Abstract—in this paper, a new positioning system is proposed for the 3-d ultrasound (US). This system combines the image registration technique and speckle decorrelation algorithm to accurately position sequential ultrasonic images without any additional positioning hardware. The speckle decorrelation algorithm estimates the relative distance of two neighboring frames and the image registration technique gets the range of the whole 3-D ultrasonic data set and makes slight modification on each frame’s position. The image registration technique is based on the reference image, which is perpendicular to the 3-D ultrasonic data set. This reference image intersects each frame of the 3-D ultrasonic data set in a line. For each frame, the intersectional line is first found and then the location in the reference image can be used to estimate the position of this frame. This system uses the data set of consecutive 2-D freehand-scanned US B-mode images to construct the 3-D US volume data, and it can be integrated into the 3-D US volume rendering system. (E-mail: dlchen88@ms13.hinet.net) © 2003 World Federation for Ultrasound in Medicine & Biology.

Key Words: Speckle decorrelation, Image registration, Frame positioning, 3-D ultrasound.

INTRODUCTION

Medical imaging plays an important role in the clinical study and ultrasound (US) is a popular technique in medical imaging due to its lower cost, high efficacy and real-time scanning. Three-dimensional (3-D) US is a newly developed technique, and it can act as parts of function in the same way as conventional computerized tomography (CT). Two-dimensional images are not enough to transmit the entire US information, but the 3-D US can offer comprehensive information of all 2-D lesion aspects, providing, in addition, simultaneously the coronal plane, and even view it at different angles. The 2-D US techniques require a single image slice whereas 3-D US techniques use a series of image slices to cover a volume. For freehand 3-D US scanning, the acquisition is usually done by moving a probe in a predefined manner, such as rotation or translation, to obtain a series of image slices. There were many researches using sequential images for 3-D reconstruction and volumetric analysis (Sakas et al. 1995; Barry et al. 1997; Weng et al. 1997; Rohling et al. 1998; Kampmann et al. 1998).

In the freehand scanning system, a 3-D position sensor is attached to the probe (Nelson and Pretorius 1998; Sato et al. 1998), so that each image slice can be given the position and orientation of the scan plane. The position and orientation information directly transmitted to the 3-D system and is used to reconstruct the 3-D volume image. The main disadvantage of this freehand technique is that the position sensor is not accurate enough for a small tumor, such as in the breast. A possible solution is to use the speckle decorrelation algorithm (Insana et al. 1994; Chen et al. 1997; Tuthill et al. 1998). Speckle is formed by the coherent scattering particles. For the statistical properties of speckle, the intensity autocorrelation acting on the speckle region follows those of the complex Gaussian, with respect to the frame position. When the correlation function is used to estimate the frame spacing, the transducer must move steadily and slowly enough to ensure that each consecutive frame is correlated. Given a series of image slices, the correlation function is calculated and a Gaussian curve is used to fit the correlation function and, then, the space of each two frames can be back-calculated. Using
the speckle decorrelation algorithm, there exist some coefficients to be realized before performing the Gaussian curve fit, such as the US wavelength at its central frequency, the distance from the transducer to the US field point, and the height of the linear array of the transducer. In this paper, a combined method of speckle decorrelation and image registration, without using these complicated coefficients, is proposed.

Medical image registration usually means to find a transformation that transforms each point in one image into the corresponding point in the other image. There are several studies of medical image registration with various tools being used broadly in clinical diagnosis. Hill et al. (1991) developed a registration technique for combining magnetic resonance imaging (MRI) and CT images. Their technique is based on user identification of point-like landmarks visible in both modalities. Pelizzari et al. (1989) proposed a popular 3-D parametric correspondence method to register tomographic brain images. They matched the positron-emission tomography (PET) images with the CT and MRI according to the structure information. Zubal et al. (1991) proposed a direct 3-D affine method to register images that supports complex landmark structure. Image registration based on moment-matching techniques is one of the other frequently used approaches. Information on volumes (Studholme et al. 1996), surfaces (Chua and Jarvis 1996) and scattered points (Toennies et al. 1990) all can be used with moment matching. Although these previous reports demonstrate good results, they need a lot of computation time. It will be helpful in clinical practice if 3-D image reconstruction can be efficiently and quickly made. The above methods may not be suitable for matching the US images with a smaller tumor. In this paper, a simple three-line match method is proposed.

**MATERIALS AND METHODS**

**Elevational speckle decorrelation**

Tuthill et al. (1998) proposed an automated 3-D US frame positioning system. In their system, the B-scan images were collected by means of a hand-held transducer moving in the elevational direction, and frame spacings were computed with a speckle-decorrelation algorithm, without additional positioning hardware. Here, the elevation direction means the direction perpendicular to the scan plane. The concept of this method is that we can monitor the scan plane motion and the motion can be detected by the changes in the speckle correlation in the elevational direction. Tuthill and colleagues proved that the intensity autocorrelation between two consecutive frames could be fitted by a Gaussian curve with respect to the frame spacing.

Because the decorrelation algorithm holds true for only the speckle regions, we need a speckle detector to find the speckle regions. In this paper, the size of the speckle region used was 5 pixels × 5 pixels × 5 frames. For a fully developed speckle, the intensity image should have an exponential distribution and a constant ratio of mean to SD of 1.0. A detector based on first-order statistics was developed (Tuthill et al. 1998). When the ratio of mean intensity to SD for a region with a moving 3-D volume was between 0.8 and 1.2, the region was classified as a speckle region. Only the pixels in the speckle regions were used to form the correlation function. The autocovariance function was used to represent the correlation function. The intensity autocorrelation $R$ for positions $r_1$ and $r_2$ is defined as

$$R(r_1, r_2) = \langle I(r_1)I(r_2) \rangle$$

(1)

and the autocovariance $C$ is

$$C(r_1, r_2) = \langle I(r_1)I^*(r_2) \rangle,$$

(2)

where $\langle \rangle$ means the expected value and $I$ means the intensity function.

The normalized correlation function of the echo signal intensities for frames $f_1$ and $f_{1+\Delta y}$ among an $m \times n$ image regions-of-interest (ROIs) is determined by:

$$C(\Delta y) = \frac{\sum_{j=1}^{m} \sum_{k=1}^{n} (I_p(j, k) - \bar{I}_p)(I_{p+\Delta y}(j, k) - \bar{I}_{p+\Delta y})}{\sqrt{\sum_{j=1}^{m} \sum_{k=1}^{n} (I_p(j, k) - \bar{I}_p)^2 \sum_{j=1}^{m} \sum_{k=1}^{n} (I_{p+\Delta y}(j, k) - \bar{I}_{p+\Delta y})^2}}.$$  

(3)

Each pixel value of frame $f_i$ needs to be converted to a linear scale (Smith and Fenster 2000) by:

$$I_p(j, k) = 10P_0(j, k)P_0,$$

(4)

where $P_0(j, k)$ is the raw B-mode pixel value in dBs and the constant $P_0$ is used to convert from a 0 to 255 log scale to a linear scale. In their work, $P_0 = 51.$

The normalized intensity correlation function can be well approximated by a Gaussian function (Chen et al. 1997).

$$C(\Delta y) = \exp[-2a_0(\Delta y)^2]$$

(5)

where $\Delta y$ is a displacement in the elevational direction, $a_0 \approx 2.72h^2/\lambda_0 u^2$, $\lambda_0$ is the US wavelength at its central
frequency, \( z \) is a distance from the transducer to the US field point, and \( h \) is the height of the linear array of the transducer. These coefficients are determined by the transducer properties. By fitting the correlation function for a set of consecutive frames to a Gaussian curve, the average frame spacing can be back-calculated.

The above equation needs some transducer properties. In fact, some transducer properties, such as the transducer’s focus and the depth of the tumor, are dependent on the scanning condition. However, the ratio of the frame spacings can be easily obtained without any transducer properties. According to eqn (5), the correlation functions of frames \( f_i, f_j \) and frames \( f_j, f_k \) in the 3-D data set can be defined individually as follows:

\[
C(f_i, f_j) = \exp\left[-2a_0D(f_i, f_j)^2\right] \quad (6)
\]

\[
C(f_j, f_k) = \exp\left[-2a_0D(f_j, f_k)^2\right] \quad (7)
\]

where \( D(f_i, f_j) \) is the distance function of the two frames \( f_i \) and \( f_j \).

Then, the ratio of the frame spacings can be derived as:

\[
\frac{D(f_i, f_j)}{D(f_j, f_k)} = \frac{\ln(C(f_i, f_j))}{\ln(C(f_j, f_k))} \quad (8)
\]

To prove the above statements, we did some experiments with a test data set and then show the result in Figs. 1 and 2. This data set IV is scanned by a real-time 3-D scanner Voluson 530D (Kretz Technik, Zipf, Austria) and its detailed information is listed in Table 1. The curves of the normalized correlation function and Gaussian function are plotted in Fig. 1. From this figure, we can find that they can match within shorter distances. As for Fig. 2, we prove the validity of eqn (8). Let the frame space of a 5-frame interval be a basis, and calculate the ratios of the frame spaces of 1-frame, 2-frame, 3-frame, 4-frame and 5-frame intervals based on eqn (8). According to the result of Fig. 2, the ratio of the frame space will increase in direct proportion to the frame interval. In other words, eqn (8) holds true.

The proposed method

To accurately position the B-scan image series, a new method is proposed that is implemented based on the image registration technique and speckle decorrelation.

Data acquisition

The sonographic image database was captured from patients with breast tumors by an ALOKA SSD 1200 scanner (ALOKA, Tokyo, Japan) and a 7.5-MHz lineal real-time transducer with freeze-frame capability. No acoustic standoff pad was used in any of the sample cases. For obtaining the volume data of a 3-D US scanning, the acquisition was done by steadily moving a probe in a predefined manner, transversely and longitudinally. The rotation of the transducer was not allowed. The sonogram was performed by transmitting the analog signals from the scanner to the capture card V3800 (ASUSTek Computer Inc., Taipei, Taiwan), which digitizes the data and generates frames of resolution 320 ×
240 pixels for a National Television Systems Committee (NTSC) video. The digital image was real-time captured and quantized into 8 bits. We also used another data set that is obtained by the real-time 3-D scanner Voluson 530D to test the correctness of our positioning system. In this real-time 3-D ultrasonic data set, the position of each frame is known and fixed. In Table 1, we describe the information of these data sets in detail.

All of these data sets were captured in two directions, the transverse direction and the longitudinal direction. In fact, only one direction is needed to reconstruct 3-D volume, and the other direction was used as a reference in reconstructing the 3-D volume. We need only one frame along the reference direction for image registration. We assume that the transducer is translated parallel to the body surface, resulting in axis-aligned images. The rotation of the transducer was not allowed, so that each frame is parallel to the other frames.

Image registration

In this section, we used a reference image to estimate the approximate position of each frame. The relationship between a reference image and the 3-D data set is depicted in Fig. 3. We can find that all of the image slices intersect the reference image in one line and frame spacings can be directly computed from the distance of these lines.

Matching function for intersectional line

There are many possible lines when two frames intersect, so we needed a matching method to find the most possible intersectional line. The similarity of any two pixels in the spatial domain can be computed from the difference of its intensity, intuitively. The smaller the difference, the more similar these two pixels are. Simply extending this ideal when we match the two lines, and the matching function of these two lines is the sum of the difference of the corresponding pixels in these two lines.

Furthermore, in the freehand scanning system, there exist some errors in the up and down directions when the transducer moves along the elevational direction. Thus, when any two lines perform line matching, we must moderately interlace these two lines to find the best matching point. According to these ideas, we can define a match function as follows:

\[
s_{i, j, k} = \sum_{k=0}^{H-1} [f(i, k) - r(j, k + s)],
\]

where \(i\) and \(j\) are line numbers, \(f\) and \(r\) are the intensity functions of pixels, \(H\) is the height of the ROI, \(k\) is the index of height in the ROI, and \(s\) is the number of shifting pixels.

Because of the noise and speckle structure of the ultrasonic data, the changes of any consecutive lines of an ultrasonic image are usually very small. If the resolution of an image is not high enough, the result of the line matching will not be very clear. The number of match lines can be increased, and the average of neighboring lines is used in the matching process to reduce the error. Hence, the line-matching function is modified as follows:

\[
s_{i, j, k} = \frac{1}{3} \left( f(i - 1, k) + f(i, k) + f(i + 1, k) \right) - \frac{1}{3} \left( r(j - 1, k + s) + r(j, k + s) + r(j + 1, k + s) \right)
\]

Take, for example \(s = 2\), and we find the minimum of three_line_match functions for \(s = 0\), \(s = 1\) and \(s = 2\), and the matching function of these two lines is set to the minimum value we found.

Finding principle intersectional line

Due to the noise and blurry nature of ultrasonic images, it is hard to find the correct intersectional line, even using the line-matching function described above. Thus, we need some restrictions and assumptions before the image registration algorithm.

First, we must select the best reference frame to obtain the better result. Here, the best reference frame means that this frame should contain as much of the tumor region as possible. In the same way, choosing the best frame in the 3-D data set that contains as much of the tumor region as possible. The \((f_0, f_1, \ldots, f_{m-1}, f_m, f_{m+1}, \ldots, f_{N-1})\) denotes the \(N\) frames in the 3-D data set,
and $f_m$ denotes the frame we chose. We marked the ROI in the frame $f_m$, which contains roughly the whole tumor and also marked the corresponding ROI region in the chosen reference frame. The ROI was made by a rectangular region that extended beyond the lesion margins by 1 to 2 mm in all directions. Because the ROI region is drawn by physicians, the center of the tumor can be expected to approximate the center of the ROI region. In addition, the frame $f_m$ and the reference frame contain roughly the biggest tumor region, so we can assume these two frames intersect near the center of the ROI. We can get the intersectional line by these two frames by this assumption. We search all of the combinations of the two lines, in which one is from the central region of ROI in the frame $f_m$ and the other is from the central region of the ROI in the reference frame. Performing the line-matching function for each set of the two lines means that the two lines that have the minimum distance will be considered to be the same line. This line is the intersectional line of the frame $f_m$ and the reference frame.

The range of the central region of the ROI in the reference frame and the frame $f_m$ can be set to 10% of the width of the ROI. For the same tumor, the ultrasonic images that contain the biggest tumor region in the reference direction and in the main direction may be very similar. So that, if the search range is too large, we may get the wrong intersectional line. If we can ensure that the reference frame and the frame $f_m$ that we chose are very accurate, then we can decrease the search range to increase the accuracy of the intersectional line we found.

**Finding other intersectional lines**

Now, we explain how to derive the position of the frame $f_{m-1}$ from the position of the frame $f_m$. In Fig. 4, if the frame $f_m$ intersects the reference frame in line $i$ of the frame $f_m$ then we will assume that all the other frames of the 3-D data set intersect the reference frame at line $i$ of themselves. In the elevational direction, if the frame $f_m$ intersect the reference frame at line $j$ of the reference frame, then the frame $f_{m-1}$ must intersect the reference frame at the line that is in the left side of line $j$ of the reference frame. Based on these facts, a line-matching function was performed on two lines, one is the line $j$ of the frame $f_{m-1}$, and the other is in the left side of line $j$ of the reference frame. The line that causes the minimum distance from the line-matching function in the reference frame is the intersectional line of the frame $f_{m-1}$ with the reference frame. Repeatedly using this method, we can obtain the intersectional lines of the frame $f_{m-1}$ to the frame $f_0$ with the reference frame. In the right side of the frame $f_m$, the intersectional lines of the frame $f_{m+1}$ to the frame $f_{N-1}$ with the reference frame can be obtained in a similar way.

The search range of the reference frame when we perform the line matching is adaptive. If we do not limit the search range, it may happen that the distance of the two intersectional lines is too far, even if these two intersectional lines are formed by two consecutive frames with the reference frame. This is an obvious error because the frames in the 3-D data set are continuous, and this error will cause all the intersectional lines obtained after this intersectional line to be wrong.

To prevent this error from happening, we set the search range to 10% of the width of the ROI initially. If the final result of the intersectional line of the frame $f_0$ with the reference frame was out of the ROI, we decreased the size of the search range. Alternatively, if the final result of the intersectional line of the frame $f_0$ with the reference frame was inside the ROI, we increased the size of the search range. This method was repeatedly used until the intersectional line of the frame $f_0$ with the reference frame was near the boundary of the ROI. The search range in the right side of line $j$ of the reference frame can be set in a similar way. After finding the search range, all the intersectional lines of all the frames in the 3-D data set with the reference frame can be obtained.

The steps of finding all the intersectional lines described above are based on some assumptions. First, the transducer must be forward scanned and cannot reverse the direction when we scan; this is why we searched only the left side of line $j$ of the reference frame. Second, the transducer must be moved almost along a straight line, so that we can assume all the frames of the 3-D data set intersect the reference frame in line $i$ of themselves.

**Degrouping of neighboring intersectional lines**

All the intersectional lines of all the frames in the 3-D data set with the reference frame obtained by the above method have a grouping effect; that is, some consecutive frames in the 3-D data set almost intersect the reference frame at the same line. This is because
the change of the consecutive lines of an ultrasonic image is very small. When scanning data, the approximate range of the inter-frame spacing is about 0.2~0.4 mm. To reduce this effect, we will change the positions of the almost-overlapping intersectional lines. When we find the intersectional lines of all the frames in a 3-D data set, we assume that all the frames of the 3-D data set intersect the reference frame at line $i$ of themselves, as shown in Fig. 4. The neighboring lines $i-1$ and $i+1$ of line $i$, shown in Fig. 5a can be used to detect and resolve the problem of the almost overlapping intersectional lines. In general, for some frames in the 3-D data set, the intersectional lines of these frames will belong to different groups when different neighboring lines of the original line $i$ are used to match. For example, in Fig. 5b, the intersectional line of the frame $f_{i+1}$ will belong to group 2 when the line $i-1$ is used to match, and it will belong to group 1 when the line $i$ is used to match. So the more accurate position of the frame $f_{i+1}$ can be calculated by averaging the positions of $f_{i+1}$ for different matching lines $i-1$, $i$, and $i+1$. After degrouping the almost-overlapping intersectional lines using the above position-averaging step, we can get a better set $P$ of the positions. These positions can provide the base of the correction after forming the speckle decorrelation algorithm.

**Speckle decorrelation for the ratio of frame spacings**

From eqn (8), the ratio of all the frame spacings in the 3-D data set can be computed without additional parameters. First, extract three frames ($f_0$, $f_1$, $f_2$) and get the ratio of the $D(f_0, f_1)$ and $D(f_1, f_2)$. Then extract three frames ($f_1$, $f_2$, $f_3$) and get the ratio of the $D(f_1, f_2)$ and $D(f_2, f_3)$ in the same way. So the ratio of the $D(f_0, f_1)$, $D(f_1, f_2)$ and $D(f_2, f_3)$ can be obtained. Repeatedly using this method, the ratio of all the frame spacings in the 3-D data set can be calculated.

Because eqn (8) holds true for only the speckle regions, we need a speckle detector to find the speckle regions. When the ratio of mean intensity to SD for a region with a moving 3-D volume is between 0.8 and 1.2, the pixel that is in the center of this volume is classified as a speckle region. Only the pixels in the speckle regions are used to form the correlation function.

Because the speckle decorrelation algorithm only gets the ratio of frame spacings, we need to know the positions of the frame $f_0$ and $f_{N-1}$. When the positions of the start frame $f_0$ and the end frame $f_{N-1}$ have been known, the other frame positions can be obtained through the ratio of frame spacings. Here, we directly use the positions of the frame $f_0$ and $f_{N-1}$ in the set of positions $P$ and then we can get another set of positions $P'$. The set of positions $P'$ provides the approximate positions of all the frames in the 3-D data set.

**Final position refinement**

Because the set of positions $P'$ is obtained based on the speckle decorrelation algorithm, the errors that are caused by this algorithm directly influence the accuracy of the frame positions $P'$. The original set of the frame positions $P$ can assist in refining the positions and reducing this error. For each frame $f_i$ between the frame $f_0$ and $f_{N-1}$ in the 3-D data set, we refined the better position of frame $f_i$ in a small range. This small refinement range for frame $f_i$ is between the central position of the frames $f_{i-1}$. In this range, the position that is the closest to the position of the frame $f_i$ in the set $P$ is the new position of the frame $f_i$, as shown in Fig. 6. In this way, all the frame positions of the 3-D data set can be refined. The entire positioning algorithm diagram is shown in Fig. 7.

**RESULTS AND DISCUSSION**

In this section, we show some experimental results and then end with some discussion. First, we test some data sets to show the improvement of our method. Second, we test the accuracy when we scan the same target repeatedly. Third, we compare the running time of each method. Finally, we discuss the parameters and the reason why the speckle decorrelation method fails.
After positioning the targeted 3-D data set, we can reconstruct the reference frame by the intersectional lines of the frames in the 3-D data set. The correctness of our positioning system can be tested by comparing the reconstructed reference frame and the original reference frame. We can also test the accuracy of the frame positions when the 3-D data set is obtained by a real-time 3-D scanner because we can know the accurate positions of the frames in this data set. In the freehand ultrasonic system, the positions of the frames in 3-D data set are unknown. Instead, we calculate the accuracy of the tumor width and area in the reconstructed reference frame.

In the freehand scanned experiments, we used three

Fig. 6. The final refinement of $P'$ by the original position set $P$ in three possible cases. (a) The position of $f_x$ in $P$ is inside the refinement range, (b) The position of $f_x$ in $P$ is outside the left boundary of the refinement range, and (c) The position of $f_x$ in $P$ is outside the right boundary of the refinement range.

The comparison of different methods

After positioning the targeted 3-D data set, we can reconstruct the reference frame by the intersectional lines of the frames in the 3-D data set. The correctness of our positioning system can be tested by comparing the reconstructed reference frame and the original reference frame. We can also test the accuracy

Fig. 7. Diagram of the entire positioning algorithm.

Fig. 8. (a) The reference frame of 3-D ball (data set 1). (b) The reconstructed reference frame by the proposed method. (c) The reconstructed reference frame (b) after filling the lost regions with neighboring lines. (d) The reconstructed reference frame by speckle decorrelation algorithm. (e) The reconstructed reference frame (d) after filling the lost regions with neighboring lines. (f) The reconstructed reference frame by the three-line match method. (g) The reconstructed reference frame (f) after filling the lost regions with neighboring lines.

of the frame positions when the 3-D data set is obtained by a real-time 3-D scanner because we can know the accurate positions of the frames in this data set. In the freehand ultrasonic system, the positions of the frames in 3-D data set are unknown. Instead, we calculate the accuracy of the tumor width and area in the reconstructed reference frame.

In the freehand scanned experiments, we used three
3-D data sets to test our positioning system. Figure 8a shows the reference frame of the 3-D ball. This image is formed by scanning the ball dipped into the agar. Fig. 8b shows the reconstructed reference frame produced by the proposed method. In the ROI region, we find the lost lines in the reconstructed reference frame and fill them with the neighboring lines, and the result is shown in Fig. 8c. The accuracy rates of the ball width and area are 98.28% and 99.66%, respectively.

For comparison, we also show the reconstructed reference frame produced by the speckle decorrelation algorithm and three-line match method, respectively. In the speckle decorrelation algorithm, we first calculate the distance ratio of each frame in the data set according to eqn (8). Then, by the positions of the first frame \( f_0 \) and the last frame \( f_N \) obtained by our method, the position of each frame can be obtained. Note that the above speckle decorrelation algorithm does not need the transducer coefficients. The reconstructed reference frame by the speckle decorrelation algorithm is shown in Fig. 8d and e. The accuracy rates are 67.24% for width and 67.69% for area. The three-line match method is also used for comparison. The reconstructed reference frame produced by the three-line match method is shown in Fig. 8f and g and the accuracy rates of the width and area are 96.55% and 97.79%, respectively. In Table 2, we show the experimental results of the 3-D ball with different methods in detail. The results of other two data sets are shown in Fig. 9 and Fig. 10. The accuracy rates of different methods are also listed in Tables 3 and 4.

In the real-time 3-D scanned experiments, the 3-D data set scanned by the real-time 3-D scanner was used for testing. The result is shown in Fig. 11 and the accuracy rates of different methods are listed in Table 5. From Tables 2–5, we can prove that the proposed method is better than the other ones.

**Repeatability test**

A good method should achieve a similar higher accuracy when scanning the same tumor repeatedly.
Hence, we scanned the 3-D ball again to obtain another test data set, V. Detailed information of the data set V is also listed in Table 1. In Fig. 12, we show the reconstructed reference frames produced by different methods of the data set V. The accuracy rates of width and area for each reconstructed reference frame are compared with the data set I and listed in Table 6. From Table 6, the proposed method can have similar better results for the same 3-D ball.

Table 3. The comparison of the three methods for data set II with different shifting pixel \( s \) and ROI height \( H \)

<table>
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<tr>
<th>ROI height</th>
<th>Shifting pixel ( s )</th>
<th>Accuracy rate</th>
<th>Proposed method (%)</th>
<th>Speckle decorrelation (%)</th>
<th>Three-line match (%)</th>
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Table 4. The comparison of the three methods for data set III with different shifting pixel \( s \) and ROI height \( H \)

<table>
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<th>ROI height</th>
<th>Shifting pixel ( s )</th>
<th>Accuracy rate</th>
<th>Proposed method (%)</th>
<th>Speckle decorrelation (%)</th>
<th>Three-line match (%)</th>
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<td>2 Width</td>
<td>99.17</td>
<td>94.50</td>
<td>89.54</td>
<td></td>
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</tbody>
</table>

**Time comparison**

The processing time of each data set with different methods is listed in Table 7. These methods are implemented on an Intel Pentium III 733 computer system (Intel, Santa Clara, CA, USA) with 256 MB ram. From Table 7, we find that the proposed method is slightly slower than the speckle decorrelation algorithm.

**Speckle influence test**

To observe the speckle influence in the matching function, we also did an experiment about the compari-
Fig. 11. (a) The reference frame of 3-D tumor (data set IV). (b) The reconstructed reference frame by the proposed method. (c) The reconstructed reference frame (b) after filling the lost regions with neighboring lines. (d) The reconstructed reference frame by speckle decorrelation algorithm. (e) The reconstructed reference frame (d) after filling the lost regions with neighboring lines. (f) The reconstructed reference frame by the three-line match method. (g) The reconstructed reference frame (f) after filling the lost regions with neighboring lines.

Table 5. The comparison of the three methods for data set IV with different shifting pixels

<table>
<thead>
<tr>
<th>ROI height</th>
<th>Shifting pixel (s)</th>
<th>Width</th>
<th>Percentage</th>
<th>Area</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
<td>1</td>
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<td>93.07</td>
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<tr>
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<td>Area</td>
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<td>78.49</td>
<td>90.85</td>
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<td>76.73</td>
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<td>Area</td>
<td>79.97</td>
<td>68.59</td>
<td>78.20</td>
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</tr>
</tbody>
</table>

Fig. 12. (a) The reference frame of 3-D ball (data set V). (b) The reconstructed reference frame by the proposed method. (c) The reconstructed reference frame (b) after filling the lost regions with neighboring lines. (d) The reconstructed reference frame by speckle decorrelation algorithm. (e) The reconstructed reference frame (d) after filling the lost regions with neighboring lines. (f) The reconstructed reference frame by the three-line match method. (g) The reconstructed reference frame (f) after filling the lost regions with neighboring lines.

Table 6. The comparison of the three methods for data sets I and V (the same target scanned twice) with shifting pixel $s = 1$ and ROI height $H = 55$

<table>
<thead>
<tr>
<th></th>
<th>Accuracy rate</th>
<th>Proposed method (%)</th>
<th>Speckle decorrelation (%)</th>
<th>Three-line match (%)</th>
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</thead>
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<tr>
<td>Data set I</td>
<td>Width</td>
<td>98.28</td>
<td>67.24</td>
<td>96.55</td>
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<td></td>
<td>Area</td>
<td>99.66</td>
<td>67.69</td>
<td>97.79</td>
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<tr>
<td>Data set V</td>
<td>Width</td>
<td>96.55</td>
<td>60.34</td>
<td>89.66</td>
</tr>
<tr>
<td></td>
<td>Area</td>
<td>95.27</td>
<td>49.00</td>
<td>88.55</td>
</tr>
</tbody>
</table>
According to Table 8, we find that matching with all pixels has the highest accuracy among the three strategies; however, the difference among them is not obvious.

**DISCUSSION**

In our experiments, we mostly adjust two parameters, $s$ and $H$, and examine the influence caused by their different values. The parameter $s$ is the number of interlaced pixels and $H$ is the height of the ROI. According to the experimental results, we find that we can achieve the best result when $s$ is 0 or 1. As to $H$, the smaller $H$ is, the better result we can achieve. Although $s$ and $H$ will influence the accuracy rate of the experimental results, the difference is actually not obvious.

The speckle-decorrelation method is already used in many aspects. However, it holds true only for the speckle region. In other words, the higher the speckle ratio is, the better it works. In our data sets, the speckle ratios of the ROI of the data set I to V are 18.65%, 16.65%, 30.59%, 12.42% and 18.65%, respectively. From the experimental results, we find that the effect of the data set III is superior to other data sets and the above point is proven.

**CONCLUSION**

With the increasing importance of clinical applications of 3-D imaging, 3-D US is more and more popular.

To reconstruct a 3-D volume image, all the frames in a volume, as well as all the instrumental information on an anatomical volume, must be available. However, this is not an easy task to do and the operator’s technique is, therefore, fundamental to scanning the ROI accurately. There are many methods to obtain a 3-D volume image. The free-hand 3-D US can be obtained by using the traditional 2-D US and a position sensor. However, the scanning manner has the drawback of different scanning speed for each physician. The second method is the real-time 3-D imaging systems. The data collected from a real-time 3-D system are the most accurate and are convenient for its clinical applications, but the major problem is in its price.

In this paper, we propose the positioning system that combines the speckle decorrelation algorithm and the image-registration technique. This system can accurately position the 3-D ultrasonic data set without any additional positioning hardware; in fact, we need only a reference frame to match it. There are some difficulties and limitations with our positioning system. First, the speckle decorrelation algorithm requires a lot of calculations when the targeted 3-D data set contains a substantial amount of the frames. This effort can be reduced by decreasing the number of the speckle regions, but this will increase the error rate of the speckle-decorrelation algorithm. In fact, only the number of frames exceeding 100 can slow down the system, so we can control the error rate and the speed in a reasonable range. Second, we assume all the frames in the 3-D data set and the reference frame are almost parallel or orthogonal. The rotation of the transducer is not allowed in the speckle decorrelation algorithm or the image-registration method. We leave this problem for future research.

**REFERENCES**


