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Automatic Transfer of Pre-Operation fMRI Markers Into Intra-Operation MR-Images for Updating Functional Neuronavigation

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Abstract

Functional magnetic resonance tomography (fMRI) is used to identify eloquent areas of the brain. In combination with a 3-D anatomical MR dataset this leads to a functional neuronavigation system. During the operation brain shifts result in an increasing inaccuracy. To preserve the advantages of functional neuronavigation for the surgeon, it is necessary to save the functional information. Since fMRI cannot be repeated with unconscious patients this task has to be fulfilled by means of image processing and pattern recognition algorithms.

In this paper we present an automatic approach for transfering preoperative markers into an intraoperative 3-D dataset. In the first step the brains are segmented in both image sets which are then registered and aligned. Next, corresponding points are determined. These points are then used to determine the position of the markers by estimating the local influence of brain shift.

1 Motivation

MR images are used for planning the procedure of the surgery before the operation as well as guiding the surgeon during the operation takes place. For this, data from fMRI-measurements are integrated into the 3-D anatomical MR dataset for neuronavigation, leading to functional neuronavigation [1], allowing an identification of eloquent brain areas. During the operation brain shift results in an increasing inaccuracy of neuronavigation, which may cause a false identification of eloquent brain areas. Intraoperative MRI can be used to update neuronavigation, thus compensating brain shift. But the fMRI information is lost because this examination can not be repeated with unconscious patients.

The goal of this project is to preserve this functional information for the intraoperative update of the neuronavigation system by automatically transfering the functional markers into the intraoperative image dataset.

While common approaches for compensating brain shift phenomena often perform an elastic registration of the entire 3-D image and often do not even need a segmentation [2, 3], we present a new approach which does not solve the brain shift problem for the entire 3-D image but for interesting local volumes only. This approach is not only fast but it is also sufficient for saving additional functional information by transfering those fMRI-markers from a preoperative dataset into an intraoperative dataset [4, 5].

In the next section the segmentation of the dataset is described. The result of this step is the identification of anatomical areas like the brain and the eyes. Section 3 describes the registration of the two datasets. In Section 4 the process of transfering the markers is described in detail.

2 Segmentation of the Dataset

The very first segmentation step is the detection of the position of markers in the preoperative dataset. Since all markers are represented by a typical grey value, this can be done by applying a simple thresholding algorithm. A very important part for the estimation of the positions of fMRI-markers in the intraoperative dataset is concerned with the registration of both datasets. A reliable calculation of the new positions is feasible only, if it is possible to register both datasets. For determining the translation and rotation parameters a double stage approach has been developed. In the first step an initial registration is obtained by using the positions of the eyes. The registration is then refined by minimizing the distance of the surfaces of the segmented brains. For this optimization is necessary to first segment the eyes and the surface of the brain.

For segmenting those meaningful anatomical areas a volume growing algorithm is applied to the datasets. Starting from a number of seed points all neighboring image pixels are iteratively merged to

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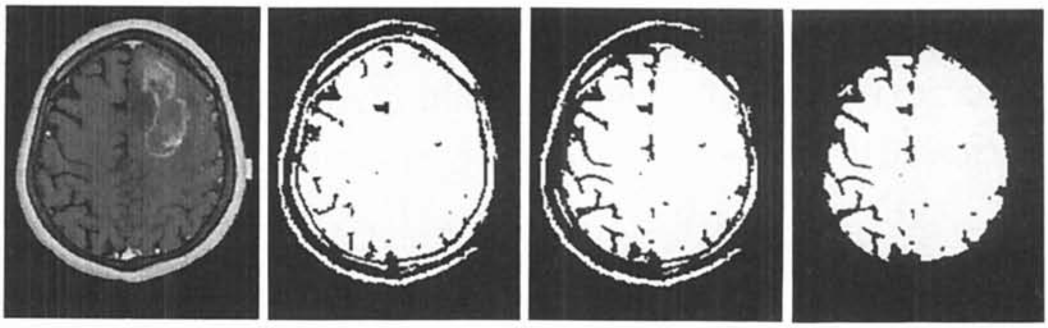

Figure 1: Segmentation of the brain: Original image, initial segmentation, after refining the volume borders, final result after removing surrounding bones

a seed point/volume by evaluating a measure of homogeneity.

Determination of Seed Points: Since the mean grey value of a volume is very important for the correct and regular growing of a volume and volumes are not splitted in this step, the choice of suited seed points is indispensable. Therefore, points $\boldsymbol{x}$ are searched which grey values $f(\boldsymbol{x})$ is similar to the surrounding grey values. This means, the gradient $H(\boldsymbol{x})$ has to be small.

$$H(\boldsymbol{x}) = \frac{1}{44} \sum_{\nu=1}^{8} D(\boldsymbol{x}, \boldsymbol{n}_\nu) + 2 \sum_{\nu=9}^{26} D(\boldsymbol{x}, \boldsymbol{n}_\nu)$$

For the calculation all 26 direct neighbors $\boldsymbol{n}_\nu$ are considered. For each neighbor the difference of the grey values $D(\boldsymbol{x}, \boldsymbol{n}_\nu) := |f(\boldsymbol{x}) - f(\boldsymbol{n})|$ is computed. Corners, $\boldsymbol{n}_1, \ldots, \boldsymbol{n}_8$, are weighted with a factor of 1 while all other neighbors are weighted with a factor of 2.

In the following all points $\boldsymbol{x}$ with a very small value for $H(\boldsymbol{x})$ are used as seed points. Since a lot of possible seed points exist in homogeneous areas a growing phase is always initiated directly after a seed point has been selected.

Volume Growing: During the growing phase all pixels that do not belong to a volume are merged with the neighboring volume where the difference of the mean grey value of the volume and the grey value of the pixel is minimal. If this assignment is ambiguous the difference to the grey value of the adjacent pixels is considered too.

2.1 Detection of Meaningful Anatomical Areas

For segmenting the eyes and the brain the segmentation step is carried out with different thresholds. For the segmentation of the brain it is necessary to choose seed points with a very small value for $H(\boldsymbol{x})$ while the segmentation of the eyes can be carried out with higher values. This yields to approximately 8000 seed points in the first case and approximately 3000 seed points in the latter one. In the growing phase the number of resulting volumes is determined by the number of seed points, since only points are merged to volumes. In the next step these volumes are merged to bigger volumes by evaluating the shape, the size and the mean grey value of adjacent volumes. In a refinement step the edges of the segmented volume are corrected and the surrounding skull is removed. A result of the segmentation step is given in Figure 1.

3 Registration of the 3D-Images

For the identification of corresponding areas the two brain volumes have to be registered. This is also done in two steps.

Initial Registration: In the first step the centers of gravity of the eyes are being aligned. For this purpose, the translation and rotation vector are determined in such a way that the lines which connect both centers of gravity are lying on top of each other.

Refinement: For a complete registration of the brains there is still an angle missing: the rotation around the axis of centers of gravity of the eyes.

This is done by minimizing the following measure. For both halves of the brain the rotational angle is determined which minimizes the difference between the surfaces of the entire brain in both datasets. One angle minimizes the difference for the left half, the other one for the right half of the brain. The angle which measure is minimal is chosen as the last unknown parameter. Usually this is the angle of that half of the brain which is not or at least fewer damaged by a tumor.

Iterative Improvement In the last step of the registration only the translation parameters are changed. For improving the results, the intraoperative dataset is moved along the $x-$, $y-$ and $z-$axis between -10 and $+10$ pixels. For each possible position the difference between the surface of the preoperative dataset is calculated. The final registration is then given by those translation parameters which

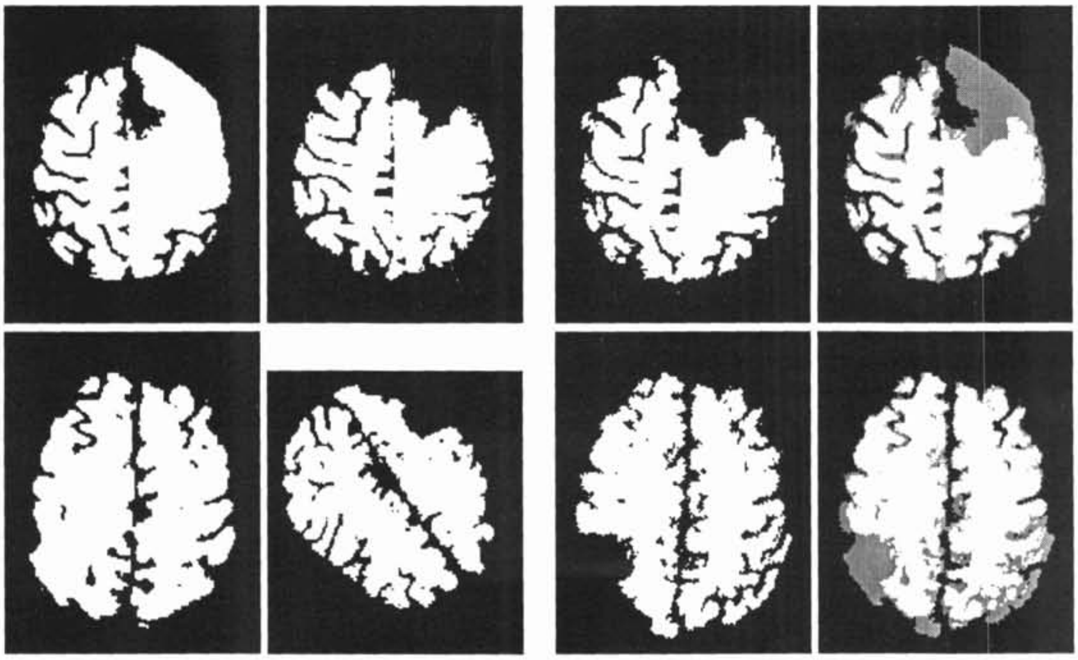

Figure 2: Result of the registration for 2 different patients: Slice number 20 of a dataset, unregistered (left pair), corresponding slice after registration and difference images (right pair)

minimize the distance. The conformity of the registration step is shown for two different examples in Figure 2.

Up to now, the two brains are registered where a special emphasis is given on a good correspondence of the surfaces.

4 Transfer of the Markers

Even for a skilled human it is not easy to identify corresponding areas in both brains. A good feature for identifying those areas is given by the brain furrows. The position and the width of the furrows might vary but the number of furrows is always the same. Therefore, the transfer of the markers is mainly based on the position of the brain furrows. In order to determine the marker position in the intraoperative dataset corresponding points are searched which fulfill the following conditions: (a)both points are located at the edge of a furrow (b) the geometrical properties (e.g. curvature, position) are identical.

Starting with these pairs of corresponding pixels further corresponding pixels are searched. This is achieved by tracing the course of the furrow. This means, for each marker in the preoperative dataset it is tried to move from the position of a start point one step towards the marker. Afterwards it is tried to repeat this movement in a similar direction in the intraoperative dataset too. The exact orientation of the movement is given by comparing all reachable points with the geometric properties of the given point from the preoperative dataset. This yields a new pair of corresponding pixels if the orientation does not differ too much. If the difference is too big or the end point of a furrow is reached the search terminates.

By following the furrow it is not only possible to move closer to the position of a marker but also to identify corresponding points which positions in the dataset are different. These are especially edge points of a furrow which position has changed during the operation.

The estimation of the position of the markers in the intraoperative dataset is carried out by considering these sets of corresponding points. But only the last point for each path along a furrow is considered because this point has the smallest distance to the marker in the preoperative dataset.

For each of these pairs in the preoperative and intraoperative dataset $(\boldsymbol{x}_p, \boldsymbol{x}_i)$ the position for the marker $\boldsymbol{m}_i$ in the intraoperative dataset is calculated by $\boldsymbol{m}_i = \boldsymbol{x}_i + (\boldsymbol{m}_p - \boldsymbol{x}_p)$. Where the position of the end point of a path in the preoperative dataset is characterized by $\boldsymbol{x}_p$, the position of the marker by $\boldsymbol{m}_p$ and the final point in the intraoperative dataset by $\boldsymbol{x}_i$. This means, the vector between the end point of a path and the position of a marker is added to the coordinates of the end point of a path in the intraoperative dataset.

Adding these vectors to each end point $\boldsymbol{x}_i$ one obtains a cluster of possible marker positions. The final position of the marker in the intraoperative dataset is estimated by summing up the coordinates of each point of a cluster and calculating the mean value for each cluster, where the coordinates of points which are closer to a marker in the preoperative dataset are weighted more than more distant points.

5 Results

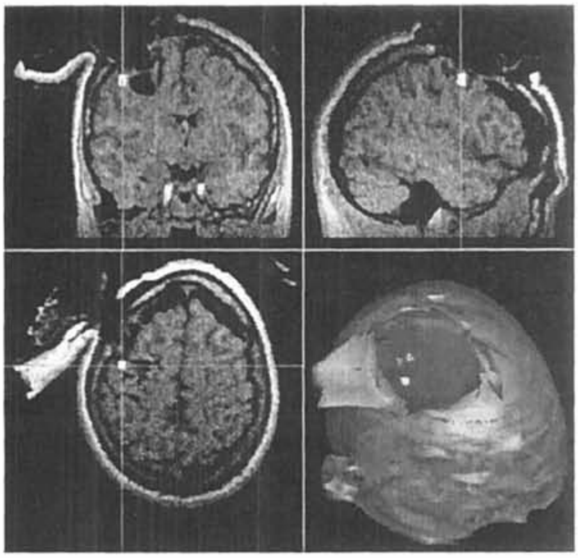

Figure 3: Graphical illustration of the estimated marker position in the intraoperative dataset

The results of the estimated marker positions in the intraoperative dataset for two different patients are shown in Figure 4. The accuracy achieved was judged very high from an expert. The mean difference to manually placed markers was less than three pixels.

6 Conclusion

An approach for preserving the information of functional MR for intraoperative images has been presented. It was shown that it is feasible to automatically transfer markers from preoperative datasets into intraoperative datasets by means of image processing techniques.

The approach has been tested on four datasets. The accuracy achieved is about 3 pixels in comparison to a manual marker placement. The computation time is less than 10 minutes on a Pentium II (350 MHz).

It is planed to evaluate the approach with further datasets and to integrate the software into the neuronavigation system.

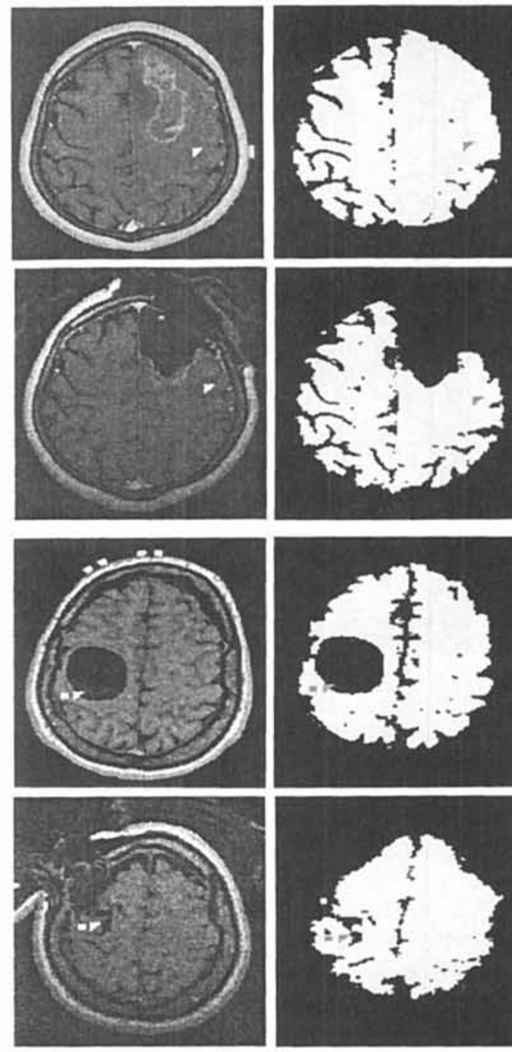

Figure 4: Estimated marker positions for two different datasets. First row: Slice from the preoperative dataset and segmented brain, second row: Corresponding slice from the intraoperative dataset and segmented brain with estimated marker positions. The marker positions are marked with geometrical figures.

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