MOTION CORRECTION STRATEGIES FOR INTERVENTIONAL ANGIOGRAPHY IMAGES: A COMPARATIVE APPROACH

Dinesh Kumar,M.S., Dinggang Shen,Ph.D., Liyang Wei,Ph.D., Ram Turlapthi**,M.D., Jasjit S. Suri,Ph.D.*
Eigen LLC, 13366 Grass Valley Ave., Grass Valley, CA 95945, USA
**University of Pennsylvania School of Medicine, Philadelphia, PA 19104, USA*
***Theda Clark Hospital, Appleton, University of Wisconsin, WI 52911, USA*

ABSTRACT

Digital subtraction angiography (DSA) is an important tool in interventional procedures and enables the surgeon to visualize the blood vessels in the projection X-ray images. Due to the motion of patient as well as motion of internal tissues constituting the background anatomy of the patient, the difference images may contain motion artifacts. The artifacts due to motion may be severe enough to make the visualization useless or erroneous and the images need to be motion compensated. Image registration is used for motion correction of DSA images such that the background mask image is placed in co-ordinates of the blood vessel enhanced image. The background structures are aligned as a result of image registration and are therefore removed from the subtraction image. There exist a large number of image registration techniques depending upon the application and the available information. In this paper, we compare two intensity based image registration techniques for motion correction of DSA images using signal-to-noise ratio as the evaluation metric. The methods discussed are: inverse consistent linear elastic image registration using b-splines and modified demons method, using a hierarchical strategy that focuses on region of intensity differences, like HAMMER. Both methods derive the driving function from image intensities, but impose different kind of constraints.

Keywords: DSA, image registration, image enhancement, SNR, b-splines, interventional procedures.

1. INTRODUCTION

Interventional procedures require real-time high quality visualization of blood vessels in the presence of normal motion of the tissues. This is especially true during the catheterization and surgical procedures. It is a common technique to inject a contrast enhancement agent into blood stream of the patient and obtain images of the desired region of interest before and after the dye has reached the field of view. The digital subtraction angiography (DSA) image [1, 2] is computed by subtracting the structural image from the image with enhanced blood vessels. However, the subtraction images generally contain background structures due to movement of patient as well as underlying anatomy. Motion results in poor quality of DSA images and in some cases, the blood vessels may even be indistinguishable from the other background structures. The motion of anatomy is quite complex and can not be accurately corrected by estimating models with low degrees of freedom such as rigid or affine transformation. In addition, the contrast of the computed images further needs to be improved for better visualization. The presented work aims at removing motion artifacts using two different strategies: modified Demons and inverse consistent image registration.

In medical imaging, image registration is used to find correspondence between a pair of similar anatomical objects. This is done by finding a deformation that maps one image into shape of the target image. The first approach studied in this paper, i.e. the modified Demons method [3] is a uni-directional method and deforms the mask image into shape of target image with only energy regularization constraints. The modified Demons method follows a hierarchical approach similar to HAMMER [4] and matches the images based on features extracted from the images to be registered. The image features used here are the intensity and the intensity gradient. The second method follows the approach of Christensen *et al.* [5], in which the correspondence is estimated in both directions such that the registration is inverse consistent. Ideally, a transformation defines a unique correspondence between the images and is therefore, inverse consistent. In general, however, the transformations estimated using only information in one direction are not inverse consistent and may contain correspondence ambiguities. B-splines have been quite popular as basis functions for registrations [6-9] due to smoothness, ease in computation, good localization properties and approximation power, and thus have been used as the basis function in the presented work. In this work, we also use Wei et al's [10] non-linear enhancement method to compute the difference images. The images for comparison were collected from 73 patients and the registration methods were compared using SNR as an evaluation criterion. The rest of the paper is organized as follows: Section 2 presents the theoretical framework of the registration methods. Results are presented in Section 3 along with discussions in section 4. The paper concludes in section 4.

2. METHODOLOGY

Image registration establishes a common frame of reference for a meaningful comparison between the two images. Image registration is often posed as an optimization problem which minimizes an objective function representing the difference between two images to be registered [3-9]. The symmetric squared intensity difference is chosen as the driving function. In addition, regularization constraints are applied so that the deformation follows a model that matches closely with the deformation of real-world objects. The regularization is applied in the form of bending energy and inverse-consistency cost. Inverse-consistency implies that the correspondence provided by the registration in one direction matches closely with the correspondence in the opposite direction. Most image registration methods are uni-directional and therefore contain correspondence ambiguities originating from choice of direction of registration. In the presented method, the forward and reverse correspondences are computed simultaneously and bound together through an inverse consistency cost term. The inverse consistency cost term assigns higher cost to transformations deviating from being inverse-consistent. While inverse consistency minimizes the correspondence ambiguity, it also helps the transformation perform better by forcing it out of local minima.

2.1 Modified Demon's Registration (Strategy # 1)

The first registration method discussed here is the modified Demon's algorithm, which is based on Thirion's Demon's registration method [3]. In this method, the registration is achieved by minimizing the following objective function:

$$E(T)=\sum_{\mathbf{x}\in\Omega}(F(\mathbf{x})-M(T(\mathbf{x})))^2+\lambda(|\nabla F(\mathbf{x})|-|\nabla M(T(\mathbf{x}))|)^2 \tag{1}$$

where $\mathbf{x}$ is a pixel defined in the domain of the fixed image, and $F(\mathbf{x})$ is the intensity of pixel $\mathbf{x}$ of the fixed image, and $T(\mathbf{x})$ is the deformation of pixel $\mathbf{x}$, and $M(T(\mathbf{x}))$ is the intensity of the corresponding pixel in the moving image. $|\nabla F|$ and $|\nabla M|$ are the gradient magnitudes of the fixed and moving images, respectively. λ is the weighting between the intensity differences and the gradient magnitude differences of the two images.

The method also follows a hierarchical attributes matching approach similar to HAMMER registration algorithm [4], which can be summarized as (1) defining an attribute vector for each point in the image, (2) hierarchically selecting the image regions for performing the image matching during the registration procedure, by using a sub-neighborhood match strategy. In order to make this 2D image registration algorithm fast, two major changes were made. First, we use a B-Spline to represent the deformation field, in order to produce the smooth deformation field without the need of point-wise deformation smoothing in each iterative registration procedure. Second, we use two simple features to define the attribute vector for each point in the image, i.e., original image intensity and gradient. The goal of the registration is to find a deformation $T(\mathbf{x})$ by minimizing the objective function in Eq. (1), in order to register the moving image onto the fixed image. The gradient descent optimization method is used to optimize the cost function and B-splines were used as the basis function.

The proposed image registration method is performed under a multi-resolution framework, in order to obtain more robust registration results and to speed-up the registration procedure. Starting from the lowest resolution, we perform the optimization and determine the deformation at that resolution, then, we up-sample the deformation (i.e. the B-Spline) at that resolution onto a finer resolution. After up-sampling, we perform optimization on the finer level resolution. This procedure continues until we obtain the result at the finest image resolution.

In order to up-sample B-Spline-based deformation from one resolution to a finer resolution, the following two steps are taken:

a) Up-sample control points: suppose the control point at the current resolution is c_x, c_y, then the control point at the finer resolution will be $R.c_x$, $R.c_y$, where R is the up-sampling rate.
b) Insert control points: at a higher resolution, we need to insert more control points in order to reflect details of the deformation.

The normal optimization procedure to obtain the control points is to iterate all the control points at each resolution, and then update the control points using the above optimization method. Since the image region that has large differences between the fixed image and the moving image is the region that we need to focus on, and we do not need to pay more attention to the region with smaller image differences since the images are matched at that region. Thus, in the proposed method, we classify the image region (or the control points) into two groups, one is the region where the local similarity of the two images is large and one is where the local similarity is small. Then, in each iteration, we only update the control points of the first group, and remain the control points in the second group unchanged. Using this adaptive selection of control points, we can obtain the following advantages:

a) Improve the calculation speed of the algorithm.
b) Prevent artifacts in the image regions with smaller differences, and it is better not to deform the moving

images in those regions with smaller image differences.

c) B-Spline deformation model using a number of regularly distributed control points to represent the deformation, and the deformation at each pixel can be determined by using B-Spline interpolation.

2.2 Inverse Consistent Image Registration Using B-spline Basis (Strategy # 2)

We use the cost function of Christensen *et al.* [5] for performing image registration over the images:

$$
\begin{aligned}
C = \quad & \sigma\left(\int_{\Omega}\left|I_1(\mathbf{h}_{1,2}(\mathbf{x})) - I_2(\mathbf{x})\right|^2 d\mathbf{x} + \int_{\Omega}\left|I_2(\mathbf{h}_{2,1}(\mathbf{x})) - I_1(\mathbf{x})\right|^2 d\mathbf{x}\right) \\
& + \rho\left(\int_{\Omega}\left\|L(\mathbf{u}_{1,2}(\mathbf{x}))\right\|^2 d\mathbf{x} + \int_{\Omega}\left\|L(\mathbf{u}_{2,1}(\mathbf{x}))\right\|^2 d\mathbf{x}\right) \\
& + \chi\left(\int_{\Omega}\left\|\mathbf{h}_{1,2}(\mathbf{x}) - \mathbf{h}^{-1}{}_{2,1}(\mathbf{x})\right\|^2 d\mathbf{x} + \int_{\Omega}\left\|\mathbf{h}_{2,1}(\mathbf{x}) - \mathbf{h}^{-1}{}_{1,2}(\mathbf{x})\right\|^2 d\mathbf{x}\right)
\end{aligned}
\quad (2)
$$

where, $I_1(\mathbf{x})$ and $I_2(\mathbf{x})$ represent the intensity of image at location $\mathbf{x}$, Ω represents the domain of the image. $\mathbf{h}_{i,j}(\mathbf{x}) = \mathbf{x} + \mathbf{u}_{i,j}(\mathbf{x})$ represents the transformation that maps image I_i to image I_j in the Eulerian frame of reference and $\mathbf{u}(\mathbf{x})$ represents the displacement field. L is a differential operator and the second term in Eq. (2) represents an energy function. σ, ρ and χ are weights to adjust relative importance of the cost function.

In equation (2), the first term represents the symmetric squared intensity cost function and represents the integration of squared intensity difference between deformed reference image and the target image in both directions. The second term represents the energy regularization cost term and penalizes high derivatives of $\mathbf{u}(\mathbf{x})$. In our work, we represent L as a Laplacian operator mathematically given as: $L=\nabla^2$. The third and the last term represents the inverse consistency cost function, which penalizes differences between transformation in one direction and inverse of transformation in opposite direction. The total cost is computed as a first step in registration. We solve the optimization problem posed in Eq. (2) by using a B-spline parameterization as in the work of Kybic and Unser [6] and in the work of Kumar and Christensen [7]. We choose B-splines due to ease of computation, good approximation properties and their local support. It is also easier to incorporate landmarks in the cost term if we use spatial basis function. We solve the above optimization problem by solving for B-spline coefficients c_i's, such that

$$\mathbf{h}(\mathbf{x}) = \mathbf{x} + \sum_i c_i \beta_i(\mathbf{x}) \quad (3)$$

where, $\beta_i(\mathbf{x})$ represents the value of B-spline at location $\mathbf{x}$, originating at index i. In our registration method, we use cubic B-splines. A gradient descent scheme is implemented based on the above parameterization. The total gradient cost is calculated with respect to the transformation parameters in every iteration. The transformation parameters are updated using the gradient descent update rule. Images are deformed into shape of one another using the updated correspondence and the cost function and gradient costs are calculated until convergence. The registration is performed hierarchically using a multi-resolution strategy in both, spatial domain and in domain of basis functions. The registration is performed at 1/4, 1/2 and full resolution using knot spacing of 8, 16 and 32. In addition to being faster, the multi-resolution strategy helps in improving the registration by matching global structures at lowest resolution and then matching local structures as the resolution is refined.

2.3 Performance Evaluation Metric

Signal-to-noise ratio was used as the performance evaluation metric of the presented method. Since we are interested in improving the contrast between the blood vessels and the background, a high signal represents a better contrast. We follow the techniques of Suri [11] and Madsen [12] for computing the SNR based on ROI. The difference between average intensity values between the foreground and the background as the signal, and the standard deviation of intensities in the background as the noise, i.e.,

$$SNR = \frac{(\mu_{Signal} - \mu_{Noise})}{\sqrt{2}\sigma_{Noise}}$$

where, μ_{Signal} represents the mean intensity value in a small region chosen in the foreground, i.e. blood vessels. μ_{Noise} represents the mean intensity value in a region with same size in the background and σ_{Noise} represents the standard deviation of intensities in the background region without any feature, i.e. without blood vessels.

3. Results

The two registration methods were performed over a total of 73 pair of images corresponding to Carotid, Renal and Neural images, and they are compared with conventional DSA. Table 1 shows the results of SNR values over a total of 73 datasets.

Table1. Comparison results of conventional DSA, and motion-corrected DSA using modified Demons and using Inverse Consistent Registration

S. No.	Method	Mean SNR	Std. Dev.	% improvement
1	Conventional DSA	3.77	2.16	-
2	Modified Demons	3.73	2.28	-1.09%
3	Inverse Consistent Registration	6.28	3.56	66.44%

It can be seen that using the SNR as the evaluation metric, the inverse-consistent image registration method, combined with non-linear enhancement, produces an improvement of 66% over the images without any registration. The modified Demons, on the other hand, reduces it slightly. This is mainly due to the reason that while modified Demons is much faster, it does not explicitly impose regularization constraints on the registration and as a result, there are some artifacts in the background region produced by the registration, which result in lower SNR even though motion artifacts are significantly reduced.

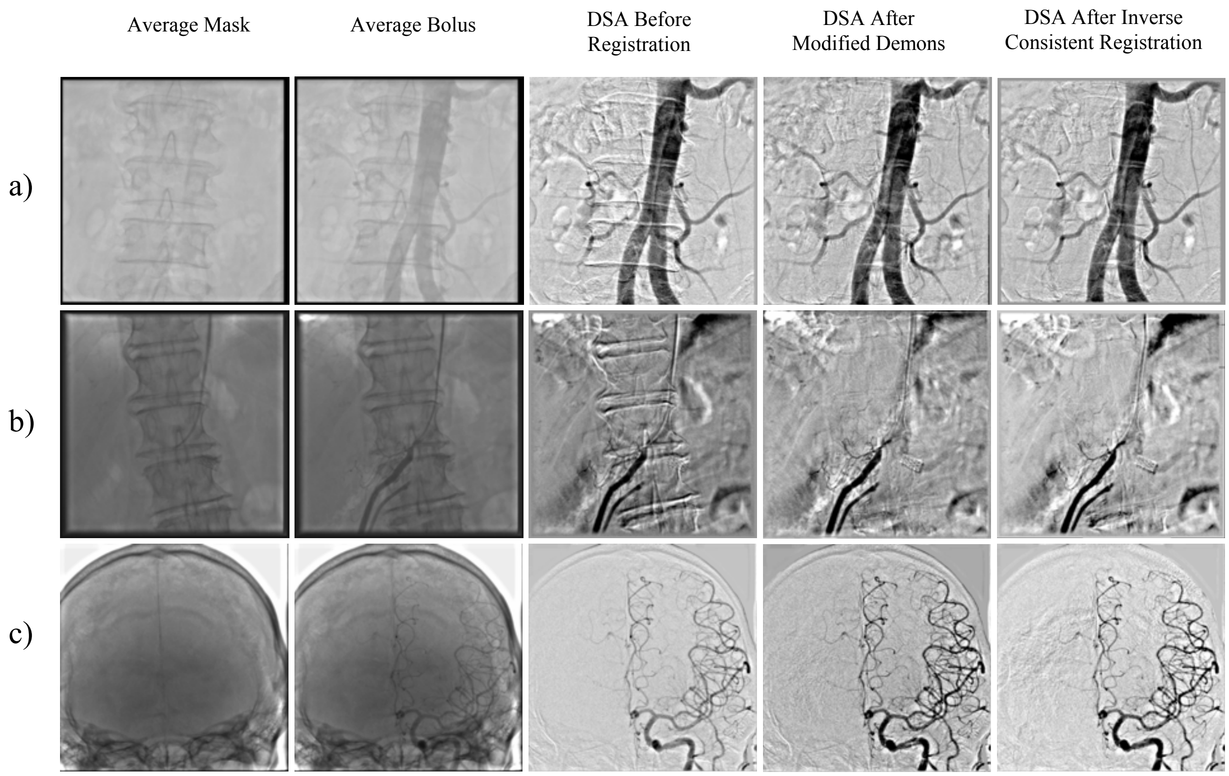

Figure 1. Image registration results for pair of images corresponding to a) iliac arteries, b) renal images and c) brain images.

4. Conclusions

In this paper, we presented two techniques to perform motion correction on DSA images: a light-weight modified Demons method with minimal regularization and a constraint-based inverse-consistent image registration method. The SNR values of the registered images were computed over a total of 73 subjects and it was found that the inverse-consistent method provides a much higher SNR value (66% more) compared to the original SNR as well as compared to the un-regularized modified Demons method. Hence, we conclude that while an un-regularized technique is fast compared to regularization-constrained method and removes large intensity differences between the images, additional constraints are needed to regularize the bending energy. On the other hand, it is worth mentioning that this result is based on our definition of SNR. Other more quality assessments might fairly compare these two registration methods.

References

[1] R. A. Kruger and S. J. Riederer, Basic concepts of digital subtraction angiography (Mosby-Year Book Inc, 1984).

[2] Y**.** Bentoutou and N. Taleb**,** Automatic extraction of control points for digital subtraction angiography image enhancement," IEEE Nuclear Science Symposium Conference, Oct. 2003, Vol. 4, 2771 – 2775.

[3] J.-P. Thirion**.** Image matching as a diffusion process: an analogy with Maxwell's demons**.** Medical Image Analysis*,* 2(3):243-260, 1998.

[4] Shen, D. and Davatzikos, C., Hammer: hierarchical attribute matching mechanism for elastic registration. IEEE Trans. On Medical Imaging, Vol. 21, No. 11, 1421:1439, Dec 2002.

[5] Christensen G.E., Johnson and H.J., Consistent image registration, IEEE Trans. Med. Imaging, Vol. 20, No. 7, July 2001, 568-582.

[6] Kybic, J. and Unser, M., Fast parametric elastic image registration. IEEE Trans. on Image Processing, Vol. 12, No. 11, Nov 2003, 1427-1442.

[7] Kumar, D., Geng, X., Hoffman, E.A., and Christensen G.E., BICIR: Boundary constrained inverse consistent image registration Using WEB-splines, IEEE conf. MMBIA, 2006.

[8] Rueckert D., Sonoda, L.I., Hayes, C., Hill, D.L.G., and Hawkes. D.J., Nonrigid registration using free-form deformations: application to breast MR images, IEEE trans. medical imaging, Vol. 18, No. 8, 1999, 712-721.

[9] Suri, J.S., Wilson, D.L., and Laxminarayan, S, Handbook of medical image analysis: Registration models (Volume-III), Kluwer Academic/ Plenum Publishers (now Springer Verlag), 2005 (ISBN: 0-306-48607-5)

[10] Wei, L., Kumar, D., Coleman, J., Suri, J., Class-based nonlinear enhancement strategies: An application for digital subtraction angiography (DSA), Submitted to ICIP, 2007.

[11] Suri, J., Guo Y., Coad C., Danielson T., Elbakri I., and Janer R., Image quality assessment via segmentation of breast lesion in X-ray and ultrasound phantom images from Fischer's full field digital mammography and ultrasound (FFDMUS) system, Jour. Technology in Cancer Research & Treatment, Vol. 4, No. 1, 2005, 1-10.

[12] Madsen, E., Zagzebski, J., Frank, G., and Rownd, J., Automated system and method for testing resolution of ultrasound scanners, Patent US 5,574,212 (1996).