A NEW METHOD FOR AE SIGNAL PROCESSING: "VIRTUAL SENSOR" TECHNIQUE

Seregy Lazarev [1], *Alexey Lazarev* [2], *Fedor Pletenev* [3] *and Alexei Vinogradov* [4]

Abstract: A new method of signal recognition is proposed upon the assumption that the AE signal is created by a highly correlated source within a solid body. It therefore should have a more stable phase than an arbitrary noise at the same frequency. Hence, in contrast to the Fourier transform, the proposed "resonance" method attempts to emphasize the phase of the signal.

Keywords: Digital signal processing, signal recognition

INTRODUCTION AND MOTIVATION

Acoustic emission (AE) is a random process which can be either continuous or transient such as shown in Fig.1. Moreover, the picture is complicated by the inevitable presence of background noise, which can be comparable or even higher than the signal of interest. Being stochastic in nature, the AE signal does not usually have a well defined structure. Therefore, recognition of the AE signal in noisy background is of crucial importance. With the rapid advent of microelectronics and cost-effective computing facilities, a broad variety of signal processing techniques have become affordable and readily available for application in AE. The Fourier analysis is still the most widely used. The Fourier transform (FT) has gained its great popularity in AE data analysis due its simplicity in procedures and interpretation and availability of fast algorithms for numeric processing.

However, the simplicity of Fourier analysis in application to AE is misleading. First of all, the FT is defined for stationary processes infinite in length while AE is a transient phenomenon by definition. Even a continuous noise-like signal is composed of a large number of overlapping transients of relatively small amplitude. FT gives what frequency components present in the signal. Based on the FT, the power spectral density function is defined over a certain period of time. Therefore it delivers only information on the average amount of energy per realization and it does not say anything on how this energy (power) is distributed in time, although it is evident that the energy can evolve strongly inhomogeneously in time, Fig.1b. Hence, for non-stationary transient processes, *the time localization* of the spectral components is essential and a transform giving the time-frequency representation of the signal is needed. The Short Time Fourier Transform (STFT) or Wavelet Transform (WT) are considerably more powerful in this respect as they are defined on much shorter time intervals, i.e. they can be regarded as local transforms in time domain, however, both these techniques are computationally much more expensive than FT. Another drawback of FT is that the amplitude spectrum given by Fourier coefficients does not consider the phase of the signal; in fact the phase spectrum is actually ignored in the spectral density.

Consider a simple example of two sine-wave signals

[1] Director Microsensors AE, Ltd.; Group Leader, Center of Innovative Technologies, Sarov, Russia
[2] Researcher, Togliatti State University, Belorusskaya 14, 445667, Togliatti, Russia
IT Engineer, Center of Innovative Technologies, Sarov, Russia
[3] Chief IT Engineer, Center of Innovation Technologies, Sarov, Russia
[4] Assoc. Professor, Osaka City University, Osaka, 558-8585, Japan
Head of the Lab., Togliatti State University, Belorusskaya 14, 445667, Togliatti, Russia

(a) $x(t) = \sin(2\pi \cdot 50t) + \sin(2\pi \cdot 1400t)$ and

(b) $x(t) = \begin{cases} \sin(2\pi \cdot 50t), & t \le t_0 \\ \sin(2\pi \cdot 1400t), & t > t_0 \end{cases}$

as shown in Fig.2 and b, respectively. Their amplitude Fourier spectra $|X(f)|$ correctly show that the same frequencies exist in both signals. However, the waveforms are quite different as the phases of the signal (b) are shifted with respect to each other.

On the other hand, it seems plausible to suppose that the AE signal of interest, which is created by a co-operative structural transformation within a solid body regardless of minute details of its origin, should have a stable phase. Therefore, the detection technique should benefit from sensing and monitoring the signal phase.

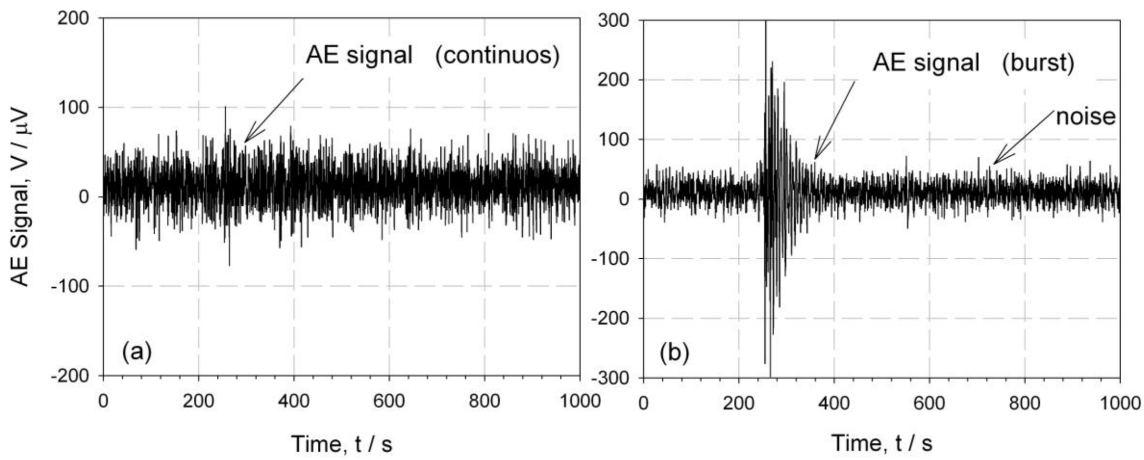

FIG. 1—Typical AE waveforms: (a) continuous and (b) transient.

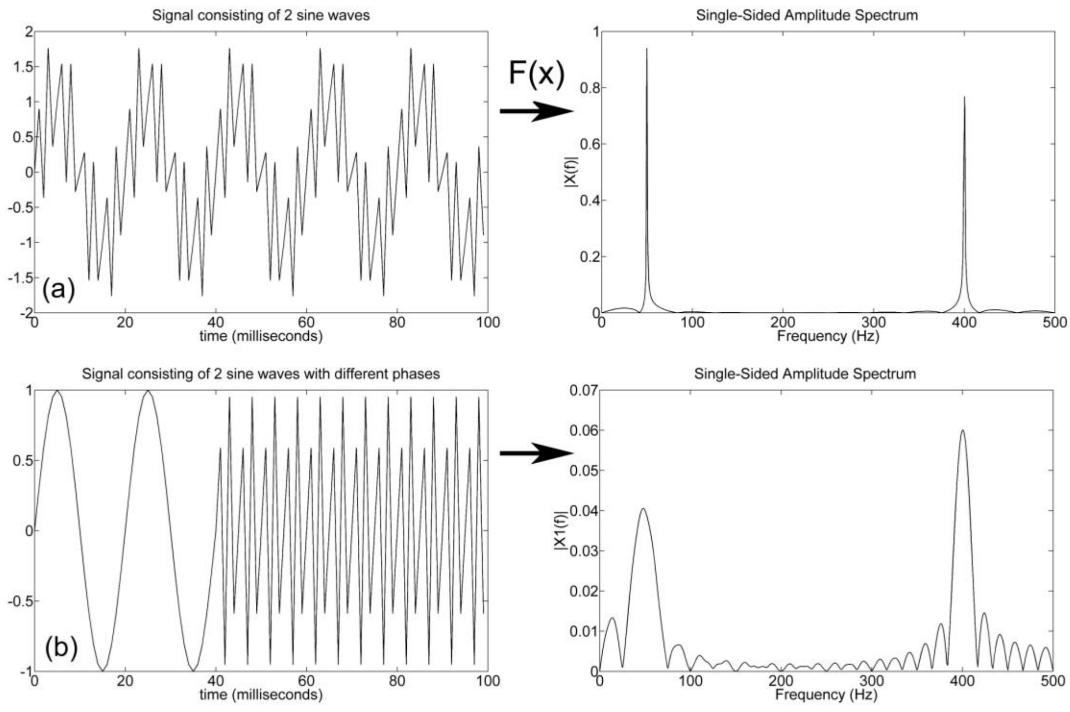

FIG. 2—Examples of FT for sum of two *sin* waves (a) with the same phase and (b) different phases.

AE is conventionally detected either by a resonant or pseudo-wideband piezoelectric sensors characterized entirely by their specific transfer functions. The incoming signal can be easily masked if its frequency content does not correspond to one or few resonances of the AE sensor. The purpose of any further processing is to rectify the signal, disclose its specific structure and emphasize its features. So does filtering (analogue or digital, Wavelet-based, FT-based, etc.): it rejects the redundant noisy frequency components and increases the signal-to-noise ratio (SNR) for frequency components of interest. The new method is oriented towards real time processing of continuously streaming AE data acquired by a fast ADC without any preset threshold. The strategic idea is to treat the electric signal form the AE sensor output as if it would be a virtual force acting on a system of resonators called *virtual sensors* (VS) with perfectly known and adjustable characteristics. Hence, our primary objective is to develop a simple and computationally effective algorithm for AE signal detection, recognition and characterization. We start with the premise that the AE signal differs from an uncorrelated background noise in that the signal, or least a part of it, contains a fraction of oscillations with a stable phase due to the time-dependent properties of the source. Hence, a resonance technique should adequately response to emphasize this feature.

VIRTUAL SENSORS: THEORETICAL CONCEPT

A virtual resonance sensor is described by the following equation corresponding to the damped harmonic motion in the forced oscillator:

$$\ddot{x} + \frac{2}{\tau}\cdot\dot{x} + \omega_0^2\cdot x = f(t) \tag{1}$$

where x – is the voltage at the VS output, $f(t)$ – external influence (say the signal from the real AE sensor), ω_0 – natural cyclic frequency of the resonant system, τ – relaxation time of the oscillator, characterizing the time of decay. The Q-factor of the resonator Q is given as:

$$Q = \frac{\tau\cdot\omega_0}{2} \tag{2}$$

The Q-factor characterizes the rate of decay of oscillations in the resonator. Good resonators have $Q >> 1$.

The Green function of eq. (1) has a form:

$$G(t) = \Theta(t)\cdot\exp\left(-\frac{t}{\tau}\right)\cdot\frac{\sin(\omega_1\cdot t)}{\omega_1}, \tag{3}$$

where

$$\omega_1 = \sqrt{\omega_0^2 - \frac{1}{\tau^2}} \tag{4}$$

Assume that we have a set of N parallel resonant sensors with damped natural frequencies ω_{0n} and relaxation times τ_n as shown schematically in Fig.2. Let us choose the relaxation times in such a way that all resonators have the same Q-factor. This yields:

$$\tau_n = \frac{2D}{\omega_{0n}} \tag{5}$$

and

$$\omega_{1n} = \omega_{0n}\cdot\sqrt{1-\frac{1}{4D^2}} \tag{6}$$

Taking $x(0) = 0$, we obtain the solution of eq.(1) for n's resonator, further referred to as *virtual sensor*, in the form:

$$x_n(t) = \frac{1}{\omega_{1n}} \cdot \int_0^t dt_1 \cdot \exp\left(-\frac{t-t_1}{\tau_n}\right) \cdot \sin[\omega_{1n} \cdot (t-t_1)] \cdot f(t_1) \tag{7}$$

In real world, the frequencies ν_{0n} corresponding to cyclic frequencies ω_{0n} ($\omega_{0n} = 2\pi\ \nu_{0n}$) should range from 50 kHz to 2 MHz, which corresponds to the frequency band most commonly used in AE technology. We now can design a bank of virtual sensors covering a range of frequencies of interest as shown in Fig.3. The virtual sensors design can vary: the sensors can be selected with or without overlapping of their responses, the response function of each sensor can be controlled individually as desired to emphasize certain frequency properties of incoming signals, etc.

Let us assume that the signal *f(t)* arriving at the input of a virtual sensor from an output of a real sensor is acquired during a time interval *T* with a time increment *Δt*. For example, let the AE signal acquisition be performed continuously during the time interval *T* = 10 s with a sampling time *Δt*=0.1 μs corresponding to the sampling rate of 10 MHz which is readily available in commercial AE systems. Hence, the whole record consists of M=10^8 readings. Let the amplitude resolution be 16 bits (typical of modern ADCs). Thus, the whole record will be of 200 Mb. The rate of data acquisition through one virtual channel will be 20 Mb/s. Therefore, if we have chosen a bank of virtual sensors, containing say 100 virtual resonators with natural frequencies ω_{01}-ω_{0N}, the volume of storage data will be 20 Gb. Evidently, one must admit that this amount of information should be either treated fully automatically or one has to squeeze the information somehow for visual observation, preferably without lost of valuable information about the peak values of frequency components in both linear and logarithmic scales. These peaks (especially if they are of low amplitude) can be masked by noise can cannot be seen by conventional techniques.

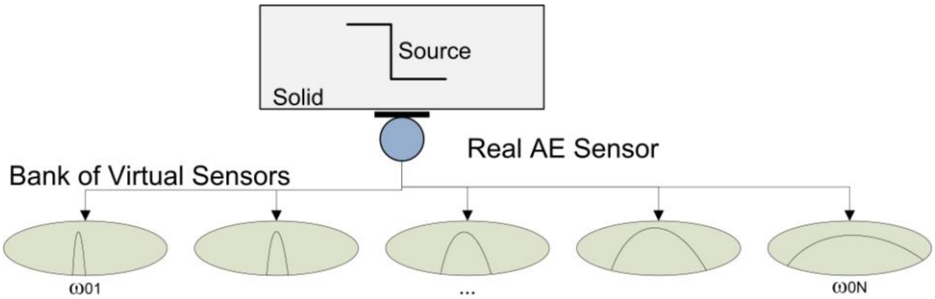

FIG. 3—Schematic of virtual sensing technique

The proposed bank of VS resembles the structure of wavelet transform, but is of course in a qualitative sense.

Let us change from continuous functions and integration to finite differences and summation. We shall choose the time increment *Δt* equal to the sampling time equal 0.1 μs. We shall have:

$$x_n(t_m) = \frac{\Delta t}{\omega_{1n}} \cdot \sum_{k=0}^{m} \exp\left(-\frac{(t_m - t_k)}{\tau_n}\right) \cdot \sin[\omega_{1n} \cdot (t_m - t_k)] \cdot f(t_k), \tag{8}$$

where

$$t_m = \Delta t \cdot m \tag{9}$$

Introducing new variables α and β

$$\alpha_n = \frac{\Delta t}{\tau_n}; \quad \beta_n = \omega_{1n} \cdot \Delta t \tag{10}$$

we obtain:

$$x_n(m) = \frac{\beta_n}{\omega_{1n}^2} \cdot \sum_{k=0}^{m} \exp[-\alpha_n \cdot (m-k)] \cdot \sin[\beta_n \cdot (m-k)] \cdot f(k) \tag{11}$$

After one more variable substitution *m-k=l* we obtain a convenient form of the VS response:

$$x_n(m) = \frac{\beta_n}{\omega_{1n}^2} \cdot \sum_{l=0}^{m} \exp(-\alpha_n \cdot l) \cdot \sin(\beta_n \cdot l) \cdot f(m-l) \tag{12}$$

To reduce computation cost it is not difficult to obtain recursive relations for (12).

IMPLEMENTATION

The proposed new strategy was implemented using Intel® C++ compiler with Intel® IPP libraries for optimized FFT calculations. Computation cost is estimated for Intel® Core™ i7 CPU Q740, 1.73GHz (with SSE 4.3) under Windows 7 (64). Using a single CPU core, an 80 channel VS transform for 10^7 samples (1 s realization sampled at 10 MHz) takes 0.23 s while the 4096 point FFT with a half window overlapping requires just 0.046 s, i.e. FFT is of 5 times faster. However, if the FFT window shifts one position on the incoming stream, as is typically implemented in many conventional FFT–based algorithms, the VS transform is about 400 times faster. One should also bear in mind extra cost for computing the power spectral density, which requires squaring FFT amplitudes followed by window smoothing.

EXAMPLES

To illustrate the proposed approach, the testing of the bank of virtual sensors has been performed using real AE streaming data realizations, acquired continuously at 2 to 10 MHz sampling rate with 16 bits amplitude resolution. Figure 4 shows the input waveform and its VS spectrogram obtained after the pensile led break test and sampled its VS spectrogram. Figure 5 compares the results of FFT and VS for a part of streaming realization obtained during jerky plastic flow of α-brass (see a paper by A. Lazarev et al. in the same proceedings). It is clearly seen that though both techniques correctly capture the AE burst corresponding to the propagating plastic fronts, the SNR is lager in VS. Apparently the amplitude FT spectrum fluctuates widely and the must be smoothed, while VS response is smooth enough since it is fully controlled by the *Q*-factor.

CONCLUSIONS AND REMARKS FOR FUTURE SCOPES

The new viable digital signal processing scheme called *virtual sensor* is proposed as a working model for computationally effective AE signal detection, recognition and characterization. The method is featured by its great flexibility in designing the desired response using a bank of independent VS.

Finally, we would like to state clearly that despite seen good perspectives, the method is still in its infancy. It has yet to be quantitatively and rigorously tested in comparison with FT, STFT and DWT for its efficiency and capacity to increase the signal-to-noise ratio and to recognize low-amplitude AE events on a noisy background. VS bank and computation optimization is also required before the method can be converted into a working tool. These are future scopes and the results will be reported elsewhere.

ACKNOWLEDGEMENTS.

Financial support from the Russian Ministry of Education through the grant-in-aid № 11.G34.31.0031 is greatly appreciated.

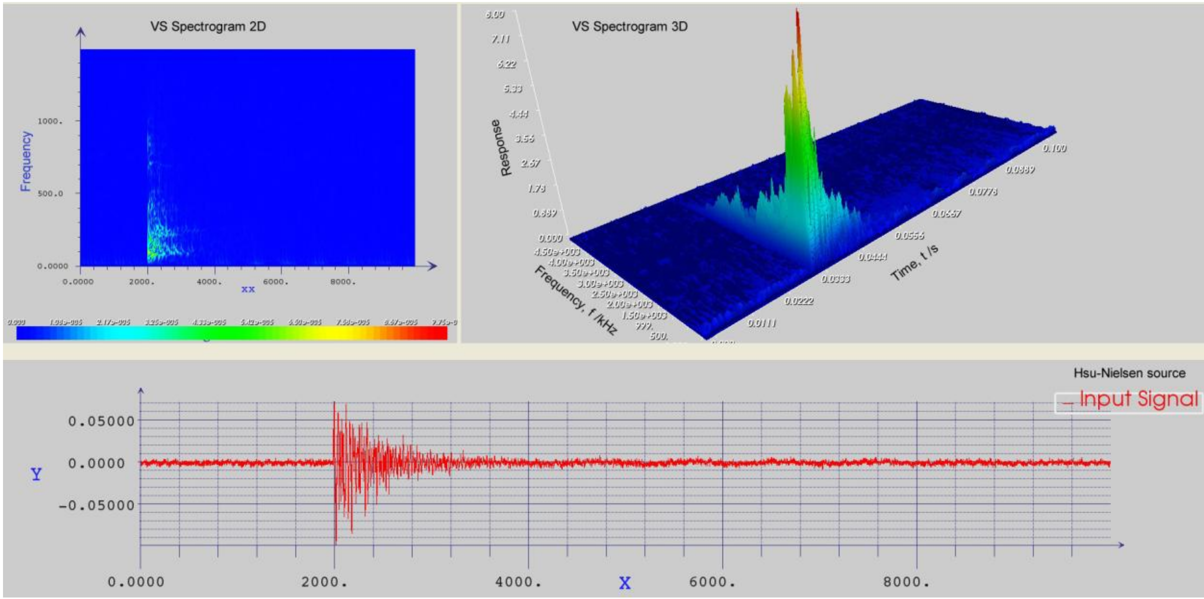

FIG. 4—Results of VS transform in application to artificial Hsu-Nielsen source signal

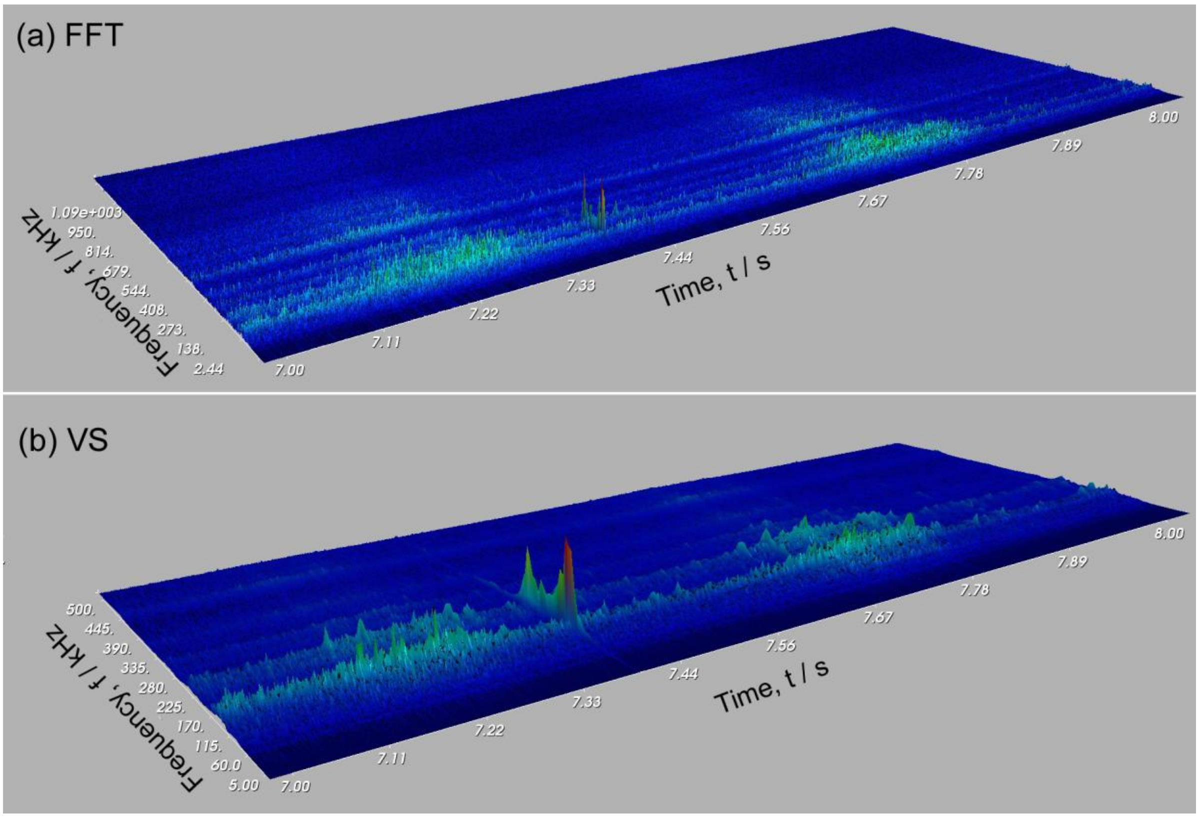

FIG. 5—Comparison of FFT amplitude spectra and VS transform in application to jerky plastic flow of CuZn α-brass: AE bursts are clearly seen in both methods, but SNR is higher for virtual sensors.