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AN APPROACH TO NONRIGID US-MRI REGISTRATION OF PELVIC ORGANS FOR ENDOMETRIOSIS DIAGNOSIS

Marius-Cristian URECHE Mircea-Florin VAIDA Stefan DRAGOS Loreta SUTA Alin VOINA
Faculty of Electronics, Telecommunications and IT, Technical University of Cluj-Napoca, Romania
28 Memorandumului Street, 400114, Cluj-Napoca, Romania, Email: Cristian.Ureche@com.utcluj.ro

Abstract:In the field of multimodal medical image registration, the main elements that researchers focus on are the transformation, the similarity metric and the optimization algorithm. There is no state-of-art registration method for pelvic organs when endometriosis is taken into consideration. This paper proposes a chain of practical implementations for the aforementioned key elements of the image registration framework so that pelvic organs and endometrial cysts are registered between ultrasound (US) and magnetic resonance imaging (MRI). For this purpose, the Free-Form Deformation (FFD) was taken into consideration as spatial transformation, in conjunction with mutual information as similarity measure and gradient descent as optimization strategy. A multi-scale image registration algorithm is implemented to increase the speed of convergence. Registration results show that our approach is feasible for multimodal medical image registration of pelvic organs.

Keywords:*medical image registration, free-form deformation, ultrasound, magnetic resonance imaging, B-spline functions.*

I. INTRODUCTION

Multimodal medical image registration became an important field in bioengineering after the impressive development of medical imaging in the past 20 years.When registering medical images of different modalities, one tries to take advantage of the particularities that characterize each imaging technique. The physical principles that are the foundation of each medical imaging technique differs fundamentally when US and MRI are taken into consideration. US exploit the echogenicity of biological tissues, while MRI employs hydrogen protons' magnetic properties to create state-of-art medical images.

However, each of the aforementioned techniques has particular advantages and drawbacks. US has the advantage of being non-invasive, real-time and suitable for all patients. But it has a couple of disadvantages that make US image processing a challenging task: low spatial resolution and low signal to noise ratio (SNR), especially due to speckle noise. On the other hand, while being the golden standard with respect to spatial resolution, contrast and very satisfactory SNR, MRI lacks the temporal resolution (i.e. it is not a real-time technique for the moment), 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 maintenance.

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].

II. DESCRIPTION OF PURPOSE

Multimodal medical image registration is of great interest as combining several imaging techniques could provide better and more accurate information. When registering MRI and US, one has to find a proper cost function as well as a good enough spatial transformation to cope with the complex deformations that are supposed to appear when performing ultrasound examinations with trans-vaginal or trans-abdominal probes.

Several approaches exist for US-MRI or US-CT image registration of the brain[2],[3], the heart[4],[5], the liver[6],[7] or the prostate[8],[9]. All the existent methods are specifically targeted for the anatomical organs in discussion and we are far from having a generic US-MRI image registration technique that works independently of the anatomical organs involved.

In our preliminary work presented in[10] we have proposed a new registration method based on features extracted from the monogenic signal. The images used in those experiments were MRI and US simulated images.

The purpose of this paper is to move forward and present how we used clinical MRI slices to simulate US images of pelvic organs with endometrial cysts and how we applied the registration framework to successfully register highly deformed US and MRI of pelvic organs.

However, due to the fact that we cannot have a real ground truth between the reference and the floating image, numerical results are hardly available when registering multimodal medical images, especially when US images are concerned. Moreover, the fact that we used

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sectorial US simulation (for a more appropriate perspective regarding real trans-vaginal echography) induced one more time difficulties for having a ground truth. These are the reasons for which we will prefer to use the term pseudo-ground-truth.

III. METHOD

As stated before, the working methodology involves two stages: the simulation of US images with Field II starting from MRI slices of pelvic organsand the registration algorithm itself.

III.iUltrasoud Image Simulation

We simulate US images starting from MRI slices to control the degree of deformation in order that we are able to create a pseudo-ground-truth. Figure 1 presents the working scenario for simulating US images. We startfrom asagittal MRI slice where the endometrial cyst is easily identifiable, and then we focused on the region of interest (ROI). Finally, we simulate US images using Field II[11], a specialized simulation program for US images. We applied the a-priori known deformation field to obtain the floating US image.

We started by selecting T2-weighted MRIs from patients affected by endometrial cysts. As we are trying to simulate trans-vaginal US images, the most suitable plan for slicing the MRI volume is the sagittal one.

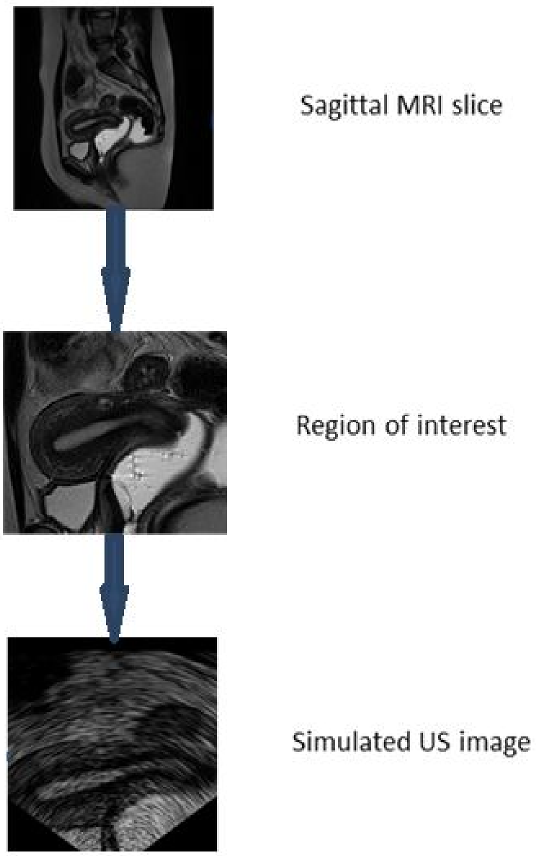


Figure 1.Simulating US images using an MRI phantom model.

Once selected the most appropriate MRI slice, we cropped the region of interest, namely the uterus, the endometrial cyst and the vagina. This selection was used as input model for Field II in order to create the scatterers map. The user is referred to [12]for a thorough explanation of our US simulation method.

The scatterers maps is given as "input phantom" for the Matlab script that uses predefined Field II functions.

We considered the model of an ultrasound probe with 32 active elements (transceivers), element height 5 mm, kerf 0.5 mm, central frequency f0=5 MHz and element width equal to the ratio between the central frequency and the speed of sound in biological tissues, which is approximately 1540 m/s.

As a result, we obtained a sectorial US simulated image like the one presented in figure 1.

III.ii Image registration using FFD with B-spline functions

Currently, Free Form Deformation (FFD) with B-Spline functions is one of the reference methods for implementing elastic deformations in the field of image registration. The advantages of this approach are:

- generality of the deformations that can be obtained;
- hierarchical processing (multi-resolution);
- compact support of B-Spline functions;
- smooth and differentiable functions.

$$\boldsymbol{\beta_0}(\boldsymbol{x}) = \mathbf{1}, \boldsymbol{x} \in \left(-\frac{\mathbf{1}}{\mathbf{2}},\frac{\mathbf{1}}{\mathbf{2}}\right), \tag{1}$$
$$\boldsymbol{\beta}_{n+1}(\boldsymbol{x}) = \boldsymbol{\beta}_n(\boldsymbol{x}) * \boldsymbol{\beta}_0(\boldsymbol{x}), \boldsymbol{x} \in \left(-\frac{\boldsymbol{n}+\mathbf{1}}{\mathbf{2}},\frac{\boldsymbol{n}+\mathbf{1}}{\mathbf{2}}\right).$$

FFD is a deformation technique used in image processing that was initially proposed by Sederberg and Parry in [13]. The method was firstly used in medical imaging domain by Rueckert et al. in [14] for the non-rigid registration of MR images and then intensively applied by Kybic and Unser in [15],[16].

Let I_M of dimensions (d_x; d_y) be the moving image. In order to introduce the FFD, we want to find an elastic transform T so that $q(x_1,y_1) = T(p(x_0,y_0))$. Let Φ be the grid of control points $\Phi_{i,j}$ and δ_x, δ_y the spacing between control points in each direction. The number of control points inside I_M is:

$$\boldsymbol{N_x} = \left\lfloor\frac{\boldsymbol{d_x}}{\boldsymbol{\delta_x}}\right\rfloor + \mathbf{1}, \boldsymbol{N_y} = \left\lfloor\frac{\boldsymbol{d_y}}{\boldsymbol{\delta_y}}\right\rfloor + \mathbf{1} \tag{2}$$

In order to mitigate the border effect, additional control points are placed outside I_M in each direction so that the total number of control points is $N_{totx} = N_x + 2$and $N_{toty} = N_y + 2$. It is worth mentioning that the larger the number of control points, the more complex the obtained deformation can be.

We make a change of coordinates:

$$\boldsymbol{u} = \frac{\boldsymbol{x}}{\boldsymbol{\delta_x}}, \boldsymbol{v} = \frac{\boldsymbol{y}}{\boldsymbol{\delta_y}} \tag{3}$$

so that pixel coordinates are expressed in terms of control points positions. It follows that:

$$\boldsymbol{T}(\boldsymbol{x},\boldsymbol{y}) = \sum_{\boldsymbol{l}=\mathbf{0}}^{\mathbf{3}}\sum_{\boldsymbol{m}=\mathbf{0}}^{\mathbf{3}} \boldsymbol{B_l}(\boldsymbol{u}-[\boldsymbol{u}])\boldsymbol{B_m}(\boldsymbol{v}-[\boldsymbol{v}])\boldsymbol{\Phi}_{\boldsymbol{i+l},\boldsymbol{j+m}}\ , \tag{4}$$

wherei=[u]-1 ;i j=[v]-1.

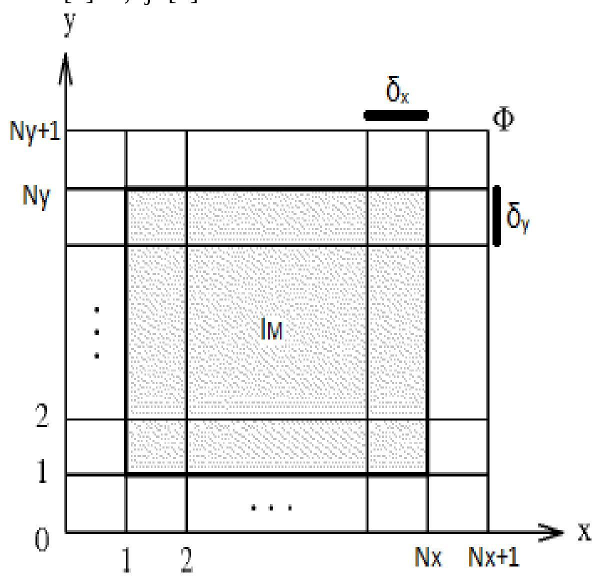


Figure 2.The moving image I_M and the grid of control points used in FFD

Figure 3presents graphically the aforementioned statements.

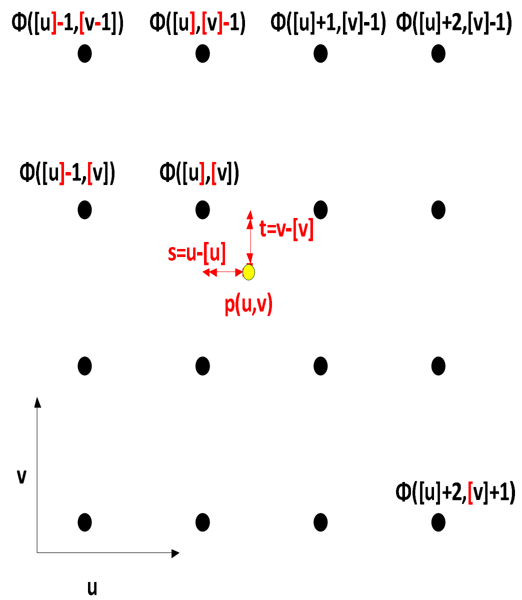


Figure 3. FFD with B-spline functions: the position of one point depends on the 16 nearest control points.

Notice from figure 3 that the displacement of any of the 16 control points will induce a displacement of the considered pixel p(u,v). Moreover, considering Δp the displacement of the pixel, there is an infinite number of control points displacements combinations for obtaining the Δp displacement of pixel p(u,v). Generally, the chosen solution is the one that minimizes the sum of squared displacements of control points [17].

The remaining of this section is devoted to present the FFD registration framework that we implemented for our experiments.

The first step involves resizing the reference and the moving image. The resizing process involves interpolation. We used bicubic B-spline functions for better accuracy.

Thereafter, the multi-scale algorithm is applied. The coarsest resolution is considered to be the first level of registration.

At each hierarchical level, the parameters that define the transformation are updated. For FFD, it's about updating the control points' positions. Initially, the control points are placed on a regular grid (equally spaced on both axes of the coordinate system). The application of FFD using a regular grid of points gives the identity transform: FFD(p)=p.

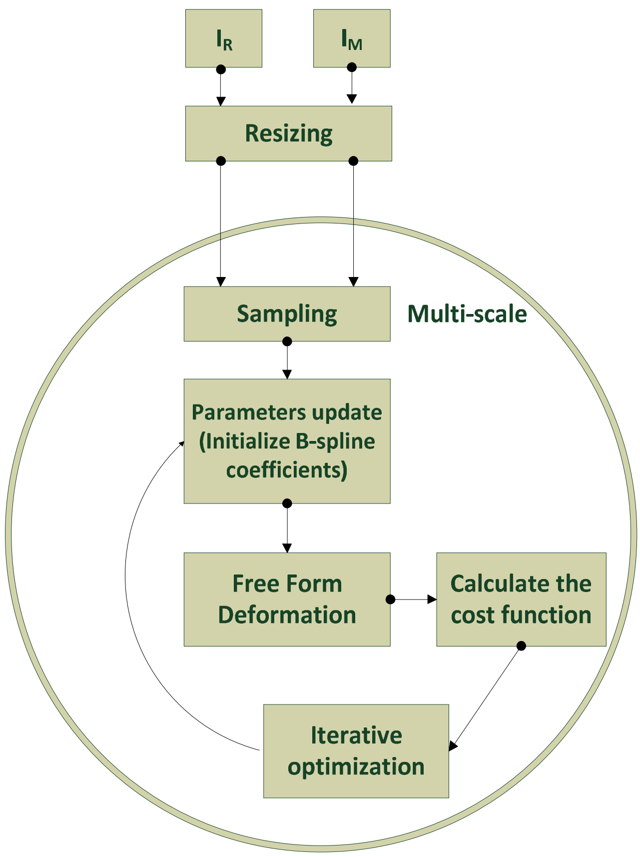


Figure 4. Block diagram of multi-scale image registration algorithm using FFD with B-Spline.

At each hierarchical level (at each image resolution used in the registration), the grid of control points is updated taking into account the result obtained in the lower hierarchy. When passing to a higher hierarchical level, the number of control points is increased.

The cost function is composed of the similarity metric (we used mutual information[18], [19] for the results shown in figure 5) and the regularization term. Given the generality of deformations that can be obtained with FFD, it is a good practice to penalize de second derivative of the deformation field.

At each iteration, the positions of control points are updated in relation with the gradient of the cost function:

$$\nabla C_{\Phi_{i,j}} = \frac{\partial C}{\partial I_M} * \frac{\partial I_M}{\partial T_{\Phi_{i,j}}} * \frac{\partial T_{\Phi_{i,j}}}{\partial \Phi_{i,j}} = \frac{\partial C}{\partial I_M} * \frac{\partial I_M}{\partial T_{\Phi_{i,j}}} \sum_{x\in\Omega_x} \sum_{y\in\Omega_y} B_{xy}, \quad (5)$$

$$(\Phi_{i,j})_{n+1} = (\Phi_{i,j})_n - \gamma_n \nabla C_{\Phi_{i,j}}$$

The aforementioned equations represent the particular case of the gradient descent technique applied when the vector of parameters $\mu$is represented by the control points' positions and the cost function is the mutual information. Generally, the iterative gradient descent technique states that:

$$\mu_{k+1} = \mu_k - \gamma_k \nabla C_{\mu_k}, \quad (6)$$

$$\nabla C_{\mu_k} = [\frac{\partial C}{\partial \mu_{\tilde{1}}}, \frac{\partial C}{\partial \mu_{\tilde{2}}}, \dots, \frac{\partial C}{\partial \mu_{\tilde{n}}}]^T.$$

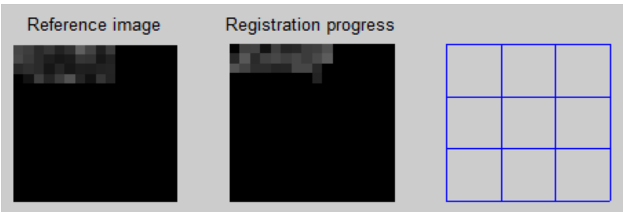
As mutual information is a similarity measure (and not a dissimilarity one), the iterative optimization algorithm stops when the value of MI surpasses an a-priori fixed threshold or when the maximum number of iterations is reached.

IV. RESULTS

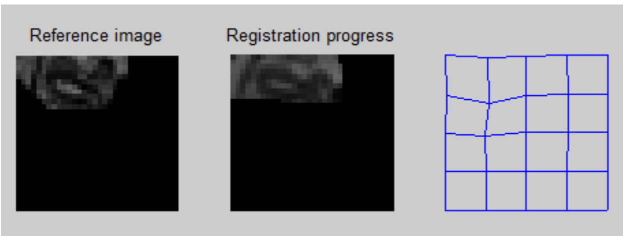
We present below intermediate result at each hierarchical level and the corresponding grid of control points. Please notice that the higher the hierarchical level, the higher the resolution. The number of control points is also increased with each hierarchical level.

For implementation, we used MIRT, the registration framework developed by Myronenko during his PhD research[20]. MIRT is in fact a collection of Matlab functions that can be used for non-rigid medical image registration.

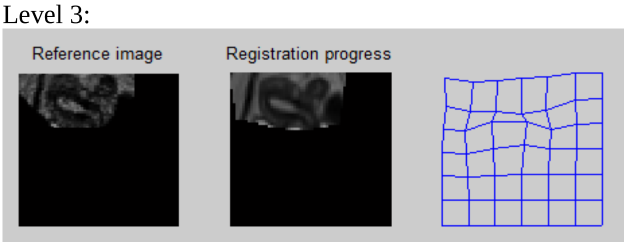
Level 1:



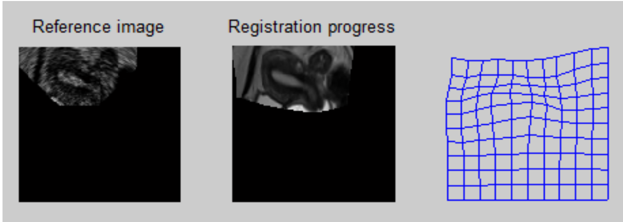
Level 2:



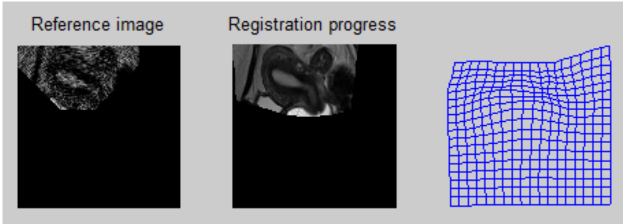
Level 3:



Level 4:



Level 5:



The results presented in figure 5correspond to the following list of configured parameters:

- similarity function: mutual information;
- regularization term: penalty of second derivative;
- number of bins used to calculate the probability density functions:32;
- number of hierarchical levels: 5;
- distance between control points at level 1: 16 pixels;
- regularization factor: 0.01;
- maximum number of iterations at each hierarchical level: 1000;
- weighting factor for gradient descent optimization method: initially 1, then adjustable in relation with the variance of the gradient of the cost function.

As shown in figure 5, the algorithm converges irrespectfully of the chosen reference and moving image. The middle column presents the registration result with US as reference image and MRI as moving image. In the right column the roles are inversed. However, the implemented registration framework is still able to cope with the situation and the optimization algorithm converges.

V. CONCLUSION AND FUTURE WORK

In this paper we presented a medical image registration framework to be used in multimodal medical imaging.

Even though the deformation between the two scans (US and MRI) is important, the implemented registration framework is able to catch the displacement field between them. Our results show that FFD with B-splines is able to capture very complex elastic deformations that characterize US scans of pelvic organs. When combined with mutual information, the registration algorithm successfully catches the displacement between the two scans.

Our future work will focus on the multimodal registration using multidimensional mutual information using feature vectors to better cope with particular characteristics of every medical imaging technique.

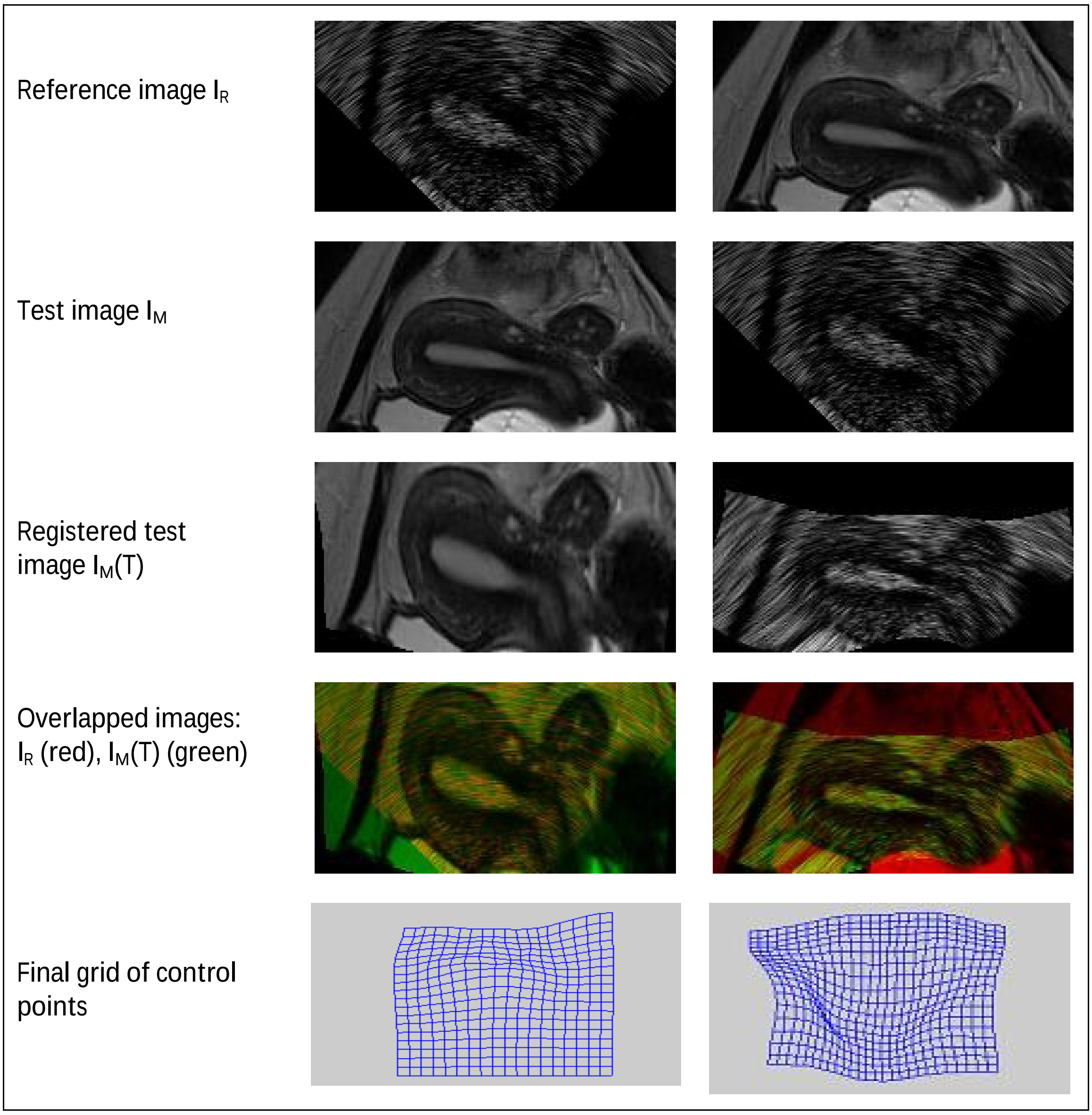


Figure 5. Results for FFD registration with B-Spline functions and native intensity images. For the images considered comparable results are obtained regardless of the way we have chosen the reference and the test image.

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