CRACK DETECTION SYSTEM BASED ON SPECTRAL ANALYSIS OF A ULTRASONIC RESONANCE SIGNALS

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ABSTRACT

A real time crack detection system is presented in order to be used as a quality control strategy for syntherized metallic pieces. The signal processing algorithm is based on the spectral analysis of the signal measured by means of ultrasonic resonance inspection. The spectrum is obtained applying an FFT based chirp algorithm and from the resonance frequencies a minimum Euclidean distance algorithm, controlled by the false alarm probability, is applied to apart the cracked or defective pieces from the production system. The system has been tested in different production environments and with different types of pieces giving for all cases satisfactory results.

1. INTRODUCTION

The resonance inspection is a technique widely used for defective pieces detection. In a serial production process it results an attractive strategy because it is a non destructive test. Each produced piece is excited to vibrate in a determined bandwidth. A resonance signal modulated by the natural resonance frequencies of the piece is produced, and its spectrum constitutes a piece signature or a piece identification signal. When a different piece is analyzed (cracked or with a different density, etc..) a change is produced in the resonance frequency set. The power of resonance inspection is based on the fact that the resonance spectrum of a part is extremely sensitive to changes in its structure and composition. The spectrum observed for different good pieces fits a frequency pattern that characterize at all the subset of good pieces. When a piece has a defect, it may happen that some of its resonance frequencies be shifted from the frequencies that marks the pattern of good parts. When this happen, the frequency bandwidth between the shifted frequency and the reference frequency is proportional to the size of the defect.

The work here presented, has been developed to operate in a serial production manufacturer environment. The techniques selected in the spectrum analysis, spectrum peak research step and classification algorithm are the result of a half-way compromise between a kick and simple signal processing stage and an efficient crack detection system.

In what follows the general scheme is presented in section 2. The signal processing steps are described with detail in section 3. In section 4 the false alarm probability is developed and some interesting spectrum results are shown in section 5.

2. GENERAL SCHEME

The general scheme for the developed system is summarized in figure 1. An analog noise signal with a flat frequency response is generated in a certain bandwidth (200 KHz is the maximum allowed) which is used to excite a piezoelectric emitter transducer to make the piece vibrate. This noise exciting signal is digitally generated and D/A converted, conferring to the system the flexibility to choose the work bandwidth. Before exciting the transducer, the noise signal is low band filtered (for reconstruction effects), and amplified. From the piece vibration, two electrical analog resonance signals are measured by two receiver transducers correctly situated under the piece to test. This two time domain signals are A/D converted at a 625 KHz rate.

Once the two time signals are captured, a spectrum analysis algorithm must be implemented in order to estimate the frequency components of these two signals. The selected algorithm to estimate the spectrum is the non parametric FFT based Chirp algorithm. The chirp transform, allows to select a certain frequency span in order to concentrate the spectral points and obtain a better resolution. The result of applying the chirp algorithm to the resonance signals are two frequency domain vectors that contain the frequency components of the piece vibrations. In order to obtain two resonance frequency vectors to be used in the classification process, a Top Hat peaks detection algorithm is applied. Finally, a classification block decides whether a piece is cracked or not.

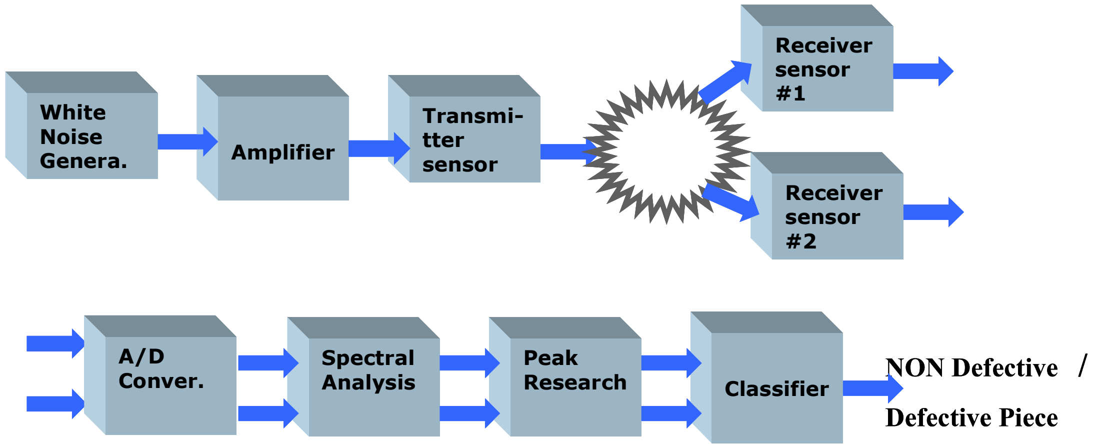

Figure 1. General Block Diagram

3. SIGNAL PROCESSING STEPS

Several parametric and non parametric spectrum analysis techniques [1], have been investigated to obtain the resonance frequencies. In this application, the chirp algorithm [2] averaged using the periodogram estimator produced the higher resolution solution. For the classification step we found major difficulties to obtain a detection algorithm because defective pieces presented a very varied behavior and only a pattern for non defective pieces was modeled to perform the decision algorithm.

3.1 Spectrum Analysis

The chirp transform, was applied to each one of the two A/D converted signals $x_1[n]; x_2[n]$. Vectors captured from a single piece are divided into L N_B-sample segments.

$$x_{i-l}[n] = x_i[n + (l-1)N_B]; \quad i = 1,2; l = 1..L; 0 \le n \le N_B - 1 \qquad (1)$$

The Z transform over a N_B segment is:

$$S_{i-l}(z) = \sum_{n=0}^{N_B-1} x_{i-l}[n] z^{-n}; \qquad i=1,2 \qquad (2)$$

Setting an starting point $z_0 = r_0 e^{jw_0}$ and a frequency resolution term $W = e^{j\Delta w}$, equation (2) can be rewritten as (3) when it is evaluated for a single frequency: $z_k = z_0 W^k$.

$$S_{i-l}(z_k) = \sum_{n=0}^{N_B-1} x_{i-l}[n](z_0)^{-n} W^{-kn} \qquad (3)$$

k=1..M-1. *M* denotes the number of frequency points computed in the selected bandwidth. Eq. (3) is computed more efficiently with $nk = \left(n^2 + k^2 - (k-n)^2\right)/2$.

$$S_{i-l}(z_k) = \sum_{n=0}^{N_B-1} y_{i-l}[k] W^{\frac{-k^2}{2}} \qquad (4)$$

where $y_{i-l}[k] = \sum_{n=0}^{N_B-1} g_{i-l}[n] \cdot h[k-n]$,

$h[n] = W^{\frac{n^2}{2}}$ and $g_{i-l}[n] = x_{i-l}[n] \cdot (z_0)^{-n} \cdot W^{-\frac{n^2}{2}}$

Eq. (4) results a convolution of signals "g_{i-l}" and "h_{i-l}" and can be computed as the inverse Fourier transform of a direct product in the frequency domain. The periodogram estimator is used to average the L processed segment spectrum.

$$\hat{S}_i(f) = \frac{1}{L} \sum_{l=0}^{L-1} S_{i-l}(f) \qquad (5)$$

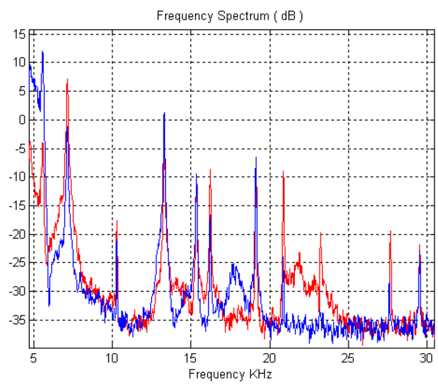

Figure 2. Chirp based periodogram spectrum obtained from a non defective piece. Blue and Red color are for signal 1 and 2 respectively.

Figure 2 shows the spectrum obtained for a non defective piece. In this example M=4096 uniformly spaced points where estimated in a 40 KHz bandwidth with L=150 averaged segments of length N_B=28673 samples pre-windowed with a Hanning window. The spectrum signals correspond to a circular axial symmetric piece. Although both signals should present same resonance frequencies, some differences are appreciated caused by the two different receiver sensor impulse responses.

3.2 Peak Research algorithm

The process of peaks detection is simplified by the use of the Top Hat algorithm [4] [5]. Top Hat algorithm is based on mathematical morphology and gives relative geometry information that simplifies resonance frequencies detection. It is based on the use of the two elemental morphology operators in mathematical morphology: dilation and erosion. With dilation and erosion, more complex operators as aperture and closing can be build. Top Hat algorithm is the result of subtracting to the original spectrum signal, the signal processed with the opening of the closing of the original signal, and setting to zero all those negative resulting points.

$$x - \wedge\{\gamma(\varphi(x)), x\} \qquad (6)$$

In (6), $\wedge\{\ \}$ denotes the minimum operator. $\gamma(\ )$ and $\varphi(\ )$ respectively denote the opening and closing operators. Noisy variations are eliminated, and only resonance frequencies remain from the spectrum signal. Figure 3 shows the top hat processed signals obtained from signals shown in figure 2.

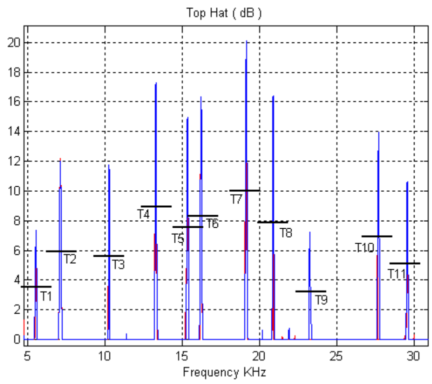

Figure 3. Top Hat processed signals. 11 peaks selected with proposed thresholds for its detection.

In order to obtain resonance frequencies, crosses by zero are detected from the two top-hat signal derivatives. An amplitude threshold, proportional to the power of each peak of the resonance frequency pattern, must be set, as a first step to detect those cracked pieces, that do no present enough energy.

3.3 Classification Algorithm

From a classification point of view [3], the detection algorithm must distinguish between two different patterns: defective pieces and non defective pieces. The classification algorithm here applied, is based in a minimum Euclidean distance criteria. Given the difficulty to obtain a simple model for the defective or cracked pieces only the non defective pieces statistical distribution has been modeled. From each measured piece, two frequency vectors are recorded that act as a piece signature. In (7) the number of frequencies recorded in previous steps is represented by N_f, and $\mathbf{f}_1$, $\mathbf{f}_2$ denote the two obtained frequency vectors:

$$\mathbf{f}_i = \left(f_{i-1} \ \ : \ \ f_{i-Nf}\right)^{\mathbf{T}}; \qquad i = 1,2 \qquad (7)$$

These two vectors are measured by the system, during a training period, for the maximum available number of non defective pieces and next parameters are measured:

Channel 1 and channel 2 mean vectors: $\hat{\mathbf{f}}_1; \hat{\mathbf{f}}_2$

Channel 1 and channel 2 covariance matrices: $\mathbf{C}_1; \mathbf{C}_2$

After the training period the classification strategy is developed applying simple criteria. For the piece number "*n*" the frequency vectors $\mathbf{f}_1[n]; \mathbf{f}_2[n]$ are measured and:

- If a component is not in the expected range: $\left(f_{i-k} - K_T\sigma_{i-k}, f_{i-k} + K_T\sigma_{i-k}\right)$ the piece is classified as defective. In the previous expression i denotes channel (i=1,2), k denotes component number ($k=1..N_f$) and K_T is a threshold selected empirically from the training period.
- The Euclidean distances $d_1 = d\left(\hat{\mathbf{f}}_1, \mathbf{f}_1[n]\right)$, $d_2 = d\left(\hat{\mathbf{f}}_2, \mathbf{f}_2[n]\right)$ are computed (for axial symmetric pieces also cross distance $d_{1-2} = d\left(\mathbf{f}_1[n], \mathbf{f}_2[n]\right)$). If previously to the distance computation, each frequency vector component is normalized to present zero mean and variance equal to one, the mean value for previous distances are: $E\left[d_1^2\right] = 1$, $E\left[d_2^2\right] = 1$, $E\left[d_{1-2}^2\right] = 2(1-\rho)$. ρ denotes the cross correlation between channel 1 and channel 2 and for a N_p pieces set is estimated as $\frac{1}{N_f}\frac{1}{N_p - 1}\sum_{n=1}^{N_p}\sum_{i=1}^{N_f} f_{1-i}[n] f_{2-i}[n]$.
- After the three normalized distance computation process, if a distance metric is not in the expected range: $\left(0, K_T\sqrt{E\left[d_x^2\right]}\right)$ the piece is classified as defective. x denotes distance (x=1,2 or 1-2), and K_T is a threshold, that is selected empirically from the training period.

Figure 4 shows histogram obtained from a frequency (15.58KHz) measured from a 150 non defective pieces set and figure 5 shows the histogram obtained for the three normalized Euclidean distances.

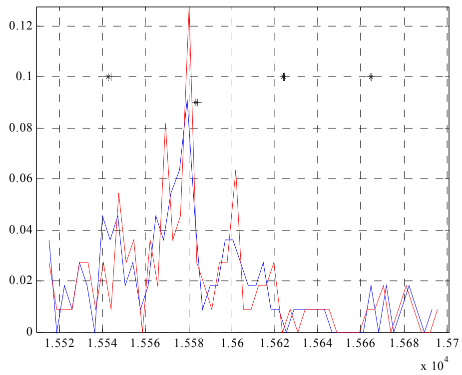

Figure 4. Histogram obtained for a single resonance frequency: 15.58KHz Blue and red for signals 1 and 2, respectively. Black dots at $f_{i-k} \pm n\sigma_{i-k}, n = -2 : +2$

Figure 5. Histograms obtained for the three Euclidean normalized distances. Blue for d_1, red for d_2, and black for $d_{1\text{-}2}$. Dots are drawn at $nE\left[\hat{d}_x^2\right]; n = 1:3$

4. FALSE ALARMA PROBABILITY

Some assumptions have been assumed to estimate the false alarm probability as a measure of the system quality.

- The two frequency vectors are gaussian distributed.
- The false alarm probability has been computed in the signal subspace domain.

The frequency vectors have been projected to the N_R main eigenvectors subspace obtained from the global covariance matrix

$$C = E\left[\begin{pmatrix} \mathbf{f}_1 \\ \mathbf{f}_2 \end{pmatrix} \begin{pmatrix} \mathbf{f}_1^{\mathrm{T}} & \mathbf{f}_2^{\mathrm{T}} \end{pmatrix}\right] \tag{8}$$

The new projected vector, has N_R components assumed distributed as:

$$\mathbf{x} : \mathbf{N}\left(0, diag\left(\sigma_1^2, .., \sigma_{N_R}^2\right)\right) \tag{9}$$

The previous threshold K_T is empirically transformed in threshold K_N for the new components, and in this conditions the false alarm probability has been computed as:

$$P_{FA} = \sum_{n=1}^{N_R} 2 \int_{K_N \sigma_n}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left(-\frac{x^2}{2\sigma_l^2}\right) dx = N_R erfc\left(K_N\right) \tag{10}$$

Table 1 shows the predicted values for false alarm probability depending on the normalized threshold K_N.

K_N	1	2	3	4
erfc(K_N)	0,16	4,6 e(-3)	2,2 e(-5)	1,5 e(-8)

Table 1. Estimated false alarm probability.

5. RESULTS AND CONCLUSIONS

With cracked pieces, resonance frequencies suffer changes as can be seen in figure 6-left, and even for some pieces, defects are traduced with the elimination of some of its resonance frequencies, figure 6-right, where red spectrum appears for a cracked piece and it is compared with the non defective set in black. When this happen, the piece is automatically rejected by the quality control system.

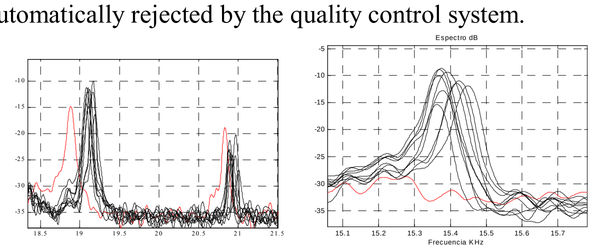

Figure 6. Spectrum partial view in dB. Frequency in KHz.

In conclusion, a crack detection system has been developed to select defective pieces from a serial production environment. The system is flexible to analyze different bandwidth until 200 KHz, and to test different kind of syntherized small pieces.

6. REFERENCES

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