A Communication Term for the Combined Registration and Segmentation

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Abstract — **Accurate image registration is a necessary prerequisite for many diagnostic and therapy planning procedures where complementary information from different images has to be combined. The design of robust and reliable non-parametric registration schemes is currently a very active research area. Modern approaches combine the pure registration scheme with other image processing routines such that both ingredients may benefit from each other. One of the new approaches is the combination of segmentation and registration ("segistration"). Here, the segmentation part guides the registration to its desired configuration, whereas on the other hand the registration leads to an automatic segmentation. By joining these image processing methods it is possible to overcome some of the pitfalls of the individual methods. Here, we focus on the benefits for the registration task.**

To combine segmentation and registration, a special communication or coupling term is needed. In this note we present a novel coupling term, which overcomes the pitfalls of conventional ones. It turned out that not only the achieved results were better, but the overall scheme converges much faster, resulting in a favorable computation time.

The performance tests were carried out for magnetic resonance (MR) images of the brain demonstrating the striking the potential of the proposed method for real live examples.

Keywords — **segistration, medical image registration, segmentation, mathematical modeling, magnet resonance imaging, neuro-imaging.**

I. INTRODUCTION

Medical image registration and segmentation are two of most challenging imaging problems.

We start by defining the non-parametric image registration problem [1] in a variational setting. Given a reference image *R* and a template image *T*, to be transformed. We wish to find a displacement field *Y* that minimizes the following functional

$$J_{REG}(Y; R, T) = D(Y; R, T) + \alpha_1 S(Y). \qquad (1)$$

Here, *S* denotes a regularizer for the displacement field *Y*. We have used the so-called elastic potential [2]. *D* is a distance measure quantifying the similarity between the reference image and the deformed template image. We have chosen the cross corelation (CC) [1] for our experiments. The parameter α_1 may be used to emphasize the distance or the smoothness term. The role of upcoming parameters is along the same line.

Next, we would like to incorporate a segmentation part into the registration functional (1). In the light of this variational formulation, it appears very natural to use as well an energy functional for the formulation of the segmentation problem.

To this end, we consider the functional

$$J_{SEG}(C; I) = E_{INT}(C) + \alpha_2 E_{EXT}(C; I) \qquad (2)$$

for the image *I*. Here, the *C* [3] denotes a finite set of smooth, closed curves, which eventually define the segmentation. The particular representation of the curves is not in the focus of this work. For the examples to be presented, we have employed the widely used implicit representations via Level Sets. E_{INT} acts solely on the curve and is therefore frequently called internal energy. It controls the smoothness of the curve. Typical smoothers are based on the length or on the area enclosed by the curve. Here, we use the length of the curve. E_{EXT} should drive the curve to its destination and is known as external energy. For our experiments we use a variation of the Mumford-Shah functional [5] introduced by Chan and Vese [4]. Their external energy reads as follows

$$E_{EXT}(C; I) = \int_{in(C)} |I - c_1| dx + \int_{\Omega \setminus in(C)} |I - c_2| dx. \qquad (3)$$

Where *in(C)* denotes the region enclosed by *C* and *Ω* an image domain. The constants c_1 and c_2 are the average gray-values of the respective integration areas.

II. METHODS

The coupling of the registration and segmentation is given by the following functional

$$J(Y, C_R; R, T) = J_{REG}(Y; R, T) + \beta_1 J_{SEG}(C_R; R)$$

$$+ \beta_2 D_C(Y, C_R; R, T) \tag{4}$$

The aim of this functional is to find a displacement field Y for the registration and a segmentation of objects in reference image C_R. The segmentation of the template image C_T is assumed to be given. Actually, a segmentation of the reference is computed and then compared to the segmentation of the template by the computed displacement field. The term D_C is responsible for the coupling between the registration and segmentation part. In the literature, only on one possibility for this measure [8] is reported

$$D_C(Y, C_R; C_T) = \int_{in(C_R)} \Phi_{T(Y)}(x)dx. \tag{5}$$

Here $\Phi_{T(Y)}$ is the implicitly signed distance function of the contour C_T. To our experience, the overall performance of this approach is not very impressive as indicated by the presented example. On top, one has to compute the function $\Phi_{T(Y)}$ which is of complexity O(n log(n)) [9], where n denotes the number of grid points.

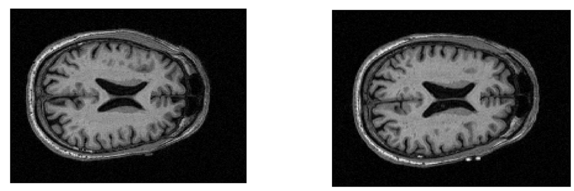
Here we propose a new distance measure for the coupling of the registration and segmentation by

$$D_C(Y, C_R; C_T) = \int_\Omega (in(C_T(Y(x))) - in(C_R(x)))^2\, dx. \tag{6}$$

Here the computation time is only O(n). Moreover, the convergence behavior is much nicer, as will be shown in the result section.

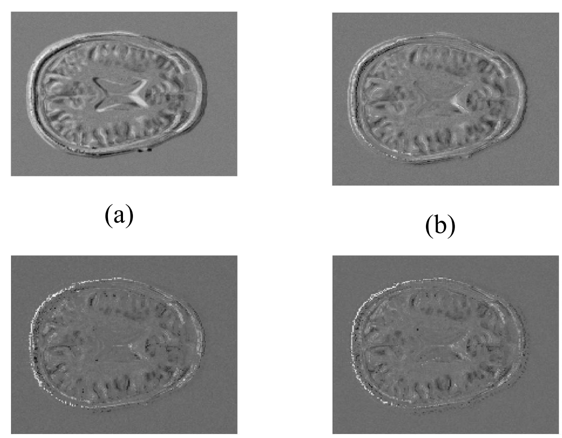
III. Results

To demonstrate the performance of the described distance measures for real clinical problems, we applied them to the segmentation and registration of two magnetic resonance images of the brain used for diagnosis and therapy of Alzheimer's disease. The data used in this article was obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (www.loni.ucla.edu/ADNI). For demonstration purposes, we comment on two - dimensional slices of the three - dimensional brain images. Figure 1(a) illustrates the reference and 1(b) the template image, respectively. The difference between the reference and the template image is displayed in Figure 2(a). It is apparent that the clinically highly relevant ventricles, as well as the skull have quite different positions in the images. Next, we turn our attention to the coupling of registration and segmentation. In all experiments we selected the parameter $\alpha_1 = 1$, $\alpha_2 = 1$, $\lambda = 0$, $\mu = 1$ (elastic potential, for details see [1]), $\beta_1 = 0{,}001$ and $\beta_2 = 0{,}001$. To obtain a benchmark registration we next registered the two images by a plain elastic registration scheme, based on (1). It is apparent from Figure 2 (b), that after this registration the alignment is improved, but the ventricles are still not optimally registered. Next, we applied the segistration scheme based on (4) for both coupling terms (5) and (6). Both attempts produce superior results as compared to the plain registration. In particular, for the medical relevant area of the ventricle system, the obtained distance is very small. The corresponding segmentation results for the reference are shown in Figure 3. All three segmentation appear visually quite satisfying. However, it should be noted that the new scheme based on (6), requires only about 2/3 iteration steps as compared to the two other approaches.



(a) (b)

Fig. 1: (a) reference image, (b) template image



(a) (b)

(c) (d)

Fig. 2: difference between the reference and (a) the template image, (b) the result of the plain elastic registration, (c) the result of the segistration with coupling term (5) (d) the result of segistration with with coupling term (6)

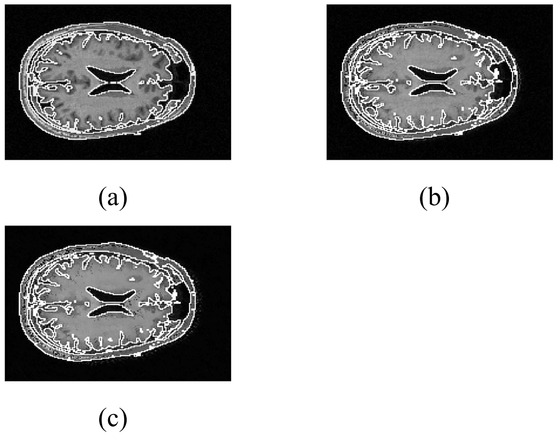


Fig. 3: segmentation of the reference image (a) without coupling, (b) with coupling and distance measure (5), (c) with coupling and distance measure (6)

IV. Conclusions

We introduced a novel communication or coupling term for a joint registration and segmentation scheme. It has been shown that this term is not only computationally very attractive but also produces very favorable results. Currently, we are implementing this promising approach in conjunction with the early diagnosis of Alzheimers disease and thereby testing its robustness. First results are very encouraging.

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