Estimation and Detection in the Presence of Ringing Noise

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***Abstract*— To minimize size and cost, most air coupled ultrasound range systems are designed as mono-static systems, where the same transducer is used for both transmission and reception. Mono-static systems suffer from a type of self interference which is referred to as ringing noise or ring-down. Ringing noise may occlude echoes from nearby targets, compromising the detection performance of the system at short ranges. This paper describes a simple method for detecting target returns embedded in ringing noise and compares the performance of the proposed method to a more common constant false alarm rate processor.**

I. Introduction

An ultrasonic Time of Flight (TOF) system may operate in one of two modes: bi-static, in which one transducer is used for transmission and another for reception; or mono-static, in which the same transducer is used for both transmission and reception. In order to minimize size and cost, virtually all commercially available ultrasonic TOF systems are designed as mono-static units [1].

In a distributed circuit, such as those encountered at high frequencies (MHz or higher), ringing noise is the result of transmitter, transducer and load impedance mismatches. These impedance mismatches result in a series of reflections of the transmit signal within the transducer, which are superimposed upon the received signal.

In lumped circuits, such as those encountered in low frequency applications, the ringing noise consists of some distorted version of the stimulus signal. Upon transmission the stimulus signal is filtered by the transducer. The transducer generally has the effect of increasing the time duration of the transmitted signal. As the received signal is amplified before acquisition, these residual components of the stimulus signal can result in strong inference which occurs shortly after transmission. Ringing noise in this situation will manifest itself as a decaying oscillatory signal (see fig. 1).

In both the distributed and lumped circuit models ringing noise can be modeled as interfering cross-talk where the transmit signal is filtered and superimposed upon the received signal. The shape of the ringing noise is related to the stimulus signal and the transducer and environmental properties. When the properties of the transducer change, which can occur with a change in environment, the shape and statistics of the ringing noise can change as well. Provided these changes occur slowly, the shape of the ringing noise can be easily estimated, and compensated for.

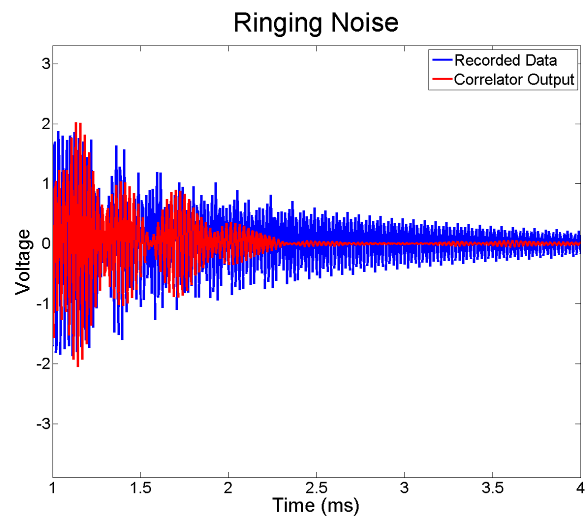

Fig. 1. An example of ringing noise as recorded from an experimental laboratory system. The blue trace shows the signal acquired by the receiver and the red trace shows the output of the system's matched filter. Ringing noise is a decaying oscillatory signal whose power decreases with time. Ringing noise can occlude target returns form nearby target This ringing noise is observed as a decaying oscillatory signal which can occlude target returns from nearby objects.

II. Previous Work

The difficulties of detecting signals embedded in ringing noise have been noted by several researchers [2] [3] [4]. Since ringing noise is a form of cross-talk associated with the stimulus signal, the power of the ringing noise begins to decrease after transmission and effectively restricts the minimum range of the system. Often times portions of the received signal which contain ringing noise are simply ignored, and the occlusion of target returns due to the interference from ringing noise creates what has been referred to as a 'blank' or 'dead' zone [4].

Chen et al observed that ringing noise results in oscillations in the envelope of their matched filter's output, which they attempt to compensate for by high pass filtering the signal.

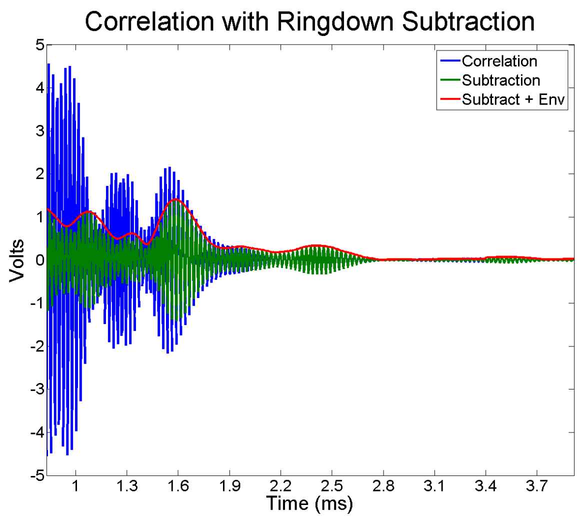

Fig. 2. An example of matched filter output (blue trace), matched filter output with subtraction of estimated ringdown (green trace) and envelope of matched filter output with ringdown subtraction. The signals shown are target-free returns. One should observe that some residual ringing noise remains after subtraction of the ringdown signal, complicating detection.

While Chen et al's method was shown to improve the SNR of their system, there are no results regarding detection performance [2].

Neal et al employed a method referred to as 'spatial averaging' to estimate the ringing noise [3], which is subsequently subtracted from the received ultrasound signal to obtain a new signal in which the interfering ringing noise is reduced. Unfortunately, estimation of ringing noise, and the subtraction thereof, is prone to errors (see fig.

Interfering signals whose power changes with time present issues with detection performance. Adaptive matched filters or thresholds are commonly employed to constrain the false alarm rate of the system to a pre-defined level. Adaptive Matched Filter (AMF) systems which employ noise spectrum estimators and utilize a pre-whitening filter are optimal [5] [6], but for many applications are too computationally intensive or require too large of a memory footprint to be useful in practical systems . Adaptive threshold computers, such as cell-averaging (CFAR-CA), smallest-of (CFAR-SO) and ordered-statistic (CFAR-OS) processors are typically employed in situations where AMFs are unrealizable [7].

While these processors are simple to implement they are limited in their capacity to detect multiple returns and their performance deteriorates in the presence of clutter transitions, which are similar to the time-varying noise power that one observes following ringdown subtraction.

III. Proposed Detector

Let's define a frame of data as the received signal which is collected from a single transmission event. Thus, a stimulus pulse is transmitted and the received signal is recorded as a vector of samples. Assume each frame of collected data contains N samples, and such that an arbitrary frame can be denoted as in eq. 1. Assume M frames of data are collected and arranged so each frame composes a row in a matrix (see eq. 2). This signal matrix represents an ultrasound data-set from which it will be assumed the ringing noise is quasi-stationary.

$$x_m(n) = [x_m(0), x_m(1), x_m(2), \cdots, x_m(N-1)]^T \quad (1)$$

$$X = \begin{bmatrix} x_0(0) & x_0(1) & \cdots & x_0(N-1) \\ x_1(0) & x_0(1) & \cdots & x_1(N-1) \\ \vdots & \vdots & \ddots & \vdots \\ x_{M-1}(0) & x_{M-1}(1) & \cdots & x_{M-1}(N-1) \end{bmatrix} \quad (2)$$

Assume two different data-sets have been collected. One, X_{FA}, consists of data which is known to be free of target returns, and thus provides a noise reference for the system. Another data-set, X_D, consists of a set of returns which must be tested for the presence of a target. If it can be assumed that X_{FA} and X_D have similar noise profiles, then one may use the signal statistics from X_{FA} to design a detector for the signals in X_D. The availability of a noise-only reference is a common assumption in AMF systems [5] [6].

After acquisition, matched filtering is performed on the data-set using a digital replica of the transmit signal ($h(n)$). Correlation processing, or matched filtering is known to improve the SNR and detection performance of a TOF system [8] [9].

$$y_m(n) = x_m(n) * h(n) \quad (3)$$

Neal et Al [3] compute an estimate of the ringing noise using a method they refer to as spatial averaging, which consists of computing the mean of each column vector in the signal matrix (Y_{FA}) (eq. 3). It has been shown that this method is effective in estimating the shape of the ringing noise. The resulting signal ($r(n)$) is referred to as the ringdown signal.

$$r(n) = \frac{1}{M} \sum_{m=0}^{M-1} Y_{FA}(m, n) \quad (3)$$

Once the ringdown signal ($r(n)$) has been computed it may be subtracted from each frame of data in the signal matrix to reduce the power of the ringing noise (see eq. 3). While our method filters then subtracts the order of subtraction and correlation important and can be interchanged without affecting the processed signal.

$$z_m(n) = y_m(n) - r(n) \quad (3)$$

While this processing scheme reduces the peak and mean power of the ringing noise, one can observe that the processed signal still suffers from strong interference, and the noise power of the processed signal varies with time (see fig. **??**). To maintain good detection performance in this time-varying noise environment, a time-varying threshold must be used.

Typically a CFAR algorithm such as cell-averaging (CFAR-CA), smallest-of (CFAR-SO) or ordered-statistics (CFAR-OS)

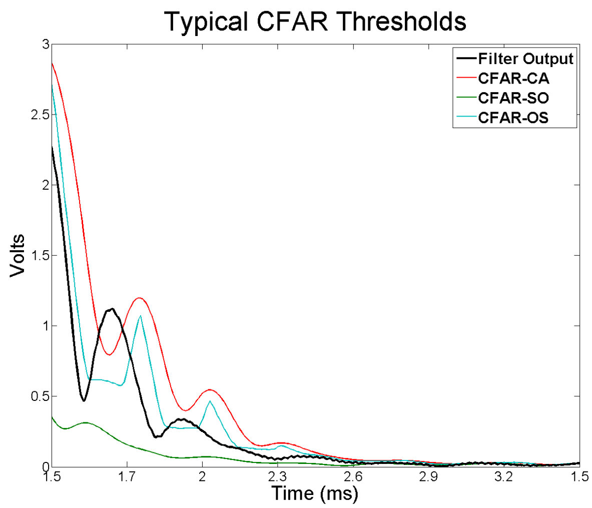

Fig. 3. An example of ringing noise is shown with the thresholds computed by several common CFAR processors. The black trace shows the signal on which detection is to be performed. The red, green and cyan traces show the thresholds computed by a cell-averaging, smallest-of and ordered-statistics CFAR processors respectively. One can observe the local minima and maxima of the signal and the computed thresholds are not well aligned, indicating that these processors will be ineffectual in the presence of ringing noise.

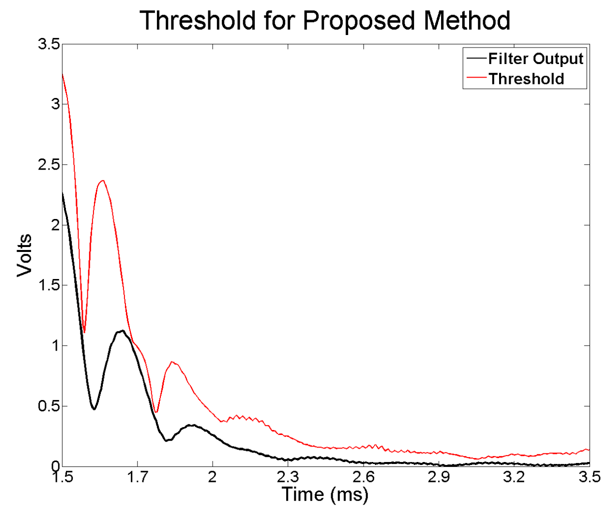

Fig. 4. An example of ringing noise is shown with the threshold computed by our proposed method. The black trace shows the signal on which detection is to be performed. The red trace shows the threshold which is used to detect the presence of an echo. The local minima and maxima of the threshold and processed signal are well aligned, this results in a sensitive detector which is capable of detecting target returns embedded in ringing noise.

would be employed to cope with these situations. Unfortunately, none of the common CFAR algorithms function well in the presence of ringing noise (see fig. 3). The oscillatory peaks that occur in ringing noise and the ringdown subtracted datasets are very similar to target returns and clutter transitions, two situations in which typical CFAR processors are known to perform poorly [7] [10]

While the typical CFAR processors do not model the ringing noise, or errors following ringdown subtraction well,these errors evolve very slowly in time. Since, the evolution of these errors is slow, and one requires a threshold which is proportional to the root mean square (RMS) power of the noise the proposed algorithm uses the standard deviation of the columns in the ringdown subtracted data-set to design a threshold. Borrowing terminology from Neal et al one might refer to this statistic as the 'spatial standard deviation'.

Since the mean ringing noise, or ringdown signal, was previously subtracted from this signal the spatial standard deviation ($\lambda(n)$) is easily calculated (see eq. 3). The spatial standard deviation can then be used to set an appropriate threshold by multiplying it by a sensitivity coefficient (see eq. 3).

$$\lambda(n) = \sqrt{\frac{1}{M}\sum_{m=0}^{M-1} z_m^2(m,n)} \tag{3}$$

$$z_m(n) \gtrless \alpha\lambda(n) \tag{3}$$

This method is shown to model the errors that occur in ringdown subtraction much more effectively than its CFAR counterparts (see fig. 4). Consequently, this processor's detection performance is significantly better in the presence of ringing noise.

IV. Experimental Results

An experimental air-coupled ultrasound system was designed using a custom circuit board, a data acquisition system and laboratory PC. The circuit board contains a preamplifier, programmable gain amplifier (PGA), anti-aliasing filters, single pole double throw switch (SPDT), a SensComp SR160T ultrasound transducer and accompanying impedance matching circuitry. This system is designed to operate with a nominal center frequency of 40kHz and a 3dB bandwidth of approximately 8kHz.

Two different data-sets were collected over the series of several days. One data-set contained a series of target-free returns, thereby providing the noise-only reference for the system, while another data-set contained the returns from 2.5cm wooden dowel which was placed at a number of different positions. The positions of the target varied in azimuthal angle and range with respect to the system. The different target placements provided returns with a number of different SNRs upon which to test our detection algorithm.

Approximately 10,000 target free data-frames were collected for the false-alarm data-set, and 5,000 data-frames were collected with the target present, or detection data-set. Half of the recorded false-alarm data-frames, which were randomly selected, were used to estimate the ringdown signal (eq. **??**) and design the threshold. The remaining data-frames in the false alarm and detection data-sets were used to evaluate the detection performance of several processors.

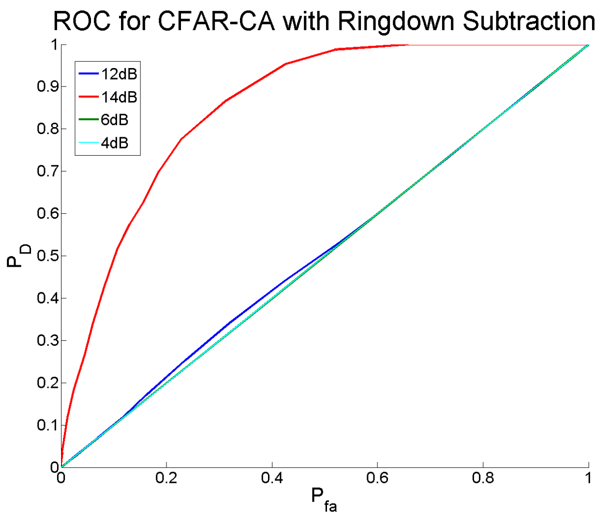

Fig. 5. Illustration of the ROC (Receiver Operating Characteristics) of a CFAR-CA (cell-averaging) threshold computer operating on the envelope of a matched filter following ringdown subtraction. The probability of detection (y-axis) is plotted against the probability of false alarm (x-axis). Several traces are shown for different SNRs, or target positions. Each point of a trace is generated by a unique threshold which is increasing as one moves from right to left in the figure. The detection performance of the system is uninformative, as observed by the detector's equal probability of false alarm and detection, until the SNR of the target exceeds approximately 12dB.

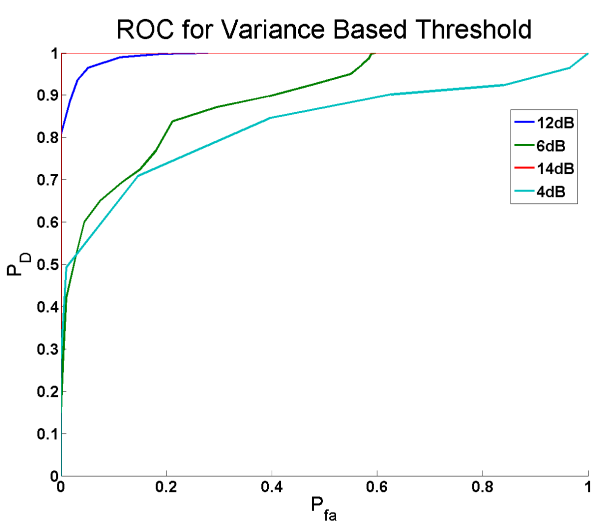

Fig. 6. Illustration of the ROC (Receiver Operating Characteristics) of our proposed detector. The probability of detection (y-axis) is plotted against the probability of false alarm (x-axis). Several traces are shown for different SNRs, or target positions. Each point of a trace is generated by a unique threshold which is increasing as one moves from right to left in the figure. Our proposed detector provides much more robust performance that its CFAR counterpart, as observed by comparing the probability of detection that is possible for a given probability of false alarm for the two methods (see figs. IV 6) .

Let us define a false alarm as an event in which any sample in a false-alarm data-frame exceeds the prescribed threshold. Define a detection as an event in which a sample which is at, or near, the known location of the target exceeds the prescribed threshold at. The constraint of the requiring the processed signal to exceed the threshold 'near' the target's known location ensures that only signal peaks associated with the target return are acknowledged as detection events.

Each data-frame in the false alarm and detection data-sets are compared to several different thresholds from two different processors. Both processors operate on the same processed signal, which is created by correlating the recorded echo with a replica then subtracting the ring-down signal, after which the envelope of this signal is extracted using a Hilbert transform.

The thresholds for the processors are designed using the 'spatial standard deviation' and CFAR-CA algorithms. Each threshold's sensitivity is manipulated by a sensitivity coefficient, which multiplies the computed threshold by a constant. As this coefficient is varied, the false alarm and detection rates of each system are determined by comparing the threshold to the signals in the false alarm and detection signal matrices. The detection and false alarm rates are used to create the Receiver Operating Characteristics for each processor (see figs. **?? ??**).

The performance of the proposed method is significantly better than its CFAR-CA counterpart as observed by the higher rate of detection possible for any given false alarm rate.

V. Conclusion

A simple, low-complexity detector based on the first and second order statistics of a target free data set can be used to compute a threshold which offers robust detection of target returns embedded in ringing noise. While this detector's performance is much higher than its CFAR counterpart, it presumes some a priori knowledge of the noise and requires a larger memory footprint than its counterpart.

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