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Lower Limbs 3D Joint Kinematics Estimation From Force Plates Data and Machine Learning

Kahina Chalabi¹, Mohamed Adjel^{1,2}, Thomas Bousquet¹,
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Abstract—This study investigated the possibility of using machine learning to estimate 3D lower-limb joint kinematics during a rehabilitation squat exercise from force plate data, that can be collected very simply outside of a laboratory and does not pose privacy issues. The proposed approach is based on a bidirectional-Long-Short-Term-Memory (Bi-LSTM) associated to a Multi-Layer-Perceptron (MLP) model. The use of MLP allows fast training and evaluation time. The model was trained and validated on nineteen healthy young volunteers using a stereophotogrammetric motion capture system to collect ground truth data. Volunteers performed squats in normal conditions and using an ankle brace to simulate pathological motion. Also additional loads were added onto lower limbs segments to study the influence atypical mass distribution. The root mean square differences between the estimated joint angles and those reconstructed with the stereophotogrammetric system were lower than 6deg with correlation coefficients higher than 0.9 in average. Furthermore, the inference time of the proposed approach was as low as 12 μ s paving the way of future reliable real-time measurement tools.

I. INTRODUCTION

The challenge of devising the least invasive instrumented clinical and sport protocols for the accurate assessment of an individual's motor capacity and performance is receiving growing attention with the recent development of affordable consumer electronics devices such as RGB, RGB-depth cameras or Inertial Measurement Units (IMU). All of these affordable sensors suffer from inaccuracies, noise, drift or occlusion issues. With the rapid development of machine learning algorithms, the last decade has seen numerous studies trying to compensate each sensor flaw to maximize the functional information extracted from low cost and easy-to-use instruments. This was done either by fusing different modalities into adaptive filters [1], [2], optimisation based approaches [3], [4], [5] or more recently and more successfully using data-driven approaches [6], [7]. For lower limbs specifically most of the studies focus on walking. For walking IMU are the most suitable as they allow ambulatory motion assessment. When using IMU suit and model-based approach the Root Mean Square Error (RMSE) ranges from 5 to 10deg depending on the investigated joint, retained biomechanical model and its calibration method [8], [9], [10]. Model-based approaches usually require numerous tuning of parameters, the cumbersome definition and calibration of

a biomechanical model [4], [5], [8] but they generalise to any type of motions. Recently, data-driven approaches have been proposed to simplify motion analysis while preserving a good accuracy. Using solely RGB cameras, markerless human pose estimation algorithms [11], [12] and a Long-Short-Term-Memory (LSTM) network, OpenCap [7] was able to efficiently estimate joint angles during walking, squatting and jumping with an average accuracy of 4.5deg. Their LSTM augments the joint center position data given by the markerless algorithm. To do so, they collected hundred of hours of reference joint center position using a stereophotogrammetric marker-based Motion Capture System (MCS) to learn the position of virtual markers from joint center positions. Using this augmented dataset of 3D marker positions inverse kinematics was performed using a classical Multibody Kinematics Optimization (MKO) [13] process implemented in OpenSim [14]. Another recent and fully opensource study [6] proposed to fuse visual and IMU data within a convolutional neural network. They assess the quality of their joint angle estimates with normal healthy motion and by simulating impaired motion using joint braces. They show that their approach was able to estimate joint angles with an accuracy of 5.9deg while being very robust to calibration errors that could be up to 30deg.

Commercial markerless system such as Theia3D (Theia Markerless, Kingston, Ontario, Canada) achieved a reliable RMSE inferior to 6deg for walking [15]. However, they require the use of several high quality videos and are relatively expensive. Such setup is not desirable for in-home or clinical settings in daily practice. Camera-based systems are also affected by the type and the number of cameras, the lighting conditions and their pose in the scene. Thus, the generalization of training data obtained in laboratories to data collected during in-home or clinical setting still have to be demonstrated. Finally, camera based system might pose privacy issues. This is specially the case for OpenCap that requires the use of proprietary cameras and the authors cloud service therefore limiting to sequence to 1min.

Interestingly, these observations were made 20 years ago by Mazzà and Cappozzo [16] that proposed to use solely 6D Ground Reaction Forces and Moments (GRFM) from force plates, to estimate joint angles during squat exercises. They postulate that it is possible, making biomechanical assumption over the constrained human motion, to determine with an optimization process the coefficients of B-splines, used to represent joint trajectories, that will fit the measured force plate data. Doing so they obtained, an estimate of

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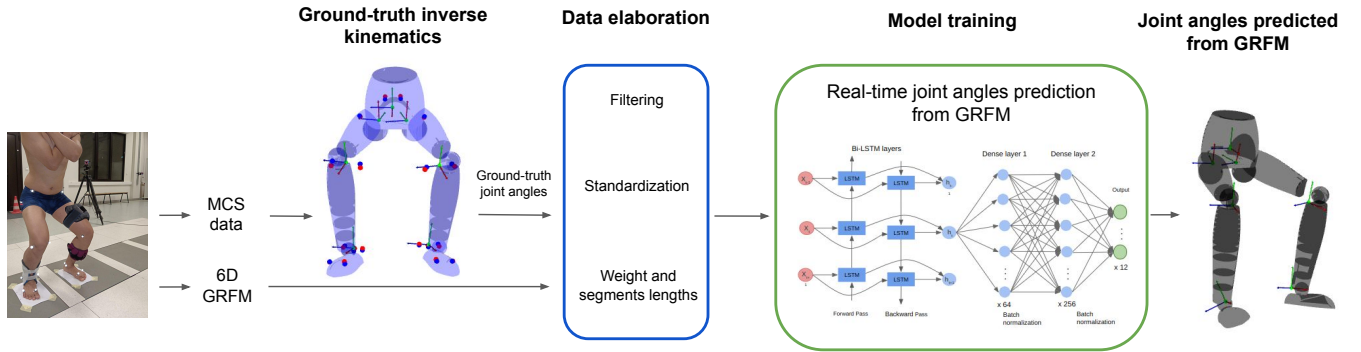


Fig. 1: Overview of the proposed method for estimating lower limbs motions using 6D GRFM data combined with a Bi-LSTM and MLP architecture. MCS data was used to determine ground truth joint angles further used for model training.

sagittal plane joint angles below 3% of error when compared to reference joint angles. Nowadays there exist several commercial [17] or research [18] 3D force plates that are affordable but accurate making such approach accessible to a larger number.

More recently, Choffin et al. [19] proposed to use embedded insoles data and a Gaussian process linear regression algorithm to estimate joint kinematics during a squat exercise. They obtained a stunning RMSE of 1deg. However, the paper lacked implementation details about the hyper parameters of the model. It was also unclear if the reported results were obtained with training or cross validation data. Moreover, the retained model was not really in 3D as it excluded ankle and hip external and internal rotational angles and most importantly an Xsens (Xsens Technologies, Netherlands) IMU suit was used as reference system. As previously mentioned such systems are not as accurate as MCS.

To the best of our knowledge these two studies were the only ones trying to estimate joint kinematics from force data only. Both studies do not consider real-time estimation of joint angles and use computationally ineffective methods. One relies on an optimization process applied to the entire data trajectory [16], while the other uses a computationally intensive Gaussian process regression [19]. Furthermore, they did not consider impaired motions and dealt only with healthy subjects.

The squat exercise engages multiple joints and muscles in one motion, making it highly effective for enhancing lower-limb muscle function [20]. It is essential for daily activities like picking up items, descending stairs, and rising from a chair. Consequently, squatting is frequently included in numerous rehabilitation protocols [20].

In this context, this paper aims to assess the feasibility of using only force plate data (6D GRFM) and a data-driven approach for real-time estimation of 3D lower limbs joint angles. The data-driven model was trained and validated for both normal and impaired squatting, incorporating segment mass modifications typically observed in patients. The overall pipeline of the paper is presented in Fig. 1.

II. METHODS

A. Mechanical model

To determine the ground truth joint angles, a mechanical model of the human body comprising 7 rigid segments connected by $n = 18$ joints was constructed. The recommendations of the International Society of Biomechanics were followed to define the orientation of segment frames and the sequence of joint rotations [21]. Specifically, the thigh segment was connected to the pelvis via three successive revolute joints, the shank was connected to the thigh through a single revolute joint, and the foot was connected to the shank with two revolute joints (see Fig. 2). The pelvis position and orientation relative to the world frame were defined through three prismatic and three revolute joints.

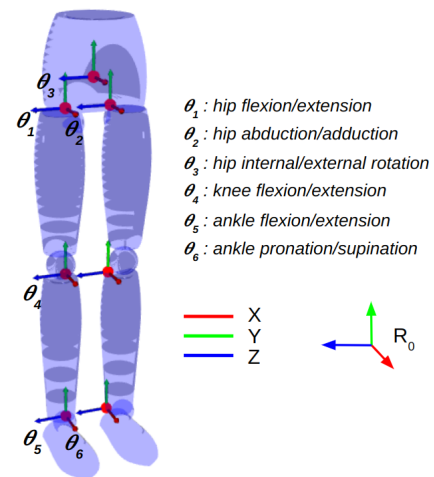


Fig. 2: Mechanical model of the human lower limbs. The model consists of 18 degrees of freedom: 6 for the position and orientation of the pelvis, and 12 for the rotations of the lower limb joints.

B. Dataset and experimental setup

Eight healthy female and eleven healthy male participants (73 ± 15 kg, 26 ± 2 years, 1.76 ± 0.1 m) gave written informed consent prior to engaging in the experimental procedures which consisted in carrying out 24 repetitions of squat during

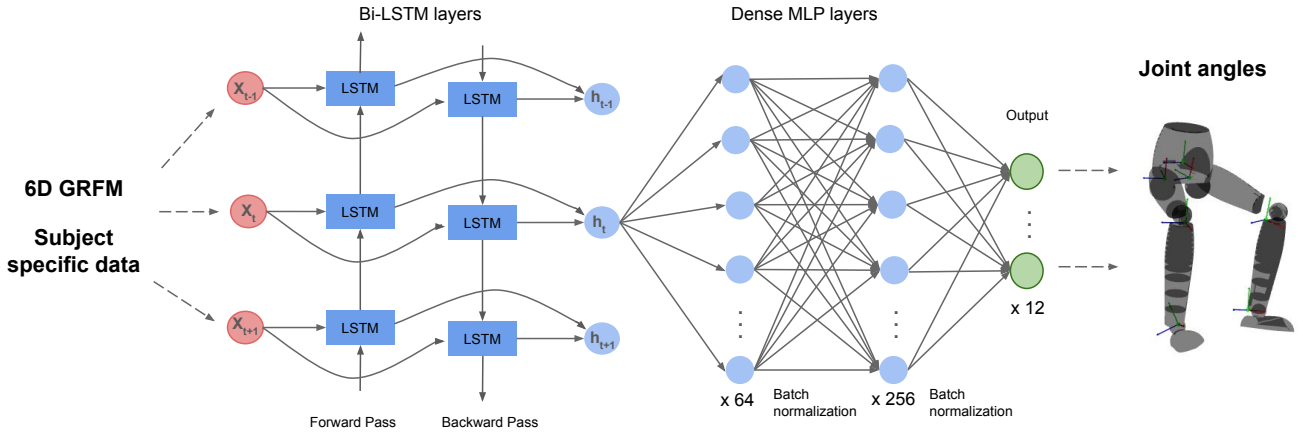


Fig. 3: Model architecture combining Bi-LSTM and MLP layers. The 6D GRFM and subject specific data are processed through the model to estimate lower limbs 3D joints kinematics.

2min trials, with 5s of standing position between each squat. Participants ensured that their feet remained at the exact same positions, indicated by two areas drawn on both force plates (see Fig. 4). The entirety of both feet remained in contact with the ground throughout the whole experiment.

The participants performed the squat under three different conditions: (1) a normal squat, (2) a squat with an ankle brace, and (3) a squat with the ankle brace and additional loads on the opposite leg. The condition 2 and 3 were used to simulate impaired motions, typically observed among post-stroke patients [22]. Obviously the brace will reduce the range of motion of the ankle as in other studies [6], [23]. The additional masses were of 1.5kg and 0.5kg for the thigh and the shank, respectively. For a stroke patient, on its paretic leg, the muscular loss of the thigh and shank were estimated to 13% and 5% [22], respectively. In average, for a person weighting 75kg the masses of the thigh and of the shank are 7.5kg and 4.5kg approximately [24]. This leads to asymmetrical segment mass of 1kg and 0.25kg. Thus, the added weights were representative of the inertial asymmetry observed in patients.

A reference MCS composed by 22 cameras (Vero v2.2, Vicon Nexus v2 [25], Oxford, UK) was used to experimentally validate the proposed approach. Reflective markers were placed on 18 anatomical landmarks on both left and right side of the lower limbs (c.f. Fig. 4). This marker set is very classical in the literature and is similar to the popular plugin-gait one [26]. From markers data, a classical MKO was used to calculate the reference joint angles [13]. Ground reaction forces and moments measurements were collected using two commercially available laboratory-grade force plates (Sensix).

Thus, the dataset was composed of 6D GRFM measured from two force plates corresponding to the left and right foot, labelled with the ground truth joint angles. 19 participants were asked to perform 3 trials of squats, with each trial lasting 2 minutes. Both data sources were acquired at 100Hz,

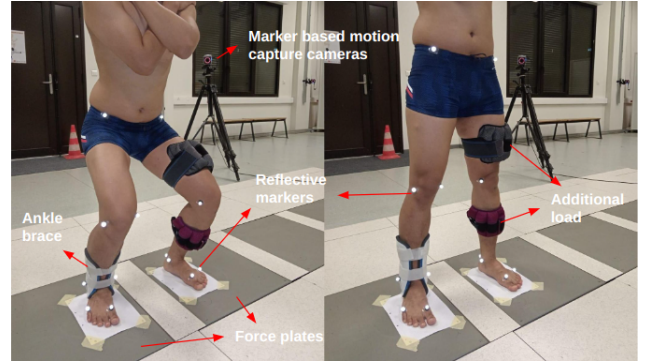


Fig. 4: Experimental setup used to acquire MCS and force plates data. The brace and additional loads were used for the impaired squat condition.

and the dataset was composed of a total of 693 240 data points. Data of 15 participants (which approximately corresponded to 80% of the total dataset) was used for the training set, and data of 4 participants was used for the validation set (which approximately corresponded to 20% of the dataset). GRFM and joint angles data points were filtered using a fifth-order zero-phase lag Butterworth filter with a cutoff frequency set at 10Hz. The dataset was completed by five additional features, representing weight and segments lengths of each subject, determined from the reflective markers and force plates, respectively. These features were added to account for the differences in morphology between subjects, such as variations in body proportions and mass distribution.

C. Inverse kinematics from GRFM and neural networks

In this study, we estimated joint angles from GRFM measurements using a neural network architecture. The architecture took as input 17 features corresponding to the 6D GRFM from two force plates, the segments lengths, and the weight of the participant. The output corresponded to the 12 lower limbs joint angles. The retained architecture combines

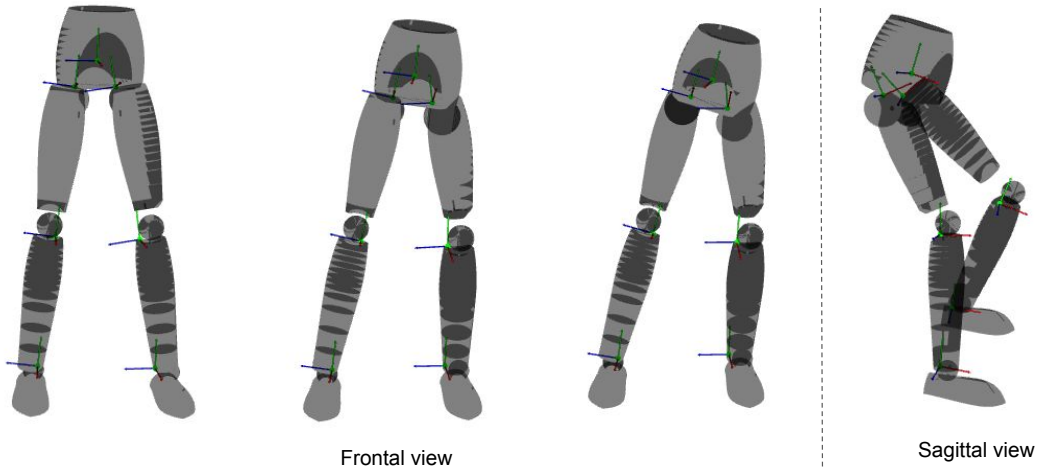


Fig. 5: Lower limbs joint angles estimated during an impaired squat, showing different phases of the movement (from left to right), and different planes of movement.

Bi-LSTM layers with MLP layers, and is particularly adapted for inference from time series data as shown in recent studies [9]. The architecture was composed by three Bi-LSTM layers of 32 units each, followed by two fully connected MLP layers, the first one composed by 64 neurons, the second one by 256 neurons. Each MLP layer was followed by ReLU activations, and batch normalization layer (see Fig. 3). The input features corresponded to 0.4s horizon time sequences of force plate data, that were standardized to have zero mean and unit standard deviation. The Mean Squared Error (MSE) between ground-truth and predicted joint angles was used as the loss function, and a regularization term was added with a weight $\lambda = 1e^{-3}$:

$$L = \frac{1}{n} \sum_{i=1}^m \sum_{j=1}^n \left(\theta_j^i - \hat{\theta}_j^i \right)^2 + \lambda \theta_j^{i,2} \quad (1)$$

with m the number of data points of the training set, n the number of joint angles. θ_j^i and $\hat{\theta}_j^i$ represent the inferred and ground truth j -th joint angle, respectively, of the i -th data point. The model was trained and validated using the dataset described in Section II-B. The training and validation processes were conducted on a CUDA-enabled Nvidia RTX4070 GPU, on $n_{epochs} = 2800$ epochs, with a training lasting approximately 1 hour. A gradient descent optimization was employed for the learning process. An adaptive learning rate was managed through a sequence of two schedulers. The first one, an exponential scheduler, allowed to start the learning rate at 0.1, and to exponentially reduce it to $1e^{-3}$ until $n_{epochs}/3$. Then a linear scheduler was used to decrease the learning rate from $1e^{-3}$ to $1e^{-4}$ until n_{epochs} . A dropout rate of 25% was set to avoid overfitting.

The computational effectiveness of the model was assessed with our GPU, and with an Intel Core i5 14400F CPU. The average inference time for a sequence of 40 data points (corresponding to 0.4s of data at 100Hz) on GPU was $12\mu s$, varying between $4\mu s$ and $20\mu s$. On CPU, the

average inference time for the same sequence was $240\mu s$, varying between $200\mu s$ and $280\mu s$. This demonstrates the possibility of using this model to infer joint angles in real-time scenarios.

III. RESULTS

Fig. 6a and Fig. 6b show representative joint angles from a randomly selected subject, that was not present in the training set. Joint angles were estimated using the proposed Bi-LSTM-MLP model and their reference values obtained from MCS for 6 normal and for 5 impaired squats, respectively. The corresponding RMSE were 2.71deg and 3.22deg in average. It was expected from the literature that the proposed approach will work well for planar squat. Moreover, one can see that the impaired squat modifies the motion with more motion in the mediolateral plane as it involves different patterns for the ankle pronation/supination and of the hip internal/external joint than for the normal motion. This is well shown in Fig. 5 that shows a snapshot animation of the estimated motion during the impaired squat. Despite these modifications the proposed approach is capable of estimating relatively accurately 3D lower limbs joint angles.

Table I, that presents the results obtained for 4 subjects of the validation set, support these statements. For all modalities the RMSE was below 6deg. The largest RMSE was observed for the normal condition but it can be explained by the fact that unconstrained squat motions are of larger amplitude than the impaired one. Similarly, the flexion-extension angles display the largest RMSE but always with a very good Correlation Coefficient (CC) above 0.87. This was expected as the learning process will focus preferentially on the joint angles displaying large variation, i.e. having the largest influence in the dataset. The poorest correlation were observable for the ankles pronation/supination angles for all modalities. This is due to the fact that these joint display motion of relatively small amplitude. Thankfully, the inertial asymmetry and ankle motion constraint modified very little the accuracy of the proposed approach. It can be explained by the fact that

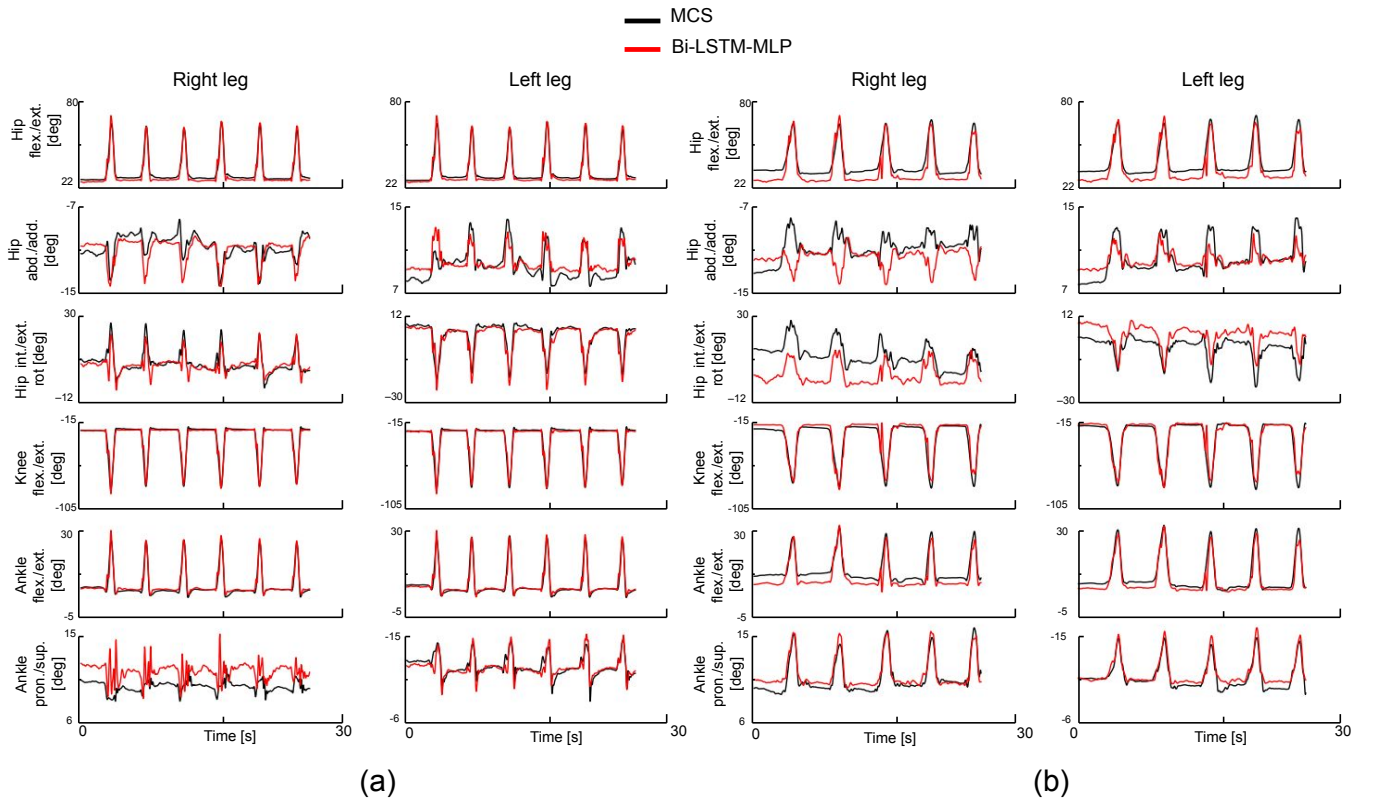


Fig. 6: Lower limbs joint angles estimated from reference MCS data (black) and from Bi-LSTM-MLP (red). (a) for a normal squat exercise and (b) for an impaired participant using brace and additional loads.

-	-	Brace		Brace and Load		Normal	
		RMSE [deg]	CC	RMSE [deg]	CC	RMSE [deg]	CC
Right	Hip flex./ext.	4.2 ± 0.8	0.96	7.8 ± 1.5	0.91	9.29 ± 2.2	0.94
	Hip abd./add.	2.5 ± 0.5	0.91	5.3 ± 0.9	0.18	2.5 ± 0.4	0.75
	Hip int./ext. rot.	3.5 ± 0.6	0.76	3.7 ± 0.5	0.75	3.7 ± 0.5	0.8
	Knee flex./ext.	5.9 ± 0.9	0.95	6.2 ± 1.3	0.94	11.4 ± 2.8	0.92
	Ankle flex./ext.	1.9 ± 0.3	0.92	2.4 ± 0.4	0.87	3.9 ± 0.9	0.89
	Ankle pron./sup.	2.2 ± 0.4	0.85	2.9 ± 0.4	0.91	4.2 ± 0.6	0.2
Left	Hip flex./ext.	4.5 ± 0.9	0.96	8.1 ± 1.5	0.92	9.1 ± 2.1	0.94
	Hip abd./add.	2.5 ± 0.5	0.93	5.1 ± 0.9	0.45	2.5 ± 0.4	0.76
	Hip int./ext. rot.	2.6 ± 0.5	0.86	2.9 ± 0.6	0.75	3.4 ± 0.5	0.73
	Knee flex./ext.	6.6 ± 0.9	0.96	6.9 ± 1.2	0.96	11.1 ± 2.7	0.92
	Ankle flex./ext.	2.4 ± 0.4	0.95	3.1 ± 0.5	0.94	4.2 ± 0.8	0.91
	Ankle pron./sup.	1.6 ± 0.2	0.83	2.9 ± 0.4	0.91	2.8 ± 0.5	0.67
	Average	3.4 ± 0.6	0.90	4.8 ± 0.8	0.79	5.7 ± 1.2	0.78

TABLE I: Comparison of joint angles obtained from Bi-LSTM-MLP, with respect to joint angles obtained from MCS data

for human motion most of the dynamics can be explained by kinematics factor rather than by the relatively minor modifications of inertial properties of the musculoskeletal system between two subjects. This was previously shown by our group, that proposed a sensitivity analysis of the influence of inertial parameters on the estimate of ground reaction forces and moments [27]. Reinbolt et al. [28] also drawn similar conclusion but with patients.

The proposed approach is compatible with real-time application, thanks to the MLP layers simplicity, as the average

inference time of $12\mu s$ with GPU and $240\mu s$ with CPU. The training time of the overall architecture was relatively fast thanks to the MPL layers, as it requires only 1h of training.

IV. CONCLUSION

This paper shows the possibility of using only force plate data to estimate lower limbs 3D joint kinematics during normal and asymmetrical squat exercises. With accuracy below or very close to 5deg and different types of motions, the proposed approach could be used for a valid motion

assessment. Five degrees of error is usually considered as reliable enough in clinical applications [29]. Even if it was not the case in this study the proposed approach based on a Bi-LSTM-MLP model can be used in real-time. This is due to the relative simple structure of the MLP that is much faster than the Gaussian process regression used previously in the literature [19]. This and the simple required experimental apparatus, requiring only two force plates, could pave the way to interactive in-home rehabilitation. Nowadays, plenty of affordable force plates or even embedded insoles can be found on the market [17], [18], [30]. Thus, the key challenge will be to use the proposed approach with less accurate embedded insoles, which could broaden its use for in-home rehabilitation. As mentioned in the introduction using force plate data is not invasive nor pose privacy issues. Thus, we believe that, the proposed approach could impact a larger number of patients or people training for muscular reinforcement using squat exercise. While it is crucial in the future to test with real patients data and to fine tune the models for those data, our proof-of-concept tested with impaired squat motions indicates that the models could generalize well to atypical mass distributions and squat movements. To ensure broader generalization, it will be essential to train the model on other types of motions, with a larger dataset including unhealthy subjects data. Also it will be interesting to analyse if the proposed approach performs for other rehabilitation tasks such as ankle/hip strategy analysis or hula-hoop motions [30]. For these analyses, transfer learning, that will be simplified by the MLP computational low cost, could be used to improve the proposed model if needed.

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