A Novel 2D-3D Registration Algorithm for Aligning Fluoro Images with 3D Pre-op CT/MR Images

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ABSTRACT

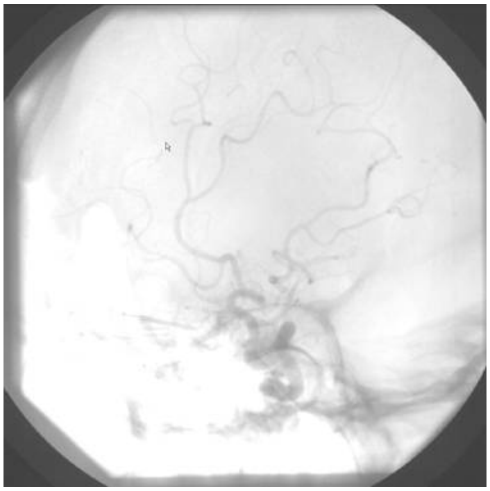
We propose a novel and fast way to perform 2D-3D registration between available intra-operative 2D images with pre-operative 3D images in order to provide better image-guidance. The current work is a feature based registration algorithm that allows the similarity to be evaluated in a very efficient and faster manner than that of intensity based approaches. The current approach is focused on solving the problem for neuro-interventional applications and therefore we use blood vessels, and specifically their centerlines as the features for registration. The blood vessels are segmented from the 3D datasets and their centerline is extracted using a sequential topological thinning algorithm. Segmentation of the 3D datasets is straightforward because of the injection of contrast agents. For the 2D image, segmentation of the blood vessel is performed by subtracting the image with no contrast (native) from the one with a contrast injection (fill). Following this we compute a modified version of the 2D distance transform. The modified distance transform is computed such that distance is zero on the centerline and increases as we move away from the centerline. This allows us a smooth metric that is minimal at the centerline and large as we move away from the vessel. This is a one time computation, and need not be reevaluated during the iterations. Also we simply sum over all the points rather than evaluating distances over all point pairs as would be done for similar Iterative Closest Point (ICP) based approaches. We estimate the three rotational and three translational parameters by minimizing this cost over all points in the 3D centerline. The speed improvement allows us to perform the registration in under a second on current workstations and therefore provides interactive registration for the interventionalist.

Keywords: 2D/3D Registration, Projective Registration, Distance Transform, Similarity Measures, Centerline Extraction, Iterative closest point

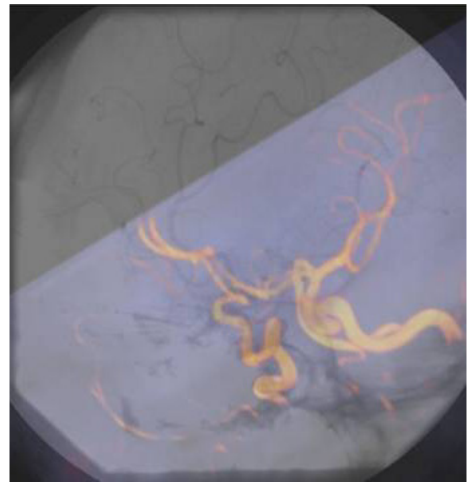
1. INTRODUCTION

Image based guidance is becoming a very important part of interventional surgery procedures. Image registration between CT and portal images has been proposed to aid patient placement for radiotherapy planning and treatment verification [1,2,3]. A number of algorithms have also suggested the use of 2D-3D registration to help in neurointerventions[4,5] and aortic stenting procedures[6,7]. It is uncommon to obtain 3D intra-operative images, and the most common imaging available intra-operatively is 2D fluoroscopy. The fluoroscope images are poor in quality because of the low radiation and low contrast-agent requirements of the modality. These along with the fact that the images obtained are projective in nature and lack depth information make it difficult for the interventionalist to navigate the guide-wire to the required location. Another problem is that fluoro image lack soft tissue information which can provide important contextual information to the interventionalist. A typical X-Ray image acquired during a neurointervention is shown in Figure 1(a).

Successful registration of the fluoro images with pre-operative 3D images (CT/MR) can greatly help the interventionalist during the procedure. The fluoro image can be augmented by overlaying the fluoro images with a volume rendering of the 3D image. In order to align the live fluoro image with the pre-operative 3D image, we need to



(a)



(b)

Figure 1: A typical fluoro image acquired during a neurointervention. The same fluoro image shown augmented with the MR time of flight image.

estimate a 6 degree of freedom (dof) volume transform, which aligns the pre-operative 3D dataset with the patient coordinate system. We can generate projections of the preoperative dataset based on the projection geometry of the C-arm. The projection geometry and the internal camera parameters of the C-arm can be obtained directly from the scanner or using a calibration routine. Overlaying the projection with the live fluoro image can provide highlighting of the vessel being navigated, even in the absence of contrast injection, provide depth information and provide anatomical context by rendering of soft tissues around the vessel. An example of such an augmented fluoro image is shown in Figure 1(b).

2. RELATED WORK

Rigid 2D-3D registration is the problem of finding a transformation that aligns a 2D image with a projection of a 3D image. The projection geometry has to be known for this, and is usually available from calibration of the C-arm. Initial approaches to 2D-3D registration relied on two or more radiographs [1]. This can be inconvenient for many interventional procedures, where space and time might not allow for multiple acquisitions per registration. Algorithmically, the approach is going to be similar for registration approaches that maximize some sort of a similarity metric between projections of the 3D image and one or more 2D images. The difference is only going to be an extra similarity term arising from the additional 2D images. The registration result will also improve with additional 2D images. Such involve an image similarity of cost function term that measures the similarity between the 2D fluoro image and the projected image of the 3D dataset. Based on how the similarity between the 2D image and the 3D image subject to the projection is evaluated, 2D-3D registration algorithms can be divided into two categories, namely intensity based and feature based methods. In the image based approach the entire image (or a region of interest) is compared with a digitally reconstructed radiograph (DRR) of the pre-operative 3D dataset based on image statistics. The main advantage of these methods is that they do not require segmentation, although definition of a region of interest improves speed and robustness. Since a new DRR has to be generated at each iteration, these approaches tend to be slow. DRR generation algorithms based on shear-warping [9], light-field rendering [10] and hardware accelerated texture rendering [11] are more efficient but compromise on the DRR quality and produce artifacts which might affect the accuracy of the registration. The similarity between the images is computed using image-based similarity measures like Mutual Information [12] [13]. Comparison of various similarity measures for 2D-3D registration can be found in [14] and [15]. The problem with image-based similarity measures is that it is expensive to compute the joint-histogram, which it has to be recomputed during every iteration of the energy minimization procedure. This makes the algorithm very slow and it is currently difficult to perform the registration in under a second which is desirable for interventional applications. Alternate, faster image similarity measures have been proposed based on volume gradients [16], but these are still slow for interventional applications.

One way to avoid this is to use feature-based similarity measures. Features mainly concentrate on only a part of the image and therefore computing the similarity is much faster than treating the whole image as one entity. The choice of the feature is an important consideration and can depend on the intended application. Centerlines of blood vessels have commonly been used as features for 2D-3D registration [17] [18]. Feature based 2D-3D registration algorithms are faster than image based ones since it is not necessary to generate DRRs. Feature based methods instead project the features directly which in much more efficient. Also the similarity computation is much faster since the similarity only needs to be computed for a small set of points rather than the whole image. The average CT image we tested was 512x512x256, and the extracted centerline had around 1000 points. This represents a huge reduction in the search space and the time to register the image. One problem with these approaches is that they need a good initial guess to converge and therefore are not very robust. In this paper we present a feature based approach with a novel method of computing the image similarity that makes the registration faster and more robust than currently used methods.

3. METHOD

We propose to register 2D fluoro images with pre-operative 3D scans of the same patient (CT/MR). The algorithm is near real-time as we use features to perform the registration and the computational cost of finding a similarity is much lower as compared to intensity-based approaches. Our idea is to use blood vessels as features for two main reasons:

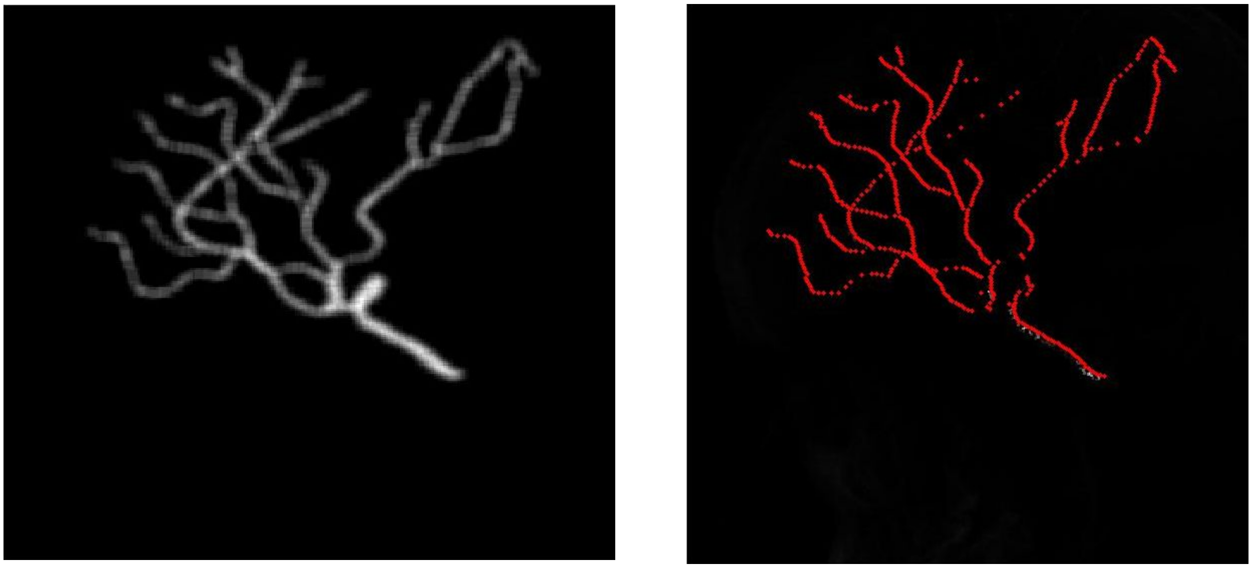
- Because of the near projective invariance of tubular objects [18]. As we lose a lot of information during the projection, this property is important to ensure that the optimizer has the least chance of getting trapped in false minima.
- A contrast agent is commonly injected into target areas during interventional procedures making it easy to segment these features.

We first describe the preprocessing required for the 3D dataset, namely the segmentation of the blood vessel and the centerline extraction. We follow it with a description of the computation of the modified distance transform for the 2D fluoro image. The similarity metric that measures the difference between the fluoro image and the projection of the 3D image along with the formulation of our energy minimization problem that estimates the required transform is described in the following section.

3.1 Segmentation and Centerline Extraction of 3D Image

We used contrast injected CT images and reconstructed 3D angio images as the 3D modality of choice. It is quite common to acquire these prior to a neurointervention. We also tested our algorithm using MR images as the 3D modality. In these cases we had an MR time of flight (ToF) acquisition, which simplified the task of segmenting the blood vessel. In all these cases, the blood vessel can be segmented quite easily by a combination of thresholding and region growing. Additionally since the 3D dataset needs to be processed only once, which can be done pre-operatively, we did not focus on developing segmentation algorithms for the 3D image. The proposed algorithm is expected to work effectively with other modalities if the blood vessels can be accurately segmented. A vascular tree segmented from a CT-angio dataset is shown in Figure 2 (a).

Once the blood vessel is segmented, we need to extract the centerline. Various algorithms have been proposed for the extraction of centerlines from binary images [19,20,21,22]. Most of these algorithms are based on the distance transform. We instead use a topology preserving thinning algorithm proposed by Palágyi et al [23]. The extracted centerline is shown in Figure 2 (b). During the registration, only these points need to be projected which is much faster than generating DRRs and consequently it makes the registration much faster. It is important to observe here that we are only interested in the points lying on the centerline and not the connectivity. This is important because the algorithm is not sensitive to missing branches or gaps that might be present in certain vessels because of inconsistent flow of contrast. This quality makes the algorithm robust to errors in the segmentation of the vascular structure and errors in the centerline extraction.



(a) (b)

Figure 2: The vascular structure extracted from the 3D volume; and (b) centerline obtained by the sequential thinning algorithm

3.2 Segmentation and Distance transform on the 2D image

The vessel in the 2D image is easily segmented by subtracting it from the zero-contrast image. In a clinical setting a reference fluoro image is acquired before the injection of the contrast. This is then digitally subtracted from the contrast injected fluoro to obtain the segmented blood vessel. Other approaches using centerlines for 2D-3D registration compute the 2D centerline from the segmented image and use ICP approaches to minimize the distance between the 2D centerline and the projection of the 3D. To make the computation of the cost function (the distance between the two centerlines) faster, we instead compute the distance transform of the segmented 2D vessel. We do not compute the 2D centerline, but instead use the distance transform image as a direct estimate of the distance between the two centerlines. We modify the distance transform such that the distances are largest farthest from the edge on the outside, and lowest (zero) at the centerline. This allows us a smooth metric that is minimal at the centerline and large far from the vessel.

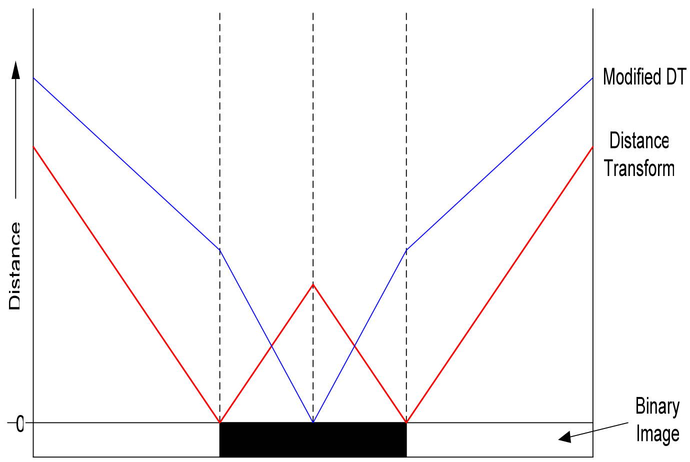
The difference between the projection of the 3D image and the 2D image is approximated by the distance between the respective centerlines. The 3D centerline is represented by a set of points, $\mathbf{x} = \{x_1, x_2,\ldots,x_n\}$, the 2D distance transform is represented by the distance map, *f(x)*. The distance between the two centerlines can be represented by,

$$D = \sum_{i=0}^{n-1} f(\Pi(\chi(\mathbf{x})))$$

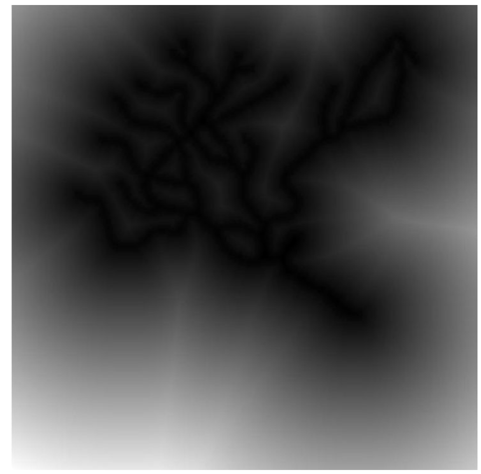
where, $\Pi(\chi(\mathbf{x})$ is the projection of the 3D centerline after the current estimate of the transform, χ, has been applied. This is extremely easy to compute since all we need to do is to transform and project *n* points and then compute the sum of the values at these indices from the distance map. The concept of the modified distance transform is illustrated in Figure 3. As can be seen, the minimum for the cost function is reached when all the points lie on the center of the segmented 2D vessel.

3.3 Initial Localization

We initial transform that is used to start the registration is obtained from the DICOM header, for acquired datasets and directly from the X-Ray system. The projection parameters are also obtained from the X-Ray system directly.



(a)



(b)

Figure 3: (a) Graphical explanation of the modified distance transform; (b) The modified distance transform computed on a vessel tree.

3.4 Energy Minimization

In order to estimate the six parameters, three translational and three for rotation, we minimize a cost function estimating the distance between the 2D vessel and the projection of the 3D centerline. Since, we have the modified distance transform, the cost function is simply the sum of the distance transform values over the projection of the 3D centerline points using the current estimate for the camera pose. We used three algorithms for minimizing the cost function, best neighbor, Powell-Brent and the gradient descent algorithm. While Powell-Brent was the best performer in terms of speed and robustness, we preferred using the best neighbor optimizer since it was most robust and the additional cost functional evaluations did not penalize us substantially. The gradient descent algorithm converged fastest, but was sensitive to the initial conditions and performed poorly when the initial guess was not close to the ground truth.

4. RESULTS

Since we only need to compute the projection of the 3D centerline, it amounts to projecting typically a few hundred points using the current estimate of the transformation and the projection matrix. This is followed by summing the values of the distance map at these points. Thus the evaluation of the cost function is approximately of 10-30 ms. Moreover, since the distance map decreases sharply towards the centerline, the algorithm is very robust to the initialization for the registration. Most registration algorithms can be sensitive to the way the rotational and translational parameters get weighted. If the initial guess is far from the actual transform then the rotational parameters can interfere with the energy minimization and force the algorithm to get trapped in local minima. To avoid this, we perform the registration in two stages; first we optimize only for the translational parameters which allows the initial guess to be refined. This is followed by a second minimization that is performed on all 6 parameters.

The average registration error was less than 0.4mm over the centerline. This shows that the algorithm converged satisfactorily and the error over all points was minimized. The average error in the estimation of the rotational parameters was 2.1^o for rotations about the x and y axis. However the error in the estimation of the rotation about the z axis was lower at 1.2^o. The trend in the estimation of the translational parameters was the right opposite. The average error in the in plane (x, y) translation was 1.3 mm whereas it was much larger along the z axis, at 13.1mm. The z values are because of the out-of-plane translation, and are higher than the in-plane error because of the small field of view (9^o) of the images. This can be alleviated by the use of additional fluoro views if available. Adding additional views should not affect the performance since the cost function evaluation is fast. The average error in the estimation of the parameters is summarized in Figure 4.

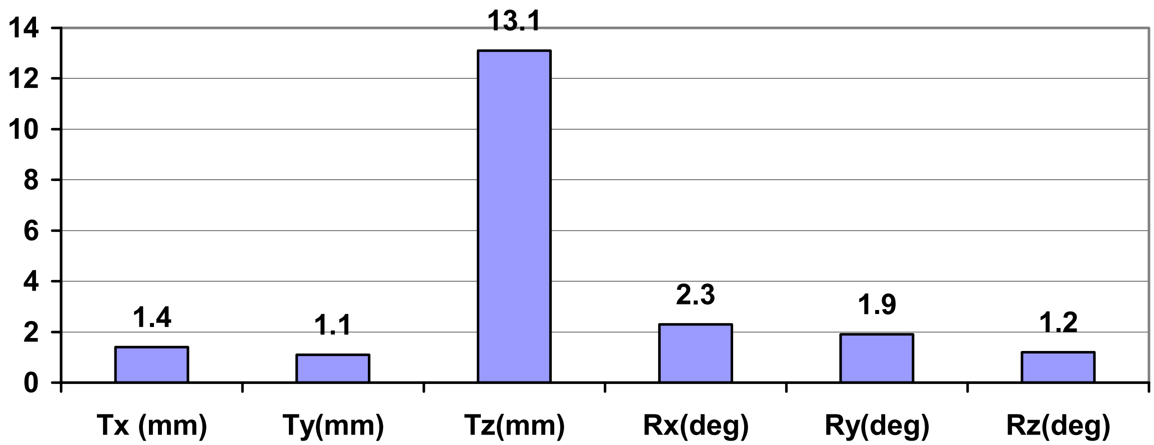


Figure 4: Average registration error in the estimation of the parameters

5. CONCLUSION

A fast and effective feature based registration algorithm is proposed for rigid registration of pre-operative 3D images (MR/CT) with intra-operative 2D fluoro images. The algorithm uses centerline of 3D vascular structures as features and thereby greatly reduces the amount of information used for the registration. This allows the algorithm to converge faster and also decreases the probability of the optimizer getting trapped in local minima. The novel method for the computation of the distance function is also proposed based on the distance transform. This also reduces the registration time and consequently the registration can be performed in near real time. Although the out-of-plane error is substantially larger than the in-plane error, this is not a serious concern for the current method since the speed of the registration method allows for a new registration to be performed in the event of a change in C-arm angulation.

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