On the use of Recurrence Quantification Analysis for Signal Modality Characterization: two applications

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Abstract

The characterization of the signals in terms of linear/nonlinear and deterministic/stochastic nature may be appropriated for knowledge extraction and machine learning algorithms. Some real-world signals exhibit signal modality characteristics that are strongly related with the physical mechanisms involved in the production of them. As an example, we can mention how the resonant sounds are more predictable than the vibrating sounds, or how the determinism of ultrasonic scans decreases as the porosity of scattering materials increases. In these situations the use signal modality derived parameters may have an easier interpretation than frequency or statistical derived parameters. In this work, we have chosen the Recurrence Plots and the Recurrence Quantification Analysis as a feasible alternative to extract signal modality information. We have successfully applied this technique in a couple of situations: characterization of maritime mammals calls, and measuring the porosity of materials by means of ultrasonic inspection.

Keywords: Signal processing, Signal modality characterization, Nonlinear analysis, Recurrence Plots, Recurrence Quantification Analysis.

1. Introduction

Signal modality characterization is an emerging and interdisciplinary field that tries to address the problem of detecting the presence of underlying nonlinear generation mechanisms in a given signal. This is mainly produced by deterministic chaos or by stochastic nonlinear dynamical systems. The study of these phenomena has been avoided during many years and yet it is a common practice to model such processes using suboptimal, but mathematically tractable models. However, an adequate detection and characterization of the nonlinear and deterministic nature of the signal can convey important information in a large number of situations such as: early symptoms of epileptic detection with EEG signals [1], nonlinear phenomena in mammalian voice production [2], stock market predictability [3], etc.

Many different authors have work on this topic employing different techniques. One of the first and most used methods is the surrogate data bootstrapping method. It basically consists on comparing a test statistic computed for an original time series and for an ensemble of surrogate data [4], which are data artificially generated in a way that mimics most of the characteristics in the original signal. The null hypothesis is that the surrogate data may be a typical realization of the same system generating the original signal. If the test statistic fails to validate the null hypothesis, then the data in test is very likely to differ in signal modality. Care must be taken when using surrogate data to ensure that statistical differences come from the desired characteristic and not from an undesired one, such as a failure of the surrogate algorithm to mimic non-stationary data.

Different kinds of surrogate generation algorithms have been devised depending on the feature being studied: linearity [5, 6], stationarity, determinism, chaos, etc. Surrogate data generation algorithms for testing linearity are the well-known AAFT and iAAFT, surrogate data generation algorithms for testing pseudo-periodic or oscillating time series are the PPS [7], and the TSS [8] and even surrogate data generation algorithms which test

The Recurrence Plots has proven to be a valuable data visualization and analysis tool in the study of complex dynamical systems.

fluctuations and trends in the data have been developed, SSS [9]. Some of the most sophisticated statistical measures applied in linear analysis are: the Kaplan's δ-ε method [10], the Deterministic Versus Stochastic plots [11], or the Delay Vector Variance (DVV) [12].

A recently new approach for signal modality characterization consists in the use of the Recurrence Plots (RP) as well as the Recurrence Quantification Analysis (RQA). The RP has proven to be a valuable data visualization and analysis tool in the study of complex, time-varying dynamical systems in a large number of disciplines such us: biology, neuroscience, engineering, finance, geosciences, etc. Recently it has been demonstrated that one of the aforementioned techniques for signal modality characterization (the DVV) can be formulated using RP concepts [13]. This opens new horizons to achieve a better analysis of the signal modality and to develop new nonlinearity tests based on the RP and RQA.

In this work, the RP tool is introduced as well as some examples of its application on real signals. In particular, signal modality analysis based on RP has been applied on marine mammals vocalizations (Section 3) and non-destructive materials inspections (Section 4).

2. Recurrence Plots

The RP representation of a time series $x(t)$ was firstly introduced by Eckmann et al. (1987). Further variations of the RP have been proposed, but one of the most commonly used can be formulated as follows. Let $x(t)$ be the time series of duration N. We can obtain the Delay Vector (DV) at instant i for an embedding dimension m and a time lag τ as:

$$\mathbf{x}(i)=[x(i),\, x(i+\tau),\, x(i+2\cdot\tau),\ldots,\, x(i+(m-1)\cdot\tau)] \quad (1)$$

The distance plot (DP) can be computed by taking a norm among all possible combinations of the DVs.

$$DP(i,j)=\|\mathbf{x}(i)-\mathbf{x}(j)\|,\quad \mathbf{x}(i)\in\Re^m, i,j=1,\ldots, N\text{-}m\cdot\tau \quad (2)$$

We have used in this work $\|\cdot\|$ as the L2-norm. Some authors also call this plot the global recurrence plot. Using $DP(i,j)$ the RP can be computed as:

$$RP(i,j)=\Theta(\varepsilon\text{-}DP(i,j)) \quad (3)$$

Where $\Theta(\cdot)$ is the Heaviside step function and ε is a given recurrence threshold. Among some other advantages, the RP representation maps the phase space diagram in $\Re^m$ into $\Re^2$. This offers a better way to analyse complex systems independently of the embedding dimension. The recurrence of states, or times when the phase space trajectory visits roughly the same area, are indicated as black points in the RP. As a result of that, the underlying dynamical system can be analysed/characterized by measuring the number and duration of recurrences. The Figure 1 panel (A) shows a fragment of the space trajectory representation of the Rössler system (in blue). The Figure 1 panel (B) shows the RP representation of the fragment of the Rössler system. In this panel, the black dots indicate that two states are within a given distance ε (computed using a given norm). When two trajectories run parallel to each other for a given number of states it produces diagonal lines in the RP. The red and green regions in the Figure 1 illustrate this idea.

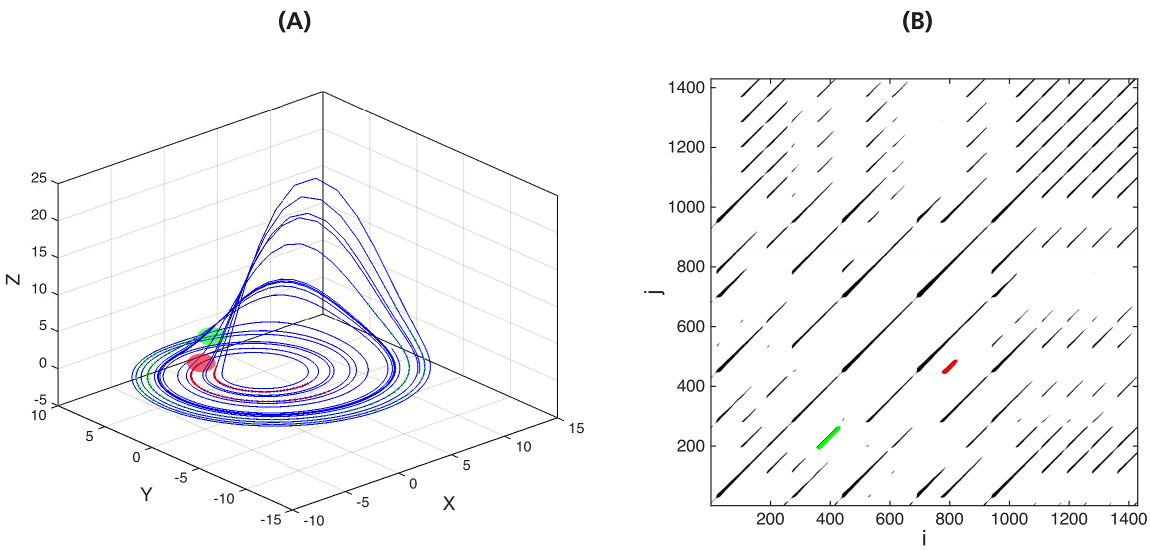


Figure 1. (A) Segment of the phase space trajectory of the Rössler system (for standard parameters b=0.2) by using its three components and (B) its corresponding recurrence plot. The points in a trajectory in (A) that run parallel within a ε distance are mapped as diagonal black lines in (B). Here we have highlighted two regions in red and green colours to illustrate this idea.

2.1. Structures in Recurrence Plots and Recurrence Quantification Analysis

The initial purpose of RPs is the visual inspection of higher dimensional phase space trajectories. The view on RPs gives hints about the time evolution of these trajectories. The advantage of RPs is that they can also be applied to rather short and even non-stationary data.

The RPs exhibits characteristic large-scale and small-scale patterns. The large-scale patterns can reveal information about homogeneity, periodicity, etc. The small-scale patterns (the texture) is formed by single dots, diagonal lines, vertical and horizontal lines. The presence of single dots occurs if the states are rare, if they do not persist for any time or if they fluctuate heavily. However the presence of diagonal lines occurs when a segment of the trajectory runs parallel to another segment. The length of this diagonal line is determined by the duration of such similar local evolution of the trajectory segments. Finally the presence of a horizontal (or vertical) line marks a time length in which a state does not change or changes very slowly. These small-scale structures are the base of the quantitative analysis of the RPs (RQA).

Among all the different measures of recurrences that compose the RQA, there is one that will be of special interest in the described applications: the percentage of points which form diagonal lines. As we have stated, the appearance of diagonal lines implies similar evolution of states at different times, which could indicate that the process is deterministic. This can be quantified as the percentage of recurrence points that form diagonal lines (DET):

$$DET = \frac{\sum_{l=l_{min}}^{N} l \cdot P(l)}{\sum_{i,j}^{N} RP(\mathrm{i,j})} \tag{4}$$

Where $P(l)$ is the histogram of the lengths l of the diagonal lines and l_{min} is the minimum length the diagonal needs to have to be considered a proper diagonal line (typically l_{min}=2).

The identification of the mechanism that generates the sound can also be addressed using signal modality characterization through the study of the structures appearing in the Recurrence Plots.

3. Signal modality application to the characterization of maritime mammals calls.

The study of the way cetaceans produce their sounds is a complex field of study. Evolution has provided maritime mammals with highly sophisticated sound production organs specially adapted to make underwater sounds. The knowledge of these organs and how they work is a key factor to understand the different repertory of sounds and what they use the different sounds for. This knowledge has been partially achieved for a limited number of species (toothed whales) and it is still an open field.

In a very summarized way, Norris and colleagues [14] showed that the sounds were generated by a source above the face of the dolphins, this discovery was later corroborated by Diercks [15], using a set of hydrophones to locate the sound source in a location inside the nostril. It was Cranford in [16] who identified a homologous anatomical structure in a wide range of species toothed. This structure was called "*Monkey-Lips-Dorsal-Bursa*" (MLDB), formed by the "*phonic lips*" and membranes "*dorsal bursae*" system that is duplicated in all species of toothed whales except the sperm whale "*Physeter macrocephalus*".

Two ways of producing sounds in cetacean species are cited in the literature. The first way is moving the air inside the nasal tubes, changing pressure between the air sacs placed at the end of the nasal cavities causing the vibration of the MLDB system located therein [17], [18]. The second way is generating resonances [19], [20] in the nasal cavities where sound production happens by resonating volumes of air. This means that these sounds are produced without the excitation or vibration of any membrane. It might be possible to identify which one of these mechanisms was employed for the generation of a given cetacean sound. If the sound was produced by a vibrating element, the sound should have a clear and recognizable pitch. On the other hand if resonating volumes of air produced the sound, no pitch should be detected.

The identification of the mechanism that generates the sound can also be addressed using signal modality characterization through the study of the structures appearing in the RPs. In order to demonstrate this idea, the two different sounds (resonating and vibrating sounds) have been recorded under a controlled and repeatable experiment at the Oceanogràfic of Valencia. In Figure 2 we can see an example of two of the sounds in time and frequency domain. The signal (A) has been produced by resonances, so the shape of the signal is quite sinusoidal because when a resonance is produced, only the first harmonics are propagated (B). In a different way, the signal (C) is made by vibrations, so the shape in time domain exhibits different pulses. In the frequency domain that behaviour corresponds to representations formed by many harmonics as is showed in (D).

Counting the number of harmonics in the frequency domain can be used to distinguishing between these two sounds. If the number of harmonics is high we can affirm that the sound was produced by a vibrating element. If the number of harmonics is low we can almost be sure that the sound was produced by a resonance. This approach needs a threshold that has to be empirically established. This can be a problem in some situations due to the fact that this threshold depends on many factors such as the gender, the age or the sound level of the individual.

The use of the signal modality for knowledge extraction is not a common practice. Nevertheless, the noticeable difference between the signals in phase space and how this affects the RPs and the RQA makes this technique an adequate way of identifying the presence of a vibrating element in the sound production of beluga whales. An example of RP obtained for the above signals is shown in Figure 3. The RP have been obtained using ε as a 10% of the maximum phase space diameter [21].

The determinism parameter can be a useful way of distinguishing between sounds produced by resonances and those produced by vibrations. To demonstrate and evaluate that, we have computed the DET parameter for five vibratory and five resonant sounds. The Table 1 gives the results, where it can be seen the mean and the standard deviation of the DET parameter allows an easy classification.

	Beluga whale sounds	
	Resonant	**Vibratory**
DET	0.95±0.011	0.71±0.108

Table 1: Results of determinism parameter (DET) obtained for the resonant and vibratory sounds produced by the beluga whales.

4. Signal modality application to measure the porosity of cement materials.

A novel and completely different application of signal modality analysis is the study and characterization of scattering materials, particularly, concrete. Concrete is a non-homogeneous material prepared by mixing cement, aggregates and water used mainly in the field of civil and building engineering [22]. The water to cement ratio and cement to aggregate ratio are important variables on concrete design which will determine its mechanical and physical properties. Due to its non-homogeneous structure and its manufacturing process, this material in its hardened state is composed by air voids, interfaces between aggregates and hydrated cement paste, micro-cracks and other defects inside its micro structure. For that reason, concrete is a very dispersive material and hard to measure (in order to know its physical and mechanical conditions) indirectly with traditional Non-Destructive Techniques (NDT) [23]. This application aims to combine traditional techniques of NDT, particularly

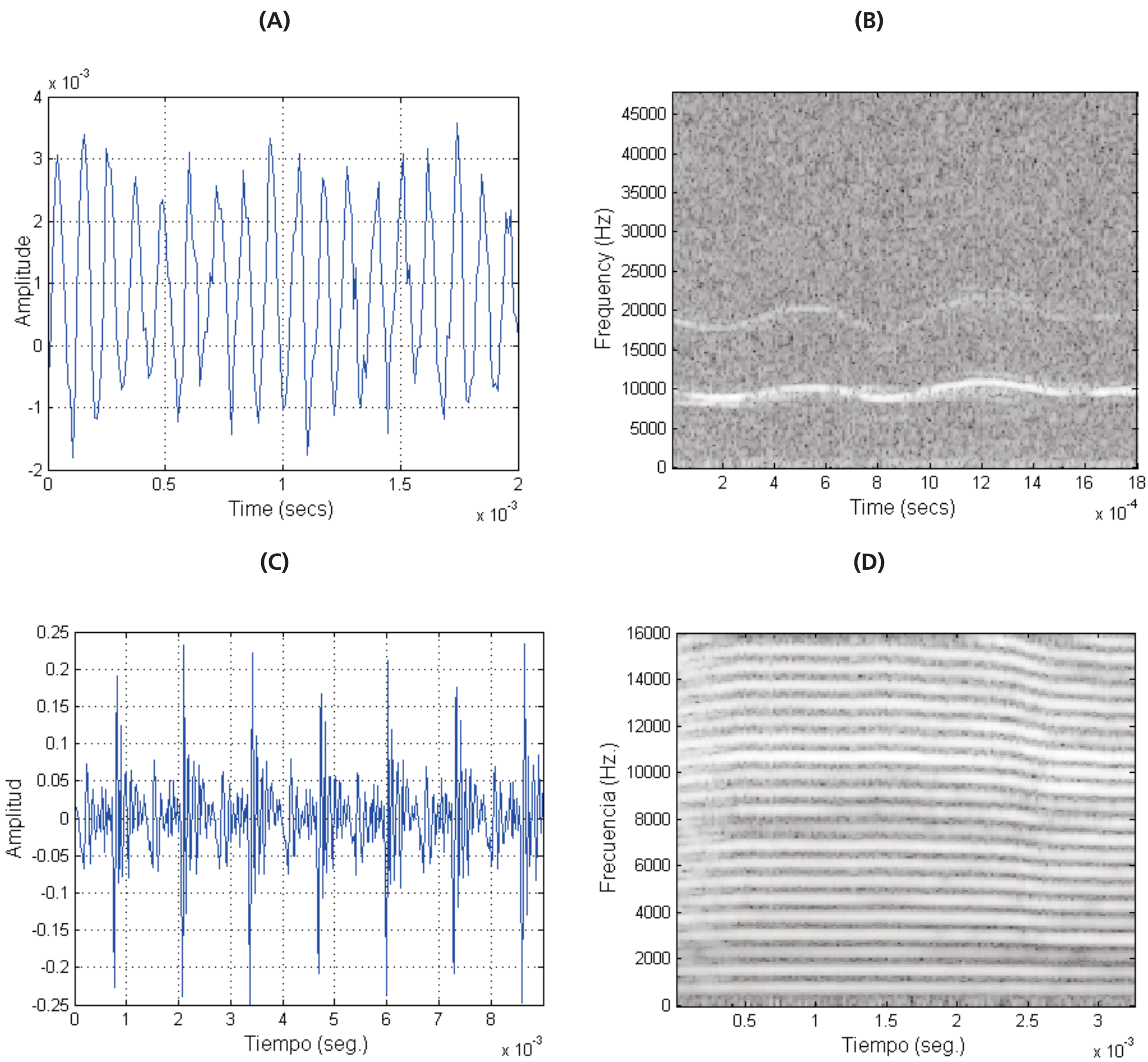
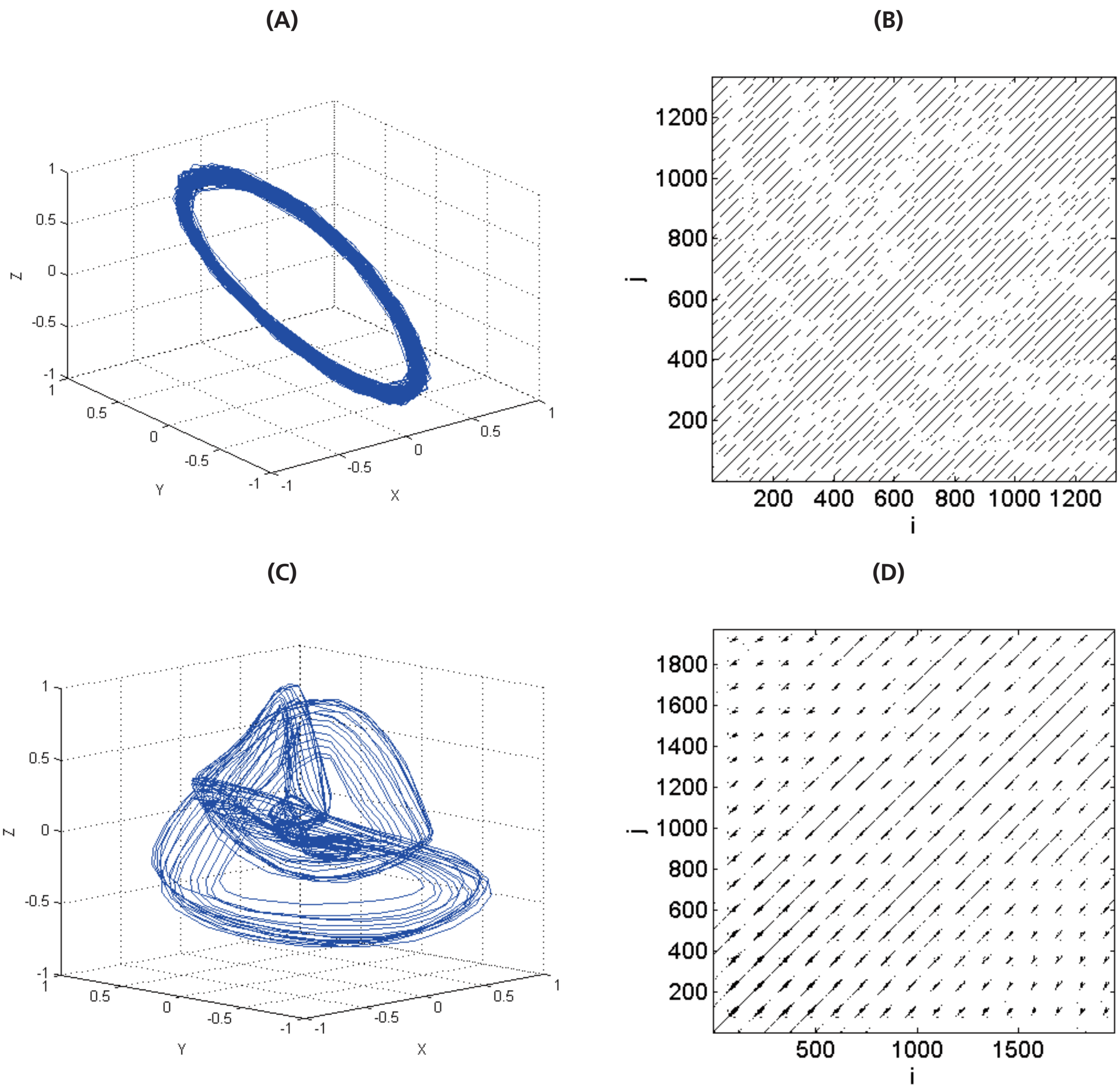


Figure 2. (A) Resonant sound in time domain and (B) in time-frequency domain. (C) Vibrant sound in time domain and (D) in time-frequency domain.



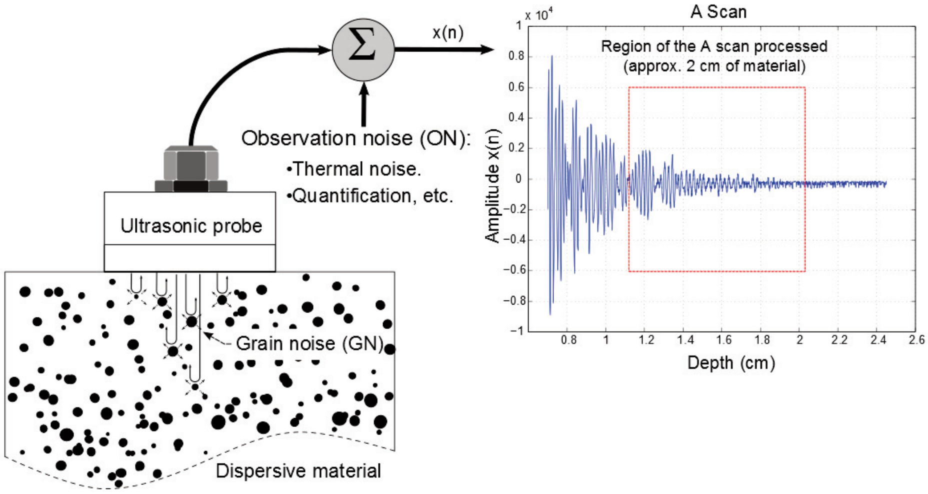
■ **Figure 3.**(A) Segment of the phase space trajectory of a resonant sound by using its three components and (B) its corresponding recurrence plot. (C) Segment of the phase space trajectory of a vibrant sound by using its three components and (D) its corresponding recurrence plot.

inspections based on ultrasounds, with a later analysis of signal modality.

Ultrasounds are acoustic waves which propagate as vibrations through mechanical materials, resulting of compression and relaxation of the particles composing the propagation medium. Due to its wave nature, ultrasounds show physical phenomena such as reflection, refraction, diffraction and interference, which depend on the inner material structure. Figure 4 shows a typical pulse-echo ultrasonic inspection setup for a scattering material analysis. In an ultrasonic inspection, the input pulse undergoes variations related to the internal microstructure of the specimen as it propagates through the material. Each grain behaves like a scattering center, producing an echo that, when superimposed on other echoes coming from other grains, conforms what is called grain noise. Similar situations are found in other related fields such as ultrasonic B-scans (speckle) and in radar (clutter) [24].

In order to show the viability of this application we have considered a cement with a mechanical compression resistance equals to 32.5 MPa and two different water/cement ratios $(\mathrm{w/c})$, 0.4 and $\mathrm{w/c}$ 0.5. So that, there are two cement paste types with different porosity (30.73% and 37.63%, respectively). The selection of an input frequency equals to 10 MHz is justified by the need to obtain enough grain noise in the receiving B-scans. This can be guaranteed by working in the Rayleigh region according to the relationship between the wavelength and the mean grain size.

Figure 5 compares the phase space, computed using Equation (1), of the ultrasonic signals measured in the two different specimens. It must be noticed that both trajectories follow decreasing trajectories (due to the characteristic decreasing exponential envelope of the signal), but both graphs differs on its smooth. The left graph corresponds to the specimen built with a $\mathrm{w/c}$ ratio equals to 0.4 (porosity equals to 30.73%) and the right

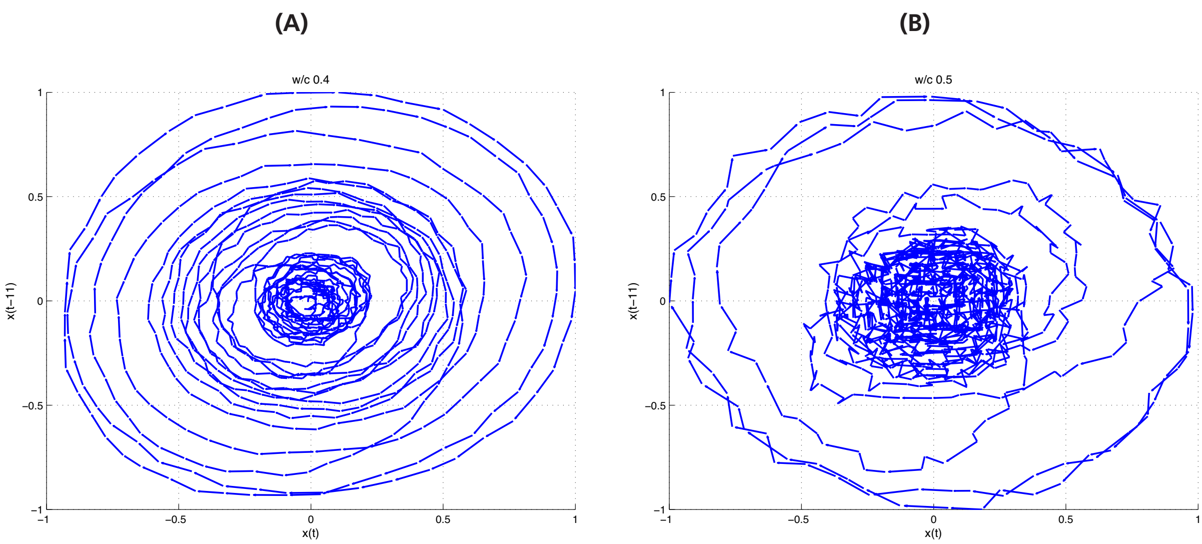


■ **Figure 4.** A pulse-echo ultrasonic inspection of scattering material and an example of the resulting signals.

graph corresponds to a specimen built with a w/c ratio equals to 0.5 (porosity equals to 37.63 %). The presence of higher number of pores results in a clear sign of randomness. This fact represents the hypothesis to think that the degree of determinism can provide a measure proportional to the porosity of the material, and therefore, related to its mechanical properties.

In order to measure the degree of determinism as it was established in the Section 2.1 and having computed the phase spaces (Figure 5), the Recurrence Plots must be computed, Equation (2) and (3). The RP presents as forms of diagonal lines the recurrence states that appear along the signal. Figure 6 illustrates the distance plots (Equation (2)) obtained from the above phase space plotted in a colormap graph. As expected, in the case of less w/c ratio (left graph) the diagonal lines appear in a more orderly and smoother way than in the right graph. Furthermore, it must be noticed that the diagonal lines are not equally distributed over the whole signal but they are focus on a temporal interval that corresponds to the higher amplitudes of the signal. Using a non-Euclidean distance may help to alleviate that "banding effect" due to the non-stationarity of the ultrasonic signal.

In order to illustrate this, Figure 7 compares the concept of applying the Euclidean distance in the expression of the DP (A), and the concept of using a new approach for computing the RP based on the angular distances (B). Using the Euclidean distance causes that only the closest points in the phase space are taken into account and not those that also follow similar paths but with different amplitude values. Therefore, the study of the diagonal lines appearing in the DP based on the Euclidean distance is not appropriate for non-stationary signals. On the other hand, Ioana et al. [25] propose a



■ **Figure 5.** (A) Phase space of an ultrasound signal measured in a w/c 0.4 sample. (B) Phase space of an ultrasound signal measured in a w/c 0.5 sample. $m=2$ $\tau=11$.

new approach for computing the RP based on the angular distances. So that, the proximity between points in the phase space stop being proportional to the Euclidean distance and is measured by the solid angle which they form with the origin Figure 7 (B).

The Equation (5) shows how to compute this angular distance plots (DP_{ang}).

$$DP_{ang}(i,j)=\frac{\mathbf{x}(i)\cdot\mathbf{x}(j)}{\|\mathbf{x}(i)\cdot\mathbf{x}(j)\|},\quad \mathbf{x}(i)\in\Re^m, i,j=1,\ldots,N-m\cdot\tau \quad (5)$$

The main advantage of this distance is that it highlights similar signals having resembling trajectories, as it is the case of transient signals with the same shape but with different amplitudes which would not have been emphasize otherwise (Figure 6).

Figure 8 shows the DP_{ang} from the same ultrasound signals whose DP was shown in the Figure 6. At a glance, it can be noticed that diagonal lines now are almost uniformly distributed in both graphs. This allows computing the DET parameter, but using DP_{ang} instead of DP when computing the RP. Moreover, the results of the parameter DET, Equation (4), are proportional to the inner structure of each specimen. In the case of a w/c ratio equal to 0.4, DET results in 0.97, and in the case of a w/c ratio equal to 0.5, DET is 0.93 (see Table 1). Both values of the parameter are close to 1, which means that the measured grain noise has a predominant deterministic component in comparison with the stochastic component, what seems logical taking into account the completely deterministic input signal. Furthermore, both results are similar but not identical since the difference in the degree of porosity was not larger than 7%.

	Water/Cement Ratio	
	0.4	**0.5**
Porosity (%)	30.73	37.63
DET	0.98±0.005	0.93±0.006

Table 2: Results of determinism obtained for the materials under study, compared to its porosity values.

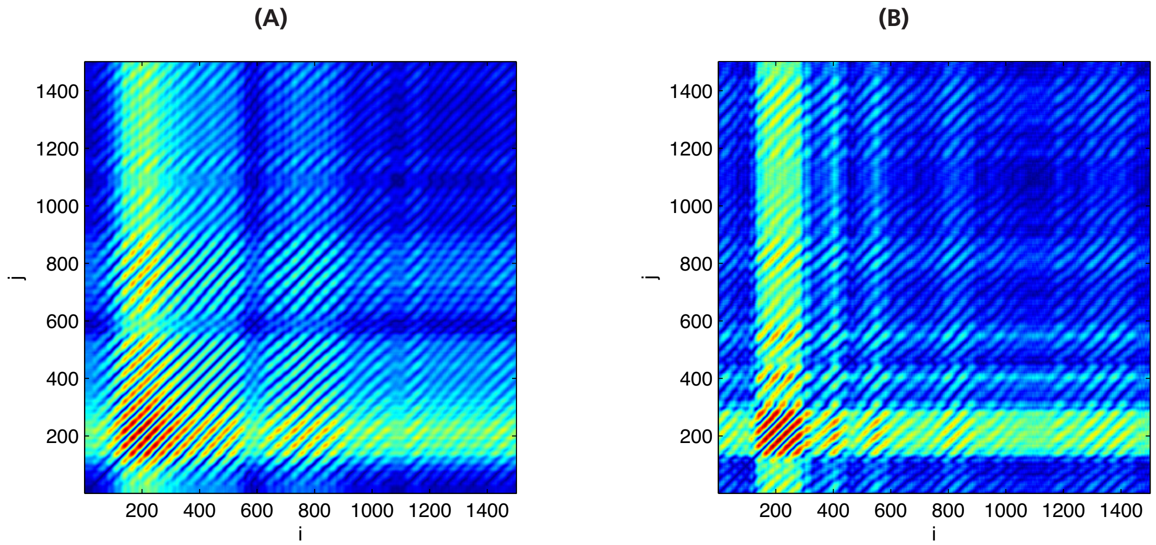


Figure 6. (A) Distance Plot of an ultrasound signal measured in a w/c 0.4 sample. (B) Distance Plot of an ultrasound signal measured in a w/c 0.5 sample. $m=2$ $\tau=11$.

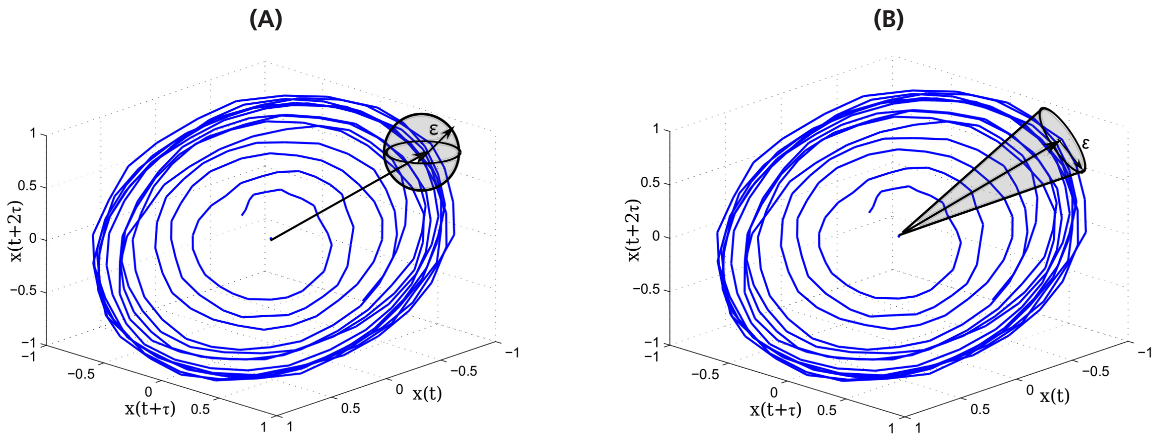
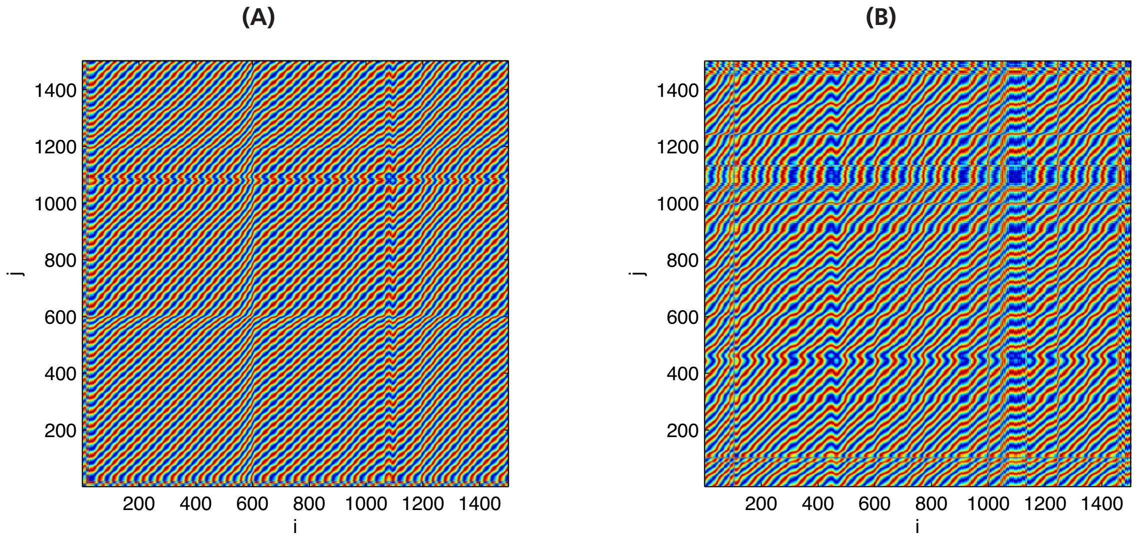


Figure 7. Comparison between the concept of computing the DP using the Euclidean Distance (A) and the angular distance (B) for an ultrasonic signal.



■ **Figure 8.** (A) Distance Plot based on angular distances of an ultrasound signal measured in a w/c 0.4 sample. (B) Distance Plot diagram based on angular distances of an ultrasound signal measured in a w/c 0.5 sample. $m=2$ $\tau=11$.

5. Conclusions

We have illustrated how the signal modality derived parameters may play a key role when trying to characterize complex real-world signals from complex processes. We have presented two real applications. In the first one we have shown how the determinism parameter allows distinguishing between resonant and vibrating sounds in beluga whale calls, without no need to count for resonances in the frequency domain. In the second one, we have employed a more complex approach that uses the angular distance recurrence plots for computing determinism. This allows overcoming the problem of variations in the diagonal line lengths due to amplitude modulations. Thanks to this approach we can use the same RQA parameter in problems where the signal is non-stationary, such us the ultrasonic inspection of dispersive materials.

Acknowledgments

The authors would like to thank the funding received from the Ministerio de Ciencia e Innovacion within the Project number TEC2011-23403.

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