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Improving Real Time Rail Monitoring with EMAT Sensors and Superlets Analysis

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Abstract. The development of online and in filed ultrasonic testing tools for rail defects detection requires advanced signal processing analysis methodologies. The objective is to properly identify the Time of Flight (ToF) of the wave in high noise measurements. We propose an estimator of this physical parameter with the use of a novel time-frequency analysis technique, adapted from the Continuous Wavelet Transform (CWT), called the Superlet Transform (SLT). It provides higher accuracy even at low Signal to Noise Ratio (SNR). We apply this estimator on a simulated example to quantify the reached performances, in terms of errors and variances.

Keywords: ultrasonic testing, EMAT, signal processing, wavelet analysis, superlets

1 Online non-contact analysis of rail with EMATs

Development of efficient maintenance plans requires early detection of damages. For rail inspection, observation of evolution of cracks allows a predictive establishment of defect propagation inside the steel. In this perspective, an online inspection process of rail is mandatory. We present in this article the results of an investigation to perform non-contact analysis of the rail surface with an ultrasonic testing technique, called Electro-Magnetic Acoustic Transducers (EMAT) [1] in high noise conditions, or low Signal to Noise Ratio (SNR).

Surface Rayleigh waves are generated to interact with surface defects, such as squats and head-checks, detected with the Time of Flight (ToF) of the wave. The non-contact advantage allows a fast moving of the sensors on the rail. A mechanical trolley has been designed within the European project IN2TRACK3, to specifically use EMAT sensors, reaching speeds up to 20 km/h, see figure 1.

However, numerous exogenous disturbances appear during the measuring processes, that complicates the detection of defects and their characterization. The non-contact aspect of EMAT requires a strict control of the distance between the sensors and the rail (called the lift-off). For this purpose, the presented new methodology analyzes noisy ultrasonic signals with high levels on noise, thanks to a recent tool called the Superlets [2], based on the wavelet transform, a linear operator for time-frequency representation of signals.



Fig. 1: EMAT trolley for online rail inspection.

2 Estimation of the Time of Flight

In ultrasonic testing, detection of defects is performed with analysis of the ToF u^* of the wave pulse from the measurement signal $x(t)$. The Rayleigh wave perturbation propagates inside the rail with a specific shape. On the oscilloscope, the signal is similar to a Gabor pulse, which is a multiplication between a cosine and a Gaussian function, whose mean is the ToF. The Gaussian function is assimilated to the envelope of the signal. A Gabor wavelet $g_\theta(t)$ is entirely described by the parameter vector $\theta = [\alpha, f, u^*, \sigma^2, \phi]^t$ with α the amplitude, f the central frequency, u^* the ToF, σ^2 the spread and ϕ the phase. It is expressed as:

$$g_\theta(t) = \alpha \exp\left(-\frac{(t - u^*)^2}{\sigma^2}\right) \cos(2\pi ft + \phi) \quad (1)$$

From the above description of a Gabor wavelet, the ToF corresponds to the time of the maximum of the envelope. Therefore, an extraction of this envelope from any empirical signal could give enough information to recover the ToF. However, signals coming from sensors contain an important level of noise. Quality of the envelope estimation is diminished.

The most simple way to find the ToF on a clean (noiseless) signal is to compute the envelope $A(t)$ from its analytical representation $x_a(t)$, calculated with the Hilbert transform (HT) H of $x(t)$. The trivial estimation \hat{u} of the ToF u^* is taken as the time which maximizes the envelope:

$$\hat{u} = \arg \max A(t) = \arg \max |x_a(t)| = \arg \max |x(t) + H[x](t)| \quad (2)$$

However, this simple estimate is very sensitive to noise, and is therefore inappropriate for real measurements. The state-of-the-art analysis methodologies used in this article are:

- Empirical Mode Decomposition (EMD) based method [3]: the EMD is an algorithm to decompose a signal in several components, each one corresponding to one mode of the signal. Decomposition is based on a heuristic procedure, lacking strong mathematical foundations. In the context of pulse waves, the objective is to identify the main mode related to the pulse. The other modes are assumed to contain information about the noise and the random perturbations. The HT is then applied on the main mode;
- Continuous Wavelet Transform (CWT) based method [4]: the pulse is extracted from the scalogram (time-frequency representation of the signal based on the convolution with a mother wavelet), the envelope is calculated, and the ToF is extracted, the same way as with the HT;
- Quasi Maximum Likelihood (QML) method [5]: an approximate statistical model is fitted to the envelope (with the HT) of the signal based on the analytical representation.

In the following, we present the Superlet Transform (SLT), which is an improvement of the CWT. They naturally share the properties of the CWT. Consequently, both CWT and SLT are usable in real-time and offline procedures, depending on the required quality of the ToF estimation.

3 Continuous Wavelet Transform

A description of the wavelet analysis formalism is now necessary to understand properly the improvements brought by the SLT. The CWT of a signal x at time u and scale $s \in \mathbb{R}^{+,*}$, using the mother wavelet Ψ is defined as:

$$\mathcal{W}_x(u, s) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{s}} \Psi^* \left(\frac{t-u}{s} \right) dt \quad (3)$$

where Ψ^* denotes the conjugate function of Ψ .

It has been demonstrated that the CWT provides an unbiased estimation of the ToF if the Morlet wavelet is used as mother wavelet. However, it is no longer possible for the central frequency of the Gabor pulse, the estimation is indeed biased (see [6]), and the bias depends on the central frequency of the pulse.

Very often, a conversion is made from a specific scale s to the related frequency ω to clarify the notation. The conversion is easily made with knowledge of central frequency of the mother wavelet used (see [4] for further details). In the following, we no longer use the scale notation, but the frequency notation ω .

4 Superlets and the Superlet Transform

The Superlet Transform (SLT) has been introduced to bypass the limitations of the time-frequency resolution of the CWT, directly related to the Heisenberg-Gabor principle. It uses the concept of Superlet which is defined as a set of wavelets with same central frequencies, but different number of cycles (and therefore frequency bandwidths). The SLT reaches higher time-frequency resolutions

by taking the geometric mean of the multiples CWT of the signal from the Superlet set. The SLT of signal x of order o is defined as:

$$\text{SLT}_{x,o}(u, \omega) = \sqrt[o]{\prod_{i=1}^o \mathcal{W}_{x,c_i}(u, \omega)} \quad (4)$$

With c_i the number of cycles in the mother wavelet of level i . Multiples methodologies exist to define the set of cycles $\{c_i\}_{i=1}^o$. The simplest one is the additive way: we define a minimum number c_1 and define $c_i = c_1 + i - 1$. A slightly more complex process is used in this article: the multiplicative way, with $c_i = c_1 \cdot i$. The SLT combines therefore multiple scalograms and achieves a super-resolution on the signal. Qualitatively, the representation is sharper and less redundant than the CWT representation. However, one easily sees that the CWT is a SLT of order 1. The proposed estimator, \hat{u}_{SLT} , using the SLT instead of the envelope of the signal is then:

$$\hat{u}_{\text{SLT}} = \arg \max |\text{SLT}_{x,o}(u, \omega)| \quad (5)$$

It uses a search of the maximum in the absolute scalogram representation, across all analyzed frequencies. The main interest of this estimator is the possibility to fusion information from many wavelet representations, and therefore eliminate noisy contents, which spread across the spectrum. More robustness is expected from this estimator, in comparison with the CWT. See [2] for other advantages of this technique.

5 Quantitative experiment

A quantitative comparison has been made with a simulation process. The objective was to study a representative example, and evaluate the performances of the proposed estimator \hat{u}_{SLT} . A Gabor wavelet with known parameters is created, and different intensities of noises are added (to reach specific levels of SNR). The parameter vector for the Gabor wavelet is set to $\theta = [\alpha, f, u^*, \sigma^2, \phi] = [10, 50 \text{ Hz}, 0.5 \text{ s}, 2.5e^{-3} \text{ s}^2, 0 \text{ rad}]$. Duration of signal is 1 second, with sampling frequency $f_e = 1000 \text{ Hz}$ (1000 samples). The five methodologies are applied, and comparison with real ToF is performed (the score used here is the Mean Absolute Error or MAE), see figure 2. For the CWT and SLT, analyzed frequency start are all integer frequencies from 1 Hz to 100 Hz (for a total of 100 frequencies analyzed). The Superlet created uses the multiplicative configuration, starting with a minimum number of cycles of $c_1 = 3$, with order $o = 5$. The Morlet wavelet is taken as the mother wavelet. Experiment is repeated 100 times to obtain Monte Carlo estimates of the MAE and the variance of absolute errors. The HT has obviously the worst errors. Performances of CWT and SLT are clearly the better, in term of both errors and variances. The computational cost of Superlets is justified only at low SNR, from the quantitative point of view. Interestingly, the wavelet-based methodologies outperform the optimization process (the QML) and the heuristic method (the EMD) and provides a more accessible calculation and estimation of the ToF, with a constant computational cost.

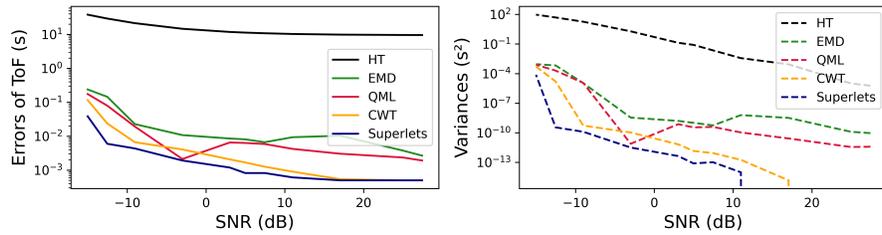


Fig. 2: Monte Carlo simulations for Time of Flight estimations with Gabor wavelet signal corrupted with noise.

6 Discussions for practical implementation

In addition to quantitative estimations, the visual analysis of signals is sometimes also useful: for an operator in-field, a quick view on a time-frequency representation gives important information. The shape of the pulse indicates whether it changes from the expected representation. A base signal is taken from a nearly noiseless EMAT recording on a rail with the trolley system from figure 1, with a 2 mm lift-off in figures 3a and 3b. This base signal is then polluted with a strong noise, with a SNR reaching -15 dB. A visual comparison of ST, CWT and STFT shows that the ST gives the cleaner shape and allows a better differentiation of the Gabor pulse from the noisy background, in the frequency range of interest.

Besides the numerous advantages of Superlets, the computational burden must be considered for an efficient online analysis tool. The time complexity of the SLT is directly proportional to order selected. For each scalogram, the complexity is linear in the number of scales analyzed. To reduce calculations, the order of the Superlet Transform must be carefully selected, to match the required precision.

7 Conclusion

The ToF estimator described in this article, based on the Superlet Transform, has shown to perform better than the usual estimators on a simulated example. The experiment was designed to approach a realistic configuration, using EMAT sensors which generate Rayleigh waves. The Gabor representation of these ultrasonic waves is a major hypothesis, which hold precisely in this situation, and must not be directly transposed on other ultrasonic signals. However, in this situation, the estimator based on SLT reached higher accuracy than all other estimators, in term of absolute errors, and variances. The gain from the classical wavelet analysis tool, the CWT, has been shown. Furthermore, it removes the need for a precise selection of the mother wavelet, since results from multiple wavelets with different numbers of cycles are merged. The next investigation step will be the in field experiment, to assess the validity of the methodology with real defects on rail, such as squats or head-check.

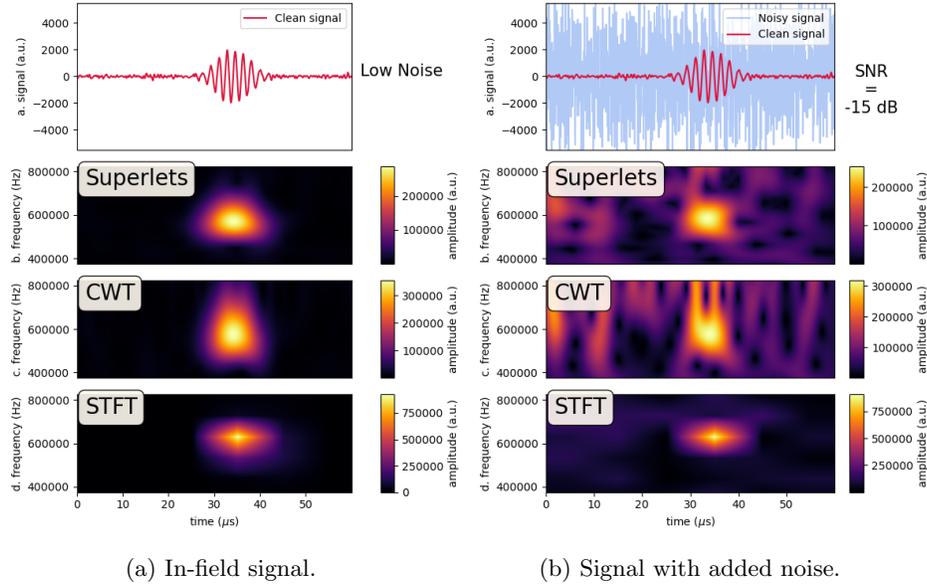


Fig. 3: Time-frequency representations of a real signal with added noise.

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