Tracking brain deformations in time-sequences of 3D US images

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Abstract. During a neuro-surgical intervention, the brain tissues shift and warp. In order to keep an accurate positioning of the surgical instruments, one has to estimate this deformation from intra-operative images. We present in this article a feasibility study of a tracking tool based on intra-operative 3D ultrasound (US) images. The automatic processing of this kind of images is of great interest for the development of innovative and low-cost image guided surgery tools. The difficulty relies both in the complex nature of the ultrasound image, and in the amount of data to be treated as fast as possible.

1 Introduction

The use of stereotactic systems is now a quite standard procedure for neurosurgery. However, these systems do no accurately issue the position of specific anatomical structures (especially deep structures in the brain) du to the intra-operative warping of the brain during surgery (brain shift).

Over the last years, the development of real-time 3D ultrasound (US) imaging has revealed a number of potential applications in image-guided surgery as an alternative approach to open MR and intra-interventional CT thanks to its comparatively low cost and simplicity of use. However, the automatic processing of US images has not gained the same degree of development as other medical imaging modalities, probably due to the low signal-to-noise ratio of US images.

We present in this article a feasibility study of a tracking tool for brain deformations based on intra-operative 3D US images. This work was performed within the framework of the European project ROBOSCOPE (see acknowledgements), which aims to assist neuro-surgical operations using real-time 3D US images and a robotic manipulator arm. The operation is planned on a pre-operative MRI and 3D US images are acquired during surgery to track in real time the deformation of anatomical structures. One can then update the preoperative plan and synthetize a virtual MR image that matches the current brain anatomy.

The idea of MR/US registration was already present in [3, 1, 6, 5, 4]. In all these works, one can only have a snapshot of the brain shift at a given time-point as the user interaction is required at least to define the landmarks. Recently, an automatic rigid registration of MR and US images was presented [10]. This work is based on image intensities and does not rely on feature extraction. However, the estimated motion remains limited to rigid or possibly affine transformations. Up to our knowledge, only [7] deals with an automatic non-rigid MR/US registration. The registration is quite fast (about 5mn), even if the compounding of the 3D US and the computation of its gradient takes about one hour. However, experiments are presented only on phantom data and our experience (see section 3) is that real US images are quite different and may lead to different results.

In this paper, we assume that a rigid MR/US registration is performed with dura matter still closed (there is no brain shift yet), for instance using the approach of [10], and we focus on the development of an automatic intensity-based non-rigid tracking algorithm suited for real-time US images sequences. We first present the registration method for two US images and how the method is turned into tracking algorithm. Then, we present qualitative results on a sequence of US images of a phantom and on a small sequence of animal brain images.

2 The tracking algorithm

When analysing the problem of tracking the brain deformation in 3D US time-sequences, we made the following observations. Firstly, deformations are small between successive images in a real-time sequence, but they are possibly large deformations around the surgical tools with respect to the pre-operative image. Thus, the transformation space should allow large deformations, but only small deformations have to be retrieved between successive images. Secondly, there is a poor signal to noise ratio in US images and the absence of information in some areas. However, the speckle (inducing localised high intensities) is usually persistent in time and may produce reliable landmarks for successive images. As a consequence, the transformation space should be able to interpolate in areas with few information while relying on high intensity voxels for successive images registration. Last but not least, the algorithm is designed in view of a real-time registration during surgery, which means that, at equal performances, one should prefer the fastest method.

Following the encouraging results obtained in [8] for the intensity based non-rigid registration of two 3D US images, we adapt in this section the method according to the previous observations.

2.1 Registering two US images

Parameterisation of the transformation We used in [8] the most natural parameterisation of a free-form transformation: the displacement of each voxel. This strategy proved to be successful when the US image carries information in all areas but induces regularization problems when the images present large uniform areas as it is the case in the phantom sequence of section 3.1. In this paper, we use a very similar but parametric scheme where the "displacement" $\mathbf{t}_i$ for each voxel position $\mathbf{x}_i$ has a Gaussian influence on its neighbourhood: $T(\mathbf{t}_1, ...\mathbf{t}_n)(\mathbf{x}) = \sum_i \mathbf{t}_i . G_\sigma(\mathbf{x} - \mathbf{x}_i)$ (see details in [9]).

Similarity energy Even if there is a poor signal to noise ratio in US images, the speckle is usually persistent in time and may produce reliable landmarks within the time-sequence. Hence, it is desirable to use a similarity measure which favours the correspondence of similar high intensities for the registration of successive images in the time-sequence. First experiments presented in [8] indicated that the simplest one, the sum of square differences ($SSD(T) = \int (I - J \circ T)^2$), could be adapted. In [2], we developed a more complex similarity measure: the sum of Gaussian-windowed local correlation coefficients (LCC). Let $G \star f$ be the convolution of f by the Gaussian, $\bar{I} = (G \star I)$ be the local mean, $\sigma_I^2 = G \star (I - \bar{I})^2$ the local variance and $LC(T) = G \star \left[(I - \bar{I})(J \circ T - \overline{J \circ T}) \right]$ the local correlation between image I and image $J \circ T$. Then, the global criterion to maximise is the sum of the local correlation coefficients: $LCC(T) = \int (LC(T)/\sigma_I . \sigma_{J \circ T})$.

We have shown in [8] and [2] how these criteria can be optimised using first and second order gradient descent techniques with a general free-form deformation field by computing the gradient and the Hessian of the criteria. Using our new parameterisation of the transformations simply amounts to a smoothing of the gradient and Hessian [9]. Therefore, it will be more robust and may escape from previous local minima while encouraging smoother transformations. In this article, the optimisation is performed using a Levenberg-Marquard like method.

Regularization energy There is a trade-off to find between the similarity energy, reflected by the visual quality of the registration, and the smoothing energy, reflected by the regularity of the transformation. Despite a weaker theoretical background, we chose for efficiency reasons to alternatively minimise each energy instead of the weighted sum of the two energies. In view of a real-time system, this is particularly well suited for the stretch energy $E_{reg} = \int \|\nabla T\|$ (or membrane model) which is very efficiently solved by using a Gaussian filtering of the transformation. Thus, the algorithm will alternatively optimize the similarity energy and smooth the transformation by Gaussian filtering.

2.2 From the registration to the tracking algorithm

In the previous section, we studied how to register two US images together. We now have to estimate the deformation of the brain between the first image (since the dura mater is still closed, it is assumed to correspond to the preoperative brain) and the current image of the sequence. One could think of registering directly US_1 (taken at time t_1) and US_n (at time t_n) but the deformations could be quite large and the intensity changes important. To constrain the problem, we need to exploit the temporal continuity of the deformation.

First, assuming that we already have the deformation $T_{US}(n)$ from image US_1 to US_n, we register US_n with the current image US_{n+1}, obtaining the transformation $dT_{US}(n)$. If the time step between two images is short with respect to the deformation rate, there should be small deformations and small intensity changes. For this step, we believe that the SSD criterion is well adapted.

Then, composing with the previous deformation, we obtain a first estimation of $T_{US}(n+1) \simeq dT_{US}(n) \circ T_{US}(n)$. However, the composition of deformation fields involves interpolations and just keeping this estimation would finally lead to a disastrous cumulation of interpolation errors as we go along the sequence.

Thus, we only use $dT_{US}(n) \circ T_{US}(n)$ as an initialisation for the registration of US_1 to US_n. Starting from this position, the residual deformation should be small (it corresponds to the correction of interpolation and systematic error effects) but the difference between homologous point intensities might remain important. In this case, the LCC criterion might be better than the SSD one despite its worse computational efficiency.

3 Experiments

In this section, we present qualitative results of the tracking algorithm on two sequence of US images: a phantom and a dead pig brain with a simulated cyst. Experiments were performed using the SSD and the LCC criterion without significative differences in the results. The registration of each image of the sequence takes between 10 and 15 minutes on a standard PC running linux for the SSD criterion, and between 20 and 30 mn for the LCC criterion.

3.1 A Phantom study

Within the ROBOSCOPE project, an MR and US compatible phantom was developed by Prof. Auer and his colleagues at ISM (Austria) to simulate brain deformations. It is made of two balloons, one ellipsoid and one ellipsoid with a "nose", that can be inflated with known volumes. Each acquisition consists in one 3D MR image and one 3D US image. The goal is to use the US sequence to track the deformations and compute the corresponding virtual MR images from the first MR image. Then, the remaining MR images can be used to assess the quality of the tracking. Results are presented in Fig. 1.

Even if there are very few salient landmarks (all the information is located in the thick and smooth balloons boundaries, and thus the tracking problem is loosely constrained), results are globally good all along the sequence. This shows that the SSD criterion correctly captures the information at edges and that our parameterised deformation interpolates reasonably well in uniform areas.

When looking at the virtual MR in more details, one can however find some places where the motion is less accurately recovered: the contact between the balloons and borders of the US images. Indeed, the parameterisation of the transformation and especially its smoothing are designed to approximate the behaviour of a uniform elastic like body. If this assumption can be justified for the shift of brain tissues, it is less obvious for our phantom where balloons are placed into a viscous fluid. In particular, the fluid motions between the two balloons cannot be recovered. On the borders of the US images, there is sometimes a lack of intensity information and the deformation can only be extrapolated from the smoothing of neighbouring displacements. Since we are not using a precise geometrical and physical model of the observed structures like in [11], one cannot expect this extrapolation to be very accurate.

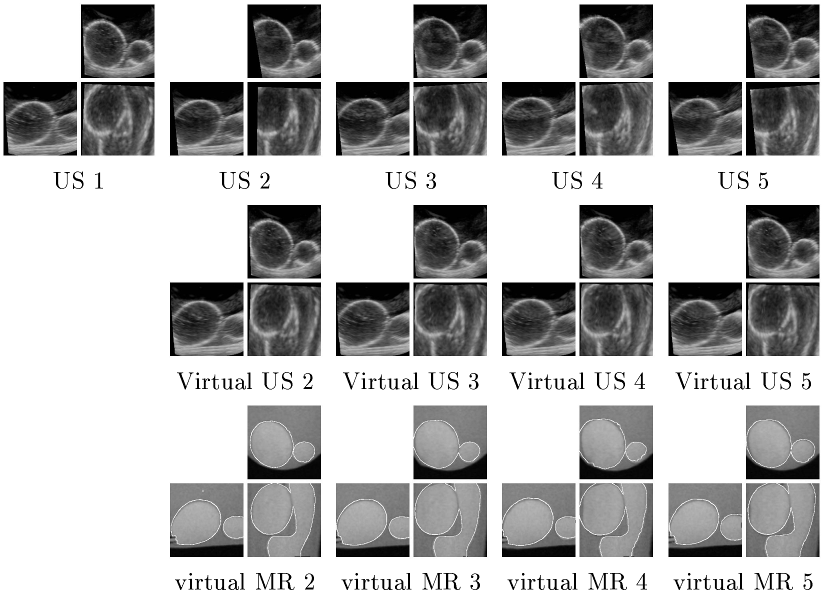

Fig. 1. Beginning of the sequence of 10 images of the phantom. **On top:** the original US images. **Middle:** the "virtual" US images (US 1 deformed to match the current US image) resulting from the tracking. **Bottom:** the virtual MR images synthetized using the deformation field computed on the US images with the contours of the "original" MR images superimposed. The volume of the balloons ranges from 60 to 90 ml for the ellipsoid one and 40 to 60 ml for the more complex one.

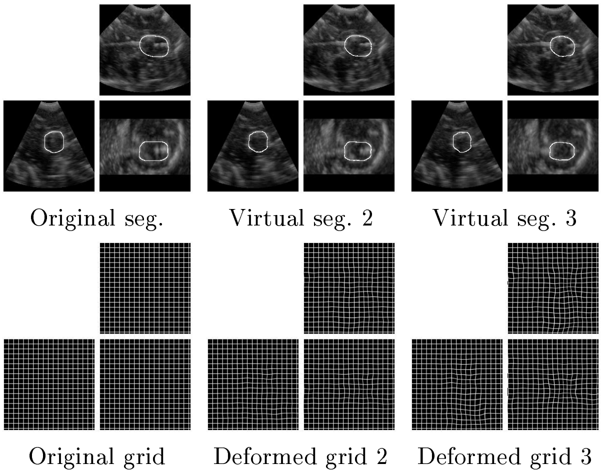

Fig. 2. Top: The 3 original images of the pig brain. The segmentation of the balloon, done on the first image, is deformed according to the transformation found by the tracking algorithm and superimposed to the original US image. **Bottom:** deformation of a grid to visualise more precisely the location of the deformations found.

3.2 Animal brain images

This dataset was obtained by Dr. Ing. V. Paul at IBMT, Fraunhofer Institute (Germany) from a pig brain at a post-lethal status. A cyst drainage has been simulated by deflating a balloon catheter with a complete volume scan at three steps. We present in figure 2 the results of the tracking. Since we have no corresponding MR image, we present on the two last lines the deformation of a grid (a virtual synthetic image...), to emphasise the regularity of the estimated deformation, and the deformation of a segmentation of the balloon.

The correspondence between the original and the virtual (i.e. deformed US 1) images is qualitatively good. In fact, if the edges are less salient than in the phantom images, we have globally a better distribution of intensity features over the field ov view due to the speckle in these real brain images. One should also note on the deformed grid images that the deformation found is very smooth.

Reducing the smoothing of the transformation could allow the algorithm to find a closer fit. However, this could allow some unwanted high frequency deformations due to the noise in the US images. We believe that it is better to recover the most important deformations and miss some smaller parts than trying to match exactly the images and have the possibility to “invent” some possibly large deformations.

4 Discussion and conclusion

We have developed in this paper a tracking algorithm adapted to time sequences of US images and not only to the registration of two images. The algorithm partly fills the goals of the ROBOSCOPE project: it is able to recover an important part of the deformations and issues a smooth deformation, despite the noisy nature of the US images. Experiments on phantom and animal data show that this allows to simulate virtual MR images qualitatively close to the real ones.

We observed that the SSD and LCC criteria produced very similar results on our examples, LCC being around 2 times slower than the SSD. Since the computation time of the US-US non-rigid registration is a key issue for real-time motion tracking, one could conclude that SSD has to be preferred to LCC. We believe that the choice of SSD is justified for the registration of successive images in the time sequence. However, for the update of the global deformation (transformation from the first image to the current one), LCC is probably necessary if the sequence was to present some important intensity changes along time.

The computation time is still far from real time for a continuous tracking of deformations during surgery but a parallelisation of the algorithm is rather straightforward for the computation of both the image and the regularization energies.

The type of transformation is a very sensitive choice for such a tracking algorithm. We made the assumption of a “uniform elastic” like material. This may be adequate for the brain tissues, but probably not for the ventricles and for the tracking of the surgical tools themselves. Indeed, they will penetrate into the brain without any elastic constraint with the neighbouring tissues. A specific adaptation of the algorithm around the tools will likely be necessary. Another possibility for errors is the occlusion of a part of a structure visible in the US, for instance the shadowing by the endoscope.

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