JOINT ANGLE ESTIMATION DURING FAST CUTTING MANOEUVRES USING ARTIFICIAL NEURAL NETWORKS

Marion Mundt[1], Sina David[2], Arnd Koeppe[1], Franz Bamer[1], Wolfgang Potthast[2,3], Bernd Markert[1]

Institute of General Mechanics, RWTH Aachen University, Aachen, Germany [1]
Institute of Biomechanics and Orthopaedics, German Sport University Cologne, Cologne, Germany [2]
ARCUS Clinics Pforzheim, Pforzheim, Germany[3]

Athletes' movement biomechanics are of high interest to predict injury risk. However, using a standard optical measurement set-up with cameras and force plates influences the athlete's performance. Alternative systems such as commercial IMU systems are still jeopardised by measurement discrepancies in the analysis of joint angles. Therefore, this study aims to estimate hip, knee and ankle joint angles from simulated IMU data during the execution and depart contact of a maximum effort 90° cutting manoeuvre using a feed-forward neural network. Simulated accelerations and angular rates of the feet, shanks, thighs and pelvis as input data. The correlation coefficient between the measured and predicted data indicates strong correlations. Hence, the proposed method can be used to predict motion kinematics during a fast change of direction.

KEYWORDS: change of direction, 3D joint angles, IMUs, artificial intelligence.

INTRODUCTION: The biomechanical analysis of motion during sports is of high interest, either to increase performance or to prevent the athlete from injuries (David et al., 2017, 2018; Elliott & Alderson, 2007). Besides the analysis of motion inside the laboratory, in-field analysis becomes more and more relevant to incorporate external factors (e.g. opponents, noise, tactics) and also internal factors (e.g. fatigue and attentiveness) to the analysis. By the application of inertial sensors to motion analysis, this kind of technique becomes feasible. Unfortunately, these systems are still jeopardised by measurement discrepancies in the joint angles that can be mainly attributed to the anatomical model that is used by the IMU systems. The linear acceleration and angular rate is measured by an IMU in its sensor frame of reference, which is not related to an anatomical frame (Figure 1). Different – more or less sophisticated approaches – are used to align the sensor frame to the anatomical frame either based on calibration movements or postures. In many cases, the magnetometer readings of the IMU are used to determine the orientation of each sensor in a global reference frame. Unfortunately, the magnetometer readings are influenced by the surrounding magnetic field, which might errors in the orientation estimation. Conversely, the potential of the measurement technology as such could be shown (Mundt et al., 2018). Therefore, it seems eligible to use the data measured by IMUs but to apply a different method for the analysis.

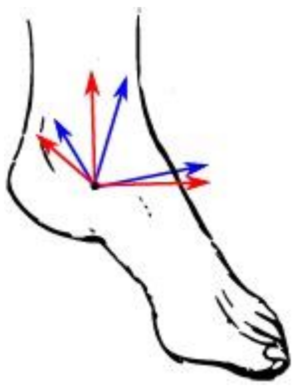

Figure 1 The orientation of the IMU sensor frame (red) is not aligned with the anatomical frame (blue). This leads to discrepancies in the calculation of joint angles.

Different machine learning approaches have shown their feasibility – amongst others – for applications in biomechanics. Applications on fast changes of directions aimed to overcome the dependency on force plates (Johnson et al., 2017, 2018) or to classify different movement strategies during a fast cutting manoeuvre (Richter et al., 2018). For the regression task, partial least squares regression was used to predict the ground reaction force time series based on marker trajectories achieving strong correlations between the measured and predicted values of r>0.95 (Johnson et al., 2017, 2018). In the classification task, an accuracy of more than 80% was achieved in distinguishing different movement strategies (Richter et al., 2018).
Based on these promising results, we applied a feed-forward neural network to predict the 3D joint angles of the hip, knee and ankle joint based on simulated linear accelerations and angular rates of the feet, shanks, thighs and pelvis during the execution and depart contact of a maximum effort 90° cutting manoeuvre. We hypothesise, that this method is able to achieve a comparable or even higher accuracy than the standard method based on an anatomical model and calibration postures or movements.

METHODS: The dataset used for training the feed-forward neural network contained 818 execution and depart contacts of 58 subjects that were normalised to 100% stance phase. More information on the participants and study design can be found in (David et al., 2017, 2018). The study was approved by the Ethics Committee of the German Sport University and all participants gave written consent.
The input data – linear acceleration and angular rate of the segments – is simulated from the marker trajectories collected by the optical motion capture system. As a first step, an anatomical model defining the segment coordinate systems based on the recommendation of the International Society of Biomechanics is set up (Wu et al., 2002). All orientations are defined for each time step as quaternions. To determine the angular rate of each sensor, the numerical quaternion derivative of each segment orientation is calculated. The segment orientations, which are defined in the joint origins, are translated to the position of the simulated IMU sensor that was defined based on a pilot study. Based on this position, the linear acceleration of the sensor is determined by calculating the numerical derivative of this trajectory twice. To keep the sequence lengths constant, forward/backward differences are used (Solà, 2017; Atkinson, 2005).

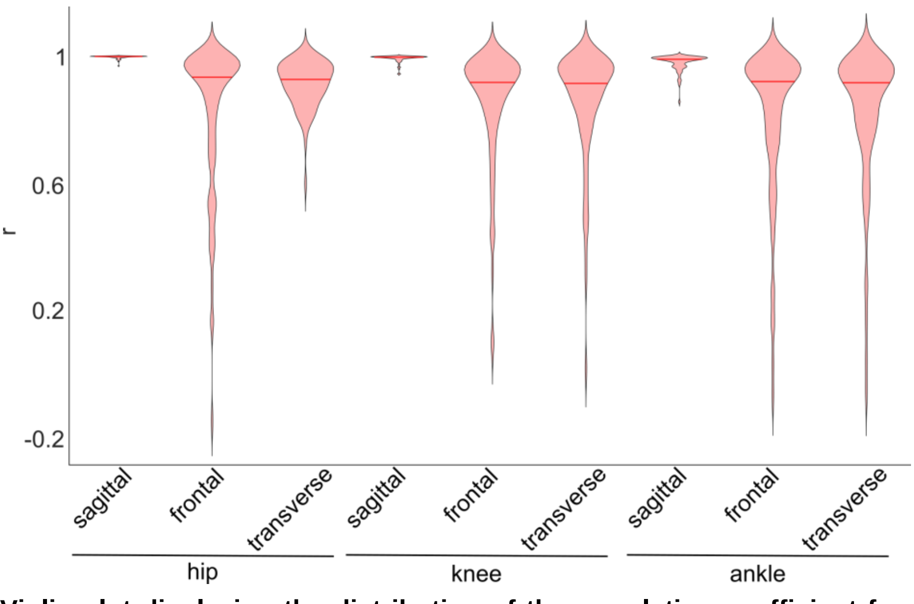

Figure 2: Violin plot displaying the distribution of the correlation coefficient for all joints and motion planes. In the sagittal plane all data is accumulated around 1, while in the non-sagittal planes outliers can be found.

Different feed-forward neural network architectures were implemented using Python supported by the Tensorflow library. All architectures were tested on their performance in estimating the joint angles of the executing leg [3 joints x 3 motion planes x 101 time frames] based on the simulated IMU data of all segments of the lower body [7 segments x [3 angular rates + 3 linear accelerations] x 101 time frames]. The number of hidden layers were varied between one and three, the number of neurons within each layer between 800 and 6000. The architecture that performed best was one hidden layer with 3000 neurones. For regularisation, dropout and early stopping were used. The dataset was divided into a training (80%), validation (10%) and test set (10%). It was ensured that no data of any subject were split across datasets. To compare the results, the RMSE, the nRMSE, the RMSE normalised to the range of each joint angle measured, and the Pearson correlation coefficient were calculated.

RESULTS: Especially in the sagittal plane angles the mean correlation coefficient indicated very good results (r_{hip} = 0.996, r_{knee} = 0.992, r_{ankle} = 0.979). In both other planes the correlation was worse (frontal plane: r_{hip} = 0.812, r_{knee} = 0.855, r_{ankle} = 0.799; transverse plane: r_{hip} = 0.913, r_{knee} = 0.846, r_{ankle} = 0.817). However, the violin plot displaying the distribution of the correlation coefficient (Figure 2) indicates that most samples are accumulated around the mean, but there are outliers, mainly in the non-sagittal planes.
The same behaviour can be found in the RMSE and nRMSE values (Figure 3). The RMSE values are smaller than 5.3° in all joints and motion planes, but the normalisation of the RMSE to the range shows mean deviations of up to 34.3%. In the sagittal plane, the mean nRMSE ranges between 3.9 and 7.4%.

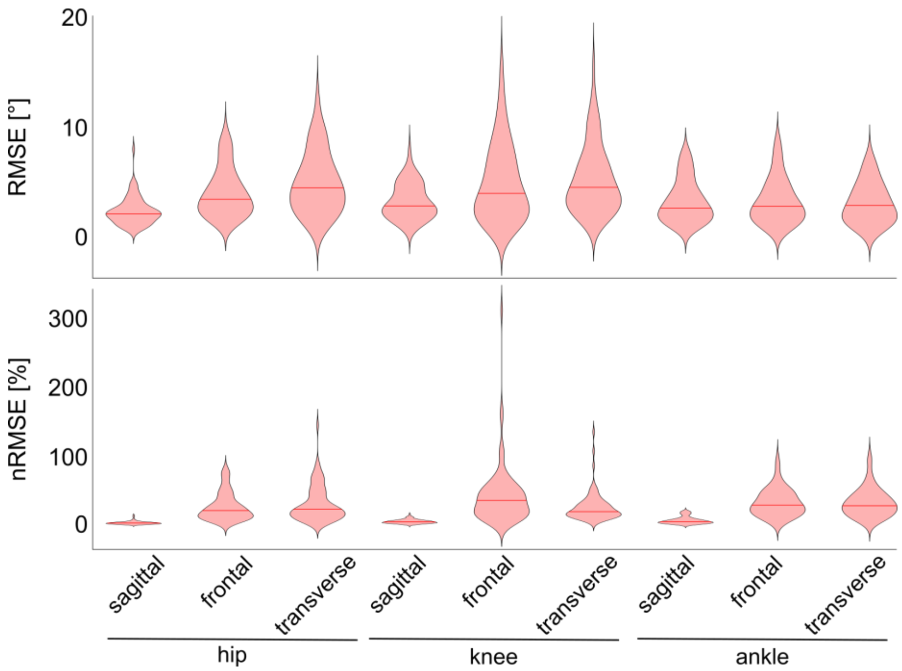

Figure 3 Violin plots of the RMSE and the normalised RMSE for all joints and motion planes. Although the mean RMSE values are all below 5.3°, this results in mean differences in the nRMSE values of up to 34.3 %.

DISCUSSION: The results of this study reveal that it is possible to use a feed-forward neural network to estimate the joint angles based on the linear acceleration and angular rate of the different segments. Thereby, the IMU system becomes independent of a constant magnetic field strength – because no magnetometer data is used – and of any kind of calibration movement or posture. The metrics for the accuracy show similar or even better results compared to different studies (Mundt et al., 2018; Nüesch et al., 2017; Robert-Lachaine et al., 2016). Since the calculation of the normalised RMSE is not standardised in the literature, differences in this value might occur. Additionally, none of the studies evaluated the measurement accuracy of the IMU system for fast movements such as cutting manoeuvres. In previous work, we have shown that it is possible to predict joint moments from joint angles during gait (Mundt et al., 2018a). If it is possible to get reliable joint angles from IMU systems, this method can also be applied for fast changes of directions and thereby increase the possibilities of unrestricted measurements of such fast motion. Additionally, it needs to be evaluated to directly predict the joint moments from IMU data. The proposed method relies on data that was simulated from optical data. One limitation of this method is that measurement inaccuracies due to soft tissue artefacts, which will affect a real IMU sensor, are excluded. Additionally, the simulated sensor position is similar for all participants and trials in this study. The robustness of the neural network against different sensor positions and orientations needs to be further evaluated. It can be assumed that a larger dataset is necessary to further improve the prediction accuracy of the algorithm.

CONCLUSION: The method proposed here shows its feasibility in estimating joint angles from linear accelerations and angular rates of the different lower body segments. The data used here was simulated from optical data. Since the markers undergo different soft tissue movements than real IMU sensors, the simulated data differs to some degrees from real IMU data. Additionally, these data do not experience any drift, as the gyroscope does. In future, there needs to be a verification of the method using real IMU data. Afterwards, the method can also be applied to in-field motion analysis. It might also be possible to use a recurrent neural network for this prediction task, so that a real-time application becomes possible.

REFERENCES:

Atkinson, K. & Han, W. (2005) Theoretical numerical analysis, Vol. 39. Springer.

David, S., Komnik, I., Peters, M., Funken, J., & Potthast, W. (2017). Identification and risk estimation of movement strategies during cutting maneuvers. *Journal of Science and Medicine in Sport*, *20*(12), 1075–1080.

David, S., Mundt, M., Komnik, I., & Potthast, W. (2018). Understanding cutting maneuvers – The mechanical consequence of preparatory strategies and foot strike pattern. *Human Movement Science*, *62*(October), 202–210.

Elliott, B., & Alderson, J. A. (2007). Laboratory versus field testing in cricket bowling: A review of current and past practice in modelling techniques. *Sports Biomechanics*, *6*(1), 99–108.

Johnson, W. R., Donnelly, C. J., Mian, A. S., & Alderson, J. A. (2017). Prediction of Ground Reaction Forces and Moments via Supervised Learning is Independent of Participant Sex , Height and Mass. *Isbs*, *2017*(June), 1–4.

Johnson, W. R., Mian, A., Donnelly, C. J., Lloyd, D., & Alderson, J. (2018). Predicting athlete ground reaction forces and moments from motion capture. *Medical and Biological Engineering and Computing*, *56*(10), 1781–1792.

Mundt, M., Koeppe, A., Bamer, F., Potthast, W., & Markert, B. (2018a). Prediction of Joint Kinetics Based on Joint Kinematics Using Neural Networks. In *36th Conference of the International Society of Biomechanics in Sports* (pp. 7–10).

Mundt, M., Thomsen, W., David, S., Dupré, T., Bamer, F., Potthast, W., & Markert, B. (2018). Assessment of the measurement accuracy of inertial sensors during different tasks of daily living. *Journal of Biomechanics*, *84*, 81–86.

Nüesch, C., Roos, E., Pagenstert, G., & Mündermann, A. (2017). Measuring joint kinematics of treadmill walking and running: Comparison between an inertial sensor based system and a camera-based system. *Journal of Biomechanics*, *57*, 32–38.

Richter, C., King, E., Falvey, E., & Franklyn-Miller, A. (2018). Supervised learning techniques and their ability to classify a change of direction task strategy using kinematic and kinetic features. *Journal of Biomechanics*, *66*, 1–9.

Robert-Lachaine, X., Mecheri, H., Larue, C., & Plamondon, A. (2016). Validation of inertial measurement units with an optoelectronic system for whole-body motion analysis. *Medical and Biological Engineering and Computing*, *55*(4), 609–619.

Solà, J. (2017). Quaternion kinematics for the error-state kalman filter. arXiv preprint: arXiv:1711.02508

Wu, G., Siegler, S., Allard, P., Kirtley, C., Leardini, A., Rosenbaum, D., … Stokes, I. (2002). ISB recommendation on definitions of joint coordinate system of various joints for the reporting of human joint motion—part I: ankle, hip, and spine. *Journal of Biomechanics*, *35*(4), 543–548.