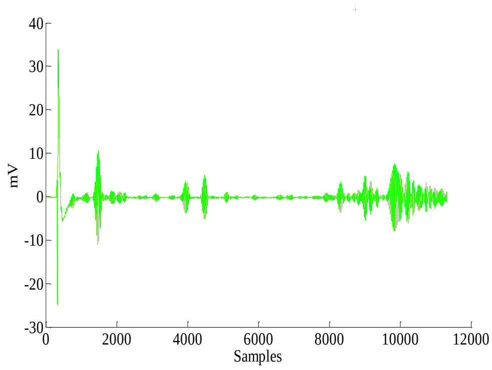
16	23,15	33,67	21,03	14,41	7,74
17	22,97	33,12	23,46	14,06	6,39

Second section will be the segments of interest. It corresponds to operating conditions. First section is irregular and involves a lot of randomness due e.g. to start-ups, stray signals from adjacent MFCs or coupling. Such phenomena are often found at the first samples; and do not provide valuable information of the overall behaviour of the pipe. Something similar is found in the third segment with the appearance of the echoes and reflections.

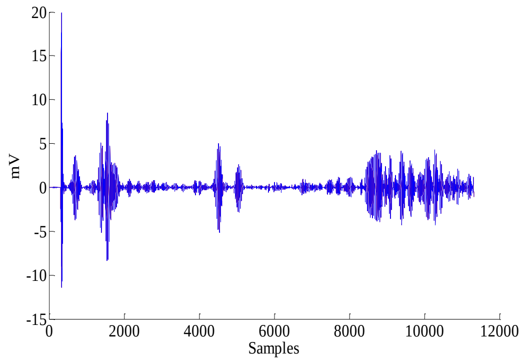
(a)



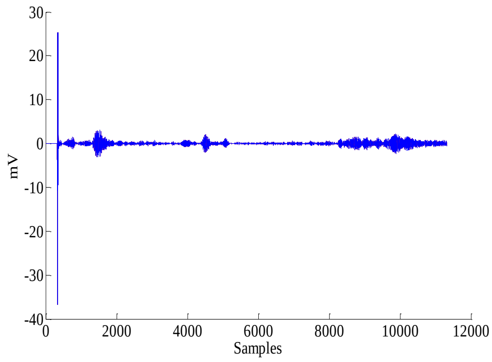
(b)



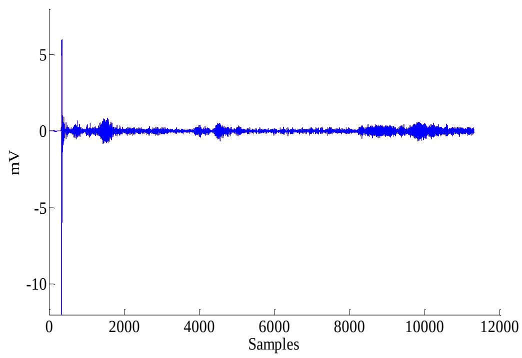
(c)



(d)



(e)



(f)

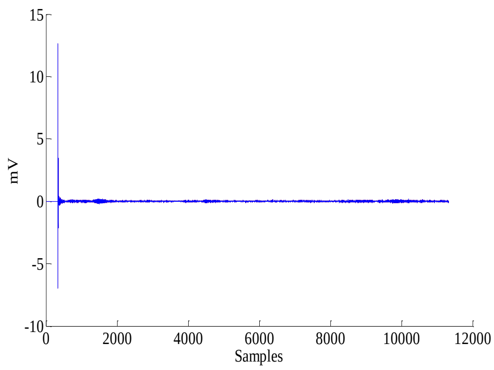


Figure 6. (a) Original signal, (b) mother or main wavelet, (c) d_4 decomposition, (d) d_3 decomposition, (e) d_2 decomposition and (f) d_1 decomposition.

The graphical pattern recognition is repeated. It is observed that the variation of the temperature and its relation with the behaviour of the pipe can be determined from amplitude changes in d_1 and d_2. The possible results can be considered as acceptable as they are comprised between the 15% and the 25% of the total energy depending on the case, taking into account the weight of these decompositions based on the energy ratios described in Table 8. These decompositions provide better results and even patterns *Y,<,P; Y,>,P; Y,<,C or Y,>,C* will be found (Table 10). The *Y,>,P* and *Y,<,P* cases are the 8.65% of the total cases for d_1 decomposition, while *Y,>,P* and cases are the 1.3% of the total cases for d_2. From a_4 to d_3 the patterns are similar to the original, being *N* patterns undesirable because of the randomness.

Table 10a. Results of the graphical pattern recognition for the first part.

	1st part									
	a_4		d_4		d_3		d_2		d_1	
	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
N	17	7.36	20	8.66	20	8.66	0	0	0	0
Y,<,P / Y,>,P	0	0	0	0	0	0	0	0	0	0
Y,<,C / Y,>,C	0	0	0	0	0	0	0	0	0	0
E, P	161	69.70	45	19.48	27	11.69	34	14.72	31	13.42
E, C	53	22.94	166	71.86	184	79.65	197	85.28	200	86.58
Total	231	100	231	100	231	100	231	100	231	100

Table 10b. Results of the graphical pattern recognition for the second part.

	2nd part									
	a_4		d_4		d_3		d_2		d_1	
	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
N	33	14.29	28	12.12	16	6.93	2	0.87	2	0.87
Y,<,P / Y,>,P	0	0	0	0	0	0	0	0	5	2.16
Y,<,C / Y,>,C	0	0	0	0	0	0	0	0	0	0
E, P	106	45.89	123	53.25	67	29	39	16.88	33	14.29
E, C	92	39.83	80	34.63	148	64.07	190	82.25	191	82.68
Total	231	100	231	100	231	100	231	100	231	100

Table 10c. Results of the graphical pattern recognition for the third part.

	3rd part									
	a_4		d_4		d_3		d_2		d_1	
	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
N	23	9.96	22	9.52	21	9.09	18	7.79	17	7.36
Y,<,P / Y,>,P	0	0	0	0	0	0	3	1.30	15	6.49
Y,<,C / Y,>,C	0	0	0	0	0	0	0	0	0	0
E, P	134	58.01	153	66.23	20	8.66	9	3.90	6	2.60
E, C	74	32.03	56	24.24	190	82.25	201	87.01	193	83.55
Total	231	100	231	100	231	100	231	100	231	100

A statistical study provides more findings on the performance of ultrasounds. This study complements the results from the pattern recognition. The lowest temperature will be taken as the reference signal for this part of the case study. This reference will be related to the remaining signals, so that conclusions can be extracted from the increases in temperature. A linear regression is performed to evaluate the reference and each ultrasound data. The outputs of the algorithm used are the fitted values, the output forecast, the standard deviation, the estimated recursive coefficients, and the coefficient of determination (R^2) adjusted for degrees of freedom. The main purpose of R^2 is to predict future results or to test a hypothesis. The coefficient determines the quality of a model to replicate the results, such that the proportion of variation in results can be explained by the model. Therefore, this factor will be selected for the analytical measurement.

The original condition and the detailed decompositions are chosen in order to demonstrate the improvement of the method in Figure 7, where the coefficients of determination for two original ultrasounds and their decomposition d_1 (above) and d_2 (below) are shown. It is observed that R^2 has a rising trend when appropriate levels are chosen and contrasted with the random behaviour of the original ultrasound, although this slight increasing trend was noticed in all cases. Furthermore, it is noteworthy that the R^2 values increase when frequencies decrease.

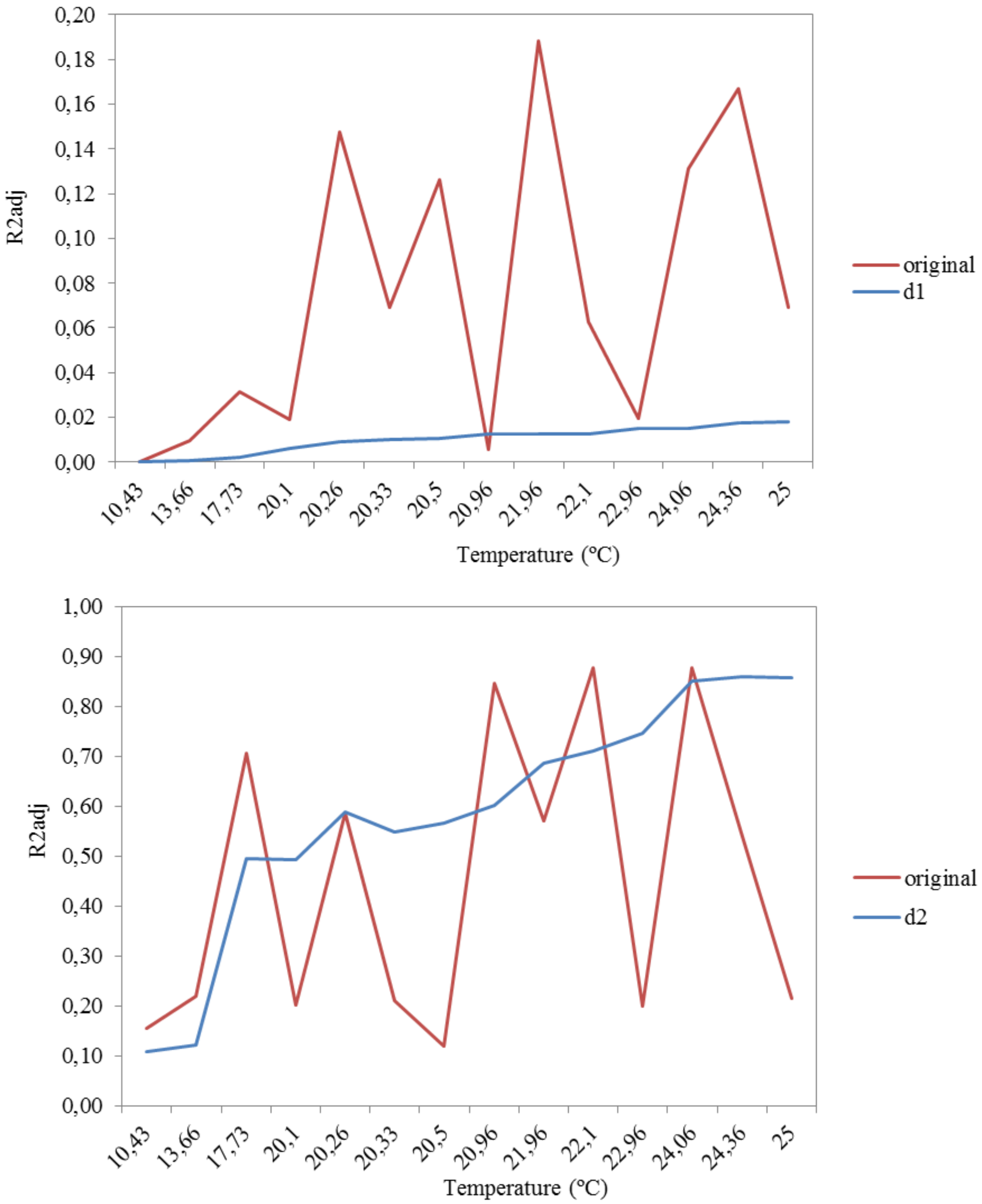


Figure 7. Original vs. d_1 and d_2 coefficients of determination.

Figure 8 plots the coefficient of determination for previous cases d_1 and d_2 along with their trends in form of a quadratic equation. A big adjustment is appreciated in cases where data is between 20ºC and 25°C.

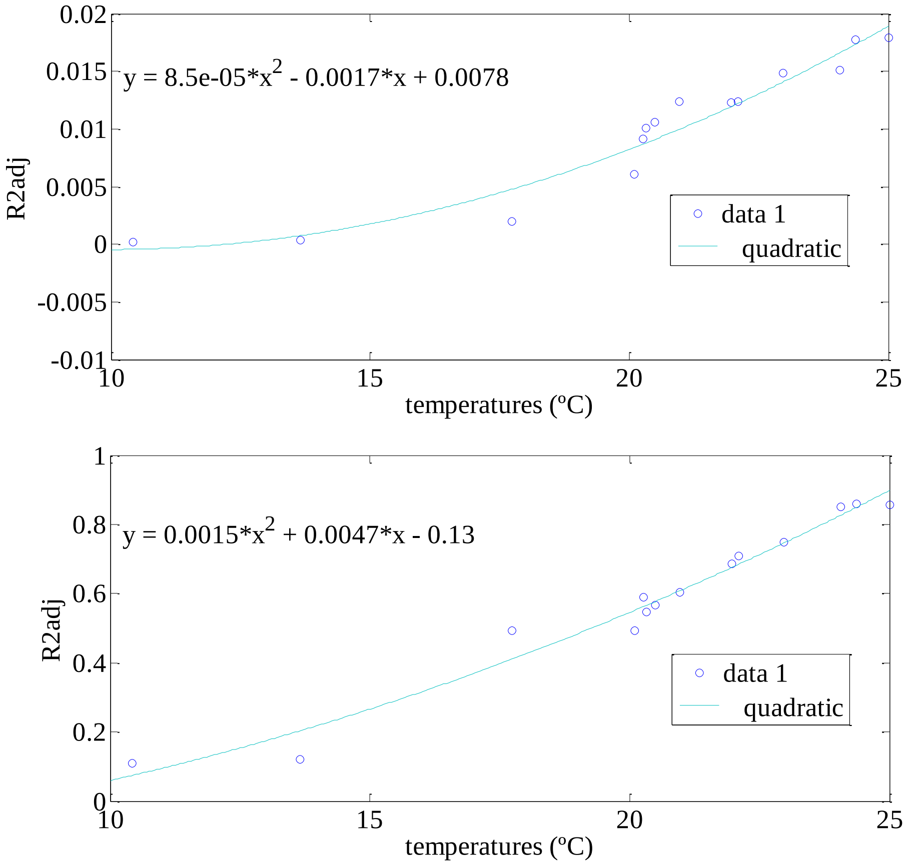


Figure 8. Trends for d_1 (above) and d_2 (below) coefficients of determination.

This ensures the monitoring of pipelines in operating conditions for the range of temperatures considered (from 7.16ºC to 31.63ºC) with a high frequency filter. The wavelet transform can be proposed to find a pattern recognition in cases where the original signals are quite similar regardless of the temperature. On the other hand, being able to adjust the performance of the pipe to an equation, an alarm system that links amplitude changes with superficial changes from R^2 can be generated.

5. Conclusions

This paper presents a novel pattern recognition approach for non-destructive tests as part of a structural health monitoring for pipes. The temperature is a key factor to solve problems related to cracks, leaks or corrosion as they can modify the characteristics of pipelines.

Pipes have been analysed using 4 MFC transducers. The strategic placement of the sensors assures the quality of the monitoring system. An algorithm based on the wavelet transform is designed for Fault Detection and Diagnosis. These signals are converted into voltage and compared to observe the relation with their temperature.

Data are analysed from different signals for the initial pattern recognition; considering that the normal conditions take place in the second section. It has been shown that the wavelet transform is enough sensitive to small changes in shape and amplitude with the selection of a suitable frequency (d_1 and d_2 levels), finding a relation between the temperature and the performance of the pipe.

An additional quantitative study supports the initial results from the pattern recognition. Selecting a reference temperature, conclusions can be extracted from increases in temperature. A linear regression is performed from an algorithm that provides, among others outputs, a coefficient of determination for each pair of signals studied. The main purpose is to predict future trends and set an alarm system as part of the SHM.

In summary, the wavelet transform is able to study the behaviour of signals from their temperatures, even when they are quite similar, searching differences in their amplitudes and anticipating future structural faults/failures.

References

[1] Acciani, G.; Brunetti, G.; Fornarelli, G.; Giaquinto, A., 2010. *"Angular and axial evaluation of superficial defects on non-accessible pipes by wavelet transform and neural network-based classification".* Ultrasonics. Vol. 50. Issue 1. pp. 13-25.

[2] Ahadi, M.; Bakhtiar, M. S., 2010. *"Leak detection in water-filled plastic pipes through the application of tuned wavelet transforms to acoustic emission signals".* Applied Acoustics, Vol. 71. Issue 7. pp. 634-639.

[3] Aktas, M.; Turkmenoglu, V., 2010. *"Wavelet-based switching faults detection in direct torque control induction motor drives".* Science, Measurement and Technology. Vol. 4. Issue 6. pp. 303-310.

[4] Aljets, D.; 2008. "*Intelligent Structural Health Monitoring (SHM) of Composite Aircraft Structures using Acoustic Emission (AE) sensor*". Faculty of Advanced Technology. Department of Engineering, University of Glamorgan, Pontypridd, United Kingdom.

[5] Anon., 2003. *"Plant analysis a fresh look at pipe maintenance and repair"*. World Pumps. Vol. 2003. Issue 437. pp. 37-39.

[6] Arora, R.; Sharma, L.; Birla, N.; Bala, A., 2011. *"An algorithm for image compression using 2D wavelet transforms"*. International Journal of Engineering Science & Technology. Vol. 3. Issue 4. pp. 2758-2764.

[7] Balakrishnan, S.; Cacciola, M.; Udpa, L.; Rao B. P., Jayakumarm, T.; Raj, B., 2012. "Development of image fusion methodology using discrete wavelet transform for eddy current images". NDT & E International. Vol. 51. pp. 51-57.

[8] Bhalla, S.; Yang,Y.W.; Zhao, J.; Soh, C.K., 2005. *"Structural health monitoring of underground facilities - Technological issues and challenges".* Tunnelling and Underground Space Technology. Vol. 20. Issue 5. pp. 487-500.

[9] Birchmeier, M.; Gsell, D.; Juon, M.; Brunner, A.J.; Paradies, R.; Dual, J., 2009. *"Active fiber composites for the generation of Lamb waves".* Ultrasonics. Vol. 49. Issue 1, pp. 73-82.

[10] Caresta, M., 2011. *"Active control of sound radiated by a submarine in bending vibration"*. Journal of Sound and Vibration. Vol. 330. Issue 4. pp. 615-624.

[11] Castanier, B.; Rausand, M., 2006. *"Maintenance optimization for subsea oil pipelines"*. International Journal of Pressure Vessels and Piping. Vol. 83. Issue 4. pp. 236-243.

[12] Chou, T.W.; Kelly, A.; Okura, A., 1985. *"Fibre-reinforced metal-matrix composites".* Composites. Vol. 16. Issue 3. pp. 187-206.

[13] Cole, I. S.; Marney, D., 2012. *"The science of pipe corrosion: A review of the literature on the corrosion of ferrous metals in soils".* Corrosion Science. Vol. 56. pp. 5-16.

[14] Cook, A. C.; Vel, S. S., 2012. *"Multiscale analysis of laminated plates with integrated piezoelectric fiber composite actuators".* Composite Structures. Vol. 94. Issue 2. pp. 322-336.

[15] Daubechies, I., 1988. *"Orthonormal bases of compactly supported wavelets".* Communications on Pure and Applied Mathematics. Vol. 41. pp. 909-996.

[16] Deraemaeker, A.; Nasser, H., 2010. *"Numerical evaluation of the equivalent properties of macro fiber composite (MFC) transducers using periodic homogenization"*. International Journal of Solids and Structures. Vol. 47. Issue 24. pp. 3272-3285.

[17] Dong, Y.; Shi, H.; Luo, J.; Fan, G.; Zhang, C., 2010. *"Application of wavelet transform in MCG-signal denoising"*. Modern Applied Science. Vol. 4. Issue 6. pp. 20-24.

[18] Eaton, M.; Pullin, R.; Holford, K.; Evans, S.; Featherston, C.; Rose, A., 2009. *"Use of macro fiber composite transducers as acoustic emission sensors"*. Remote Sensing. Vol. 1. Issue 2. pp. 68-79.

[19] Elfergani, H. A.; Pullin, R.; Holford, K.M, 2013. *"Damage assessment of corrosion in prestressed concrete by acoustic emission".* Construction and Building Materials. Vol. 40. pp. 925-933.

[20] Eristi, H., 2013. *"Fault diagnosis system for series compensated transmission line based on wavelet transform and adaptive neuro-fuzzy inference system"*. Measurement. Vol. 46. Issue 1. pp. 393-401.

[21] Gaing, Z. L., 2004. *"Wavelet-based neural network for power disturbance recognition and classification".* IEEE Transactions on Power Delivery. Vol. 19. Issue 4. pp. 1560-1568.

[22] Genovese, L.; Neelov, A.; Goedecker, S.; Deutsch, T.; Ghasemi, S.; Willand, A.; Caliste, D.; Zilberberg, O.; Rayson, M.; Bergman, A.; Schneider, R., 2008. *"Daubechies wavelets as a basis set for density functional pseudopotential calculations"*. Journal of Chemical Physics. Vol. 129. Issue 1, pp. 104-109.

[23] Hameed, Z.; Honga, Y. S.; Choa, Y. M.; Ahnb, S. H.; Song, C. K., 2009. *"Condition monitoring and fault detection of wind turbines and related algorithms: A review"*. Renewable and Sustainable Energy Reviews. Vol. 13. Issue 1. pp. 1-39.

[24] Hariharan G.; Kannan, K., 2010. *"Haar wavelet method for solving FitzHugh Nagumo equation"*. International Journal of Computational & Mathematical Sciences. Vol. 4. Issue 6. pp. 281-285.

[25] Ivanov, I. V., 2011. *"Finite element analysis and modelling of active fiber composites including damages"*. Computational Materials Science. Vol. 50. Issue 4. pp. 1276-1282.

[26] Iyer, S.; Sinha, S. K.; Tittmann, B. R.; Pedrick, M. K, 2012. *"Ultrasonic signal processing methods for detection of defects in concrete pipes"*. Automation in Construction. Vol. 22. pp. 135-148.

[27] Jia, M.; Wang, Y., 2003. *"Application of wavelet transformation in signal processing for vibrating platform"*. Journal of Shenyang Institute of Technology. Vol. 22. Issue 3. pp. 53-55.

[28] Kim, K-B.; Hsu, D. K.; Barnard, D. J., 2013. *"Estimation of porosity content of composite materials by applying discrete wavelet transform to ultrasonic backscattered signal"*. NDT & E International. Vol. 56. pp. 10-16.

[29] Konka, H. P.; Wahab, M. A.; Lian, K., 2013. *"Piezoelectric fiber composite transducers for health monitoring in composite structures"*. Sensors and Actuators A: Physical. Vol. 194. pp. 84-94.

[30] Lee, H-S.; Yoon, J-H.; Park, J-S.; Yi, Y-M., 2005. *"A study on failure characteristic of spherical pressure vessel"*. Journal of Materials Processing Technology. Vol. 164–165. pp. 882-888.

[31] Lee, T-H.; Choi, I. H.; Jhang, K. Y., 2008. *"Single-mode guided wave technique using ring-arrayed laser beam for thin-tube inspection".* NDT&E International. Vol. 41. Issue 8. pp. 632-637.

[32] Lee, J-R.; Chong, S. Y.; Jeong, H.; Kong, C-W., 2011. *"A time-of-flight mapping method for laser ultrasound guided in a pipe and its application to wall thinning visualization".* NDT & E International. Vol. 44. Issue 8. pp. 680-691.

[33] Lim, M. K.; Cao, H., 2013. "Combining multiple NDT methods to improve testing effectiveness". Construction and Building Materials. Vol. 30. pp. 1310-1315.

[34] Lim, H.J.; Sohn, H.; DeSimio M. P.; Brown, K., 2013. *"Reference-free fatigue crack detection using nonlinear ultrasonic modulation under various temperature and loading conditions".* Mechanical Systems and Signal Processing. In Press.

[35] Liu, Z.; Kleiner, Y., 2013. *"State of the art review of inspection technologies for condition assessment of water pipes".* Measurement. Vol. 46. Issue 1. pp. 1-15.

[36] McNeill, L.S.; Edwards, M., 2002. *"The importance of temperature in assessing iron pipe corrosion in water distribution systems".* Environmental Monitoring and Assessment. Vol. 77. Issue 3. pp. 229-242.

[37] Morsi, G. W.; El-Hawary, M.E., 2010. *"Novel power quality indices based on wavelet packet transform for non-stationary sinusoidal and non-sinusoidal disturbances"*. Electric Power Systems Research. Vol. 80. Issue 7. pp. 753-759.

[38] Naslain, R.R., 1998. *"The design of the fibre-matrix interfacial zone in ceramic matrix composites".* Composites Part A: Applied Science and Manufacturing. Vol. 29, Issues 9-10. pp. 1145-1155.

[39] Ni, S-H.; Huang, Y-H.; Lo, K-F.; Lin, D-C., 2010. *"Buried pipe detection by ground penetrating radar using the discrete wavelet transform"*. Computers and Geotechnics. Vol. 37. Issue 4. pp 440-448.

[40] Ogura, S.; Koga, K.; Takahashi, F.; Ozaki, N., 1986. "*Development of an ultrasonic inspection system using array transducers*". Nuclear Engineering and Design, Vol. 94. Issue 3. pp. 367-391.

[41] Park, G.; Farrar, C.; Lanza di Scalea F.; Coccia, S., 2006. *"Performance assessment and validation of piezoelectric active-Sensors in structural health monitoring"*. Smart Materials and Structures. Vol. 15. Issue 6. pp. 1673-1683.

[42] Patil, S.; Kasturiwala, S.; Dahad, S.; Jadhav, C., 2011. *"Wavelet tool: Application for human face recognition"*. International Journal of Engineering Science & Technology. Vol. 3. Issue 3. pp. 2392-2398.

[43] Peng, X-L.; Hao, H.; Li, Z-X.; Fan, K-Q., 2013. *"Experimental study on subsea pipeline bedding condition assessment using wavelet packet transform"*. Engineering Structures. Vol. 48. pp. 81-97.

[44] Redhead, A.; Frank, A.; Pinter, G., 2013. *"Investigation of slow crack growth initiation in polyethylene pipe grades with accelerated cyclic tests"*. Engineering Fracture Mechanics. Vol. 101. pp. 2-9.

[45] Rushing, J.C.; Edwards, M., 2004. *"The role of temperature gradients in residential copper pipe corrosion"*. Corrosion Science. Vol. 46. Issue 8. pp. 1883-1894.

[46] Sahraoui, Y.; Khelif, R.; Chateauneuf, A., 2013. *"Maintenance planning under imperfect inspections of corroded pipelines"*. International Journal of Pressure Vessels and Piping. Vol. 104. pp. 76-82.

[47] Sohn, J. W.; Choi, S.; Kim H. S., 2011. *"Vibration control of smart hull structure with optimally placed piezoelectric composite actuators"*. International Journal of Mechanical Sciences. Vol. 53. Issue 8. pp. 647-659.

[48] Song, G.; Sethi, V.; Li H. N., 2006. *"Vibration control of civil structures using piezoceramic smart materials: A review"*. Engineering Structures. Vol. 28. Issue 11. pp. 1513-1524.

[49] Sporn, D.; Schoenecker, A., 1999. *"Composites with piezoelectric thin fibers. First evidence of piezoelectric behavior"*. Material Research Innovations. Vol. 2. Issue 5. pp. 303-308.

[50] Tang, X.; Tao, G.; Joshi, S. M., 2007. *"Adaptive actuator failure compensation for nonlinear MIMO systems with an aircraft control application"*. Automatica. Vol. 43. Issue 11. pp. 1869-1883.

[51] Thien, A. B.; Chiamori, H. C.; Ching, J. T.; Wait, J. R.; Park, G., 2008. *"The use of macro-fiber composites for pipeline structural health assessment"*. Structural Control and Health Monitoring. Vol. 15. Issue 1. pp. 43-63.

[52] Ye, J.; He, Y.; Chen, X.; Zhai, Z.; Wang, Y.; He, Z., 2010. *"Pipe crack identification based on finite element method of second generation wavelets"*. Mechanical Systems and Signal Processing. Vol. 24. Issue 2. pp. 379-393.