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A Robust Technique for 2D-3D Registration

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Abstract—**A robust 2D-3D registration method with a wide capture range is presented. The method registers pre-operatively collected 3D Computed Tomography (CT) data sets of a single bone fragment to its intra-operative fluoroscope images. The registration technique relies on hardware rendering of CT data on consumer-grade graphics cards to generate digitally reconstructed radiographs (DRRs) in real time. We also employ Unscented Kalman Filter to solve for the non-linear dynamics governing this 2D-3D registration problem. The method is validated on phantom models of three different anatomies, namely scaphoid, pelvis and femur. We show that, under the same testing conditions, our proposed technique outperforms the conventional simplex-based method in capture range and robustness while providing comparable accuracy and computation time.**

I. Introduction

Registration of CT to fluoroscope images is a fundamental task in Computer-Assisted Orthopaedic Surgery (CAOS) and Radiotherapy (CART). In the case of CAOS, registration of pre-operative CT to a set of intra-operative fluoroscope images can be used to create a precise link between the virtual patient (i.e. the pre-operative CT) displayed on a screen and the physical patient in the operating room (OR) so that the CT image can be used to guide the intervention. In the case of CART, registration of CT to portal images allows precise configuration of treatment beams so that the radiations are focused on tumors/lesions thus the damage to healthy tissues remains minimal.

The CT to fluoroscope registration problem can be briefly described as finding a geometric transform that positions the CT in the patient's coordinate space so that a user-defined similarity measure between the CT and a set of fluoroscope images is optimal. Usually the CT is captured pre-operatively and used for surgical/treatment planning; and the fluoroscope images are captured intra-operatively and used to update the surgical/treatment plan dynamically. A clinically usable CAOS or CART system requires accurate, fast and robust registration between the two data sets.

One can formulate the CT to fluoroscope registration as a 2D-3D registration problem. A number of methods have been proposed to address this problem in the literature. More detailed reviews on this topic can be found in [1, 2, 3, 10, 14, 15, 16, 17]. A commonly adopted approach is to generate intermediate simulated 2D fluoroscope images, called digitally reconstructed radiographs (DRRs), from the 3D CT and compare the simulated fluoroscope images with the real ones. Registration is achieved when the DRRs closely resemble the real fluoroscope images. Multiple fluoroscope images from different viewing angles are often used in the process to compensate for the loss of depth information in the acquired 2D fluoroscope images. The majority of the previous work has focused on how to generate DRRs quickly and realistically [8, 9, 10, 11, 12, 13] or on how to define/select a similarity measure between DRRs and fluoroscope images. Those methods often relied on either the simplex or, if calculation of derivatives is possible, the gradient-descent optimization method to search for an optimal registration. In this paper, due to the non-linear nature of the CT to fluoroscope registration problem, we propose to use the Unscented Kalman Filter (UKF) [7] as the optimization method. The proposed registration method requires no calculation of derivatives, deals with multiple observations simultaneously, estimates the variance along with the state, and uses an improved hardware-based technique for fast DRR generation. We believe that these features could potentially benefit the CT to fluoroscope and other 2D-3D registration problems. To validate our approach, we extensively test our method on various phantom data sets and compare it with a conventional simplex-based approach.

The remaining of this paper is organized as follows: Section II gives the details of our technique; Section III describes the testing scenarios and presents the experimental results; and Section IV concludes the paper.

II. Method

Our method consists of four major components: a transform that positions the CT in the patient's coordinate space; a hardware-based volume rendering engine that generates DRRs at interactive rates; a similarity measure that compares the DRRs with the corresponding fluoroscope images; and the UKF that recursively optimizes the transform parameters. Figure 1 shows how these components interact with each other to search for an optimal registration solution. Once the algorithm is initialized, it runs iteratively until some pre-defined stopping criteria are met. One iteration of the algorithm works as follows:

1) Apply the current transform to CT;
2) The transformed CT is fed to the volume rendering engine along with the fluoroscope images' imaging parameters, including the C-arm focal positions and the intensifier transforms;
3) For each fluoroscope image, a corresponding DRR is

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generated by the graphics hardware;

4) A set of similarity measures is computed for all <DRR, fluoroscope> pairs;
5) The computed similarity measures are fed to the UKF along with the current transform parameters as well as their variances;
6) The UKF updates the transform parameters and the variances.

The above process repeats until a set of optimal similarity measures is achieved or the updates to the parameters or variances are sufficiently small. In the following paragraphs we discuss each of the components in detail.

A. Transform and its Initial Value

The transform used to position the CT in the OR coordinate frame is a simple rigid transform with six parameters: three Euler angles for rotation and three scalars for translation. Most 2D-3D registration methods require an initial transform that is close to the unknown real solution to start the registration. Our method is no exception. We find an initial guess of the transform parameters by manually selecting a few landmarks from both CT and fluoroscope images, e.g. three to four visible points on the bone surface, and solving an absolute orientation problem using the singular value decomposition (SVD) based technique [5]. If the landmarks are selected carefully, the computed initial parameters can yield an initial mean target registration error (mTRE) [6] within 3cm, which is often sufficient to start our registration method.

B. Hardware-based Volume Rendering Engine

We use an improved hardware-based technique, i.e. the Adaptive Slice Geometry Volume Rendering Algorithm [8], for fast DRR generation. The algorithm improves the common view-aligned 3D texture-mapping based method by adaptively slicing the volume based on image content. Firstly, the CT is partitioned into a set of axis-aligned bounding boxes (AABBs) based on a user-defined transfer function that removes the empty voxels. Then the AABBs are sliced perpendicular to the viewing direction (i.e. the focal axis of the C-arm) in order back to front. Finally, the powerful OpenGL features of consumer-grade graphics cards, including 3D texture mapping, multi-texturing, and fragment programs, are employed to render and blend the slices into a final DRR. We tested our implementation on an ATI Radeon X800 card with 256MB video memory by rendering CT volumes of size 512x512x256 into DRRs of size 473x473, and have achieved the speed of 20-50 frames per second, depending on the image content in CT.

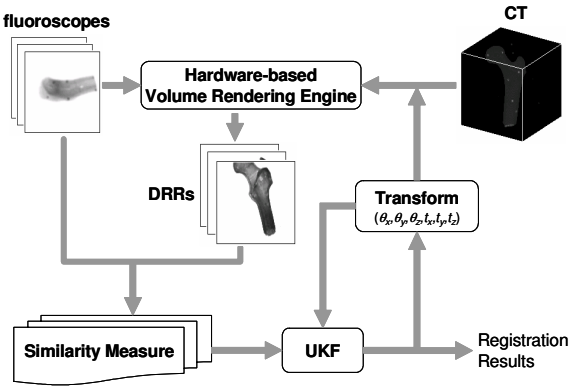

Fig. 1. The UKF-based approach for CT to fluoroscopes registration.

C. Similarity Measure

A variety of similarity measures [2, 4, 10] have been proposed for comparing a DRR with a fluoroscope image. A few examples are normalized correlation, variance weighted correlation, mutual information, pattern intensity, gradient difference, and gradient correlation. Different measures have very different behaviors in the parameter space, depending on the type of transform used, the initial conditions, and the contents of original image data. We do not bias towards any particular similarity measure. Any or a combination of them can be used with our method in a plug and play fashion.

D. Unscented Kalman Filter

UKF [7] is a sequential least squares optimization technique employed for solving non-linear systems. It estimates both the state and its covariance matrix, and no calculations of Jacobian or Hessian are required. Instead, UKF assumes that the unknown state is a Gaussian-distributed random variable (GRV) and uses a minimal set of carefully chosen sample points along with the corresponding observations to learn about the behaviors of a true non-linear system. The sample points, which are generated using the Unscented Transform (UT) [7], completely capture the true mean and variance of the GRV and, when propagating through the non-linear system, capture the posterior mean and variance accurately up to at least the second order Taylor series approximation. Figure 2 illustrates the workflow of UKF, which contains the following three stages:

1) Calculate sigma points from the current state and variance using UT;
2) Propagate the sigma points through the known dynamic state and observation models;
3) Compute the gain and update the state as well as its covariance matrix using the computed gain and the known observations.

The general equations and details about the UKF can be

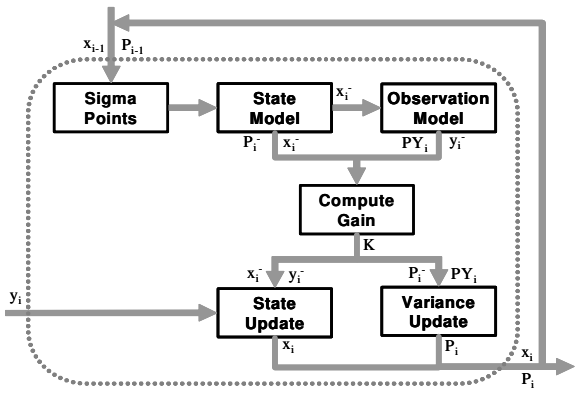

Fig. 2. The UKF algorithm.

found in [7]. In our proposed method for CT to fluoroscope registration, the state and observation models have the following forms:

$$x = [\theta_x, \theta_y, \theta_z, t_x, t_y, t_z]^T$$

$$x_i = x_{i-1} + N(0, \sigma_x^2)$$

$$y_i = SM(x_i) + N(0, \sigma_y^2)$$

where x is the transform parameters to be estimated, SM is the non-linear similarity measure between the DRRs and the corresponding fluoroscope images as a function of transform parameters, σ_x and σ_y are the variances of the process and measurement noises intrinsic to the system. As multiple fluoroscope images are used in our method, y is a multiple dimensional measurement vector.

Since the registration goal is to achieve an optimal similarity value for all <DRR, fluoroscope> pairs, the known observations are constant in our method, which is the optimal value of the selected similarity measure. For example, in the case of normalized correlation, the value is 1.0.

III. Experiments and Results

A. Data Sets

We evaluate our method using three different phantoms: a small scaphoid bone, a large pelvis, and a long and thin femur, all with embedded fiducial markers for gold-standard validations. For the scaphoid and pelvis phantoms, the CT data were registered to synthetic fluoroscope images, i.e. DRRs. The DRRs were generated from three orthogonal views with the CT positioned in the origin of the reference space. For the femur phantom, the CT was registered to three real fluoroscope images. Table I lists the specifications of all testing images, and Figure 3 shows the CT and the corresponding DRRs/fluoroscope images for each phantom.

TABLE I
Data Specifications

Data	Size (voxels)	Resolution (mm^3)
Scaphoid	256^2 x 64	0.375^2 x 0.525
Pelvis	256^2 x 256	1.176^2 x 0.766
Femur	256^2 x 128	0.625^2 x 1.445
Fluoroscopy/DRR	256^2	0.836^2

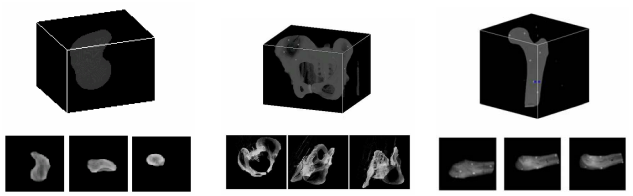

Fig. 3. The CT volumes and the corresponding DRRs/fluoroscope images.

B. Experiments

A conventional simplex-based method was implemented along with our UKF-based approach for the purpose of comparison. For each phantom data set, 100 experiments were performed for both methods with the initial transforms generated by adding random rotations (±12°) and translations (±12mm) to the gold-standard. For the CT to DRRs registrations, the gold-standards were known. For the CT to fluoroscope registration, the gold-standard was computed by a fiducial registration [5] using the embedded markers. Normalized correlation was used as the similarity measure in all experiments, and the same set of process and measurement noise assumptions was made for all experiments using UKF-based method.

C. Results

We recorded the initial and final mTREs for each experiment. The mTRE was computed as the average difference between the positions of some CT points mapped by the evaluated transform and the gold-standard. We used 20 randomly selected points from the region bounding the bones for mTRE calculation. Figure 4 shows the registration results, and Figure 5 shows the image differences between the DRRs and the corresponding fluoroscope images before and after registration for one experiment of the femur data with the UKF-based method.

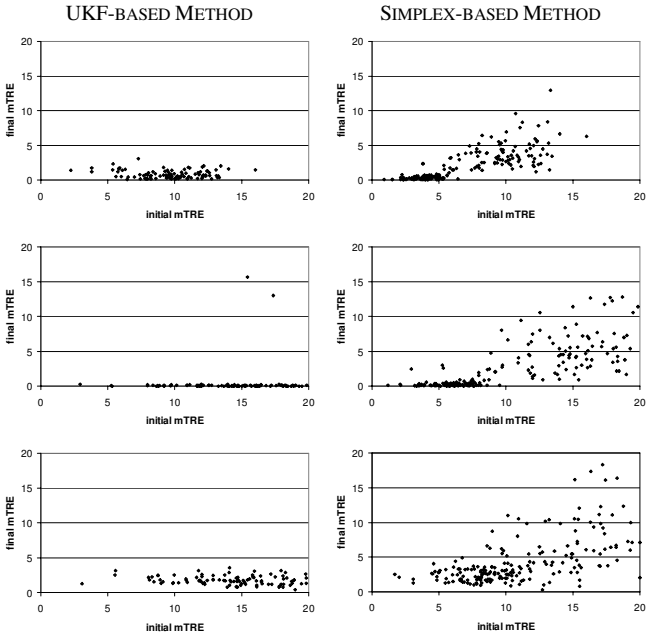

Fig. 4. Registration results – initial mTREs vs final mTREs. All units are in mm. First row: scaphoid; Second row: pelvis; Third row: femur.

We compare the capture range, accuracy and computation time of the two methods. Capture range is defined as the distance from the gold-standard that at least 95% of registrations are successful. It is measured as an initial mTRE and reflects the robustness of an algorithm. A registration is said successful if the final mTRE is within 2mm for the scaphoid and pelvis data and 3mm for the femur data. Accuracy was evaluated using the statistics of the successful registrations, which include the mean and standard deviation of the final mTREs. Since DRR

generation is the dominant operation in both methods, the computation time was measured as the average number of DRR generations required to reach successful registrations. Table II – IV show the results of capture range, accuracy and computation time for each phantom data set with different methods.

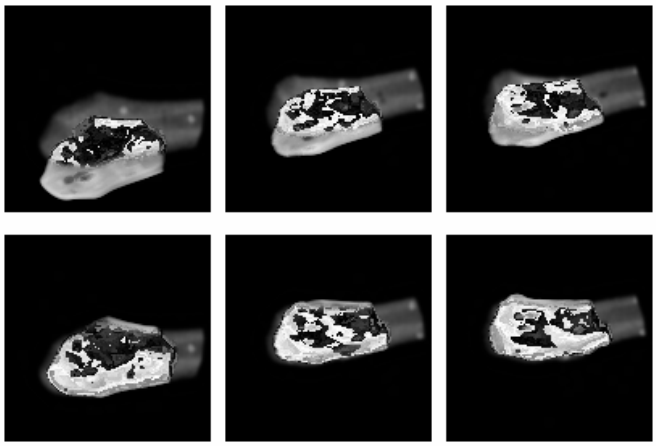

Fig. 5. The image differences between the DRRs and the corresponding fluoroscope images for one experiment of the femur data with the UKF-based method. Top: before registration; Bottom: after registration.

TABLE II
COMPARISON OF CAPTURE RANGE

Method	Scaphoid	Pelvis	Femur
UKF-based	12mm	20mm	11mm
Simplex-based	5.8mm	9.6mm	8mm

TABLE III
COMPARISON OF ACCURACY

Method	Scaphoid	Pelvis	Femur
UKF-based	0.80±0.58mm	0.11±0.10mm	2.42±0.57mm
Simplex-based	0.32±0.21mm	0.25±0.20mm	2.53±0.56mm

TABLE IV
COMPARISON OF NUMBER OF DRRS REQUIRED

Method	Scaphoid	Pelvis	Femur
UKF-based	760	650	700
Simplex-based	620	630	580

D. Discussion

From Figure 4 and Table II, it is obvious that the UKF-based approach consistently has a larger capture range than that of the simplex-based method. Any accuracy under 1mm is considered acceptable for the CT to synthetic fluoroscope registration experiments. Generation of a single DRR took about 0.04 seconds on average. Table III and IV indicate that the two methods have very similar performance in accuracy and computation cost.

IV. CONCLUSION

We presented a new method for registering 3D CT data sets to 2D fluoroscope images that uses UKF for robust optimization and a hardware-based adaptive geometric slicing technique for fast DRR generation. The experimental results showed that our UKF-based method outperforms the conventional simplex-based method by having a larger capture range while providing comparable accuracy and computation time. Future work will include the extension of the proposed method to register multi-fragment bone fractures simultaneously to a set of intra-operative fluoroscope images, which will be used in computer-assisted trauma surgery.

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