Registration of intramodal medical images using a novel s-distance approach

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Abstract. In this paper a new fully automatic method for registration of intramodal medical data is proposed. The method combines edge detection at different thresholds with chamfer distance transformation. The result is a distance map which is weighted by the importance of the edges which are extracted. As an alternative to the user-dependent non-automatic registration methods this approach offers a good assessment of similarity in the intramodality case. The elimination of the less significant features in the registration process has resulted in a greatly improved efficiency over the voxel-based methods.

Keywords: registration, similarity measure, s-distance, chamfer distance, cross-metric, intramodal data.

1 Introduction

New developments in tomographic scanner technology has led to an explosive growth in availability of volumetric medical data. For diagnostic and therapeutic purposes different imaging modalities are applied to the same patient. The importance of correlation and integration of such volumetric information is becoming increasingly recognized in the medicine. A number of different registration techniques has been developed in the past. To make the registration feasible, most authors proposed methods that rely either on user interaction or a priori knowledge. The most representative class of the non-automatic methods which are based on the intrinsic features is the surface-based matching [1]. The second class of the automatic methods represents the voxel-based matching. Such techniques derive their registration on the basis of voxel grey-value correspondence alone and rely mostly on the scatter-plot histogram [2]. These two approaches represent extremes of behaviour. The algorithm based on the scatter-plot histogram works in the feature (distribution) space and does not validate what occurs in the data domain. The surface matching assesses the similarity in the Euclidean image space. In this work we are pursuing the investigation of cross metrics approach which measures similarity in both the distribution and image spaces.

2 The registration method

The defining of anatomically relevant object's surfaces in the volumetric data sets demands user's involvement. Thresholding is the simplest segmentation method capable of providing the corresponding features, but the threshold level can vary from study to study even for the same patient. If the selected threshold is too high, then the significant boundaries may not be computed. On the other hand, if the threshold is set too low, then a large number of meaningless features is produced. Hence we need a method that will differentiate between less and more meaningful features (strong and weak surfaces) and be invariant with respect to the imaging conditions. In this paper we describe a new fully automatic method for registration of intramodal medical data. The method provides a new distance measure which takes into account not only the feature's location but also its strength - we call it s-distance (distance to the *strongest* surface).
We assume, that an *object* volume is geometrically transformed in the registration process to fit a *reference* volume. The rigid transformation $\mathcal{T} : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ which aligns the *object* with the *reference* is parameterized by the parameter vector $v = (r_x, r_y, r_z, t_x, t_y, t_z) \in \mathbb{R}^6$ and denoted by $\mathcal{T}_v$. From mathematical point of view we consider problem of the form:

$$v_{opt} = arg\ min\ \{\ C(v) \mid v \in \mathcal{M}\ \} \tag{1}$$

where $C : \mathbb{R}^6 \rightarrow \mathbb{R}$ is a continuous real-valued function which assigns a quality of match value to the transformation $\mathcal{T}_v$, $\mathcal{M} \subset \mathbb{R}^6$ and $\mathcal{M}$ is a six-dimensional interval $\mathcal{M} = \{v \in \mathbb{R}^6 : r_{xmin} \leq r_x \leq r_{xmax}, \ldots, t_{zmin} \leq t_z \leq t_{zmax}\}$.
In the preprocessing phase the method consists of two stages: generation of the s-distance volume for the *reference* volume, and extraction of the strongest surfaces in the *object* volume. A gradient operator is applied initially to both data sets. In the first stage the gradient magnitude volume is binarized using decreasing threshold levels - at each level the chamfer distance operator is applied. The sum of all chamfer distances from each threshold level produces the s-distance volume. Figure 1 (*left*) illustrates the concept of the threshold decrementing for the *reference* gradient volume. The associated s-distance volumes at each iteration step are shown in Fig. 1 (*right*). Since the voxels with small gradient magnitudes (weak surfaces) are not relevant to the feature discrimination process, we can stop it before the smallest threshold level is achieved (the last 2-3 iterations are not performed). Thus, the s-distance volume contains in each point the weighted distance to the nearest strongest surface. The weight depends on the statistical significance of the neighborhood points in the iteration process. In the second stage, voxels which belong to the upper 70% of the gradient magnitude grey-values only are accepted as *object* features. The resulting volume contains the most significant voxels only. The cost function is defined in the following way:

$$C(v) = \sum_{i=1}^{N} \frac{g_R(\mathcal{T}_v(\mathbf{p}_i)) \cdot g_O(\mathbf{p}_i)}{h(g_O(\mathbf{p}_i))} \tag{2}$$

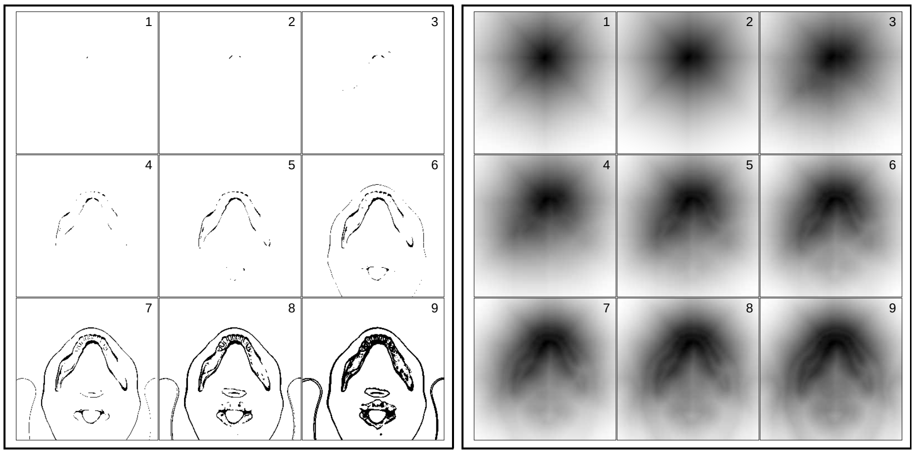

Fig. 1. Successive threshold levels during the s-distance iteration (*left*) and successive iteration steps of the s-distance computation (*right*).

where $g_O(\mathbf{p})$ is a grey-value of the *object* gradient volume voxel $\mathbf{p}$, $g_R(\mathcal{T}_v(\mathbf{p}))$ is a grey-value of the s-distance volume voxel at the position $\mathcal{T}_v(\mathbf{p})$, and $h(g_O(\mathbf{p}_i))$ is the histogram value for $g_O(\mathbf{p}_i)$. N is the number of *object* voxels in the gradient volume. Weighting of the product term, based on the relative statistical quality of the *object* feature is much more constraining than using only the product term alone. Several general observations about the s-distance method can be made. First, the s-distance in contrast to the chamfer distance takes into account not only feature locations but also their magnitudes. Thus, the influence of weak features on the chamfer distance value is significantly reduced in the s-distance approach. By reducing this negative influence on the quality of the extracted features and by weighting the feature's role in the evaluation of the cost function, based on its relative statistical or spatial significance, the presented approach provides important registration gains over the surface-based and voxel-based methods.

3 Results and discussion

We have found in our experimental analysis [3] that the accuracy of registration using s-distance approach was comparable to that of mutual information matching (see Tab. 1). Moreover, automatically extracting the necessary feature information and using a new distance measure to estimate the optimal matching transformation have resulted in a superior performance features over the surface-based and voxel-based methods (in the intramodality case). When only voxels with the largest gradient magnitude are accepted as object features, the amount of the data effectively processed is much smaller than the original *object* data. In Tab. 2 the scale of the *object* size reduction for different data sets is presented. This results in a large speed-up compared to other voxel-based regis-

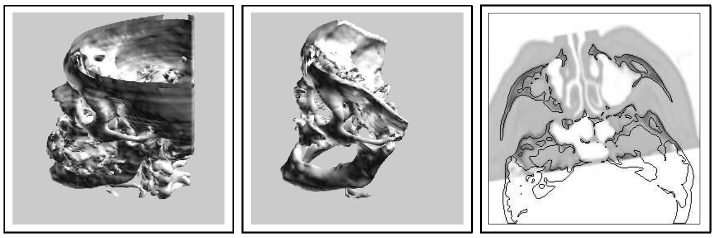

Fig. 2. CT–CT test data registered using s-distance approach.

tration algorithms e.g. cross-correlation, information entropy and mutual information. Shown in Tab. 3 run times for the new method and different voxel-based registration methods show that on average the algorithm based on the s-distance reduced the registration time by a factor of three over the cross-correlation and the scatter-plot based methods. To obtain numerically a solution of the optimization problem (1) we have applied a simulated annealing algorithm [4] which belongs to the class of non-deterministic optimization methods. In contrast to the deterministic algorithms deteriorations of the objective function can also be accepted. This allows to avoid being trapped in local minima. In Fig. 2 there is presented a CT–CT data pair registered using s-distance approach.

It has been observed that cost functions based on the magnitude of gradient as the feature are very susceptible to the presence of high magnitude values near the volume boundary. The small changes in the values of the parameter vector decide about presence or absence of these strong features in the intersection volume. It can lead to a global minimum which is anatomically incorrect. Another aspect of working with real-world data sets is the presence of imaging artifacts. Since the s-distance based method as well as many other registration techniques rely on the use of the gradient operator, the artifacts which cause sharp grey-value variations will affect the results.

4 Conclusions

In the presented new registration method for monomodality data, the size of the *object* is reduced as dramatically as in the surface similarity approach. The advantage over the surface similarity method is that the feature points are extracted automatically. Utilizing the most significant features only results in a significant

Table 1. Difference between v_{opt} estimated by s-distance and mutual information.

Data sets	r_x [°]	r_y [°]	r_z [°]	t_x $[mm]$	t_y $[mm]$	t_z $[mm]$
MR (feet)	0.482	0.426	0.368	-1.650	0.039	-0.698
MR (knee)	2.025	-0.414	1.308	-0.536	0.438	-1.644
MR (head)	-0.042	0.303	-0.080	0.139	2.300	0.845
CT (head)	1.577	-0.011	-0.289	0.471	-0.970	2.321

Table 2. Object size after reduction of the gradient data set to voxels belonging to the higher 70 % of the grey-values spectrum.

Modality	*Matrix resolution*	*Data size*	*Object size*	*Reduction to*
MR (feet)	128×128×128	4096 KB	87 KB	2.1 %
MR (knee)	256×256×64	8192 KB	115 KB	1.4 %
MR (head)	256×256×29	3712 KB	191 KB	5.1 %
CT (head)	512×512×80	40 MB	285 KB	0.7 %

Table 3. Sample running times for 100 cost function evaluations (in CPU seconds) for different data set pairs and different cost functions.

Cost function	MR–MR (feet)	CT–CT (head)	MR–MR $(\text{head})_{128\times128}$
Mutual information	699	1078	155
Information entropy	675	1077	150
Cross-correlation	694	1093	151
s-*distance*	189	297	41

reduction of run time and memory requirements compared with the voxel-based methods. We found that the accuracy of the s-distance based registration for the test data sets is comparable with the *mutual information* accuracy. This issue, however, will require further exploration and evaluation. The new method is susceptible to the presence of high magnitude values near the volume boundary. Some imaging artifacts will also affect the results.

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