

Performance analysis of a defect detection algorithm in ultrasonic B-scans: An application to foreign bodies detection

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Abstract

As the technology becomes cheaper and industries are conscious of the quality control importance, ultrasonic inspection becomes more popular. However, automatic inspection systems instead of manual ones should be designed if a successful implantation is desired. Signal processing algorithms play an important role on the designing of these systems. Unfriendly environment found in production lines cause that these systems should make intensive use of noise reduction algorithms. This work presents a review of the problem and an empirical modeling of the noise. A detection algorithm is proposed based on the experiments carried out by the researchers. This algorithm has been analyzed to obtain a controlled false alarm detector. Performance analysis of the proposed detector using simulations is presented.

Keywords: Statistical Signal Processing, Signal Processing Applications, Ultrasonic Signal Processing, Nondestructive testing using ultrasonics.

1. Introduction

It is very usual to find quality control of materials using ultrasonics in the metallurgical, construc-

tion or automotive industry. In these sectors, the inspection is manually done, or if an automatic device is used, the time used to inspect the product is not crucial. However, in large-scale production systems, is less frequent to find quality control using ultrasonics. Explanation of this situation can be found if we take into account that most of the large-scale production systems are designed to produce small profit margin items. However, as the price of the electronic and ultrasonic systems stops being an obstacle, it is feasible to think of designing ultrasonic systems for automatic quality control. One of the industry sectors that could take advantage of this is the food sector. While ultrasound inspection has been applied in other industries, in the food sector, inspection has been made traditionally by human operators and recently by machine vision. However, there are many situations where image analysis is not enough to solve some inspection problems. One typical problem is the foreign bodies detection in packaged food. A foreign body is any strange matter not related with the food ingredients that can appear in the food that should be digested later by a consumer. This situation only appears accidentally and occasionally, but the impact on the consumer is tremendous and the damage to the commercial brand image can be quite serious. The application of ultrasound in the food industry depends on the food ingredients and texture. In those products

The VFD is a nonlinear device that introduces a large amount of noise

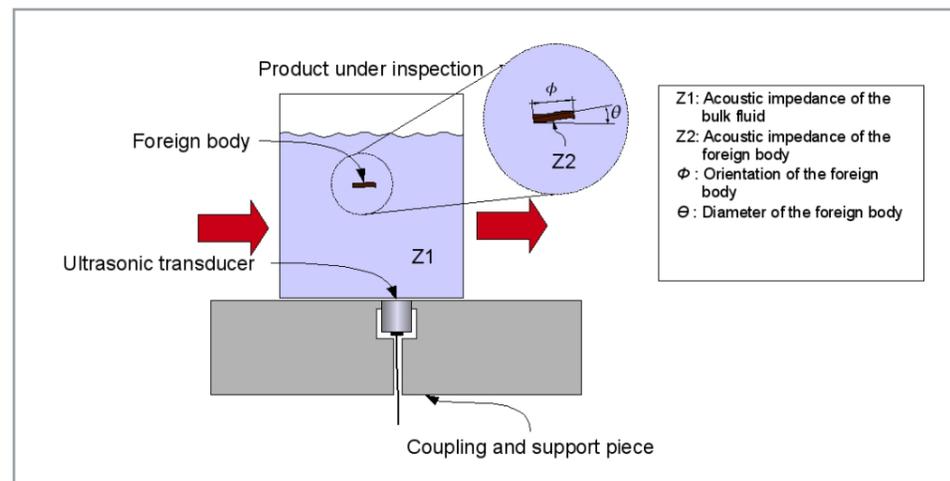
where the mixture is quite homogeneous like sauces, creams, jams, beverages, dough, etc. is possible to identify foreign bodies with different textures due to changes in the acoustic impedance. The main advantages of this non-destructive technique are related with their availability to be applied on-line and the ability to detect foreign bodies with similar density but with different textural properties [1].

In this work we are going to study, from the signal processing point of view, ultrasonic inspection for foreign body detection in a production line. The description of the problem will be presented in section 2. Later, in section 3, statistics of the noise present in the system will be studied. With the obtained results, a preprocessing and detection algorithm will be proposed in section 4. Finally, in section 5, the performance of this detector will be analyzed by simulations.

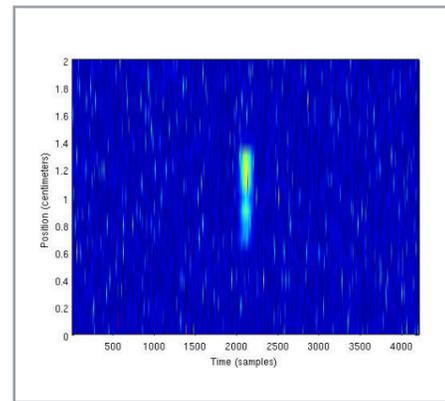
2. Problem description

Let us assume that we are inspecting a homogeneous product while it is travelling in the transport belt of a production line. The inspection is done from the bottom of the product using a single-element ultrasonic transducer continuously working in pulse echo mode (see Figure 1). We will assume also, that the geometry of the product is appropriate for this kind of inspection and that the problem of ultrasonic coupling is somewhat solved. It has to be taken into account that not all products manufactured by the described process are suitable for this kind of inspection. However, there are a large number of situations where the previously described inspection can be applied (sauces, creams, jams, beverages, dough, etc.).

During the continuous operation of the ultrasonic transducer, traces similar to that obtained in Sonar applications are acquired. The collection of these traces during the transit of the product over the ultrasonic transducer is a matrix called



■ Figure 1. Problem description and main physical variables that affect the foreign body detection.



■ Figure 2. A synthetic B-scan with a simulated foreign body echo in presence of noise.

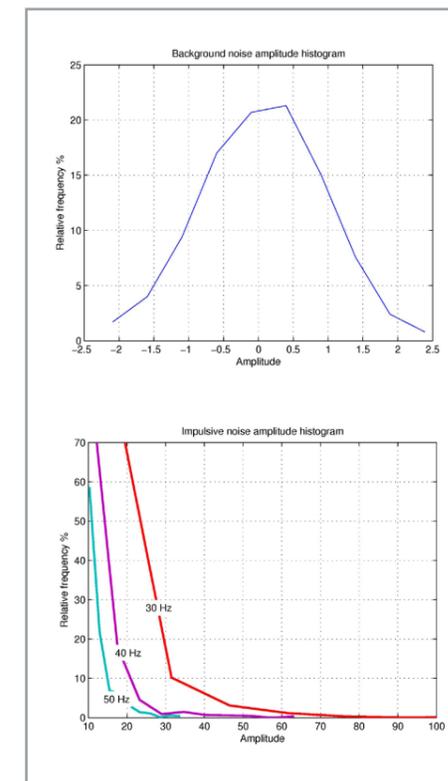
B-scan (see Figure 2) that will serve for diagnosis and defect detection.

In industrial applications of non-destructive testing using ultrasonics is very frequent to find alternating current (AC) motors. These AC motors are commonly running in the vicinity of non-destructive testing equipment and are used for example for operating transport belts. The rotational speed of these engines is controlled by the Variable Frequency Drive (VFD). The VFD is a nonlinear device that introduces a large amount of noise that is picked up by the ultrasonic receiver electronics difficulting the foreign body detection. This noise finally appears as additive impulsive noise randomly scattered all around the ultrasonic B-scan.

In some situations the presence of noise could be minimized with a good hardware and shielding design. However there are other situations where it is not possible to make such a design, for instance impossibility to use relatively short cables between the transducer and the ultrasonic pulser/ receiver. In these situations signal processing algorithms can help to remove the impulsive noise and design better detectors.

3. Noise statistics analysis

We are going to study in this section the statistics and the variables that affect the noise distribution. As we have previously stated, noise from two different sources appear: background noise due to many different factors (small vibrations, observation noise, quantification, etc) and impulsive noise mainly due to electromagnetic interference of the VFD. All these noises could be modeled as additive noise scattered all around the ultrasonic B-scan. An adequate modeling of these noises is required for an optimum defect detector design. In order to study the noise statistics a system similar to the one shown in Figure 1 was implemented. We measured B-scans for different frequencies powering the induction motor that provides relative transducer-product movement. A foreign-body-free product was employed so that any echoes appearing in the B-scan are due to noise and the product-air interface echo. We tested the system for four different frequencies of the VFD in the range $\{f_{VFD} = \{0 \text{ Hz} - 50 \text{ Hz}\}\}$. The analysis when $f_{VFD} = 0 \text{ Hz}$ allows to study the background noise, on the other hand the range $f_{VFD} = \{30 \text{ Hz} - 50 \text{ Hz}\}$ allows to study the impulsive noise. The Figure 3 shows the measured probability density function for the noise sources analyzed. The results obtained are similar to what some other authors have measured in similar situations [2].



■ Figure 3. Estimated probability density function of the background noise (Left figure, background noise for $f_{VFD} = 0 \text{ Hz}$ and right figure, background noise for $f_{VFD} = \{30 \text{ Hz} - 50 \text{ Hz}\}$).

The empirically estimated distributions resemble a Gaussian distribution for the background noise and an exponential distribution for the impulsive noise. A Kolmogorov-Smirnov test [3] was applied to the aforementioned distributions to guarantee that the statistical distributions proposed could be assumed. The null hypothesis of the test was that the measured noise statistics has the expected distributions (Gaussian or exponential). The null hypothesis was accepted at the 95 % of significance level for both cases.

4. The proposed algorithm

It has to be taken into account when designing signal processing algorithms for defect detections in the industry the need of real time processing. Production lines work fast and the distance from product to product is, in most of the situations, a few centimeters. Fast and efficient algorithms should be designed to achieve possible detection before the next item enters into the detection system.

In what follows, and without loss of generality, we are going to assume that the noise that difficults a possible detection is Gaussian (as the Gaussian noise we have previously analyzed). In the case that some impulsive noise was present, it could be almost completely removed from the ultrasonic B-scan using algorithms described in [4]. The proposed detector is composed of a pre-processor and a detector as shown in Figure 4. In the next section we will describe with detail all its elements.

4.1. Preprocessor

The first element of the detector algorithm (see Figure 4) performs the data mapping from the 2D ultrasonic B-scan to the 1D ultrasonic A-scan. Although some information could be loosed in this process, complexity reduction and the need of real time processing prevail over this fact in the proposed detector. After that, envelope detection was performed using Hilbert Transform. Finally a low pass filter was applied.

Let us call \mathbf{B} the $M \times N$ matrix containing the ultrasonic B-scan of a foreign-body-free product ($\tilde{B}(m, n)$). If all the impulsive noise has been successfully removed the matrix could be modeled as a result of the background noise, as a 2-D stochastic process with Gaussian statistic $\sim \mathcal{N}(0, \sigma^2)$.

If the mapping of the 2-D B-scan into a 1-D vector is done using the equation (1) then the 1-D vector can also be modeled as a Gaussian stochastic process $\sim \mathcal{N}(0, \frac{\sigma^2}{M})$ [5].

$$x(n) = \frac{1}{M} \sum_{m=1}^M B(m, n)$$

[1]

Fast and efficient algorithms should be designed for real time detection

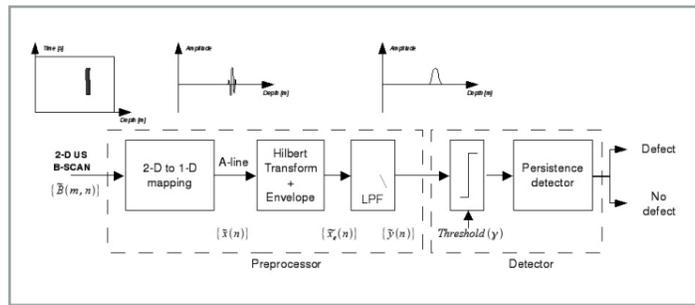


Figure 4. Proposed detector

The 2-D to 1-D mapping technique proposed in equation (1) gives good results when the foreign body echoes extend to most of the B-scan (in the averaged dimension) and in moderate noise conditions. Although the small size of typical foreign bodies, sound beam divergence angle of many commercial ultrasonic transducers produce this effect. After mapping, the Hilbert Transform ($\hat{x}(t)$) was computed and the envelope was calculated according to equation (2).

$$x_e(n) = \sqrt{\tilde{x}^2(t) + \hat{x}^2(t)} \quad [2]$$

According to [6], if $\{\tilde{x}(t)\}$ is a zero mean stochastic Gaussian process, the Hilbert Transform $\{\hat{x}(t)\}$ is also a Stochastic Gaussian process with zero mean and the same autocorrelation that $\{\tilde{x}(t)\}$. Using again [6], we can state that the result of equation (2) $\{x_e(t)\}$ is a Rayleigh distributed process with mean $E[x_e] = \frac{\sigma}{M} \sqrt{\frac{\pi}{2}}$ and variance $var[x_e] = \frac{4-\pi}{2} \frac{\sigma^2}{M}$.

The last step of the preprocessor consists in filtering $\{x_e(t)\}$ with a low-pass filter with impulse response given by $h(n)$. If we assume that is an ideal discrete low-pass filter with cutoff pulsa-

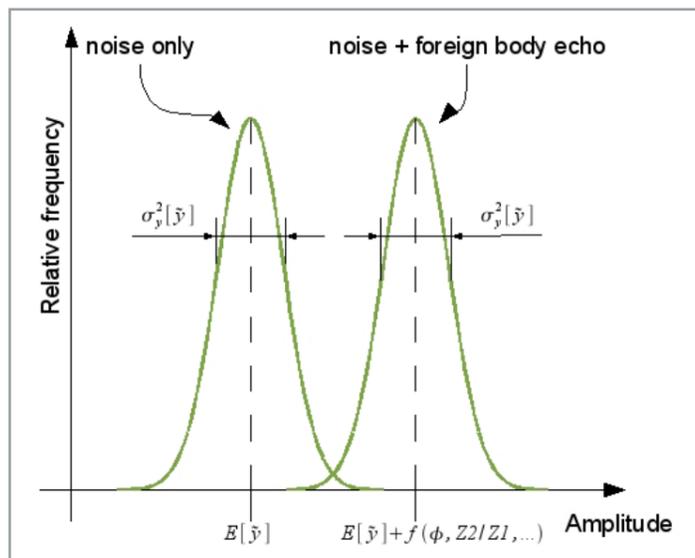


Figure 5. Variables that affects the random variable when a foreign body is present.

tion then the output process $\{\tilde{y}(t)\}$ can be obtained according to equation (3).

$$y(n) = x_e(n) * h(n) \quad [3]$$

According to the central limit theorem if the digital filter given by $h(n)$ has enough taps, the statistics of the random process at the output, will be Gaussian [7]. The mean and variance of the discrete stochastic process at the output of the filter can be obtained using discrete stochastic process filter relationships. The values calculated are given in equations (4) and (5).

$$E[\tilde{y}] = \frac{\sigma}{M} \sqrt{\frac{\pi}{2}} H(0) = \frac{\sigma}{M} \sqrt{\frac{\pi}{2}} \quad [4]$$

$$\sigma_y^2 = var[\tilde{y}] = \frac{4-\pi}{2} \frac{\sigma^2}{M} \sum_{-\infty}^{\infty} |h(n)|^2 \quad [5]$$

In the equation (4), $H(0)$ is the continuous frequency response of the system described by $h(n)$.

4.2 Detector

The problem of detecting foreign bodies can be assimilated to a problem of detecting an unknown signal in White Gaussian Noise (WGN). When no foreign body is present in the ultrasonic B-scan, at the output of the preprocessor we obtain WGN with mean and variance given by equations (4) and (5) respectively.

If a foreign body is present in the product, and so in the ultrasonic B-scan, it produces an offset value at the output signal of the preprocessor. This offset affects only a fraction of consecutive samples of the process. The amplitude of the offset depends on the amplitude of the echo, and as we have previously described, this amplitude depends on many factors that are out of our control: impedance mismatch, orientation, size of the foreign body, etc. The only information that we can use for the detector design is the fact that due to the Hilbert transform and envelope detector the offset will always be positive. All possible detectors analysis can be found in [8]. A very simple, but not the only, alternative is to assume that if we analyze a small number of consecutive samples the problem can be assimilated to a DC level of unknown amplitude in WGN (see Figure 5). Assuming this we can write:

$$\begin{aligned} \mathcal{H}_0: y(n) &= w(n) \quad n = 0, 1, \dots, L-1 \\ \mathcal{H}_1: y(n) &= A + w(n) \quad n = 0, 1, \dots, L-1 \end{aligned} \quad [6]$$

Where $y(n)$ is the output of the preprocessor and $w(n)$ is the WGN with mean and variance given by equations (4) and (5). The parameter L gives the number of consecutive samples where we

can consider approximately constant the echo amplitude value.

where A is unknown and depends on all the factors we have mentioned $A = f(\phi, \theta, Z2, Z1)$. The Neyman-Pearson (NP) test produces that:

$$T(x) = \frac{1}{L} \sum_{n=0}^{L-1} y(n) > \frac{\sigma_y}{NA} \ln(\gamma) + \frac{A}{2} = \gamma'$$

The threshold γ' can be calculated for a given PFA using:

$$\gamma' = \sqrt{\frac{\sigma_y^2}{L}} Q^{-1}(P_{FA})$$

which is independent of A . Since the test is actually the NP detector, it is optimal in that yields the highest Detection Probability (PD) for a given False Alarm Probability (PFA). Note, however, that PD will depend on the value of A (size, orientation and acoustic impedance of the foreign body, etc.).

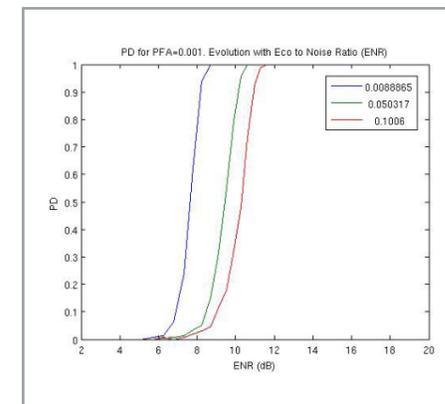


Figure 6. PD evolution with the echo to background noise ratio (ENR). PFA=1e-3: simulation for three different energies (cutoff frequencies) of the preprocessor low-pass filter.

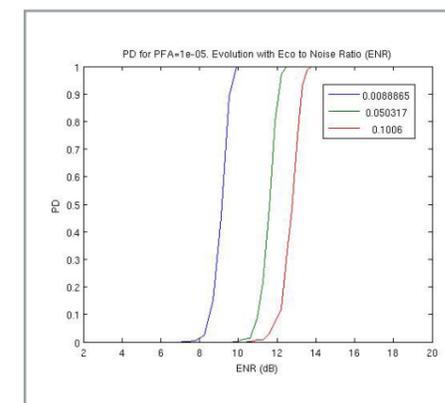


Figure 7. PD evolution with the echo to background noise ratio (ENR). PFA=1e-5: simulation for three different energies (cutoff frequencies) of the preprocessor low-pass filter.

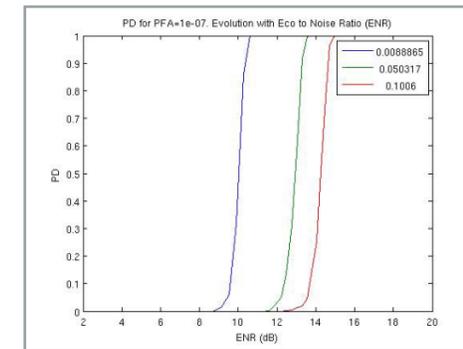


Figure 8. PD evolution with the echo to background noise ratio (ENR). PFA=1e-7: simulation for three different energies (cutoff frequencies) of the preprocessor low-pass filter.

5. Performance analysis of the proposed detector using simulations

In this section we are going to simulate the PD of the proposed algorithm for a given PFA. The simulations were done with MATLAB and all the percentages shown in the figures and tables were obtained by 500 Monte Carlo runs.

As we have previously stated the nature of the problem (unknown physical parameters of the foreign body) makes it difficult to guarantee a PD for a given PFA. Figures 6-9 show the PD in noise when the power amplitude of the foreign body echo changes. A parameter called Echo to Noise Ratio (ENR) gives this relationship. Figure 6 shows the PD evolution with the ENR for a PFA equal to 1e-3, the figure 7 for PFA equal to 1e-5 and the Figure 8 for PFA equal to 1e-7. The PD curves for three different energies (cutoff frequencies) of the preprocessor low-pass filter are shown. As it was predicted by equation (5), lower energy low-pass filter allows greater reduction on the background noise. In the figures 6-8, it

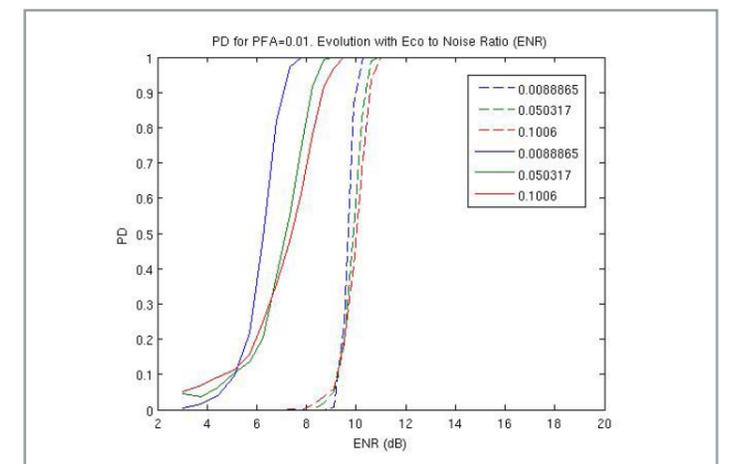


Figure 9. Comparison of the PD evolution with and without the Hilbert Transform for PFA=1e-2.

The NP detector guarantees the highest detection probability for a given PFA

can be appreciated how we can obtain higher PD for the same ENR if we use the lowest energy low-pass frequency.

Part of the reasonable good ability of the detector to work with low ENR is due to the Hilbert Transform and envelope block shown in Figure 4. We have repeated one more time the simulations for a $PFA=1e-2$, but this time the Hilbert Transform block was omitted. The results shown in figure 9 demonstrate how we can obtain approximately the same PD with 2 dB less of ENR. In practice, this will benefit into a better ability of the system to detect smaller and more difficult to detect foreign bodies.

6. Conclusions

In this work we have analyzed the noise statistics of an ultrasonic system designed for foreign body inspection. The system was designed to be used in the alimentary industry; however the system could be easily adapted to work on other products of many other industries.

After analyzing the noise picked up by the ultrasonic receiver electronics, due to surrounding AC engines, a detector has been proposed. The detector is composed of a preprocessor and a threshold detector. The performance of the detector has been analyzed through simulations. We have identified some signal processing variables that are strongly related to physical characteristics of foreign body. By manipulating this variables we can make the system to detect smaller foreign bodies while maintaining the PFA of the detector.

Validation of the results, by means of a system prototype is being done by the researchers of the iTEAM (UPV) alongside with the AINIA research center.

References

- [1] M. Edwards, Detecting foreign bodies in food, CRC Press, 2004.
- [2] W. Henkel and T. Kessler. A simplified impulse-noise model for the xDSL test environment. October 1999.
- [3] D. J. Sheskin. Handbook of Parametric and Nonparametric Statistical Procedures. Chapman and Hall CRC, 4 edition, 2007.
- [4] R. Miralles, R. Molina. A Comparative Study of the Impulsive Noise Reduction Algorithms in Ultrasonic B-scans, EUSIPCO 2009 - The 17th European Signal Processing Conference, 24th -28th August, Glasgow, 2009.
- [5] R. S. Witte and J.S. Witte, Statistics, Wiley, 2006.
- [6] F. Marvasti, Nonuniform Sampling: Theory and Practice, Springer, 2001.
- [7] A. Papoulis, Probability, Random Variables, and Stochastic Processes, Mac Graw-Hill, 1984.
- [8] S. M. Kay, Fundamentals of Statistical Signal Processing, Detection Theory, Prentice Hall, 1998.

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