3D Ultrasound Image Reconstruction from Non-Uniform Resolution Freehand Slices

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ABSTRACT

The reconstruction of 3D ultrasound (US) images from mechanically registered but otherwise irregularly positioned B-scan slices is of great interest in image guided therapy procedures, such as that used for the treatment of prostate cancer. Conventional reconstruction method simply interpolates slices from the same angle and then compounds the interpolated data from different angles. This method results in spatial resolution far inferior than the in-plane resolution of each B-Scan slice. We propose a novel reconstruction method which properly weights the frequency components of data sets from different angles in a Wiener filter/MMSE fashion. Simulation results for synthetic US images are presented to demonstrate the excellent reconstruction.

1. INTRODUCTION

Medical ultrasound is a widely used imaging modality for its real-time, non-radioactive, low-cost and portable nature and has long been used to evaluate part of body like liver, heart, kidney and the fetus during pregnancy, *etc.* While the majority of clinical ultrasound is based on 2D cross-sectional slices in current stage, a lot of recent researches have shown their interest in 3D ultrasound, which is anticipated to have a lot of advantages over conventional 2D ultrasound by increasing spatial anatomical detail, facilitating accurate measurement of organ volumes and improving diagnostic comprehensibility [1].

3D ultrasound images can be either acquired by 3D probe or reconstructed from a series of 2D slices [2]. A 3D probe sends and receives echoes from a 2D array of elements, instead of from conventional 1D array, to allow real-time 3D imaging. Although it may represent a promising approach for 3D imaging, the probe is cost prohibitive and suffers from poor signal to noise ratio due to some technical problems [3]. Another alternative 3D ultrasound approach is freehand imaging system. It is a combination of conventional 2D ultrasound device with relatively inexpensive 3D position sensor. When a user moves the probe slowly and steadily over a particular anatomical region, *B*-scans ultrasound data together with their 3D spatial coordinates are recorded into the computer. Freehand imaging allow user to get images at arbitrary positions without any constraint. The cost and flexibility make freehand system a popular choice for 3D imaging [4].

In freehand imaging, the acquired 2D slices are interpolated onto a cubic grid for visualization and analysis. A lot of 3D interpolation algorithms have been proposed to estimate the missing points in 3D volume. These include the voxel nearest neighbor [5], pixel nearest neighbor [6], bilinear and distance-weighted interpolation [7]. The 3D volume's image quality depends on variables such as transducer geometry, frequency, focal zone position and time gain compensation. Within a slice, the resolution (in-plane) is determined by the pulse bandwidth and transducer aperture. In the direction perpendicular to the slice (elevation), the resolution is determined by the thickness of the slice and the inter-slice distance. In general, the in-plane resolution is much higher than the elevation resolution due to the transducer thickness and large elevation sampling intervals. The volume interpolated from a single sweep data set therefore has non-uniform spatial resolution. This effect is shown in Figure.1.

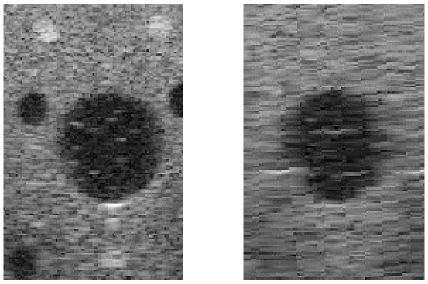
(a) (b)

Figure 1. Bilinear reconstruction volume from freehand 2D slices, (a) cross-sectional view; (b) sagittal view.

In clinical imaging, the operator usually acquires several sets of B-scans of the same target region from different interrogation angles and different sweep directions to increase the details in each look. Another benefit of this technique is that redundant data are acquired with statistically independent speckle patterns (Speckle is a naturally occurring artifact in all coherent wave imaging systems.) Compounding those data, the underlying image information will sum constructively while the speckle artifact will be averaged out, resulting in a reduced speckle image. This technique – known as ‘spatial compounding’ has been proven effective [8].

However, there is a trade-off between speckle reduction and spatial resolution [9]. Because data at each angle have vastly different in-plane and elevation resolutions, averaging data sets of different angles results in a 3D volume with much lower resolution than the in-plane resolution. Figure 2 shows a 3D volume compounded by two data sets acquired in orthogonal directions. Compared with Fig.1, although the volume increases details in sagittal direction, cross-sectional image gets blurred.

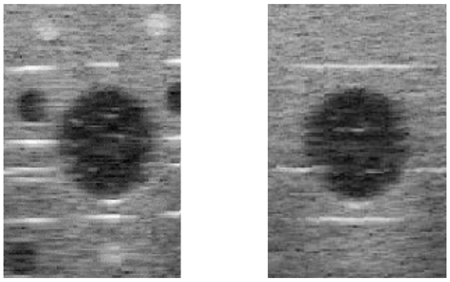
(a) (b)

Figure 2. Compounded 3D volume, (a) cross-sectional view; (b) sagittal view;

In this paper, we present a novel method of reconstructing uniform high-resolution 3D images from non-uniform resolution freehand slices. Our method reconstructs the frequency components of the 3D image by optimally (in the minimum mean-squared error sense) weighting the frequency components of data sets of different angles. The result is that details (high frequency components) in every look angle are better preserved. We will compare our reconstruction with that using current technique in a synthetic data example.

2. FREQUENCY DOMAIN RECONSTRUCTION

The reason of resolution degradation becomes clear when we consider the compounding process in frequency domain. Data of each sweep only occupy a strip in the frequency domain, with narrow bandwidth in the elevation direction. The direction of the strip is different for each data set, reflecting the different direction and look angle of each sweep. The strips overlap mostly in the low frequency band. When multiple data sets are averaged, the high frequency components of individual data sets will be weighted down, relative to the low frequency components, thereby lowering the resolution. Our approach does not weight the frequency components of the data set equally. Rather, we weight them according to the SNR at the particular frequency, in a MMSE sense similar to the Wiener filter. In more detail, let $s(\mathbf{x})$ be the ideal 3D ultrasound image at a spatial point $\mathbf{x} = (x, y, z)$. $g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_m(\mathbf{x})$ are m sets of 3D volume data of the same region reconstructed from interpolating 2D slices acquired from the different angles. The image acquisition and sampling process for the ith volume is modeled as

$$g_i(\mathbf{x}) = h_i(\mathbf{x}) * s(\mathbf{x}) + n_i(\mathbf{x}), \quad i = 1, 2, \ldots, m \tag{1}$$

where $h_i(\mathbf{x})$ represents the i’th strip filter with low bandwidth in the i’th elevation direction. For example, $h_1(\mathbf{x})$ may be a moving average filter in the x-direction, while $h_2(\mathbf{x})$ may be a moving average filter in the y-direction, etc. $n_i(\mathbf{x})$ is white additive noise generated in the sampling process and has variance σ^2. In the frequency domain, Eq. (1) can be written as:

$$G_i(\mathbf{k}) = H_i(\mathbf{k}) S(\mathbf{k}) + N_i(\mathbf{k}), \quad i = 1, 2, \ldots, m \tag{2}$$

According to standard statistical signal processing theory [10], the MMSE estimate of $S(\mathbf{k})$ given $G_i(\mathbf{k})$ is

$$\hat{S}(\mathbf{k}) = \frac{H_1^*(\mathbf{k})G_1(\mathbf{k}) + H_2^*(\mathbf{k})G_2(\mathbf{k}) + \ldots + H_m^*(\mathbf{k})G_m(\mathbf{k})}{|H_1(\mathbf{k})|^2 + |H_2(\mathbf{k})|^2 + \ldots + |H_m(\mathbf{k})|^2 + \sigma^2} \tag{3}$$

Note that if there is only one filter, Eq. (3) reduces to to well known Wiener filter. If there are multiple filters, Eq. (3) naturally weights them according to the SNR at the particular frequency. Therefore in any direction, high resolution data sets will be weighted much more than low resolution data sets. If the data sets are acquired with reasonable well distributed angles, we could expect a 3D reconstruction with uniformly high resolution in all directions. We also observe that this reconstruction algorithm is very computationally affordable, since each frequency component of the reconstruction is estimated separately, and the transformation between spatial and frequency domains can be done via FFT. In the next section, we shall demonstrate our method’s superior performance using synthetic ultrasound data sets.

3. SIMULATION EXAMPLE

In a preliminary validation of the proposed new reconstruction technique, we consider date sets that are synthesized but yet with realistic speckle patterns and noise statistics. The benefits of using synthetic data are that they are easier to obtain and there is no data registration error and no truncation of the field of view. This allows us to focus on evaluating the resolution degradation problem due to compounding disparate resolution data.

The 3D ultrasound signal $s(\mathbf{x})$ can be simply modeled as [11]:

$$s(\mathbf{x}) = [t(\mathbf{x}) \cdot n(\mathbf{x})] * h(\mathbf{x}) \qquad (4)$$

where $t(\mathbf{x})$ is the echogenicity model of the object being imaged, $n(\mathbf{x})$ is a multiplicative zero mean Gaussian white noise and $h(\mathbf{x})$ is the impulse response of a hypothetical ultrasound imaging system. In this paper, $h(\mathbf{x})$ is modeled as

$$h(x,y,z) = \exp(-\frac{x^2+y^2+z^2}{2\sigma^2}) \cdot \sin(2\pi f_0 / cy) \qquad (5)$$

where x,y,z denote axial, lateral and elevational coordinates respectively, σ represents the beam-width of transmitting ultrasonic wave and c is the speed of ultrasound in tissue, f_0 is the center frequency.

The simulation process is as follows: First we synthesize two ideal 3D ultrasound images $\mathbf{I}_1$ and $\mathbf{I}_2$ which are imaged in the same region but have independent speckle pattern. The phantom consists of a set of spheres with different radii. Figure 3. (a) – (d) display $\mathbf{I}_1$ and $\mathbf{I}_2$'s cross-sectional and sagittal image respectively. Both $\mathbf{I}_1$ and $\mathbf{I}_2$ have the uniform spatial resolution in each direction.

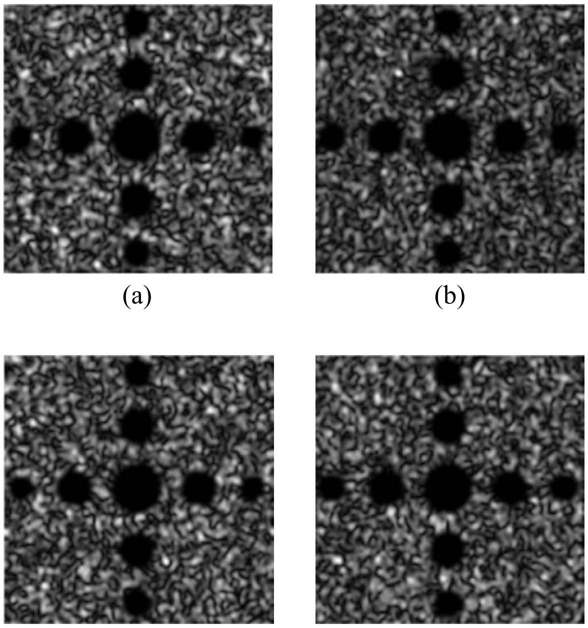
(a) (b)
(c) (d)

Figure 3. Two synthetic 3D ultrasound images,
(a) $\mathbf{I}_1$'s cross-sectional view; (b) $\mathbf{I}_1$'s sagittal view;
(c) $\mathbf{I}_2$'s cross-sectional view; (b) $\mathbf{I}_2$'s sagittal view.

The acquired image is the average of several adjacent slices due to transducer thickness. So we convolve $\mathbf{I}_1$ with a directional moving-average filter and sample the filtered image in this direction to get a series of 2D slices. Suppose the transducer's thickness is N slices, we sample every $N/3$ slice to get acceptable aliasing error. This corresponds to an elevation sampling interval of 1-2mm, which is entirely practical. We process $\mathbf{I}_2$ in the same way but filter it in the orthogonal direction to get another set of 2D slices. These two sets of 2D slices are reconstructed to 3D images $\mathbf{J}_1$ and $\mathbf{J}_2$ using the ideal Shannon interpolator. Figure 4 (a)-(d) shows $\mathbf{J}_1$ and $\mathbf{J}_2$'s cross-sectional and sagittal image respectively (N=15 resolution cell). Note the different in-plane and elevation resolutions.

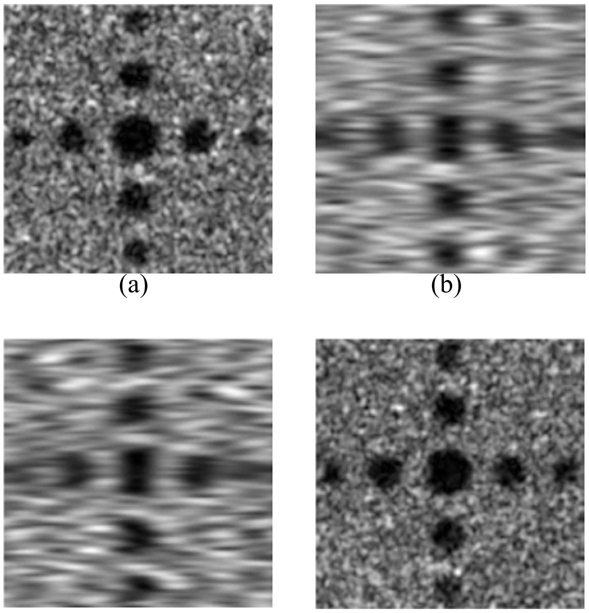
(a) (b)
(c) (d)

Figure 4. Two reconstructed 3D ultrasound images,
(a) $\mathbf{J}_1$'s cross-sectional view; (b) $\mathbf{J}_1$'s sagittal view;
(c) $\mathbf{J}_2$'s cross-sectional view; (b) $\mathbf{J}_2$'s sagittal view.

We then generated 3D compounded ultrasound images $\mathbf{R}_1$ and $\mathbf{R}_2$ using conventional method and our method respectively. Figure 5 (a)-(d) displays the results. Judging from the appearance of two compounded images, one may argue that speckle is reduced but the lesions are blurred using the conventional method, while the reconstruction using our method preserves high resolution in every direction.

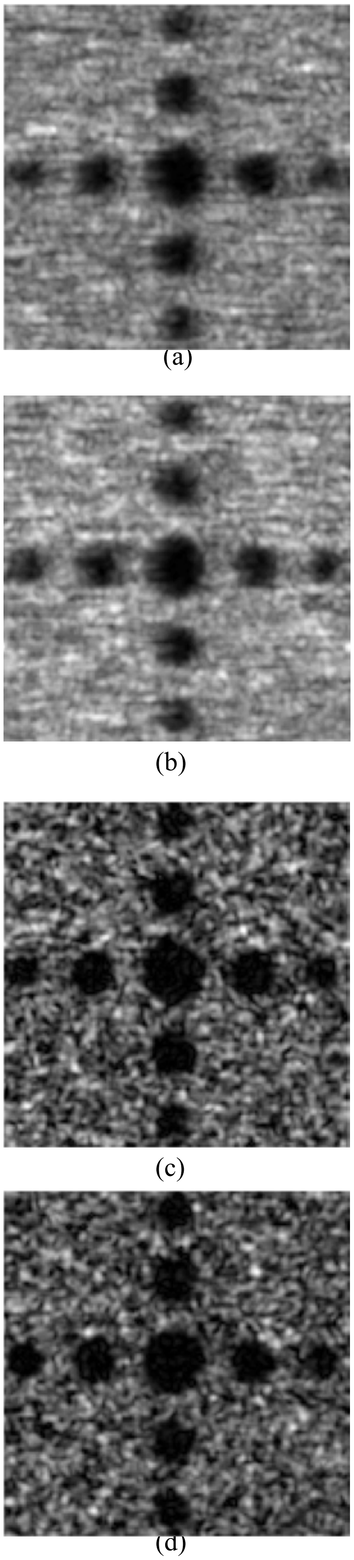

Figure 4. Two compounded 3D ultrasound images, (a) $\mathbf{R}_1$'s cross-sectional view; (b) $\mathbf{R}_1$'s sagittal view; (c) $\mathbf{R}_2$'s cross-sectional view; (b) $\mathbf{R}_2$'s sagittal view.

4. CONCLUSIONS

Conventional ultrasound compounding only considers the data spatial redundancy and simply averages all data sets. Our method takes into account the different degrees of redundancy for different frequency components. The frequency components are weighted not equally but according to the Wiener filter/MMSE principle. The result is that high frequency components are better preserved. We demonstrated the algorithm with the compounding of 2 data sets, and the advantages are clear. It is expected that the performance difference to be even bigger if more data sets are compounded. This technique could increase small lesion detectability and give more accurate measurement of organ volume, which will benefit radiation therapy.

5. REFERENCES

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