Smart knee prosthesis kinematics estimation and validation in a robotic knee simulator

Arami A., Aminian K.

Laboratory of Movement analysis and Measurement, Ecole polytechnique Fédéral de Lausanne (EPFL), Switzerland, arash.arami@epfl.ch, kamiar.aminian@epfl.ch

Abstract-In this work we present the smart knee prosthesis designed for in-vivo kinematics measurement and its validation in two knee simulators, i.e. a robotic knee simulator to provide realistic condition, and a manual simulator with more degrees of freedom. The sensor configuration including three magnetic sensors was designed, and the machine learning techniques were used to translate the magnetic measurements to knee rotations. First the concurrent flexion-extension and internal-external rotations were estimated via linear and nonlinear estimators, and technically validated in a manual knee simulator against motion capture system. Then the flexion-extension estimation was validated in a robotic knee simulator providing the realistic sagittal kinematics of treadmill and over-ground walking. The obtained results showed the high accuracy and precision of the estimates.

Keywords-Knee Kinematics;Smart Knee Prosthesis; Robotic Knee Simulator

1. INTRODUCTION

Even though over a million knee prostheses implanted each year only in the EU and USA [1], none provide feedback information to allow continuous and objective monitoring of the patient knee function. A few studies have been done on instrumented prostheses while their focus was mainly on measurement of in-vivo forces [2], [3], [4] and their designs have not been compatible with the commercially-available prostheses. Proposed instrumented prostheses were implanted in a few subjects and used for different biomechanical studies such as the relation between external knee adduction moment and medial contact force [5], knee contact forces during activity of daily living [6]. Recently we introduced a smart knee prosthesis including force sensing and kinematic measurement units in which all the electronics were integrated into the polyethylene insert, bringing versatility to the design and compatibility with commercially-available prostheses [7]. In our previous studies, implanted kinematics measurement systems in the smart prostheses were designed to estimate internal external rotation (IE) [8], and flexion extension (FE) and abduction adduction rotations (AA) [7] without soft tissue artifact (STA). However the kinematic estimators were not designed to estimate combinations of different rotations, e.g. concurrent rotations in different anatomical planes. Those estimators were only tested in a manually-operated knee simulator, and far from realistic patterns of activities. The goal of current study is two-folded; first to complete the previous design for measuring multiple concurrent knee rotations, then validate the system not only in a manual but also in a robotic knee simulator which replicates realistic gait patterns.

2. MATERIAL AND METHODS

Sensor Configuration and Estimation Models

A posterior-stabilized mobile bearing prosthesis (F.I.R.S.T, Symbious, CH) was used in this study, which consists of a Femoral part (FP), a Tibial part (TP) and an ultra high molecular polyethylene insert (PE). Using the fluoroscopic collected data of 19 subjects, bearers of the same prosthesis, no considerable AA was observed in stance phase during treadmill gaits [9]. In this study, we thus focused on design of sensor configuration and estimators to of the two other rotations, FE and IE rotations which can occur concurrently. The designed system includes three 2D AMR sensors configured inside PE, and two small permanent magnets integrated into FP and TP to translate their movements to measureable changes in the distribution of the magnetic field in PE. The magnets were encapsulated in the guiding pin of the FP and the central screw of TP (Fig. 1). First AMR sensor was placed above the TP magnet (M1) to be dominantly influenced by this magnet; the two other sensors were configured based on a sensitivity analysis. Separate estimators for IE and FE angles were designed. A set of candidate inputs were considered, i.e. the channels of sensors (Si_j channel j of sensor i) and all pairs of their one by one multiplication. Two types of estimators were built based on linear regression (LR) of the selected inputs (x) and multi-layer Perceptron (MLP). For the LR estimators a correlation-based forward selection algorithm [10] was applied to find the inputs linearly correlated to the target angles. However for the MLP estimators a mutual information (MI) based input selection was used (x_k is the kth selected input) to
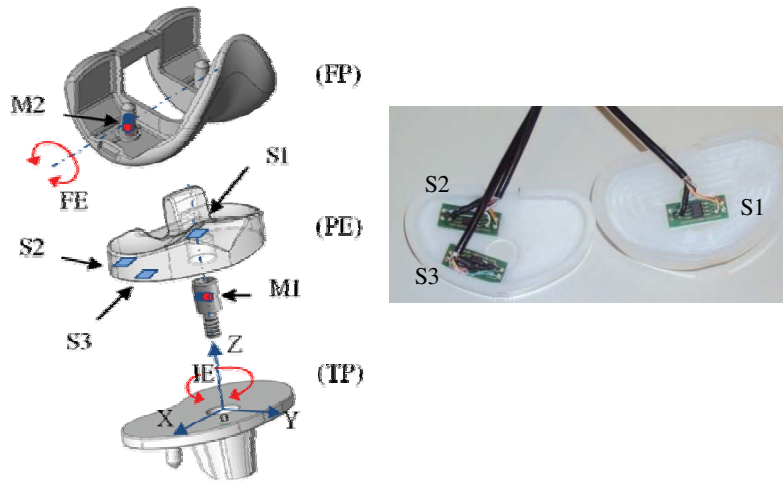
Figure 1. Configured sensors (S1, S2, S3) in PE and magnets (M1, M2) in FP and TP of the prosthesis

maximize the relevance to the target angles and minimize the redundancy between the selected inputs (1).

$$x_k^* = arg\ max_{x_k}(MI(x_k ,\theta)- \sum_{x_j \in\ selected\ inputs} \lambda\times MI(x_k ,x_j)). \qquad (1)$$

Here λ was fixed to 0.7 to bring a tradeoff between the two criteria. The weights of LR estimators were obtained via ordinary least square, while the weights of MLP were obtained via applying the Levenberg-Marquat algorithm [10] to the training dataset. The obtained estimators are as below:

$$\hat{\theta}_{LR}^{IE} = w_0 + w_1 S2_2 + w_2 S1_1 + w_3 (S2_2 \cdot S3_2). \qquad (2)$$

$$\hat{\iota}_{LR}^{FE} = w_0 + w_1 S2_1 + w_2 S1_1 + w_3 (S2_1 \cdot S3_1) + w_4 (S2_2 \cdot S3_2). \qquad (3)$$

$$\hat{\theta}_{MLP}^{IE} = MLP (S1_1, S2_2 \times S3_2, S2_1 \times S1_1). \qquad (4)$$

$$\hat{\theta}_{MLP}^{FE} = MLP (S2_2, S2_1 \times S3_1, S3_1 \times S1_1, S3_1). \qquad (5)$$

Reference Systems and Validation

The following sections outline two different validation setups for the designed kinematics estimation system.

Manual Knee Simulator for Concurrent Estimation of FE and IE angles

The instrumented knee prosthesis was fixed in a manually-operated knee simulator [7] in which we performed 79 IE rotations in range of [-10.41° 8.2°] concurrent with 60 FE in range of [1.6° 73.61°]. The knee simulator was equipped with reflective markers. The measurements of the AMR sensors synchronously performed against a stereophotogrammetry motion capture system including four Mx3+ cameras (Vicon, UK). The precision of the reference system, estimated in static measurements, were 0.34° and 0.22° for FE and IE angles respectively. The training and validation subsets containing 70% and 30% of all data respectively were randomly selected. We repeated this random subset selection for eight times (repeated random sub-sampling validation). This resulted in eight training and eight validation subsets. Then the training subsets were used to design and tune the estimators and the corresponding validation subsets were used only to evaluate the estimators. The differences between each estimator's results and the reference angles were calculated for each subset. Finally, we computed the expected value and standard deviation of the mean error (E), the standard deviation of error (SD), the RMS error (RMS) and the coefficient of determination (R^2) over all eight subsets.

Robotic Knee Simulator for Sagittal Kinematics Estimation during Realistic Gait Patterns

A robotic knee simulator was designed and realized to simulate different activity patterns for testing the designed smart knee implant prior to a subject implantation. This automated knee simulator includes three axial hydraulic actuators to simulate the hip movement or body weight, the quadriceps and hamstring muscles activities (Fig. 2). At the current state, the knee simulator is capable of performing controllable movement in the sagittal plane, therefore only the sagittal kinematics estimations can be validated with this system.

Two datasets were used to generate realistic simulations of knee activities. First the X-ray fluoroscopic data collected from three subjects, bearing similar F.I.R.S.T prostheses, walking on a treadmill were used as the

STA-free reference kinematics for the prosthetic knee [9]. Second, the over-ground gait cycles of one of the subjects provided in 4th grand challenge to predict in-vivo knee forces [11] were used. Both datasets were only used for kinematics measurement validation of the implantable system. To control the simulator, first the FE rotations were extracted from the datasets, and approximated with Fourier series. These Fourier series separately, for each subject, were coded into the simulator interface controlling software as the reference angle and applied to the hip axial actuator which was controlled using a proportional integral derivative (PID) controller (Fig. 3). The robotic knee simulator was also equipped with reflective markers and its kinematics measured by a similar reference system, four Mx3+ cameras (Vicon, UK). In addition, a squat movement, FE:[15.11° 67.56°], was generated in the knee simulator which used as the training data to tune the weights of the FE estimator, i.e. an LR estimator. Then the estimator was validated during gait cycles of the different subjects using similar performance indices as the previous section.

3. RESULTS

Concurrent Flexion-Extension and Internal-External Angle Estimation

Table 1 shows the performance of different estimators for concurrent estimation of FE and IE. The nonlinear estimator (r_{MLP}^{FE}) had better performance for FE estimates than the linear regression estimator; however in the case of IE rotations the results were very close. Considering the best estimators, the errors (mean ± SD) were 0.0°±0.9° and 0.2°±1.1° for IE and FE respectively, i.e. about four times the precision of the reference system.

FE Estimation in the Robotic Knee Simulator

A typical FE estimation against the reference measurement is shown in Fig. 4.a. The performance indices' mean and standard deviations over the four simulated patterns of gait (validation dataset) are shown in Fig. 4.b. The RMS error of FE estimates was equal or lower than 1.5°. The R^2 for FE estimation was 0.99±0.00.

4. DISCUSSION

This work showed how a magnetic sensor configuration can be used for estimation of flexion-extension and internal-external rotations when they occur concurrently. Comparing to the single angle (FE or IE) estimation (in presence of one magnet), FE and IE concurrent estimations (in presence of two magnets) is very challenging. Actually, having magnets on FP and TP, rotation of each part acts as a distortion for the estimators
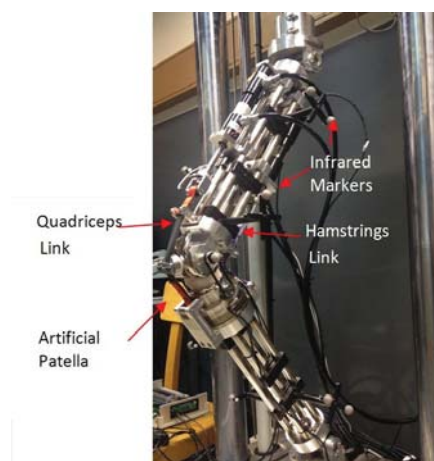

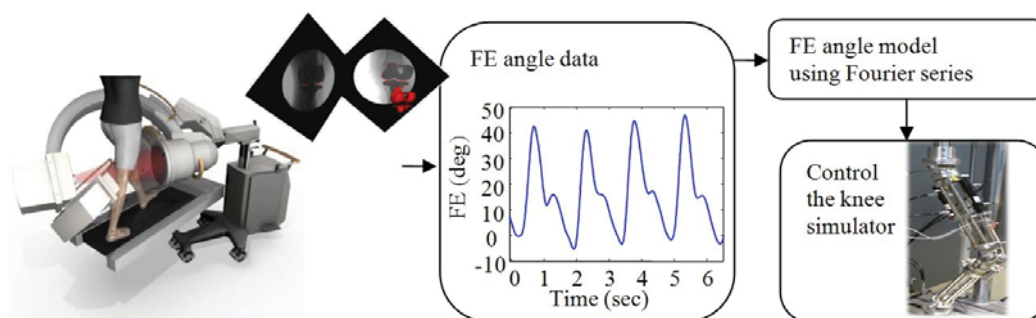Figure 2. Robotic knee simulator

Figure 3. Controling the robotic knee simulator with data acquired from X-ray flouroscopy

Table 1. Performance of different estimators over the validation subsets (manual knee simulator)

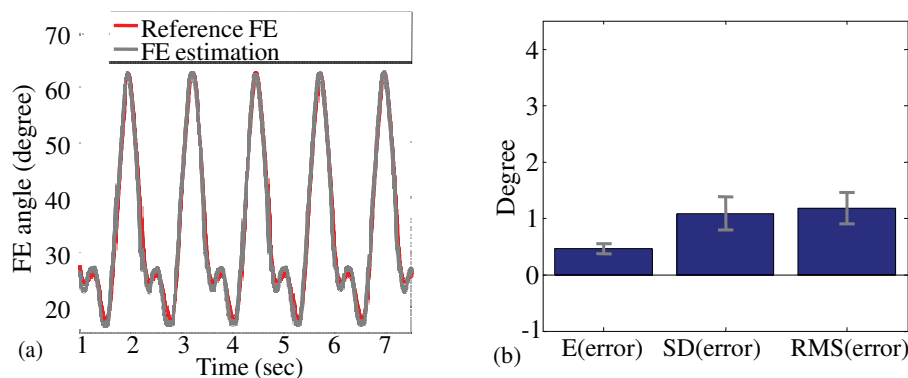| Estimators	E(error)°	SD(error)°	RMS(error)°	R²
$\hat{\theta}^{IE}_{LR}$	0.0±0.1	0.9±0.0	0.9±0.0	0.97±0.01
$\hat{\theta}^{IE}_{MLP}$	-0.1±0.3	1.0±0.1	1.0±0.2	0.97±0.01
$\hat{\theta}^{FE}_{LR}$	0.0±0.8	3.4±0.2	3.4±0.2	0.98±0.00
$\hat{\theta}^{FE}_{MLP}$	0.2±0.3	1.1±0.2	1.2±0.2	0.99±0.00

Figure 4. (a) estimates in a typical gait FE, (b) performance on four simulated gaits (robotic knee simulator)

of the other angle. To properly cope with this problem, first the sensor configuration was designed to maximize the sensitivity and minimize the mutual effect of rotations. Then different estimators for the concurrent estimation of FE and IE were designed to separate the information related to each rotation, and first validated in a manual knee simulator. The result showed that the linear regression estimators are sufficiently accurate for IE estimations with an RMS error of 0.9°, and using MLP estimator did not improve the performance. However to estimate the FE precisely, MLP estimators provided better results (RMS error 1.2°) than LR estimators, manifesting the nonlinearity of the relation between the inputs, e.g. the crude magnetic measurements, and FE.

A robotic knee simulator was designed and fed with four different subjects' gait patterns. By simulating different patterns of treadmill and over-ground gaits the designed sensor configuration and estimator were validated in close-to-reality condition. The obtained RMS error for FE angle estimation was lower than 1.5° that is very low comparing to the range of FE rotations 48.07±5.31°. This error is lower than the estimated STA error for FE angle [9]. In the next step the knee simulator needs to be completed by adding controllable degrees of freedom to validate the concurrent estimation of FE and IE in realistic setup prior to a subject implantation.

5. ACKNOWLEDGMENT

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