Intraoperative Registration of Pathology for Adjuvant Postoperative Radiotherapy
Steven Lin
With: Kareem Fakhoury, Matthew Hauser
CISII Project 4

I explored two separate papers. One is a more rudimentary discussion of image registration, and the other concerns the optimization of a deformation field formed by B-splines, by maximizing the mutual information metric.

Paper 1:

J. B. A. Maintz and M. A. Viergever. **A survey of medical image registration.** *Med. Image Anal.*, 2(1):1 –36, 1998.

This paper is concerned with the categorizing and comparing of image registration techniques. This is done by examining 9 criteria.

Criteria 1, Dimensionality – This is the discussion of the dimensions of the transformation. For our purpose, the algorithms should concern 3-D to 3-D transformation.

Criteria 2, Nature of Registration –This criterion deals of what is the registration performed on. There are two types, extrinsic and intrinsic. Extrinsic requires that a marker be placed on the patient, allowing for fast registration algorithms since the data set is small. Intrinsic uses only the image of the patient. The objects that the registration can be performed on could be landmark based (where a piece of anatomy is identified by the user), segmentation based (where a similar geometry is identified and use to register the two), and voxel property based (which depends only on the gray values of the image). For this project, we would need mostly intrinsic with a composite of landmark and the other two types of registration.

Criteria 3 and 4, Nature of Transformation and Domain of Transformation – Nature of transformation speaks to the types of result desired. So this can be subcategorized into rigid, affine, projective, and curved. Of these four, curved is of particular interest to our project but rigid may also be important. Domain of transformation discusses the universality of a transformation technique, so whether an image is transformed using several methods or just one. In this project, we will most likely adopt a composite transformation of curved and rigid transformation, to avoid unnecessary calculation in unaffected tissues.

Criteria 5, Interaction – This speaks to the degree of human to machine interaction. In our case, the tools that we would be exploring are semi-automatic. This means that we may be required to adjust certain parameters and identify landmarks, but the work is done by the algorithm.

Criteria 6, Optimization Procedure – Optimization can be done by explicitly calculating the parameters of the final solution or searched for. This will be discussed in greater details in Paper 2; however, we will be searching for the parameter rather than calculating it.

Criteria 7, Modalities Involved – This concerns the number of different technologies involved. Where there is only one, the algorithm is referred to as monomodal; where there are multiple, the algorithm is multimodal. Our algorithms would be monomodal as we are using CT-CT strictly.

Criteria 8 and 9, Subject and Object – Subject discusses whether the images are between the subject and self (intraoperative), subject and another subject (interoperative), or subject and a statistical atlas. In our case, even though we should have two separate algorithms, we will be using only one subject. The object refers to the anatomy being scanned. In our case, we are interested in the head and neck region.

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This paper was rather simple but provided valuable insight into our project. A large and beginning step into the project is the comparison of existing deformable registrations, and possibly finding one that fits. This paper not only allows us to narrow our search, but also provide a basic foundation of knowledge that would allow us to understand the tools that we are given. And, additionally, the paper provides numerous monomodal, deformable registration techniques for CT-CT when scanning the head. This would be most valuable should we come to the next portion of our project, where we attempt to create a new algorithm.

Paper 2:

S. Klein, M. Staring, and J. P. W. Pluim**. Evaluation of optimisation methods for nonrigid medical image registration using mutual information and B-splines.** *IEEE Trans. Image Process.*, 16(12):2879 – 2890,December 2007.

This paper is focused on discussing the family of optimization methods that parameterize a deformation field formed of B-splines by maximizing a mutual information matrix. Essentially, the optimization procedure hopes to increase the overlap between the fixed image and the deformed image. This can be described with the equation, $\hat{\mu} = \arg\min C\ (\mu; I_f, I_M)$, where C is a mutual information metrics. In order to optimize, the parameters are searched through an iterative process: $\mu_{k+1} = \mu_k + a_k d_k$. Essentially a_k is the gain factor and the d_k is the search direction. There are three different types of methods, deterministic gradient based, stochastic gradient based and evolution strategy.

Deterministic gradient based: In this type of optimization process, the direction is determined by identifying the negative of the gradient. The gain factor is calculate through a set equation (GDD), through the Moré-Thuente routine (GDL) or through an approximation of the inverse Hessian of the cost function (Quasi-Newton). The Moré-Thuente routine is used in both the GDL and Quasi-Newton. The difference being that the subroutine is used to directly compute the gain factor for GDL, but for the QN method the inverse Hessian is first evaluated using a LBFGS. The Nonlinear Conjugate Gradient, determines the direction through a linear update to the previous direction factor.

Stochastic gradient based: There are three methods covered by this paper on this subject. These methods differ from the deterministic gradient methods by approximating the gradient instead of explicitly calculating it. The Kiefer-Wolfowitz and Simultaneous Perturbation operates based on a finite difference approximation. This follows the form of $[\tilde{g}_k]_i = \frac{C(\mu_k + c_k e_i) - C(\mu_k - c_k e_i)}{2c_k}$. The KW method considers a scalar increase of c_k at every iteration. Whereas, the SP method operates by randomly applying the scalar. Lastly, the paper discusses the Robbins-Monro method, which assumes that there can be an approximation of the gradient. This makes the KW and SP methods subsets of the Robbin-Monro method.

Evolution Strategy- In each iteration of the evolution strategy there are three phases, offspring generation, selection and recombination. During the offspring generation, λ directions are generated from $\mathcal{N}(0, C_k)$ where only previously successful directions are favored. During selection, out of the λ directions, only the p most effective directions are selected. Finally, during the recombination phase, the direction factors are then summed with a series of weighing factors.

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In order to measure the correctness of the algorithms, registration was performed on four CT scans of the heart with each of the methods. This was done by measuring the distance in the deformation field generated by the algorithm. This can be calculated by

$$D(u_1 u_2) = \frac{1}{|I_f|} \sum_{x_i \in I_f} ||u_1(x_i) - u_2(x_i)||$$

The solution deformation field is generated by using randomized Gaussian blobs and used to deform the fixed image. It is found that RM is the most effective both in terms of accuracy and computation time.

Additionally, five patients were CT'ed months apart. The images from the before were registered to the images after. The results were tested for precision using the above formula. In addition the Dice similarity index between the transformed and after image is found in order to measure the overlap and therefore the accuracy of the registration. Again, it is found that the RM method is the most accurate albeit not the most precise. The QN and NCG are more precise while requiring more computational time.

This paper was relatively useful as an introductory level for this family of optimization methods. In addition, its experiment on the progressive tissue deformation of the chest CT's are somewhat relevant to this project. In this case the Robbins-Monro, Quasi-Newton and Nonlinear Conjugate Gradient would all be applicable. The reason being that computational would not be a huge factor. Though the paper lacks detail in the implementation of algorithm, the general effectiveness of each optimization algorithm narrows down future research.