ESTIMATION OF JOINT AND TENDON LOADING DURING RUNNING USING ARTIFICIAL IMU DATA AND UNSUPERVISED NEURAL NETWORKS

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This study aimed to estimate lower-limb joint- and tendon loads during treadmill running by combining artificial IMU (artIMU) data of four virtually placed sensors on the shanks and feet with a self-organising neural network approach. To achieve this, we simulated IMU (artIMU) data from marker trajectories of 28 runners, running at 2.5, 3.5, and 4.5 m/s on a treadmill. A Kohonen self-organising map was trained with the artIMU data, and the joint and tendon loading was reconstructed as the hidden variables of the network. A leave-one-subject-out cross-validation resulted in a good to excellent estimation accuracy ($R^2 > 0.87$ and nRMSE <16%) with an exception for the hip joint reaction force. This approach will allow for longitudinal in-field estimation of joint and tendon loading in the future to better monitor and understand running-related injuries.

KEYWORDS: Unsupervised learning, inertial measurement unit, self-organising map, musculoskeletal loading, injury

INTRODUCTION: Recreational running offers numerous health benefits, but lower limb injuries are common among runners (Videbæk et al., 2015). Understanding and addressing the cause of injuries is crucial for enhancing overall well-being. The most frequent injuries include medial tibial stress syndrome, Achilles tendinopathy, plantar fasciopathy, and patellofemoral pain (Willwacher et al., 2022). Biomechanical risk factors like joint moments and impact-related variables contribute to these injuries, but controversies on the precise nature of the associated biomechanical loading mechanisms persist (Gruber, 2023; Schmida et al., 2022). Although there is common agreement that most running-related injuries are due to overuse and thus best assessed during longitudinal studies on data collected within the runners' natural environment, most studies are laboratory-based (Willwacher et al., 2022). However, advancements in sensor technology, specifically body-worn sensors like inertial measurement units (IMUs), enable measuring running biomechanics outside the laboratory. While IMUs show promise, challenges remain, such as the inability to directly quantify the loading of structures, and joint and tendon kinetics outside the lab. Researchers are thus exploring solutions, including machine learning algorithms, to estimate kinetics from kinematics or IMU data. Nevertheless, although supervised learning algorithms yield high accuracy (Johnson et al., 2021; Pogson et al., 2020; Wouda et al., 2018), they require separate training for each variable. This study, therefore, focuses on overcoming practical and methodological limitations by estimating biomechanical load metrics at a joint- and tendon-specific level during running. An unsupervised learning approach, employing Kohonen's self-organising maps (SOMs) is explored for estimating biomechanical loads from IMU data. We hypothesize that a SOM can estimate loading across different musculoskeletal levels, after being trained with data from only a small number of IMU sensors.

METHODS: The publicly available dataset of Fukuchi et al. (2017), containing marker trajectories and 3D ground reaction force (GRF) of 28 recreational runners during treadmill running at 2.5, 3.5, and 4.5 m/s was used. Marker trajectories and GRF were filtered at 15 Hz and 50 Hz respectively using a 2nd order low-pass Butterworth filter. All data were then further processed with the OpenSim API (version 4.3, SimTK, Stanford, USA) for MATLAB.

A generic musculoskeletal model (Bedo et al., 2020) was adjusted by removing all the upper-body segments to provide a modified lower-limb and pelvis model. Static trials for each runner were used to scale the model to the runner's dimensions. Muscle-tendon forces were estimated by minimising the sum of the squared muscle activations using Static Optimization. Hip, knee (medial and lateral) and ankle joint contact forces were calculated using Joint Reaction Analysis. Patellar and Achilles tendon forces were calculated as the sum of the quadriceps (vastus lateralis, medialis, intermedius, and rectus femoris) or calf (gastrocnemius lateralis, medialis, and soleus) muscle-tendon forces respectively. All forces were normalised to each runner's body weight. Time series data for each stride of the right leg were identified by using a 50 N GRF threshold for touchdown and take-off.

To generate four artificial IMUs (artIMU) virtually positioned on the shanks and feet, the 3D marker trajectories of the lower limbs were utilized. First, the joint origins were defined according to the ISB recommendations for the pelvis and ankle joint centre (Wu et al., 2002), the definition of Harrington et al. (Harrington et al., 2007) for the hip and according to Pennock and Clark for the knee joint centre (Pennock & Clark, 1990). Using the joint origins, the segment coordinate systems of the segments were defined and translated into quaternions. Finally, the artIMU sensor positions and orientations were differentiated into 3D accelerations and angular velocities. For each participant, ten ground contact phases were extracted and used as input data to the Kohonen self-organizing map.

To train an unsupervised learning Kohonen self-organizing map (MATLAB R2023a, SOM Toolbox V 2.1 (Vesanto, 2000)), a matrix, containing the 3D accelerations and angular velocities of the artIMUs of ten ground contacts per athlete for the three different speeds [30830 (28 participants x 10 trials of different length x 3 speeds) x 24 (4 artIMUs x 3 channels of accelerations and 3 angular velocities)] was constructed. The initial connection weights of the neurons were set by the first two principal components of each input dataset (Kohonen, 2001). We aimed to estimate the progression of the patellar and Achilles tendon forces, and the vertical hip, medial and lateral knee and ankle joint reaction forces of the stance leg as the hidden variables. After training, each of the 30830 input vectors is associated with one of the neurons of the SOM. As the network reduces the dimensionality of the input matrix, each neuron is associated with several of the input vectors. The sample number of the set of input vectors and their Euclidean distances (quantization error, QE) from each neuron's codebook vector was calculated by the som_bmus function. Subsequently, the values of the hidden variables at the given sample numbers for each neuron were extracted and the weighted average based on the QE was calculated. The larger the QE between the vector and the neuron, the lower the contribution of the value of the hidden variable to the final estimated hidden variable. By doing so, the hidden variables corresponding to each neuron could be reconstructed. To validate the network, a leave-one-out subject cross-validation was performed. To avoid leakage the data was split on a participant level. The accuracy of the model's estimation was assessed using the R^2 and the nRMSE between the estimated test data and the measured data of the test set. R^2 values between 0.3 – 0.5 were considered low, between 0.5 – 0.7 moderate, between 0.7 – 0.9 as good and above 0.9 as excellent.

RESULTS: Estimating the forces of the patellar and Achilles tendons resulted in an excellent accuracy with R^2 of 0.91 - 0.94 and nRMSE values of 11.79 – 17.09% respectively (Table 1). The peak tendon forces are underestimated for the higher speeds (Figure 1).

The estimation accuracy for the medial and lateral knee joint reaction forces and the ankle joint reaction force was good to excellent with R^2 values ranging between 0.82 and 0.93 and nRMSEs between 13.28 and 21.22%. The accuracy for the hip joint reaction force in comparison was lower and achieved R^2 values of 0.49 – 0.66 and nRMSEs of 24.57 – 27.71% (Table 1). Accuracy was also running-speed dependent with decreasing accuracies at higher running speeds. The prediction accuracy for the medial knee joint showed lower nRMSEs than for the lateral side (13.28- 13.81 and 15.46 – 21.22% respectively, Table 1). As for the other hidden variables, the peak joint reaction forces were underestimated for the higher speeds.

Table 1: Estimation accuracy (mean ± SD) indicated by the R² and the nRMSE (%) for the test split for the different hidden variables across the three running speeds.

	Tendon Forces		Joint Reaction Forces			
R^2	Patellar	Achilles	Hip	Knee (medial)	Knee (lateral)	Ankle
2.5 m/s	0.91 ± 0.04	0.94 ± 0.02	0.66 ± 0.14	0.90 ± 0.04	0.82 ± 0.10	0.93 ± 0.02
3.5 m/s	0.93 ± 0.03	0.93 ± 0.02	0.56 ± 0.16	0.89 ± 0.03	0.86 ± 0.07	0.93 ± 0.02
4.5 m/s	0.93 ± 0.03	0.91 ± 0.03	0.49 ± 0.16	0.88 ± 0.04	0.87 ± 0.06	0.92 ± 0.02
nRMSE (%)						
2.5 m/s	17.09 ± 9.311	13.08 ± 4.72	24.57 ± 7.10	13.75 ± 3.63	21.22 ± 12.00	14.19 ± 5.58
3.5 m/s	13.91 ± 5.881	11.79 ± 4.38	27.28 ± 8.65	13.28 ± 2.58	16.72 ± 6.79	13.31 ± 3.91
4.5 m/s	13.15 ± 4.477	12.44 ± 4.21	27.71 ± 8.20	13.81 ± 2.56	15.46 ± 4.38	13.46 ± 3.60

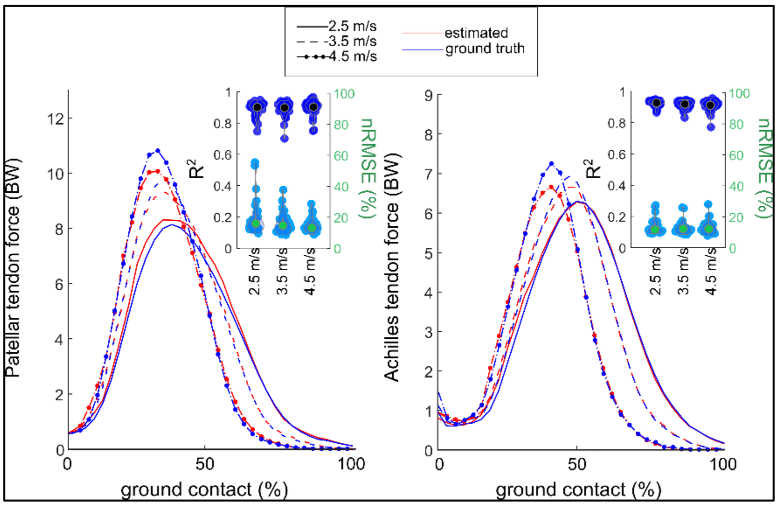

Figure 1: Average progression of the patellar and Achilles tendon forces. Blue: Ground truth, red: estimated tendon forces of the test split. Mean tendon forces at 2.5 m/s (solid lines), 3.5 m/s (dashed lines) and 4.5 m/s (dashed-dotted lines). Violin plots for the R² (primary vertical axis) and nRMSE (secondary vertical axis) for all three running speeds.

DISCUSSION: The presented results of this study show that using a self-organising Kohonen neural network trained with IMU data from only four artIMUs attached to the shanks and feet is sufficient to estimate joint loading and tendon forces. Notably, these estimations are based on data that were not presented to the SOM during its training. The network reduced the high-dimensional input data from 30830 x 24 to 880 x 24, thereby extracting 880 distinct states of the movement, each belonging to one of the SOM neurons. Assigning the joint and tendon loadings to these states allowed us to estimate the progression of joint and tendon loads. The average estimation accuracies were R^2 = 0.90 (range 0.82 – 0.94) for all but one variable (hip joint reaction force). To our knowledge, there is only one other study that has estimated tendon loads during running from wearable IMUs (Rasmussen et al., 2023). The estimation of tendon forces was of higher accuracy with our approach when compared to the supervised approach presented by Rasmussen et al. (R2: 0.92 vs 0.49 for the Achilles tendon and 0.92 vs 0.90 for the patellar tendon). However, they achieved their results by using a wrist-worn IMU only.

The source of most running-related injuries is overuse or frequent overloading of soft tissue structures. As with many injury assessment attempts from other sportive disciplines, studies often lack longitudinal field data to base their research on due to the lack of loads that cannot be measured in the field. The presented system's minimal setup - four IMUs and a smartphone - facilitates large-scale longitudinal data collection. Real-time processing and feedback to runners are feasible, enabling monitoring of biomechanical load changes. Tracking the increase of joint loading, could be implemented on portable devices to warn runners when loading exceeds safe levels. Researchers and clinicians could benefit from the longitudinal data collection that makes it more likely to detect the onset of an overuse injury and the related risk factors. While the presented results are promising, limitations need to be addressed. From the accuracy distributions (Figure 1) it became apparent, that the model still needs to improve to be generalisable across conditions and participants. The study, conducted with 28 participants, may not cover diverse running populations, and further assessments across speeds and cohorts are required.

CONCLUSION: Kohonen's self-organising maps (SOMs) demonstrate promising results in accurately estimating musculoskeletal loads from artIMUs. This neural network is fast and requires minimal computational power, which makes it suitable for smartphone or smartwatch usage. Future studies must validate its applicability in overground running with real IMUs. The strong agreement between ground truth and estimated data for joint and tendon loadings facilitates prospective studies to identify or confirm running-related injury risk factors. For athletes and coaches, this approach allows precise monitoring of injury-relevant signals during training and competition without invasive or costly equipment.

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