Lecture 8
Fourth stage

Medical Imaging Processing II

Image Registration

By

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Image registration

Medical images are increasingly being used within healthcare for diagnosis, planning treatment, guiding treatment and monitoring disease progression. Within medical research (especially neuroscience research) they are used to investigate disease processes and understand normal development and ageing. In many of these studies, multiple images are acquired from subjects at different times, and often with different imaging modalities. In research studies, it is sometimes desirable to compare images obtained from patient cohorts rather than just single subjects imaged multiple times. Furthermore, the amount of data produced by each successive generation of imaging system is greater than the previous generation. This trend is set to continue with the introduction of multislice helical CT scanning and MR imaging systems with higher gradient strengths. There are, therefore, potential benefits in improving the way in which these images are compared and combined. Current clinical practice normally involves printing the images onto radiographic film and viewing them on a light box. Computerized approaches offer potential benefits, particularly by accurately aligning the information in the different images, and providing tools for visualizing the combined images.

Image registration is the alignment of two or more images so they best superimpose. This task has become increasingly important in medical imaging as it is used for merging images acquired using different modalities (for example, MRI and PET). Registration is also useful for comparing images taken of the same structure at different points in time. In functional magnetic resonance imaging (fMRI), image alignment is needed for images taken sequentially in time as well as between images that have different resolutions. To achieve the best alignment, it may be necessary to transform the images using any or all of the transformations described previously. Image registration can be quite challenging even when the images are identical or very similar (as will be the case in the examples and problems given here). Frequently the images to be aligned are not that similar, perhaps because they have been acquired using different modalities. The difficulty in accurately aligning images that are only moderately similar presents a significant challenge to image registration algorithms, so the task is often aided by a human intervention or the use of embedded markers for reference.

Approaches to image registration can be divided into two broad categories: unassisted image registration where the algorithm generates the alignment without human intervention, and interactive registration where a human operator guides or aids the registration process. The former approach usually relies on some optimization technique to maximize the correlation between the images. In the latter approach, a human operator may aid the alignment process by selecting corresponding reference points in the images to be aligned: corresponding features are identified by the operator and tagged using some interactive graphics procedure.

1. <u>Unaided Image Registration</u>

Unaided image registration usually involves the application of an optimization algorithm to maximize the correlation, or other measure of similarity, between the images. In this strategy, the appropriate transformation is applied to one of the images, the input image, and a comparison is made between this transformed image and the reference image (also termed the base image). The optimization routine seeks to vary the transformation in some manner until the comparison is best possible. The problem with this approach is the same as with all optimization techniques: the optimization process may converge on a sub-optimal solution (a so-called local maximum), not the optimal solution (the global maxi- mum). Often the solution achieved depends on the starting values of the transformation variables. An example of convergence to a sub-optimal solution and dependency on initial variables is found in Problem 8.

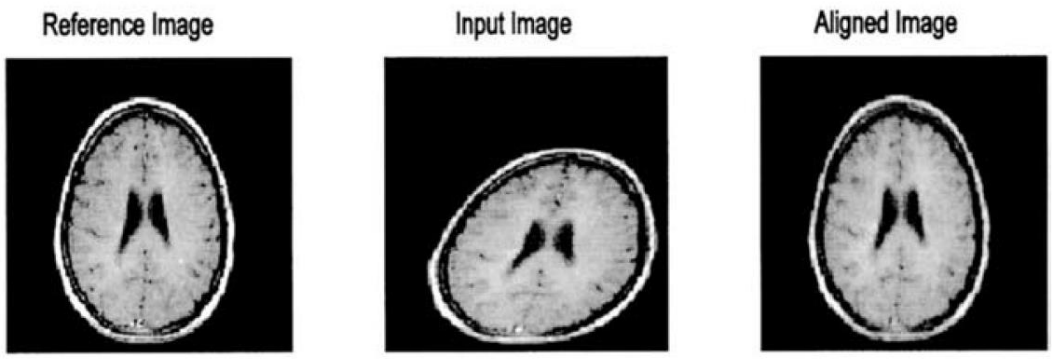

FIGURE 1 Unaided image registration requiring several affine transformations. The left image is the original (reference) image and the distorted center image is to be aligned with that image. After a transformation determined by optimization, the right image is quite similar to the reference image.

The results achieved by this registration routine are shown in Figure 1 The original reference image is shown on the left, and the input image. is in the center. As noted above, this image is the same as the reference except that it has been distorted by several affine transformations (horizontal scratching, vertical compression, and a tilt). The aligned image achieved by the optimization is shown on the right. This image is very similar to the reference image. This optimization was fairly robust: it converged to a correlation of 0.99 from both positive and negative initial values. However, in many cases, convergence can depend on the initial values as demonstrated in Problem 8. This program took about 1 minute to run on a 1 GHz PC.

Interactive Image Registration

Several strategies may be used to guide the registration process. In the example used here, registration will depend on reference marks provided by a human operator. Interactive image registration is well supported by the MATLAB Image Processing Toolbox and includes a graphically based program, that automates the process of establishing corresponding reference marks. Under this procedure, the user interactively identifies a number of corresponding features in the reference and input image, and a transform is constructed from these pairs of reference points. The program must specify the type of transformation to be performed (linear, affine, projective, etc.), and the minimum number of reference pairs required will depend on the type of transformation. The number of reference pairs required is the same as the number of variables needed to define a transformation: an affine transformation will require a minimum of three reference points while a projective transformation requires four variables. Linear transformations require only two pairs, while other more complex transformations may require six or more point pairs. In most cases, the alignment is improved if more than the minimal number of point pairs is given.

The reference and input windows are shown along with the reference points selected in Figure 2A and B. Eight points were used rather than the minimal four, because this was found to produce a better result. The influence of the number of reference point used is explored in Problem 9. The result of the transformation is presented in Figure 2. This figure shows that the realignment was less that perfect, and, in fact, the correlation after alignment was only 0.78. Nonetheless, the primary advantage of this method is that it couples into the extraordinary abilities of human visual identification and, hence, can be applied to images that are only vaguely similar when correlation based methods would surely fail.

FIGURE 2A A reference image showing the reference points as black.

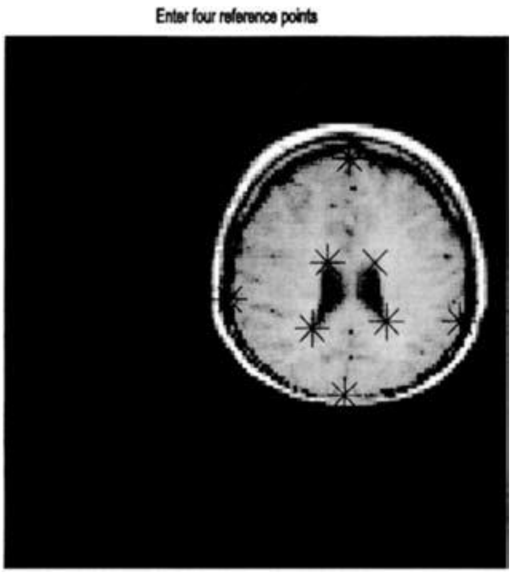

FIGURE 2B Input image showing reference points corresponding to those shown in Figure 2A.

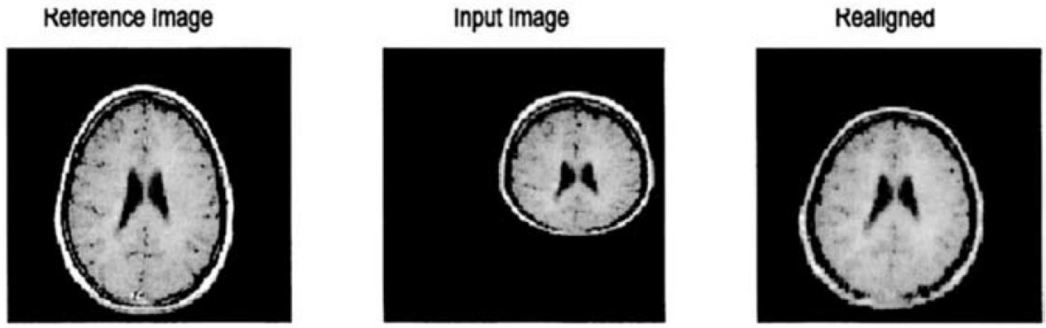

FIGURE 3 Image registration using a transformation developed interactively. The original (reference) image is seen on the left, and the input image in the center. The image after transformation is similar, but not identical to the reference image. The correlation between the two is 0.79.

Sparse Image Registration and Its Uncertainty

The feature detection and feature matching are two critical steps in the sparse methods. The flow chart of the sparse approach is illustrated in Figure below , where each functional block is detailed in the sequel.

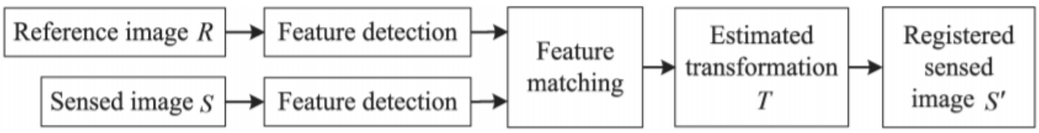

Figure 4. Flow chart of sparse approach.

Dense Image Registration and Its Uncertainty

The dense image registration estimates the optimal transformation T by searching the largest similarity (or the smallest dissimilarity) between the reference image R and the registered sensed image

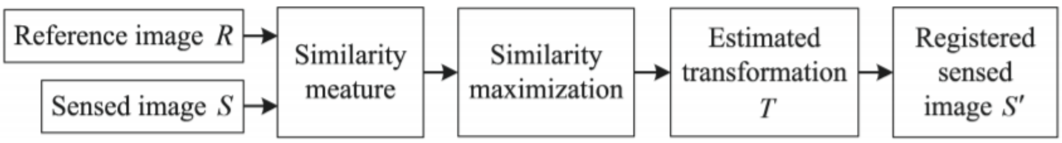

Figure 5. Flow chart of dense approach.

Basics of Image Registration

For two (or more) images of the same scene taken at different time, from different sensors, or from different viewpoints, one is chosen as the reference image (R) and the other one is chosen as the sensed image (S). we focus on the projective transformation model between the reference image and sensed image, which is a commonly used model in image registration. Denote pixel coordinates in the reference image R as (v, w) and their mapping counterparts in the sensed image S as (g, h). The projective transformation from R to S can be expressed based on the homogeneous coordinates (Homogeneous coordinates can easily express the translation transformation as matrix multiplications while Cartesian coordinates cannot) as

$$[g\ h\ 1] = [v\ w\ 1]\,T = [v\ w\ 1]\begin{bmatrix} t_{11} & t_{12} & t_{13} \\ t_{21} & t_{22} & t_{23} \\ t_{31} & t_{32} & t_{33} \end{bmatrix}$$