A new filter bank design for Split-Spectrum algorithm

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Abstract- *The most important aspect when designing Split-spectrum algorithms is the filter bank design. There are two main trends commonly followed. One is based on constant bandwidth Gaussian filters equally spaced in frequency and the other one uses wavelets as a multi-resolution time-scale method. In this paper we present an alternative that combines both techniques taking advantage from the best of each. It is based in the use of variable bandwidth filters but in this case filters are equally spaced in frequency and are energy gain equalized so that all bands have the same contribution from the possible echo defect. With this new design we improve the insensitivity of the echo defect to the tuning frequency. Improvements in the signal to noise ratio gain after recombination are reported in this contribution. We show the results obtained after simulations using simple stationary models for the grain noise with a single defect. SNR enhancement factor was selected as the figure of merit to make the comparisons among the different methods. These results are contrasted with real processed signal obtained in laboratory from pieces of aluminum alloy, showing the interest of the proposed new filter bank structure and recombination methods.*

1. INTRODUCTION

The main objective of signal processing techniques in NDT is to eliminate or reduce as far as possible the effect of the grain noise to improve the SNR in detection [1][2].

Although there are many methods, most of them based on time-frequency decomposition, the most used method due to its simplicity and the good results provided is the Split Spectrum Processing (SSP) algorithm, widely studied and with a long history in the field of NDT [3]. Despite this, the processes involved in this algorithm which affects its improvement and optimization are not very clear yet, and it is not easy to find studies which justify the use of certain algorithms to the detriment of others, nor from standpoint of efficiency in terms of the gain neither in terms of complexity of calculation or interpretation of the results.

This work seeks to deepen in some of the parameters involved in the design of different algorithms based on SSP techniques, reviewing the influence they have on the results in order to establish objective criteria for selecting the different methods.

2. MODELING OF THE PULSE-ECHO SYSTEM

2.1 Approach to the problem

The basic principle of operation in ultrasonic NDE consists in the emission of an ultrasonic wave in a transducer coupled to the material, which propagates through it so that part of the energy is reflected when it collides a discontinuity, while the rest is scattered or reflected on the surface opposite to the emission. The amplitude of received echoes is directly related to the acoustic pressure of the reflected wave, including coherent and incoherent noise.

Dispersion experienced by the wavefront is dependent on frequency, depending on the size, number and distribution of the scatterers of the material, thus not all the frequencies will be reflected equally, phenomenon called frequency diversity [4]. Thus, when the wavefront collides on a reflector comparable to its wavelength, the reflector acts as an omnidirectional, spherical and frequency selective emitter, scattering better high frequencies than low.

For the evaluation of the methods used in structural noise reduction it is necessary to use models that describe the signals coming from the inspected material. If we wish to model the scattering processes through analytical models, it is necessary to know the exact mechanisms of the physical phenomena involved in the generation of the obtained ultrasonic signal, which is very difficult to achieve in practice, so generally, stochastic models are used considering the received signal as a random process.

2.2 Transducer Modeling

Regarding the transducer, the models used frequently are based on either deterministic Gaussian envelope signals or decreasing exponentials, depending on the transducer to be modeled (focused or not focused, for example).

In the first case, the response of the transducer can be modeled using a band pass signal with Gaussian envelope [5], and in the second with a growing potential term combined with a decreasing exponential, modulated to the desired central frequency. In both cases, the desired waveforms can be achieved by modifying the appropriate parameters.

Finally, beamforming techniques [5] can be used to achieve better control over the transducer frequency response.

2.3 Material modeling

The stochastic models consider the signal received from the material as an stochastic process that allows both modeling and perform simulations and deductions about the nature of the phenomenon as validate various algorithms used for the reduction of structural noise [6][7].

For modeling the ultrasonic signal coming from the structure of a dispersive material, the grain noise is usually regarded as the additive composition of the echoes from the small individual reflectors or inhomogeneities of the material, so the received signal could be expressed analytically as:

$$r(t) = \sum_{k=1}^{K} g_k(t - \tau_k)$$

with K the number of grains, g_k the echo from the k-th reflector and τ_k the scatterer located at the distance $z = \tau_k c/2$, being c the propagation velocity in the material. Depending on the criterion used to model this response, models can be classified in stationary and not stationary.

Stationary models assume that the statistical parameters of the process do not vary with the depth and, particularly, that the impulsional response of the scatterers and the attenuation coefficient do not depend on the frequency, just on the features of the material. Thus, received signal could be expressed as [8]:

$$r(t) = \sum_{k=1}^{K} e^{-2\alpha \cdot z_k} \cdot h_{sk}(t - \tau_k) * x(t)$$

where $x(t)$ is the mechanical transducer response, α is the attenuation coefficient and $h_{sk}(t)$ is the impulsional response of the *k-th* reflector.

In practice, the attenuation may be compensated easily, so the stationary model would be:

$$r(t) = \sum_{k=1}^{K} h_{sk}(t - \tau_k) * x(t)$$

This is a reasonably valid simplification if the length traveled by the ultrasonic wavefront is small, or the transducer is narrowband.

Combining this model with the transducer-material model, the material impulse response $h(t)$ is modeled as a random white process consisting of a sequence of deltas weighted by its reflection coefficient, assuming, by the central limit theorem, when the number of reflectors is high the sum adopts a Gaussian distribution.

$$h(t) = \sum_{k=1}^{K} \rho_k \delta(t - \tau_k)$$

The general expression would be as follows:

$$R(\omega) = X(\omega) \cdot \left\{ \sum_{k=1}^{K_s} \rho_{sk} \cdot e^{-j2\omega z_k/c} + \sum_{k=1}^{K_d} \rho_{dk} \cdot e^{-j2\omega z_k/c} \right\}$$

with ρ_{sk} and ρ_{dk} the reflection coefficients of the material and defects respectively.

In both cases, the first part of the sum would be the contribution due to the structure of the material (grain noise) and the second the due to the defects. Just would remain to add a fraction of white Gaussian noise to model the incoherent noise.

2.4 Model validation

Next figure shows (figure #1) the results obtained using a stationary model of material with a Gaussian-type envelope transducer and a sample taken on a piece of aluminum alloy in which a small hole has been done close to the end of the piece:

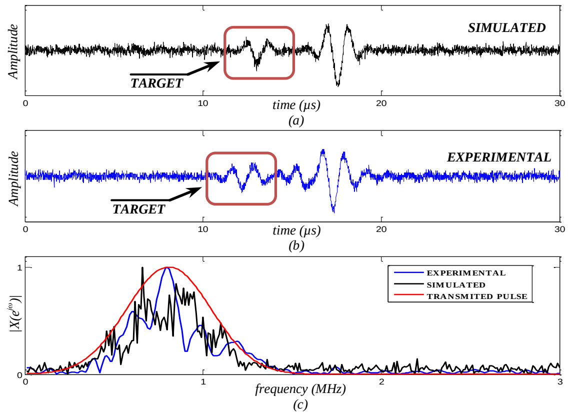

Figure #1: Simulated signal (a), experimental signal (b) and spectrum (c).

As can be seen, the model is able to reproduce quite accurately the environment of the real test by simply adjusting properly the parameters involved in the design. It is also found that in low dispersive materials, as in stationary models, the spectrum of the received signal occupies the same band that the spectrum of the transducer, but with random spectral contributions due to the fact that the reflections depend on the size of the grain.

3. THE SSP ALGORITHM

3.1 Approach to the problem

Preceding sections described the basic principles of operation of the inspection by ultrasound, and particularly the frequency diversity phenomenon, whereby when the transmitted wavefront collides with a reflector greater than its wavelength, part of the energy is reflected, regardless of frequency. Because of this, the spectral power density of the received signal should contain information on the same bandwidth that the transmitted pulse or, if it is a very dispersive material, at least in the lower part of the band due to the low pass filter effect of the material.

In other hand, when the wavefront collides with a reflector of size comparable to its wavelength, some of the energy is dispersed, so that the spectral power density of the received echo will contain information only on some localized bands. Since the distribution and size of these reflectors is random, it will also the received power distribution.

The following figure (figure #2) shows the spectrum of a signal generated according to the stationary model with a single defect located approximately in the centre of the scan.

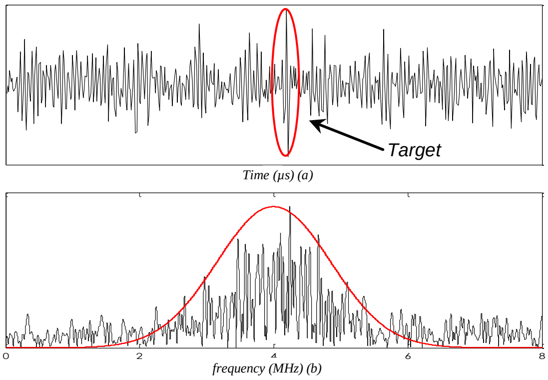

Figure #2: Scan obtained in a dispersive material with a defect at 16 µs using a 4MHz transducer with 2MHz bandwidth. (a) time (b) frequency

If its spectrogram is calculated, it can be appreciated (figure #3) that where the defect is present its power density spreads all around bandwidth of the transmitted pulse. However, in the rest, contributions occupy only one portion of the spectrum depending on the size, position and orientation of the reflectors that, as mentioned, will be random.

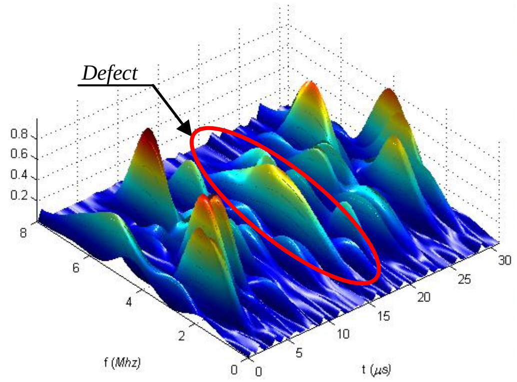

Figure #3: Spectrogram of the previous signal.

This shows that the most appropriate strategy would be to perform a time-frequency analysis and search the time in which the power of the echo is distributed homogenously in the bandwidth of the transmitted pulse.

3.2 The SSP algorithm

This algorithm exploits the frequency diversity phenomenon according to the foregoing previously. Its objective is to reduce as far as possible the grain noise by applying a frequency decomposition and discriminating the areas in which the spectral contribution is not homogeneous. To do this, a broadband signal is used and the received signal is filtered with a filter bank [8]. Then, resulting signals are processed on a non-linear combination providing information about the location of the possible defect.

Next figure (figure #4) shows the schema of the algorithm:

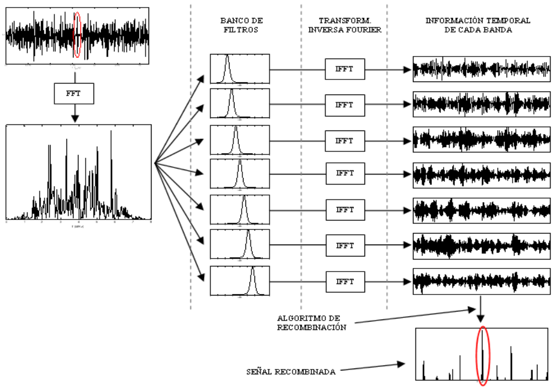

Figure #4 SSP algorithm schema

To perform the filter bank, the bandwidth of interest must be selected. Then, this bandwidth is split in equally spaced sub-bands obtaining information about the spatial distribution of the energy in each one. Finally, this information will be combined to highlight the areas where there is significant contribution of energy in all bands.

At this point, should be remarked that one of the main objectives of this work is to optimize the performance of the SSP algorithm in terms of improving the SNR with the lowest possible complexity, i.e. with the fewest number of bands and the simplest filters.

3.3 The SSP algorithm parameters: the Bank of filters.

The first step in the SSP algorithm is the division of the signal in different bands (figure #5b), which is done with a bank filter, whose specifications depend on the following factors:

- Number bands [9][10][11]
- Inspection bandwidth [12][13]
- Bandwidth of each filter [9][14][15][16]
- Overlap between different bands [9][15]
- Filter type [9][10][17]

3.4 New filter bank design: Filters equally spaced in frequency and energy gain equalized

In this work, it is studied the possibility of using an alternative design for the filter bank, based on equally spaced filters but in this case with variable bandwidth proportional to its central frequency and designed that they all have the same energy (figure #5a) in order to equalize the contribution of each band.

Thus accomplished:

- The transfer function of the filter bank is adapted to that of the transmitted pulse
- More influence of the lower bands is achieved
- More incidence of the prunning effect is achieved

Comparing the sum of the contribution of all the bands with that of the original design, it is shown that when using the new filter bank, all the bandwidth transmitted by the transducer is taken into account for the analysis, fitting it to the response of the material. Then, selecting properly the bank parameters (number of filters and bandwidth), it can be achieved a response adapted to that of the material.

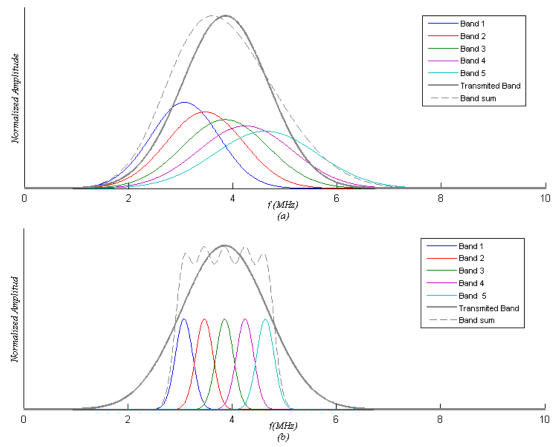

Figure #5: Filter bank example.
(a) Variable bandwidth (b) Fixed bandwidth

4. RECOMBINATION METHODS

4.1 Introduction

There are multiple methods of recombination, but the most frequently used due to its good results are Minimization (MIN) and of Polarity Thresholding (PT). However, in spite of its reliability, both have certain limitations: Minimization algorithm has very little resolution and high SNR values cannot be achieved, and Polarity Thresholding, although it is able to provide very good resolution, needs a lot of bands to achieve substantial gain in the SNR values.

In addition of these, two modifications of the previous algorithms will be explored: Normalization (NORM), based in Minimization method, and Scaled Polarity Thresholding (SPT), in order to check their behavior compared to previous, with both the traditional filter bank and the new one proposed.

Finally, in this paper we propose the use of the Frequency Multiplication method (FM), that provides very high resolution and achieves the best results in the SNR when combined with the new design of filter bank, with less number of bands than the rest of algorithms.

4.2 Recombination methods

Thereafter the following notation will be used; $y(n)=F\{x_1(n),x_2(n),x_3(n),\dots,x_L(n)\}$ is the result obtained after processing and recombination of the signal at n, $x_i(n)$ is the result of the filtering of the i-th band at n , and L is the number of bands. Thus, algorithms are defined as follows:

▪ Minimization (MIN) [15][16]; for each instant in time (distance), takes the minimum of the absolute value from all bands

$$y(n) = min\{|x_1(n)|, |x_2(n)|, |x_3(n)|, \dots, |x_L(n)|\}$$

▪ Normalization (NORM) [18]; for each instant in time (distance), takes the minimum of the absolute value from all bands, previously normalized by the maximum value of each of them

$$\hat{x}_i(n) = \frac{x_{i(n)}}{\max\limits_n x_{i(n)}}$$

$$y(n) = min\{|\hat{x}_1(n)|, |\hat{x}_2(n)|, |\hat{x}_3(n)|, \dots, |\hat{x}_L(n)|\}$$

▪ Polarity Thresholding (PT) [15][17]; for each instant in time (distance), takes the minimum of the absolute value from all bands, only when the value in all of them has the same sign, assigning a zero otherwise.

$$y(n) = \begin{cases} min\{|x_1(n)|, |x_2(n)|, \dots, |x_L(n)|\} & \begin{cases} si\ x(n) > 0 \forall n \\ si\ x(n) < 0 \forall n \end{cases} \\ 0 & resto \end{cases}$$

▪ Scaled Polarity Thresholding (SPT) [19]; for each instant in time (distance), takes the minimum of the absolute value from all bands and scale it by a factor that depends on the number of samples with the same sign.

$$y(n) = \left|\frac{N_+ - N_-}{S}\right| min\{|x_1(n)|, |x_2(n)|, \dots, |x_L(n)|\} \cdot 4L$$

With N_+ the number o positive samples, N_- the number of negative samples S the number of samples

▪ Frequency Multiplication (FM) [15]; for each instant in time (distance), takes the product of the samples from all bands.

$$y(n) = |x_1(n) \cdot x_{21}(n) \cdot x_3(n) \cdot \dots \cdot x_L(n)|$$

5. EVALUATION OF THE SSP ALGORITHM

5.1 Previous considerations

To simulate the transducer pulse *x(t)* it will be considered an impulse response of Gaussian envelope centered at 4 MHz and with 2 MHz of bandwidth. To reproduce the SSP algorithm, it will be considered scans with a single defect in its centre and with variable reflection coefficient ρ, all that immersed in a dispersive environment modeled by the stationary model previously described (figure #2), adding certain amount of white noise to take account of the incoherent noise present in the scan. In all cases simulations are undertaken according to the Monte Carlo method with 1000 iterations by simulation, varying the number of filters of the Bank from 2 to 20 bands and the type filter Bank used, repeating the experiment for the two different filter bank designs.

Signal to noise ratio enhancement factor (Signal to Noise Ratio Gain SNRG) was selected as the figure of merit to make the comparisons among the different methods (GSNR), measured as the difference between SNR al the input (SNRin) and SNR after applying the algorithm (SNRout), taken that relationship as:

$$SNR = \frac{\sum_{D+\frac{P}{2}}^{D-\frac{P}{2}} y^2(n)}{\sum_0^{N-1} y^2(n)}$$

$$G\ SNR = \frac{SNR_{OUT}}{SNR_{IN}}$$

Where D is the defect location, P the pulse width and N the record length.

5.2 SNR Out Vs. SNR in

The following figure (figure #6) represents the average SNRout versus the average SNRin for the different recombination methods previously studied and for the two types of filter bank, varying in all cases the number of inspection bands from 2 to 20.

The effectiveness of the method is given by the slope of the RSNout curve, which shows the ease with which the algorithm is able to detect a defect. Values close to 1 SNRout indicate that the noise (coherent and incoherent) is absolutely removed from the scan after processing it.

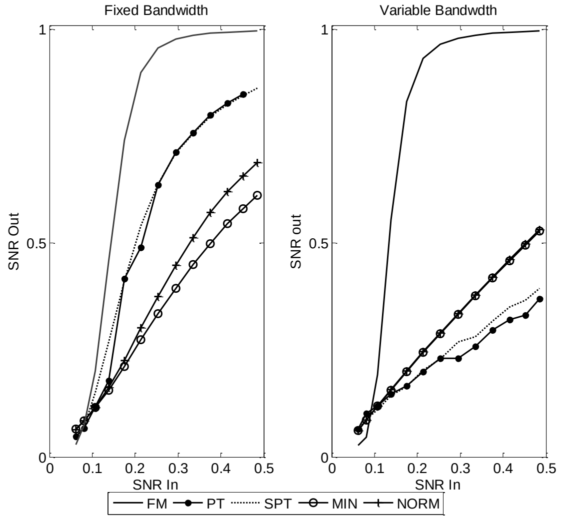

Figure #6: SNRout Vs. SNRin using fixed bandwidth filters (left) and variable bandwidth filters (right)

As shown in the figure, in both cases the most effective recombination method is the FM, being slightly steeper the slope when using the new filter bank. In the traditional model, PT and SPT methods also provide good results, followed finally by methods based on Minimization, being slightly better NORM than MIN. It should be noted that using fixed bandwidth filter, in all cases the slope is more than ½, which implies that the SNR gain will be greater than 1. However, using variable bandwidth filters, the slope of PT-based methods is less than ½ and therefore the SNR gain will be less than 1.

5.3 Variation of the SNR Gain vs. number of bands

The following figures (figure #7) show the average SNR gain vs. the number of bands used, with either the fixed and variable bandwidth filters and for all the recombination methods.

As can be seen in figures, the MF method is not only the method that get the best values for the SNR gain, but also the one which needs the less number of bands to achieve high values, so that using these methods the system complexity would be considerably reduced.

The best gain values and the higher speed of convergence are achieved when combining the new filter bank with the MF method, although it is true that for the rest of methods the gain worsens.

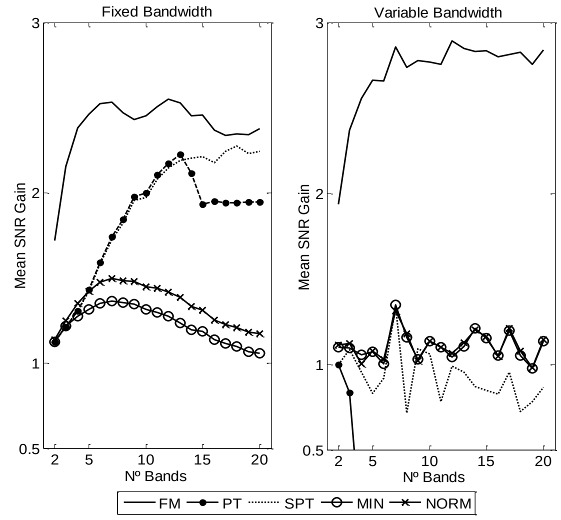

Figure #7: Mean SNR Gain Vs. number of bands using fixed bandwidth filters (left) and variable bandwidth filters (right)

5.4 Experimental results

After the analysis of the behavior of the different algorithms with simulated signals, it is time to check if the observed effects are reproduced with signals coming from real ultrasonic inspections, studying the SNR Gain obtained with each algorithm. Thus, it has been used a set of scans obtained from the inspection of a piece of Duralumin with a 1 cm diameter hole in its structure that simulates an effect, where has been used a transducer with a central frequency of 2 MHz and 1 MHz of bandwidth.

Next figure (figure #8) shows the results obtained after applying the different algorithms to one scan, where it is clearly seen the coincidence with the trends observed in simulations for the different methods and filter banks.

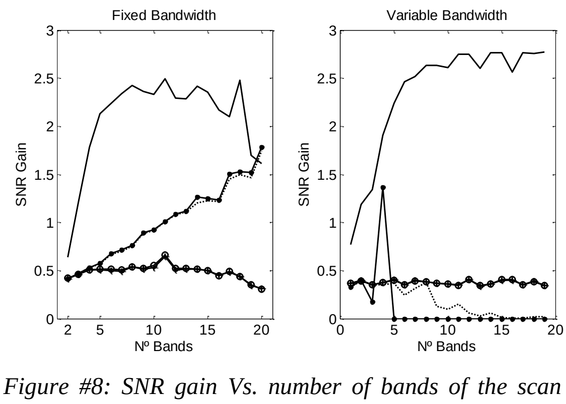

Figure #8: SNR gain Vs. number of bands of the scan using fixed bandwidth filters (left) and variable bandwidth filters (right)

In both cases, using fixed or variable filters, the FM method provides the best results, achieving very high values of SNR gain for a few bands. The maximum values are obtained with only 7 to 9 bands, decreasing slightly from this point in the case fixed bandwidth and increasing slightly in the case of variable bandwidth, which is the combination that best results provides. In fact, using the PT method with the fixed bandwidth design, it would be needed up to 35 bands to achieve the same results as with 7 bands in the case of FM and the new filter bank design.

The following figures show the results obtained after the application of the different methods to the scan of the example, with the traditional filter Bank (figure #9), and the new filter bank design (figure #10), using 9 bands in both cases. In these figures can be checked easily the improvement achieved in the time (space) resolution using the new design, in addition of all effects commented previously.

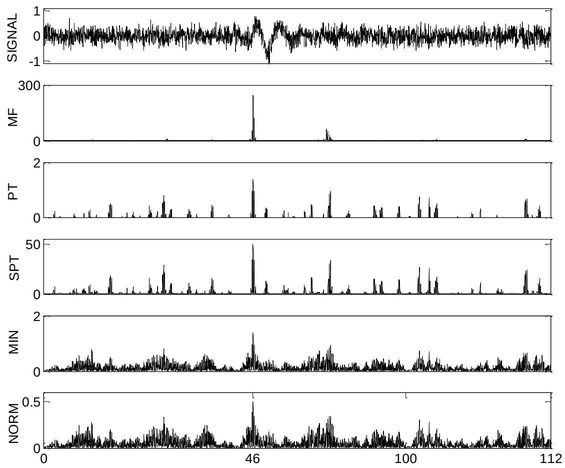

Figure #9: Output of the different methods of the scan using fixed bandwidth filters (time in microseconds)

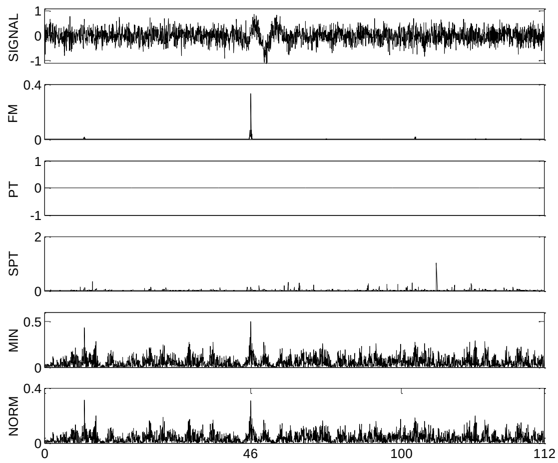

Figure #10: Output of the different methods of the scan using variable bandwidth filters (time in microseconds)

6. CONCLUSIONS

From the results it can be concluded that the stationary models used to simulate the signal and the algorithms assessment are adjusted enough to assume a valid approximation of real signals.

A new design filter Bank has been introduced, based on variable bandwidth filters, equally spaced and energy equalized, that has been demonstrated very efficient to maximize the SNR gain with the fewest possible bands in the filter bank.

On the behavior of the different algorithms, it has been proved that, in the case of a single defect, FM method provides the best values on the SNR gain, improving these considerably in the case of using the new filter bank proposed. In this case the gain remains approximately constant with the number of bands from the maximum, obtained between 5 to 9 bands. In any of the other methods, the use of this filter type worsens the result, so does not seem appropriate its use.

In future work will deepen into the behavior of the new filter bank and the FM method using not stationary models for the material and testing the obtained results with highly dispersive materials. The influence the rest of the parameters of the filter bank have in the behavior of the new design will also be the objective of a detailed study.

7. ACKNOWLEDGMENTS

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