AUTOMATIC MULTI-PARAMETRIC MR REGISTRATION METHOD USING MUTUAL INFORMATION BASED ON ADAPTIVE ASYMMETRIC K-MEANS BINNING

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ABSTRACT

Multi-parametric MR image registration combines different imaging sequences to enhance visualisation and analysis. However, alignment of the different acquisitions is challenging, due to contrast-dependent anatomical information and abundant artefacts. For two decades, voxel-based registration has been dominated by methods based on mutual information, calculated from the joint image histogram. In this paper, we propose a modified framework — based on an asymmetric cluster-to-image mutual information metric — that increases registration speed and robustness. A new parameter, the homogeneous dynamic intensity range, is used to determine to which image clustering is applied. The framework also includes a semi-automatic 3D region of interest, multi-resolution wavelet decomposition, and particle swarm optimization. Performance of the framework, and its individual components, were evaluated on two diverse datasets, comprising cardiac and neonatal brain datasets. The results demonstrated the method was more robust and accurate than mutual information alone.

Index Terms — Multi-parametric registration, k-means binning, histogram specification, ROI-tracking.

1. INTRODUCTION

For two decades, research on multi-modal and multi-parametric registration of 3D CT and MRI data has relied on entropy-based voxel similarity measures, such as mutual information (MI)[1]. Mutual information is usually calculated from the joint intensity histogram, calculated by equidistant binning of the image intensities. However, with equidistant bins the quality of the result depends critically on the number of bins chosen to quantise the data: too many bins results in the dispersion of single anatomical structures across multiple bins — due to intensity inhomogeneities — while too few bins results in the combination of disparate anatomical structures within the same bin. There are many non-equidistant binning strategies, for example histogram equalization or k-means clustering[2]. However, important information can also be lost by inappropriate clustering. An asymmetric cluster-to-image non-rigid registration method was proposed to reduce this problem for multi-modal CT-MR alignment. It only performs k-means clustering on the CT data[3]. However, when registering multi-parametric MR data it is unclear which dataset should be the target for k-means binning, and experiments demonstrate that the selection of which image to cluster has a significant effect on accuracy.

This paper presents a novel co-registration framework that is shown to be more robust to intensity differences between images than using mutual information alone. The performance of the framework is demonstrated using two quite different sets of data from ongoing clinical studies (cardiac data and neonatal brain data). Experiments were performed to show how the different stages of the proposed framework are important to the accuracy and robustness of the results.

2. METHODS

Given a floating image, \( \mathcal{F} \), and a reference image, \( \mathcal{R} \), registration aims to find the transformation, \( \mathcal{T} \), that optimizes a given similarity measure, \( S(\mathcal{R}, \mathcal{F} \circ \mathcal{T}) \), where \( \mathcal{T} \) is the transformation applied to \( \mathcal{F} \). Our method constrains \( \mathcal{T} \) to be a rigid-body transformation, which is calculated within a semi-automatic 3D region of interest (ROI), described in section 2.1.

One of the images (either the reference or floating image) is chosen to undergo k-means intensity binning. A new parameter, the homogeneous dynamic intensity ratio (HDIR) described in section 2.2, is used to determine which image the k-means binning is applied to. The data with the larger dynamic range is chosen for asymmetric k-means binning. Meanwhile, the non-clustered image is corrected by ranked histogram specification to achieve similar intensity homogene-
ity with the clustered image. The similarity between $\mathcal{R}$ and $\mathcal{F} \circ \mathcal{T}$ (one of which has undergone k-means binning, the other ranked histogram specification) is measured using mutual information. The optimal transformation is estimated using a particle swarm optimizer (PSO) [4]. Finally, a wavelet decomposition-based multi-resolution scheme is incorporated to increase the speed and robustness of the result.

2.1. Registration region of interest

Limiting the registration calculation to a specific region of interest can greatly improve registration robustness. Indeed, it may be essential where different regions of the image undergo separate transformations. Two strategies were used for semi-automatic definition of the regions of interest on the data in this project: for the neonatal brain datasets a fixed-size enclosing cuboid was placed over the brain; for the cardiac data an adaptive scheme was developed that is described below.

For the cardiac data, a square ROI is first defined on the $k$th slice, $\mu_k$, of the $K$-slice 3D data $\mu = \{ \mu_k \}, k = 1, 2, \cdots, K$. Once the ROI, $\mathcal{R}_{\mu_k}$, is picked on $\mu_k$, the optimal ROI, $\mathcal{R}_{\mu_j}$, on the neighbouring slice, $\mu_j$, $j \in \{ k-1, k+1 \}$, is tracked by minimizing the sum of square difference (SSD) of intensities:

$$\hat{\mathcal{R}}_{\mu_j} = \arg \min_{\mathcal{R}_{\mu_j} \in \Omega_{\mu_j}} \sum (\mathcal{R}_{\mu_k} - \mathcal{R}_{\mu_j})^2, \quad (1)$$

where $\Omega_{\mu_j}$ is the search area, defined on $\mu_j$ but centred on the same coordinate with $\mathcal{R}_{\mu_k}$. This results in a bi-directional growth of the 3D ROI, starting from $\mu_k$ and ending when it covers the entire 3D dataset.

These 2D ROIs may then be refined, for example using a circular Hough Transform [5] to automatically detect objects, such as the aortic wall in abdominal data, or the left-ventricle in short-axis cardiac data, as shown in figure 1(a). Figure 1(b) shows the trajectory of the automatically tracked 2D-ROI centres from a standard contrast enhanced CT dataset acquired in a clinical trial on an Aquilion ONE (Toshiba Medical Systems, Japan).

Initial alignment can be achieved by registering the 2D-ROI centres using the iterative closest points (ICP) algorithm [6]. Alternatively, if the correspondences between slices are known, least square methods can be applied to solve this problem analytically, using singular value decomposition (SVD)[7]. Figure 1(c) and 1(d) show examples of initial alignments obtained on T2*-weighted (T2*W) and delayed enhancement cardiac MR data.

2.2. Intensity Distribution Correction and K-means Binning

The motivation for calculating MI using asymmetric k-means binning in CT-MR multi-modality registration is to overcome the histogram dispersion problem, without breaking the ability to distinguish detailed structures [3]. When applying asymmetric k-means binning to multi-parametric MR data the optimal target for the k-means binning needs to be selected carefully. Clustering the image with less dynamic intensity range, and more severe inhomogeneities, may emphasize the dispersion effects on histograms. A histogram-based measure, HDIR, was derived to measure the dynamic intensity ranges and inhomogeneities of the reference and floating images.

Let $\rho_\mu(\bullet)$ be the probability densities function (PDF) of the normalized voxel intensity, $i \in [0, 1]$, of image $\mu$. A probability $\hat{\rho}_\mu$ is defined as:

$$\hat{\rho}_\mu = \sum_{i \in [b_L, b_U]} \rho_\mu(i), \quad (2)$$

where $b_L$ and $b_U$ are two thresholds defined on image intensity. Given two images, $\mu$ and $\nu$, the HDIR is:

$$\text{HDR} = \frac{\text{std}(\hat{\mathcal{H}}_\mu)\hat{\rho}_\mu}{\text{std}(\hat{\mathcal{H}}_\nu)\hat{\rho}_\nu}, \quad (3)$$

where $\hat{\mathcal{H}}_\mu$ is the intensity histogram for image $\mu$, excluding the intensity values larger than $b_U$ or smaller than $b_L$, and similarly $\hat{\mathcal{H}}_\nu$ is the truncated histogram for $\nu$. std(\bullet) represents the standard deviation of the histogram. $\hat{\rho}_\mu$ and $\hat{\rho}_\nu$ are the probabilities calculated using equation 2 for $\mu$ and $\nu$. Here $b_L = 0.05$ and $b_U = 0.95$ were used.

If the $\text{HDR} \geq 1$ then the k-means binning is applied to image $\mu$, otherwise to $\nu$. Ranked histogram specification is applied to the other image to correct its intensity distribution. Let $\phi_\mu$ and $\phi_\nu$ the cumulative density function (CDF) of the two images. When $\text{HDR} \geq 1$, conventional histogram specification [8] maps the intensity distribution of $\nu$ by a transformation function $\psi_{\nu \rightarrow \mu} = \phi_\mu^{-1}(\phi_\nu(\bullet))$. But different from [8], here we introduce transformation functions $f_{\mu}(\bullet)$ and $f_{\nu}(\bullet)$ which re-arranges the histograms of image $\mu$ and $\nu$ in descending order by $\rho_\mu$ and $\rho_\nu$. Then calculate the CDFs of both re-arranged histograms, denoted as $\phi_{f_\mu}(\bullet)$ and $\phi_{f_\nu}(\bullet)$. The transformation function of this re-arranged histogram specification then becomes $\psi_{\nu \rightarrow \mu} = f_{\nu}^{-1}(\phi_{f_\nu}^{-1}(\phi_{f_\nu}(f_{\mu}(\bullet))))$.

To reduce the sensitivity of k-means to initialization of cluster centres, we deployed the “top-to-down” k-means method[3], except that we uniformly initialize a large number of cluster centres at the start. Then neighbouring clusters with distances smaller than a threshold are merged. This framework performs k-means clustering and intensity distribution correction simultaneously, as shown in figure 2.

2.3. Registration Framework Implementation

To improve speed and robustness, a multi-resolution approach based on the discrete wavelet transformation, was used. Registration starts from the lowest to the highest resolution. When performing k-means clustering, with an $L$-level wavelet pyramid, the largest number of cluster centres, $N_k$, on the $k$th layer of the pyramid is limited to $\max(48, 8 \ast k), k = 1, 2, \cdots, L$. \[54x388\]
For robust registration and efficient searching, we use global, gradient-independent, optimizers. In our previous work [9], the DIRECT optimization algorithm [10] was used. Despite various improvements it still struggles to avoid local optima. In this work we use a PSO [4] to search for the optimal transformation. Experiments show that only 60 initial particles are necessary to solve these rigid-body registration problems.

3. EXPERIMENTS AND VALIDATION

The registration method was validated using two diverse datasets, both acquired as part of on-going clinical trials. Both sets of data were registered using the three-level multi-resolution framework described above.

3.1. Cardiac Data

Multi-parametric MR data was acquired from 30 patients. Data were contiguous throughout the short axis, and were ECG-gated for diastole during an expired breath-hold. These constraints mean a rigid-body transform was sufficient for this application. Each subject had one delayed enhancement volume, one pre-contrast, and at least three post-contrast T2*W volumes. All data have a resolution of $1.56 \times 1.56 \times 10$ mm, and suffer from significant inhomogeneities and motion-related artefacts. The ROI was defined to cover the whole left ventricle and main structures of the heart. We tested 45 post-to-pre-contrast T2*W image registrations, and 53 T2*W to delayed enhancement image registrations.

The registration performance was evaluated by manual corrections performed by experienced clinicians. Errors were calculated in the form of Euclidean distances and Euler angles.

3.2. Neonatal Data

Thirty-one neonatal brain volumes were acquired at 38–44 weeks post-menstrual age during natural sleep. Data with different contrasts (T1-weighted MPRAGE, T2-weighted SPACE) were obtained. Some neonatal motion between scans, and repositioning of waking neonates between acquisitions, was experienced. The data were aligned using a rigid-body transform, calculated within a $51 \times 51 \times 41$ mm ROI, manually centred on the brain. Registration accuracy was assessed using the target registration error (TRE), calculated from 18 corresponding landmarks placed on each volume (giving a total of 1908 corresponding landmarks).

<table>
<thead>
<tr>
<th></th>
<th>Translation</th>
<th>Rotation</th>
</tr>
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<tbody>
<tr>
<td>T2<em>W to T2</em>W</td>
<td>1.76</td>
<td>0.81</td>
</tr>
<tr>
<td>T2*W to DE</td>
<td>1.55</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Table 1. Translational and Rotational Errors of Cardiac Registration: voxels and degrees of manual correction.

Furthermore, to test the importance of each step in the
overall registration framework, several components were either omitted completely or exchanged with alternative methods. The changes were: (a) Gaussian pyramid instead of the wavelet pyramid; (b) omitting the k-means step; (c) omitting the histogram specification step; (d) replacing the with the DIRECT optimizer; and (e) reversing the decision of clustered and non-clustered image. Finally, the results were also compared with our previous algorithm [9]. Registrations with TREs larger than 8 mm are easy to detect by visual inspection, and are considered failures.

4. RESULTS

4.1. Cardiac Data

The average rotational and translational errors across the 98 registrations are shown in table 1. The mean translational and rotational errors are 1.61 voxels (approximately 2.66 mm) and 0.68 degrees, respectively. 55% of the registrations achieved sub-pixel accuracy, and 40% could not be improved further by manual adjustment.

4.2. Neonatal Data

Table 2 illustrates the results from the 31 T2W–T1W MR registrations. The new algorithm presented here gave smaller TREs than our previous methodology, and produced fewer complete failures. Omitting or exchanging any of the algorithm steps described earlier resulted in worse registration accuracy.

5. DISCUSSION

We have introduced a multi-parametric MR data registration framework that is more robust to data intensity differences than mutual information alone. Registration performance was evaluated using multi-parametric cardiac and neonatal data. Omitting or exchanging any of the algorithm steps led to larger registration errors. Many parts of the algorithm may be trivially parallelized.

6. REFERENCES


