Medical Image Registration with Robust Multigrid Techniques

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Abstract. In this paper we describe a new method of medical image registration based on robust estimators. We propose a general hierarchical optimization framework which is both multiresolution and multigrid with an adaptative partition of the volume. The approach may easily be adapted to different similarity measures (optical flow, mutual information or correlation ratio for instance) and may therefore be used either for mono-modality or for multi-modality registration. Here, we concentrate on the estimation of the optical flow leading to a single-modality non-linear registration. We aim at registering two MRI volumes of two different subjects. Results on real data are presented and discussed. Since this work is in progress, we expect more attractive and extensive results for the time of the conference.

Keywords Registration, atlas matching, incremental optical flow, multigrid minimization, robust estimators.

1 Introduction

1.1 Context

Since the development of modern imaging techniques (MRI, X-ray, PET, etc.), registration has become an important task in brain imaging. Nowadays surgeons must face not only the huge volume of data, but also the complementarity between the different images. As a matter of fact, these informations are not redundant but complementary, and should not be neglected for the health of the patient. Functional data must therefore be merged or compared with the use of an atlas. In order to build such an atlas, it is necessary to appraise the anatomical variability, what implies the registration of the anatomy of different subjects. We distinguish several registration applications:

- Registration of images of the same subject with the same modality. It is useful for surgeons, either to follow the development of a disease, or for operations (dynamic acquisition during the operation or validation of an operation).
- Registration of images of a same subject with different modalities. This problem arose with the development of different images, either anatomical (MR, X-ray) or functional (fMRI, PET, EEG, MEG). Merging these images is desirable so that no information is excluded from the diagnostic.

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– Registration of brains of different subjects. Such a registration allows to build an anatomical atlas of the cortex. Atlases such as [13,17] appear to be inadequate (legibility, capacity to evolve, difficulty of interpretation [8]). The major problem in building an atlas is the important variability of the human brain. To take it into account, a non-linear registration process is necessary.

1.2 Background

Medical image registration is a very productive field, from a bibliographical point of view. [11] present a complete review and classification of different registration procedures. Methods are usually classified using the following criterions: the nature and the dimension of the homologous structures to match, the domain of transformation (local or global), its type (rigid, affine, projective or "free form"), the similarity measure and the minimization scheme. We have selected a few methods that seem relevant to us:

The first method is Talairach's stereotactic referential [17]. The purpose is to enclose all the brains in the same box, which size and orientation are known. It uses a piecewise linear transformation. Many methods use geometric attributes that are extracted and then matched. They may be points [3], curves [15] or surfaces [16]. The extraction of these landmarks is of course a crucial problem (Is the extraction reliable? what is the number of landmarks that will invariably be present?), but the way these landmarks are matched -and the way the registration is computed throughout the volume- is also critical. Methods have been developed to overcome this problem: the TPS algorithm [3], spline transformations [16], or the ICP algorithm [15].

Other registration procedures are inspired by mechanical models, either elastic [1], or fluid [4]. Fluid models allow to reach, in theory, any displacements, but these methods are highly time-consuming.

Finally many registration procedures are "voxel-based" methods: Thirion [18] proposes the demon method, by reference to Maxwell's demons; Collins [5] estimates a locally affine transformation that maximizes the cross correlation of the image gradient.

1.3 Method

We propose in this paper a $3D$ method to estimate the optical flow, which is related to the work presented in [12]. The estimation of a dense displacement field leads to a non linear single modality registration. The problem is expressed in a Bayesian context as the minimization of a cost function. We introduce robust estimators in order to be less sensitive to the noise of acquisition (MRI data) and to preserve the discontinuities of the dense displacement field.

Finally the optimization procedure is multiresolution and multigrid, in order to accelerate the estimation and to improve its accuracy. We designed an adaptative partition of the volume in order to refine the estimation on the regions of interest and to avoid useless efforts. This minimization framework, including the multiresolution/multigrid plan and the robust estimators, is not limited to the estimation of the optical flow, but may be used as well for other similarity measures (mutual information, correlation ratio for example). We are focusing on different applications:

– Registration of MRI data of different subjects. The purpose is the automatic segmentation and labeling of the cortex and the possibility to exchange symbolic information from one brain to another.
– Registration of data from the same subject, for instance for fMRI acquisitions. The goal is to correct the movement of the head during the time of the protocol in order to ease the use and the interpretation of the data. In that case, only a global affine field will be sought.

2 Optical Flow Estimation

2.1 General Formulation

The optical flow hypothesis, introduced by Horn et Schunck [9], assumes that the luminance of a physical point does not vary much between the two volumes to register. It gives: $f(s+\mathsf{d}\boldsymbol{w}_s, t_1) - f(s, t_2) = 0$ where s is a voxel of the volume, t_1 and t_2 are the index of the volumes (temporal index for a dynamic acquisition, index in a database for multi-subject registration), f is the luminance function and $\mathsf{d}\boldsymbol{w}$ the expected $3D$ displacement field. Generally, a linear expansion of this equation is preferred : $\boldsymbol{\nabla} f(s,t) \cdot \mathsf{d}\boldsymbol{w}_s + f_t(s,t) = 0$ where $\boldsymbol{\nabla} f(s,t)$ stands for the spatial gradient of luminance and $f_t(s,t)$ the difference between the two volumes.

With the linearization, we are less sensitive to constant changes in the luminance due to the acquisition but only the projection of the displacement on the luminance gradient may be estimated. Furthermore, the linearization makes the estimation more sensitive to noise. For these reasons, it is necessary to introduce a prior regularization on the solution. Within a Bayesian framework [7], and using the MAP estimator, the problem is formulated as the minimization of the following cost function:

$$U(\mathsf{d}\boldsymbol{w}; f) = \sum_{s \in S} [\boldsymbol{\nabla} f(s,t) \cdot \mathsf{d}\boldsymbol{w}_s + f_t(s,t)]^2 + \alpha \sum_{<s,r> \in \mathcal{C}} ||\mathsf{d}\boldsymbol{w}_s - \mathsf{d}\boldsymbol{w}_r||^2 \qquad (1)$$

where S is the voxel lattice, $\mathcal{C}$ is the set of neighboring pairs (the 6 neighborhood system may be used for instance) and α controls the balance between the two energy terms. The first term represents the interaction between the field (unknown variables) and the data (given variables), whereas the second term expresses the smoothness constraint. The weakness of this formulation are known:

a. The optical flow constraint (OFC) is not valid in case of large displacements because of the linearization.
b. The OFC might not be valid in all the regions of the volume, because of the noise of acquisition, intensity non-uniformity in MRI data, occlusions.

c. The “real” field is not globally smooth and it probably contains discontinuities that might not be preserved because of the quadratic cost.

To cope with the (b) and (c) limitations, we replace the quadratic cost by robust functions. Furthermore, to face the problem (a), we use a multiresolution plan and a multigrid strategy to improve the minimization at each resolution level.

2.2 Robust Estimators

Cost function (1) takes into account all the voxels and all the pairs of neighbors equally. This is not very robust, that's why we would like to reduce the importance of possible inconsistent data, or to avoid smoothing discontinuities of the field that must be preserved. Therefore, we introduce robust functions [10] and more precisely robust M-estimators [2]. An M-estimator ρ has the following properties:

a. ρ is increasing on $\mathbb{R}^+$. b. $\phi(u) \triangleq \rho(\sqrt{u})$ is strictly concave on $\mathbb{R}^+$. c. $\lim_{x\to\infty} \rho'(x) < \infty$.

(a) implies that ρ is a cost function. (b) implies that the graph of ρ is the inferior envelope of a set of parabolas. We have:

$$\exists \psi \in C^1([0,M],\mathbb{R}) \text{ such that } \forall u, \rho(u) = \min_{z\in[0,M]} \left(zu^2 + \psi(z)\right) \tag{2}$$

where $M \triangleq \lim_{u\to 0^+} \phi'(u)$. Furthermore one gets :

$$z^* \triangleq \arg\min_{z\in[0,M]} \left(zu^2 + \psi(z)\right) = \frac{\rho'(u)}{2u} = \phi'(u^2)$$

where $\frac{\rho'(u)}{2u} = \phi'(u^2)$ decreases from M to 0 according to (b) and (c).

The robustness of such an estimator is provided by the fact that the function ϕ' decreases. We introduce two robust estimators, the first one on the data term and the second one on the regularization term. According to (2), the cost function (1) can then be modified as:

$$\begin{aligned} U(\mathsf{d}\boldsymbol{w},\delta,\beta;f) &= \sum_{s\in S} \delta_s \left(\boldsymbol{\nabla} f(s,t)\cdot \mathsf{d}\boldsymbol{w}_s + f_t(s,t)\right)^2 + \psi_1(\delta_s) \\ &+\alpha \sum_{<s,r>\in\mathcal{C}} \beta_{sr} \left(||\mathsf{d}\boldsymbol{w}_s - \mathsf{d}\boldsymbol{w}_r||\right)^2 + \psi_2(\beta_{sr}) \end{aligned} \tag{3}$$

where δ_s and β_{sr} are auxiliary variables (acting as “weights”) to be estimated. This cost function has the advantage to be quadratic with respect to $\mathsf{d}\boldsymbol{w}$. When a discontinuity gets larger, the contribution of the pair of neighbors gets lower by the reduction of the associated weight β_{sr} ($\beta_{sr} = \phi_2'(||\mathsf{d}\boldsymbol{w}_s - \mathsf{d}\boldsymbol{w}_r||^2)$). In the same way, when the adequation of a data with the model is not correct, its contribution gets lower as the associated weight δ_s decreases ($\delta_s = \phi_1'([\boldsymbol{\nabla} f(s,t)\cdot \mathsf{d}\boldsymbol{w}_s + f_t]^2)$).

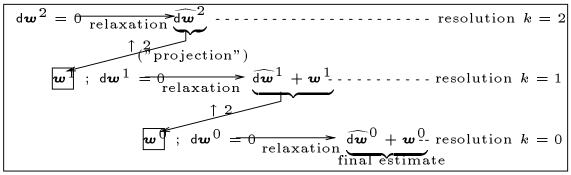

Fig. 1. Incremental estimation of the optical flow

2.3 Multiresolution and Multigrid Approaches

In case of large displacements, we use a classical incremental multiresolution procedure (see fig. 1). We construct a pyramid of volumes $\{f^k\}$ by successive Gaussian smoothing and subsampling in each direction. At coarsest level, displacements are reduced, and cost function (3) can be hopefully used. For the next resolution levels, only an incremental $\mathrm{d}\boldsymbol{w}^k$ is estimated to refine estimate $\hat{\boldsymbol{w}}^k$, obtained from the previous level. This is done using cost function (3) but with $\boldsymbol{\nabla} f^k(s+\hat{\boldsymbol{w}}^k_s, t_2)$ and $f^k(s+\hat{\boldsymbol{w}}^k_s, t_2) - f^k(s,t_1)$ instead of $\boldsymbol{\nabla} f^k(s,t)$ and $f^k_t(s,t)$.

Furthermore, at each level of resolution, we use a multigrid minimization (see Fig. 2). We aim at estimating an increment field not for one voxel, but for a group of voxels in order to have temporarily a larger system of neighborhood. The energy is consequently smoother, and has fewer local minima. As a matter of fact, the cost (3) is highly non convex, and we might be trapped into a local minimum. Moreover, this minimization strategy, where the starting point is provided by the previous result - which we hope to be a gross estimate of the desired solution -, improves the quality of the estimation and makes it possible to use a deterministic relaxation instead of a stochastic one.

The multigrid strategy consists in partitioning initially the volume into cubes of size 2^{3l} at the grid level l. The cost function (3) can then be expressed according to the partition and a 12-dimensions parametric model is estimated as an increment on each cube. The total field is therefore piecewise affine. The displacement increment estimated on a cube depends on the total displacement estimated on the neighborhood of this cube, what implies that the field will be continuous between the cubes, and we do not have a "block" effect.

When we change the grid level, we also change the partition of the volume by dividing, regularly or not, the previous partition. The criterion of subdivision may be either the measure of the way the model fits the data, or a prior knowledge such as the presence of an important anatomical structure where the estimation must be accurate (segmentation of the cortex, identification of the cortical sulci). Consequently, we can distinguish between the regions of interest, where the estimation must be precise, and the other regions where computation efforts are useless.

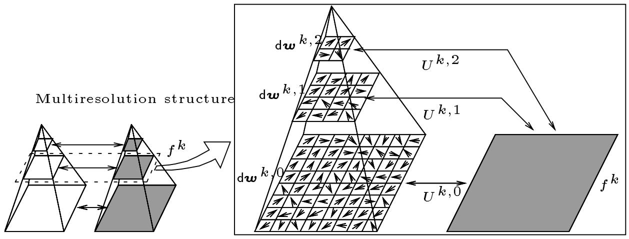

Fig. 2. Three-level multigrid relaxation at a given resolution level k

3 Results

Results of the $3D$ method are presented on figure 3. Two $3D$ MRI-T1 volumes of two different subjects are registered. The reconstructed volume -with trilinear interpolation- is presented, computed with the target volume and the final displacement field. We also present two volumes of difference, one before and the other after registration. The adaptative partition is also presented. We refine the estimation in the regions of interest (cortex) whereas we do not waste computation time on regions that do not necessitate too much attention.

The difference volumes are to be interpreted carefully, since we get the superposition of two errors: the first one is the registration error, the anatomical variability that we could not apprehend. The second error is due to the difference of acquisition of the two volumes, which implies that the two original histograms of the two volumes are different.

We notice that if some anatomical structures (ventricle, bulb) are correctly registered, errors remain, in particular for cortical sulci. As a matter of fact the variability is very high on these regions. It has been shown that this critical issue cannot be correctly solved with voxel-based methods [6].

The computation takes 1 hours on a Ultra Sparc 30 (300 Mhz). The volumes are $256 \times 256 \times 200$. We use 3 levels of resolution because the displacement amplitude may reach 30 voxels. We stop at the grid level 2 of the finest resolution, because below this grid level the estimation of 12 parameters is inconsistent. It should be noted that only 10 minutes are necessary to perform the estimation until the grid level 3 of the finest resolution (where the cubes are $7mm$ large), this means that almost 85% of the computation time is due to the last grid level.

4 Conclusion and Perspectives

We have presented in this paper a new registration method based on a robust $3D$ estimation of the optical flow with promising results on real data. We use an efficient minimization framework, both multiresolution and multigrid with robust estimators. This optimization scheme is not limited to the estimation of the optical flow, but may as well be adapted to other similarity measures, leading to different registration applications. The adaptative partition of the volume improves the computation time but does not degrade the estimation in the regions of interest. We purchase different perspectives:

– The multigrid partition must be optimized so that no efforts are made in certain regions (outside the brain for instance) whereas the estimation is as accurate as possible in the regions of interest (cortex, cortical sulci).
– It could be desirable to correct the histograms -if it is not a constant bias- of the two volumes [14], as the method is dependent on the optical flow hypotheses. But if the difference of the two histograms is affine, only one additional parameter needs to be estimated. This way to cope with the problem is certainly more correct than any histogram modification.
– We intend to extend this minimization procedure to multi-modality registration. To that purpose, the similarity measure in the cost function must be replaced by another (e.g. mutual information or correlation ratio).

References

1. R. Bajcsy, S. Kovacic. Multiresolution elastic matching. *CVGIP*, 46:1–21, 1989. 681
2. M. Black, A. Rangarajan. On the unification of line processes, outlier rejection, and robust statistics with application in early vision. *IJCV*, 19(1):57–91, 1996. 683
3. F. Bookstein. Principal warps: Thin plate splines and the decomposition of deformations. *IEEE PAMI*, 11(6):567–585, 1989. 681
4. G. Christensen, R. Rabbit, MI. Miller. Deformable templates using large deformation kinematics. *IEEE Trans. Image Processing*, 5(10):1435–1447, 1996. 681
5. L. Collins. *3D Model-based segmentation of individual brain structures from magnetic resonance imaging data*. PhD thesis, Mc Gill University, Montreal, 1994. 681
6. L. Collins, G. Le Goualher, R. Venugopal, A. Caramanos, A. Evans, C. Barillot. Cortical constraints for non-linear cortical registration. *Proc. Visu. in Biomed. Computing*, LNCS 1131, pages 307–316. Springer, September 1996. 685
7. S. Geman, D. Geman. Stochastic relaxation, gibbs distribution and the bayesian restauration of images. *IEEE PAMI*, (6):721–741, 1984. 682
8. B. Gibaud, S. Garlatti, C. Barillot, E. Faure. Computerised brain atlases vs. decision support systems : A methodological approach. *Artificial Intelligence in Medicine*, 14(1):83–100, 1998. 681
9. B. Horn, B. Schunck. Determining optical flow. Artif. Intell. 17:185-204, 1981. 682
10. P. Huber. *Robust statistics*. Wiley, 1981. 683
11. J. Maintz, MA. Viergever. A survey of medical image registration. *Medical Image Analysis*, 2(1):1–36, 1998. 681
12. E. Mémin, P. Pérez. Dense estimation and object-based segmentation of the optical flow with robust techniques. *IEEE Trans. Image Processing*, 7(5):703–719, 1998. 681
13. M. Ono, S. Kubik, C. Abernathey. *Atlas of the cerebral sulci*. Verlag, 1990. 681
14. J. Sled, A. Zijdenbos, A. Evans. A nonparametric method for automatic correction of intensity nonuniformity in MRI data. *IEEE TMI*, 17(1):87–97, 1998. 686
15. G. Subsol, JP. Thirion, N. Ayache. A general scheme for automatically building 3D anatomical atlases : Application to a skull atlas. INRIA RR 2586, 1995. 681

16. R. Szeliski, S. Lavallée. Matching 3D anatomical surfaces with non-rigid deformations using octree-splines. *SPIE geometric methods in computer vision*, 2031:306–315, 1993. 681
17. J. Talairach, P. Tournoux. *Co-planar stereotaxic atlas of the human brain*. Georg Thieme Verlag, 1988. 681
18. JP. Thirion. Image matching as a diffusion process: an analogy with Maxwell's demons. *Medical Image Analysis*, 2(3):243–260, 1998. 681

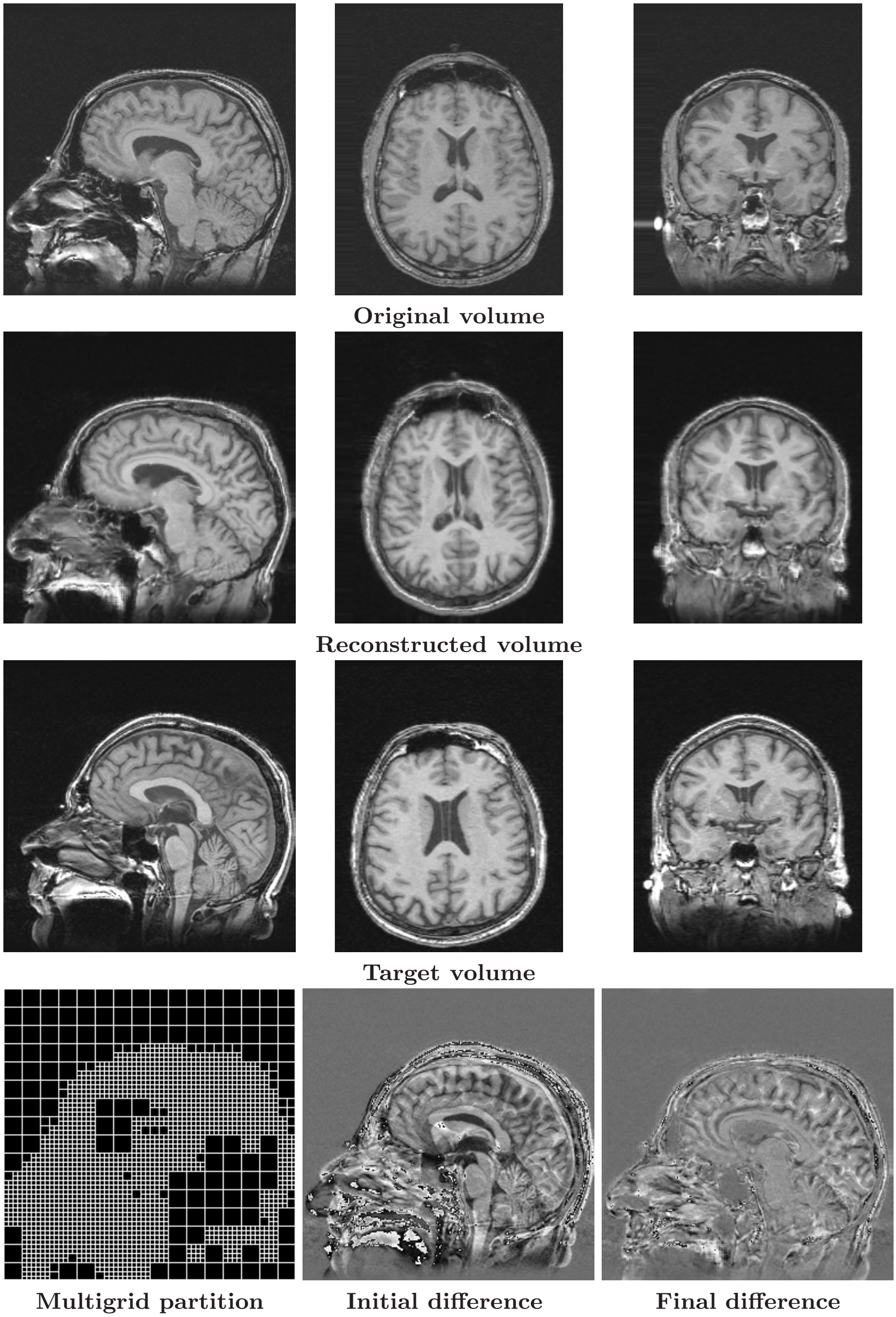

Fig. 3. Final results of the registration