registration, similarity measure, s-distance, cross-metric, intramodality data, search space topography

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AUTOMATIC ALIGNMENT OF INTRAMODAL TOMOGRAPHIC DATA USING S-DISTANCE APPROACH

The alignment of volumetric datasets is an important problem in the processing of medical data. It is a prerequisite to numerous image based applications in diagnostic and therapeutic routines. In this paper, a new method is proposed for matching of 3D intramodality medical images. Our approach is based on some generalization of feature distance definition. Analogous to the standard surface matching, our algorithm uses also the chamfer distance like metric to define the quality of match function, however, the evaluation of the distance map is performed in a different way. The s-distance method is a step towards an automatic extraction of features, where each feature's role in the registration process is weighted based on its relative statistical or spatial significance. 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 less significant features in the registration process has resulted in a greatly improved efficiency over the voxel-based methods. Studying certain properties of the search space topography provides some insights into the performance of the proposed method as well as the standard registration algorithms in the rigid body registration problem.

1. INTRODUCTION

Advances in medical imaging instrumentation and computer technology have opened more possibilities and made more visual information available to physicians than ever before. These developments have dramatically improved medical diagnostics and treatment. The demand for automatic processing and analysis of medical images is continuously increasing. Over the last two decades substantial progress has been made concerning the mathematical and numerical treatment of these issues. Registration constitutes one of the research mainstreams in the area of medical data processing and is essential for many diagnostic and therapeutic procedures in the modern medicine. Generally, matching algorithms have a powerful range of applications covering apart from medicine such areas as computer vision, satellite imagery, data mining or genetics. A number of different registration techniques has been developed in the past. They can be categorized taking into account different criteria [1]. To make the registration feasible, most authors proposed methods that rely either on user interaction or a priori knowledge. The automatic techniques derive their registration automatically on the basis of voxel grey-value correspondence alone. The most representative class of the non-automatic methods is the surface-based matching [2] and the second class of the automatic methods represents the voxel-based matching [3], where dominant algorithms rely on the

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scatter-plot histogram [4,5]. In our research we are pursuing the investigation of alternatives to the user-dependent non-automatic registration algorithms. In this paper a new automatic registration method is introduced. Based on the specification and analysis of different similarity measures [6], major inspiring elements for the design of this method are presented. This section also includes a formal statement of the optimization problem. The Section 3 introduces details of the new method developed in this work. The next section describes several experimental results which demonstrate that the new method is a very effective registration technique for intramodality data sets. Certain properties of the search space topography are also discussed. Finally, some limitations of the method are outlined. Section 4 concludes by summarizing the results of this work.

2. METHODOLOGY

For the registration algorithms the difficulty arises in finding a relationship between two 3D data sets acquired from the same subject. There is a number of registration techniques making use of the operator's anatomical knowledge. In such approaches the crucial point of the method is the interactive segmentation of the homologous points, surfaces or volumes in both data sets. The matching transformation is then sought taking into account the segmented corresponding objects. Such user guided segmentation process can be interpreted as some kind of voxel's grey-value transformation. Assigning new grey-values to all voxels in both data sets results in two single-modality data volumes. Though these two new data sets contain information in a binary form only, for many medical applications it is sufficient to achieve good estimation of the matching transformation. The majority of the anatomical features can be more easily recognized by their boundaries than by their interior grey-values. Thus an automatic feature extraction procedure should provide us with an adequate identification and description of coherent tissue boundaries. Identified features should reflect and enhance the similarity between the two volumetric data. Because in the volumetric medical data there are no explicitly defined surfaces, the traditional method applies a three-dimensional gradient operator to the volume data to estimate strength and orientation of present surfaces. Another approach could be for example the use of the Laplace operator. Experiments[6,7] with various intramodality and intermodality data pairs showed, however, that the using of the gradient-to-gradient matching criterion produces consistently better results than other operator configurations. As in the case of the user guided segmentation, where the original grey-value data have been transformed into the binary volumes, the goal of applying the gradient or other operators is to enhance the similarity between both data sets. We transform the grey-values of both volumes into a common grey-value representation and estimate the optimal alignment by means of the cross-correlation measure. In fact, the majority of the voxel-based cost functions has a good assessment of similarity in the intramodality case[6]. Such intermediate representations should maximally emphasize common features in the two data sets. The defining of anatomically relevant object's surfaces in the gradient volumes 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 of the gradient magnitude 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. In situations where the noise is substantial, poor local gradient measures can drive the registration process to undesirable results. 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. Below, a new method is proposed that provides an automatic way of extracting image features and which works more efficiently with respect to the memory requirements and computation time than the voxel-based registration techniques.

2.1. FORMULATION OF THE OPTIMIZATION PROBLEM

Intra- and intermodal registration of 3D medical data from different studies of the same subject can be considered as an optimization problem where the objective is to minimize a misregistration function, or alternatively, to maximize a similarity function between some features of the two data sets. In the surface-similarity approach the feature space is a set of surface points (voxels) whose extraction is done in a segmentation step. In the voxel-similarity approach, the feature space is composed of all voxels with corresponding grey-values. Let us define a *model* as a finite set of features in the first data set and an *object* as a finite set of features in the second one. We assume, that the *object* is rigidly transformed in the registration process to fit the *model*. Expressing the three-dimensional transformation T as a sequence of 3 rotations and 3 translations let us define a 4x4 homogenous coordinate transformation matrix M parameterized by a 6-components vector $v = [r_x, r_y, r_z, t_x, t_y, t_z]$, where, $r_x\ r_y, r_z$, and t_x, t_y, t_z are rotations around and translations along each of the three principal coordinate axes accordingly. In the registration process the transformation T maps every feature location in the object data to another location in the *model* volume. A transformation defined by the matrix M and the parameter vector v we denote by T_v. Our objective function we will define in such way that favourable properties decrease its value. Finally we can consider an optimization problem formulated as follows:

$$v_{opt} = \arg\min\left\{ C(v) \,\middle|\, v \in M \right\} \tag{1}$$

where $C(v)$ is a continuous real-valued objective function, which assigns a quality of match value to the transformation T_v and $M \subset \Re^6$ is a set of permissible parameter vectors, which satisfy some constraints.

3. THE REGISTRATION METHOD

A new distance measure is proposed which takes into account not only the feature's location but also its strength. We will call it s-distance (distance to the *strongest* surface). In the preprocessing phase the method consists of two stages. In the first one a new distance volume for the *model* data set is computed. This volume will be called the s-distance volume. The following procedure is used to generate the s-distance volume:

1. Median filtering of *model* data is initially performed to reduce the data noise.
2. The gradient operator is applied to the smoothed *model* volume. Magnitudes of the gradient vector are used to produce a companion volume to the original data. We will call this volume simply a gradient volume.

3. The gradient volume is binarized using decreasing threshold levels. At each level the chamfer distance operator[8] is applied to the actual binary gradient volume. The sum of all distance volumes from each threshold level produces the s-distance volume.

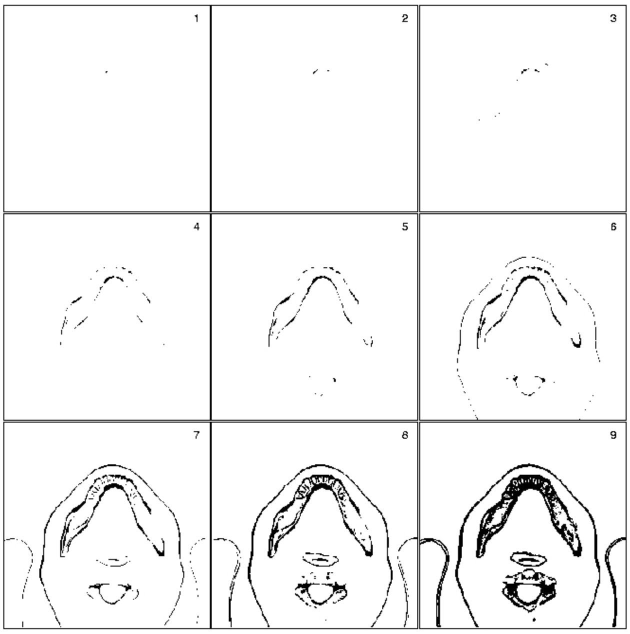

Fig.1: Successive threshold levels during the s-distance iteration.

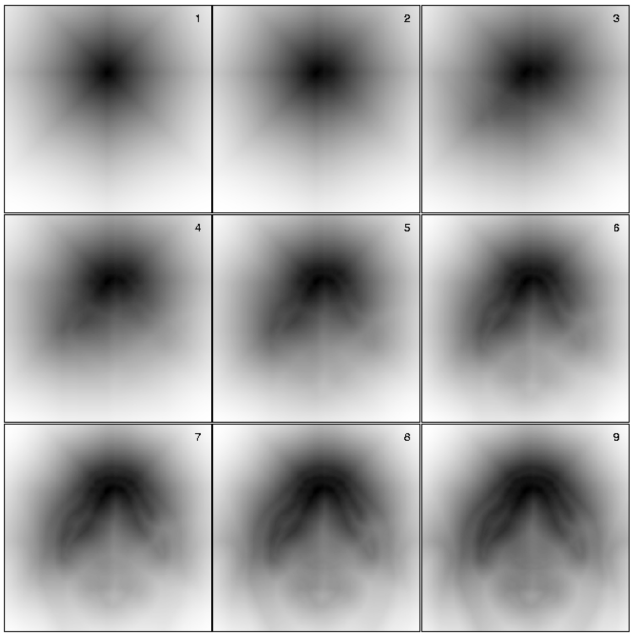

Fig.2: Successive iteration steps of the s-distance computation.

Figure 2 illustrates the concept of the threshold decrementing for the gradient volume. The importance of the feature voxel depends on the magnitude of the gradient vector at the voxel location. The associated s-distance volumes at each iteration step are shown in Figure 2. 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.

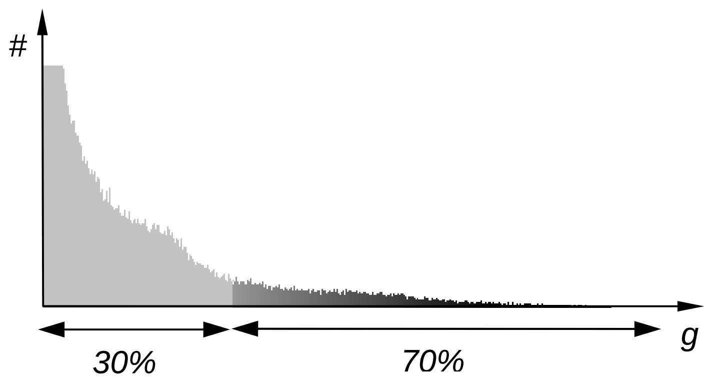

Fig.3: Histogram of the gradient data.

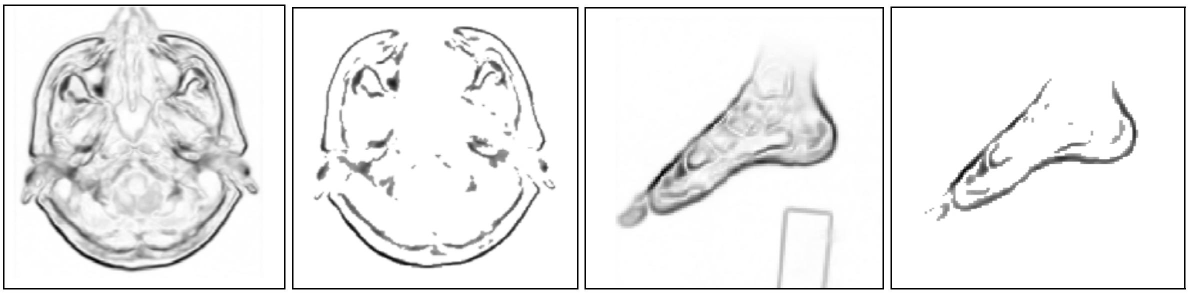

Fig.4: Magnitude of the gradient (left) and 70% of the highest grey-values (right) in each pair of images.

The second part of the preprocessing stage is the extraction of the strongest surfaces in the object gradient volume. This is done by accepting as features only such voxels which belong to the upper 70 % of the gradient magnitude grey-values. We eliminate points with small responses of the 3D gradient operator (see Figure 3). The voxels belonging to the lowest 30 % of the grey-values are ignored. The resulting volume contains as features the most significant voxels only. In Figure 4 (in each pair of images) are shown cross-sections of different gradient volumes and feature volumes extracted using this procedure. The cost function is defined in the following way:

$$C(v) = \sum_{i=1}^{N} \frac{g_R(T_v(\mathbf{p}_i)) \cdot g_O(\mathbf{p}_i)}{h(g_O(\mathbf{p}_i))} \qquad (2)$$

where $g_O(\mathbf{p}_i)$ is a grey-value of the object gradient volume voxel $\mathbf{p}$, $g_R(T_v(\mathbf{p}))$ is a grey-value of the s-distance volume voxel at the position $T_v(\mathbf{p})$, 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 (there is a small number of strong surface features and a large number of voxels with small magnitude) is much more constraining than using only the product term alone. Several general observations about the s-distance can be made. First, the s-distance in contrast to the chamfer distance takes into account not only feature locations but also their magnitudes. Figure 5 shows a grey-value profile of a line in the chamfer distance volume. The line position is depicted in the Fig. 1-8. The chamfer distance volume has been computed for the threshold level showed in Figure 1-8. The grey-value profile of the corresponding line from the s-distance volume is shown in Figure 6. The dotted lines in both figures (Figures 5 and 6) denote the segmented object and the grey-value profile of the gradient volume respectively.

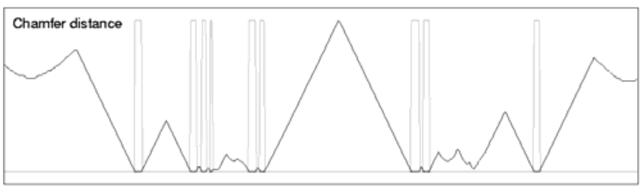

Fig.5: Chamfer distance of the segmented CT data.

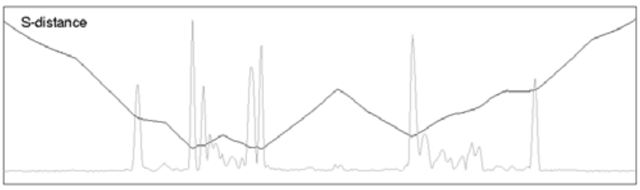

Fig.6: S-distance of the CT-gradient data.

Comparing these two figures, we can see that the influence of weak features on the chamfer distance landscape is significantly reduced in the s-distance approach. By reducing the noise 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 strength in the gradient volume the presented approach provides in the intramodality case important registration gains over the surface-based and voxel-based methods.

4. RESULTS AND DISCUSSION

Automatically extracting the necessary feature information in both data sets 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 Table 1 the scale of the object size reduction for different data sets is presented.

Tab.1: 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*
MRI (feet)	128×128×128	4096 KB	87 KB	2.1 %
MRI (knee)	256×256×64	8192 KB	115 KB	1.4 %
MRI (head)	256×256×29	3712 KB	191 KB	5.1 %
CT (head)	512×512×80	40 MB	285 KB	0.7 %

This results in a large speed-up compared to all of the tested voxel-based registration algorithms. Shown in Table 2 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.

Tab.2: Sample running times for 100 cost function evaluations (in CPU seconds) for different data set pairs and different cost functions.

Cost function	MRI-MRI (feet)	CT-CT (head)	MRI-MRI (head) (128×128)
Mutual information	699	1078	155
Information entropy	675	1077	150
Cross-correlation	694	1093	151
s-distance	189	297	41

To obtain numerically a solution of the optimization problem (1) we have applied a simulated annealing algorithm [9] 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.

We will use a notion of topography to produce a simplified view of some aspects of the cost function behavior in the search space. The 2D misregistration graphs [6] will help us to imagine the topography of the search space in the rigid-body case (6 degrees of freedom). The graph is computed for each pair of the principal axes. In the 6D case we have 15 different graphs. In this work special attention was given to the methodological aspects of the registration process, topography of the search space and efficiency in the similarity assessment. The following criteria were taken into account in the evaluation of the search space topography: size of the catchment basin, peak of correlation and roughness of the landscape surface.

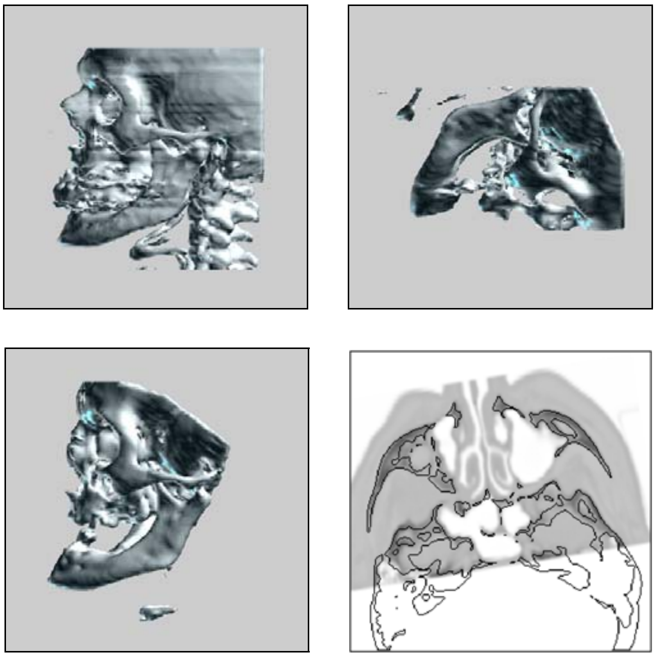

Fig.7: CT-CT test data before (top) and after registration (bottom).

In Figure 7 there is presented the CT-CT data pair before (top) and after registration (bottom). In Figure 8 are presented three 2D misregistration graphs for this pair of data. Comparing the landscapes of the cost function based on the s-distance with the corresponding surface similarity landscapes (see Fig. 9), it is easy to see that the new similarity measure preserves the favorable property of the surface similarity: the large basin of catchment. The correlation peak is sharper than the peaks in the surface misregistration landscapes. Such properties of the search space topography result in very good convergence properties even on large feasible sets. 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. This influences negatively the ability of the s-distance based cost function to recognize a global optimum properly. The situation where the strong, significant features are pushed out of the intersection volume 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.

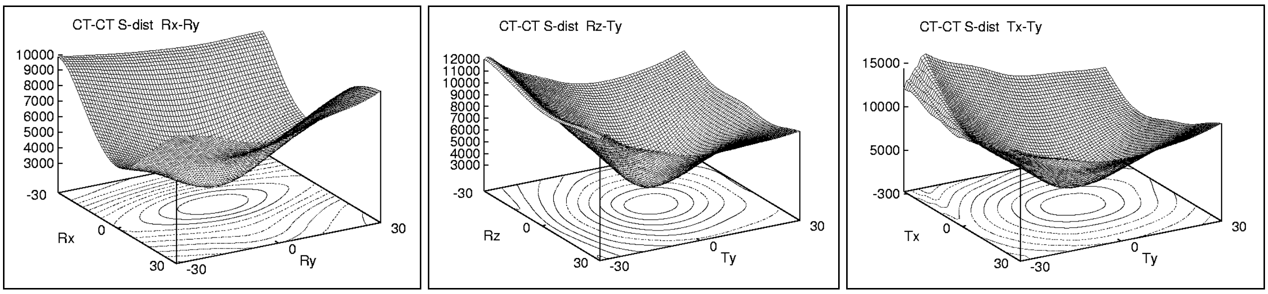

Fig.8: 2D misregistration graphs : s-distance of the CT-CT test data.

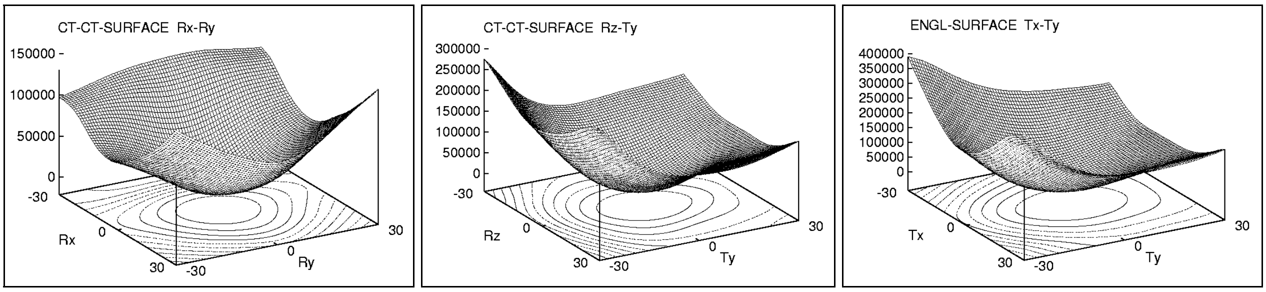

Fig.9: 2D misregistration graphs : surface misregistration of CT-CT test data.

These unwanted features may arise from various sources. They can cause significant problems in the registration process. 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.

5. CONCLUSIONS

Despite many years of research in the imaging and pattern recognition areas, segmentation of tissues and differentiation of objects in tomographic data sets are still very difficult tasks. The principal difficulty for the segmentation lies in the very nature of the medical data. The grey-value representation of anatomical objects in the tomographical data is highly differentiated. The user guided feature extraction procedure performed individually on two data sets delivers homologous features which dramatically enhance the similarity between them. This similarity includes coherence of the feature's shape as well as grey-value conformance. The main limitation of such methods is that they require an expert observer to identify corresponding features. In the presented new registration method for intramodality 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 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.

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