

Multimodality Image Registration by Gradient Enhanced Generalized Clustering

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INTRODUCTION

Multimodality image registration is a powerful technique that allows images from different modalities to be compared on a pixel-by-pixel basis. Recently, algorithms based on maximizing the mutual information¹ (MI) between voxel intensities of images have gained wide acceptance because they generally have good accuracy and do not require implicit assumptions about the image intensities. However, some problems have been noted with MI. Occasionally, it is sensitive to the size and shape of the image background and the amount of overlap between the images².

Problems with MI can be better appreciated in the generalized clustering framework³, which has been shown to incorporate several important voxel-similarity-based algorithms. In this framework, each pair of corresponding voxels in the overlap region of the images is assigned a matching score. MI assigns a score in the form $\log(\mathbf{P}_{12}/\mathbf{P}_1\mathbf{P}_2)$, based on the joint intensity histogram. The term $(\mathbf{P}_{12}/\mathbf{P}_1\mathbf{P}_2)$ compares the probability of observing the voxel intensities together in the image (\mathbf{P}_{12}) to the probability of observing them together by chance ($\mathbf{P}_1\mathbf{P}_2$). This ratio is converted to a score by the log function. The total score is normalized by the overlap volume to obtain the match metric of MI.

In the context of the present framework, problems with MI can be readily seen. Firstly, background voxels can influence the registration significantly (due to their sheer number) since the match metric is calculated as the average score from all the voxels. Secondly, when the overlap region is small, the match metric can be skewed easily by a few voxels with high matching scores, leading to overestimation. The aim of this work was to overcome these problems by specifically designing a match metric that ① placed more emphasis on "complex voxels" (i.e. those with more image structure); ② would not overestimate the match metric for small overlap. Different choices for the match metric, interpolation and optimization schemes were examined systematically to optimize registration robustness. We present the best choices found.

METHODS

Registration Procedure: Images were first interpolated trilinearly to isotropic voxels, with the size determined by the minimum voxel width of the original images. Adjacent voxels were averaged to create a multiresolution pyramid, where the voxel width doubled for every new resolution. Starting from the lowest (coarsest) resolution, the images were superposed in tentative orientations. At each orientation, a joint histogram between the voxel intensities was constructed, and the match metric was determined. The images were reoriented iteratively until the match metric was optimized. Then, the registration proceeded to the next (finer) resolution until the finest resolution had been reached.

Match Metric: To place more emphasis on "complex voxels", we investigated weighing the score of each voxel pair by a gradient term, versus weighing the average score by a total gradient term. The latter approach turned out to be much more robust:

$$\text{Match Metric} = \left[\sum_i |\nabla I_1(i)| |\nabla I_2(i)| \right] \left[\frac{1}{N+1} \sum_i \log \left(\frac{P_{12}(i)N}{P_1(i)P_2(i)} \right) \right]$$

where I = voxel intensity; P_{12} = joint probability of observing the intensities of the current voxel pair together in the images; P_n = marginal probability of observing the intensity of the current voxel in image n ; N = number of overlapping voxels. The summations were performed over every pair of corresponding voxels (i) in the overlap region. Joint and marginal probabilities were estimated from the joint intensity histogram.

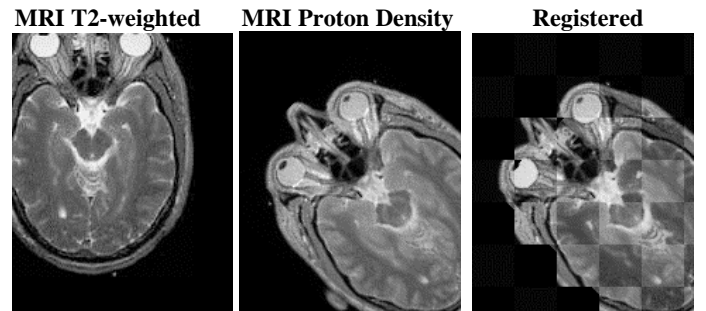
Interpolation: The voxels were interpolated by nearest neighbor after stochastic jitter. (i.e. A normally distributed random offset (mean=0, $\sigma=0.5$) was added to each coordinate.) The joint histogram was blurred with a $[\frac{1}{4}, \frac{1}{2}, \frac{1}{4}]$ triangular filter, applied twice along each axis before estimating the joint and marginal probabilities from it.

Optimization: The rigid-body registration parameters (i.e. amount of image translation and rotation) were iteratively optimized by a stochastic annealing scheme. Each set of parameters was generated from the existing set by adding a small step in random directions in parameter space. The new parameters were retained if they improved the match metric, or by chance otherwise according to a small probability. If the match metric did not improve after several steps, the parameters were restored to the last best values. The step size and the probability of accepting worse steps were gradually reduced over time.

Images: The registration algorithm was tested on 4 pairs of 2D images from different modalities (MR Proton Density (PD)/T2-weighted; MR PD-weighted/CT; MR-/optical microscopy; MR/SPECT).

RESULTS

The algorithm was successful in registering all but the MRI/SPECT pair. In comparison, MI registration failed for all but the MR-PD/CT pair. Registration errors were determined (and estimated for the MR/optical pair since gold standard was unavailable) to be $\sim 1^\circ$ and sub-voxel in translation. As an example, the figures below show the initial MRI-Proton Density/T2-weighted pair and the registration results with the two images superposed in a checkerboard pattern.



DISCUSSION AND CONCLUSION

Compared with MI, the new algorithm was more robust in registering images that were far apart initially, even without the help of a gross alignment step. The new match metric tends to have fewer local maxima and consequently a larger convergence range (in parameter space) than MI. However, both match metrics were unable to register the MRI/SPECT pair, which visually showed less resemblance to one another than the other pairs.

We term the new algorithm "Gradient Enhanced Generalized Clustering" since it combines the strengths of clustering-based and edge-based registration methods by expressing the match metric as a product of two terms: a gradient-matching term and a generalized clustering term. For the gradient-matching term, we chose the (unnormalized) cross-correlation of the intensity gradient⁴. For the generalized clustering term, we chose a modified version of MI, with $(N+1)$ replacing N in the denominator to prevent overestimation of the match metric for small N (i.e. when the overlap region is small). We have experimented with other matching functions for both terms, and found this combination to give the best registration results overall.

Success of the registration depended critically on the optimization algorithm and careful tuning of its parameters. More efficient algorithms such as simplex were often stuck in local maxima. The simulated annealing approach was much more robust, albeit at the expense of more computing time. The processing time to register a pair of 157×200 images was approximately 20s on an SGI Octane.

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