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Direct Comparison of Feature Tracking and Autocorrelation for Velocity Estimation

Gregory R. Bashford, *Senior Member, IEEE*, and Derek J. Robinson

Abstract—Feature tracking is an algorithm for estimating tissue motion and blood flow using pulse-echo ultrasound. It was proposed as a computationally simpler alternative to other techniques such as autocorrelation and time-domain cross correlation. The advantage of feature tracking is that it selectively extracts easily identifiable parts of the speckle signal (e.g., the local maxima), reducing the amount of information being processed. Studies on feature tracking to date have used stationary, speckle-generating targets to simulate blood flow. Also, feature tracking has not been compared with accepted commercial methods. This study directly compares feature tracking performance with the complex autocorrelation method, which is the most common color flow algorithm. Experiments were performed with both a rotating string phantom and a commercial flow phantom surrounded by tissue-mimicking material, using 2.25 MHz and 3.5 MHz transducers, under more realistic signal-to-clutter (-15 to -35 dB) and signal-to-noise ratios (SNR) (15 dB to 3 dB) than previous translating-phantom tests. The feature tracking approach is shown to produce mean estimates comparable to autocorrelation ($R^2 = 0.9954$ and 0.9960 for 6-sample and 12-sample autocorrelation, respectively, and $R^2 = 0.9998$ for both 6-sample and 12-sample feature tracking) for velocities ranging from 10 to 100 cm/s. The variance of feature-tracking estimates is shown to compare favorably to the complex autocorrelation approach using the same number of ensemble flow samples (19 to 28% lower standard deviation for 3.5 MHz, 36 to 55% lower standard deviation for 2.25 MHz). However, linear regression of the feature locations does not produce an appreciable improvement in estimation variance. Discussion of the need for further research, particularly in the areas of feature detection and feature correspondence, is given.

I. INTRODUCTION

ACCURATE measurement of blood flow, especially under diseased or stressed physiology, is critically important. Ultrasound has been used for many years to detect and quantify blood flow. It is known that current methods use the echo signal from moving blood to estimate velocity in one dimension. This technology is sufficiently developed to be found in almost every commercial ultrasound machine. However, measurement of three-dimensional (3-D) volume blood flow remains problematic. Three-dimensional volume blood flow is a more useful measurement to physicians

than one-dimensional velocity. Currently, volume blood flow must be extrapolated from one-dimensional velocity measurements and an assumed blood vessel cross-sectional area. Unfortunately, this method leads to large estimation errors. Therefore, physicians often will use simplified parameters such as the pulsatility index or resistive index. However, 3-D volume blood flow is more important to physicians than these parameters or 1-D velocity. Therefore, there is a need to develop methods (algorithms) that will allow 3-D measurement of volume blood flow. This need is particularly evident in echocardiography, given the rapid clinical adoption of live 3-D ultrasound in cardiology.

There are two main reasons why efforts to extend flow measurement to 2-D and 3-D have not been widely adopted by industry: availability of 3-D ultrasound data capture equipment and computational complexity of 3-D flow estimation. With the recent advancements in 2-D transducer arrays and 3-D ultrasound machines, the first reason mostly has been eliminated. However, the second reason (computational complexity) remains.

Feature tracking is a motion detection algorithm originally identified as a method of reduced computational complexity (as compared to conventional and research methods) [1]–[3]. Although proof-of-concept has been demonstrated with stationary tissue phantoms in 1-D [4] and 3-D [3], much work remains to be done before feature tracking is deemed acceptable for clinical use under ordinary physiological conditions. In particular, the proof-of-concept experiments were performed under unrealistically high signal-to-noise (SNR) and signal-to-clutter ratios. Also, feature tracking has not been directly compared with other methods of flow estimation. The purpose of this paper is twofold: to test the feature tracking approach under more realistic SNR and signal-to-clutter values, and to compare the feature tracking approach with a conventional method—autocorrelation. In this paper, only 1-D experiments and analysis will be considered. Extension to 2-D and 3-D will be the focus of future studies.

II. BACKGROUND

On most commercial ultrasound machines, two forms of blood motion estimation mainly are used. The first is termed spectral Doppler, in which a greater number of ensemble samples (typically 64 – 128) are used to obtain information about the entire Doppler spectrum, which is graphed on-screen in the form of a time-frequency plot. This estimation is performed at one specific location in the

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body (chosen by the user manually with a cursor). The second is often referred to (in the clinical environment) as color Doppler, in which fewer ensemble samples (typically 6–16) are used to quickly estimate a single parameter, the mean frequency of the Doppler spectrum. Color Doppler uses the autocorrelation method [5], which is fast enough to calculate the mean velocity of many locations in the body at typical frame rates (10–30 frames/second). In practice, a color is superimposed over the gray-scale image corresponding to the magnitude and direction of flow. Although both methods provide quantitative information, in general practice spectral Doppler is used for quantitative information about blood flow in a smaller volume of space, and color Doppler is used for qualitative information about blood flow across a larger volume of space. Power Doppler is a variant of color Doppler that shows the energy in the Doppler signal rather than the velocity. Both methods measure blood velocity in one dimension only—along the axis of the beam (i.e., toward or away from the transducer), although color Doppler displays information in two dimensions. Continuous-wave (CW) Doppler is a lesser-used method to estimate blood flow, which is actually the only method listed here that detects the true Doppler shift frequency. The other methods use the phase shifts between pulse-echo interrogations [6].

Other methods have been proposed to extend blood flow measurement to two or even three dimensions. Multiple transducers can provide flow information in more than one dimension if the transducers are mounted confocally; in this approach, the velocity vector is obtained at one location in space but not over a broad field of view [7]–[9]. Multiple subapertures within a single transducer may substitute for additional transducers [10]. Estimating the transit time across the ultrasound beam was proposed for measuring flow parallel to the transducer face [11]. Velocity also may be estimated from information in the bandwidth of the received signal [12]. The spatial quadrature technique was proposed to estimate lateral motion by using a modulation in the acoustical field in the lateral direction [13], [14]. Time-domain cross correlation of successive pulsed interrogations has been validated, and a real-time system has been developed in two dimensions [15]–[17]. Maximum-likelihood estimators have been proposed [18], [19]. Other reviews can be found in the literature [20], [21]. In these methods, the challenges in moving from two dimensions to three dimensions lie in the computational burden of the algorithms, the physical barriers of using multiple transducers, or the time constraints on acquiring sufficient ensembles within a volume.

Feature tracking was first suggested as the localization, and tracking, of a particular feature of the 1-D ultrasound speckle pattern—a local maximum of the signal amplitude [1]. It is distinguished from other speckle-tracking methods (such as cross correlation and its variants) in that the features are assigned to discrete locations in space and tracked in time. In other speckle-tracking methods, the morphology of the speckle pattern in the kernel window is not considered. The advantage of feature tracking is

that it selectively extracts easily identifiable parts of the echo signal, reducing the amount of information being processed and leading to lower computational requirements. Subsequently, a feature tracking theory was extended to three dimensions, showing that 3-D ultrasound features are identifiable [22] and that their movement corresponds to target motion [3]. An estimation method combining feature tracking and 3-D cross correlation was developed by Morsy and von Ramm [23]. The 3-D studies in both [3] and [23] showed the feasibility of feature tracking using the simplest type of experimental setup—an ultrasound tissue phantom that was manually translated between interrogations. This type of target is good for proof of concept because the scatterers comprising the echo signal do not move relative to each other between interrogations, and they do not move during the interrogation itself. However, the static phantom did not test feature tracking under realistic physiological blood flow conditions. The next step is to test feature tracking under more realistic SNR and signal-to-clutter values.

It is hypothesized that feature tracking is a trade-off between accuracy and computational complexity. For example, the autocorrelation algorithm requires as many complex multiplications and additions as ensemble samples, plus a four-quadrant arctangent operation. Feature tracking in its simplest form requires only one subtraction regardless of the number of ensemble samples. More accuracy is expected from algorithms which use more information from the echo signal, such as autocorrelation, cross-correlation techniques, or variants thereof. Motivation for pursuing the feature tracking approach is shown by this example adapted from Morsy and von Ramm [23] comparing feature tracking and 3-D cross-correlation. Assume that a tracked volume consists of N^3 resolution cells, with k samples per resolution cell. If the kernel size is one resolution cell and the search window is m^3 resolution cells, then each correlation search requires $(mk - k + 1)^3 k^3$ multiplication operations. This must be repeated N^3 times for the volume, resulting in $N^3(mk - k + 1)^3 k^3$ total operations. In contrast, feature tracking needs only $N^3/4$ comparison operations, because on average, one 3-D peak is found for every four 3-D resolution cells [22]. The computational efficiency is increased by a factor of $4(mk - k + 1)^3 k^3$, which, even for modest values of $k = 4$ and $m = 5$, is over six orders of magnitude. Of course, some computational effort will be expended in peak location and feature correspondence. Feature tracking complements the work of others by treating the ultrasound echo signal as being composed of discrete features that may be tracked.

If indeed feature tracking is a trade-off between accuracy (estimation variance) and computational efficiency, it is important to study whether this variance renders the method unacceptable. The experiments performed here compare the error variance with a well-accepted method, which is complex autocorrelation. The experiments in this study are restricted to one dimension; for, if the error variance is not acceptable in one dimension, it will not be in three dimensions. Our intent is to extend feature tracking

to 2-D and 3-D (in future work), given that the performance is acceptable in 1-D (the purpose of the present manuscript).

III. FEATURE TRACKING

The feature tracking algorithm is described here in a general way. Details of the experimental procedures performed for this study are described in Section IV. In a continuous-time signal $x(t)$, local maxima and minima can be found from the locations in which the slope is zero, i.e.:

$$\frac{dx(t)}{dt} = 0. \quad (1)$$

Because minima are low-amplitude values and more easily lost in noise, typically the maxima are selected for feature tracking. In a discrete-time or sampled signal, zero-slope locations usually do not exist as two adjacent sample points would need to be identical. Instead, locations are found in which the first-order approximation to the derivative (first-order difference) changes sign from positive to negative, i.e., values of n (sample number) where:

$$\frac{x[n] - x[n-1]}{T_s} > 0 \text{ and } \frac{x[n+1] - x[n]}{T_s} < 0. \quad (2)$$

In practice a smoothing filter is applied in the time direction to avoid multiple noise peaks being detected. Note that T_s , the sampling period, will be positive and thus the peak-finding algorithm is simply two differences and two comparison operations. At this point, a list of candidate peak locations is stored in memory. Next, a size threshold and intensity threshold may be applied (sifting). The intensity threshold is the amplitude a peak must possess to be retained for tracking, and the size threshold is the breadth a peak must possess to be retained for tracking. These thresholds may be optimized, depending on experimental conditions. Now, the final (sifted) peak locations are known for the first pulse-echo signal. A second pulse-echo signal will be sampled at a time equal to one over the pulse repetition frequency (PRF) later, and successive pulse-echo interrogations may be acquired. After the last signal has been acquired, the data set is filtered in the ensemble direction with a wall filter. Then, for each peak found in the first signal, a corresponding peak is found in the last signal. The peaks in signals between the first and last signal may be used to help correspond the initial peak location and final peak location. The estimated target movement is calculated by comparing differences in peak locations from the first and last signals.

IV. MATERIALS AND METHODS

A. Experimental Materials

One of the purposes of this study is to compare the feature tracking estimates (mean and standard deviation)

with estimates from a conventional method—that of autocorrelation. To compare mean estimates, it was decided to use a Doppler string phantom in order to achieve a controlled, steady target velocity. To compare standard deviation of estimates under realistic SNR and signal-to-clutter conditions, it was decided to use a commercial flow phantom.

The experimental setup used for mean velocity comparison is shown in Fig. 1. An unfocused 2.25 MHz, 60% bandwidth piston transducer (A397R, Panametrics, Waltham, MA) was mounted on a transducer stand and directed at a string phantom at an angle of 45 degrees. A pulser/receiver (500PR, Panametrics, Waltham, MA) was used to excite the transducer (−150 V spike). A Doppler string phantom (Mark 4, JJ&A Instruments, Duvall, WA) was used as a target. This phantom uses a motor to drive a loop of surgical suture around a series of pulleys. Translation stages (lateral and elevation) were mounted to a custom-built table in the department's shop. The platform also is adjustable in the axial dimension and angle between the transducer axis and the string. The string speed was set to constant-velocity mode and varied from 10 to 100 cm/s. The PRF was set at four times the effective Doppler frequency, given the string velocity and scan geometry. The resulting PRF ranged between 640 Hz (for a string velocity of 10 cm/s) to 6400 Hz (for a string velocity of 100 cm/s). At this frequency, the main peak of the power spectrum of the moving target was halfway between direct current (DC) (stationary flow) and the Nyquist limit of PRF/2 to avoid aliasing effects. Each data set consisted of 128 pulse-echo interrogations separated by a time interval of 1/PRF. Each pulse-echo signal consisted of 34.4 microseconds of data centered about the string target. For each string speed, 10 data sets were recorded. The echo signal was received by an 8-bit, 100 MHz computer scope card (NI-DAQ5112, National Instruments, Austin, TX). Signals were recorded via a LabVIEW (National Instruments, Austin, TX) virtual instrument program. Each data set was organized into a matrix, in which each column was a pulse-echo signal in time.

The experimental setup used for comparing standard deviation of estimates in an environment with realistic SNR and signal-to-clutter values was similar to that in Fig. 1, except the string phantom was replaced with a flow phantom. In this second set of experiments, an Optimizer RMI 1425 flow phantom (Gammex, Middleton, WI) designed to simulate blood flow was used. This phantom contains a tube (5 mm inside diameter, 1.25 mm thickness) through which blood-mimicking fluid is pumped. The fluid has acoustic properties similar to blood (speed of sound 1550 m/s, density 1.03 g/cc). The tube is surrounded by tissue-mimicking material (speed of sound 1540 m/s, attenuation 0.5 dB/cm/MHz). The phantom was varied between volume flow rates of 2.5, 5.3, 7.2, 9.6, and 12.0 ml/s (corresponding to an average velocity of 13, 27, 37, 49, and 61 cm/s). Experiments were performed with two focused piston transducers, one a 2.25 MHz (Panametrics A304S, F# = 3.0, −6 dB bandwidth 49%), and the other

Fig. 1. Experimental setup used for comparing mean velocity estimates of feature tracking and autocorrelation.

a 3.5 MHz (Panametrics A382S, $F\# = 3.0$, -6 dB bandwidth = 35%). The PRF was adjusted for each frequency as in the string phantom case (set to four times the effective Doppler frequency, if possible; or set to maximum PRF of pulser/receiver). For the 2.25 MHz experiments, the PRF ranged from 2650 Hz to 5470 Hz. For the 3.5 MHz experiments, the flow phantom was varied only up to 7.2 ml/s due to limitations in the PRF ability of the pulser/receiver (max useful PRF = 6720 Hz). The signals were received by a dedicated 14-bit, 100 MHz A/D card (PXI-5122, National Instruments, Austin, TX). Each data set consisted of 128 pulse-echo interrogations separated by a time interval of $1/\text{PRF}$. Each pulse-echo signal consisted of $20.5 \mu\text{s}$ of data centered about and fully including the phantom tube. In feature tracking and autocorrelation processing, only data corresponding to the tube ($6.5 \mu\text{s}$) was analyzed.

The signal-to-clutter ratio in the experimental setup with the flow phantom ranged from -15 dB to -35 dB. The signal-to-clutter ratio was measured in the following manner. Three of the data sets for each frequency were filtered in the time dimension (using the smoothing filter described in Section IV-B). The fast Fourier transform was taken in the row (ensemble) direction. The average magnitude of the spectrum across the rows representing the tube was calculated. The spectral magnitude at frequencies corresponding to fluid flow was compared to the spectral magnitude at DC zero frequency by inspection.

The SNR in the experimental setup ranged from 15 dB down to 3 dB. The SNR was measured in the following manner. One thousand pulse-echo signals were acquired with the flow phantom velocity set to zero. The average of the 1000 signals was calculated to estimate the mean signal. Then, for each signal, a noise signal was produced by subtracting the mean signal from the raw signal. The SNR for each signal was calculated by dividing the stan-

dard deviation of the mean signal by the standard deviation of the noise signal. The SNR was calculated in a range gate corresponding to the inside of the flow phantom tube. The SNR present in the system without adding artificial noise was 15.0 dB for the 3.5 MHz setup and 10.4 dB for the 2.25 MHz setup. Artificial noise was added to the system for selected experiments by generating normally distributed random numbers with a certain variance in MATLAB (The MathWorks, Natick, MA). The amount of noise variance to add in order to achieve a specified SNR was empirically determined by repeating the SNR measurement above after adding varying amounts of noise variance. Experiments were run with no additional noise added, noise corresponding to 6 dB SNR added, and noise corresponding to 3 dB SNR added.

B. Off-Line Processing

All data processing was performed in MATLAB. The data were filtered in both the time direction and in the ensemble direction. In the time direction, for the 2.25 MHz transducer, a 10th-order Butterworth infinite impulse response (IIR) bandpass filter was designed (-3 dB cutoff frequencies 1.36 and 3.86 MHz) to match the transducer spectrum and applied to the data. For the 3.5 MHz transducer, a 12th-order Butterworth IIR bandpass filter (-3 dB cutoff frequencies 1.89 and 5.29 MHz) was used. No initialization was used in the bandpass filter and no samples were discarded because the samples corresponding to the tube were at least several hundred samples from the start of the signal. In the ensemble direction, a 2nd-order Butterworth IIR highpass filter (wall filter) was designed (-3 dB cutoff frequency 6.3% of $\text{PRF}/2$) to cancel stationary echoes, and applied to the data. No initialization was used in the wall filter; however, the first 10 samples were

Fig. 2. A gradient search locates features in one dimension. Top, raw data of a 6- μ s portion of an ultrasound echo signal from a string target. Bottom, filtered data overlaid with results of gradient search for feature location.

discarded. A sample raw RF signal and filtered signal with feature locations are shown in Fig. 2.

Although a refined feature location and feature correspondence algorithm is beyond the scope of this paper, a simplified algorithm was devised for the purposes of comparing feature tracking to autocorrelation. First, a portion of the RF signal corresponding to the tube location is examined for an initial peak. The local maxima of this signal portion are examined to see if they meet amplitude (height) and time (width) thresholds. For this study, the thresholds were selected subjectively by manual inspection of several flow signals. The height threshold was 6E-3 V for the 3.5 MHz experiments and 3E-3 V for the 2.25 MHz experiments, which roughly corresponded to the average magnitude of the flow signal for both frequencies. The width threshold was 0.1 μ s for both frequencies, which was roughly 1/4 and 1/3 of the wavelength for the 2.25 and 3.5 MHz experiments, respectively. Optimizing these thresholds is beyond the scope of this paper, but it is indicated for future study. The location of the first local maximum that passes the thresholds was taken as the initial feature location. In subsequent pulse-echo signals, a feature was found by examining the data immediately around the location of the previous feature. The local maximum nearest the location of the previous feature was taken as the next feature location. After the initial feature, subsequent local maxima were not compared to threshold values. This process was repeated N times, where N is the number of flow samples to acquire. For the experiments, N was 6, 8, 10, or 12. A final variance threshold was applied in the following manner. The variance of the $N - 1$ differences in peak locations was calculated. If the variance was above a certain threshold (5.5 samples² for 3.5 MHz experiments, 30 samples² for 2.25 MHz experiments), the data

set was not processed further for either feature tracking or autocorrelation. The N features were processed in three different ways. First, an estimate of the Doppler frequency $\hat{f}_{d,ac}$ using an autocorrelation algorithm was taken:

$$\hat{f}_{d,ac} = \frac{\text{PRF} \times \text{angle}(X(2:N)X(1:N-1)^T)}{2\pi}, \quad (3)$$

here, X is the signal samples (ensemble direction in vector format), the angle function denotes the four-quadrant complex argument, and the multiplication within is a matrix multiplication (dot product). The frequency estimate was converted to a velocity estimate $\hat{v}_{ac}$ by the Doppler equation:

$$\hat{v}_{ac} = \frac{\hat{f}_{d,ac}c}{2f_t \cos \theta}, \quad (4)$$

where c is the speed of sound, f_t is the transmit center frequency, and θ is the Doppler angle. Second, the difference in sample location of the N th feature and the first feature was taken as the feature tracking estimate $\hat{v}_{ft}$ (including a factor for time conversion):

$$\hat{v}_{ft} = \frac{(\text{peak}(N) - \text{peak}(1))}{N - 1} \frac{c\text{PRF}}{2f_t \cos \theta}. \quad (5)$$

Third, linear regression was applied to the N features to determine if knowledge of the locations of all N features (rather than just the first and last locations) could lead to a lower-variance estimate, albeit through more computational complexity. For each velocity setting on the string phantom or flow phantom, a minimum of 30 peaks were tracked. For feature tracking, the actual time length of the data that a feature would traverse varied upon the target velocity and number of ensemble samples, and ranged from 0.3 to 1.5 μ s. For all estimation methods, the signal and noise bandwidth did not change between methods (the same data were analyzed).

V. RESULTS

Graphs of the estimated velocity versus actual velocity for the string phantom experiments are shown in Figs. 3 and 4. Fig. 3 shows the results for estimates using 6 ensemble samples, and Fig. 4 shows the results for estimates using 12 ensemble samples. The results for 8 and 10 ensemble samples (not shown) were similar. A bar chart of the average standard deviation of the string phantom estimates, as a percentage of the average velocity, is shown in Fig. 5. Table I shows the average decrease in the standard deviation of estimates between autocorrelation and feature tracking, and between feature tracking and linear regression.

Results from the flow phantom experiments are shown in Figs. 6–11. In contrast to the string phantom, a range of velocities is present in the tube and, therefore, average velocity (as calculated from the known flow rate and tube

Fig. 3. String phantom estimation results for autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of six data points. Error bars indicate ± 1 standard deviation.

TABLE I

PERCENT DECREASE OF AVERAGE STANDARD DEVIATION FOR THE STRING PHANTOM ESTIMATES.

	Ensemble length			
	6	8	10	12
Autocorrelation to feature tracking	-48.1	-48.7	-52.4	-58.7
Feature tracking to linear regression	-4.5	-5.4	-6.9	3.9

diameter) and maximum velocity (twice the average velocity with an assumed parabolic flow profile) are shown. Figs. 6, 7, and 8 show results from the 3.5 MHz experiments for SNR values of 15, 6, and 3 dB, respectively. Figs. 9, 10, and 11 show results from the 2.25 MHz experiments for SNR values of 10, 6, and 3 dB, respectively. More estimates were performed toward the center of the tube rather than the edge of the tube, which explains the higher-than-average velocity results. Only results for ensemble lengths of eight samples are shown; in general, the estimation variance decreased with an increase in ensemble length as expected.

A bar chart of the average standard deviation of the flow phantom estimates, as a percentage of the average velocity,

Fig. 4. String phantom estimation results for autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of 12 data points. Error bars indicate ± 1 standard deviation.

Fig. 5. Mean standard deviation as a percentage of average velocity for the string phantom experiments.

Fig. 6. Flow phantom estimation results for 3.5 MHz, 15 dB SNR using autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of eight data points. Error bars indicate ± 1 standard deviation.

Fig. 7. Flow phantom estimation results for 3.5 MHz, 6 dB SNR using autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of eight data points. Error bars indicate ± 1 standard deviation.

is shown in Figs. 12 and 13. Fig. 12 shows results for the 2.25 MHz experiments at 6 dB SNR, and Fig. 13 shows results for the 3.5 MHz experiments at 6 dB SNR. Table II shows the average decrease in the standard deviation of estimates between autocorrelation and feature tracking for the flow phantom experiments. Table III shows the average decrease in the standard deviation of estimates between feature tracking and linear regression for the flow phantom experiments.

VI. DISCUSSION

Overall, Figs. 3 and 4 show that the feature tracking mean estimates agree with the actual target velocities and compare well with the autocorrelation approach ($R^2 = 0.9954$ and 0.9960 for 6-sample and 12-sample autocorrelation, respectively, and $R^2 = 0.9998$ for both 6-sample and 12-sample feature tracking). It should be noted that accurate results in autocorrelation rely on correct user input of the transducer center frequency, but the feature tracking approach is not affected by error in estimation of the transmit center frequency. In addition, the variance in estimates is generally lower for feature tracking than autocorrelation. This may be due in part to the variance

threshold on the feature tracking estimates; however, autocorrelation estimates are performed in the same location as the feature tracking estimates. This merely shows that at locations in which features are easily tracked are not necessarily locations of low-variance autocorrelation estimates. Fig. 5 and Table I show that the average standard deviation in the estimates is about 50% lower for feature tracking than autocorrelation.

Figs. 6–11 show that, for a velocity-spread environment such as a flow phantom, the mean estimates are comparable to autocorrelation and the variance of feature tracking compares favorably to autocorrelation. Figs. 12 and 13, and Table II show an average standard deviation reduction from 19.0 to 28.4% for 3.5 MHz, and 36.1 to 55.3% for 2.25 MHz. These results suggest that feature tracking has the potential to perform well in a noisy environment.

It is interesting to note the time-length of data required to track a feature for potential improvement of the autocorrelation results by averaging. The equivalent time length of data a peak traversed ranged from $0.3 \mu\text{s}$ (3.5 MHz, 6 ensemble) to $1.5 \mu\text{s}$ (2.25 MHz, 12 ensemble). The corresponding time-bandwidth product is close to unity (RF bandwidth of transducers about 1.2 MHz). This indicates that averaging over the time segment would not tend to improve the autocorrelation variance. Also (al-

Fig. 8. Flow phantom estimation results for 3.5 MHz, 3 dB SNR using autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of eight data points. Error bars indicate ± 1 standard deviation.

though not performed in this paper), multiple peaks may be simultaneously tracked that overlap the time segment needed to track one feature.

Another interesting result is the fact that the linear regression estimates had comparable (did not have appreciably lower) variance than the feature-tracking estimates for both string phantom and flow phantom experiments. Prior to this study, it was hypothesized that linear regression would have a lower variance (due to the additional information of feature location at each ensemble sample) at the expense of additional computation, but this was not borne out in the results.

To rule out dependence of estimation error on feature amplitude, two additional studies were performed using data from the string phantom experiments. For each feature tracking estimate performed in the data, a new autocorrelation estimate was made at the same depth, but the first sample was chosen from a random column (ensemble number). The resulting estimation error was compared with the first sample's (complex) amplitude and phase. The results are shown in Fig. 14, indicating no dependence on the complex phase (as expected), but a modest increase in variance with a decrease in data amplitude. It may be argued that at smaller data amplitudes, the noise contributes to a greater extent (the local SNR is lower). A

Fig. 9. Flow phantom estimation results for 2.25 MHz, 10 dB SNR using autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of eight data points. Error bars indicate ± 1 standard deviation.

similar comparison for feature-tracking estimates is shown in Fig. 15, with little dependence on estimation for either feature amplitude or phase. Ten ensemble samples were used for the flow estimation in both Figs. 14 and 15.

In this study, IIR filters in both the time dimension (pulse-echo direction) and ensemble dimension (stationary echo cancellation or wall filters) were applied rather than finite impulse response (FIR) filters. IIR filters have the advantage of requiring fewer coefficients to achieve a desired response than FIR filters, and having the disadvantage of possible nonlinear phase response (leading to waveform distortion). In the time dimension, filters were used that were approximately linear phase across the pass-band. Distortion effects are small, but nevertheless do affect the position of the feature location, and they may be a source of error in the feature location process. This effect is acceptable in the simple 1-D experiments performed here, but it should be studied as feature tracking is extended to 3-D. In the ensemble direction, the phase response also is approximately linear across the Doppler spectrum. As the feature-tracking process is extended into 2-D and 3-D, alternative approaches may be necessary such as forward-reverse filtering (in which the filtered signal is reversed and run through the filter again to produce the final output). The phase distortion created in the forward filter

Fig. 10. Flow phantom estimation results for 2.25 MHz, 6 dB SNR using autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of eight data points. Error bars indicate ± 1 standard deviation.

is negated in the reverse filter, ensuring a zero-phase response. Also, filter initialization may be required to minimize transient effects.

The fact that the feature tracking estimation variance is comparable or better than the autocorrelation method is encouraging because feature tracking represents a significant decrease in computational complexity than autocorrelation. In a MATLAB simulation of 1,000,000 flow estimates, the time to perform complex autocorrelation was over three orders of magnitude longer than the time to perform feature tracking. This result is interesting but not complete, as some effort must be expended in order to locate features in the data set. The amount of computational effort required depends on the particular feature location algorithm used, which requires additional study.

Future studies in feature tracking will be designed to further the aim of extension into three dimensions. For example, specific feature identification and tracking algorithms need to be developed and refined. Feature identification and tracking will require more complex (though related) logic than that presented here. Optimization of amplitude and width thresholds are needed, which may vary depending on center frequency and bandwidth. It is hypothesized that there are optimal thresholds that trade off estimation accuracy and the time required to form es-

Fig. 11. Flow phantom estimation results for 2.25 MHz, 3 dB SNR using autocorrelation (top), feature tracking (middle), and regression (bottom), for ensemble lengths of eight data points. Error bars indicate ± 1 standard deviation.

Fig. 12. Mean standard deviation as a percentage of average velocity for the 3.5 MHz, 6 dB SNR flow phantom experiments.

Fig. 13. Mean standard deviation as a percentage of average velocity for the 2.25 MHz, 6 dB SNR flow phantom experiments.

TABLE II

PERCENT DECREASE OF AVERAGE STANDARD DEVIATION BETWEEN AUTOCORRELATION AND FEATURE TRACKING FOR THE FLOW PHANTOM EXPERIMENTS.

Frequency	SNR	Ensemble Length				Mean
		6	8	10	12	
3.5 MHz	15 dB	-20.5	-17.9	-18.6	-19.2	-19.0
	6 dB	-26.9	-22.5	-25.8	-22.7	-24.5
	3 dB	-40.0	-29.0	-26.0	-18.5	-28.4
2.25 MHz	10 dB	-36.9	-39.2	-37.9	-30.4	-36.1
	6 dB	-56.3	-66.4	-54.7	-44.0	-55.3
	3 dB	-36.8	-43.3	-45.8	-49.7	-43.9

TABLE III

PERCENT DECREASE OF AVERAGE STANDARD DEVIATION BETWEEN FEATURE TRACKING AND LINEAR REGRESSION FOR THE FLOW PHANTOM EXPERIMENTS.

Frequency	SNR	Ensemble Length				Mean
		6	8	10	12	
3.5 MHz	15 dB	0.70	-1.78	0.27	0.23	-0.15
	6 dB	0.65	0.41	-0.05	-2.28	-0.32
	3 dB	-2.56	-3.42	3.18	0.12	-0.67
2.25 MHz	10 dB	-4.35	0.07	1.02	3.47	0.05
	6 dB	-0.50	3.50	0.13	2.21	1.33
	3 dB	0.68	-0.07	-0.04	-2.49	-0.48

Fig. 14. Percentage error of the string phantom autocorrelation estimate versus amplitude and phase of the first complex sample in the ensemble.

Fig. 15. Percentage error of the string phantom feature tracking estimate versus amplitude and phase of the feature detected in the first ensemble sample.

timates over a field of view (i.e., the higher the threshold, the more flow estimates will be rejected, and the more data that must be examined to estimate flow at a particular location). Although linear regression did not show much improvement over feature tracking, other methods (perhaps involving linear prediction filters such as the Kalman filter) should be tested for improvements in flow estimation accuracy.

VII. CONCLUSIONS

We have shown that the feature-tracking approach exhibits a comparable estimation mean to the conventional complex autocorrelation approach, and a favorable estimation variance, under realistic SNR and signal-to-clutter ratios. The purpose of the study (to ensure that feature tracking does not significantly depart from a conventional method in terms of estimation variance) was satisfied. Using a similar number of flow samples, 1-D flow estimates may be formed with potential reduction in computational complexity. Further study is indicated to extend feature tracking to 2-D and 3-D for the application of this technique to blood flow instrumentation.

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