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Estimating Range of Lower Body Joint Angles with a Sensorized Overground Body-Weight Support System

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Abstract— **Recent trends in rehabilitation and therapy are turning to data-driven approaches to personalize treatment. Due to such approaches, data collection methods have become more complex and expensive, in terms of financial resources, technological knowledge, and time required to implement the data collection method. Such costs might deter clinical applications of otherwise good data collection methods. Hence, a method to collect data in a non-intrusive manner is proposed. Sensors are embedded into a commonly used rehabilitation tool, the walking trainer, for gait data collection. This study shows that, in principle, lower body joint angles can be collected in a non-intrusive manner, with a slight trade off to precision. In this study, the focus would be on the pelvic and hip movements, since the pelvic segment of the human body is implicated in a variety of gait problems**

Clinical relevance — **The proposed usage model allows clinicians access to additional kinematic data, while minimizing changes to existing clinical evaluation processes and being non-intrusive. Having additional kinematic data would give further insight into a patient's current state, thereby improving the efficiency of individualized therapy.**

I. Introduction

Current trends in medicine and physical therapy indicates that data-driven approaches to personalize interventions are becoming more popular [1], [2], [3]. Although these approaches might have proven to be useful in the laboratory, they require expensive equipment and profound technical knowledge. In the case of the gold standard in gait analysis, the motion capture system (Mocap) represents a huge cost, both financially and technologically, on the clinicians/physical therapists. This might deter applications of objective methods in gait evaluation. Recent works have proposed the use of wearable devices, like IMUs, to alleviate the problem of cost and ease of use [4], [5]. Although IMUs are cost-effective and have reasonable precision, attaching sensors to patients involves an extra step in the clinical evaluation process, which might increase time spent for evaluation. Therefore, it is proposed that data collection should be performed in a non-intrusive manner, by integrating sensors into commonly used rehabilitation devices. In this paper, an overground Body Weight Support (BWS) walking trainer was selected as a candidate to examine the feasibility of such a data collection method. This paper examines the feasibility of estimating the pelvic and hip range of joint angles (RoM) with a sensorized BWS trainer [6]. Such a device would be able to collect additional gait information that would help clinicians to better understand the patient's current condition. The hips and pelvis were the focus for this paper as the pelvis is anatomically important for human gait [7], and constrains to pelvic movement is correlated to the reduction in the RoM of the lower limbs [8]. Furthermore, it has been shown recently that assisting pelvic movement during rehabilitation can improve gait recovery in stroke patients [9]. As pelvic movement play such a central role in gait, being able to collect more data on this phenomena would greatly enhance understanding of how the pelvis affect gait.

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II. Materials and Methods

There are two objectives of this study. First, is to validate a method based on a neural network model to estimate the RoM of pelvic tilt, upward obliquity and pelvic rotation. The second objective is to validate another method based on an inverted pendulum model to estimate the RoM of hip flexion.

A. Experiment Location

Data collection was conducted in a large room with a 10m long walkway. The Vicon Motion capture (VICON MX System with 16 T20S Cameras, Vicon, Oxford, UK, sampled at 100 Hz) was installed in the room for motion capture.

B. Sensorized Overgound Walking Trainer

A walking trainer (All-in-One Walking Trainer, Ropox A/S, Naestved, Denmark), with attached sensors, was used for participants (Figure 1). Briefly, strain gauges (SG) were added to the lifting arm of the walking trainer to measure the amount of body weight unloaded by the frame of the walking trainer. A Laser Range-Finder (LRF) attached to the undercarriage of the walking trainer (39 cm above the ground), measures the distance of the shin to the undercarriage. This allows us to calculate the step length of the participant. For more information on exact sensor placement and verification tests of on the sensorized walking trainer, please refer to [6]. LRF and SG were sampled at 80 Hz.

C. Software

The Deep Learning Toolbox (Version 13.0) in Matlab 9.7 (R2019b Update 8) (The MathWorks, Inc., Natick) was used to implement a Bidirectional Long-Short Term Memory (LSTM) network model. This network model was used to associate a participant anthropomorphic parameters, strain gauge values and step parameters with pelvic joint angles.

D. Experiment Protocol

The experimental procedures involving human subjects were approved by the Institutional Review Board of University of Tsukuba Hospital. 4 healthy participants (23 - 36 yrs), with no history of neurological diseases, were recruited. Participants reported that they had no muscular injuries at the start of the experiment. Sixteen autoreflective markers were placed bilaterally on the anatomical positions: Anterior Superior Iliac spine, Posterior Superior iliac spine, Lower Lateral 1/3 surface of the thigh, Flexion-Extension axis of the knee, Lower Lateral 1/3 surface of shank, Lateral Malleolus of the ankle, Posterior peak of the calcaneus of the heel and the Lateral second metatarsal bone of the toe. These marker positions were used for gait tracking during the experiment. Marker placements are obtained from the Vicon documentation (Lower limb marker placement section) [10].

Participants were put into a BWS harness and attached to the walking trainer (Fig 1). In each trial, participants walked 10m in a straight line at a self-selected speed, with a therapist operating the walking trainer. Participants were instructed to walk with their own power as much as possible, with the therapist guiding direction of movement. Participants were stopped upon reaching the end of the 10m walkway. Each trial was repeated 3 times for 3 different body weight support percentages (25%, 50% and 75% of BWS).

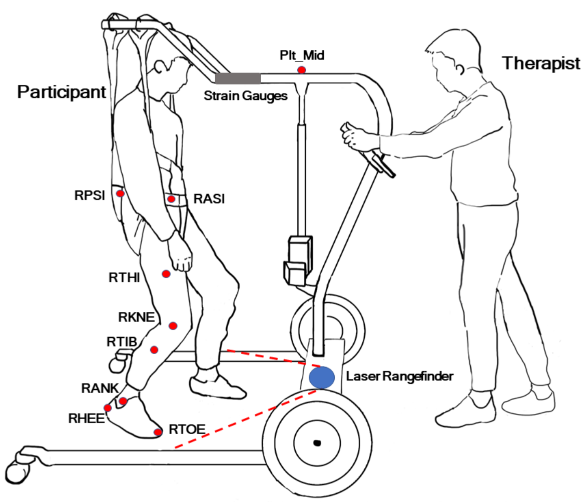

Fig. 1. Participant in overground BWS system and therapist guiding. Markers are only displayed for the right side of the participant's body, but in the experiment, the same set of markers are also placed on the left side of the participant's body.

E. Preprocessing of data

Step data from participants were collected with the LRF, SG, and Mocap. Motion tracking data was downsampled to 80 Hz and synchronized to match the extracted data from the LRF and SG values.

The start and end of every trial were manually labelled to exclude the initiation and ending of gait. Extracted data from the LRF, strain gauges and Mocap system, were filtered with a moving average window using the movmean function (windows size 10) in Matlab to smooth the data. Data from every trial were consolidated into a dataset (36 trials in total (4 participants * 9 trials)). The dataset was normalized by removing the mean and standard deviation of each trial. The mean and standard deviation values were stored for comparison against Mocap joint angles after LSTM prediction. The dataset was then indexed for training and testing the LSTM.

Input and outputs of the LSTM are listed in Table I. For outputs, only the angles calculated from the left side of the pelvis were used as values on the contralateral side are essential the same, but with a different sign.

Inputs	Outputs
Cond (BWS %)	Pelvic Tilt (Left)
Height (m)	Upward Obliquity (Left)
Weight (kg)	Pelvic Rotation (Left)
Leg Length (m)	
ST Right Vertical (grams)	
ST Right Horizontal (g)	
ST Left Vertical (g)	
ST Left Horizontal (g)	
LRF Left Foot X Pos (mm)	
LRF Left Foot Y Pos (mm)	
LRF Right Foot X Pos (mm)	
LRF Right Foot Y Pos (mm)	
LRF Step Length (mm)	
LRF Step Width (mm)	

TABLE I

TABLE OF VARIABLES USED IN TRAINING

F. Training and testing the LSTM

The LSTM model depicted in Figure 2. Two different validation tests were conducted with the LSTM. They are:

- **Subject specific validation:** All trials from a selected participant were extracted from the dataset and used as a test set, while the remaining data was used as the training set.
- **Condition specific validation:** All trials from a selected BWS condition (i.e. picking from the set of [25%, 50%, 75%] BWS value) were extracted and used as a test set, while the remaining data was used as the training set.

For each of the validation test, the LSTM network was trained in sequence-to-sequence mode for 2000 epochs. As the LSTM is currently not calibrated to perform online prediction, LSTM output pelvic angles were "unstandardized" by adding the mean and standard deviation of the first lap in each BWS condition. For example, LSTM output pelvic angles using the the second and third lap of the 50% BWS condition will be "unstandardized" with the mean and standard deviation from the first lap of the 50% BWS

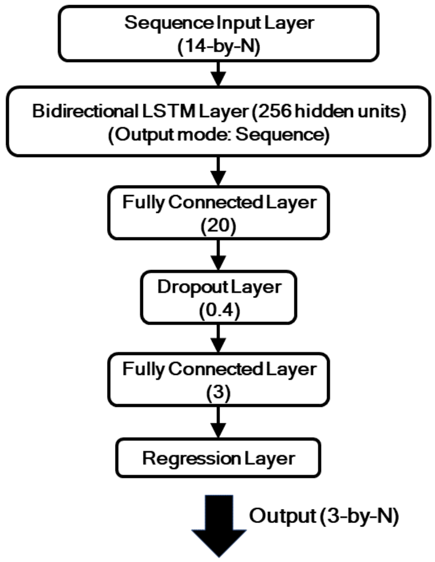

Fig. 2. Bidirectional LSTM layers and parameters

condition. As for the comparison metric, the RoMs were calculated for comparison for each trial. The absolute error between the RoMs were calculated between the Mocap and LSTM estimations.

G. Validating hip angles calculated from the LRF against Mocap

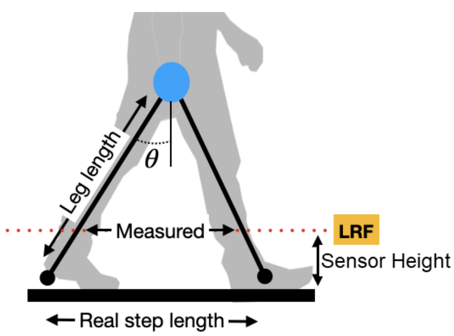

Fig. 3. Estimation of hip flexion, based on step length calculated with the LRF

An inverted pendulum model of the human leg was assumed to estimate hip flexion angles (Figure 3). This is based on the equation from [6]:

$$\frac{D_{LRF}}{2 * \sin\theta} + \frac{H}{\cos\theta} - L = 0 \tag{1}$$

where θ represents the combined hip flexion and extension angles. Based on the equation, the estimated value of θ is the one that solves Equation 1.

III. Results

Figure 4 depicts an example of the LSTM output against the joint angles calculated from the Mocap.

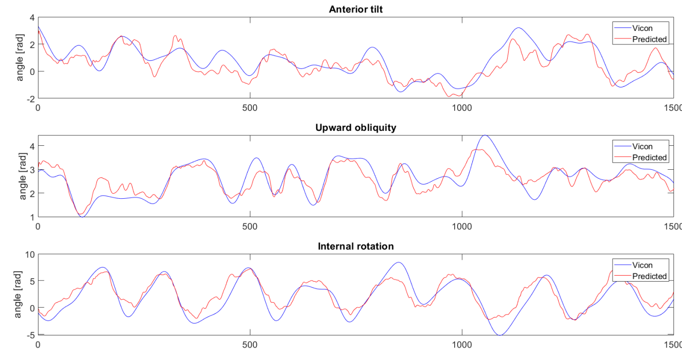

Fig. 4. A representative plot of the output generated

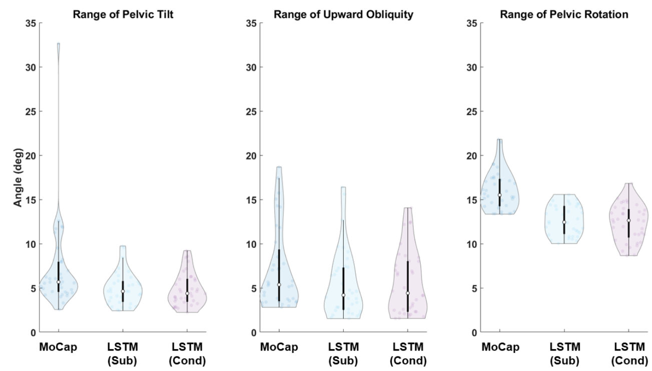

Fig. 5. Range of pelvic movement calculated from MoCap and estimated from LSTM outputs. This results are for the Subject specific (Sub) and Condition specific (Cond) validation conditions

Figure 5 depicts the RoM distributions for the two different validation conditions. Pelvic Tilt RoM values from the Mocap has a mean of (7.15° ± 5.09), with the LSTM prediction for both validation conditions being 5.41° ± 2.29 (Sub) and 5.33° ± 2.33 (Cond) respectively. Upward Obliquity RoM were (7.21° ± 4.64 (Mocap)), (5.76° ± 3.82 (LSTM (Sub))) and (5.71° ± 4.12 (LSTM (Cond))). Finally, Pelvic Rotation RoM were (15.98° ± 2.19 (Mocap)), (13.41° ± 2.34 (LSTM (Sub))) and (12.95° ± 1.70 (LSTM (Cond))) respectively.

The absolute errors between the Mocap and LSTM estimates (Figure 6) were (2.18° ± 3.56 (Pelvic Tilt)), (2.04° ± 1.57 (Upward Obliquity)), (3.14° ± 1.89 (Pelvic Rotation)) for the Subject Specific condition and (2.35° ± 3.96 (Pelvic Tilt)), (2.28° ± 1.94 (Upward Obliquity)), (3.36° ± 2.34 (Pelvic Rotation)) for the Condition Specific condition

Figure 7 depicts the hip flexion RoM distributions for all trials. Range of hip flexion/extension angles for all trials from the Mocap are 25.09° ± 5.00. Estimated hip flexion/extension angles are 29.85° ± 5.81. The absolute error between the Mocap and the LRF values are 5.66° ± 5.29

IV. Discussion

The RoM was chosen as it is a common measure used in stroke assessment [11]. Even in recent years, this measure is still in use [12], [13]. Estimating the range of pelvic joint angle using and LSTM appear to be feasible, as the

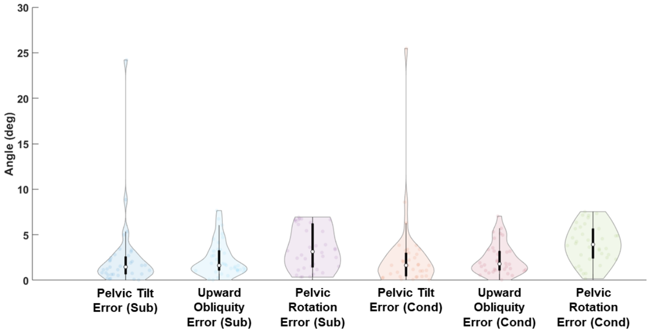

Fig. 6. Range of pelvic movement calculated from MoCap and estimated from LSTM outputs. This results are for the Subject specific (Sub) and Condition specific (Cond) validation conditions

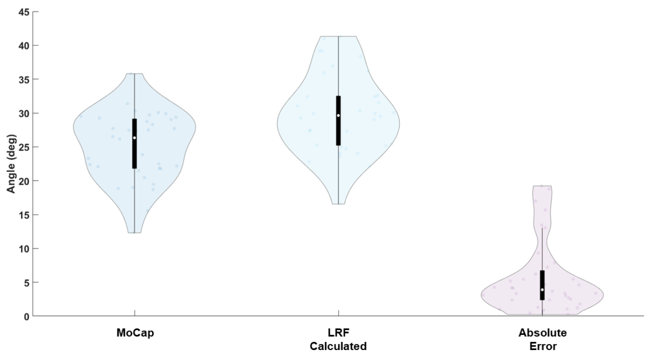

Fig. 7. Range of hip flexion calculated from MoCap and estimated from the inverted pendulum model with LRF data

error rates between the Mocap and LSTM appear to be low enough to be practically used (2 to 3° in absolute error). Considering that clinical assessment methods evaluates the change in the RoM instead of using the actual joint angle value, the margin of error might not affect overall assessment. Furthermore, a review by [14] suggest that an error margin with 2 to 5° is reasonable.

Similarly, the hip flexion/extension angles estimated from the LRF seem to agree well with the Mocap measurement, with a small margin of absolute error.

One limitation of this method is that the LSTM is currently not made for online estimation. However, it is shown, in principle that the range of pelvic joint angles can be estimated using a combination of strain gauges, anthropomorphic parameters and step parameters. As a test of feasibility, the range of joint angles is a practical metric at this current time. A definite future consideration will be the extension of the LSTM to be able to handle online estimation of joint angles.

Another limitation is the lack of data, since only 4 participants were recruited, due to restrictions imposed during the current Covid-19 pandemic. Future work will include a larger study with more participants in order to obtain a better dataset for estimation.

Future considerations would be to test the sensitivity of the LSTM on patient data to verify if changes in range of joint angles can be detected accurately.

ACKNOWLEDGMENT

Violin plots (Figure 5, 6 and 7) were made with code from [15]

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