# Registration of 3-D Multimodality Brain Images by Curve Matching

Hui Li, B. S. Manjunath, and Sanjit K. Mitra
Department of Electrical and Computer Engineering
University of California
Santa Barbara, CA 93106

**Abstract**

*The 3-D multimodality brain image registration algorithm proposed in this paper is based on the matching of feature curves which are defined by the intersections of the interhemispherical fissure plane (IFP) and the skull surface. The IFP is detected by a principal axes technique while the skull boundary in each scan is extracted by tracing the outermost closed contour. The feature curves are rotated to lie on 2-D planes which are parallel to each other so that the problem is reduced to a 2-D curve matching task. MRI-PET image registration result is presented.*

## 1 Introduction

The problem of 3-D image registration arises mainly in the field of medical image analysis [1]. The widespread application of computerized medical imaging devices enables the integration of information from multiple modalities, which is beginning to play an important role in neurological research, diagnosis and treatment [2]. Proper registration of multisensor data is a prerequisite for their synergetic usage. However in practice it is very difficult to scan the same plane of the patient using different sensors or when the images are acquired at different times.

Existing 3-D image matching methods broadly fall into two categories: those that make use of the external markers [3, 4] and those so-called retrospective methods that do not rely on any external markers. Methods in the later category can be further divided into manual-based methods and computer-based automatic methods. In manual registration, user interaction is needed to associate the corresponding anatomical landmarks [5, 6] which include landmarks on the skull surface and internal cerebral landmarks. The interhemispherical fissure plane that separates the left and right sides of the brain is used in an interactive registration system in [7]. By contrast computer-based semi-automatic/automatic methods tackle the problem by extracting and matching the common structures present in both the data sets. A widely used structure is the surface of the human skull [8, 9].

In this paper we propose an automatic method for registering MRI and PET scans of the human head. The proposed approach is based on the extraction and matching of the feature curves present in the 3-D data. Section 2 describes the proposed 3-D image registration scheme. Section 3 presents experimental results of MRI-PET image registration.

## 2 3-D Registration by Curve Matching

In order to aid description of our algorithms, a cartesian coordinate system is set up such that for normal brain scans the x-axis points in the opposite direction of the nose, the y-axis points in the direction of the right ear and the z-axis points to the top of the head. We make the following assumptions: (1) the voxel sizes of the multi-sensor images are known – thus the scaling factors along all three axes can be computed; (2) transmission PET scans are available so that the skull boundary can be detected, and (3) the tilt along the x-axis is small for the reasons explained below. Our overall strategy bears a resemblance to the manual registration method proposed in [7]. The main idea is to use the interhemispherical fissure plane (IFP) in both MRI and PET data sets as a landmark. When the human head is rotated along either the y-axis or the z-axis the symmetric property of the brain scans is preserved, so that the IFP can still be reliably detected. If the rotation along the x-axis is large, the brain scans are no longer symmetric with respect to the interhemispherical fissure. Consequently it will be difficult to extract IFP automatically. The feature curves are defined by the intersection of the

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IFP and the brain surface and are matched using a one-dimensional search method. As a result, the complexity of the matching problem is greatly reduced. A step-by-step outline of the algorithm is listed first, followed by more detailed description.

### The registration procedure

1. The skull boundaries are extracted from each of the image slices.
2. Two end points of the interhemispherical fissure along the skull boundaries are detected based on the symmetric nature of the human head.
3. The IFP is approximated by fitting a plane to the detected end points.
4. Two feature curves can be formed by connecting the intersections of the skull boundaries with the IFP.
5. The feature curves are rotated such that the IFP is orthogonal to the y-axis.
6. The feature curves from different data sets are normalized to the same scale based on the known voxel sizes, and are smoothed and resampled at equal intervals.
7. At this stage, feature curves from the two data sets are in parallel and can be matched by a 1-D exhaustive search method.
8. The 3-D transformation parameters are computed. One data set is transformed and resampled by trilinear interpolation to match with the other data set, or vice versa.

The important steps are now explained in the following sections. See [10] for more details.

**Skull boundary extraction** A method based on the Laplacian of Gaussian operator is adopted for contour extraction [10, 11, 12]. The outermost contour corresponding to the skull boundary is obtained by choosing the longest closed contour from the set of retained contours. The above method works well for most brain scans except for some of the scans at eye or ear levels where sharp discontinuities occur. An active contour model (ACM) [13] is employed to overcome this problem. The contour from the neighboring slice is used as the initial condition for the ACM algorithm so that no manual intervention is needed.

**IFP detection** The human head is symmetric with respect to the IFP. Under normal imaging conditions, the scans are taken at planes perpendicular to the IFP. Consequently the 2-D head scans are symmetric with respect to the two end points of the IFP. For each scan, these two end points can be detected by a principal axis technique. The orientation of the principal axis of a skull contour can be computed [10]. The intersections of the skull boundary and the straight line passing through the centroid of the closed contour with this orientation are the estimated end points of the IFP. The IFP is then approximated by fitting a plane in the least squares sense to the end points detected from all the image slices.

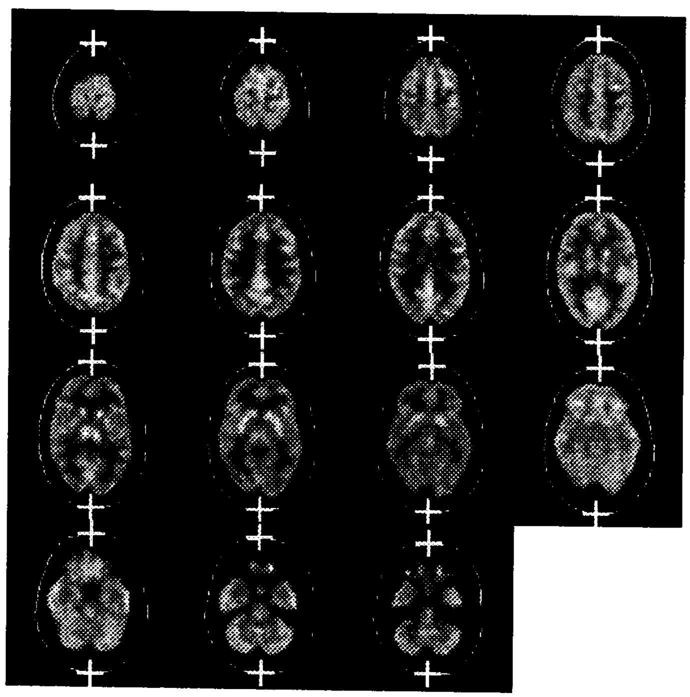
**Feature curve matching** Two feature curves are formed by connecting the intersections of the skull boundaries with the IFP. The 3-D curves obtained in this way in fact lie on their respective 2-D planes. The feature curves from different sensor data sets are then normalized to the same scale based on the known voxel sizes. A rotation matrix is computed that would transform the IFP to be orthogonal to the y-axis. This partial transformation is applied such that the feature curves from the MRI and PET data are parallel with each other. In order to remove staircase effects due to the lack of resolution in the z direction, a smoothing operation is applied to x and z coordinates of the feature curves (y coordinate is a constant now). The smoothed curves are then resampled at equal intervals. At this stage the two sets of feature curves are at the same scale, with the same sampling interval and on two different x-z planes. Now the matching of feature curves can be formulated as a traditional 2-D curve matching problem and is accomplished by a 1-D sequential search scheme [10].

The overall transformation parameters can be computed by combining several partial transformations [10]. Subsequently, the MRI data is transformed and resampled by trilinear interpolation to match with the PET data, or vice verse. The efficiency of the proposed approach is achieved by first reducing the 3-D volume matching problem to a 2-D curve matching problem, and then solving the 2-D matching problem using a 1-D sequential search method.

## 3 Experimental Results

The MRI data set consists of 50 slices of $256 \times 256$ images. The pixel size is $0.859 \times 0.859$ $mm^2$ and the plane separation is 3 $mm$. The PET data set consists

(a)



(b)

Figure 1: (a) 12 slices of a 50-slice MRI data set. (b) A 15-slice PET data set. In both figures the extracted skull boundaries are superimposed on the images, together with cross markers denoting the detected end points of the interhemispherical fissures.

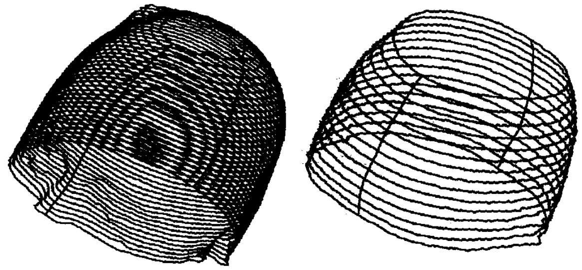


Figure 2: 3-D views of stacks of skull contours with the feature curves from MRI (left) and PET (right) data sets.

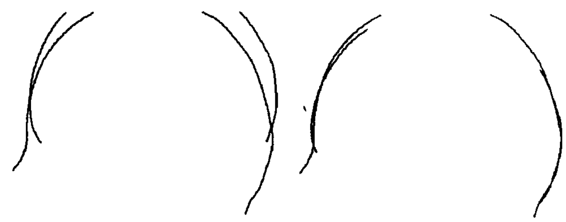


Figure 3: 2-D views of the feature curves before and after registration.

of 15 slices of 128 × 128 images. The pixel size is 1.74533 × 1.74533 $mm^2$ and the plane separation is 6.75 $mm$. Figure 1 (a) and (b) show 12 MRI scans and all 15 PET scans, with cross markers denoting the detected end points of the interhemispherical fissures. The skull contours from both data sets are stacked up and are displayed in 3-D views in Figure 2. Also shown in this figure are the feature curves which are defined by the intersection of the skull surface with the estimated IFPs. The 2-D views of the feature curves before and after 2-D matching are shown in Figure 3. The final registration result is shown in Figure 4 where 15 slices of the new images are generated from the MRI data set to match with the PET images. The general orientation and specific anatomical landmarks after the registration seem to be in good agreement.

## 4 Acknowledgments

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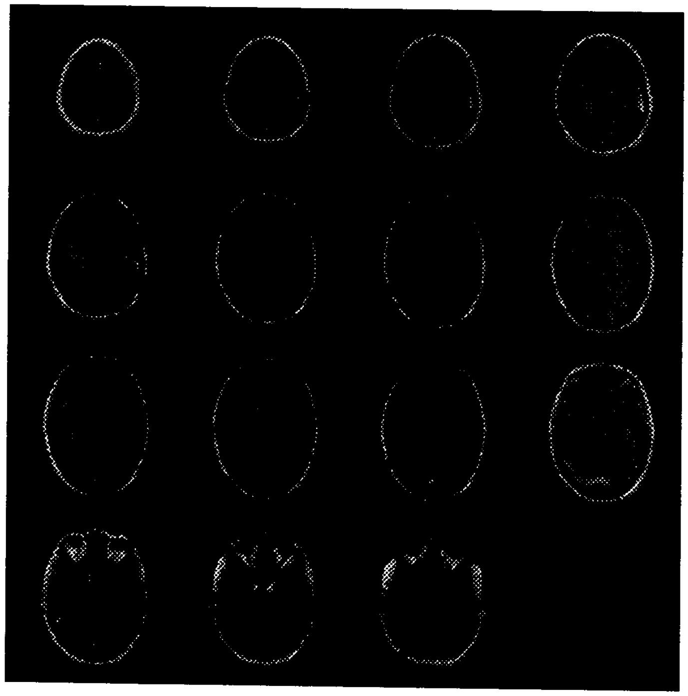
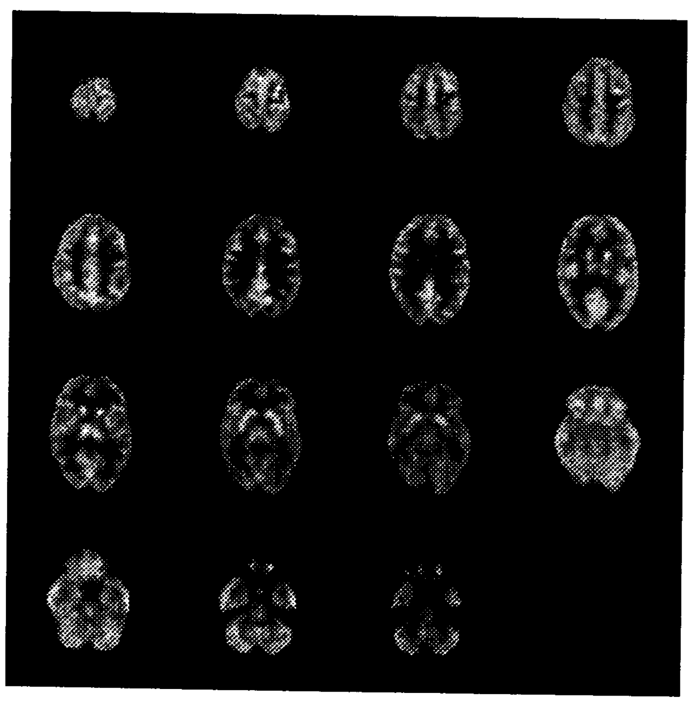


(a)



(b)

Figure 4: New images in (a) are generated by trilinear interpolation from MRI data set to match with the PET images in (b).