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A computationally efficient 3D/2D registration method based on image gradient direction probability density function

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ABSTRACT

Three-dimensional (3D) to two-dimensional (2D) registration is an essential problem in many medical applications. This problem aims at finding the rigid transformation parameters to match the projected image of a 3D model to the real one to estimate the 3D pose of the anatomical model. This class of image registration is computationally intensive due to the large number of solution assessments necessary to search the complex solution space. Moreover, the convergence of the solution process is contingent on a manual initialization of the solution close to the optimal solution. In this paper, we address both of these challenges by introducing a registration method which is significantly faster and less sensitive to initialization than existing methods. The method explores the properties of image gradient probability density function for registration and uses a weighted histogram of image gradient directions (WHGD) as the image feature. This simplifies the computation by searching the parameter space (rotations and translations) sequentially rather than simultaneously. Our experiments demonstrated that the proposed method was able to achieve sub-millimeter and sub-degree accuracy with 5% of the solution assessments needed by an established existing method. The accuracy was not sensitive to the initial solution as long as it was within 90° and 30 mm of the true registration, which is a substantial improvement over the existing methods.

1. Introduction

Three-dimensional (3D) to two-dimensional (2D) image registration is essential in many medical applications such as preoperative surgery planing, intra-operative therapy guidance [1], patient placement for radiotherapy planning and treatment verification [2,3], radiosurgery [4], cranial neurosurgery [5,6], neurointerventions [7,8], spinal surgery [9,10], orthopedic surgery [11,12], and aortic stenting procedures [1,10,13,14]. The goal of 3D to 2D (3D/2D) registration is to find the rigid transformation parameters which convert the coordinate system of a 3D model of the subject to the real clinical one [15,16]. Such a transform consists of three translation and three rotation parameters along and around X, Y, and Z axes (6 degrees of freedom). These parameters are calculated by finding the 6 degrees of freedom, which maximize the similarity of the clinical 2D radiographic image of the subject to a 2D projection of the 3D model. The X and Y axes are the coordinates of the 2D image plane (the fluoroscopy video frame), and the Z axis is perpendicular to the image plane.

One application of 3D/2D image registration, which motivated the method introduced in this paper, is the estimation of the 3D kinematics of in-vivo bone movement. An accurate estimation of bone kinematics is crucial in the image guided evaluation of musculoskeletal disorders and surgeries. In this application, the bone movement is captured through a 2D fluoroscopy video. To find the 3D pose of the bone at any instant of the motion, a 3D model of the bone, which is reconstructed by the segmentation of a computed tomography (CT) image series, is registered to every frame of the fluoroscopic video. The results are the six transform parameters for every frame of the video. These parameters transform the 3D bone model to the 3D bone pose at the time when each of the frames were captured (Fig. 1).

The registration of the 3D model to the 2D fluoroscopic image is achieved by matching a 2D perspective projection of the 3D model to the 2D fluoroscopic image. The registration process consists of an optimization algorithm which searches the six dimensional space of all transform parameters for the parameter values which result in the maximum similarity between the 2D fluoroscopic image and a per-

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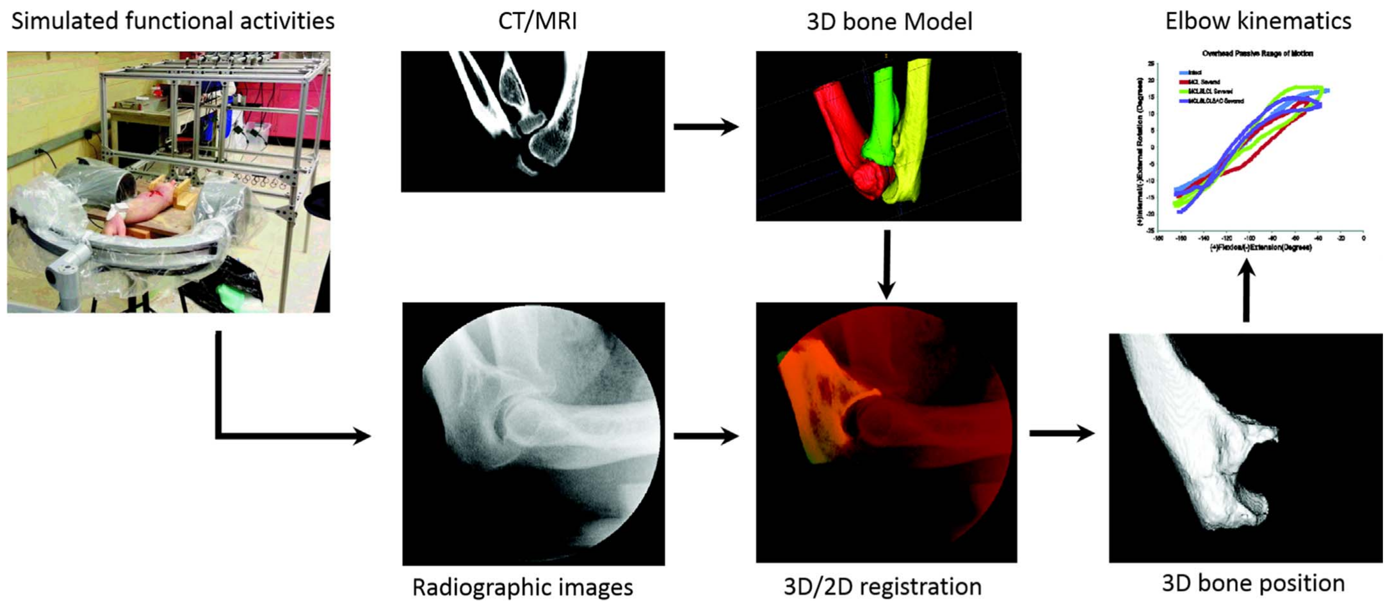

Fig. 1. Image guided Evaluation of Musculoskeletal Disorder and Surgery through 3D/2D image registration. The C-arm captures the movement of the elbow joint bones through fluoroscopic video frames. The 3D bone models are constructed from CT image series. A model-based tracking approach is used for registering 3D bone models to fluoroscopic images and estimating 3D bone positions. 3D bone kinematics are then calculated from bone positions.

spective projection of the 3D model onto the image plane. This 2D projection is called the digitally reconstructed radiograph (DRR) and is the result of a simulation of the fluoroscopic imaging process. The camera parameters in the simulation are set up after the camera parameters of the fluoroscopic imaging machine using camera calibration [17]. The DRR is calculated by casting rays from a ray source to an image plane while the rigidly transformed 3D bone model is located in between. The intensity value of each pixel in the DRR is the integral of the volume intensities that the ray from the ray-source to that pixel has passed through [18]. Since the location of the ray-source and the image plane are set up after the fluoroscopy machine, it is assumed that if the DRR matches the fluoroscopy image, the pose of the bone in the 3D space must have been the same as the real bone at the moment the fluoroscopy image is captured.

The registration process is computationally intensive. The registration includes the assessment of many transform parameters, which require the generation of many DRRs. DRR generation is a time-intensive problem due to numerous memory access operations [18]. This problem has usually been addressed by using alternate ways to either estimate or precalculate the DRRs, which come at the cost of quality, or memory and precalculation time [1,18–20]. Developing a registration method with the minimal number of required DRRs would be ideal.

In addition to the computational cost, the existing methods are sensitive to the initial guess of the bone position. If the initial position of the bone is too far from the true registration, the optimization algorithm might be stuck in local optima and not converge to registration. Therefore, most existing methods require the user to manually and visually position the 3D model in the vicinity of the optimal answer. A manual location of the 3D model, however, is labor-intensive and prone to error as the 3D position of the bone model, based on its 2D projection is not always evident visually.

In this work, we propose a novel method to address the problems of computation time and algorithm sensitivity to the initial solution. Our method uses a weighted histogram of gradient directions as an image feature to measure the similarity of the DRR and the fluoroscopy image. The histogram works as an estimation of the probability density function (PDF) of gradient directions on the 2D bone image. In the result section, our proposed method is shown to produce high registration accuracy in substantially reduced processing time. This is achieved due to the fact that in our method, the parameters are optimized sequentially rather than simultaneously. In addition to reduction in time, the quality of the results was insensitive to the initial distance from the true registration within 90° of it. This is a substantial improvement over existing methods, which require the 3D volume to be manually registered to the vicinity of the true registration for the method to work.

2. Method

The test runs were done on a 3D volumetric model of a ulna bone. The model was reconstructed through a segmentation of a series of CT images from a cadaver elbow. The resolution of the CT images was 0.39 mm by 0.39 mm with an inter-slice distance of 0.62 mm and the segmentation was performed using the ITK-Snap software [21]. The choice of ITK-Snap for segmentation was arbitrary and our results are independent of the segmentation method. The resolution of the DRRs generated was 250 by 256 pixels with a pixel size of 1.23 by 1.23 mm.

The reconstructed ulna model was used in 100 independent runs of our algorithm to test its efficiency. The algorithm was programmed in MATLAB (The Mathworks Inc., Natick, MA, USA). As done in [22], at each run, a DRR resulting from a random position of the bone model was produced and used as a reference (fluoroscopy) image for the rest of the run. To simulate a clinical image, the proximal-distal axis of the bone was set to have an angle less than 45° with the image plane. This position of the bone in space was used to measure the registration accuracy of the algorithm. The difference between the 3D position resulting from the registration and the real one was considered as the registration error. Since the 3D position of the bone is determined by three translation and three rotation parameters, the registration error is shown as six numbers, each depicting the difference between the real value of the relevant transform parameter and the one found by the algorithm.

For the translation and rotation of the 3D bone model, a coordinate system is required. This coordinate system could be defined globally, such as the coordinate system of the DRR image plane, or locally and intrinsic to the bone model. In this work, after the bone model is positioned halfway between the DRR image plane and the ray source, the transformations are done according to the coordinate system of 3D bone model. This coordinate system may be defined clinically, using the