A Novel Time-Domain Method of Analysis of Pulsed Sine Wave Signals

Alireza K. Ziarani, *Member, IEEE*, Adalbert Konrad, *Fellow, IEEE*, and Anthony N. Sinclair, *Member, IEEE*

***Abstract*—Sine wave packs are used in nondestructive evaluation of materials, most commonly in the form of ultrasonic waves. An example of such methods is the use of electromagnetic acoustic transducers (EMATs) in the evaluation of metallic structures. Reflected EMAT signals are often highly polluted by noise. Elimination of noise and extraction of peak amplitude are important signal processing tasks associated with the analysis of EMAT signals. This paper presents a method of noise elimination and information extraction for pulsed sinusoids. The functionality of the proposed method is exemplified through noise reduction and peak detection of EMAT signals. The proposed method offers a simple and robust technique of signal analysis which is suitable for real-time industrial applications since it requires a relatively low level of computational resources.**

***Index Terms*—Electromagnetic acoustic transducers (EMATs), noise elimination, peak detection, pulsed sine waves, ultrasonic nondestructive evaluation (NDE).**

I. Introduction

TRANSMISSION of bursts of ultrasonic waves into a medium is a well-known technique for acquisition of useful information about the structure of the medium under study. Ultrasonic waves are often used in nondestructive evaluation of materials. Various techniques for generation of ultrasonic waves for NDE of metallic structures exist among which electromagnetic acoustic transduction has attracted considerable attention over the years due to its favorable noncontact testing feature. However, this method suffers from serious shortcomings due to the poor quality of the received signals which are often highly polluted by noise [1], [2]. A significant amount of literature deals with the various methods of improvement of the quality of received electromagnetic acoustic transducer (EMAT) signals. Coil design considerations constitute a major research trend in this regard [3]. Electromagnetic field computation has been used to assist the design of coil geometry [4]. Also, there has been considerable interest in adapting signal processing methods for noise elimination [5], [6] and flaw identification [7], [8].

In the NDE of materials using bursts of ultrasonic energy, i.e., pulsed sine waves, it is often desirable to detect the peak of the received signal, its amplitude and its time of arrival [1]. In order to detect such features of the received noisy signal, it is necessary to improve the signal quality by elimination of electrical noise. Time averaging of a repeated signal can reduce random electrical noise. Its main problem, however, is the long measurement time needed which limits its applicability to real-time NDE [2]. Narrow band filtering is used as the primary method to improve signal quality. A notch filter with a sharp notch is effective in eliminating the electrical noise, but renders the equipment sensitive to potential frequency drifts. Moreover, the output signal of such a filter has to be analyzed for detection of the peak and its arrival time. Fourier transform analysis could be used but, in this case, all the time information about the peak position will be lost [1].

Preliminary results of the application of a recently introduced time-domain method of extraction of sinusoidal signals of time-varying nature buried under noise to EMAT signal quality enhancement were presented in [9] by the aid of computer simulations. This paper presents an improved method of noise elimination for pulsed sine wave signals. The aim is to detect the arrival time of the envelope peak which is necessary in order to make accurate travel time measurements of ultrasonic echoes. The structure of the proposed method is presented and its behavior is demonstrated by the aid of computer simulations. Experimental verification of the performance of the proposed method is then exemplified by the refinement and information extraction of EMAT signals.

II. Extraction of Sinusoids in Noise

This section reviews the core algorithm which is employed in the structure of the proposed method of analysis of highly polluted signals presented in Section III. Consider a sinusoidal signal polluted by some noise of unknown frequency composition and expressed by

$$u(t) = A\sin(\omega t + \delta) + n(t) \tag{1}$$

where $n(t)$ represents the totality of the imposed noise, A and ω are potentially time-varying amplitude and frequency of the sine wave, respectively, and δ is the constant phase of the sinusoid. The total phase of the sine wave is $\phi = \omega t + \delta$. If time-variations are sufficiently slow, parameters A, ω, and ϕ are constant values A_o, ω_o, and ϕ_o within any short time interval.

Least squares error between the input signal $u(t)$ and the sinusoidal signal $A\sin(\omega t + \delta)$ embedded in $u(t)$ may be minimized by employing a gradient descent method [10]. The result is the following set of nonlinear differential equations to govern the dynamics of a signal processing algorithm aimed at extracting the potentially time-varying sinusoidal signal buried

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in $u(t)$ without any assumption on the composition of the imposed noise:

$$\dot{\hat{A}} = \mu_1 e \sin\hat{\phi} \tag{2}$$

$$\dot{\hat{\omega}} = \mu_2 e \hat{A} \cos\hat{\phi} \tag{3}$$

$$\dot{\hat{\phi}} = \hat{\omega} + \mu_3 \dot{\hat{\omega}} \tag{4}$$

where error $e(t)$ represents the difference between the input signal polluted by noise and the extracted sinusoid, i.e.

$$e(t) = u(t) - \hat{A}\sin\hat{\phi}. \tag{5}$$

In the above equations, $\hat{A}$, $\hat{\phi}$, and $\hat{\omega}$ are estimated values of amplitude, total phase and frequency of the extracted sinusoidal signal $y(t)$, respectively. Parameters μ_1, μ_2, and μ_3 are positive numbers which determine the speed of the algorithm in the estimation process as well as in tracking variations in the characteristics of the input signal over time.

The following theorem, proved in [11], deals with the existence, uniqueness and stability of a periodic orbit for the dynamical system described by (2)–(5).

Theorem 1: Assume that $u(t)$ is given by (1) wherein all the parameters are unknown but bounded. The dynamical system represented by (2)–(5) has a locally unique and hyperbolically stable periodic orbit $\gamma(t)$ in a close neighborhood of $\gamma_o = (A_o, \omega_o, \phi_o)$.

This theorem guarantees i) the convergence of the solution of the dynamical system to the periodic orbit associated with the sinusoidal signal in $u(t)$ and ii) the tracking of its variations over time. In terms of the signal processing performance of the algorithm, it extracts a sinusoidal component of its input signal, directly estimates its amplitude, phase and frequency, and adaptively tracks their variations over time.

The structure of the core algorithm is very simple and consists of only a few arithmetic operations. Fig. 1 shows a block diagram representation of the algorithm. The initial point of the flow of the dynamics is set by the values of initial conditions of integrators generating amplitude $A(t)$, phase $\phi(t)$, and frequency $\omega(t)$. In the presence of multiple sine waves, each sinusoidal component is specified by its frequency. Therefore, the initial condition of the frequency integrator (shown explicitly in Fig. 1) is of particular importance; the algorithm extracts that sinusoidal signal whose frequency is closest to the pre-set initial condition of the frequency integrator. Numerical implementation of the core algorithm is straightforward. For example, the following is the discretized form of the governing equations of the algorithm in which a first order approximation is assumed:

$$\begin{aligned} A[n+1] &= A[n] + T_s\mu_1 e[n]\sin\phi[n] \\ \omega[n+1] &= \omega[n] + T_s\mu_2 e[n]A[n]\cos\phi[n] \\ \phi[n+1] &= \phi[n] + T_s\omega[n] + T_s\mu_2\mu_3 e[n]A[n]\cos\phi[n] \\ y[n] &= A[n]\sin\phi[n] \\ e[n] &= u[n] - y[n]. \end{aligned}$$

where T_s is the sampling time and n is the time step index.

The Matlab Simulink™ programming environment is used to produce the graphs presented in this paper. In the first numerical experiment, the input signal $u(t)$ consists only of a pure

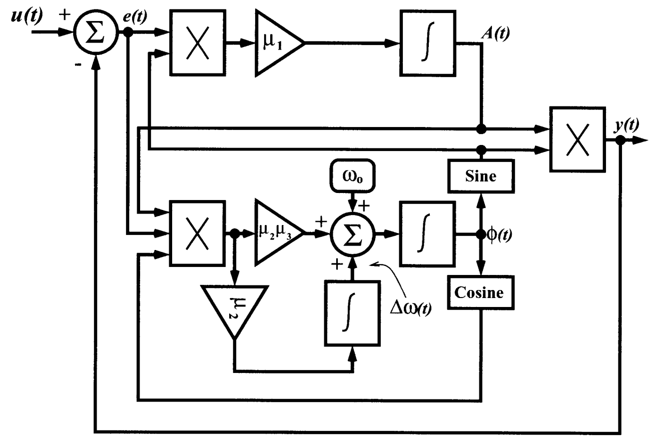

Fig. 1. Employed core algorithm in a block diagram representation.

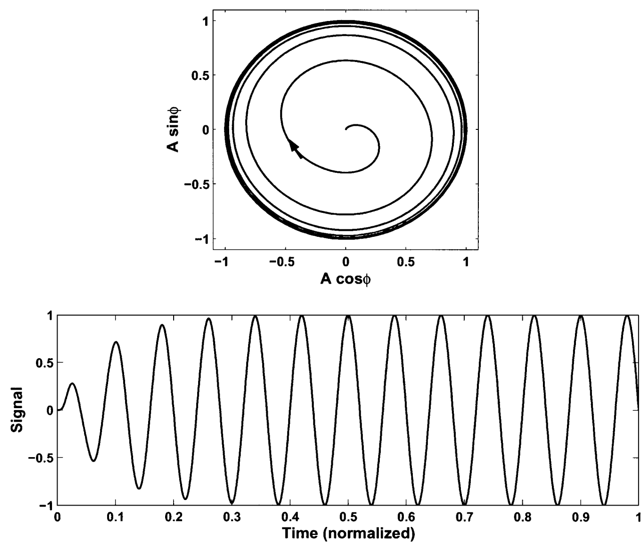

Fig. 2. Illustration of the convergence of the core algorithm. The input signal is a unit-amplitude sine wave. The top graph shows convergence of the dynamics to the periodic orbit associated with the extracted sinusoid; the bottom graph shows the flow of the dynamics in the time domain.

unit-amplitude sinusoid. Fig. 2 shows convergence of the algorithm in response to such an input signal. The pre-set initial frequency in Fig. 2 is the same as the frequency of the incoming sinusoid. To show the frequency retrieval property of the algorithm, in another numerical experiment the initial frequency of the algorithm is deliberately set to be about 50% off the frequency of the incoming sinusoid. Fig. 3 shows convergence of the algorithm in frequency.

The core algorithm exhibits a high degree of immunity with respect to noise. Fig. 4 shows this property. The noise present in the input signal is of about the same energy as the polluted sinusoid (i.e., $\mathrm{SNR} = 0$ dB). The convergence is achieved in a few cycles with a steady state error of about 5% in this experiment. The estimation accuracy is a function of the degree of the pollution in the input signal on the one hand and the desired convergence speed on the other hand. For example, the estimation error in the experiment of Fig. 4 can be reduced to 0.5% by reducing the values of parameters μ_1, μ_2 by a factor of about 10. This results in a convergence time of about 10 X longer. Therefore, the estimation accuracy is fully controllable by the adjustment

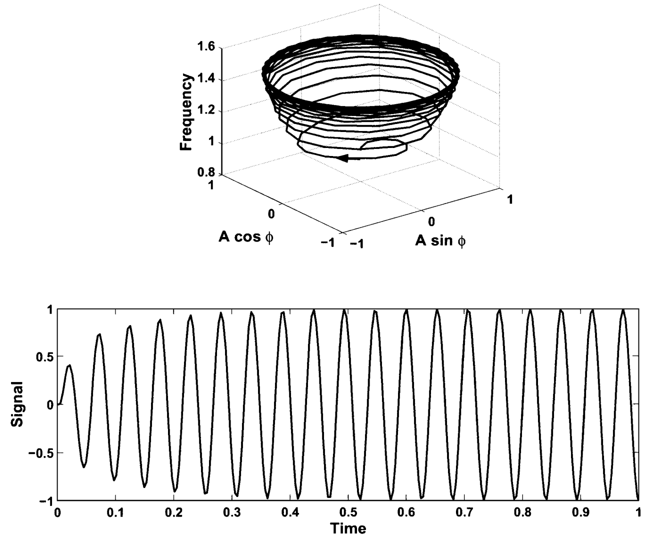

Fig. 3. Illustration of the frequency tracking property of the core algorithm. The top graph shows convergence of the algorithm to the periodic orbit associated with the extracted sinusoid; the bottom graph shows the same phenomenon in the time domain.

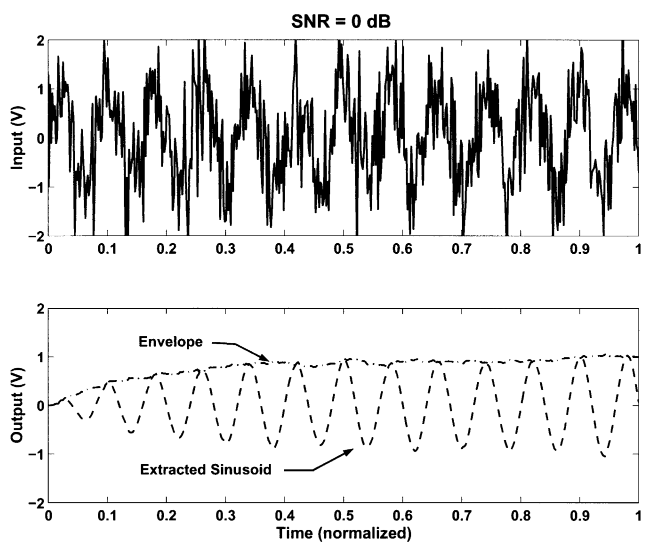

Fig. 4. Performance of the core algorithm in the extraction of a sinusoid and its amplitude, present in a highly noisy input signal.

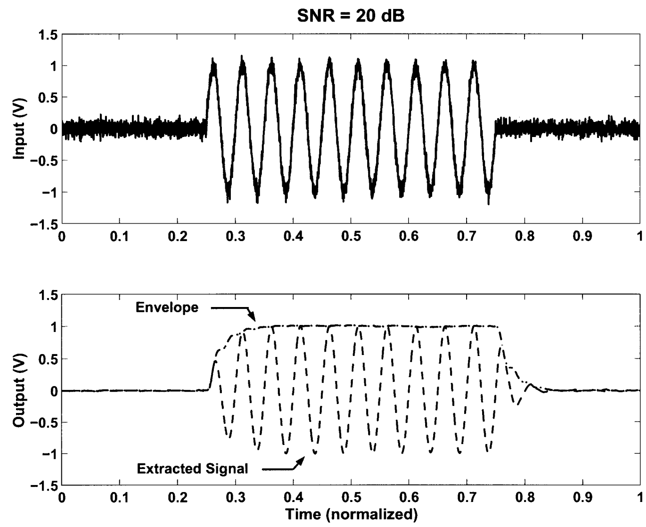

Fig. 5. Performance of the core algorithm in the extraction of a pulsed sinusoid and its amplitude, present in a noisy input signal.

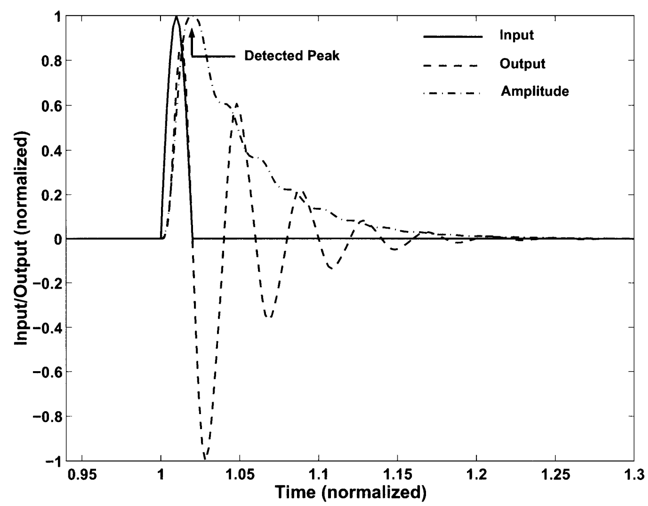

Fig. 6. Illustration of the convergence delay of the core algorithm in detecting the peak of the input signal. The line style (solid line for the input, dotted line for the output, and dash-dotted line for the amplitude) is used consistently in all the figures of this paper.

of parameters μ_1, μ_2, and μ_3 in a trade-off with convergence speed. For each particular application, one can choose a suitable set of parameters. In general, as the frequency of the operation increases, proportionally higher values of parameters μ_1 and μ_2 have to be used to retain the same convergence speed in terms of the required number of cycles for convergence. Therefore, it is reasonable to divide the values of these two parameters by the nominal frequency of the input signal when expressing their values. A typical set of parameters, used in the simulations of this chapter, is $\mu_1 = 10$, $\mu_2 = 200$ and $\mu_3 = 0.08$, where the values of μ_1 and μ_2 are normalized with respect to the nominal frequency of the incoming signal. It is noteworthy that the algorithm is very robust with respect to variations in the values of parameters; variations of up to 50% of magnitude in the parameters have been observed to have negligible effect on the performance.

The presented core algorithm performs very well when the sinusoidal component of the input signal is amplitude modulated. The algorithm basically looks for a sine wave; in its absence, i.e., when its amplitude is zero, it returns zero for the estimated amplitude and generates a zero-amplitude signal. Fig. 5 illustrates this point. Notice that the output signal follows the sinusoidal component of the input signal with a delay which is due to the convergence time of the algorithm. This effect is more clearly illustrated in Fig. 6 where the algorithm is excited by a short-time (half cycle of a sine wave) signal. Observe that the detected place of the peak is delayed. This time delay is a complex function of parameters μ_1, μ_2, μ_3 and the values of initial conditions; fortunately, it is a relatively flat function of frequency; for each parameter setting this delay is a constant number. The value of this delay, most conveniently measurable by simulation as done in Fig. 6, can be used to correct the arrival time of the

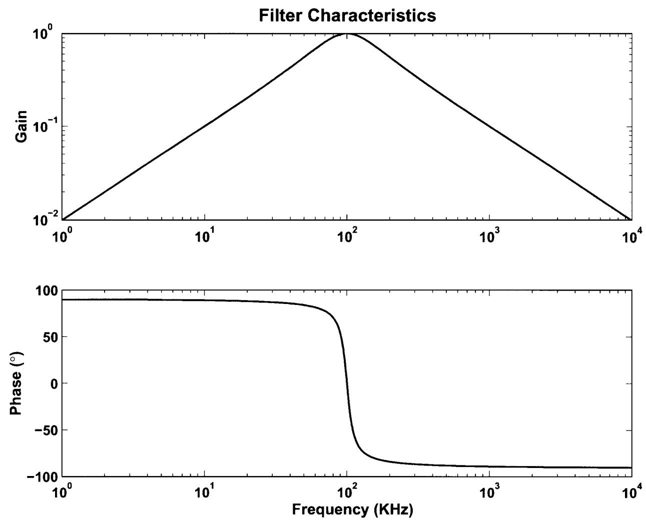

Fig. 7. Gain and phase characteristics of the inlaid notch filter. The center frequency of the notch filter in these graphs is assumed to be $f_0 = 100\ \mathrm{KHz}$ for ease of visualization.

peak; it is sufficient to just subtract this constant number from the arrival time detected by the algorithm.

III. Proposed Method

The proposed method of time-domain signal analysis consists of a) the elimination of noise from the input signal by passing it through the core algorithm, b) the estimation of amplitude of the extracted sinusoid, and c) the comparison of instantaneous amplitude with a defined threshold to determine the peak. Note that b) is accomplished without further effort since the noise elimination algorithm automatically provides a direct estimate of the amplitude. The time of arrival of the peak is conveniently detectable by time-gating of the peak detection scheme; the estimated arrival time is then to be reduced by a constant time delay.

In order to further enhance the noise immunity of the algorithm, the use of a simple second order band pass filter at the input of the core algorithm is proposed. This filter is implemented in digital form. If the nominal frequency of the input signal is $f_o = \omega_o/2\pi$, the transfer function of the band pass filter is given by

$$F(s) = \frac{100}{s^2 + 100s + \omega_o^2}.$$

This filter improves the signal to noise ratio (SNR) of the input signal of the core algorithm. However, it also introduces undesired attenuation and phase delay (see Fig. 7), especially if any drift from the nominal frequency occurs, which may happen as a result of equipment aging and other reasons. Due to the capability of the algorithm to estimate all the parameters of the extracted sinusoid, both these effects can be compensated for as demonstrated in Fig. 8.

IV. Experimental Verification

Data from an experimental setup for conducting EMAT tests are used to demonstrate the performance of the proposed method in signal refinement and analysis. The modulator

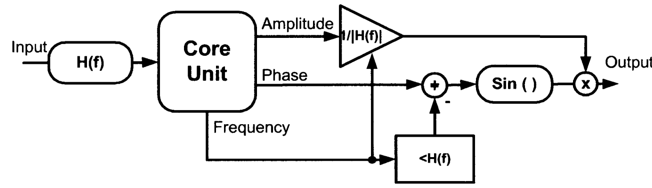

Fig. 8. Block diagram of the enhanced algorithm for noise elimination and peak detection of pulsed sinusoids.

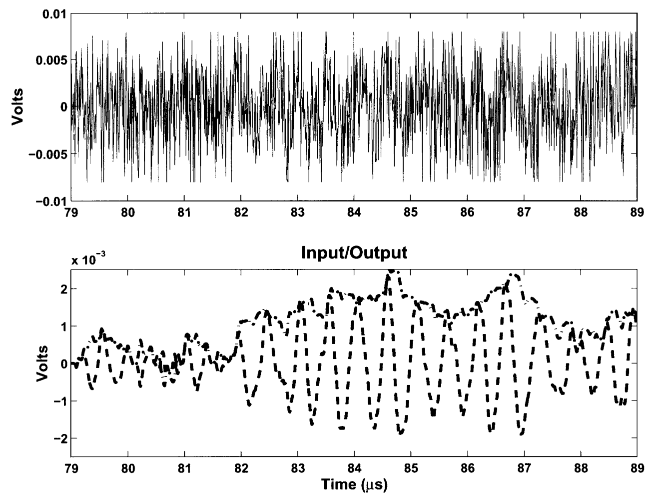

Fig. 9. Performance of the proposed method in noise elimination and peak detection of a highly noisy EMAT signal. The top graph shows the input signal. The refined EMAT signal and its amplitude are shown in the bottom graph.

generating high current/voltage signals to feed the EMAT transmitter produces a smoothly curved pulsed sinusoidal signal at about 1.8 MHz. The received EMAT signal is amplified and sent to a digital oscilloscope to measure the voltage across the receiver coil. Digitization is done at a high sampling frequency (102.4 MHz) to preserve signal integrity.

Fig. 9 shows the performance of the proposed method for a set of 1024 points of recorded data. The received sine wave pack is reflected back from the bottom of a metallic cube under examination. In order to produce a worst-case scenario, no attempt was made to obtain good signal quality while recording the EMAT signals. The SNR of the input signal is estimated to be $-10\ \mathrm{dB}$. It is observed that the proposed method is fully capable of removing the electrical noise. However, the ripples detected during the periods of absence of the pulsed sine wave are somewhat undesirable. They are not electrical noise as will be later justified by reference to the frequency spectra; such ripples may be due to the pulse generator, with a possible contribution of ultrasonic echoes from small flaws in the test specimen. Fig. 10 compares the frequency spectrum of the input signal to that of its refined variant. It is clear that the algorithm does not affect the frequency content of the desired signal and acts on the electrical noise only. Therefore, it is justified that what is passed through the signal refiner is in fact of sinusoidal shape at the EMAT operating frequency, whatever its interpretation may be.

In an attempt to provide a "correct" version of the received EMAT signal, the signal received by the EMAT receiver has been averaged 2048 times by a digital oscilloscope. The resultant averaged signal has 1024 data points. This averaged signal

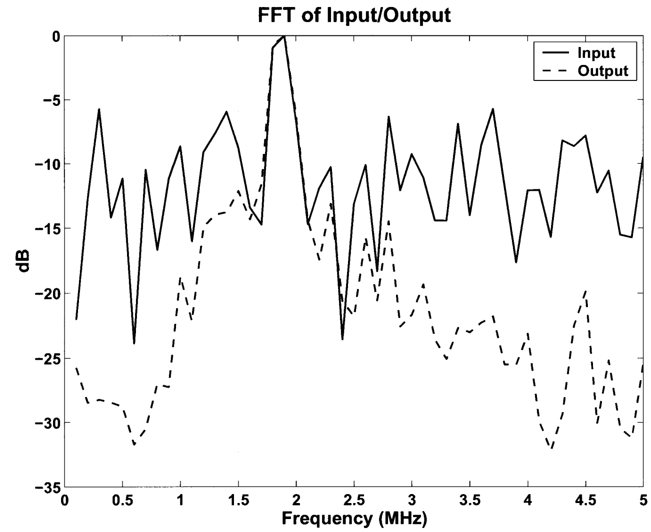

Fig. 10. Frequency spectrum of the noisy input and *clean* output signals.

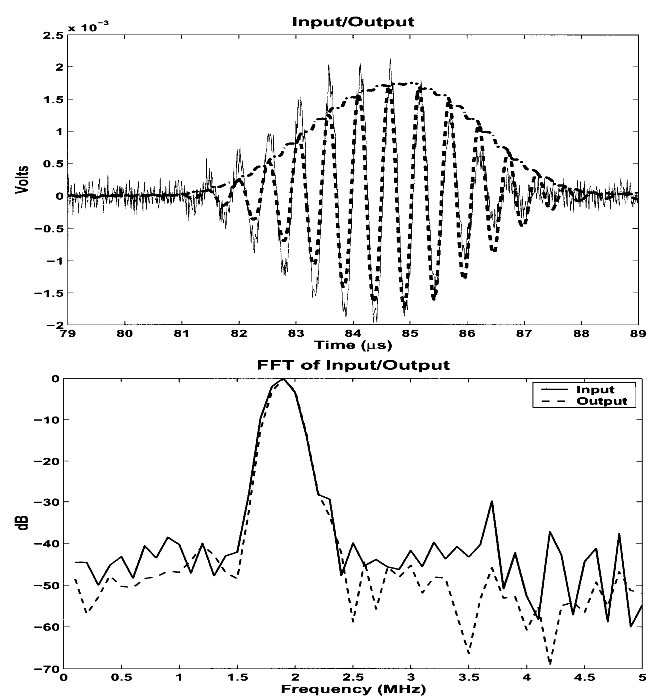

Fig. 11. Performance of the proposed method in further noise elimination and peak detection of an EMAT signal which has been averaged 2048 times. The top graph shows the input signal and the output signal and its detected amplitude. The frequency spectra of the input and output signals are shown in the bottom graph.

was observed to be still a bit noisy. It was then used as the input signal to the proposed algorithm. Fig. 11 shows further refinement achieved by the proposed algorithm. It goes without saying that the time of arrival as detected by the algorithm in both cases of Figs. 9 and 11 has to be shortened by the amount of the convergence time-delay, which was numerically determined to be about one cycle for this setting of parameters.

V. Conclusion

The effectiveness of a novel time-domain method of signal analysis is presented by demonstrating elimination of noise, estimation of arrival time, and detection of peak amplitude value for EMAT signals. However, the methodology is general and may be employed in signal conditioning and information extraction of any pulsed sinusoidal signal which is highly polluted by noise and whose frequency may also vary with time. The main features of the proposed method are its high noise immunity and robustness while demanding limited computational resources due to the simplicity of its structure. These features render the proposed algorithm favorable for industrial applications where real-time operation is desirable.

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