ATLAS-BASED REGISTRATION OF MRI BRAIN IMAGES WITH THE USE OF POINT SIMILARITY MEASURES

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ABSTRACT

High-dimensional deformable registration of MRI brain images is presented here. The deformation is driven by local forces estimated from point similarities based on joint histogram and with the use of prior information obtained from tissue probability maps available in selected commonly used brain atlases. Three point similarity measures are tested in an experiment with data obtained from standard Simulated Brain Database.

1 INTRODUCTION

Image registration methods have been used in many clinical applications in recent years. One of their application field is the atlas-based registration of MRI brain images. A subject image is transformed into the brain-based coordinate system (stereotaxic space), where it can be further processed with a number of applications such as tissue classification, anatomical labeling, voxel-based or deformation-based morphometry. Each of the applications needs a different level of the subject image alignment with a template image, ranging from rigid or affine trasformations to low or high-dimensional deformations.

In this paper, we focus on the high-dimensional deformable registration of multi-modal data because the character of the intensities in the subject and the template images differs often. Some authors [1], [2] apply an intensity transformation to one of the images, in order to use one of already settled high-dimensional mono-modal registration algorithms. Recently Rogelj et al. [3] proposed several point similarity measures allowing to solve the high-dimensional deformable registration directly from multi-modal data. We adapt here some of his ideas to the specific problem of MRI brain images located in the stereotaxic space.

2 METHODS

The whole process of image alignment is usually split into two stages. In the first one, the subject image is transformed to the same coordinate space as the template image is. In the second one, a deformable registration is performed to supress the misalignments remaining after the first step. Here, the deformable registration is further subdivided into a low-dimensional and a high-dimensional registration. Multiresolution affine registration based on mutual information [4] turned out to be a proper technique for the first step. The following low-dimensional deformable registration has been solved in our previous work by block matching technique with the use of multimodal region similarity measure. The subject image is subdivided into blocks for which optimal translations are searched. The local results are then interpolated with the use of radial basis functions to compose a free-form deformation. The size of the image blocks is subsequently decreased, but it cannot be arbitrary small, as the local translations are computed independently for each region and no voxel interdependencies are taken into account when the deformation is calculated.

To make the deformable registration more precise, the high-dimensional registration is added here. We follow the concept of Rogelj et al. [3], see fig. 1 for the basic scheme. At first, local translations $\boldsymbol{F}$ (usually referred as forces) are calculated at each voxel as an estimate of a gradient of a similarity function with respect to the template image M. Then, a spatial deformation model is used to compute the deformation $\boldsymbol{U}$ of the subject image N from the local forces. The process is iterated with a predefined number of iterations or until a global similarity measure stops increasing.

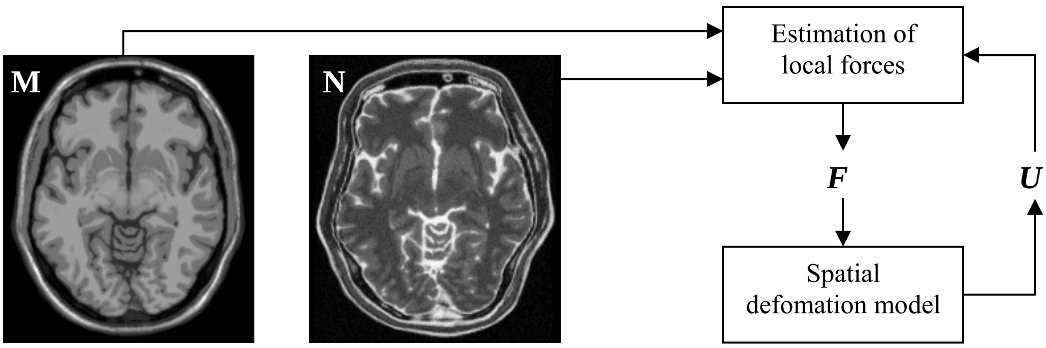

Fig. 1: *Deformable registration scheme (see the text for details).*

The spatial deformation model proposed in [5] is used here. It is defined by:

$$U_F = k_E F, \tag{1}$$

$$U^{(i)} = \left(U^{(i-1)} + U_F^{(i)} * G_I\right) * G_E. \tag{2}$$

The first part (1) follows Hook's law to compute unregularized displacements. It says that the points move proportionally to the applied forces $\boldsymbol{F}$ with the constant k_E. The second part (2) regularizes the displacements by convolution filters $\boldsymbol{G}_I$ and $\boldsymbol{G}_E$ which define spatial deformation properties of the modeled material. If $\boldsymbol{G}_E = \delta$ (Dirac's delta function), the displacement field in the current iteration $\boldsymbol{U}_F^{(i)}$ is computed by summing the already obtained displacements $\boldsymbol{U}^{(i-1)}$ with the correction displacements $\boldsymbol{U}_F^{(i)}$ regularized only by filter $\boldsymbol{G}_I$. This configuration corresponds to an incremental model which allows large deformations and precise registration. The configuration with $\boldsymbol{G}_I = \delta$ corresponds to an elastic model. The forces are regularized only by filter $\boldsymbol{G}_E$ which becomes wider for the forces in earlier itearations. The pure elastic model makes it impossible to absolutely correct local misalignments, but it models deformation properties of the real tissues better than the incremental model. The gaussian kernels are used here as a separable aproximation to the elastic kernel proposed in [6]. The behaviour of the combined elastic-incremental model depends on the ratio between the standard deviations σ of the Gaussians. Bigger σ corresponds to wider filter impulse response and to a stiffer material whereas narrower impulse responses model more flexible material.

In this paper, we use three multimodal point similarity measures for local forces estimation, in order to compare their functionality in an experiment. First similarity measure is defined by:

$$S_{CP}(i) = P(i_N | i_M), \qquad (3)$$

It is the same measure which was used in our previous work for block matching, where similarities of intensity pairs in all voxels of a block were summed. It was first proposed in [7]. The similarity of an intensity pair $\boldsymbol{i}$ is given by conditional probability that a subject image intensity i_N occurs when given a template image intensity i_M. The conditional probabilities are computed from a joint histogram of the images M and N. The joint histogram can be computed only from correctly registered images. As the registration is not known, an assumption, that the previous registration techniques aligned the images enough to expect only small deformation, has to be accepted.

The second similarity measure was designed according to the idea given in [3]. A segmentation-based point similarity function is defined there as a probability of an intensity pair belonging to one of the true classes of image intensities:

$$S_S(i) = P(C_T | i) = \sum_{l=1}^{L} P(C_l | i) P(C_T | C_l), \qquad (4)$$

where C_l denotes intensity class representing a tissue type pair, C_T is a set of all true intensity classes which correspond to the same tissues in both images and L denotes number of classes found in the joint histogram by an exhaustive search. In our case, intensities of MRI brain images form classes for certain tissues, thus this type of similarity measure appears to be suitable for them. In addition, the true classes for MRI brain images are known in advance: white matter (WM), gray matter (GM) and celebrospinal fluid (CSF). Therefore L=3, the term $P(C_T|C_l)$=1 for each l and (4) can be reduced to:

$$S_S(i) = P(C_T | i) = \sum_{l=1}^{3} P(C_l | i) \ . \qquad (5)$$

A posterior probability $P(C_l|\boldsymbol{i})$ shows the chance that certain intensity pair $\boldsymbol{i}$ belongs to a certain class C_l and it is according to Bayes rule defined by:

$$P(C_l | i) = \frac{p(i | C_l) P(C_l)}{p(i)}, \qquad (6)$$

where $p(\boldsymbol{i})$ is probability density function of intensity pair $\boldsymbol{i}$ estimated from joint histogram. A set of samples is used to compute class probabilities $P(C_l)$. Class conditional probability density functions $p(i|C_l)$ are aproximated by gaussian distributions with mean values and covariance matrixes estimated also from the set of samples. The spatial coordinates of the samples are derived from tissue probability maps which are available in the case of atlas based template image. The tissue probability maps are sampled in the predefined number of spatial locations with the highest probabilities.

Another multimodal point similarity measure for images without formed tissue classes is proposed in [3]. Each intensity pair $\boldsymbol{i}$ is treated as its own intensity class C_i with probability $P(C_i)=p(\boldsymbol{i})$, mean values $\boldsymbol{i}$ and $P(C_i|i)= \delta(\boldsymbol{i})$. The similarity function is then defined as:

$$S_U(i) = P(C_T|i) = P_M(C_T|i) \cdot P_N(C_T|i) = P(i_N|i_M) \cdot P(i_M|i_N) = S_{CP}(i) \cdot P(i_M|i_N) , \qquad (7)$$

$$S_{UH}(i) = \log(P(C_T|i)) . \qquad (8)$$

The logarithmic function is applied in (8) to make the similarity function dependent on uncertainity rather than probability.

The displacement field ***U*** is successively updated during the registration process. To update the joint histogram, the subject image has to be deformed in every iteration. The calculation of the deformed image intensities incorporates a scatter data interpolation method which brings a big computational load in the case of 3D data. Scatter data interpolation methods are avoided in our implementation by using generalized partial volume estimation (GPVE) proposed in [8]. Weights corresponding to an interpolation kernel function are calculated for each of the template image voxel in the certain neighbourhood of the displaced subject image voxel. The weights are accumulated for all intensity pairs and the resulting sums of weights replace usual numbers of occurences. The same approach was used here also for the calculation of the similarity measures S_{PC} and S_{UH}. The neighbourhood contains 27-64 voxels for 3D data and 4-16 pixels for 2D data in case of B-spline function of the 3rd order as the kernel interpolation function. A similar situation arises when the set of samples has to be determined to compute the similarity measure S_S. Spatial locations in the tissue probability map correspond with locations in the template image, but they differ from positions of the displaced voxels in the subject image. Again, the number of occurences are replaced by sums of weights calculated by locally bounded weight functions used usually in the Shepard scatter data interpolation. In this way, the deformed image has not to be computed during the registration process which is accelerated in this way.

				$e1_{RMS}$ = 1,93 mm			$e1_{RMS}$ = 2,92 mm			$e1_{RMS}$ = 3,90 mm			$e1_{RMS}$ = 4,83 mm		
				$e2_{RMS}$, mm			$e2_{RMS}$, mm			$e2_{RMS}$, mm			$e2_{RMS}$, mm		
ps1	***ps2***	***n*, %**	***rf*, %**	S_{PC}	S_S	S_{UH}	S_{PC}	S_S	S_{UH}	S_{PC}	S_S	S_{UH}	S_{PC}	S_S	S_{UH}
T1	T1	0	0	1,30	1,42	1,42	1,93	2,44	2,06	2,83	3,51	2,90	3,90	4,50	4,01
T1	T1	3	20	1,38	1,43	1,44	2,02	2,33	2,16	2,80	3,35	3,06	3,76	4,44	4,04
T1	T1	3	40	1,38	1,49	1,41	2,01	2,39	2,11	2,78	3,36	2,99	3,69	4,34	4,07
T1	T2	3	20	1,36	1,66	1,45	2,11	2,60	2,29	3,10	3,54	3,30	4,11	4,45	4,32

Tab. 1: *Comparison results for registration with various point similarity measures.*

3 RESULTS

The performance of the algorithm with various point similarity measures was evaluated by computing a decrease of displacement error which was caused by a synthetic deformation. 2D images obtained from Simulated Brain Database were padded to the size of 217x217 pixels (the pixel size was 1x1 mm) and then deformed by random translations at 10% randomly selected pixels. The combined incremental-elastic spatial deformation model with random convolution kernel widths 10±5 mm was used iteratively to obtain final displacement fields. The deformations were applied on 20 image pairs, repeatedly for various initial displacements formulated by root-mean-squared error $e1_{RMS}$, level of noise *n*, intensity nonuniformity *rf*, and pulse sequenses of the template and subject images *ps1* and *ps2*. The spatial deformation model for registration was set by σ_{GI}=4 mm and σ_{GE}=1 mm. The registration process was terminated when global similarity based on mutual information stopped increasing, which was after 5-15 iterations. Residual displacements $e2_{RMS}$ after the registration are summarized in tab. 1.

4 CONCLUSION

The algorithm for high-dimensional registration of MRI images was presented and three different point similarity measures for multi-modal data were studied here. The similarities were measured with the use of joint histogram and tissue probability maps from MRI brain atlases. The results of registration were best for similarity measure S_{PC} which is based on intensity distribution only. The initial displacement error was decreased by 15-30%. A global similarity measure mutual information was increased in all cases. In our implementation, interpolation in the feature space was used, so that it was unnecessary to compute the deformed subject image during the registration process. If only the resulting displacement field is the object of examination, then the deformed image does not need to be computed once.

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