Nonrigid Multimodal Medical Image Registration Using Features Extracted from the Monogenic Signal

Marius-Cristian Ureche, Mircea-F. Vaida, Ligia-D. Chiorean
Technical University of Cluj-Napoca, Romania
{cristian.ureche, mircea.vaida, chiorean.ligia}@com.utcluj.ro

Abstract - **Multimodal medical image registration is a challenging task as anatomical structures might have different appearances depending on the physical principles that are the foundation of the imaging modality. The task is even more difficult to perform when ultrasound (US) images are used in the registration process because of their low resolution and low signal to noise ratio (SNR). We present a multi-scale method whose aim is to automatically register ultrasound and magnetic resonance (MR) images using features extracted from the monogenic signal and local phase-based images. We use an elastic approach based on free-form deformation (FFD) and mutual information (MI) as similarity measure. Finally we compare our results with pure local phase-based image registration techniques.**

Keywords: nonrigid image registration; local phase-based image; free-form deformation; multi-scale feature extraction algorithm; the monogenic signal.

I. INTRODUCTION

Medical imaging techniques evolved in the last 50 years to improve diagnosis, surgery and therapy. At the beginning of the 21st century there is a constant concern about the degree of invasiveness each medical imaging technique might have. It is generally accepted that US and MRI are non invasive techniques that do not use ionizing radiation as opposed to computed tomography (CT), single-photon emission computed tomography (SPECT) or positron emission tomography (PET). However, while MR is the golden technique nowadays with respect to spatial resolution, contrast and very satisfactory SNR, it lacks the temporal resolution (i.e. it's not a real-time technique), it is not suitable for all patients (for instance, patients with pacemaker devices are not allowed to perform MR scans) and moreover MRI devices are not mobile and have very high costs of purchasing, operating and maintaining. On the other hand, US modality has the advantages of being non-invasive, real-time and suitable for all patients. However it has a couple of disadvantages that make US image processing a challenging task: low spatial resolution and low SNR, especially due to speckle noise.

The goal of medical image registration is to establish a spatial relation between regions in one image and the corresponding regions in another image. In the case of multimodal medical image registration, the images that should be put in correspondence are acquired using different imaging techniques and hence, different anatomical characteristics are put into correspondence in order to obtain fused information used for diagnosis, surgery and therapy [1].

Medical image registration became a strategic research axis in the field of medical image processing by the end of the 20th century and it was certainly pushed forward by the enormous advances in the field of computational power.

A. Image registration framework

A very generic registration framework was presented by Klein et al. in [2]. Mathematically, the registration task can be formulated as an optimization problem in which the cost function that acts as a similarity / dissimilarity and regularization agent is minimized with respect to the spatial transformation T of the position of pixels:

$$\hat{T} = \arg\min_T C(T; I_R, I_M)\,, with \tag{1}$$
$$C(T;\ I_R, I_M) = -S(T;\ I_R, I_M) + \gamma R(T). \tag{2}$$

where I_R is the reference (fixed) image, I_M is the moving (floating, test) image, T is the spatial transform of pixel coordinates that is to be applied to the moving image in order to register it with the reference image, C is the cost function, S is the similarity measure, R is the regularization function. As stated earlier, C tries to evaluate two different criteria in medical image registration: the anatomical structures' similarity S between reference and moving image and the realistic degree of transformation performed especially by elastic transforms. It should be a trade-off (adjusted by the coefficient γ) between a very accurate geometric transform and the physical meaning of that transform with respect to the particularities of medical imaging modalities. For instance, image reflections have no meaning for medical images. Moreover, even that tissues' movements during interventions are elastic they still don't have many degrees of freedom. When using elastic registration, one should always use a regularization term in order to avoid unrealistic warping of medical data. Well known examples for R are the curvature term, the elastic energy and the volume preserving penalty term [3].

Basically, there are two different ways to solve the above optimization problem: parametric and nonparametric approaches.

Nonparametric methods try to optimize the cost function by minimizing an energetic functional (e.g Euler-Lagrance equation). This approach is not used in our work, but the reader is referred to Fisher and Modersitzki [4] for an exhaustive overview of the nonparametric optimization methods.

Instead, we use the parametric model of optimization, where the spatial transformation is modeled by a vector μ containing the values of the transformation parameters.

Henceforth, (1) is an optimization problem that depends only on the vector's parameters μ:

$$\widehat{T_\mu} = \arg\min_T C(T; I_R, I_M). \quad (3)$$

The number of parameters in the vector μ depends on the geometrical transformation that is used for registration. For instance, a rigid 2D transformation has three parameters, an affine 2D transformation has six parameters etc.

B. Mutual information as similarity measure

One of the key elements for a successful image registration strategy is the similarity measure used during the optimization algorithm. For intermodal registration, the choice of the objective function is determined by the nature of the images to be registered. When ultrasound images are used, the problem of properly choosing the similarity measure is even more complicated because of the speckle noise that characterizes ultrasound images.

However, it was shown that objective functions based on information theory performed satisfactorily in many cases of multimodal medical image registration. The reason resides in the fact that similar anatomical structures have different pixel intensity values in acquired images because different imaging techniques exploit different properties of biological tissues. For instance, MR imaging exploits essentially the hydrogen protons density in tissues, while US imaging exploits the difference of acoustic impedance between adjacent tissues. That is, there is no evidence that corresponding anatomical structures will have similar intensity levels in the final images acquired with both medical imaging techniques. For this reason a statistical similarity measure has better results than classical objective functions such as the sum of square of differences (SSD) or the correlation coefficient (CC). However the choice of the similarity measure is highly dependent on the application and on the anatomical structures studied.

Mutual information (MI) has proved to be a satisfactory similarity measure for many cases [5], [6], [7]. A good review of registration methods based on MI is presented in [8].

In information theory, the MI of a vector of two variable I_R and I_M gives a measure of the statistical dependence of both variables:

$$MI(I_R, I_M) = H(I_R) + H(I_M) - H(I_R, I_M) \quad (4)$$

It should be noticed that the smaller the joint entropy $H(I_R, I_M)$ (hence the bigger the value of MI), the better the result of the registration.

C. Elastic transformation based on FFD

The aim of the registration algorithm is to find a correspondence function or transformation that properly maps points (pixels in 2D, voxels in 3D) from the test image into the space of the reference image.

FFD was firstly used in computer vision for warping optical images [9] and then introduced by Kybic and Unser in the medical image registration field in [10], [11], [12]. The FFD based on B-splines for the 2D case can be obtained from the 2D tensor of 1D cubic B-splines:

$$T(x,y) = \sum_{l=0}^{3}\sum_{m=0}^{3} B_l(u-[u])B_m(v-[v])\Phi_{i+l,j+m} \quad (5)$$

Where $u = \frac{x}{N_x}$, $v = \frac{y}{N_y}$, i=[u]-1, j=[v]-1, N_x is the control points grid spacing on the x axis, N_y is the control points grid spacing on the y axis and $\Phi_{i+l,j+m}$ are the control points.

The reader is advised to consult the references above for a thorough explanation of the FFD based on B-spline functions as the space in here does not permit an exhaustive explanation.

II. Local Phase-Based Images And Features Extraction From The Monogenic Signal

Mellor and Brady proposed in [12] the first multimodal image registration technique based on phase mutual information. They based their work on the monogenic signal proposed by Felsberg et al. in [13], [14] which is an isotropic n-dimensional extension of the analytical signal defined for 1D functions.

The idea behind the monogenic signal is that it performs a split of identity. The local phase describes the local structure of the image, while the amplitude denotes its local energy. Since we are working with medical images obtained from different imaging modalities (MR and US), we are not particularly interested in the native intensity of pixels, but in the structure of the image (edges, ridges etc). Hence local phase based images extracted from the monogenic signal represent a coherent approach.

The monogenic signal can be thought of as an incomplete quaternion:

$$f_{MS}(x,y) = [f(x,y), f(x,y) * h_1(x,y), f(x,y) * h_2(x,y)] \quad (6)$$

where $h_1(x,y)$ and $h_2(x,y)$are the impulse responses of the quadrature band-pass filters used to obtained the Riesz transform of the signal f(x,y) [13] (see section III for details).

The basic approach is to use phase images of both native MR and US images and then apply a registration algorithm based on mutual information. Good results were obtained by Zhang and Noble in [15], [16] where they registered real-time 3D US to MR cardiovascular images. The drawback of their methods is that they used simplified transformation models (affine, poly-affine) because of their real-time constraint (elastic transformations need much more time to be computed).

Our idea is to use for multimodal US-MR registration the work of Kovesi [17] related to feature extraction from phase congruency and continued by Rajpoot and Noble in [18].

III. Proposed Method

We propose a four-step method for nonrigid medical image registration of US and MR images. Each step can be thought of as a sequence of atomic operations executed in a multiscale manner.

Step 1: Extract the monogenic signal from both US and MR images. The monogenic signal is the n-dimensional generalization of the 1D analytical signal. Since we are working with 2D images, we will make the assumption that we are dealing with two-variable functions.

$$f_{MS}(x,y) = f(x,y) - (i,j) f_R(x,y),\ where \tag{7}$$

$$f_R(\bar{x}) = \frac{\bar{x}}{2\pi|\bar{x}|^3} * f(\bar{x}) \tag{8}$$

is the Riesz transform, (i,j) are the two imaginary axes of the incomplete quaternion and $\bar{x} = [x\ y]^T$.

Operation 1-a: Apply a rotationally symmetric (isotropic), zero-mean filter to obtain a band-pass image I_b in the frequency domain. We have chosen to apply the log-Gabor filter whose transfer function is given in (9) where ω_0 is the central frequency of the filter and k is the scaling factor.

$$H_{LG}(u,v) = exp - \left(\frac{(\log(\sqrt{u^2+v^2}/\omega_0))^2}{2(\log(k/\omega_0))^2}\right) \tag{9}$$

Operation 1-b: Apply the oriented band-pass quadrature filters defined in (10) to obtain the Riesz transform.

$$\left(H_1(u,v), H_2(u,v)\right) = \left(i\frac{u}{\sqrt{u^2+v^2}}, i\frac{v}{\sqrt{u^2+v^2}}\right) \tag{10}$$

Operation 1-c: Obtain the local phase images from the components of the monogenic signal:

$$i_b(x,y) = h_{LG}(x,y) * i(x,y) \tag{11}$$

$$i_{H1}(x,y) = h_1(x,y) * i_b(x,y) \tag{12}$$

$$i_{H2}(x,y) = h_2(x,y) * i_b(x,y) \tag{13}$$

$$\varphi(x,y) = \tan^{-1}\frac{i_b}{\sqrt{{i_{H1}}^2+{i_{H2}}^2}} \tag{14}$$

So far, we have extracted the local phase images that were used for registration using mutual information of the phase in [12], [15] and [16].

Step 2: Use the feature asymmetry (FA) proposed by Kovesi in [17] and extended in a multi-scale manner by Rajpoot and Noble in [18] to extract features:

$$FA_{2D}^{Rajpoot}(x,y) = \sum_{scale}\frac{\left\lfloor |i_b| + \left\lfloor\sqrt{i_{H2}^2+i_{H3}^2}\right\rfloor - T_{scale}\right\rfloor}{\sqrt{i_b^2+i_{H2}^2+i_{H3}^2+\varepsilon}} \tag{15}$$

In (15) T_{scale} is the threshold parameter at each scale and $\lfloor\ \rfloor$ represents the operator that zeros the negative values [17].

Step 3: Combine local phase-based image with FA image to better extract the core of the structures (see fig. 2-(a)):

$$R(x,y) = \alpha\varphi(x,y) + (1-\alpha) FA_{2D}^{Rajpoot}(x,y) \tag{16}$$

Step 4: Perform image registration using a combined transform: a coarse rigid registration followed by a finer elastic transformation based on cubic B-splines.

$$T_{total} = T_{coarse-rigid} + T_{fine-elastic} \tag{17}$$

Operation 4-a: Perform rigid transformation to diminish the effect of operator dependant acquisition of the US image. It should be stated that rigid transformations consists only of planar rotation and translations along the x and y axis (for 2D images). Additionally, one can use scaling and shearing factors to implement a more generic transform – the affine transform.

Operation 4-b: Apply an elastic transform based on FFD that uses 2D cubic B-splines as it was suggested by Lee in [9], Unser in [19] and Kybic in [10] and [11]. We used a multi scale approach: the result from a coarser level was used as initial transformation for the next finer level.

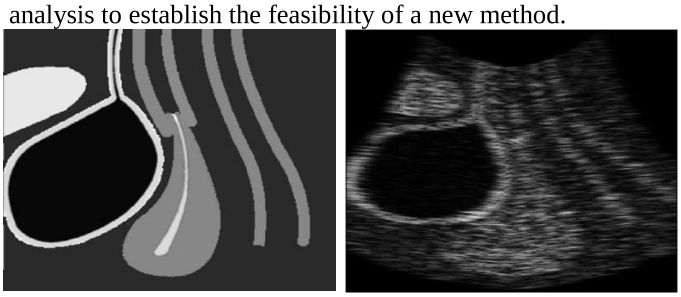
IV. Experiments And Results

We used for our experiments simulated data. As the ground truth of real US to MR registration is hardly to be known, the advantage of simulated images is that we can have a kind of standard transform that is known a-priori and that maps one image into the space of the other image. This way, we could evaluate the performance of the registration algorithm.

For simulating MR images we used SIMRI 2.0 simulator [20] with a gradient echo sequence. We have a-priori configured specific parameters such as relaxation times T_1 and T_2, the density of hydrogen protons, all of which are well known parameters for MRI.

To the best of our knowledge there is no mathematical relation found between the properties that MRI is based on (density of hydrogen, T_1, T_2) and the reflectivity of tissues that is exploited in US. We simulated US images taking the MRI as input, by making the assumption that the amplitude of scatterers' reflectivity is proportional to the intensity of the pixel in the simulated MRI. We simulated our US images using Field II [21] and the model of a sectorial probe.

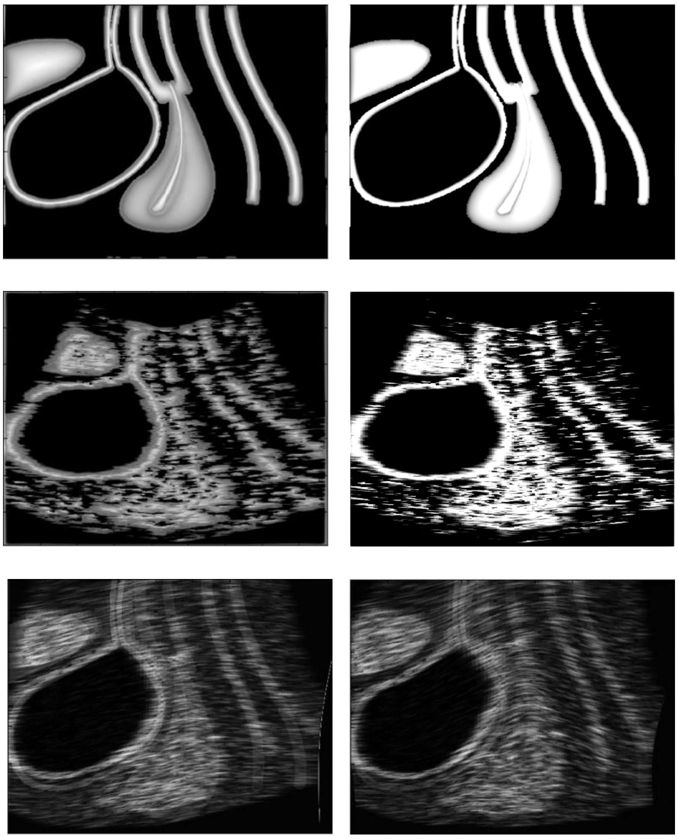
We started our simulations from a very simplified version of the gynecological organs drawn by a specialized doctor. Simplified models are of extreme importance for preliminary analysis to establish the feasibility of a new method.



(a) (b)

Fig. 1. Simulation of medical images using MR (a) and US (b) techniques

The numerical implementation of the algorithms to extract features from the monogenic signal was performed in Matlab R2008a using a Pentium Dual Core, each core clocked at 2.00 GHz, and 2GB of RAM. The registration step was implemented in Matlab using MIRT framework. We have also done the registration using Elastix, a configurable medical image registration application developed over ITK.



(a) (b)

Fig. 2. Multimodal image registration: column (a): our proposed method that combines FA and local phase; column (b): registration based on local phase images

Our preliminary results prove the feasibility of the method.

The basic idea here is that US images have very poor resolution and so they hardly contain ridges (symmetric features). As a consequence, FA can detect the majority of features in US images (edges are also called asymmetric features). Compared to pure local phase-based registration methods, the image obtained as a combination between the local phase and FA measure ensures a better extraction of the core structures, which is particularly useful in US images (see column (a) of fig. 2).

V. Conclusions And Future Work

In this paper we presented a new method for nonrigid multimodal medical image registration targeted to the registration of US and MR images. Our preliminary results show that a combination of local phase (which characterizes the structure of the image) and FA measure (which extracts edges) contribute to a satisfactory registration result. We will move on to validate our method using real clinical images as well as US and MR images from open source databases. Future developments of our registration framework will try to conceive a new similarity metric for US images, invariable to intensity variations caused by speckle and shadows.

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