AN EFFICIENT IMAGE REGISTRATION METHOD FOR 3D POST-OPERATIVE ANALYSIS OF TOTAL KNEE ARTHROPLASTY

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ABSTRACT

Image registration is the process of spatially aligning one image to another. It has applications in different areas of medical image analysis. It can be used to assist the investigation of joint kinematics in conditions such as ligament injury, osteoarthritis, and after joint replacement. Analysing the 3D movement of joints after total knee arthroplasty surgery is crucial as the correct position and relative movement of knee implants will significantly impact the success of the surgery. However, most studies on this area are not very accurate or computationally expensive, or invasive, and still insufficient and developing. In this paper, we propose a non-invasive and robust 3D to 2D registration method, which can be used for 3D evaluations of the status of knee implants. This method addresses several challenges with regard to the registration of the implants. The experimental results show that the proposed method is not only robust but also fast.

KEYWORDS

Model to image registration, medical image analysis, similarity measure, Edge Position Difference

1. INTRODUCTION

Image registration is the process of aligning images (two or more) of the same scene taken at different times, from different viewpoints, and/or by different sensors [1]. While for mono-modal registration, the images to be registered are acquired by the same sensor, for multi-modal image registration the images can be taken from different devices or imaging protocols, which makes the registration process much more challenging. 3D to 2D registration is applied in many medical

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areas to provide 3D information about the inside of the human body. This method aligns 3D data, such as CT, MRI or a model, to 2D radiographs.

In total knee arthroplasty (TKA), artificial knee implants replace the natural knee joint of a patient. Analysing the 3D movement of joints after total knee arthroplasty surgery is crucial as the correct position and relative movement of knee implants will significantly impact the success of the surgery. Although total knee replacement surgeries offer among the greatest success rates of all orthopaedic operations, it is still not known if the implanted knee moves as planned. The kinematic analysis of artificial joints by 3D to 2D image registration can be very useful for determining the long-term viability of the implants for individual patients. In addition, it can contribute to improvements in TKA surgical techniques.

One of the most popular and accurate methods for measuring joint kinematics is roentgen stereo photogrammetric analysis (RSA) [2]. However, this method is invasive because it requires the implanting of tantalum beads into the bone before the image capturing process. Although non-invasive methods based on video/optical tracking systems [3] have been proposed, these methods suffer from low accuracy, and the markers used on the skin may move independently of the underlying bone. Consequently, 3D to 2D image registration methods are mostly now being applied in this area as these methods are non-invasive.

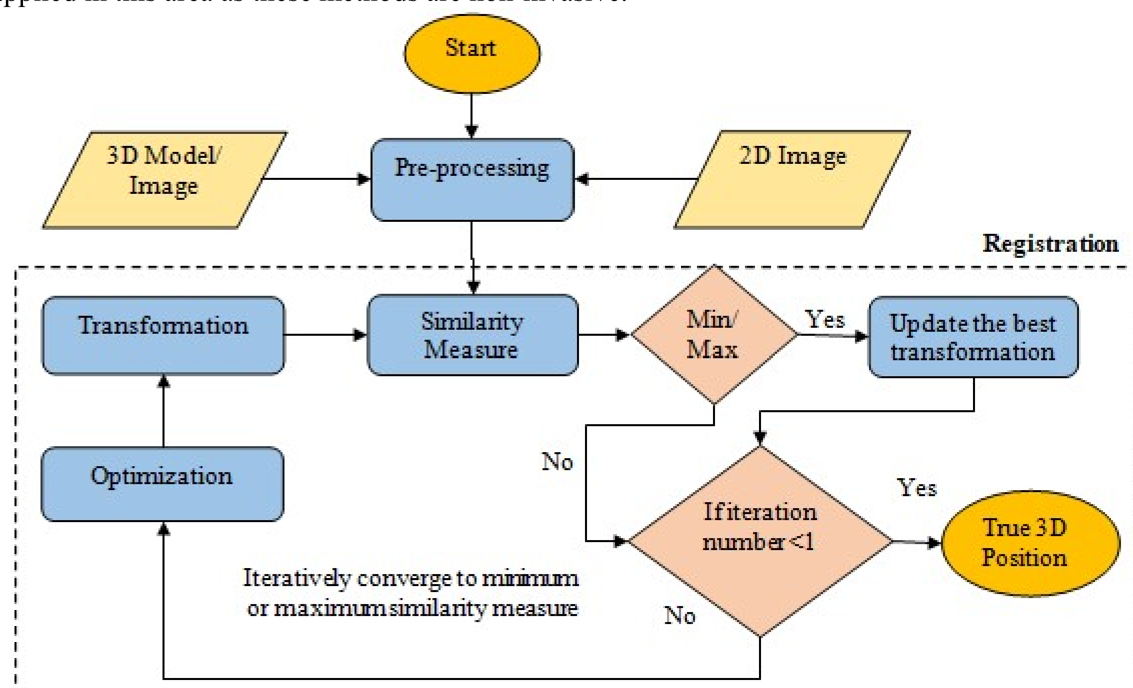


Figure 1. A simplified flowchart as an example for a 3D to 2D image registration.

The three main parts of an image registration method are: a geometric transformation, a similarity measure and an optimization method. The geometric transformation can be divided into rigid and non-rigid categories. The type of transformation is usually chosen according to the nature of the data to be registered. The similarity measure is an integral part of image registration as it is used to determine when the best alignment has been reached. In order to determine the parameters of the transformation model that minimize the similarity measure, an efficient optimization method should be applied. A simplified flowchart as an example for a 3D to 2D image registration can be seen in the Figure 1. A number of pre-processing steps such as segmentation, distortion correction, noise reduction and dimensional correspondence can be performed on the input images. Then, in the registration process, the similarity measure between the images to be registered is computed. In the next step, the transformation parameters are optimized, and then a transformation is performed with new values of transformation parameters. After computing the similarity measure between the images, if the computed similarity measure is less than the minimum of similarity measure or more than the maximum similarity measure computed before (depends on the similarity measure the maximum or minimum similarity measure is computed), the best transformation parameters are updated. These iterative steps are repeated to find the best transformation parameters for the registration.

Multi-modal image registration techniques are generally divided into the two categories of feature-based [4] or intensity-based [5, 6, 7] methods according to the similarity measure used in the registration process. However, a number of methods like those proposed in [8, 9] can be included in both classes as they apply a combination of feature and intensity-based similarity measures. The authors in [10] proposed a 3D to 2D registration method, which is tolerance to the initial distance from true registration. It applied a probability density function of gradient directions and a weighted histogram of image gradient directions (WHGD) as the image feature for the matching process between images to be registered. The authors in [7] proposed a registration method for 3D postoperative analysis of total knee arthroplasty using the normalized correlation coefficient (NCC) similarity measure. This method allowed a comprehensive analysis of the postoperative condition of the patient's knee by attempting 3D postoperative analysis of the TKA components. However, this method needs bi-planar x-ray images which exposes patients to a higher level of x-ray radiation when compared to single-plane x-ray imaging techniques. In addition, although bi-planar x-ray fluoroscopy images may lead to more accurate results, they constrain the motion of the patients. While using single-plane fluoroscopy allows the patient free motion in the plane between the x-ray source and the image intensifier. A new improved 3D-2D fluoroscopy registration algorithm for TKA analysis was proposed in [11]. It focused on the out-of-plane translation and rotation movements which are difficult to measure precisely using a single plane approach. However, the experiments were performed by registering 3D CT images of a Sawbones model with 2D fluoroscopy frames. As there are a number of limitations for capturing CT images of the implanted joints in the human body, a robust 3D computer aided design (CAD) model to 2D single-plane registration method was proposed in [12]. This method performs the registration by computing a similarity measure based on an intensity and a contour score for the images to be registered, and applied a simulated annealing optimization method. However, the method is slow, and a small amount of user supervision is necessary in the optimization algorithm. In [13] a prediction model was proposed for the implanted knee components using a particle filter to evaluate the relative pose/position of the femoral and the tibial implants.

The invasive or non-invasive nature of the registration method, computation time, accuracy and robustness against a large range of initial displacements are usually the most important features used to evaluate a registration method. For providing 3D motion information of natural knee bones, a 3D CT image can be captured and used in the registration method. However, in the case of implanted knee components, instead of a postoperative CT image, a 3D CAD model of the designed implants is available to be registered with the 2D fluoroscopy images acquired after performing the TKA surgery. The implanted joint components are made of metal, and appear as silhouettes of solid objects in the x-ray image. Consequently, the 3D model and 2D x-ray images from these implanted joints do not provide distinguishable information about the internal structure of the implants. Because of these challenges, the proposed methods for registration of artificial human joints are still in the developing stage.

In this paper, we proposed a non-invasive and robust 3D CAD model to 2D single-plane fluoroscopy image registration method for human knee joints, which can be used for 3D postoperative analysis of total knee arthroplasty. This method is based on a new multi-modal similarity measure, which provides a fast and robust coarse-to-fine registration for 3D kinematics. Experimental results show that the proposed method provides a sufficient trade-off between robustness and computation time for TKA registration. Although we focus on the 3D analysis of TKA components, the proposed method can be applied to other joints such as the ankle or hip. The remainder of the paper is arranged as follows: the proposed registration method is explained in section 2. The experiments carried out to evaluate the performance of the proposed method and the analysis of the experimental results are described in section 3. Finally, the paper is concluded in section 4.

2. The Proposed Registration Method

The proposed 3D CAD model to 2D x-ray image registration method is based on the new edge position difference (EPD) similarity measure which is briefly explained in section 2.1. The new method registers 3D CAD models of the joint implants of each individual with postoperative single-plane x-ray fluoroscopy images. Using the proposed method, the 3D transform parameters are calculated by registering the femoral and tibial components from the models with the frames from a single-plane X-ray video one after another. A rigid body transform is applied in the proposed method. This transformation in 3D space is defined by six parameters: translations in the x, y and z directions denoted by T_x, T_y and T_z respectively, and rotations about the x, y and z axes denoted by R_x, R_y and R_z respectively. In 3D to 2D fluoroscopy image registration, T_x, T_y and R_z are considered to be in-plane parameters while T_z, R_x and R_y are out-of-plane parameters because they are changed by 3D motion perpendicular to the fluoroscopy imaging plane. In the first step of the proposed registration method, the input data is pre- processed. After that, the in-plane transformation parameters are roughly estimated. This step is followed by finding the out-of-plane rotation parameters R_x and R_y and improving the in-plane parameters. Finally, the out-of-plane translation parameter T_z is found and the other five parameters are updated to achieve the best alignment.

2.1. The Edge Position Difference Similarity Measure (EPD)

The edge position difference (EPD) [14] measure is a fast multi-modal similarity measure which is based on the minimum difference between the position of binary edge images. These edge images are produced by using an edge detection method on the two images to be registered.

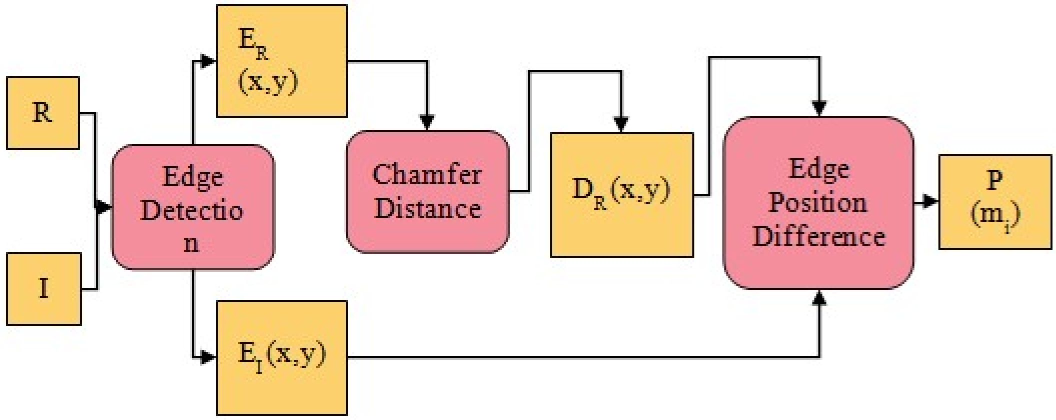


Figure 2. A simplified flowchart for calculating the EPD similarity measure.

Asimplified flowchart for calculating the EPD similarity measure is shown in Figure 2. In the EPD computation process, at first, an edge detection method is applied to the input images R and I in order to convert the intensity images to binary edge images $E_R(x,y)$ and $E_I(x,y)$ respectively. In the next step, a 2D chamfer distance algorithm is used. One of the advantages of the chamfer distance is that it can provide a good approximation to Euclidean distance while it is computationally efficient as it works on small neighbourhoods around pixels, and it requires only a two-pass process over the image to obtain the distances. This method is employed to compute the distance $D_R(x,y)$ to the nearest edge pixel in the binary image of the reference image ($E_R(x,y)$). Finally, the edge position difference, P, between the two images R and I is computed. It is computed by summing the distance to the nearest edge of image R, $D_R(x,y)$, at locations which correspond to edges in the other binary image $E_I(x,y)$. If β_1 is defined as the set of pixel locations where $T(E_I) = 1$, the edge position difference is calculated as follows:

$$P(m_i) = \sum_{(x,y)\in\beta_1} D_0(x,y) \tag{1}$$

where m_i are the parameters that define the transform T. For example, in a 2D rigid-body transform the new pixel locations (x', y') in the transformed image are given by:

$$x' = \cos(m_1)x - \sin(m_1)y + m_2 \tag{2}$$

$$y' = \sin(m_1)x + \cos(m_1)y + m_3 \tag{3}$$

In the proposed method a steepest descent optimization algorithm is used to find the set of transform parameters that minimize $P(m_i)$. This approach requires the calculation of the gradient of P with respect to each transform parameter. These partial derivatives are given by:

$$\frac{\partial P}{\partial m_i} = \frac{\partial P}{\partial x'}\frac{\partial x'}{\partial m_i} + \frac{\partial P}{\partial y'}\frac{\partial y'}{\partial m_i} \tag{4}$$

where

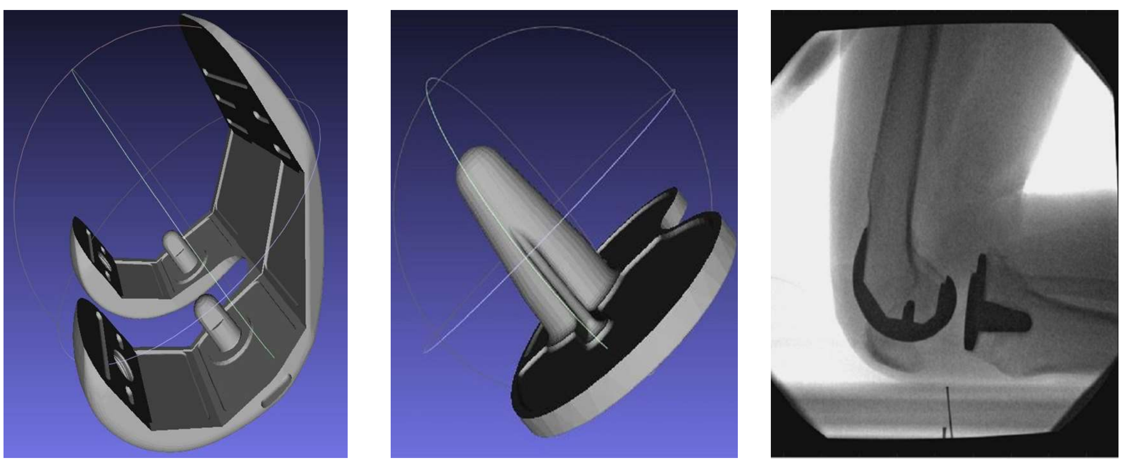
$$\frac{\partial P}{\partial x'} = \sum_{(x,y)\in\beta_1} \frac{\partial D_0(x,y)}{\partial x'} \text{ and } \frac{\partial P}{\partial y'} = \sum_{(x,y)\in\beta_1} \frac{\partial D_0(x,y)}{\partial y'} \quad (5)$$

are the spatial gradients of the distance to the nearest edge and $\partial x'/\partial m_i$ and $\partial y'/\partial m_i$ can be found from the equations (2) and (3) defining the geometric transform.

2.2. Pre-Processing

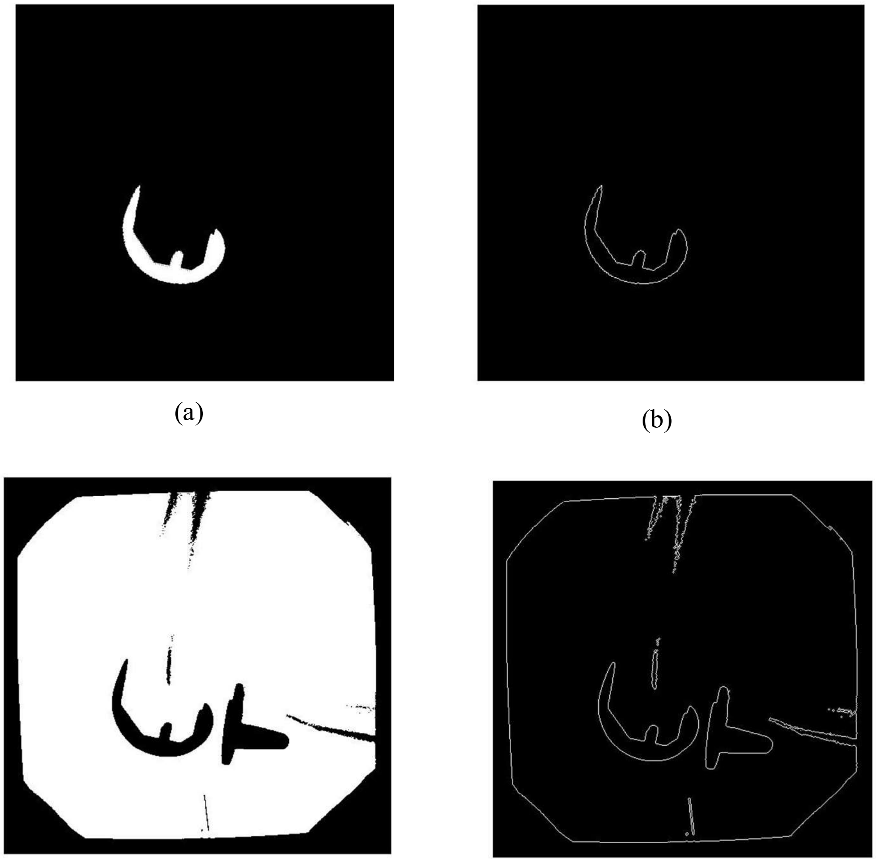
In the proposed method, at first, the input 3D model as well as the 2D single-plane fluoroscopy images are pre-processed to prepare them for registration. For the fluoroscopy images, the distortion caused by the curved nature of the image intensifier is corrected. Each fluoroscopy frame is then segmented and converted to a binary image by performing a simple threshold segmentation of the implant. As the implants captured are made of metal, they are clearly distinguishable from human tissue and bone in radiographs.

An example of the 3D CAD models of knee implants (femoral and tibial implants) and a fluoroscopy frame captured after TKA surgery can be seen in Figure 3.The 3D models are converted to 3D volumes and then projected to a 2D digitally reconstructed radiograph (DRR) by summing the voxel values of the transformed 3D volume in the z direction. The 2D projected image is then converted to a binary image by the threshold-based method.



(a) (b) (c)

Figure 3. (a), (b) Examples of femoral and tibial components respectively. (c) A fluoroscopy frame captured after TKA surgery.



(a) (b)

(c) (d)

Figure 4. (a) and (c) show a 2D projected image of a 3D model of a femoral knee component and its corresponding fluoroscopy image respectively after the binarization process. (b) and (c) show the images after removing interior pixels of the femoral and tibial components.

As can be seen in Figure 4, these steps are followed by applying a morphological operation on the 2D binary images (2D DRR and 2D fluoroscopy binary frame). This operation removes interior pixels to leave an outline of the implants. In this operation, a pixel is set to zero if all its 4-connected neighbours are one, thus leaving only the boundary pixels.

The proposed method is compared with the registration method [15] which is based on the sum-of-condition variance (SCV) [16] similarity measure. When computing the SCV, after performing the previous pre-processing stages on the input data, a filling morphological operation is used to fill isolated interior pixels in the TKA components in the fluoroscopy frames as well as the 2D DRR image. A Laplacian-of-Gaussian (LoG) filter is then used on the images to find, and highlight, the areas of rapid changes (edges) after a smoothing process and removing noise. These pre-processing steps are followed by applying three coarse-to-fine registration steps which involve a) finding in-plane transformation parameters, b) finding out-of-plane rotation parameters around the x and y axis while improving the in-plane parameters and c) finding out-of-plane rotation parameters around the x and y axis while improving the in-plane parameters and out-of-plane translation parameters. These steps are explained in detail in sections 2.3, 2.4 and 2.5.

There are a number of reasons that we divided the registration method into different steps when finding the best 3D position for the models. As the out-of-plane transformation parameters are changed by 3D motion perpendicular to the fluoroscopy imaging plane, finding these parameters is much more complicated when compared to finding the in-plane parameters. In addition, while in-plane parameters can be estimated by an iterative search applying a number of 2D transformation for the 2D DRR of the model, finding out-of-plane parameters needs 3D transformations in each iteration of the search to be accurate. Therefore, if we estimate in-plane parameters first, the search range for the in-plane parameters becomes smaller, which reduces the processing time required in the next steps. While large out-of-plane translations (when an object moves towards or away from the X-ray source) result in only relatively small changes of scale in the fluoroscopy image, a small out-of-plane rotation can cause a considerable change in the shape or contours of the bone segment. Therefore, in the next step, out-of-plane rotations are estimated, and the in-plane parameters are updated. Finally, the translation in the z direction (T_Z) is found, and the remaining transformation parameters are improved.

2.3. Finding The In-Plane Transformation Parameters

The first step in the proposed registration method is searching the in-plane transformation parameters (T_x, T_y, R_z). In each iteration of the search, the 2D DRR of the implant is trans- formed by the new values of T_x, T_y, R_z, and then the EPD similarity measure is used to compute the similarity between the transformed 2D DRR image and the 2D fluoroscopy image. If the EPD similarity measure computed in this iteration is less than the minimum similarity measure computed in previous iterations, then the optimal in-plane parameters (T_x, T_y, R_z) are updated. These steps are repeated for the entire search range.

2.4. Finding Out-Of-Plane Rotation Parameters Around The *x* And *y* Axis, And Improving The In-Plane Parameters

Finding out-of-plane transformation parameters are much more challenging than estimation of the in-plane parameters. In this step, the proposed method estimates the out-of-plane parameters (R_X and R_Y), and refines and updates the in-plane parameters. Unlike the previous step (finding in-plane parameters), which transforms the 2D DRR image by the new values of the in-plane parameters, for finding out-of-plane rotation parameters, a new search is performed with each change of R_X and R_Y. Each new transformation is applied on the 3D volume of the implant, and after that it is projected to a 2D image. Inside this search, a steepest descent optimization method is employed to refine the in-plane parameters (T_X, T_Y and R_Z). The iterations continue until the most accurate alignment between the input images is found.

2.5. Finding The Out-Of-Plane Translation Parameter In The *Z* Direction And Improving The Remaining Transformation Parameters

Finally in this step, the translation in the z direction (T_Z) is found, and the remaining transformation parameters are improved by using the steepest descent optimization method. Starting with the parameters found by the previous step, a search on a smaller range space of the out-of-plane parameters (R_X and R_Y) is performed. In this step, the in-plane parameters as well as T_Z are optimized simultaneously to achieve the best final transformation parameters which align the 3D CAD model of the implanted component and its image in the fluoroscopy frame.

3. EXPERIMENTS AND ANALYSIS

In order to evaluate the performance of the proposed method, it is compared with the registration method in [15] based on the SCV similarity measure which is optimized by a standard Gauss-Newton method. This registration method focused on CT to x-ray image registration. The method, however, can be used for CAD model to x-ray image registration. Although the similarity measures and optimization methods used in the method and in the proposed method are different, the same process of registration as explained in section 2 was used for both methods. The two methods were used to perform 3D to 2D registration on clinical data captured at the Canberra Hospital, Australia. The main application of the 3D model to 2D image registration for human knees at the Canberra Hospital for producing a 3D moving model of knee kinematics for each patient by registering a 2D x-ray fluoroscopy video, consisting of approximately 300 frames, with 3D models of femoral and tibial components which were implanted during TKA surgery. Although being robust against large initial displacement is one of the challenges of 3D to 2D image registration, in this application, as there is not expected to be a large amount of movement between the implants in each fluoroscopy frames and the subsequent frame, if the first frame can be registered well (the first frame is usually first registered manually, and then using the proposed method), the next frames are expected to be in a similar 3D position. In addition, although it may seem that the registration computation time may not be very important, when a large number of frames must be registered for each patient, the processing time becomes quite significant.

The data from the hospital that we chose to perform experiments on consists of the 3D CAD models and 2D fluoroscopy frames of the knee implants of two different patients. For each patient, a 3D model of a femoral and a tibial component were registered with two 2D fluoroscopy frames containing the same femoral and tibial implants. In order to examine the robustness of the proposed method against initial displacement, a set of 3D rigid body transforms were applied to the 3D volume of the femoral and tibial implants. In all cases, we created 60 displaced versions of each patient's 3D model. In total, for evaluating the performance of the proposed method, 480 displaced version of the femoral and tibial models were registered with x-ray images. The initial displacement was measured using the maximum registration error (MRE) given by:

$$\mathrm{MRE} = \max_i \left(\sqrt{(x_i' - x_i)^2 + (y_i' - y_i)^2 + (z_i' - z_i)^2} \right) \qquad (6)$$

where (x_i', y_i', z_i') is the location of the ith pixel in the 3D model after registration has been applied, and (x_i, y_i, z_i) is the position of the pixel when the 3D model of the femoral or the tibial components is correctly registered to the fluoroscopy frame. The 60 displaced versions were divided into 3 sets of 20 with initial MRE values in the ranges of 0-20, 20-40 and 40-60 respectively. All the experiments have been performed using Matlab R2017b, and on the same computer with an Intel(R) Core(TM) i7-4790 CPU @ 3.60GHZ, with 16 GB of installed memory (RAM), and a 64-bit operating system.

To compute the accuracy of the registration method proposed in [12], the authors performed tests on a cadaver knee. The ground truth was determined by touching the implants using a hand-held probe. Then the probe was tracked using an optical sensor to estimate the position of the implant. The convergence analysis was also performed as a part of the experiments in

[12] when ground truth was not available. As we do not have access to the ground truth for evaluating the accuracy of our proposed method, we performed a number of experiments to show the precision and convergence of our proposed method, and compared this with the SCV method. At first, the best 3D position of the femoral and tibial models for registration are found manually. Then, in order to have a more accurate 3D position, we apply the proposed method on the data to be registered to improve the 3D position of the models for each fluoroscopy frames. In the next step, for each frame to be registered, the mean of the 3D position found by registering all 60 displaced versions of each patient's 3D model is set as the best 3D position of the models for the registration for that frame for each patient. The performance of the algorithms was evaluated by computing the difference between the final values of the six transform parameters produced by the registration algorithms and the best values of the transform parameters required for registration. If the difference in T_Z was less than 3 pixels and the difference for the remaining parameters was less than 1 pixel, the registrations were assumed to have succeeded.

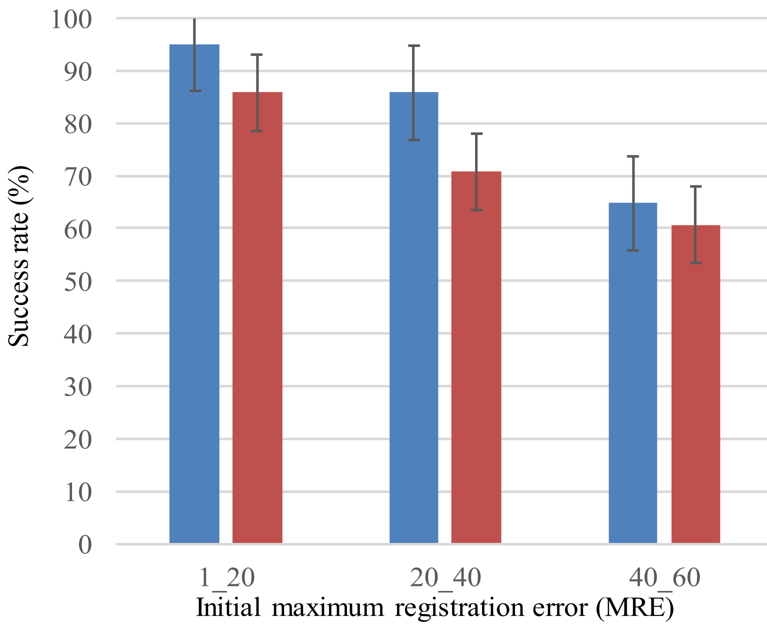


Figure 5. The success rate of the EPD and SCV algorithms.

Figure 5 shows the mean success rate of registration for the femoral and tibial components in the fluoroscopy frames of the two patients for each range of initial MRE values for both algorithms. As can be seen in the figure, the proposed coarse-to-fine registration method based on EPD had a higher success rate when compared to the SCV method for all ranges of initial MRE between 0-60. It had 95 and 86 percent success rate when the initial MRE was in the range of 0-20 and 20-40 respectively.

Table 1. Computation time (Seconds).

Method	**Computation Time**
SCV	436
EPD	89

Table 1 shows the computation time required for the algorithms to register the images for one starting position. As can be seen from this table, the proposed method is almost 4.5 times faster than the registration method based on the SCV measure.

4. CONCLUSIONS

The proposed method is a non-invasive and robust registration method which provides 3D information of knee joint kinematics. The method does not need any postoperative CT scan because the 3D models designed for implants for an individual can be used in the registration. As a result, it has become possible to perform 3D TKA analysis any time after the surgery simply by taking single-plane radiographs. The proposed method uses the new edge position difference (EPD) multi-modal similarity measure accompanied with a steepest descent optimization method. The method applies coarse-to-fine registration steps to find the transformation parameters leading to the best alignment between the model and the x-ray images to be registered. The experimental results show that, not only does the proposed registration method have a higher success rate, but it is also much faster than the most relevant competing approach. In the future, we are going to improve the optimization step for the proposed registration method to increase robustness and reduce computation time.

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