Estimated ankle/knee joint moments in ambulatory running: an AI-driven inverse dynamics approach

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***Abstract*—Inertial measurement units (IMUs) are commonly used for measuring runners outside the lab, but current IMU-based motion capture solutions require a large number of sensors. Therefore, we propose an AI-driven inverse dynamics approach that requires three IMUs (placed on pelvis and lower legs) and pressure insoles to estimate lower-body kinematics and joint reaction moments during running. These joint reaction moments could give insight in the muscle contribution in joint loading, such as tibial bone loading. Results show good agreement with the reference for ankle reaction moments, while knee reaction moments have larger errors. The proposed method shows good potential, but better estimation of more proximal joint kinematics/kinetics is required in combination with measuring shear forces.**

***Index Terms*—machine learning, inverse dynamics, running, ambulatory movement analysis, inertial measurement unit (IMU)**

I. Introduction

Injuries of the lower extremity have a high occurrence (~37%) among runners [1]. About 80% of all injuries is considered an overuse injury, caused by the repetitive impacts while running [2]. Common parameters for impact analysis are the peak tibial acceleration (PTA) or the impact peak of the ground reaction force (GRF), which showed possible relationships with potential injury [3]. However, they do not represent the actual total compression forces occurring in, for example, the ankle joint [4], where muscle forces also play an important role in compressive joint forces [4]. Joint moments could give insight in muscle force contributions, for example in tibial bone loading estimation [4]. Biomechanical analysis of running has provided substantial insights in relations between various aspects that can impact injury, such as running form, fatigue, shoe wear, etc. [1]. However, such analyses are typically performed inside a gait laboratory equipped with three-dimensional optical motion capture systems and force plates [5].

Advances in ambulatory movement sensing allow for taking the kinematic analysis of running out of the lab by using inertial measurement units (IMUs), such as in road-race conditions [6]. A full biomechanical analysis also requires kinetic data to obtain (joint) loading information. It has been shown that ankle/knee joint loading can be estimated by adding insoles to the measurement setup [7]. Such a measurement setup requires a large number of sensors, which results in a long setup time and extensive data analysis. Efforts to minimize this setup, by using machine learning to substitute information from body segments without sensors, have shown good potential [8]. However, research on directly estimating knee joint loading using machine learning shows that inter-individual outcomes are less accurately estimated [9].

Inverse dynamics analysis allows for taking into account individual differences, such as kinematics, body shape, segment lengths, etc., which can provide the required insights for individual biomechanical running analysis. Therefore, we aim to decrease the number of IMUs required in such a minimal sensor setup to allow for more accessible biomechanical running analysis. Our approach is to estimate lower-body joint angles with only three IMUs placed on pelvis and lower legs, using an artificial neural network (ANN) based on [8]. These joint angles will be used in combination with data from the pressure insole as input to the inverse dynamics analysis to estimate ankle and knee moments. We hypothesize that this will result in estimated joint moments that agree well with the method based on an eight-IMU full body setup [7]. Results of this study could benefit inverse dynamics analysis approaches for estimating joint loading in an outdoor setting and its relation to potential running injuries, but also in other sporting activities.

II. Methods

A. Dataset

A dataset collected by Wang et al. was used for training/testing our proposed approach for estimating joint moments in an ambulatory running setting [7], [10]. The dataset contains data of 9 young adults running at 6.3, 8.1 and 9.9 km/h on an instrumented treadmill (custom Y-mill, Motekforce-Link, Culemborg, The Netherlands), while measuring body kinematics using eight IMUs (Xsens MVN Link, Movella, Enschede, The Netherlands), and vertical ground reaction forces (vGRF) and center of pressure (CoP) using pressure insoles (Moticon, Munich, Germany). Two subjects were excluded from this analysis, because the pelvis sensor was placed in a different orientation compared to the other subjects. Inverse dynamics analyses were performed using the OpenSim gait2392 model [11]. Additional details of the data acquisition and analysis can be found in [10].

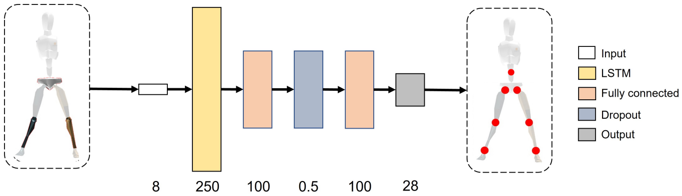


Fig. 1: *The network structure (and number of neurons in the layer shown under the bars) for estimation of joint angles using sensor orientation data of 3 IMUs. Data is represented as quaternions, resulting in an input-layer with 8 inputs. The second layer is an LSTM layer (with 250 neurons) that takes into account relations over time that exist within the input data. The LSTM layer connects to a fully connected layer (with 100 neurons), dropout layer (dropout of 0.5) and the output layer (with 28 outputs), where the output is joint angles of the ankles, knees, hip joints and lumbar joint (in quaternions).*

B. Learning Approach

The proposed learning approach takes relative IMU orientation (in quaternions) of the lower legs to the pelvis as input in the ANN to estimate lumbar, hip, knee and ankle joint angles (in quaternions), which is schematically represented in Figure 1. The relative orientations are used as input to the ANN as this removes the real-world heading orientation from the input data. The output of the ANN (joint angles) are represented as quaternions, because an Euler angle representation (which is used in OpenSim) suffers from discontinuities and is therefore not suitable for a recurrent regression approach. Additionally, the pelvis sensor orientation is used to define the orientation of the OpenSim model, as the pelvis segment is used for orienting the model in the local frame.

A recurrent LSTM layer is used because it was shown to be effective for estimation of cyclical motions [12]. Further layers of the ANN are chosen to limit possible overfitting to the training data. The neural network toolbox of MATLAB R2023a (Mathworks, Inc., Natick, MA, USA) was used to design, train, and evaluate the ANN described above. ANNs were trained for 2,000 iterations using an initial learning rate of 0.1, with the Adam optimizer functionality.

The data of seven runners was divided such that 5 subjects were used for training, 1 subject was used for validation and 1 for testing. To ensure that no additional overfitting to a specific running speed was occurring, the trials of running at 8.1 km/h were excluded from the training/validation set, but were part of the testing set.

C. Inverse Dynamics

Joint angles estimated using the proposed ANN approach are converted to Euler angles and used as kinematic input for the inverse dynamics. Furthermore, the CoP and vGRF from the pressure insoles are obtained (assuming that the pressure insoles are aligned with the foot coordinates, as in [7]), to obtain joint moments with the inverse dynamics simulations from OpenSim, using settings as described in [7]. As reference, a full-body IMU setup (8 IMUs: on feet, lower legs, upper legs, pelvis, and sternum) was used, in combination with the one-dimensional vGRF and CoP from the pressure insoles to run the OpenSim inverse dynamics analysis.

D. Outcome Measures

Initial contact was detected when the vGRF measured by the insoles exceeded 50 N, where each stride was resampled to 200 samples to normalize each stride to 0-100% of the stride cycle. 40 strides in the middle of each running trial were evaluated, assuming that steady state running was achieved in that period. Only the right leg was evaluated (similar results were obtained for the left leg) for conciseness. First, outcomes from our proposed ANN approach will be compared to joint angles obtained by Wang et al. with their eight-IMU full-body sensor setup [10]. Next, output of the inverse dynamics analysis of OpenSim (normalized to the subject's body weight) based on our minimal sensor approach will be compared to that based on the results of Wang et al. [10]. Both the kinematic and kinetic outcomes of our method will be compared on similarity (Pearson's correlation coefficient, ranges according to [13]) and accuracy (root mean squared errors (RMSE)) to the previously described reference.

III. Results

The mean Pearson correlation coefficients and RMSE $\pm$ standard deviation of the ankle/knee angles/moments for all subjects are shown in Table I, for each running velocity. On average, the ankle/knee angles show very strong correlations (> 0.9) and RMSE smaller than 12 degrees for all running velocities. No significant differences can be observed between the running velocities. These estimated kinematic outcomes are used to drive the OpenSim inverse dynamics simulation, which resulted in the mean ankle/knee moment correlation/RMSE as shown in Table I. The ankle moments in Y- (ab-/adduction) and Z-direction (flexion/extension) are highly correlated with the reference OpenSim approach, while the X-direction (eversion/inversion) shows larger errors and smaller correlations. A similar pattern is visible for the knee moments, however, these are less correlated and with higher errors compared to the ankle moments.

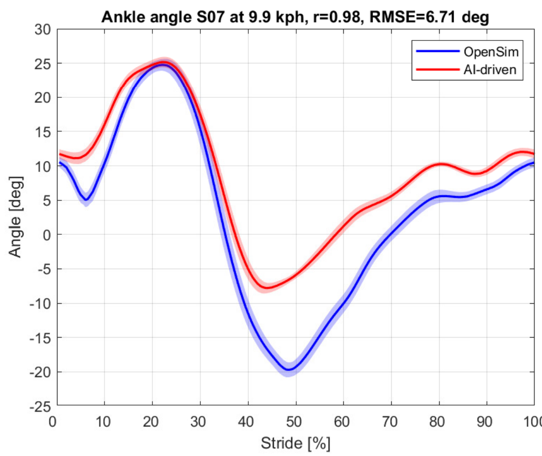
Figure 2 shows the estimated right ankle (Figure 2a) and knee (Figure 2b) angles of a representative subject running at 9.9 kph, normalized to a complete stride cycle. Ankle and knee reaction moments of the right leg are shown in Figures 3a and 3b, where dashed lines show the estimates from the AI-driven OpenSim approach and solid lines the reference OpenSim approach of Wang et. al [7].

IV. Discussion

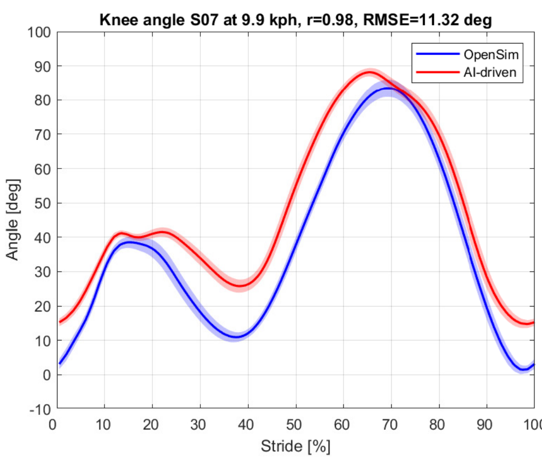
This study aimed to estimate knee and ankle angles with only three IMUs (placed on the pelvis and lower legs) by using an ANN. Furthermore, ankle and knee moments were estimated using this limited IMU setup combined with pressure insoles to perform inverse dynamics analysis with OpenSim. The obtained joint angles and moments were compared with an

TABLE I: *The mean Pearson correlation coefficients ± standard deviation (7 different test subjects, using 40 strides) is shown in the left columns for the different angles/moments at different running speeds. The RMSE ± standard deviation is shown in the right columns for the same conditions.*

		Pearson correlation				**RMSE**		
		6.3 km/h	**8.1 km/h**	**9.9 km/h**		**6.3 km/h**	**8.1 km/h**	**9.9 km/h**
Ankle angle [deg]		0.87 ± 0.05	0.89 ± 0.10	0.89 ± 0.08		7.78 ± 2.56	7.63 ± 2.27	8.47 ± 3.09
Knee angle [deg]		0.92 ± 0.05	0.89 ± 0.21	0.97 ± 0.02		11.05 ± 3.24	11.44 ± 3.46	11.20 ± 1.65
Ankle reaction moment [Nm/kg]	X	0.56 ± 0.65	0.47 ± 0.61	0.48 ± 0.64		0.25 ± 0.11	0.24 ± 0.14	0.23 ± 0.12
	Y	0.96 ± 0.02	0.97 ± 0.03	0.95 ± 0.07		0.07 ± 0.02	0.08 ± 0.04	0.12 ± 0.09
	Z	0.99 ± 0.01	0.99 ± 0.01	0.99 ± 0.01		0.10 ± 0.06	0.10 ± 0.08	0.10 ± 0.06
Knee reaction moment [Nm/kg]	X	-0.08 ± 0.25	-0.15 ± 0.29	-0.02 ± 0.17		0.25 ± 0.10	0.23 ± 0.11	0.22 ± 0.08
	Y	0.30 ± 0.31	0.42 ± 0.42	0.44 ± 0.36		0.12 ± 0.04	0.13 ± 0.07	0.18 ± 0.13
	Z	0.42 ± 0.26	0.45 ± 0.28	0.43 ± 0.25		1.19 ± 0.77	1.25 ± 0.92	1.35 ± 0.96

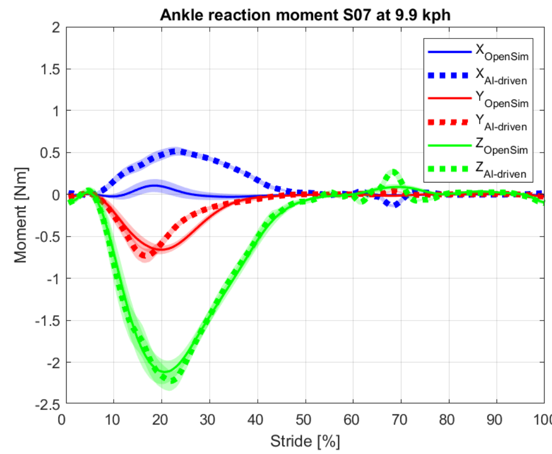


(a) *Sagittal ankle angle.*

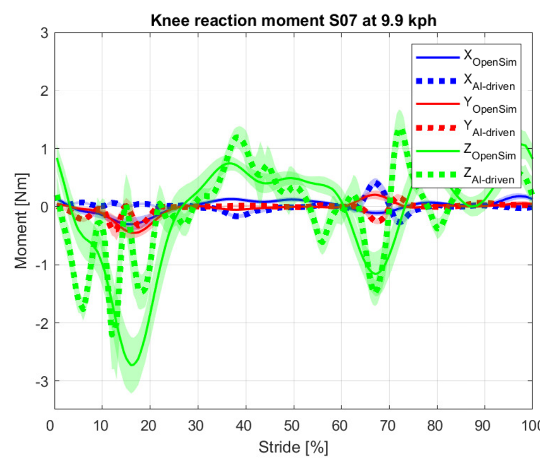


(b) *Sagittal knee angle.*

Fig. 2: *Sagittal joint angle comparison (mean and standard deviation band over 40 right strides) between the proposed approach (AI-driven - red) and the reference (OpenSim - blue) for the ankle (a) and knee (b), normalized over the stride cycle.*



(a) *Ankle reaction moment, Pearson* $(r_X = 0.39, r_Y = 0.94, r_Z = 1.00)$ *and RMSE (Nm/kg)* $(RMSE_X = 0.20, RMSE_Y = 0.07, RMSE_Z = 0.06)$



(b) *Knee reaction moment, Pearson* $(r_X = -0.35, r_Y = 0.29, r_Z = 0.55)$ *and RMSE (Nm/kg)* $(RMSE_X = 0.18, RMSE_Y = 0.15, RMSE_Z = 0.84)$

Fig. 3: *Reaction moment comparison (mean and standard deviation band over 40 right strides for the different axes) between the proposed approach (AI-driven - dashed) and the reference (OpenSim - solid) for the ankle (a) and knee (b), normalized over the stride cycle.*

eight-IMU full-body setup and pressure insoles from [7]. The proposed method is able to estimate joint angles and moments, for use in joint loading estimates, such as tibial bone load [13]. Furthermore, this approach ensures a limited IMU setup time for running in an outdoor setting.

On average, estimating lower-body kinematics from a three IMU-based setup shows strong correlation compared to an eight-IMU full-body setup. Joint angle estimates show larger differences at peak values, where in most cases our approach underestimates range of motion. This is likely a result of excluding the evaluation subject of the training dataset of the ANN, which means it extrapolates to this unseen subject. Similar results were shown in Wouda et al. for training a subject-specific (RMSE >3 degrees) ANN compared to training on multiple subjects (RMSE >11 degrees) [8]. However, obtained joint angles in this work show better time coherence, which is due to applying a LSTM-layer in the ANN.

Using the estimated kinematics in combination with vGRF to drive the OpenSim simulation to estimate joint moments shows moderate to very strong correlation for the ankle moments (depending on the axis) and weak to moderate agreement for the knee moments (depending on the axis). This is in line what was reported by Wang et al., namely that more proximal joint moments are estimated with decreased accuracy using a wearable setup (IMUs combined with insoles) due to the lack of shear force information [7]. In combination with errors of the kinematics that accumulate over the distal to proximal segments, larger differences in knee moments are observed that also show a more variable shape compared to the reference. However, peak knee moments values appear to be similar between the proposed approach and the reference, which will require additional evaluation.

Two subjects had to be excluded from the results because the sensor orientation on the body segment was different compared to the other seven subjects. This resulted in different in- and output relations for those subjects, which were not accurately modeled by the trained ANN. This could be improved by implementing a calibration procedure to use segment instead of sensor orientations. In this manner, the approach would be agnostic of the sensor orientation and potentially improve results for all subjects.

Previous work of the authors estimated both kinematics and kinetics using a three IMU sensor setup [8]. This could be combined with inverse dynamics analysis to remove dependency on pressure insoles. However, a different approach for estimating CoP would then be required. This CoP estimation can be an interesting focus for future research to further minimize the sensor setup and run an ambulatory inverse dynamics analysis based on only three IMUs.

A limitation of this work is that while kinematics of heel/forefoot strikers are different, a single ANN was trained without taking into account their foot landing pattern. This might explain the smaller range of motion in the estimated joint angles of the representative subject. One could train different ANN for these running phenotypes, or provide additional features as input to the ANN to help distinguish these different kinematics and therefore improve the joint angle estimation of specific foot strikers. Furthermore, the running speed evaluated (6.3 to 9.9 km/h) in this study is relatively low. Higher running speeds need to be evaluated in further research, as this can induce higher errors in IMU and pressure insole measurements.

The ANN structure and inputs (sensor placement) were chosen based on previously obtained results [8], however, other combinations (more or less sensors, or different machine learning approaches) of these should be investigated to ensure this is the optimal approach for combining estimated kinematics with inverse dynamics analysis.

V. Conclusion

AI-driven joint angle estimation using a three-IMU setup shows good agreement with an eight-IMU full body setup. In combination with pressure insoles, the three-IMU setup was still able to accurately estimate ankle moments, while more proximal joints require improvement of the estimated kinematics as well as inclusion of shear force information. Overall, the proposed method shows potential in estimating joint moments to be used in joint load estimation, such as tibial bone loading, in an outdoor running environment.

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