Image Registration Using Rigid Registration and Maximization of Mutual Information

Smriti Raghunathan[1)], Don Stredney [2)], P Schmalbrock[3)], Bradley D Clymer[4)]

1) Biomedical Engineering, The Ohio State University, 2) Ohio Supercomputing Centre,
3) Radiology, The Ohio State University, 4) Electrical and Computer Engineering, The Ohio State University

Abstract

With rapid advances in Medical Imaging, an ever increasing array of diagnostic images will be collected for each patient, including images acquired either using different modalities (CT, MR, PET, etc), or using the same modality and different acquisition methods, or taken at different times e.g. for treatment follow-up studies. It may also be of interest for research purposes to compare image data of different patients.

To make most effective use of this wealth of information it is necessary to find convenient ways to combine such image data wherein there may exist differences in resolution, position, and/or orientation of the objects in the different images.

Therefore, we need to superimpose these different images such that the co-ordinate system of each data set is transferred to the co-ordinate system of a fixed referenced data set.

The work presented here is a work in progress. The objective of the work presented is to find a fully automated registration technique that provides good registration results. T1- weighted and T2- weighted images of the temporal bone were acquired at 1.5T, in vivo. The images were registered using Rigid Registration with **Maximization of Mutual Information (MI)** and **Mean Squares** as the metrics. Rigid Registration techniques involve translations and rotations. Maximization of Mutual Information involves finding a transformation from the co-ordinate frame of one image to that of the other image such that the mutual information between the two is maximized. Using Mean Squares involves minimizing the distance between the grey scale values of the original and transformed image. The registration algorithms were implemented in ITK

In order to gauge how well the images have been registered, a set of anatomical points were marked by an expert and the Mean Square Error between the images was found using these points. Based on this analysis, we found that registration using mutual information provides us with a better and faster registration technique.

Introduction

The treatment for internal auditory canal tumors (schwannomas) is not always clear. The tumors may be treated with surgery or radiation therapy. In case of older patients, the tumors are monitored every six months and if it is found that the tumors are not growing too rapidly then in many cases they are left untreated.

Typically, the linear dimensions of the tumor are measured on a 2D-image. However, it was found that more definitive assessment of tumor growths is achieved using image based tumor volume measurements [Schmalbrock, et al]

Currently the most accurate methods for defining tumor boundaries on MRI images uses manual tracing. However, since very large data sets need to be compared e.g. for multi-year follow-up on individual patients, or for research studies aimed at assessing best treatment option, there is a need to find automated ways of tracing the tumors A problem that arises in the automated tracing of tumors is that the boundaries for the tumors may not be clear cut, as shown in Figure 1A.

Multispectral analysis may be used to mark the boundaries of the tumors, as shown in Figure 1B. This requires combining the images such that they all have the same co-ordinate system. Hence the need for automated registration techniques. Automated volume measurements of the tumors is also needed for follow up studies. This too requires the images sets to be registered.

The registration techniques and results presented in this paper were performed on contrast enhanced T1-weighted and steady-state T2-weighted images acquired at 1.5T to study schwannomas.

The set of images used comprises of contrast enhanced T1-weighted and T2- weighted images of a single slice from the same patient. For the preliminary work presented here, **2D** rigid registration was performed using maximization of mutual information and mean squares

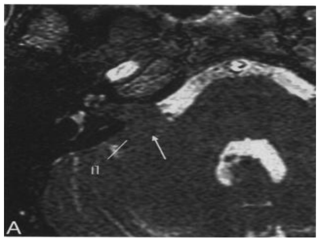


Figure 1A: The tumor is isointense with the brain tissue [Schmalbrock, et al]

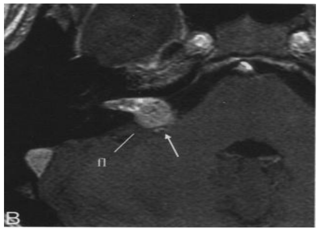


Figure 1B: On the contrast enhanced image, the hyperintense tumor is easily distinguishable [Schmalbrock, et al]

Methods

MRI Acquisition: Pre- and post-contrast T1-weighted images were acquired at 1.5 Tesla (GE Medical Systems) using a 3D- gradient echo sequence with

- TR/TE of 30/4.2ms
- flip angle of 30o
- 20x20cm field of view
- 512x288 matrix (resolution 0.39x0.69mm)
- 60 slices of 1.5mm.

T2-weighted images were acquired with a motion compensated 3D gradient echo sequence with

- TR/TE of 17/3.5
- flip angle of 40o
- 20x15cm field of view
- 512x256 matrix (resolution 0.39x0.58mm)
- 60 slices of 0.4mm.

Registration: 2D rigid registration using mutual information as a metric was implemented to align each set of contrast enhanced T1-weighted and T2-weighted images. The image intensity values of each image are considered to be random variables. Mutual Information (MI) measures how much information one random variable contains about the other random variable. MI is calculated based on the entropies of each of the random variables.

The entropy of a random variable, X, is given by:

$$H(X) = - \int pX(x) \log pX(x)\, dx$$

The joint entropy of two random variables, X and Y, is given by:

$$H(X,Y) = - \int pAB(a,b) \log pAB(a,b)\, da\, db$$

If X and Y are the random variables defining the image intensities of the two images in a set, then the MI between the two images is given by:

$$I(X,Y) = H(X) + H(Y) – H(X,Y)$$

Typically, the marginal and joint probability densities of the image intensities are not available and have to be estimated from the image data. This is done using Parzen Windows. In this method, intensity samples, S, from the image are taken and super-position kernel functions K(·) are centered on the elements of S as shown in Figure2

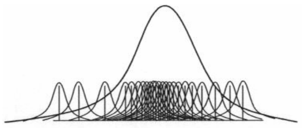


Figure 2: Kernel functions (Gaussian in this case) are superimposed centered on the intensity samples obtained from the image [pg 285, ITK software Guide]

The function used as the smoothing kernel needs to have a zero mean and must integrate to one. The Gaussian and B-spline functions are commonly used smoothing functions. If N is the number of samples, the estimation of the random variable, X, is then given by

$$P(x) = 1/N\Big(\sum_{j \in N} K(x-sj)\Big)$$

The registration algorithm was implemented in ITK using the Mattes Mutual Information algorithm. In this algorithm, a single set of intensity samples is drawn from the image. The marginal and joint probability density function (PDF) is evaluated at discrete positions (uniformly spread bins) using these samples. Entropy values are computed by summing over the bins. A zero order B-spline kernel is used to compute the PDF of the fixed image, while a third order B-spline kernel is used to compute the PDF of the moving image. The implementation of the algorithm in ITK allows the user to specify the number of histogram bins and number of samples to be used for the calculation of the PDF . The optimizer used for the implementation of this algorithm is the regular step gradient descent optimizer.

Rigid registration allows translations, rotations and possible scaling. The idea behind the implementation of this algorithm is that at each iteration, the mutual information between the two images is computed. The moving image is rotated and/or translated and the MI between the moving and fixed images is recomputed. The process continues until the MI between the two images is maximized.

The optimizer drives the registration algorithm. At each iteration the optimizer takes a step in the direction of the gradient. When the gradient changes direction abruptly, a local extrema is assumed and the optimizer reduces the step length by a half. The initial step length, maximum and minimum allowable step lengths for convergence are all specified by the user. To prevent the optimizer from getting trapped in a local extrema, the user may also specify the maximum number of iterations to convergence.

The results obtained using MI as the metric were compared with those obtained using simple mean squares as the metric. This was also implemented in ITK. Here at each iteration the mean squared distance between the grey levels of each image is computed. The moving image is rotated and/ or translated and the mean squared distance is recomputed. This continues until the mean squared distance between the two images is minimized.

For both metrics considered, the contrast enhanced T1-weighted images was the fixed image and the T2-weighted image was the moving image

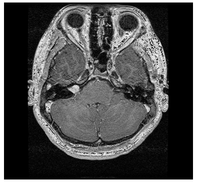
Criterion for Comparison:

- A set of anatomical points were marked by an expert
- The Mean Square Error (MSE) between the images was found using these points

If (x_1, y_1) and (x_2, y_2) are the co-ordinates of one of the marked points in the contrast enhanced T1-wieghted and T2-weighted images, respectively, and (X1, Y1) are the co-ordinates of the same point in the registered T2 image, then the MSE is computed as the average of

$$\sqrt{\ }((x_1–X_1)^2 + (y_1–Y_1)^2+\ldots+(x_{10}–X_{10})^2 + (y_{10}-Y_{10})^2$$

Results



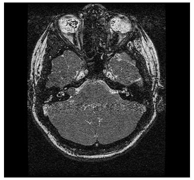


Figure 3: The image above (left) is the original contrast enhanced T1-weighted image. The image next to it (right) is the original T2-weighted image

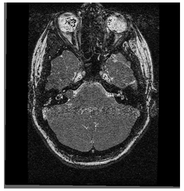


Figure 4: The image above (left) is the registered T2-weighted image using MI as the metric. The image next to it (right) is the registered T2-weighted image using Mean Squares as the metric

- The original images were converted from DICOM to PNG format for the purpose of registration. Future work will involve trying to use original images in DICOM format for registration.
- The **MSE** for the image set registered using MI as the metric was **12.639**
- 114 iteration, 1min (real time) to converge,
- The **MSE** for the image set registered using Mean Squares as the metric was **13.259**
- 200 iterations (maximum iterations allowed), 8min (real time) to converge

Conclusion and Future Work

- Registration using MI as a metric produces a smaller MSE than that using Mean Squares as a metric.
- Difference in the MSE for the two cases is not very large. Future work will involve further manipulation of the algorithm parameters to see if better results may be obtained
- Registration using MI is faster than that using Mean Squares
- Future work will involve extending these ideas and implementing these algorithms to registered 3D data sets

References

1. Schmalbrock P, et al. Assessment of Internal Auditory Canal Tumors: **A Comparison of Contrast-Enhanced T1-Weighted and Steady-State T2-Weighted Gradient-Echo MR Imaging.** *AJNR Am J Neuroradiol 1999;* 20:1207-1213
2. ITK Software Guide