

# SPARSE SIGNAL MODEL FOR ULTRASONIC NONDESTRUCTIVE EVALUATION OF CFRP COMPOSITE PLATES

Nicolas Bochud<sup>1</sup>, Angel M. Gomez<sup>2</sup>, Guillermo Rus<sup>1</sup> and Antonio M. Peinado<sup>2</sup>

<sup>1</sup>Dpt. of Structural Mechanics, Universidad de Granada,

Politécnico de Fuentenueva, 18071 Granada, Spain, {nbochud,grus}@ugr.es

<sup>2</sup>Dpt. of Signal Theory, Networking and Communications, and CITIC-UGR, Universidad de Granada,  
Campus de Fuentenueva, 18071 Granada, Spain, {amgg,amp}@ugr.es

## ABSTRACT

Signal processing has been proven to be a useful tool to characterize damaged materials under ultrasonic nondestructive evaluation. In this work, we hypothesize that the transfer function of multilayered materials for a through-transmission configuration can be represented as a classical all-pole model with sparse coefficients. To test this hypothesis, we propose an analysis-by-synthesis scheme which, by assuming an underlying sparse digital signal model of the specimen, infers the order and extent of the model parameters corresponding to a certain impact damage level. Then, we exploit the sparse structure of the obtained digital filter for practical NDE applications, with emphasis on impact damage identification of carbon-fiber reinforced polymer plates.

**Index Terms**— Signal processing, sparse signal modeling, all-pole filter, non-destructive evaluation, ultrasonics

## 1. INTRODUCTION

Carbon-fiber reinforced polymers (CFRP) are high performance advanced materials with a growing applicability due to their extreme strength-to-weight and rigidity-to-weight efficiency ratios. One of the major concerns associated with composites is their vulnerability to impact damage, which may occur in the phase of manufacturing, service or maintenance. During an impact the fibers absorb part of the energy and distribute some of the load through the laminate thickness. This excess of energy may lead to delamination, sub-surface matrix cracking, fiber-matrix debonding and fiber fracture [1], which in turn can induce severe degradation in the residual material mechanical properties, while remaining invisible from the surface. Thus, non-destructive evaluation (NDE) techniques are required to discriminate between the different failure mechanisms in composites and to guarantee their reliability. Among them, ultrasonics are currently one of the most frequently used NDE techniques that have been proven to provide effective results at relatively low cost for the purpose of identifying and quantifying CFRP laminates impact damage [2].

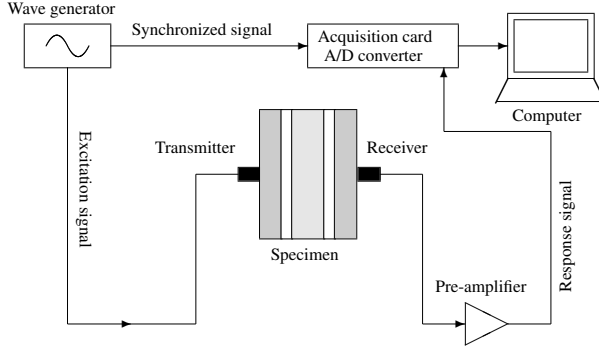
Due to their structural complexity, composites require special treatment in ultrasonic signal interpretation. The random nature of the signal generation, the imperfections of the acquisition system, as well as the difficulties in understanding ultrasonic echoes motivate the use of signal processing techniques [3]. Thus, an essential element in NDE systems is the analysis of the captured signal, by

means of a robust parameter extraction, to obtain relevant information from the tested specimen. First work devoted to ultrasonic NDE of materials focused on deconvolution [4], and on filtering techniques for noise reduction [5]. Later developments in this field have been successfully extended to advanced materials, such as composites. In particular, the cepstrum has been used for ultrasound signal characterization due to its deconvolution properties [6, 7]. Other related proposals dealt with the extraction of wavelet coefficients for ultrasonic NDE of composite material structures [8]. Recently, the split spectrum processing (SSP) technique and the expectation-maximization (EM) algorithm have been proposed for their ability to resolve echoes associated with delaminations in CFRP detected by ultrasonic methods [9]. However, most of the aforementioned studies deal with the simple detection of damages. Thus, the final step of the system is limited to a binary classification between damaged/undamaged states. This consumes a huge amount of experimental data and requires an expensive training process, but does not provide any quantification of the damage level and location. Moreover, most of the signal processing techniques are applied in an heuristic way, without bridging the extracted parameters to the material properties.

This study presents a digital signal model  $H(z)$  to characterize the specimen being tested. An important point of this proposal is to provide a model with a small number of parameters, since low complexity models are desirable for fast, practical and accurate NDE systems. To this end, we assume that the model parameters have a particular sparse distribution, which may be inherently related to the material's mechanical and geometrical properties, and thus to its health state. This hypothesis is based on the conclusions from our previous work [10], where we introduced two different digital signal models based on a simplified physical analysis of the ultrasonic wave propagation inside a CFRP plate. Results showed that cepstra extracted from these models, in which coefficients were distributed at several lags, were more discriminative than other spectral estimation methods. In the present work, we propose an analysis-by-synthesis scheme, which compares the predicted signals with the ones obtained from laboratory experiments conducted on a CFRP plate [11]. In such a way, by means of a minimization procedure, we obtain the optimal order and extent of the model parameters, and thus show that a sparse signal model may be a useful tool to model wave propagation phenomena in multilayered materials. To our knowledge, our study draws for the first time a parallel between sparse signal modeling and its applications to ultrasonic NDE signal processing.

The remainder of the paper is organized as follows: Section 2 outlines the main aspects of the proposed methodology. Section 3

Thanks to the Consejería de Economía, Innovación y Ciencia de la Junta de Andalucía (Spain) through Projects P08-TIC-03911 and P11-CTS-8089 for funding.



**Fig. 1.** Experimental configuration of the excitation-propagation-measurement system.

presents the results obtained from the analysis-by-synthesis stage, and validates them with a damage recognition experiment, while Section 4 discusses the feasibility of this modeling, concluding with ongoing work issues.

## 2. MATERIAL AND METHODS

The proposed methodology consists of three elements: The (1) signal acquisition of the ultrasonic signals obtained from the wave interactions with a CFRP plate, a (2) sparse signal model that idealizes the ultrasound-composite interactions, and is solved by the Prony's method, and an (3) analysis-by-synthesis scheme, which is used to predict the optimal coefficient positions corresponding to a certain damage level.

### 2.1. Experimental setup

The specimen tested is a CFRP symmetric plate that consists of five layers. Damages were generated by applying several free-fall impact energies (0.388, 0.674, 1.313, 2.280, and 5.385 Joules) [11], varying the mass and height of each impactor to obtain five relevant damage locations. The specimen was excited by a low-frequency ultrasonic sine-burst at a central frequency of 5 MHz, consisting of one cycle of  $0.2 \mu\text{s}$  and 5 Vpp amplitude. This excitation signal was generated by an arbitrary wave generator (Agilent 33220). The response signals were registered during  $10 \mu\text{s}$ , that is, up to the time for which there were no more reflections from the specimen/transducers interfaces. The response signals were sampled with a high resolution A/D converter after 40 dB pre-amplification stage, applying a sampling frequency of  $F_s = 200 \text{ MHz}$ , providing  $N = 2000$  samples, which were uniformly quantized with 12 bits.

Initially, the response signal was measured at the undamaged location for calibration. Then, the measurement procedure was repeated  $N_r = 10$  times on each location (labeled from 0 to 5), to generate a relevant data set that accounts for the uncertainties due to the variability of the transducers alignment with respect to the impact location. Each of these measurements corresponds to the resulting average of 300 captures of the signal, providing an effective reduction of noise for the detected response signal, increasing the signal-to-noise ratio around 25 dB. Figure 1 depicts the experimental setup used to register the ultrasonic signals.

### 2.2. Sparse signal model

In this work, we propose a digital signal model for wave propagation in multilayered materials. A through-transmission configuration is adopted, representative of the successive reflections that suffer the transmitted signal between layers and specimen/transducers interfaces. In first place, the through-transmission configuration is considered as a discrete-time linear system. Thus, the material under investigation can be represented by a transfer function, which relates the discrete excitation and response signals [12]. Our proposal extends the intuitive physics-based all-pole signal model proposed by Fuentes *et al.* [10], solely inspired by concepts drawn from signal theory. In [10], the authors presented a simplified analysis of the complex wave propagation pattern within the plate, and showed that the model of the damaged specimen could be improved by including a fixed virtual interface which introduces a middle-term and long-term predictor, along with the typical short term predictor, in the transfer function. This model can effectively account for the multiple transmissions/reflections due to the multilayered structure and the damage. This sparse-like distribution of the model coefficients is exploited in our proposal.

However, it must be considered that the structural complexity of the material suggests that flaws may occur at different locations, and that a single virtual interface cannot account for all possible failure mechanisms. Moreover, a fixed interface does not respond to the phenomena associated with crack propagation due to increasing damage energies. Thus, it is reasonable to assume that a multilayered material can be modeled with a sparse transfer function, whose prediction coefficients behave dynamically, depending upon its damage state. We thus assume that the discrete-time transfer function  $H(z)$ , which represents a multilayered composite material in a through-transmission configuration, can be represented by a delayed classical all-pole filter with sparse coefficients,

$$H(z) = \frac{bz^{-M}}{1 + \sum_{k=1}^p a_k z^{-k}} \quad (1)$$

where most of the coefficients  $a_k$  are zeros. The polynomial order  $p$  of the denominator is  $2M$ , where  $M$  corresponds to a sample delay equivalent to the time needed by the incident wave to cross the total thickness of the multilayered structure [10]. As experimentally observed, the numerator consists of a gain  $b$  plus a total thickness-equivalent sample delay  $M$ .

### 2.3. Analysis-by-synthesis scheme

The final goal of NDE systems is to provide consistent damage information that characterizes the specimen health state. Our proposal suggests that the underlying mechanical properties of the specimen are inherently associated to the sparse prediction coefficients  $a_k$  of the denominator in Equation (1). Thus, one may assume that damage will affect those coefficients both in amplitudes and positions. Provided the coefficient position vector  $\mathbf{k}$ , Prony's method allows us to obtain the optimal amplitudes for a filter with a given input/output signals. Unfortunately, there is no method that provides both optimal positions and amplitudes. Thus, we apply an analysis-by-synthesis scheme to find the values of the coefficient position vector  $\mathbf{k}$  that best fit the experimental response signals  $y^{(C)}(n)$ , as depicted in Figure 2.

Given the transfer function  $H^{(C)}(z)$  corresponding to a certain damage class  $C \in [0 - 5]$ , the excitation signal  $x(n)$  applied to the

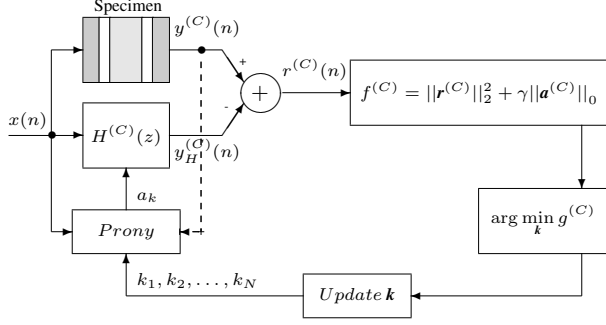


Fig. 2. Analysis-by-synthesis scheme for a damage class  $C$ .

specimen can be filtered, resulting in an approximation  $y_H^{(C)}(n)$  of the experimental response signal  $y^{(C)}(n)$  measured from the specimen, and corresponding to the same damage class  $C$ . Generally, the model coefficients are found such that the 2-norm of the residual  $r(n)$  (the difference between the observed signal and the predicted one) is minimized. In this case, since  $H^{(C)}(z)$  is an all-pole filter with sparse coefficients, we can reasonably assume that the optimal predictor is not the one that only minimizes the 2-norm but the one that also leaves the fewest non-zero prediction coefficients, i.e. the sparsest one. Sparsity is often measured as the cardinality, that is the so-called 0-norm [13, 14]. Thus, the specimen can be analyzed by defining a modeling error (or energy) in terms of the mean squared error between the actual response signal  $y^{(C)}(n)$  and the modeled response  $y_H^{(C)}(n)$ , plus a sparsity term that accounts for the number of non-zeros coefficients in the transfer function,

$$f^{(C)} = \|r^{(C)}\|_2^2 + \gamma \|a^{(C)}\|_0 \quad (2)$$

where  $\gamma$  is an empirical regularization term, defined so that the modeling error due to the sparsity term corresponds to a certain amount of the least squared error. It is noteworthy that setting  $\gamma = 0$  leads to a standard linear prediction form. To account for all the  $N_r$  measurement repetitions within a damage class  $C$ , a slightly different cost functional  $g^{(C)}$  is introduced as,

$$g^{(C)} = \frac{1}{N_r} \sum_{i=1}^{N_r} f_i^{(C)} \quad (3)$$

Then, the parameters  $\mathbf{k}$  that characterize the coefficient positions are found by a search algorithm that minimizes the cost functional  $g^{(C)}$ ,

$$\hat{\mathbf{k}} = \arg \min_{\mathbf{k}} g^{(C)} \quad (4)$$

Binary genetic algorithms [15] are applied to minimize Equation (4), and provide the analysis-by-synthesis optimal solution.

### 3. EXPERIMENTAL RESULTS

#### 3.1. Analysis-by-synthesis solutions

This section presents the results obtained from the analysis-by-synthesis stage for the optimal position  $\mathbf{k}$  of the prediction coefficient vector  $\mathbf{a}$  corresponding to each damage class  $C$ . In order to reduce part of the noise and focus on the frequency band of interest, the experimental response signals  $y(n)$  have been previously decimated to  $F_s = 25$  MHz (250 samples). For the specimen tested,

the resulting thickness equivalent sample delay is  $M = 14$ . The simulations have been performed for a wide range of regularization terms  $\gamma \in [3 - 8] \cdot 10^{-5}$ . Table 1 summarizes the optimal results.

As can be observed, the coefficient position vector  $\mathbf{k}$  changes slightly from one damage level to the next one. Some coefficients vanish and/or appear at new positions, due to the symmetry break of the plate structure. It is worth to point out that diagonal patterns which appear along increasing damage levels (e.g. from positions 13 to 18 and from 16 to 21) may be related to wave velocity reductions, i.e. to stiffness reduction of the specimen layers. Unfortunately, a direct physical interpretation from the  $a_k$ -domain is not easily assessable.

#### 3.2. Damage recognition experiment

To evaluate the discriminative capability of the proposed model, a set of experiments have been carried out. For this task, a damage recognition system based on cepstral distances is developed. As in [10, 16], each experiment has been previously preprocessed with a Hamming window of 250 samples in the time-domain. The tested techniques employ the real cepstrum  $c(n)$ , which is defined as,

$$\log |H(\omega)| = \sum_{n=-\infty}^{\infty} c(n) e^{j\omega n} \quad (5)$$

where  $H(\omega)$  is the spectrum estimate obtained from the signal model. Precisely, the way the spectrum is estimated characterizes each applied technique. Thus, the approach called *Real cepstrum* consists of using the periodogram obtained directly from the windowed signal, and corresponds to our baseline (i.e. non-parametric technique). The technique labeled as *LPC cepstrum* is based on the use of a standard all-pole model with order  $p = 28$ , as described in our previous works [10, 16]. Finally, the method named *Dynamic cepstrum* is based on the sparse signal model described by Equation (1), and whose coefficient positions  $\mathbf{k}$  were determined according to the optimal results depicted in Table 1.

For an optimal use of the available data set, the training/test is performed using the *leaving-one-out* technique. Therefore, 9 signals are used to train a reference cepstral vector corresponding to a certain damage level, while the remaining signal is used for test. Rotating the measurements enables us to train the system always with 9 signals, while testing is performed over  $6 \times 10 = 60$  signals. The performance of the system is measured through a weighted error factor. Let the results of the test be a confusion table  $R(i, j)$ , with  $i, j = 1, \dots, 6$ , where  $R(i, j)$  represents the number of measurements at damage level  $i$  that have been classified as a damage level  $j$ . The weighted error factor is then defined as,

$$w_{err}[\%] = 100 \times \frac{\sum_{i=1}^6 \sum_{j=1}^6 R(i, j) \cdot \frac{|i-j|}{3}}{60} \quad (6)$$

Thus, when the erroneously recognized class corresponds to a damage close to that of the correct class, the error has less influence on the error rate. Table 2 shows the results obtained for the different cepstrum-based techniques, along with our proposal. As can be observed, minimal weighted and absolute errors (1.67 % and 3 %, respectively) are obtained with the dynamic approach. It is also worth to note that a sparse modeling, with a lower number of parameters, has a better discriminative capability than classical spectrum estimation approaches.

Damage level	$a_k$ -coefficient positions																												NZ
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	
Damage 0																													15
Damage 1																													15
Damage 2																													14
Damage 3																													13
Damage 4																													14
Damage 5																													19

**Table 1.** Analysis-by-synthesis optimal solution for the positions of the non-zero coefficients  $a_k$  (indicated by grey cells), along with the number of non-zero (NZ) coefficients ( $\gamma = 6e - 5$ ).

Cepstrum-based techniques	Number of non-zero $a_k$	$w_{err}$ [%]	err [%]
Real cepstrum	—	8.33	23.33
LPC cepstrum	28	2.00	6.67
Dynamic cepstrum	13 – 19	1.67	3

**Table 2.** Classification errors for different cepstrum-based techniques.

#### 4. CONCLUSIONS

This study shows the capability of a sparse signal modeling to discriminate the damage level of a CFRP plate subjected to different impact energies. First, an analysis-by-synthesis scheme has been proposed, to infer the order and extent of the model parameters corresponding to a certain impact damage level. Then, the performance of the proposed parametrization has been evaluated by a system based on cepstral distances that recognizes the specific damage level corresponding to a given test signal, leading to the following conclusions: (1) It has been demonstrated that modeling the complex wave propagation pattern using a sparse transfer function provides better results than other classical spectrum estimation techniques. (2) It has been shown that the prediction coefficients behave dynamically, depending upon the damage state of the material. Ongoing works may include a further study of the relation between the sparse prediction coefficients and the underlying material mechanical properties, in order to provide a consistent quantification of the damage parameters.

#### 5. REFERENCES

- [1] A. Ruosi, M. Valentino, G. Peluso, and G. Pepe, "Analysis of low-velocity impact damage in reinforced carbon fiber composites by hts-squid magnetometers," *IEEE Transactions on Applied Superconductivity*, vol. 11, no. 1, pp. 1172–1175, 2001.
- [2] Q. Shen, M. Omar, and S. Dongri, "Ultrasonic nde techniques for impact damage inspection on cfrp laminates," *Journal of Materials Science Research*, vol. 1, no. 1, pp. 1–15, 2012.
- [3] S. C. Wooh and I. M. Daniel, "Enhancement techniques for ultrasonic nondestructive evaluation of composite materials," *Journal of Engineering Materials and Technology*, vol. 112, pp. 175–182, 1990.
- [4] S.K. Sin and C.H. Chen, "A comparison of deconvolution techniques for the ultrasonic nondestructive evaluation of materials," *IEEE Transactions on Image processing*, vol. 1, pp. 3–10, 1992.
- [5] N. Bilgutay, J. Popovics, S. Popovics, and M. Karaoguz, "Recent developments in concrete nondestructive evaluation," in *Proceedings of IEEE ICASSP*, 2001, vol. 6, pp. 3393–3396.
- [6] S.C. Wooh and C. Wei, "Cepstrum-based deconvolution of ultrasonic pulse-echo signals from laminated composite materials," in *Proceedings of the 12<sup>th</sup> Engineering Mechanics Conference, ASCE*, 1998, pp. 1–4.
- [7] K. Harrouche, J.M. Rouvaen, M. Ouafoutou, M. Ourak, and F. Haine, "Signal-processing methods for analysing the structure of carbon-epoxy-resin composite," *Measurement Science and Technology*, vol. 11, pp. 285–290, 2000.
- [8] S. Legendre, J. Goyette, and D. Massicotte, "Ultrasonic nde of composite material structures using wavelet coefficients," *NDT&E International*, vol. 34, pp. 31–37, 2001.
- [9] A. Benammar, R. Draï, and A. Guessoum, "Detection of delamination defects in cfrp materials using ultrasonic signal processing," *Ultrasonics*, vol. 48, pp. 731–738, 2008.
- [10] B. Fuentes, J. L. Carmona, N. Bochud, A. M. Gomez, and A. M. Peinado, "Model-based cepstral analysis for ultrasonic non-destructive evaluation of composites," in *Proc. of IEEE ICASSP*, Kyoto, March 2012, pp. 1717–1720.
- [11] A.A. Fahim, R. Gallego, N. Bochud, and G. Rus, "Model-based damage reconstruction in composites from ultrasound transmission," *Composites Part B: Engineering*, vol. 45(1), pp. 50–62, 2012.
- [12] F. Häggglund, J. Martinsson, and J. E. Carlson, "Model-based estimation of thin multi-layered media using ultrasonic measurements," *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, vol. 56, no. 8, pp. 1689–1702, 2009.
- [13] D. Giacobello, M.G. Christensen, M.N. Murthi, S.H. Jensen, and M. Moonen, "Sparse linear prediction and its applications to speech processing," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol. 20, no. 5, pp. 1644–1657, 2012.
- [14] J. Koloda, A.M. Peinado, and V. Sánchez, "Speech reconstruction by sparse linear prediction," *Advances in Speech and Language Technologies for Iberian Languages*, pp. 247–256, 2012.
- [15] D. Goldberg, "Genetic algorithms in search, optimization and machine learning," 1989.
- [16] N. Bochud, A. M. Gomez, G. Rus, J. L. Carmona, and A. M. Peinado, "Robust parametrization for non-destructive evaluation of composites using ultrasonic signals," in *Proc. of IEEE ICASSP*, Prague, May 2011, pp. 1789–1792.