Two Bit Correlation—An Adaptive Time Delay Estimation

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***Abstract*—Time delay estimation is a very important operation in ultrasound time-domain flow mapping and correction of phase aberration of an array transducer. As the interest increases in the application of one and a half-dimensional (1.5-D) and two-dimensional (2-D) array transducers to improving image quality and three-dimensional (3-D) imaging [1], [2], the need of simple, fast, and sufficiently accurate algorithms for real-time time delay estimation becomes exceedingly crucial. In this paper, we present an adaptive time-delay estimation algorithm which minimizes the problem of noise sensitivity associated with the one bit correlation [3] while retaining simplicity in implementation. This algorithm converts each sample datum into a two bit representation including the sign of the sample and an adaptively selected threshold. A bit pattern correlation operation is applied to find the time delay between two engaged signals. By using the criterion of misregistration as an indicator, we are able to show that the proposed algorithm is better than one bit correlation in susceptibility to noise level. Analytical results show that the improvement in reducing misregistration of the two bit correlation over its counterpart is consistent over a wide range of noise level. This is achieved by an adaptive adjustment of the threshold to accommodate signal corruption due to noise. The analytical results are corroborated by results from simulating the blood as a random distribution of red blood cells. Finally, we also present a memory-based architecture to implement the two bit correlation algorithm whose computation time does not depend upon the time delay of the signals to be correlated.**

I. Introduction

Time-delay estimation is a very important operation in ultrasound time-domain flow mapping and correction of phase aberration of an array transducer. As the interest increases in the application of one and a half-dimensional (1.5-D) and two-dimensional (2-D) array transducers to improving image quality and three-dimensional (3-D) imaging [1], [2], the need of simple, fast, and sufficiently accurate algorithms for real-time time delay estimation becomes exceedingly crucial.

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Signals received from two remote sensors at different locations or received from the same sensor during different time periods can be related by the following:

$$x_1(t) = s(t) + n_1(t)$$
$$x_2(t) = \alpha s^k(t + D) + n_2(t)$$

where D denotes a time delay, n_1 and n_2 are additive noise components, and α and k denote linear and nonlinear pattern deformations. Due to the difficulties associated with modeling nonlinear deformation, in general the time delay estimation is implemented by assuming $k = 1$. One common method of determining time delay, D, is by computing the cross-correlation function of $x_1(t)$ and $x_2(t)$. Assuming high signal-to-noise ratio (SNR), the cross-correlation function can be converted into an autocorrelation function of $s(t), R_{s,s}(t)$, as follows:

$$\begin{aligned} R_{x_1,x_2}(\tau) &= E[x_1(t)x_2(t-\tau)] \\ &= \alpha R_{s,s}(D-\tau) + R_{s,n_2}(\tau) + R_{s,n_1}(D-\tau) \\ &\quad + R_{n_1,n_2}(\tau) \\ &= \alpha R_{s,s}(D-\tau) + R_{s,n_2}(\tau) + R_{s,n_1}(D-\tau) \\ &\approx \alpha R_{s,s}(D-\tau). \end{aligned}$$

From the cross-correlation function, the time delay D is set to τ for which $R_{x_1,x_2}(t)$ is maximal. A variety of pattern correlation algorithms have been developed to determine the cross-correlation function depending upon different applications [4]–[14].

The success of applying multidimensional array transducers to medical applications relies upon an efficient but simple algorithm to estimate the arrival time differences of signals received at different array elements [8]. An efficient time-delay estimation algorithm is also crucial for ultrasound time domain flow mapping techniques [9]–[12]. Algorithms [3], [12] have been developed to reduce the complexity associated with cross-correlation computation [13]. Among them, one of the simplest type is the one bit correlation approach in which signs of each pair of samples are compared and a sum of all matches is used to determine which patterns have the most resemblance [3]. This correlation algorithm demonstrates a comparable performance in both time-domain flow mapping and correction of phase aberration [3], [6], but it is not without disadvantages.

The major disadvantage of one bit correlation is its low noise immunity. It can be shown that the misregistration, due to the additive noise, associated with one bit correlation is increased linearly as the noise level is increased. To compensate for the noise immunity and retain its simplicity in implementation, a new adaptive time-delay estimation approach is proposed in this paper. The new approach consists of a two bit correlation algorithm in which a noise tolerance level for low-amplitude samples is introduced so that the possible sign switching due to noise is considered. Throughout this paper, the noise is meant to represent all those from the sources that may contribute to changes on the received speckle patterns. These sources include noise generated by electronic and acoustic components. In the application of ultrasound to blood flow measurements, the speckle patterns or the received backscattered signals from blood may also be affected by hemodynamic and hematological factors, such as shear rate, cell aggregation, and others [15]–[17].

It is shown analytically that the proposed algorithm is less sensitive to noise than the one bit correlation. The improvement in reducing misregistration by 40% is demonstrated by both the analytical and simulated results. To further improve the accuracy of pattern correlation, a new statistic averaging scheme is also reported. The proposed process which is simple to implement takes only reliable data for averaging; the reliability of data is evaluated based upon the occurrence count of each datum. A comparison of the proposed process against the conventional averaging algorithm and a mean square error (mse) based filter is given.

II. Time-Delay Estimation

A. Two Bit Correlation

The proposed two bit correlation algorithm compares signals based on signs of samples and an adaptively selected threshold. The correlation proceeds, first, with a data conversion shown below in which a sample s_i is transformed into a two bit representation

$$s_i = \begin{cases} 1^+ & \text{for } s_i > T \\ 1^- & \text{for } 0 \leq s_i \leq T \\ 0^- & \text{for } -T \leq s_i < 0 \\ 0^+ & \text{for } s_i < -T \end{cases}$$

where the threshold, T, is adjusted with regards to system noise level. The $+$ and $-$ signs are used to denote the amplitude of a signal sample. 1^+ means a sample is positive and the magnitude is higher than the threshold. 1^- means a sample is positive but the amplitude is lower than the threshold. 0^+ means a sample is negative and the magnitude is higher than threshold, and a sample is referred to as a 0^- if it is negative and its magnitude is lower than the threshold. The two bit correlation finds the time delay between two signals, $X(i)$ and $Y(i)$, by evaluating the signal pattern similarity with the following:

$$\rho(m, T) = \sum_{i=1}^{W} X(i) \oplus Y(i+m) \tag{1}$$

TABLE I
Truth Table for Operator $\oplus$

$\oplus$	1^+	1^-	0^-	0^+
1^+	1	1	0	0
1^-	1	1	1	0
0^-	0	1	1	1
0^+	0	0	1	1

where m is a time lag, T is the threshold, W is the window length of the engaged data, and $\oplus$ is a pattern correlation operation that compares two samples based on Table I.

The operation $\oplus$ is defined, based on the fact that the probability of changing the sign due to noise is inversely proportional to signal amplitude. With *a priori* knowledge, the two bit correlation sets a tolerance level for pattern correlation, i.e., 1^- is considered to have a high probability of being corrupted by 0^- and vice versa. The two bit correlation can be proved to be less sensitive to noise if a proper threshold is chosen from *a priori* information. A detailed discussion of a heuristic approach to set the threshold is given in the next section.

A backscattered acoustic signal from red blood cells has been modeled as a Gaussian random signal [18], [19] in which the received signals are considered as a lump sum of echo signals from a large number of scatterers. This model is based on the Central Limit Theorem [20] which states that the probability distribution function from a large sum of random variables approaches a Gaussian distribution

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-x^2/2\sigma^2}$$

where σ is the variance of random variable x. For a short time period, both signal and noise are assumed stationary and with constant power. Therefore the signal amplitude distribution can be described by a zero-mean Gaussian distribution with a variance σ_s. The variance of the induced noise is denoted as σ_n. The amplitude distribution of the backscattered signal from porcine whole blood (hematocrit 44%) measured *in vitro* is shown in Fig. 1. The data are taken from a porcine blood sample contained in a plastic container, both sides of which are covered with cellophane and stirred with a magnetic stirrer to prevent sedimentation of blood cells. Signals are taken with a 10-MHz focused transducer. Each point represents an average taken from 50 A-lines. Each A-line consists of 1500 samples digitized at a sampling frequency of 200 MHz. More details on the experimental arrangement are given in [21]. The abnormally high probability density function near the zero crossing point may have resulted from the finite precision of appied A/D conversion and limited sampling rate. The concern of this paper is on the condition in which the signal power is greater than or equal to the noise power because the bit pattern is highly unreliable when the SNR is below 0 dB. As shown in Fig. 2, there are four regions where a signal or noise sample may exist. Consider that s_2 is a corrupted signal sample of s_1 as a result of the additive noise component n. Therefore s_2 is $s_1 + n$. The corruption of a sample by noise may move the sample from one region to another. Under certain conditions,

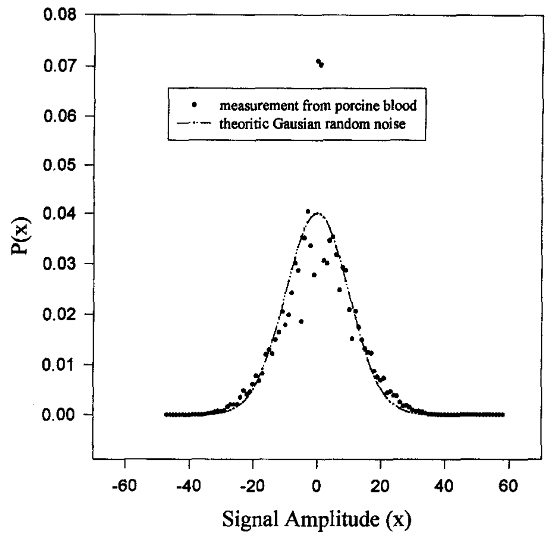

Fig. 1. Probability density function of backscattering signal from a porcine blood sample measured *in vitro.*

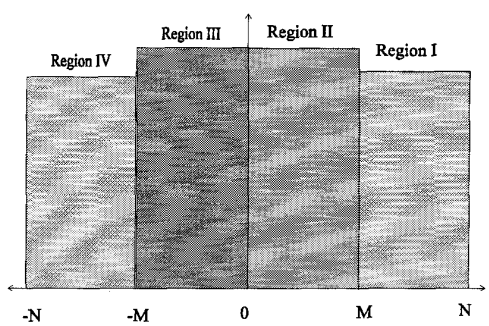

Fig. 2. Two bit partition of signal/noise regions.

TABLE II
REGION SWITCHING AS A RESULT OF ADDITIVE NOISE

Region switch associated with one bit correlation	Region switch associated with two bit correlation
I→III, III→I, II→III, III→II, II→IV, IV→II, IV→I, I→IV	I→III, III→I, II→IV, IV→II, IV→I, I→IV

the sign of the sample is changed and a mismatch happens when one bit correlation is used. By imposing a threshold, the two bit correlation reduces the probability of mismatch associated with one bit correlation. A set of conditions that create mismatches for either one bit or two bit correlation is listed in Table II, where $A \rightarrow B$ represents a sample moved from region A to B because of the induced noise sample n.

When matching signals with less information, such as one bit or two bit correlation, the likelihood of mismatching samples may increase relative to the situation where full information is available. To account for the additional mismatches when using one bit or two bit correlation, a quantity, the mismatch ratio, is introduced. It is defined as the additional percentage that pattern matching fails as a result of encoding data with less resolution. Considering the signal/noise distribution and sources of mismatching listed in Table II, the mismatch ratios associated with the one bit and two bit correlation are, respectively

$$\begin{aligned}\mathrm{Miss}_{\text{one bit}} = &\left(\frac{1}{2\pi\sigma_n\sigma_s}\right)\\ &*\left(\sum_{s=T+1}^{N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-1}^{-N} e^{-n^2/2\sigma_n^2}\right)\right.\\ &+\sum_{s=-T-1}^{-N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s}^{N} e^{-n^2/2\sigma_n^2}\right)\\ &+\sum_{s=0}^{T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-1}^{-N} e^{-n^2/2\sigma_n^2}\right)\\ &\left.+\sum_{s=-1}^{-T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=s}^{N} e^{-n^2/2\sigma_n^2}\right)\right)\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{Miss}_{\text{two bit}} = &\left(\frac{1}{2\pi\sigma_n\sigma_s}\right)\\ &*\left(\sum_{s=T+1}^{N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-1}^{-N} e^{-n^2/2\sigma_n^2}\right)\right.\\ &+\sum_{s=-T-1}^{-N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s}^{N} e^{-n^2/2\sigma_n^2}\right)\\ &+\sum_{s=0}^{T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-(s+T+1)}^{-N} e^{-n^2/2\sigma_n^2}\right)\\ &\left.+\sum_{s=-1}^{-T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=(T+1+s)}^{N} e^{-n^2/2\sigma_n^2}\right)+\Delta\right)\end{aligned} \tag{3}$$

where Δ is a factor that is not seen in Table II; it represents the additional percentage of mismatches induced by imposing a noise tolerance. Consider the situation where signal s is 1^+, i.e., $T < s \leq N$ if signals are quantitized into a range between $-N$ and N, and $s' = s + n$ is the corrupted signal with noise n. In situations where s and s' are two samples from the same speckle with one corrupted by the induced noise n, s and s' are counted as a mismatch by one bit correlation if $-N \leq n < -s$. The probability for this case to occur is

$$\frac{1}{\sqrt{2\pi}\sigma_s}e^{-s^2/2\sigma_s^2} * \frac{1}{\sqrt{2\pi}\sigma_n}\sum_{n=-s-1}^{-N} e^{-n^2/2\sigma_n^2}.$$

To summarize signal amplitude between $-N$ and N, the mismatch ratio of one bit correlation can be calculated from (2). By applying the same criterion, the mismatch ratio of two bit correlation can be calculated from (3). The difference between the mismatch ratios of one bit and two bit correlation results from the situation where a signal sample with amplitude changed between 1^- and 0^- is considered "tolerated," i.e., two samples with different signs and magnitude below T are counted as a match by the proposed two bit correlation. More details on the derivation of (2) and (3) can be found in [22]. This formulation reduces the probability of counting two matched samples as mismatched when signals are corrupted

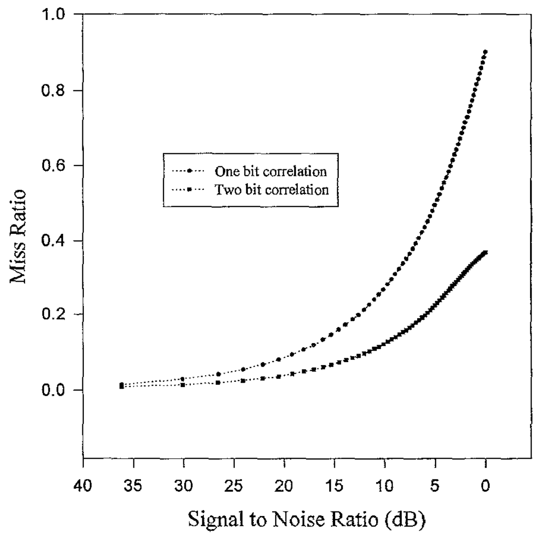

Fig. 3. Theoretical miss ratios of one bit and two bit correlation plotted versus SNR.

by noise. With the same argument, the two bit formulation contributes an additional factor, represented by Δ, to counting a false match where two samples are considered as mismatched by the one bit correlation. Considering the situation where signals are corrupted by the induced noise that results in s changed from 1^+ to 1^- and s' changed from 0^+ to 0^-, this is returned as a false match if the noise tolerance is imposed. The factor Δ is given by

$$\Delta = \left(\frac{1}{2\pi\sigma_n\sigma_s}\right) * \left(\sum_{s=T+1}^{N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s+T}^{-s} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=-(T+1)}^{-N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-T}^{-s-1} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=T+1}^{N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-1}^{-s-T} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=-T-1}^{-N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s}^{-s+T} e^{-n^2/2\sigma_n^2}\right)\right).$$

As the noise is increased, the number of reliable samples, which are bit transformations of the original signal, is decreased. The effect of a reduced number of samples for correlation on time-delay estimation has been studied by several investigators [14], [22] and can be delineated by a factor β

$$\beta = e^{k*(W/W'(\sigma_n))} = e^{k*(4\sigma_s/4\sigma_s-\sigma_n)}$$

where W is the number of samples for the gated signal, $W'(\sigma_n)$ is the reduced number of reliable samples, and k is a constant which is added to generalize the equation. The equation is obtained by assuming that the number of reliable samples decreases linearly as the noise amplitude is increased, and from previous studies [14] it was known that the curve of jitter, i.e., standard deviation of estimated time step, is increased exponentially as the window length is decreased. It is for this reason that we chose a general exponential function to describe the relationship between miss ratio and reliable sample count. Two observations can be made for W': 1) W' is equal to W if σ_n is zero, and 2) W' is $3/4 * W$ if the SNR is 0 dB because 1/4 of the samples are unreliable if the effective signal amplitude is the same as the noise amplitude. By introducing β, the misregistration rates for one bit and two bit correlation are given by

$$\text{Miss}_{\text{one bit}} = \left(\frac{e^{k*(4\sigma_s/4\sigma_s-\sigma_n)}}{2\pi\sigma_n\sigma_s}\right) * \left(\sum_{s=T+1}^{N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-1}^{-N} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=-T-1}^{-N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s}^{N} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=0}^{T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-1}^{-N} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=-1}^{-T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=s}^{N} e^{-n^2/2\sigma_n^2}\right)\right)$$

$$\text{Miss}_{\text{two bit}} = \left(\frac{e^{k*(4\sigma_s/4\sigma_s-\sigma_n)}}{2\pi\sigma_n\sigma_s}\right) * \left(\sum_{s=T+1}^{N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s-1}^{-N} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=-T-1}^{-N}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-s}^{N} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=0}^{T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=-(s+T+1)}^{-N} e^{-n^2/2\sigma_n^2}\right) + \sum_{s=-1}^{-T}\left(e^{-s^2/2\sigma_s^2} * \sum_{n=(T+1+s)}^{N} e^{-n^2/2\sigma_n^2}\right) + \Delta\right). \tag{4}$$

The reduction of miss ratio by a two bit correlation over one bit correlation as a function of noise level is seen in Fig. 3 where the miss ratio is plotted as a function of SNR for $N = 128, \sigma = 64, \sigma_n$ going from 1 to 64, and k set to 0.62 which is determined by assuming $\text{Miss}_{\text{one bit}}(\sigma_n = \sigma_s) = 0.9$.

B. Noise Level Evaluation

As discussed, the performance of a two bit correlation depends on the proper adjustment of noise tolerance, T. An adaptive method of adjusting T is then required for the two bit correlation to properly convert signals. In this section, we present an analytical solution for setting the noise tolerance level, T, from one bit correlation.

First, we define $\rho^1_{\max}(\sigma_n)$ as the maximal match count returned from a one bit correlation with a system noise level of σ_n. Four observations on $\rho^1_{\max}(\sigma_n)$ can be made: 1) the

$\rho^1_{\max}(\sigma_n)$ decreases as noise level σ_n is increased, 2) $\rho^1_{\max}(0)$ is equal to W where W is the width of the applied window for pattern correlation, 3) $\rho^1_{\max}(\sigma_s) \cong (1-1/4)*W$ if σ_s is equal to the effective signal amplitude, and 4) it is reasonable to assume that the decrease in $\rho^1_{\max}(\sigma_n)$ is linearly proportional to the noise level σ_n. From the aforementioned discussions, $\rho^1_{\max}(\sigma_n)$ may be represented by the following:

$$\rho^1_{\max}(\sigma_n) = -\frac{1}{4}\frac{W}{\hat{\sigma}_s}\sigma_n + W \tag{5}$$

where $\hat{\sigma_s}$ is the estimated root mean square amplitude of the acquired signals. Because $\rho^1_{\max}(\sigma_n)$ may be changed as a result of a false match, $\rho^1_{\max}(\sigma_n)$ is evaluated from a set of signals from which the mean, $\hat{\rho}^1_{\max}$, is calculated. Therefore the noise tolerance level, T, is chosen as σ_n which is given by

$$T = \sigma_n = \frac{4\hat{\sigma}_s * (W - \hat{\rho}^1_{\max})}{W}. \tag{6}$$

C. Memory-Based Architecture

In this section, a memory-based architecture designed to implement the two bit correlation is presented. To introduce concurrent operations for the time-delay estimation, the bit pattern correlation operator defined in Table I can be formulated as follows:

$$\begin{aligned} x \oplus y &= \text{sign}(x)\cdot\text{sign}(y) + \overline{\text{sign}}(x) \\ &\quad \cdot \overline{\text{sign}}(y) + \text{amp}(x)\cdot\text{amp}(y) \end{aligned}$$

$$\text{sign}(a) = \begin{cases} 1 & \text{if } a \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

$$\text{amp}(a) = \begin{cases} 1 & \text{if } |a| \leq T \\ 0, & \text{otherwise.} \end{cases}$$

The first two terms are the same operations associated with the one bit correlation in which only signs of samples are compared, and the third term is a factor to accommodate for the additive noise. A two-stage associative memory (AM or content-addressable memory CAM [23]) based architecture is shown in Fig. 4. This architecture can be used to evaluate time delay between two interrogated signals in n steps where n is the number of samples to be interrogated. Two AM's are used for the concurrent pattern matching. One is stored with data generated from sign conversion and the other from amplitude conversion. The size of each word is n and word count is m if m is the number of translation steps. Data stored in the memory cells are a sequence of shifted versions of the signal collected at cycle $i-1$ obtained by imposing a shift operation between two neighboring words in the associative memories. As samples are generated through bit conversion, the data collected at cycle $i-1$ are sequentially propagated through the memory bank by shifting one bit at a time. At the end of bit conversion, the signal collected at cycle i can be compared to all the words in the memory bank in a bit-serial word-parallel order [23]. Each word is associated with a counter which is updated at the end of each bit comparison. After n concurrent comparisons, the counters are stored with the counts of matches. To find the best match, a second bit-serial word-parallel AM is used to find the maximum in k steps for $k = \log_2 n$. Therefore the overall time needed to evaluate the time step difference between two signals is determined by the length of samples which is n. By imposing a reset/latch control on each counter, the same architecture can be used for multigate time delay estimation with the same time complexity. The process proceeds with latching and resetting the counters at the end of finding the time delay of each gated sample. As the following set of samples are compared with data in the memory cells, the record of match counts from the previous delay estimation is simultaneously propagated to the second AM for maximal searching.

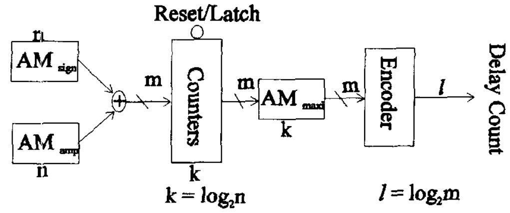

Fig. 4. A memory-based architecture for two bit correlation.

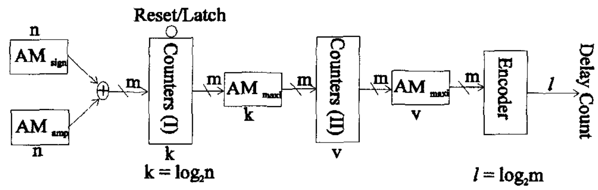

Fig. 5. A two bit correlator with majority averaging.

D. Majority Averaging Process

Results of time-delay estimation, in general, can be refined through an ensemble averaging process. The accuracy of an ensemble process largely depends on the sample space, i.e., error is prone to occur for small sample counts. Under certain conditions in which the sample space is limited, an average of all samples may yield a biased answer, especially in evaluating time step difference with a wide range of arrival time differences. In this paper, we present a simple majority averaging scheme to find the time delay from a moderate count of samples. The algorithm finds the average by counting the occurrences of each delay step. The delay step with the highest occurrence is considered as the ensemble average. This method is feasible because 1) a reliable time delay estimation shall provide a correct estimation with better than 50% accuracy, and 2) the misregistration due to false hits may result in a significant bias if sample count is small. To accommodate the potential discrete truncation error associated with time-delay estimation, the counting of delay step n is increased by one for a delay step of n and $n \pm 1$. An implementation of the proposed ensemble averaging method associated with a two bit correlation is shown in Fig. 5 where the second counter bank and the additional associated memory are added to find the average from 2^v samples. In contrast to other pattern correlation algorithms, the counter architecture allows for more than one peak for each delay step evaluation; this tolerance has the advantage of compensating for the error due to false peaks

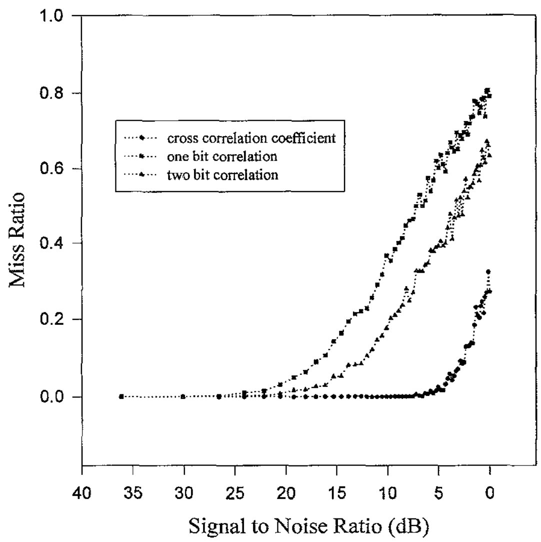

Fig. 6. Simulation results of miss ratios for one bit, two bit, and cross correlation.

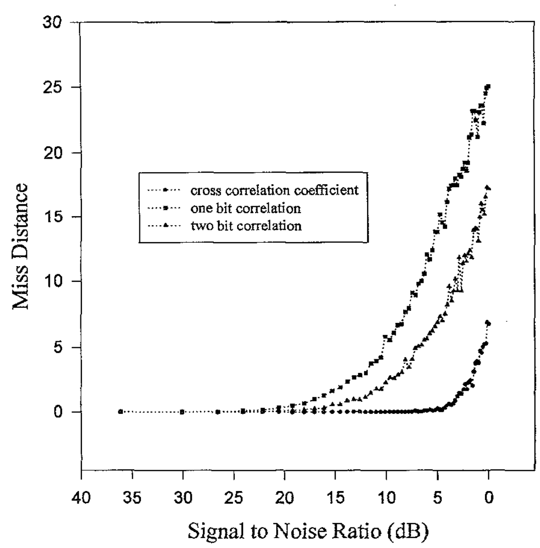

Fig. 7. Simulation results of miss distances for one bit, two bit, and cross correlation.

which have similar correlation coefficients (match counts for bit correlation) as the matched pattern.

III. Simulation and Discussion

Computer simulation of echo ultrasound signal is an efficient way of testing time-delay estimation algorithms where system parameters such as SNR can be easily controlled. In this paper, echo signals are generated as a sum of reflections from a set of randomly distributed scatterers. The governing equation that is used to describe echo signals from a set of scatterers is presented as follows [18]:

$$R(t) = e^{-i\omega t} \sum_i c_i a\left(t - \frac{2Z_i}{v}\right) b(|R_i - R_0|) \frac{e^{i2\beta Z_i}}{Z_i}$$

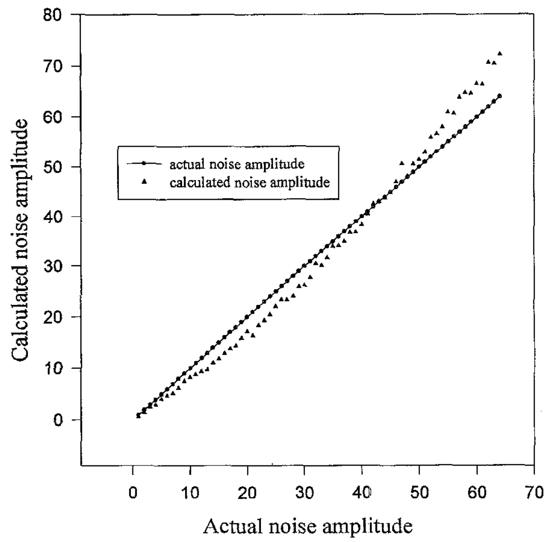

Fig. 8. Estimated noise amplitude versus true noise amplitude.

where $a(t)e^{-i\omega t}$ is the transmitted signal [24]. Beam profile function $b(R_i)$ is used to describe spatially dependent beam sensitivity and is modeled as a Gaussian function [25]. Time delay and phase shift at location Z_i is described by $(2Z_i/v)$ and $\exp(2i\beta Z_i)$ in which v is the sound velocity in the medium and β is the wavenumber. In this model, the insonified region is partitioned into grids of size $\lambda/20 \times \lambda/20$ where λ is the wavelength, and the cell number of grid i is c_i which is assigned with a random number to denote a uniform random cell distribution [19]. The signals are generated with 8-bit resolution. For each generated A-line signal, 100 corrupted signals are generated by adding noise samples generated from a uniform spectrum associated with random phases to the true signal. The corrupted signals are then correlated to the original signal with a translated window equal to half of the signal length (128 samples), i.e., one half of the original signal is used as a target and is correlated to the corrupted signals. A match with no translation is considered as a hit, otherwise it is counted as a miss. For each noise level, three correlation algorithms are applied to implement pattern correlation. One is normalized cross-correlation function and the other two algorithms are the one bit [3] and two bit correlation. There are 20 A-lines programmed for averaging and the threshold of the two bit correlation is determined from 20 corrupted signals. The results are shown in Figs. 6 and 7. Fig. 6 shows the percentage of misregistration whereas Fig. 7 shows the averaged miss distance, which is defined as an average of the absolute difference between correlated delay step and true delay step. From both figures, the two bit correlation shows approximately a 40% improvement over one bit correlation among a wide range of noise levels. The expected improvement as seen from the analytical results is less than that from simulations. This can be explained by the difference of estimated noise amplitude from the true value, as shown in Fig. 8. It is observed that half of the noise levels are underestimated and the other half are overestimated. The incorrect estimation is a result of assuming a linear relation

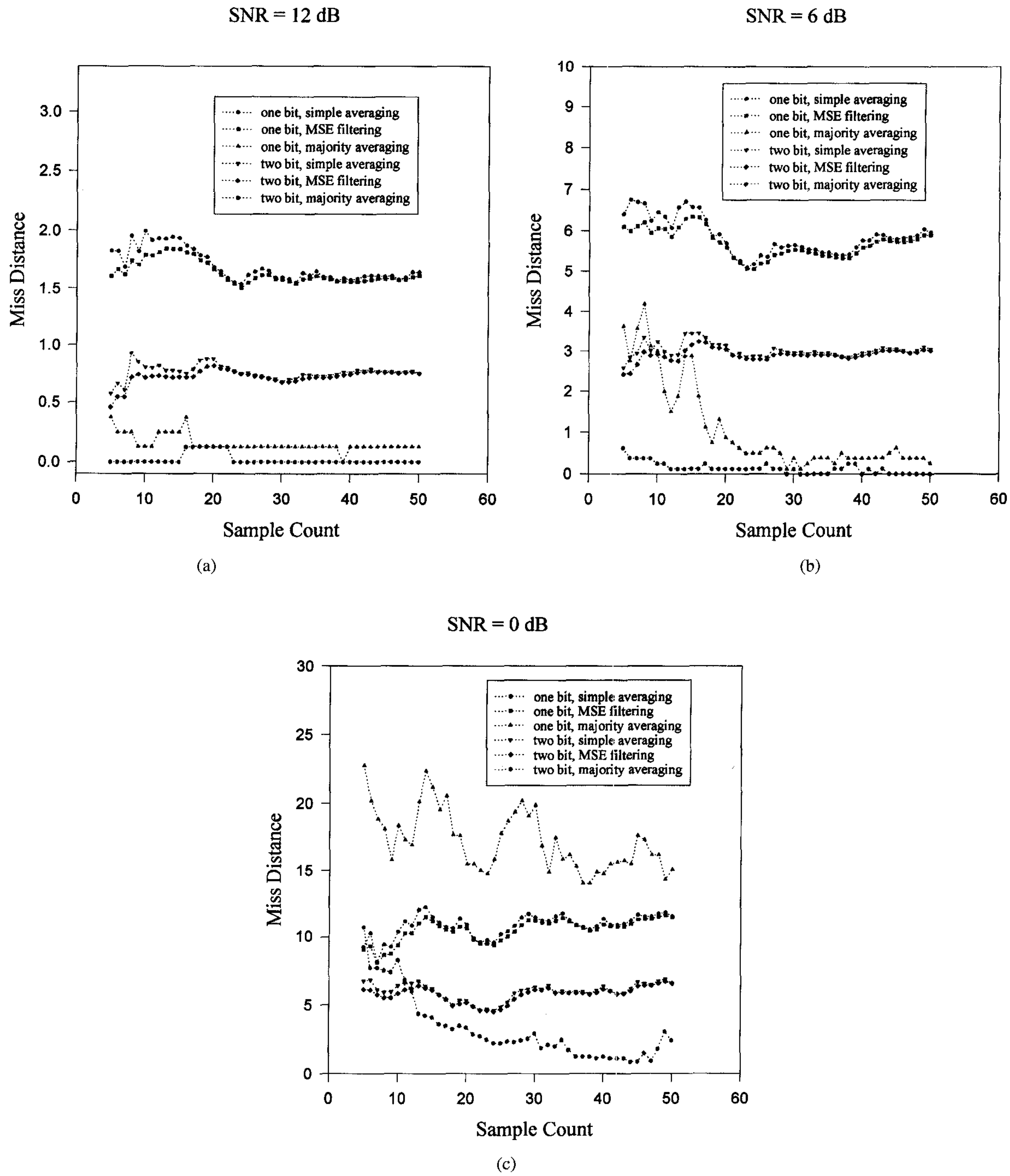

Fig. 9. Miss distance of one bit and two bit correlation with the difference ensemble averaging process: simple averaging, Kalman filtering, and majority averaging. (a) SNR = 12 dB. (b) SNR = 6 dB. (c) SNR = 0 dB.

between maximum match count and noise level as defined by (5). Both analytical and simulation results show that cross correlation with bit patterns may result in high misregistration at low SNR conditions. Consequently, it is clear that bit pattern correlation's (one bit and two bit) are not suitable for high noise conditions such as a system with SNR below 0 dB. To increase the hit ratio, group registration schemes [10], [12], [26] can be applied to reduce misregistration.

Moreover, three ensemble averaging processes, namely 1) averaging, 2) mse-based filtering, and 3) majority averaging are programmed to study the influence of sample space on ensemble averaging processes. The mse-based filter is modified from the Kalman filter [27] in which the weight coefficient, $k(n)$, is recursively adjusted based upon minimizing mse. The ensemble averaging process of an mse filter is as follows:

$P(1) = \delta^2$ /* assumed value */
$S(1) = 0$
for $n = 1$ to sample_count
$k(n) = P(n)/[P(n) + \delta_v^2(n)]$ /*$0 \leq k(n) \leq 1$* /
$S(n+1) = S(n) + k(n)[X(n) - S(n)]$
$P(n+1) = [1 - k(n)]P(n) + \delta_w^2(n+1)$
end

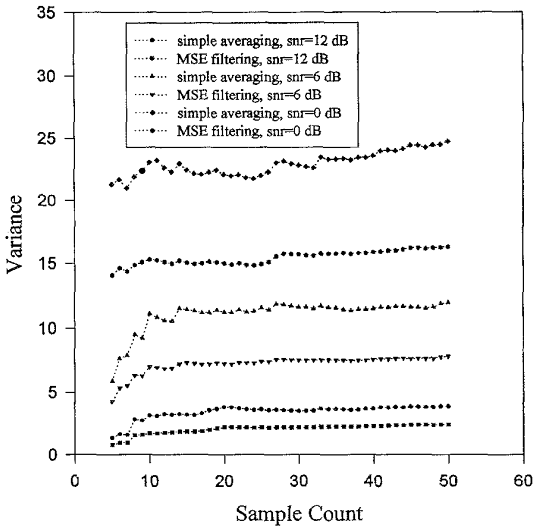

Fig. 10. Variance distributions of simple averaging and Kalman filtering at variant SNR's.

where $S(n)$ is the estimated value, $X(n)$ is the observed (measured) data, $P(n)$ is the mse, and δ_w and δ_v are system noise and variance of estimation. δ_w is assigned by taking a variance from 200 samples and δ_v is the variance of the sample lot. The simulation is programmed with each piece of data taken from 80 different A-lines with a sample count from 1 to 50. The results are given in Fig. 9 which shows that the association of majority averaging and the two bit correlation yields almost no misregistration as the sample count reaches 40. These samples take 8 ms for a system with a line repetition rate of 5 KHz, which is not unusual for most medical ultrasound devices. Both the simple averaging and mse filter show a bias estimate because the fluctuation of the measured time step is very high, as shown in Fig. 10 where it is observed that the variance of mse filtering is significantly reduced as expected. The biased result is a consequence of taking the absolute difference which accumulates as the number of samples increased.

IV. Conclusion

In this paper, a new time-delay estimation algorithm is reported. The two bit correlation is particularly suitable for the real-time ultrasound flow mapping and correction of phase aberration of a multidimensional transducer array. The benefit of using two-bit encoding instead of three-bit or more was demonstrated by Bloom *et al.* [28]. They show that, whereas a binary decision causes a loss in information equivalent to the effect of a 3-dB reduction in SNR, a ternary decision with optimal threshold setting results in a loss equivalent to only a 1.5-dB reduction in SNR, and a four-level decision results in a loss equivalent to only a 1.1-dB reduction. A two-bit encoding reduces the loss of information significantly with little overhead in increasing number of bits for data representation. Another common difficulty associated with time-delay estimation algorithms is that there may be undetected misregistrations which will contribute to the bias of the estimated data. This problem is partially solved by using a weighted function [29]. To improve the accuracy of the ensemble averaging process, a new ensemble averaging approach which uses majority averaging instead of constant (or variance-based [29]) weighing to improve the accuracy of the averaging process is proposed. Its superior accuracy over other ensemble averaging processes was demonstrated by simulations. The simplicity in implementation makes it a valuable method for applications where a real-time capability is desired. Further investigation of the two bit correlation in conjunction with block correlation algorithms [10] for flow measurements is underway.

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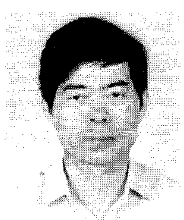

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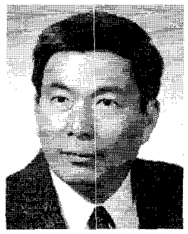

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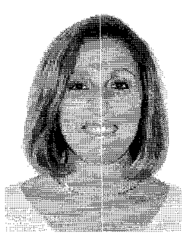

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