

Automatic fiducial localization in brain images

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Abstract. Point-based registration is one of the most popular registration methods in practice. During registration, we use external fiducial markers that are rigidly attached through the skin to the skull. Determining the coordinates of the fiducials without human selection is crucial for a fully automatic point-based image registration. In this paper, an image processing technique for automatic fiducial detection is presented. The technique, which is fast, automatic and accurate, has two major steps: Edge map construction and curvature-based object detection. Experimental results are promising compared to the manual selection by experts with no error for 56 CT images and 3% error for 66 MR images.

Keywords: Fiducial point detection, edge map construction, curve-based corner detection

1. Introduction

Many methods have been used to register medical images. Point-based registration is the most popular method in practice and used by many commercial navigation systems. Point-based registration involves the determination of the coordinates of corresponding points in different images (or physical space) and the estimation of the geometrical transformation using these corresponding points. The points may be either intrinsic or extrinsic. Intrinsic points are derived from naturally occurring features, *e.g.*, anatomic landmark points. Extrinsic points are derived from artificially applied markers, *e.g.*, tubes containing copper sulfate. The estimation of fiducial points' locations on brain images is important to perform a successful point-based registration. As we all know, manual selection is flawed and inefficient during the surgery. As a first step of registration, there is some research already done about automatic fiducial detection in the last few years. Matthew et al proposed an automatic technique for marker localization using an intensity based search and classification [1]. Their algorithm requires prior information on marker size and shape and could only be used for cylindrical markers. Tan *et al* [10] proposed a template-based technique based on shape information. Their technique is targeted for volumes. Lewis *et al* developed an ultrasound module based method for detection and location of subcutaneous fiducials, which involved additional hardware equipment [2]. Other techniques requiring additional hardware include articulated arms [3, 4], optical triangulation systems [5], and magnetic field digitizers [6]. In this paper we present a fiducial detection algorithm using intensity information in image space, which is fully automatic and avoids using additional hardware. The rest of this paper is organized as follows: in Section 2 we introduce our algorithm including ratio-based segmentation, ray-based outline search, corner detection and point clustering. The results are given in Section 3 followed by discussion in Section 4.

2. Methods

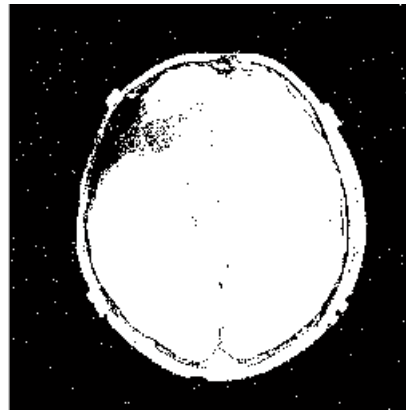
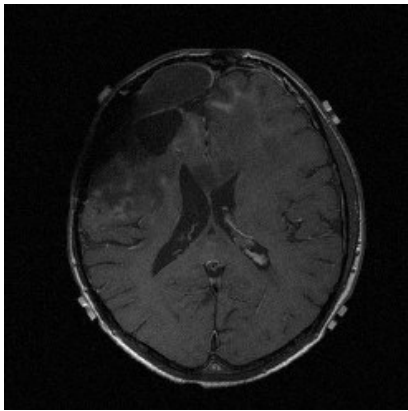
The two steps, edge detection and curvature based 2D object detection are discussed in detail in the following sections.

2.1 Edge Map Construction

As the first step, a ratio-based thresholding method [7] is used to segment the foreground object from background in the original images. At the optimum threshold, an obvious change of ratio between two region pixel numbers will occur. From the set of potential threshold values thus located, a subset of final threshold values can be automatically determined. The first thresholding value will be used for foreground/background segmentation. The steps for performing segmentation using the ratio curve are as follows:

- Compute the image histogram and smooth it using a Gaussian filter to suppress small intensity variations
- Obtain the ratio curve. Assume the pixels in an image be represented by L gray levels, $[1, 2, \dots, L]$, and let h_j denote the number of pixels with gray level j . Then the number of pixels at or below threshold is $N_1 = \sum_{j=1}^i h_j$, and those above the threshold is $N_2 = \sum_{j=i+1}^L h_j$. Therefore the ratio of the two numbers is $R = N_1/N_2$, and the ratio curve exhibits a variation of R .
- Compute the second derivative of ratio curve to obtain the normalized rate curve. The normalized rate curve is also smoothened to flatten small peaks and valleys. The locations of the resulting minima and maxima determine the candidate threshold values.

The segmented result on an example image is depicted in Fig.1



(a) Original Image

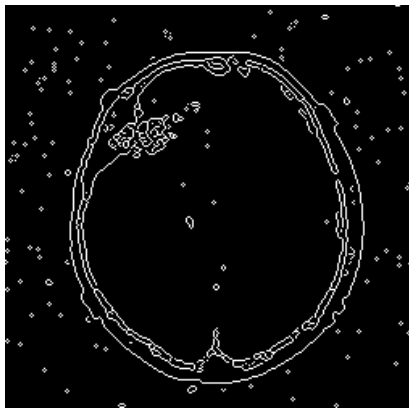
(b) Segmented Object

Figure 1: Foreground/background Segmentation

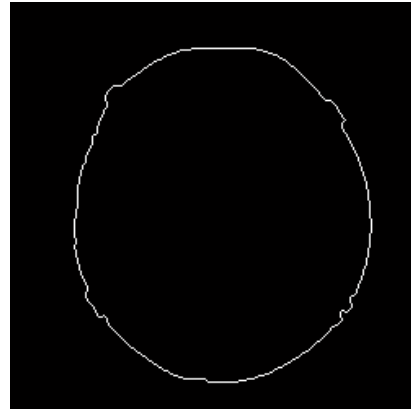
In the segmented foreground, we employ morphological recursive erosion, dilation and grayscale reconstruction techniques [8] to fuse small gaps and to eliminate

unwanted noises, often present in pathological images. Canny edge detection is used next to find edges [8]. (Figure 2.a)

Among the numerous detected edges, the outline of brain is selected by the following ray search procedure: 1) Rank the pixel number in each edge object and choose the top half as our candidates; 2) Set four rays from corners to the image centre; 3) The first edge to intersect any of the rays will be considered the outline of the brain. The Gaussian smoothing filter is applied before the procedure to eliminate the small objects and noises. (Figure 2.b)



(a) Initial Edge Map



(b) Outline selected

Figure 2: Outline Selection

2.2 Curvature-based fiducial detection

Once the outline of the brain is identified, corners are detected within this outline. Single-scale feature detection finds it hard to detect both fine and coarse features at the same time. On the other hand, multi-scale feature detection [9] is able to solve this problem. Using an adaptive local curvature threshold instead of a single global threshold as in the original and enhanced CSS (Curvature Scale Space) methods the angles of corner candidates are checked in a dynamic region of support for eliminating falsely detected corners. Here the curvature is defined as [9]:

$$k(u, \sigma) = \frac{\dot{X}(u, \sigma)\ddot{Y}(u, \sigma) - \ddot{X}(u, \sigma)\dot{Y}(u, \sigma)}{(\dot{X}(u, \sigma)^2 - \dot{Y}(u, \sigma)^2)^{1.5}}$$

Where $\dot{X}(u, \sigma) = x(u, \sigma) \otimes \dot{g}(u, \sigma)$, $\ddot{X}(u, \sigma) = x(u, \sigma) \otimes \ddot{g}(u, \sigma)$, $\dot{Y}(u, \sigma) = y(u, \sigma) \otimes \dot{g}(u, \sigma)$, $\ddot{Y}(u, \sigma) = y(u, \sigma) \otimes \ddot{g}(u, \sigma)$, and \otimes is the convolution operator while $g(u, \sigma)$ denotes a Gaussian function with deviation σ .

We compute curvature at a fixed low scale for each contour to retain all true corners. And all of the curvature local maxima are considered as corner candidates, including the false corners. Among the initial candidates, adaptive local threshold and angel of corner are used to remove the false corners and boundary noise. Corner selection result is shown in Figure 3.

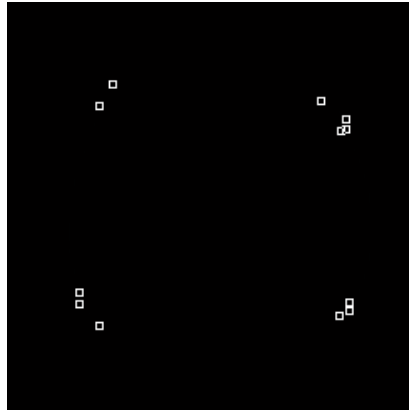


Figure 3: Corner Detection

Next, K-means is used to cluster the selected corner points into several classes based on point positions. Polynomial curve fitting is then used to find the coefficients of a polynomial $P(x)$ of degree 3 that fits the data in each class. Thus, a fitted curve is plotted in each group (Figure 4). The center point of each curve is selected and back projected onto the brain contour. The resulting points are the center of the fiducial markers (Figure 5).

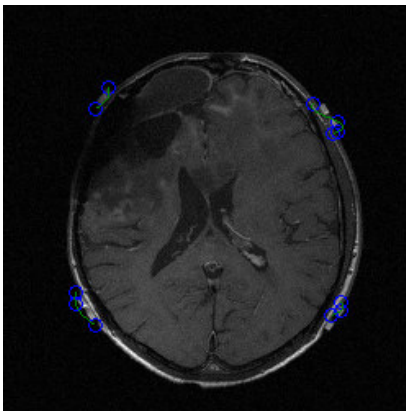


Figure 4: Curve Fitting

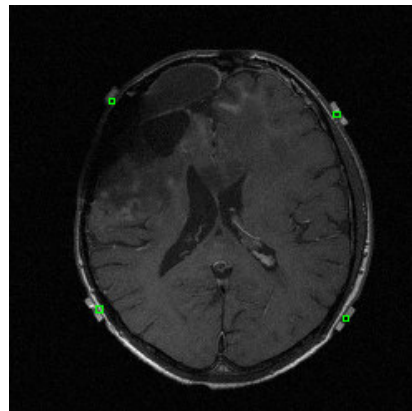


Figure 5: Final Result

3. Experimental Results

The proposed technique was tested on 122 images from different patients and different modalities: CT (512x512x56) and MR (256x256x66) (forward and reverse readout gradient T1, PD and T2). All experiments were performed on 1.5GHZ CPU workstation with 512MB Memory PC using Matlab 7.0 and Visual C++ 6.0.

The detected fiducial points were compared with manually selected points by experts. If distance between selected points and ground truth is more than 0.5 mm, we classify it as a wrong detection. For CT images, the error rate is zero using 56 images. For MR images, the error rate is 3% (2 out of 66 images). The average distance is less than 0.4mm. The experimental results indicate that the algorithm is reliable and accurate.

4. Conclusion

In this paper, we proposed a novel automatic fiducial points detection algorithm usable in different image modalities. This will be useful for automatic point based registration [11]. The proposed technique was tested using CT and MR images with perfect detection in CT images and 2 errors out of 66 MR images.

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