Synthesising motion sensor data from biomechanical simulations to investigate sensor placement and orientation variations

Adrian Derungs[1], Oliver Amft[1]

Abstract— **We propose a motion sensor data synthesis approach to investigate the performance effect of sensor placement and orientation variation on health marker estimation. Using OpenSim we simulate walking motion of patients after stroke while synthesising inertial sensor data. We defined 384 sensor positions with 192 sensors simulated at each leg's thigh. To demonstrate how synthesised sensor data could be used to analyse the performance of functional ability estimation, we derived scores from Lower-Extremity Fugl-Meyer-Assessment (LE-FMA) using regression methods. We evaluated our approach using a public dataset, including 8 stroke patients and showed that LE-FMA scores could be estimated with an error below 0.12 points on average, compared to manually derived scores. We further show that sensors should preferably be placed at the front of the thigh. Our approach demonstrates the potential of combining biomechanical simulations and acceleration synthesis with algorithms for health marker estimation, thus providing rapid insight into sensor positioning and orientation variation.**

I. INTRODUCTION

Monitoring and assessing functional ability of patients after stroke, i.e. during walking, is essential to evaluate recovery trends and to devise rehabilitation strategies. The functional ability has been frequently assessed using wearable inertial sensors, classification or regression methods and compared to clinical reference scores. However, how sensor positioning and orientation variation influenced score estimation was often neglected due to laborious data recordings and high patient burden implied in evaluating different sensor positions or orientations. In particular, evaluating multiple sensor positions is often inappropriate during clinical studies. As functional assessment scores may vary depending on motion pathology, data from other investigations, potentially involving other patients are hardly transferable. Alternative approaches to analyse effects of sensor placement and orientation on functional ability scores are needed.

Simulation approaches and realistic motion data synthesis could resolve the challenge, as effects of sensor positioning and orientation variations could be investigated and score estimation algorithms evaluated without additional sensor data recordings. However, human motion modelling is complex. Beside considerations of anatomical features, including muscles, joints, and ligaments, simulating forward and inverse kinematics are computationally expensive. So far, rigid body models were approximated on the cost of accurate, realistic biomechanical simulations. However, rigid body models are inappropriate for motion evaluation and functional ability assessments. While attempts are being made to create human motion using primarily data-driven deep learning methods, there are various problems to obtain accurate movement representation (see Sec. Related Work for details).

In contrast, biomechanical simulations and data synthesis could be used for investigating effects of sensor placement and orientation variations on clinical score estimation. Software tools, e.g. AnyBody and OpenSim enable users to investigate human motion based on motion capture data. In this work, we utilise OpenSim [1] to estimate the walking ability of patients after stroke according the Lower Extremity Fugl-Meyer Assessment (LE-FMA) using validated biomechanical models and synthesised acceleration.

In particular, we provide the following contributions:

1. We present an acceleration data synthesis approach to investigate sensor placement and orientation variations. We use biomechanical walking simulations from eight stroke patients and analyse 384 sensor positions.
2. We evaluated regression-based, LE-FMA score estimation methods using features derived from synthesised acceleration. We analyse effects of sensor placement and orientation variation on the estimation accuracy using the standardised RMSE metric in a leave-one-participant-out cross-validation (LOPO-CV).

II. RELATED WORK

Several approaches were made to investigate the influence of sensor positioning and sensor orientation on activity recognition, mostly based on real-life measurements using inertial measurement units. For example, Kunze *et al.* investigated effects of sensor placement variations on activity recognition and distinguished between on-body and within-body placement, and orientation [2]. Different strategies were suggested to mitigate placement effects, e.g. using placement and rotation independent frequency features. Förster *et al.* [3] investigated self-calibration algorithms to overcome sensor displacements using orientation-robust features derived form 10 sensors attached to one leg. Thiemjarus [4] described device orientation as classification task using a waist-worn sensor, where each orientation required own training data. Although, a classification accuracy of 90.9 % was reached, the placement and orientation of the waist-worn accelerometer was constrained by a rigid sensor clip. Most attempts made so far were limited in using physical sensor measurements only, which limit replication and extension.

Deep learning methods seem promising for generating spatio-temporal motions as shown by Ghosh *et al.* [5]. However, requiring lots of training data and complicated tuning

[1] Adrian Derungs, Oliver Amft, Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Chair of Digital Health, Henkestr. 91, 91052 Germany, (adrian.derungs, oliver.amft)@fau.de

of the training process realistic functional motion models are not achieved, yet. Hence, we present an alternative approach to combine real motion sensor data synthesis and biomechanical simulation for investigations of sensor placement and orientation variation on health marker estimation.

Continuous score estimation using body-worn sensors in patients after stroke can be used to monitor changes in functional abilities and behaviour, e.g. in the acute stroke phase in the clinic [6] or during longitudinal measurements over several months in a day-care centre [7]. Typically, motion was recorded with wearable sensors and features for subsequent classification [8] or regression methods [9] extracted to estimate scores, which were then compared to a clinician assessed reference. For example, Wang *et al.* [10], used a support vector regression (SVR) and 10-fold cross-validation, to estimate the Fugl-Meyer score with an error of 2.13 point. Contrary to approaches based on defined assessment tasks and the use of wearable sensors, we estimated the LE-FMA score using biomechanical walking simulations and motion capture body-kinematics from which we synthesised acceleration and subsequently derived features.

III. METHODS

We first detail our simulation and synthesis approach, then we describe the score estimation as shown in Figure 1.

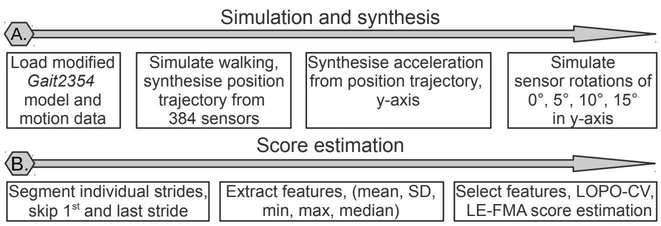

Fig. 1. A) We simulate motion-capture data using the modified musculoskeletal *Gait2354-model*, deriving position trajectories of 384 sensors. Then, we synthesise acceleration data with simulated sensor rotations. B) Subsequent to the stride segmentation, we extract features and use LOPO-CV regression-based LE-FMA score estimation.

A. Simulation and synthesis

Simulation: We used OpenSim[1] to synthesise acceleration from the 23 degree-of-freedom musculoskeletal human model (*Gait2354*), including 54 musculotendon actuators of the lower body, torso, and head. Subsequently, we simulated walking of patients after stroke, using the public dataset by Knarr *et al.* [11]. Position trajectories of each sensor were generated using OpenSim's *body kinematics tool*.

Sensor model for synthesis: We defined our sensor model as direct link connection (*WeldJoint*) between sensor and bone in the *.xml*-file of the *Gait2354-model*. The *Gait2354-model* contains parameter definitions of the musculoskeletal structure and biomechanical properties of bones, joints and muscles. Sensors were designed as $5\,mm^3$ cube without inertia, and scaled in volume by factors of 0.001, 0.005, and 0.003 in x-, y-, and z-axis, respectively. Using parametrised coordinates with respect to the femur, equal sensor placement

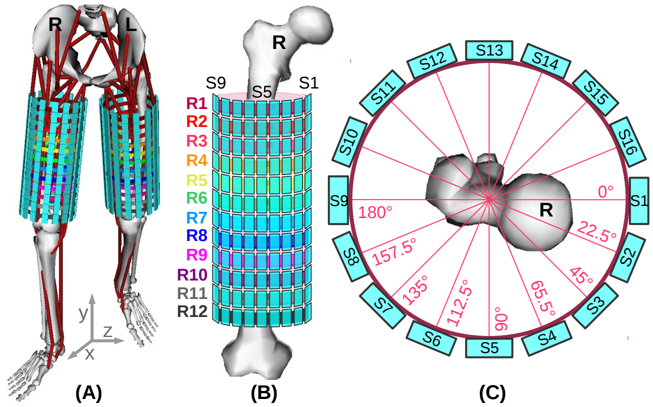

Fig. 2. (A) The modified *Gait2354* model shows sensor positions on both thighs and OpenSims' reference coordinate system. (B) Detailed illustration of the femur and the sensor arrangement (frontalview). Coloured numbers (R1-R12) indicate where sensors are placed vertically along the femur. The numbers S1, S5, and S9 indicate how sensors are distributed around the femur, here for the visualisation only the frontal sensors are illustrated. (C) Illustration of sensor positions, placed around the femur (topview).

on both thighs was guaranteed. Using OpenSim walking simulations, we derived position trajectories of our sensors three Cartesian coordinates x-axis (anterio-posterior), y-axis (vertical) and z-axis (lateral). Subsequently, we used MATLAB[2], to synthesise y-axis acceleration ($\vec{\mathrm{A}}_{\mathrm{S}}$) using the second derivative of the position trajectory as following:

$$\vec{\mathrm{A}}_{\mathrm{S}} = \frac{\mathrm{d}^2\vec{\mathrm{p}}}{\mathrm{dt}^2} \tag{1}$$

where $\vec{\mathrm{p}}$ refers to the simulated position trajectory derived from the simulated model.

Sensor placement and sensor rotation: In this work, we simulated a total of 384 sensor positions distributed uniformly in a 12 by 16 matrix, resulting in 192 sensors on each thigh, as illustrated in Figure 2. Furthermore, we simulated sensor rotations α of $0°$, $5°$, $10°$, and $15°$ resulting in a damping of the acceleration by factors of 1.0, 0.996, 0.985, and 0.966, respectively, according to Equation 2:

$$\vec{\mathrm{A}}_{\mathrm{SR}} = \begin{cases} \vec{\mathrm{A}}_{\mathrm{S}} \cdot \sin(90+\alpha) \\ \vec{\mathrm{A}}_{\mathrm{S}} \cdot \sin(90\text{-}\alpha) \end{cases} \tag{2}$$

where $\vec{\mathrm{A}}_{\mathrm{SR}}$ represents the rotated acceleration. Rotations of $\pm 5°$, $\pm 10°$, and $\pm 15°$ result in the same damping factors, hence negative rotations were not included in the analysis.

B. Score estimation

Feature extraction and selection: Based on the stride segmentation approach [7], we derived features from the vertical y-axis from each sensor of both legs. To account for variation in the first and last stride due to the acceleration and deceleration when starting/stopping the treadmill, we removed the first and last stride for the subsequent feature extraction. We extracted 20 features from each stride, including *stride duration time, maximum, minimum*, and *dominant frequency* for which we calculated *mean, standard deviation,*

[1]OpenSim, Version 3.3, Simbios, Simbios/SimTK, Stanford, California, United States.

[2]MATLAB, Release 2017b, The MathWorks, Inc., Natick, Massachusetts, United States.

median, maximum, and *minimum*. To avoid over-fitting of the regression, the exhaustive feature selection was restricted to retrieve five features.

Regression: We estimated the LE-FMA score using generalised linear models (GLM) and SVRs with radial bias function kernel (RBF) [3] according to earlier work [9].

IV. EVALUATION

We subsequently summarise the dataset and performance metric used for the LE-FMA score estimation evaluation.

Dataset: We used SimTK's public dataset[4] by Knarr *et al.* [11], including 8 hemiparetic patients (age 63 ± 8.6 years, 3 men, > 6 months post-stroke) with chronic stroke for our evaluation. Patient details are summarised in Table I. During pre-intervention training sessions with self-selected treadmill speed, patients' motion data and kinematics were recorded with a Vicon motion-capture system. Subsequently, patient-specific forward simulations were created using the *Gait2354* model, which we used for our evaluation.

TABLE I

PATIENTS WITH ANONYMOUS ID, TIME SINCE STROKE (TSS), SELF SELECTED WALKING SPEED (SSS), AND HINT OF AFFECTED SIDE (AFF).

ID	Gender	AFF	Age [years]	TSS [months]	SSS [m/s]	LE-FMA	ID	Gender	AFF	Age [years]	TSS [months]	SSS [m/s]	LE-FMA
1	M	Right	66	19	0.3	21	5	F	Right	54	55	0.5	17
2	M	Left	70	21	0.5	13	6	F	Right	58	12	0.3	13
3	F	Right	65	15	0.3	18	7	M	Right	46	8	0.4	15
4	F	Right	65	18	0.5	18	8	F	Left	70	9	0.3	22

Each pre-intervention treadmill walk was assessed by a clinician, using the LE-FMA standard clinical assessment and used as reference in this work. The LE-FMA assesses the sensorimotor function in six subcategories, i.e. reflex activity, volitional movement (within synergies, mixing synergies, and with little or no synergy) normal reflex activity, and coordination/speed. A maximum of 34 points can be reached, indicating peak physical performance.

Performance evaluation: For the score estimation using GLM and SVR, we used a LOPO-CV. In each validation fold, data of one patient was left out for the training and used in testing. The root-mean-square error (RMSE) was computed between the estimated score and the assessed reference score. In addition, we normalised the RMSE (nRMSE) relating the RMSE to the maximum LE-FMA score, hence the errors could be stated on a relative scale. The RMSE and nRMSE was derived for each of the 384 sensors and for all rotations (0°, 5°, 10°, and 15°).

V. RESULTS

We first visualise exemplarily the LE-FMA scoring error derived with the GLM, illustrating position effects on the estimation accuracy in Figure 3. The LE-FMA scoring error for the GLM and SVR for simulated rotations 0°, 5°, 10°, and 15° are shown in Figure 4 for affected and less-affected thighs. On average, with 0° simulated rotation the nRMSE for the affected thigh was 7.2 % and 5.87 % on the less-affected thigh using the SVR. With the GLM, the nRMSE

[3]Support Vector Machine Toolbox, V 2.1, Steve Gunn.

[4]https://simtk.org/projects/fesprediction

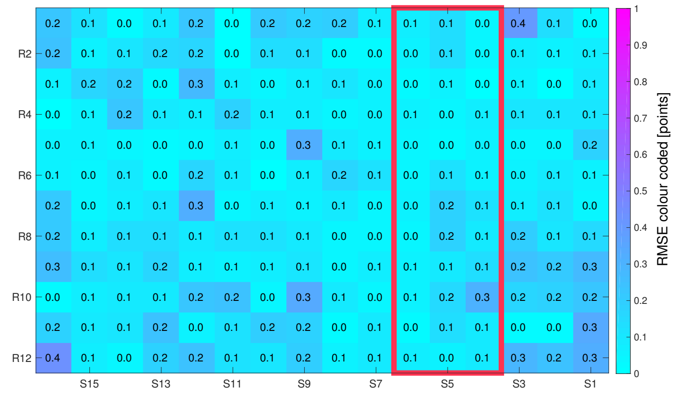

Fig. 3. LE-FMA scores estimation error projected to the 192 sensor positions on the thigh. The colour code shows, that the RMSE is below 0.52 points on average when using GLM, and features derived from the affected leg. This illustration shows a simulated rotation of 0°. Although RMSEs show a homogeneous pattern, for practical measurements, sensor position on the thighs' front (highlighted in red rectangle) are preferable. S1,…, S15 represent sensor names, R1,…, R12 mark vertical sensor positions.

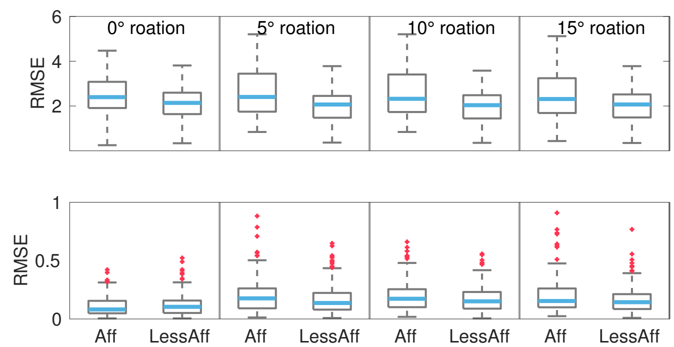

Fig. 4. LE-FMA score error. Top figure boxplots show the RMSE estimated with SVR, boxplots in the bottom figure show the RMSE estimated with GLM. The affected thigh is denoted with Aff, the less-affected thigh with LessAff. Rotation simulation included, 0°, 5°, 10°, and 15°.

was 0.32 % on the affected side and 0.36 % on the less-affected side with 0° simulated rotation. In general, the GLM yielded lower RMSE, compared to the SVR for all simulated rotation angles on the affected and less-affected thigh.

Figure 5 summarises the features frequency for the SVR and GLM with 0° simulated rotation for the affected thigh, when restricting the feature selection to five features. On average, when using the SVR, a total of 2.51 features were selected for the score estimation for each sensor position. In contrast, the GLM required 5 features on average to achieve the best estimation for each sensor position.

Figure 6 shows the effect when restricting the feature selection of the GLM to one, three, and five features, respectively for all rotations 0°, 5°, 10° and 15°. For all rotations, the RMSE decreases when more feature were included in the estimation. Although, more features might decrease the RMSE further, the resulting accuracy is sufficient to assess the LE-FMA score due to the integer interval scale.

VI. DISCUSSION AND CONCLUSION

We presented a simulation and acceleration synthesis approach based on a validated biomechanical musculoskeletal model. We showed how that approach is suitable for

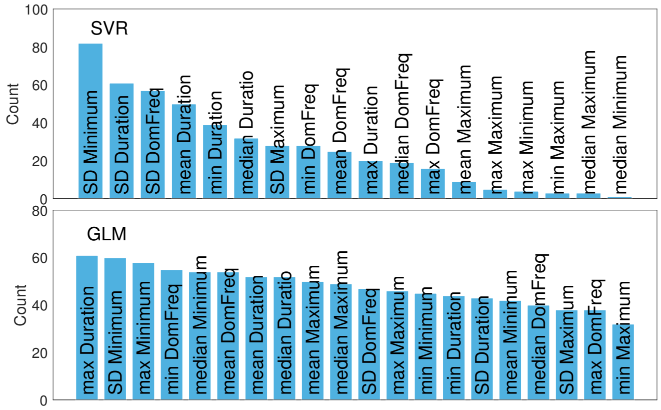

Fig. 5. Total feature count when using features derived from the affected thigh with a simulated rotation of 0°. The top figure shows that the three most used features for the SVR include the standard deviation of the *Minimum, Duration*, and *Dominant frequency* of the segmented strides. The bottom figure shows that the GLM required more features. The three most selected features were: *max. Duration*, *SD Minimum*, and *max. Minimum*.

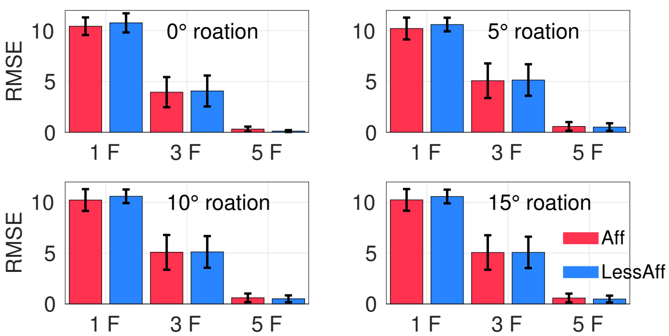

Fig. 6. RMSE progression with increasing feature number for the GLM are shown for simulated rotations 0°, 5°, 10° and 15°. The graphs shows that RMSE errors for rotations up to 15° are negligible, when using 5 features. 1F, 3F, and 5F indicate the count for restricting the feature selection to one, three, and five features, respectively.

investigating sensor placement and orientation variations. Moreover, using motion captured walking data of stroke patients we could estimate the LE-FMA scores with low estimation errors. In particular, when using the GLM, our estimation was below 0.5 points. However, the GLM required more features for the estimation compared to the SVR. More investigations to analyse the estimation performance are required, e.g. to analyse rotation independent features in combination with the SVR, or models with different kernels.

Our approach demonstrates for the first time that the combination of biomechanical simulations and data synthesis provide a valuable tool for investigating sensor placement and orientation variations without the need of multiple motion recordings based on wearable sensors. The evaluation of our approach with treadmill walking data form patients after stroke suggest that the score estimation accuracy increases when using data from the less-affected side instead of the affected side. In the rehabilitation of the upper body functionality, therapies focus on the affected side, thus sensors were typically attached to the affected wrist to quantify and evaluate recovery [8]. However, due to the bipedal walking movement, measurements of the less-affected side might provide valuable insight on recovery, too.

Our results are in line with Wang *et al.* [10], where scores of the upper body Fugl-Meyer assessment were estimated with an error of 2.13 scores using accelerometers. Moreover, we showed that our approach scales to hundreds of sensors, thus enabling flexible investigations on multiple positions. Hence our approach is an alternative to methods based on inertial measurement units and laborious recordings [3].

So far our approach is limited to walking and the devised sensor model is restricted to acceleration synthesis simulation of rotations. Additional features could be included in the sensor model. For example, the link between the sensor and the bone could be adapted to account for muscle movement or layers of clothes. Nevertheless, we believe that even in the current form, our approach can provide valuable insight into health marker estimation performance, here the LE-FMA. Based on biomechanical models and motion kinematics, functional motions of stroke patients could be investigated and best body position for score estimations determined. Hence, beside gaining insights in stroke patients' motion, algorithms for score estimation could be evaluated.

References

[1] S. L. Delp, F. C. Anderson, A. S. Arnold, P. Loan, A. Habib, C. T. John, E. Guendelman, and D. G. Thelen, "OpenSim: Open-Source Software to Create and Analyze Dynamic Simulations of Movement," *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 11, pp. 1940–1950, Nov. 2007.

[2] K. Kunze and P. Lukowicz, "Sensor Placement Variations in Wearable Activity Recognition," *IEEE Pervasive Computing*, vol. 13, no. 4, pp. 32–41, Oct. 2014.

[3] K. Förster, D. Roggen, and G. Tröster, "Unsupervised Classifier Self-Calibration through Repeated Context Occurences: Is there Robustness against Sensor Displacement to Gain?" in *ISWC 2009: International Symposium on Wearable Computers*. IEEE Press, 2009, pp. 77–84.

[4] S. Thiemjarus, "A Device-Orientation Independent Method for Activity Recognition," in *2010 International Conference on Body Sensor Networks*, Jun. 2010, pp. 19–23.

[5] P. Ghosh, J. Song, E. Aksan, and O. Hilliges, "Learning Human Motion Models for Long-Term Predictions," in *2017 International Conference on 3D Vision (3DV)*, Oct. 2017, pp. 458–466.

[6] J. Gubbi, A. S. Rao, K. Fang, B. Yan, and M. Palaniswami, "Motor recovery monitoring using acceleration measurements in post acute stroke patients," *BioMedical Engineering OnLine*, vol. 12, p. 33, 2013.

[7] A. Derungs, C. Schuster-Amft, and O. Amft, "Longitudinal Walking Analysis in Hemiparetic Patients Using Wearable Motion Sensors: Is There Convergence Between Body Sides?" *Frontiers in Bioengineering and Biotechnology*, vol. 6, 2018.

[8] Parnandi, E. Wade, and M. Mataric, "Motor function assessment using wearable inertial sensors," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 86–89.

[9] A. Derungs, J. Seiter, C. Schuster-Amft, and O. Amft, "Estimating physical ability of stroke patients without specific tests," in *Proceedings of the 2015 ACM International Symposium on Wearable Computers (ISWC '15)*. ACM Press, 2015, pp. 137–140.

[10] J. Wang, L. Yu, J. Wang, L. Guo, X. Gu, and Q. Fang, "Automated Fugl-Meyer Assessment using SVR model," in *2014 IEEE International Symposium on Bioelectronics and Bioinformatics (IEEE ISBB 2014)*, Apr. 2014, pp. 1–4.

[11] B. A. Knarr, T. M. Kesar, D. S. Reisman, S. A. Binder-Macleod, and J. S. Higginson, "Changes in the activation and function of the ankle plantar flexor muscles due to gait retraining in chronic stroke survivors," *Journal of NeuroEngineering and Rehabilitation*, vol. 10, Jan. 2013.