Registration of Low Dose bi-Planar Acquisitions for Motion Analysis

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*Abstract***—In this paper, we introduce a 2d-3d registration method for searching the motion of knee bones. We use a low dose bi-planar acquisition system that provides us with simultaneous frontal and profile radiographs in different positions, and the 3d volume reconstruction of the standing position. The purpose here is to reduce the user intervention during the motion tracking. The registration method is based on the central slice Fourier Transform theorem. Motion results with rotations and translations using synthetic data are shown.**

I. INTRODUCTION

FOR ^a better understanding of musculoskeletal disorders, a global physiological modeling of the human system of locomotion would be of a great interest. The challenge is to study the joints motion of a patient in a standing and weight-bearing position. This paper proposes a step towards this long-term objective, thanks to a recent acquisition system called EOS. EOS provides two simultaneous low dose radiographic images of the patient in the standing position.

We introduce here an automatic registration algorithm, well adapted to this modality. The low-dose characteristics of EOS allow us to study several positions of the bones during the motion. Our global purpose is the study of the ligament laxity in the knee.

In the next section we will start with a state of the art of the registration methods used for searching bones motion. In section III, a brief description of the EOS modality used is made. In section IV, we describe the algorithm that we use and we show some results on synthetic data in the section V.

II. ESTIMATION OF THE MOTION OF BONES

For clinical applications, previous works [1] [2] proved that it is useful to merge kinematic parameters and morphological information to well-understand the morphofunctional relationships in the joints.

Earlier in 1984, Lafortune [3] implanted pins directly into the bones and tried to evaluate the motion of bones by following these pins and to extract kinematic parameters. However such method could not be generalized and such invasive experiments could not be made for a large number of patients. A more widespread method is to follow skin markers during the motion in order to deduce the motion of the bone. Such methods were used with different types of skin markers: optical, magnetic or else. However the elasticity of the skin and muscles perturbs the bone motion acquisition [4] and it is highly difficult to separate the two motions. Many works tried to reduce this problem by placing the markers where there is less noise [5], or placing a large number of markers on the skin [6], [7]. But no final good solution was shown to provide results without errors and efforts are still be made in this way. Another approach consists in a 3d-3d registration of successive positions as in [8] where the drastic problem of MRI segmentation is managed thanks to a consensusdriven simultaneous registration. In our case, we have several pairs of radiographs during the motion but only one reconstruction in the standing position. Instead of performing reconstruction of a volume data, another approach is to generate digital radiograph reconstruction (DRR) of the bone volume in different positions until the DRR fits the true radiograph of the bone [9]. In general, the data volume is a CT acquisition while radiographs are obtained with fluoroscopy. Such algorithms are composed of a DRR generation step, a similarity measure step and an optimization step. In each part of the algorithm, several methods have been used. For the generation of DRR, the most intuitive is the simulation of the X ray passage through the volume with Ray casting algorithms or such. This type of generation is time consuming and is considered as a bottle neck step of the global method. Some other works tried to generate DRR in less time by using smarter algorithms [10] or suitable hardware [11]. Other methods used cylindrical harmonics [12] or Fourier transform [13] for the generations of DRR.

The second step in the global algorithm is to compare the DRR to the radiograph using a metric. Different metrics

Manuscript received April 7, 2009. This work was supported by the French society Biospacemed in the framework of an industrial convention (CIFRE) with the french National Association of Research and Technology (ANRT).

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have been used for this purpose [14]. The third step is an optimization method that allows converging quickly to the optimum solution. The choice of the metric has to be suitable with the DRR and the choice of the optimization method should also take into account the form of the function to be optimized.

In such a method, the results will depend: (i) on the capability of the method generating DRR to produce good radiographic simulations (ii) on the capability of the metric used to discriminate between images, (iii) and on the optimization method to converge quickly to a global optimum.

III. MODALITY AND INPUT

The images are acquired using low-dose bi-planar radiographs. This modality provides simultaneous frontal and profile radiographs allowing a surface reconstruction of bone segments [15]. Compared to fluoroscopy, this modality has also the advantage of providing a large acquisition area that allows moving the bone segment without being outside of the acquisition area.

As input, our algorithm will take the reconstruction of the bone volume in the initial position, and a set of pairs of radiographs (frontal and profile) of the knee in different positions.

IV. REGISTRATION

We are looking for rigid motions composed of rotations and translations between the initial and the final position of the bone. To simplify the search space composed of three rotations and three translations, we start by seeking the rotation part of the motion and then we look for the translation in a second step.

Passing through Fourier Transform, we can split the process into the estimation of the rotation (firstly) and the translation (secondly) as shown later.

A. Rotation Estimation

We choose a quaternion representation for the rotation formulation [16]. It is known that a unit quaternion (called versor) can be written as (1) and corresponds to a rotation of an angle α around the axis u .

$$
q = \cos(\frac{\alpha}{2}) + \sin(\frac{\alpha}{2})u \tag{1}
$$

As an example, a rotation with a versor (0, 0, 0.01) corresponds to a rotation of an angle of about 1.1° around the Z axis.

The Fourier Transform was used as a method for generating DRR [13] in a global algorithm scheme like described above. However, we do not finish the process, as described, by an inverse Fourier Transform to have a classical DRR. Instead of that, and preparing a comparison of the images in the frequency domain, we calculate the Fourier Transform of the radiographs too and we compare DRRs and radiographs in the frequency domain. Fig. 1

Fig. 1. Described algorithm scheme

shows the scheme of the algorithm for finding rotation.

The Fourier projection slice theorem states that a centered slice extracted from a frequency domain of a data volume represents the Fourier Transform of a projection of the volume in a direction perpendicular to the slice.

Let $F(u, v, w)$ be the 3D Fourier Transform of the data volume *f.*

$$
F(u, v, w) = \iiint f(x, y, z) e^{-2i\pi(ux + vy + wz)} dx dy dz \qquad (2)
$$

Without losing generality, we suppose that the projection is performed along the first axis. Its Fourier Transform corresponds to the slice in the Fourier volume passing by the origin and perpendicular to the first axis as shown on (3) and (4) :

$$
P_X(f)(y, z) = \int f(x, y, z) dx
$$
\n(3)
\n
$$
F(P_X(f))(v, w) = \iiint f(x, y, z) dx e^{-2i\pi(yv + zw)} dy dz
$$
\n
$$
= F(0, v, w)
$$
\n(4)

with P_X the projection of the volume along the *X* axis.

Thus, to obtain the rotation of the bone, we have to find the axis along which the projection (radiograph) has been taken. So, the problem now consists in finding two perpendicular slices passing through the center of the Fourier volume that are the most similar ones to the Fourier Transform of the frontal and profile EOS radiographs.

By using the Fourier Transform, we separate the rotation and the translation existing between two images *f* and *g* , respectively in the module and the phase of the frequency data (6).

$$
g(x, y, z) = f(R(x, y, z) + T)
$$
(5)

$$
F(g)(u, v, w) = \iiint g(x, y, z)e^{-i2\pi(ux + vy + wz)}dxdydz
$$

$$
= e^{i2\pi(u\Delta x + v\Delta y + w\Delta z)}\iiint f(R(x, y, z))e^{-i2\pi(ux + vy + wz)}dxdydz
$$
(6)

with *R* the rotation and *T* a translation of vector (∆*x*,∆*y*,∆*z*) corresponding to the rigid motion.

B. Discrete Formulation

In this first step, using only Fourier Transforms module, the rotation is searched by comparing the slices of volume transform and the radiographs transforms. While Zosso [17] uses a Mattes metric in such an algorithm scheme for finding rotations, we consider an Euclidean distance *d* on the norm of the Fourier Transform of the images as shown in (7):

$$
d^{2}((F(I_{1}), F(I_{2})), (F(I_{1}), F(I_{2}))) =
$$

\n
$$
\sum_{u} \sum_{v} (\left\| F(I_{1})(u, v) \right\| - \left\| F(I_{1})(u, v) \right\|)^{2}
$$

\n
$$
+ \sum_{u} \sum_{v} (\left\| F(I_{2})(u, v) \right\| - \left\| F(I_{2})(u, v) \right\|)^{2}
$$
\n(7)

with $F(I_1)$, $F(I_2)$ the Fourier Transform of the frontal I_1 and profile radiographs I_2 , and $F(I'_1) F(I'_2)$ the slices extracted from the Fourier Transform of the data volume. We use Fast Fourier Transform for calculating the discrete Fourier Transform on the radiographs and the volume. *and* $*v*$ *are the line and column indices of the* data.

We think that Mattes metric, such as Kullback-Leibler distance, is more appropriate to calculate similarity between intensity images as in [18], [14]. In the frequency domain, using Euclidean distance and hence comparing information in each frequency is more appropriate.

When searching the appropriate slice by rotation of the Fourier volume, we use B-spline functions to interpolate the voxels. For the optimization step of the algorithm, we choose a gradient descent method well adapted to the versors.

C. Translation Estimation

Once the rotation is found, the translations between the two positions of the bone can be searched. We use the phase information existing in the Fourier Transform of the radiographs and from the slices finally extracted from the data volume. Translation information can be found using the difference between phases. By calculating once again the Fourier Transform of this difference, we obtain a deltadistribution on the point corresponding to the translation as shown in equation (8):

$$
F(\boldsymbol{\varphi})(u,v,w)=\delta_{\Delta x,\Delta y,\Delta z}
$$
 (8)

where φ is the exponential factor of equation (6):

$$
\varphi(u,v,w) = e^{i2\pi(u\Delta x + v\Delta y + w\Delta z)}
$$

Hence, the translation corresponds to the indices of the highest value pixel.

V. RESULTS

We use synthetic data as input with a $1x1x1$ mm³ resolution to the first experiments for the validation of the

Fig. 2. 3d synthetic data used for experiments 256x256x256

Fig. 3a. Profile projection of the synthetic data used 256x256

Fig. 3b. Frontal projection of the synthetic data used 256x256

algorithm. The volume created (Fig 2) was moved with a known motion and simulations of radiographs were performed (Fig 3). During the algorithm operation, we suppose that we do not have any idea about the motion of the volume and we try to find the motion previously applied.

Table I provides tests results with different rotations. The first two groups of rotations are small rotations (with less than 10°) and the third ones are rotations with higher amplitudes (up to about 45°). The second group implies rotations around the three axes.

The results show that the algorithm estimates small

Versor applied				Versor found			
0	0	0.01	0	0	0.002		
0		0.03	0		0.03		
θ		0.05	0		0.045		
0		0.08			0.085		
0.03	0	0.03	0.035	0	0.035		
0.01	0	0.05	0.005	0	0.045		
0.05	0	0.01	0.045	0.01	0.01		
0.03	0.03	0.03	0.025	0.013	0.025		
0	0	0.3	∩	0	0.27		
0		0.35	0	0	0.31		
		0.4			0.38		

Vector part of the versor, the scalar one can be deduced knowing the norm of a versor.

 TABLE II TRANSLATIONS SEARCHING RESULTS

Translation applied				Translation found			
	10			10			
	5	θ		5.			
	10	\mathcal{F}		10	3		
3	10	5	3	10	5		
3	10		3	10			
	10	3		10	3		

Values are in millimeters

rotations with good accuracy with a maximum error of about a degree. For the larger ones, the results are also very interesting. Certainly the error is larger, but the results can be used as an appropriate initial position to another search step with different parameters for the optimization process.

Table II shows some results of tests made to determine the translation motion. The data volume was turned and translated. The rotation is then estimated as in the first experiences and then the translations are searched. The versor applied in the tests of the table II is (0, 0, 0.03) and the rotation was found exactly. In all cases, we found the exact translation. However, it is clear that the translation is limited as the bone structures must stay within the volume studied. Another condition to find the exact translation is to have found the right rotation in the previous step.

VI. CONCLUSION

In this paper, we present an algorithm for 2d-3d registration for the knee bones. Using the EOS modality, we can have a large number of bi-planar radiographs with low dose of X-ray to follow the bones motion. This registration method does not require much user intervention. Even though, we use this method for registering knee bones, it can also be used for a high number of articulations.

We explore the capability of the method to find small and large rotation and translations using synthetic data.

In a future work, more experiments will be made including real data with multiple bones. In this case, image processing could be needed to select the bone area that we want to track. Bone motions in other articulations will also be studied using this registration method.

ACKNOWLEDGMENT

The authors wish to thank Dominique Zosso for helpful discussion.

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