A METHOD FOR FRAME-BY-FRAME US TO CT REGISTRATION IN A JOINT CALIBRATION AND REGISTRATION FRAMEWORK

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ABSTRACT

A method is presented for achieving robust joint calibration and registration in ultrasound (US) to CT registration for computer assisted orthopedic surgery. We propose using an effectively real-time frame-by-frame registration algorithm during US image acquisition. This approach provides more control to the surgeon, is more robust to initial conditions, and is computationally efficient. We then use the estimated registration of the frame-by-frame method to initialize a joint calibration and registration algorithm, and this is shown to produce over all more accurate and repeatable results. Experiments are performed using simulated US images of the lumbar vertebra and the distal femur as potential areas of interest for surgical applications.

Index Terms— Point-to-surface registration, Kalman filtering, ultrasound, computer-assisted surgery, calibration

1. INTRODUCTION

In computer-assisted orthopaedic surgery (CAOS), surgeons often benefit from enhanced visualization by registering a pre-operatively acquired medical image, such as from CT or MRI, to the patient's anatomy during surgery. Registration is usually achieved by digitizing bone surface points from the patient using a navigated pointer, and determining the optimal transformation between the pre-operative data and the points. The use of navigated 2D ultrasound (US) imaging for acquiring bone surface points to be used in registration is an ongoing area of research, and one of the main advantages of using US is that points can be acquired non-invasively. This can render certain procedures minimally-invasive as well as provide bone surface points from surgically inaccessible regions [1, 2].

Concerning the use of US, a navigation system typically provides the positions of the US probe, the bone(s) to be operated, and possibly other tools used for the intervention. Navigation is made possible by using dynamic reference bases (DRBs), which are markers that are rigidly attached to the objects in question. A registration algorithm would provide the rigid transformation between the pre-operative dataset (typically CT in the domain of orhopedics) and the tracked DRB that is attached to the anatomy. In this scenario, the transformation between the US image and the DRB attached to the US probe also needs to be determined, and this is typically referred to as US calibration. US calibration is another active area of research, and most approaches propose that calibration be performed in a water bath using some phantom of known geometry. The resulting transformation depends on eight parameters: six parameters of a rigid transformation as well as one scaling parameter for each dimension of the US image.

Moghari et al. proposed using the Unscented Kalman Filter (UKF) for rigid registration in CAOS, and showed that it had improved performance compared to the Iterative Closest Point method [3]. The advantage of the Kalman filter is that it is a computationally efficient least-squares solver, which is an ideal feature for intraoperative registration applications. Furthermore, the UKF was originally formulated to avoid some of the linearizations that occur in the classic formulation of the Kalman Filter and the Extended Kalman Filter (EKF) [4].

The work presented in this paper can be regarded as an extension of the work done by Moghari et al. whereby the workflow is adjusted to reduce effective computation time and increase the surgeon's control over the registration, by considering that registration could be performed during the US image acquisition, as suggested in our previous work [5, 6]. Using this approach, the surgeon would then be more able to interpret the quality of the image acquisition and judge whether more US images would be needed, thus providing more control and helping to ensure an improved and less time-consuming registration. Once the image acquisition is complete, and a suitable registration is provided, the method of joint US calibration and registration proposed by Barratt et al. [1] can then be used to refine the outcome. Barratt et al. perform joint calibration and registration by optimizing the necessary parameters over the complete set of US-acquired bone surface points, using a Levenberg-Marquardt algorithm to minimize their cost function [7].

As will be demonstrated by the experiments presented in this paper, using our frame-by-frame UKF registration would improve the outcome of Barratt's joint calibration and registration algorithm in terms of accuracy, robustness to initial conditions, and furthermore fewer iterations would be needed for convergence once the US images are acquired.

Several orthopedic procedures could benefit from an US-based navigation system, and the areas of interest would be the proximal femur, the pelvis, the distal femur, the shoulder, as well as the spine. For the experiments described herein, we will consider one lumbar vertebra and the distal femur as examples for target applications.

2. CALIBRATION AND REGISTRATION FOR NAVIGATED ULTRASOUND

The problem at hand is in finding the transformation that would place the CT-generated surface model in the coordinate space of the anatomy. The quality of a registration result would depend on the quality of the measurement data. In the case of US images, the latter statement implies that the quality of the registration result would depend on the quality of the US calibration in addition to other factors.

Barratt et al. [1] introduced a framework for registering a point set obtained from US imaging while simultaneously optimizing calibration parameters. In their application, anatomical objects with

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attached reference marker are imaged by a navigated ultrasound system. Using the tracking data and the estimates of the calibration and registration parameters, the point cloud obtained from US can be mapped to the CT image space. The distances between the mapped US points and the CT surface are directly related to the quality of the calibration and registration parameter estimates and can therefore be used as a cost function for optimizing these parameters.

After acquiring a set of US images, the cost function representing the sum of squared distances between mapped US points and the CT surface is optimized using the Levenberg-Marquardt (LM) algorithm. The authors show that registration accuracy is improved when calibration parameters are included in the optimization scheme. Hence they provide a method to improve the measurement data while performing US-CT registration.

As in [1], we will assume that an initial estimate for the calibration parameters is available, which is realistic in the sense that it could quickly be obtained pre-operatively with the use of a calibration phantom [8]. Furthermore, it will also be assumed that bone surface points could be automatically segmented from the US images with some degree of error.

2.1. Registration Based on the Unscented Kalman Filter

For the UKF-based registration method, Moghari et al. [3] define the measurement $\mathbf{z}_k$ as the set of points in world coordinates acquired by segmenting the US images. At a given time step k, the state $\mathbf{x}_k$ is comprised of the true parameters that represent the transformation between the US points and the corresponding points on the surface model, denoted by $\hat{\mathbf{z}}_k^-$. The estimate of this state, which will be determined by the UKF, is denoted $\hat{\mathbf{x}}_k$, and is a 6×1 vector $[\alpha, \beta, \gamma, t_x, t_y, t_z]^T$ representing the parameters of a rigid transformation. The CT surface points $\hat{\mathbf{z}}_k^-$ form the predicted measurement of the UKF at time step k, and are obtained by searching for closest points using Euclidean distances.

The predicted measurement $\hat{\mathbf{z}}_k^-$ is defined by:

$$\hat{\mathbf{z}}_k^- = h(\hat{\mathbf{x}}_k) \quad (1)$$

$$\hat{\mathbf{z}}_k^- = \mathbf{T}_{REG}(\hat{\mathbf{x}}_k) \cdot \hat{\mathbf{z}}_0^- \quad (2)$$

where the matrix $\mathbf{T}_{REG}$ is a 4×4 rigid transformation matrix using the estimate of the parameters, $\hat{\mathbf{x}}_k$, at time step k. $\hat{\mathbf{z}}_0^-$ are the initial coordinates of the corresponding surface points.

At each prediction step of the UKF, the estimated state $\hat{\mathbf{x}}_k$ is applied to the surface at the initial position, S_0, producing S_k. Correspondence is determined between the US points $\mathbf{z}_k$ and S_k, which yields $\hat{\mathbf{z}}_k^-$, and when the frame-by-frame registration procedure is completed, the resulting state is applied to S_0.

The predicted state and predicted state error covariance are propagated in the prediction step using:

$$\hat{\mathbf{x}}_k^- = \hat{\mathbf{x}}_{k-1} \quad (3)$$

$$\mathbf{P}_k^- = \mathbf{P}_{k-1} + \mathbf{Q}_k \quad (4)$$

In the subsequent correction stage the estimates are updated using the usual Kalman filter equations:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k \left(\mathbf{z}_k - \hat{\mathbf{z}}_k^-\right) \quad (5)$$

$$\mathbf{P}_k = \mathbf{P}_k^- - \mathbf{K}_k \mathbf{P}_{zz} \mathbf{K}_k^T \quad (6)$$

where the Kalman gain $\mathbf{K}_k = \mathbf{P}_{xz}\mathbf{P}_{zz}^{-1}$ is obtained using the Unscented Transform to compute the predicted state-measurement and the predicted measurement covariances [3].

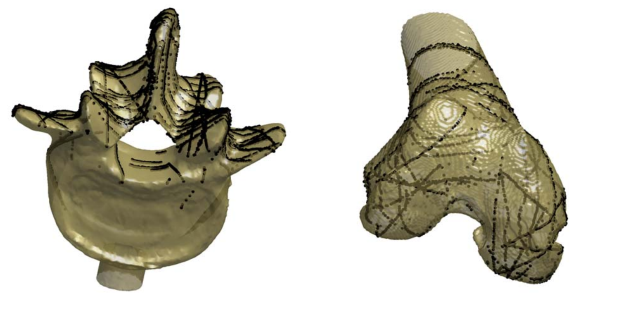

Fig. 1. Simulated US points overlaid onto (left) L4 lumbar vertebra and (right) distal femur

2.2. The Frame-by-frame Calibration and Registration Procedure

Moghari et al. [3] applied the UKF to estimate rigid transformation parameters in US-to-CT registration. By their implementation, the UKF iterates N times, where N is the number of points in their $\mathbf{z}_k$, and for each iteration, the number of points is gradually increasing. While this approach usually provides smooth filter behavior, it does not take advantage of the Kalman filter's sequential real-time nature. For the work presented here, we propose using the UKF to update the registration as navigated 2D US images are acquired.

Each US frame is treated as one signal, which yields a coplanar cloud of points, $\mathbf{z}_k$. The registration is updated with each newly acquired frame, and so the time step k is now related to the number of US frames, as they are acquired, rather than the number of points. During image acquisition, the surgeon can then receive visual and numerical feedback in terms of how well the algorithm fits the surface to the US-acquired points. The result of this approach is that the acquisition can be halted once the registration has sufficiently converged.To stabilize the frame-by-frame processing, a small subset of points from prior US frames is used to complement the point sets of new frames. That is to say, all or most segmented points of frame k are kept at iteration k, but 10 randomly chosen points from each previous frame are also used in the algorithm. The additional information from prior frames would help ensure that the anatomy of interest is well-described in 3D. The frame-by-frame UKF registration would begin once the first three frames have been acquired in order to avoid an underdetermined problem in the first iterations.

As in [3, 6] points are vertically concatenated to form $3N \times 1$ vectors for both the measurement $\mathbf{z}_k$ and predicted measurement $\hat{\mathbf{z}}_k^-$ For these experiments we augmented the UKF only with the state, and $\mathbf{P}_{zz} = \mathbf{P}_{yy} + \mathbf{R}_k$ with $\mathbf{R}_k$ a $3N \times 3N$ matrix. $\mathbf{Q}_k$ and $\mathbf{R}_k$ are initialized and updated such that the registration behaves smoothly, and further discussion on the selection and updating of the state and measurement covariances can be found in [3, 4]. Using Wan's notation [9], we used standard values for the UKF scaling parameters, that is $\alpha = 1e^{-3}$, $\beta = 2$ and $\kappa = 0$.

Barratt et al. propose a three-step process to ensure convergence of their joint calibration and registration algorithm, whereby first the registration parameters are estimated, then the rigid calibration and registration parameters are estimated jointly, and finally the calibration, registration and the scaling parameters are estimated [1]. In the following experiments, it will become clear that this approach is not optimal, and can be time-consuming when considering that the frame-by-frame registration can provide a suitable estimate during US image acquisition.

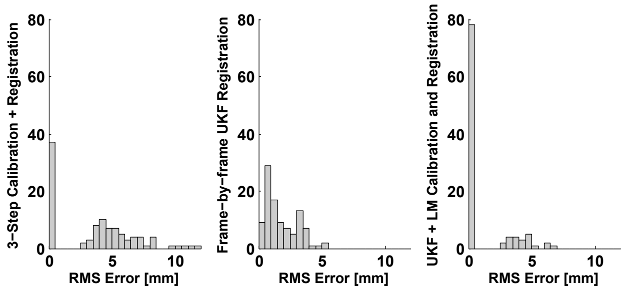

Fig. 2. Fitting error for the vertebra, histograms show RMS errors for: (left) 3-step LM method (middle) Frame-by-frame UKF registration (right) Combined approach

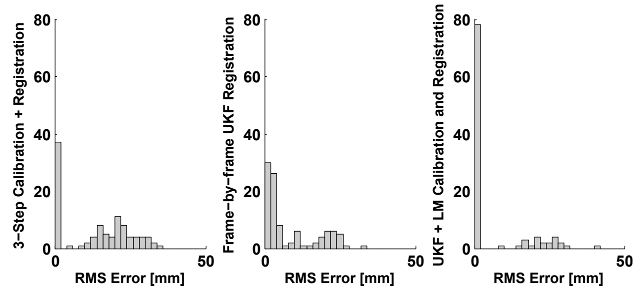

Fig. 3. Corresponding surfaces error for the vertebra, histograms show RMS errors for: (left) 3-step LM method (middle) Frame-by-frame UKF registration (right) Combined approach

The estimated parameters of the frame-by-frame UKF registration will be used to initialize the method of Barratt et al., which will in turn be used to jointly estimate the calibration and registration parameters in a post-acquisition refinement step. It should be noted that rather than using a three-step process, the method of Barratt et al. will be used to immediately estimate the calibration and registration parameters. The result of this approach is that fewer iterations are required for convergence, and the calibration and registration outcome is more accurate than the three-step approach used in [1].

2.3. Experiments

In order to obtain a precise performance evaluation for the method, simulated data was used in the first series of experiments. Based on a bone surface model segmented form CT, ultrasound imaging was simulated and a dataset representing US frames from different imaging directions was created. The set of true parameters is therefore known and can then be used as a gold standard to measure the accuracy of the algorithms.

Two datasets containing 36 simulated images each were created. For the first dataset, images of the distal femur included portions of the femoral shaft, inner and outer tuberosity as well as the condyles, which are locations that would be accessible on a real patient using flexion and extension of the knee joint, avoiding the area covered by the patella. Another dataset represented the L4 vertebra imaged in anterior-posterior direction. Using US on the spine, areas facing the back of the patient can be imaged. These include the spinous process, the articular processes and the transverse processes. Figure 1 shows the two surface models and the surface points obtained by simulating ultrasound imaging.

The convergence behavior of the algorithms was evaluated by running a series of experiments with random starting estimates selected within a certain range around the ground truth parameters. For each dataset, the algorithms were used 100 times, using a different randomly-generated starting point in each case.

For the vertebra dataset, the calibration parameters were perturbed within a range of $\pm 5[deg]$, $\pm 9[mm]$ around the true parameters for rotation and translation; scaling parameters were chosen within $\pm 10\%$ of the true scaling parameters. These ranges represent the differences between the pre-operative calibration and intra-operative calibration after covering the probe with a sterile wrap and remounting the marker shield. The range of the scaling parameters represents the variations in speed of sound that can occur on human tissue. Registration parameters were chosen within $\pm 10[deg]$ for rotation and $\pm 18[mm]$ for translation aiming to cover the range of parameters obtained by a rough initial registration estimate. The distributions of all the randomly-generated parameters was uniform.

More erroneous values were generated for the distal femur data. The calibration parameters laid within a range of $\pm 10[deg]$, $\pm 24[mm]$ for rotation and translation and $\pm 10\%$ for the scaling parameters. Registration parameters were chosen within $\pm 20[deg]$ for rotation and $\pm 48[mm]$ for translation.

Robustness to noise and artifacts in ultrasound imaging was tested by adding isotropic Gaussian noise $\mathcal{N}(0, 0.3[mm^2])$ to the simulated ultrasound images. In real ultrasound images, we expect noise to be anisotropic depending on the imaging direction and the depth in tissue.

3. RESULTS

To evaluate the registration outcomes, both the fitting errors of the algorithms as well as the final point-to-point errors were examined. The fitting error is computed as the RMS distance between corresponding points between the US and surface model datasets. The point-to-point errors were computed as the RMS distance between corresponding points between the surface points at the ground truth position and the surface points at the position estimated by each algorithm, and provides a more meaningful measure for evaluating the algorithms.

The histograms in figures 2, 3 and 4 illustrate the different scenarios of interest. The leftmost histogram contains the results for the three-step joint calibration and registration method of Barratt et al. The middle histogram shows the results of the frame-by-frame UKF registration algorithm that would be performed during image acquisition. The rightmost histogram shows the results of the method of Barratt et al. (only one step rather than three) when initialized with the frame-by-frame UKF registration estimate. Immediately it can be seen that the combined methods yield greater accuracy and more consistent behavior than the three-step approach.

Fig. 2 illustrates the RMS fitting error for the different scenarios. Using a value of $2[mm]$ as the threshold for an acceptable registration outcome, the three-step LM algorithm yielded 37 out of 100 registrations that satisfy the criterion. 64 cases satisfied the criterion for the frame-by-frame UKF method, and the combined algorithm yielded 78 cases of successful registration.

Looking at the RMS errors of corresponding points on the two surfaces (ground truth and estimated position) in fig. 3, the three-step LM algorithm again had 37 cases of successful registration. With 30 cases falling below $2[mm]$, the frame-by-frame UKF had

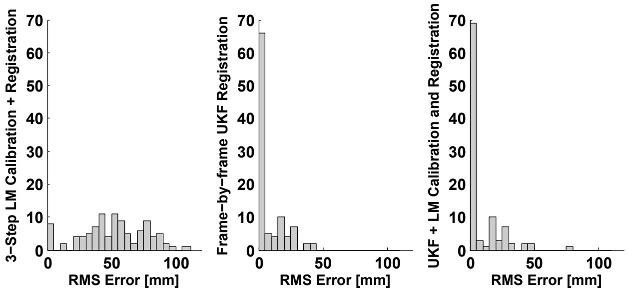

Fig. 4. Corresponding surfaces error for the distal femur, histograms show RMS errors for: (left) 3-step LM method (middle) Frame-by-frame UKF registration (right) Combined approach

fewer successful registrations using this error measure. This implies that although the frame-by-frame approach can fit the measurement data effectively, the outcome in terms of the registration parameters may not be ideal and would affect the quality of the registration. The frame-by-frame UKF had an average RMS error of $1.22[mm]$ for the 30 successful cases. Nevertheless, using the frame-by-frame UKF estimates in the combined approach yielded consistent results, with 78 successful registrations, which is the same amount as for the fitting error measure. The combined approach had an average RMS error of $0.13[mm]$ for the successful cases.

For the distal femur, we can use a slightly larger threshold of $3[mm]$ for what is considered to be an acceptable registration. Judging by the results of fig. 4 the effects of the wider range of erroneous starting positions can be observed, particularly with the three-step LM algorithm. Only 8 registrations fell within the criterion, much less than for the vertebra experiments. The frame-by-frame UKF yielded improved results, with 50 successful registrations, due to the fact that the US images sufficiently spanned the distal femur from different directions. The frame-by-frame UKF had an average RMS error of $1.66[mm]$ for the successful cases. Again, the combined frame-by-frame UKF registration and the joint calibration and registration of Barratt et al. produced the best results, with 64 registrations below a $3[mm]$ RMS error, with an average of $0.39[mm]$

Finally, the frame-by-frame UKF-based registration reduced the number of iterations required by the LM algorithm to converge. The mean number of iterations needed for convergence of the three-step LM algorithm was 36.5 for the vertebra and 35.6 for the distal femur experiments. Using the frame-by-frame approach for initialization, the LM algorithm converged in an average of 15.7 iterations for the vertebra and 11.6 iterations for the distal femur trials. The frame-by-frame UKF registration required less than one second per iteration, that is to say less than one second for each newly acquired US image, and is therefore a suitable algorithm for intra-operative use since it would not slow down the surgeon's workflow.

4. CONCLUSIONS

The combined frame-by-frame UKF and joint calibration and registration method has shown to provide improved registration outcomes under non-ideal initial conditions for US to CT registration of bones.

When initialized appropriately, the three-step method of Barratt et al. has proven to be accurate as well as computationally efficient [1]. However, we proposed that the UKF could be used to perform registration during US image acquisition, which would enable the surgeon to have more control over the quality of the outcome. Despite the presence of calibration error in the US data, the UKF demonstrated stable behavior while optimizing only the registration parameters. Furthermore, we demonstrated that using the frame-by-frame registration would improve the performance of the joint calibration and registration method, which would not begin until the all the US images have been acquired. The approach suggested in this paper also removes restrictions on the quality of the initialization needed for registration.

In the future it would be interesting to explore how joint calibration and registration could be performed using the notion of frame-by-frame registration, such that the registration algorithm would not need more time for computation after the US images have been acquired. Also, it will be necessary to address the assumption made here that some method for the automatic segmentation of bone contours would provide suitable data for the registration algorithm, and this can perhaps be answered by expanding the methods to work with intensity values [10]. Future work should then consist of the automatic treatment of patient or cadaveric data.

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