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Wearable motion sensors and digital biomarkers in stroke rehabilitation

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Abstract: We propose three novel digital biomarkers for the longitudinal performance monitoring and movement evaluation of hemiparetic patients, e.g. after stroke. We devised convergence points (CP) for the bilateral walking analysis based on gait parameters, e.g. stride duration using regression-modelling to estimate similarity between body sides. The physical activity (PA) was devised to evaluate the energy expenditure of all extremities during training and free-living. The functional range of motion (fROM) is a digital biomarker to quantify the upper arm reaching ability, represented in 3D visualisations. In this work, we detail CP, PA, and fROM to derive rehabilitation insights for personalising therapies. We evaluated the proposed digital biomarkers in a clinical observation study with 11 patients after stroke during their rehabilitation including therapy and self-paced daily routines.

Keywords: Inertial measurement unit, stroke, hemiparesis, gait parameter, gait analysis, digital twin, free-living.

https://doi.org/10.1515/cdbme-2020-3058

1 Introduction

Wearable motion sensors, including inertial measurement units (IMUs) could be used to measure patient mobility or physical activity in free-living. Digital biomarkers are parameters designed to provide clinically interpretable information for diagnosis and therapy control, e.g. regarding mobility, physical activity, or the range of motion [1, 2, 3]. Especially in stroke rehabilitation, digital biomarkers related to walking, activity levels or postures, can support therapy decision making, e.g. to adapt therapy strategy and tailor training programmes to patient-specific needs. For example, basic gait parameters, e.g. stride count and stride duration, compared between affected and less-affected body sides could enable clinicians to recommend specific training plans, including walking on (weight-supported) treadmill, balancing exercises or strength training of selected muscle groups.

Wearable sensor-based approaches to quantify hemiparetic patient performance are currently often restricted to the clinical setting, where patients perform the tasks of a clinical assessment. Although, it has been shown that wearable motion sensors and machine learning algorithms can measure movement and predict clinical assessment scores based on sensor data features, the evaluation of patients without specific tests is insufficiently investigated.

With wearable sensors, i.e. IMUs, patient movement in free-living could be monitored, thus mobility behaviour and activities could be evaluated continuously. Further, while using daily activities for the patient evaluation, no specific tests [5], which could be a burden to patients are needed. Digital biomarkers could provide clinicians and patients interpretable feedback besides estimated clinical assessment scores and help devising personalised therapy recommendations based on continuous measurement [8]. For example, walking can be analysed based on stride counts, continuously derived over months, to evaluate potential changes over time.

In this work, we show that wearable sensors and digital biomarkers offer opportunities to investigate changes during the recovery process in patients after stroke. We propose three novel digital biomarkers for longitudinal, bilateral movement evaluation, which are viable for therapy and free-living.

2 Wearable motion sensors

Wearable motion sensors, i.e. accelerometers and gyroscopes have been used in stroke rehabilitation for objective movement measurements, while patients performed specific assessment tasks [4]. Clinical scores, e.g. based on the Fugl-Meyer Assessment or the Wolf-Motor-Function Test were estimated, using sensor data features and machine learning approaches, e.g. classification and regression.

In contrast, utilising wearable sensors to derive digital biomarkers that describe movement behaviour or even recovery trends without the need of specific tests is not exploited. Initial attempts to design and use digital biomarkers are currently being made. For example, Kourtis et al. discuss digital biomarkers for Alzheimers' disease and the opportunity for mobile and wearable devices. In particular, disease specific metrics and sensors are highlighted, including IMUs for gross motor function analysis, touch screens for fine motor movement evaluation, microphones for speech pattern and language analysis, and other sensor modalities [6]. However, designing digital biomarkers for personalised objective patient evaluation that are designed for specific (neurological) diseases require domain knowledge, i.e. medical understanding of patient abilities and limitations. For example, wearable sensors, digital biomarkers, and personalisation are investigated to determine the efficacy of drug interventions in neurological diseases, e.g. Parkinsons's disease and Multiple sclerosis [7].

3 Methods to extract digital biomarkers

Digital biomarkers are sought to evaluate patients in free-living and meet an objective and quantifiable clinical need. Often, clinical concerns are related to movement ability and physical activity. The following digital biomarkers have been developed and evaluated to assess patients after stroke in free-living.

3.1 Convergence points (CP)

The CP evaluates bilateral walking for gait parameters derived from affected and less-affected body sides. We implemented an unsupervised walking extraction algorithm and used a stride segmentation algorithm that extracts alternating steps. Subsequently, we derived gait parameters, i.e. stride count, normalised stride count, stride duration, stride cadence and upper body sway. The gait parameters were derived for every day and their mean and standard deviation values were used to estimate convergence between body sides. Further, we evaluated our algorithm for the stride parameter extraction with a reference derived from an expert [1].
CPs are a hypothetical point in the future, indicating when similarity between body sides would be reached at the current parameter trajectory. A relatively large CP time indicates differences between body sides that, however, could be overcome by the therapy. In contrast, a relatively low CP time indicates that agreement between body sides is soon achieved so that the therapy could start focussing on other body parts. Further effects, i.e. compensation mechanisms might also be observed due to inconsistent CP estimation during measurement windows of several days, hence clinicians could investigate imbalances in body sides that might indicate pain or limited joint movements [1].

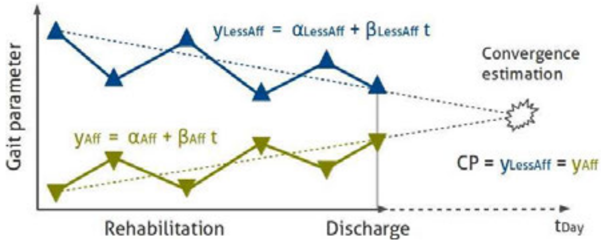

Figure 1: Sequential recovery trend analysis: conceptual representation of movement parameters across the rehabilitation duration. Linear trend lines on the affected and less-affected side are used to derive the CP estimation per gait parameter.

3.2 Physical Activity (PA)

The PA evaluation in patients after stroke could mitigate health risks caused by sedentary behaviour, which is frequently observed in hemiparetic patients. We analysed the affected and less-affected body side for the upper and lower body during therapies and free-living. We applied personalised regression models to estimate energy expenditure level while patients attended therapy and while performing activities of daily living. In this analysis we did not select specific activities, e.g. walking, sitting, lying. Instead, we used data annotations for guided therapy and free-living activity, and expressed energy expenditure by mapping metabolic equivalents (MET) to energy levels [2].

3.3 Range of motion (fROM)

We investigated an approach to analyse the functional range of motion (fROM) of the upper arms. We used the Madgwick sensor fusion algorithm to estimate the orientation of the upper arms and visualised reaching abilities of patients after stroke with 3D posture cubics [3], see Figure 2.
We analysed differences in fROM between affected and less-affected body sides during activities performed in therapy and free-living. We quantified the duration of a limb's position in a posture cubic relative to the day-long monitoring, similar to histograms. For example, the approach allows us to quantify whether patients could reach with their elbow positions above or just below the shoulder joint.

4 Stroke rehabilitation study

4.1 Participants

A total of of eleven hemiparetic outpatients were included in our study (5 females, aged 34 to 75 years, 4 wheelchair users). All study participants visited the day-care centre in the rehabilitation clinic at the Reha Rheinfeleden (Switzerland). Before the data recordings began, all patients signed a written

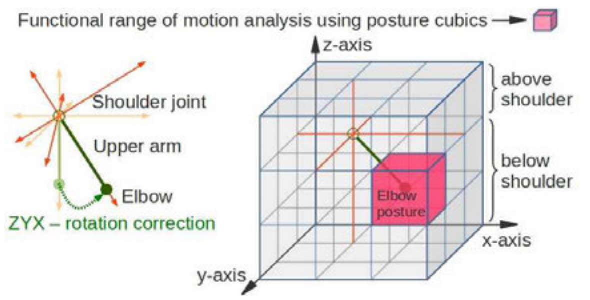

Figure 2: Posture cubics as digital biomarker for fROM analysis. The upper arm range of motion around the shoulder is segmented into 27 spatial posture cubics, to indicate the reaching ability

consent form for the study participation in accordance to the approved study protocol by the Swiss cantonal Ethics committee (Canton Aargau, Switzerland, Application Number: 2013/009). During the study, patients spent between 16 to 79 days at the day-care centre. We expected to observe changes during the longitudinal study. Especially in patients, which were dependent on a wheelchair at the beginning of the rehabilitation, we expected a transition towards an independent walking patient.

4.2 Study design

Based on expected needs and health state, each patient that participated in the study, received a personalised therapy schedule. The day-care centre is specialised in the rehabilitation of outpatients to improve movement abilities in therapies and promoting re-integration and independence in free-living. Therefore, patients at the day-care centre attend therapies and followed their freely chosen daily routines, i.e. activities of daily living to accustomise to free-living. During the study, patients were observed by study examiners, who annotated activities and daily routines with a custom smartphone app that was time-synchronised with the IMUs, for up to 3 times per week and 8 hours per day. During the study duration of 1 to 3 months per patient, a total of 102 days of motion data were recorded (9.3 on average per patient). We devised an activity and routine annotation catalogue with a total of 51 activities, including activity primitives (e.g. walking, walking up/downstairs, arm and leg flexion/extension, arm rotation, writing, using phone, drinking), to describe patient activities and the rehabilitation context, i.e. therapy or free-living [1, 2, 3, 5].

4.3 Wearable motion sensors

We used six Shimmer3 IMUs, symmetrically attached to patients' upper and lower arms, and upper legs. During data recordings, we regularly checked sensor positions and orientations, to ensure correct alignment according to defined movement axis. All sensor modalities (3-axis accelerometer, gyroscope, and magnetometer) were sampled with 50Hz and sensor data were stored on the internal SD-card.

5 Results

To estimate CPs, we first extracted walking segments from each monitoring day with an average sensitivity (walking segment detection rate) of 69.3% across patients who needed a wheelchair and for those who could walk [1]. The average specificity (rejection rate of non-walking segments) was greater than 94%, confirming that non-walking activities were successfully rejected [1]. For estimating the digital biomarkers, it is not essential to retain every relevant data section, i.e. walking segment here, but to maintain adequate coverage over the day [10]. The subsequent automatic stride segmentation was compared to manually derived stride reference, resulting in relative errors of the stride duration, cadence and stride count below 5.5% on both body sides [1]. CP estimates revealed inter-patient variability within and across gait parameters and that the patient behaviour was influenced by individual therapy schedules [1].
The physical activity analysis showed on average 16.1% higher PA of the affected arm during therapies and 5.3% higher PA of the affected leg during therapies [2]. In contrast, average differences between therapy and free-living in the less-affected side were below 4.5% [2].
Posture cubic visualisations showed distinctive patterns between body sides, depending on the rehabilitation context [3]. Figure 3 shows differences between therapy and free-living in the affected arm of a selected patient, indicating low posture cubic activation above the shoulder, especially in free-living [3].

6 Towards free-living

We investigated novel digital biomarkers for movement and trend analyses in patients after stroke. The digital biomarkers that have been proposed and evaluated in a longitudinal observation study are suited to investigate the affected and less-affected body side, which we consider a prerequisite for gaining insights into hemiparetic patients after stroke.
In particular, the unsupervised extraction of walking-related gait parameters to continuously estimate CPs is a considerable advantage compared to subjective gait assessments in clinics.
The PA investigation showed that the energy expenditure level of all extremities can be estimated based on wearable motion sensor data. i.e. accelerometers. Results confirmed that patients after stroke tend to a sedentary behaviour, which

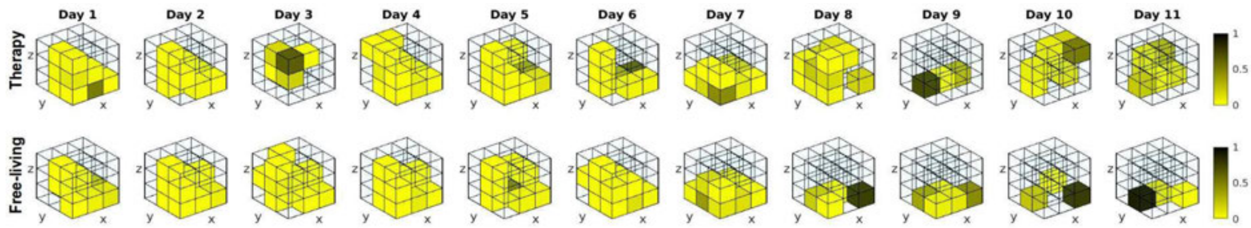

Figure 3: Posture cubic visualisation of the affected upper arm range of motion during therapy and free-living of a selected patients after stroke. Coloured posture cubics show the time spent in an elbow orientation corresponding to the cubic volume during a recording day. During therapy the upper arm was moved above the shoulder in Days 3, 8, and 10. In free-living above shoulder cubics were rarely reached in Days 1–6, remaining days indicate increased posture cubics activated below the shoulder.

could lead to a worsening of the general health and well-being. Therefore, longitudinal PA evaluation could help clinicians to monitor patients' activity level and help to plan interventions with guided therapy exercises. Consequently, patients might not only improve motor abilities, but also train cardiovascular and cardiopulmonary body functions, which is considered beneficial in stroke rehabilitation.

The continuous fROM-estimation derived from the affected and less-affected body sides showed that patients tend to involve mostly the less-affected side in free-living behaviour. To avoid the unilateral use of upper extremities, patients might benefit from gaming application, e.g. implemented on a smartphone to train bothy body sides in free-living.

We believe, the introduced digital biomarkers have the potential for monitoring and evaluation of patients after stroke in free-living. Especially, monitoring with wearable sensors and continuous evaluation based on digital biomarkers becomes increasingly relevant in healthcare to obtain actionable insights in patients' health and well-being [9].

However, further research is needed, i.e. to investigate the potential of CPs, METs, and fROMs as clinical tools. Since stroke rehabilitation is a long process that can last over months and years, movement changes are subtle and gradual. Especially the subtle movement changes require further research to distinguish improved movement ability due to recovery from movement compensation mechanisms. Wearable motion sensors are particularly suited to identify gradual changes and can be sufficiently integrated in everyday life to maintain data coverage.

Our approach holds promise to complement classic assessments in clinical settings by providing data and insight in free-living, i.e. after discharge from the rehabilitation clinic.

Author Statement

The research was funded by the EU Marie Curie framework iCareNet (Grant Number 264738) and the Dutch Technology Foundation STW (12184). Authors state no conflict of interest. Informed consent has been obtained from all individuals included in this study. The research related to human complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the ethics committee of the canton Aargau, Switzerland.

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