A Symmetry Similarity Measure via the Log-Gabor Transform for B-Mode Ultrasound Images and Magnetic Resonance Volumes

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Abstract— **This paper presents a similarity measure that enables the comparison between B-mode ultrasound images and magnetic resonance volumes. Based on the different MR slices a 3D volume was reconstructed, aiming to obtain virtual 2D slices and to improve the comparison with B-mode images. Symmetry Similarity Measure (SSM) values range from** -1 **to** 1**, where** 1 **is the maximum similarity measure, which is based on frequency approach to symmetry with Log-Gabor filters. SSM was tested in anatomic ex-vivo organ pieces of** $20-30$ **cm**^{3} **of volume. Virtual MR slices, corresponding to different degrees of inclination were computed, aiming to find the most similar MR slices with the fixed B-mode image. This will serve for the evaluation of ultrasound image quality. For the analyzed images, a maximum SSM of** 0.94 **was found for virtual slices coincident with the B-mode images acquisition, as expected.**

I. INTRODUCTION

The study of intra-modality registration of medical images has been the focus of scientific attention in the last years [1]. We are studying 2D/3D medical image registration methods to improve comparison between ultrasound images and MR slices co-registered from the same sample. This will serve for ultrasound image quality. Similarity measures were successfully employed into intra-modality registration [2, 3, 4, 5]. In this paper we extend a local phase based processing to 3D MR and also with US image using Log-Gabor filters [6], which allows arbitrarily large bandwidth. Our measure of similarity uses a frequency based on consecutive circles representing different scales. The scales of the filters vary geometrically, giving rise to a logarithmic frequency scale. We construct a local phase symmetry which produces a similarity value between MR slices and US images.

II. ALGORITHM SIMILARITY MEASURE

Our method is divided into three stages: (A) MR volume reconstruction, (B) B-Mode Ultrasound and (C) Computation of SSM. Figure 1 shows a schematic representation. Firstly, the MR volume reconstruction problem consists in taking 2D MR slices of the tissue and using these slices to determine the translation transformation that aligns the coordinate system of the 3D MR. Among rigid registration algorithms, B-spline registration are computationally very attractive due to its flexibility and robustness [4]. At the end of this stage the marching cubes algorithm generates a polygonal mesh of a 3D MR isosurface [7]. Secondly, B-mode ultrasound processing implies image segmentation. We employed a particular implementation of a quasi-blur filter as described in [5] to obtain US edge segmentation. This quasi-blur filtered image is employed jointly with an average filtered image. Finally, a frequency analysis is employed to design a similarity measure.

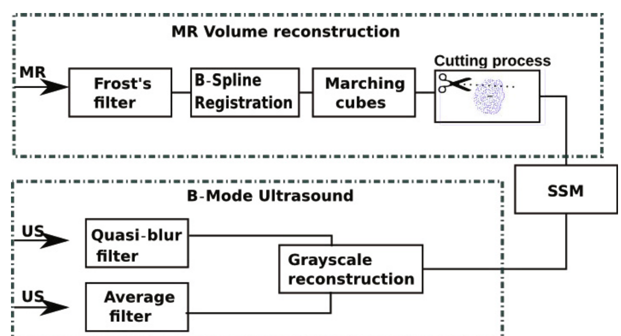

Fig. 1 Schematic overview of 2D/3D measure of similarity. For noise reduction of MR, image Frost's filter was employed. Then, B-spline registration alignment the slices. These ordered slices are used to create an MR isosurface. Likewise, virtual cutting of MR isosurface creates rendered images and virtual MR slices. At the same time, B-mode ultrasound image is processed by grayscale reconstruction. SSM operates together with rendered image of MR isosurface and US reconstructed image.

A. *MR Volume Reconstruction*

The 3D reconstruction encompasses in first place a noise reduction step, and then an alignment step and finally a 3D surface reconstruction phase. We implemented a B-spline registration [8], where our control points are obtained by using the Curvature Scale Space (CSS) [9]. The marching cubes algorithm is used as 3D surface generator [7].

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A1 Noise Reduction

The Frost filter is an adaptive filter that eliminates noise by using a Gaussian kernel. Its impulsional response is presented in Equation (1).

$$\mathcal{N}_s = \delta * k_1 \exp\left(\frac{\sigma^2}{\mu^2}\right), \tag{1}$$

where $*$ represents the convolution operation, δ is Dirac delta function, k_1 is a normalization constant to preserve the mean pixels value, and σ and μ are the standard deviation and mean respectively inside a moving window.

A2 Unimodal B-Spline Registration

For the purpose of MR slice alignment, unimodal B-spline registration was employed. Typically, B-spline registration uses a mesh of control points to parametrize a deformation field. The basic idea is to use a mesh of control points and consider two consecutive slices, named as S_k and S_{k+1}. Thus each slice makes a displacement in connection with the next slice. The displacement $\mathcal{U}$ is defined at each voxel within the fixed image. The field $\mathcal{U}$ is parametrized by a sparse set of control points $\mathbf{x} = (x, y, z) \in \mathbb{Z}^3$ obtained by Curvature Scale Space (CSS) [9]. The displacement $\mathcal{U}$ can be described as:

$$\mathcal{U}(\mathbf{x}) = \sum_{i=0}^{3}\sum_{j=0}^{3}\sum_{k=0}^{3} \beta_i(x)\beta_j(y)\beta_k(z), \tag{2}$$

where $\beta(\cdot)$ are the spline basis functions. As a result a B-spline vector is created. The next step consists in the optimization of the coefficient. Mutually, the B-spline vector and the unimodal registration define an optimization as follows:

$$\mathcal{B}_c = \frac{1}{k-1}\sum_{i=2}^{k-1}\left(S_{i-1}(x,y,z) - \mathcal{U}(S_i)\right)^2, \tag{3}$$

where $k-1$ denotes the number of voxels displaced in the image S_{k+1}. The cost function is defined by:

$$\mathbb{J} = min\left\{\mathcal{U}_i(\mathbf{x}) - a_i\left[\frac{\partial \mathcal{B}_c}{\partial \mathcal{U}_i(x)} + \frac{\partial \mathcal{B}_c}{\partial \mathcal{U}_i(y)} + \frac{\partial \mathcal{B}_c}{\partial \mathcal{U}_i(z)}\right]\right\}, i \in \mathbb{Z} \tag{4}$$

Here, i denotes the iteration number and a_i is a scalar gain factor. To solve this optimization problem, a gradient descent method [10] was employed. Then, the unimodal B-spline registration the MR slices are aligned.

A3 Marching Cubes

The marching cubes algorithm creates a cube from two adjacent slices.The algorithm determines how the surface intersects this cube, then marches to the next cube [7]. A cube $\mathcal{C}_i$ is formed by 4 edge pixels of S_k and 4 edge pixels of S_{k+1}. The $\mathcal{C}_i$ cubes cover all pixels belonging to the edges, generating a reconstructed volume. This volume is cut into the MR slices (Fig. 2).

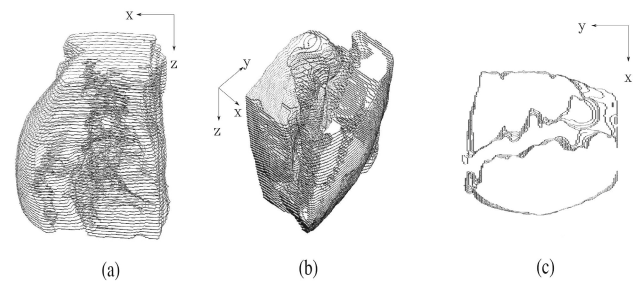


Fig. 2 3D heart reconstruction in different views. (a) acquisition position, which is the reference view to experimental process; (b) lateral position inclines 10° at z axis; (c) Virtual MR slice.

B. Ultrasound B-Mode Images Processing

Concerning B-mode images, our aim is not to produce a perfect edge segmentation, but to produce US images with sufficient edge quality to enable an effective SSM computation (Fig. 3). Consider a US image υ_s, a quasi-blur filtered image $\mathcal{M}_i(\upsilon_s)$ [5] and an average filtered image $\mathcal{P}(\upsilon_s)$. The grayscale reconstruction of the image $\mathcal{P}(\upsilon_s)$ from $\mathcal{M}_i$ is denoted $\mathcal{R}ec$ and defined as the maximal of all components of image $\mathcal{P}$ that intersect marker $\mathcal{M}_i$.

$$\mathcal{R}ec = max\{C_k : C_k \cap \mathcal{M}_i \neq 0\}, \tag{5}$$

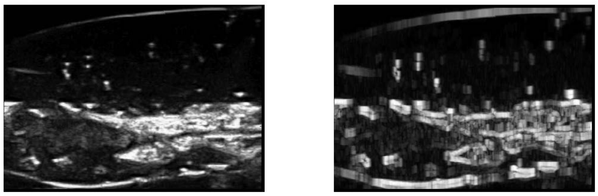
where C_k is the minimum value into a moving window of $[3\times 3]$ on an $\mathcal{P}(\upsilon_s)$ image [11].

B1 Quasi-Blur Filter

A quasi-blur filter $\mathcal{M}$ is generated from the US image (υ_s) using the following method. We implemented a window h of $[15\times 1]$ pixels. If we use a $\mathcal{M}_i$ to represent a set of the pixels within the windows h center about i then $\mathcal{M}_i$ is as follows:

$$\mathcal{M}_i = b - c, \tag{6}$$

where c is the minimum value of the window h, and b is an intermediate value between the maximum value within the window and c.



(a) Original B-mode image kidney (b) Reconstructed image

Fig. 3 Ultrasound B-Mode images processing. (a) the US B-mode was obtained by Ultrasonix MDP, (b) Grayscale reconstruction together with Quasi-blur filter generate an edge segmentation.

C. SSM Computation

We employ Log-Gabor filters G, which can be used to capture local image properties jointly with phase and amplitude at a particular frequency scale n. Log-Gabor filters can be constructed with arbitrary bandwidth [2]. These filters are developed by dividing the frequency domain into concentric circles, with each band between two consecutive circles representing different scales. Log-Gabor function into two dimensions turned to a particular orientation ϕ_o, which is constructed by masking a radian Log-Gabor function. A $2D$ Gabor function is given by:

$$G(\omega,\phi) = exp\left[-\frac{log(\omega)/\omega_o))^2}{2(log(k\omega_o))^2} - \frac{(\phi-\phi_o)^2}{\tau\sqrt{2log2}}\right], \quad (7)$$

ω_o is the frequency center of the filter, k is a scaling factor, is $\tau = 180/N$ where N determines the number of orientations employed. Let $I(x)$ be the image to analyze, and let $\mathcal{R}(x) = Re\{\mathcal{F}(G(w))\}$ and $\mathcal{I}(\mathbf{x}) = Im\{\mathcal{F}(G(w))\}$ be the real and the imaginary parts of the filter response respectively and $\mathcal{F}$ denotes a Fourier transform operation. The amplitude $\mathcal{A}(\mathbf{x})$ of the transform is given by:

$$\mathcal{A}(\mathbf{x}) = \| \mathcal{F}(G(w)) \|_2, \quad (8)$$

and the energy $\mathcal{E}(\mathbf{x})$ as defined below:

$$\mathcal{E}(\mathbf{x}) = |\mathcal{R}(\mathbf{x})| - |\mathcal{I}(\mathbf{x})|, \quad (9)$$

Next, we define a mean over all orientations for a fixed scale n for $\mathcal{E}(\mathbf{x})$ as:

$$\mathcal{E}_\phi(\mathbf{x}) = \frac{1}{N}\sum_N \mathcal{E}(\mathbf{x})_N. \quad (10)$$

The use of N orientations average in the above equation plays a critical role for the unique characterization of n scales [6]. According to its value at each point $\mathbf{x}$ in the image $I(\mathbf{x})$, different responses can be obtained for each scale of Log- Gabor filter. Finally, the SSM is defined as follows. Let $\mathcal{X}_i$ be the mean over all orientations of one scale into the $\mathcal{R}ec$ image, $\overline{\mathcal{X}}$ be a mean energy over all scales of $\mathcal{R}ec$, $\mathcal{Y}_i$ be the mean energy response of one scale into the virtual MR slice, $\overline{\mathcal{Y}}$ be a mean energy over all scales of virtual MR slice. Thus SSM is given by:

$$SSM = \frac{\sum_{i=1}^{n}(\mathcal{X}_i - \overline{\mathcal{X}})(\overline{\mathcal{X}} - \overline{\mathcal{Y}})}{\sqrt{\sum_{i=1}^{n}(\mathcal{X}_i - \overline{\mathcal{X}})^2}\sqrt{\sum_{i=1}^{n}(\mathcal{Y}_i - \overline{\mathcal{Y}})^2}}, \quad (11)$$

III. Results and Discussion

For the experimental part, ultrasound and MR images $[252 \times 500]$ pixels from cylindrical-shaped porcine tissues samples, fixed in formaldehyde solution, were acquired. These samples were placed into a PVC cylindrical container in order to perform the magnetic resonance and the ultrasound image approximately in the same radial position. The B-mode images $[307 \times 459]$ pixels were acquired using a commercial ultrasound scanner (Sonix-MDP) driving a linear array transducer with a central frequency of 10 MHz. The original MR slices were acquired using a small animal 7-Tesla MR scanner (Variant Agilent, Santa Clara, CA, USA). The acquired volume of the samples is within the range $20-30$ cm^3. The described SSM was implemented and tested on MATLAB and Meshlab software with 1.2s of CPU time process. Figure 2 shows a 3D MR of a heart sample. We considered the three-dimensional structure within a volume xyz, where xy is the frontal face of acquisition direction. In order to evaluate SSM, we conducted 3 analysis as follows:

Analysis (1)**:** We sliced up a volumetric image in 10 slices in horizontal plane, thereafter the slices were rotated $-10°$ to $10°$ in the y−plane. As expected, SSM had a variation depending on the degree of inclination. The result is shown in Fig. 4.

Analysis (2)**:**We sliced up volumetric image in 10 slices in a transverse plane zy. The results are shown in Fig. 5.

Analysis (3)**:**We sliced up a volumetric image 5 slices in horizontal plane. The result of SSM in plane zy are as follows: the maximum SSM is -0.25 and the minimum is -0.11.

Our analysis of SSM conclusively showed its suitable to deal with the problem 2D/3D registration between ultrasound images and MR. The results contained in Figs. 4 and 5, substantially bear out our initial hypothesis. The results in Fig. 4 referred to a scenario where SSM is computed for images in the same acquisition plane, and so, high similarity values

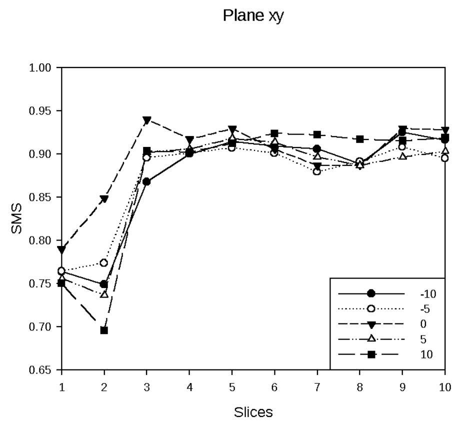


Fig. 4 Maximum similarity measure was 0.94 with 0° of inclination and the lowest SSM was 0.70 with −5° of inclination.

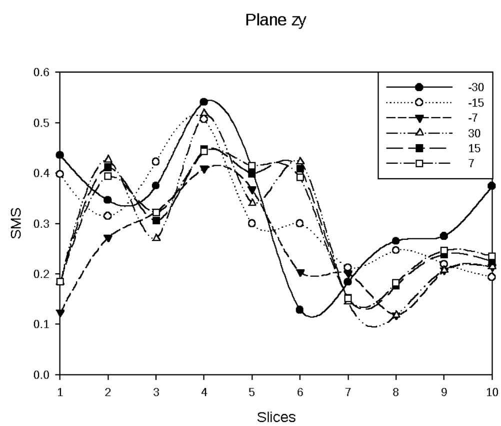


Fig. 5 Maximum similarity measure was 0.54 with −30° of inclination and the lowest SSM was 0.14 with −7° of inclination.

were obtained. Fig. 5 referred to similarity measures where the image were in perpendicular acquisition planes, and much lower SSM values were observed. Also, we presented simulation results that will provide a twofold contribution: (1) obtained a correspondence between ultrasound image and MR virtual slice, and (2) confirmed the effectiveness of the SSM algorithm. Hereafter, this similarity measure will be extended to other imaging modalities.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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