A method to qualitatively assess arm use in stroke survivors in the home environment

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Abstract: Wearable sensor technology has enabled unobtrusive monitoring of arm movements of stroke survivors in the home environment. However, the most widely established method, based on activity counts, provides quantitative rather than qualitative information on arm without functional insights, and is sensitive to passive arm movements during ambulatory activities. We propose a method to quantify functionally relevant arm use in stroke survivors relying on a single wrist-worn inertial measurement unit. Orientation of the forearm during movements is measured in order identify gross arm movements. The method is validated in 10 subacute/chronic stroke survivors wearing inertial sensors at 5 anatomical locations for 48 h. Measurements are compared to conventional activity counts and to a test for gross manual dexterity. Duration of gross arm movements of the paretic arm correlated significantly better with the Box and Block Test ([Formula: see text]) than conventional activity counts when walking phases were included ([Formula: see text]), and similar results were found when comparing ratios of paretic and non-paretic arms for gross movements and activity counts. The proposed gross arm movement metric is robust against passive arm movements during ambulatory activities and requires only a single-sensor module placed at the paretic wrist for the assessment of functionally relevant arm use.

DOI: https://doi.org/10.1007/s11517-016-1496-7

Originally published at:
Leuenberger, K; Gonzenbach, R; Wachter, S; Luft, A; Gassert, R (2017). A method to qualitatively assess arm use in stroke survivors in the home environment. Medical Biological Engineering Computing, 55(1):141-150.
DOI: https://doi.org/10.1007/s11517-016-1496-7

A method to qualitatively assess arm use in stroke survivors in the home environment

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September 15, 2015

ABSTRACT

Objective: To develop a method to quantify functionally relevant arm use in patients with stroke.

Design: Cross-sectional observational study.

Setting: At home.

Participants: Patients (n=10) with subacute/chronic stroke.

Interventions: Subjects wore five sensor modules (wrists, shanks and trunk) containing inertial measurement units for up to 48h.

Main Outcome Measures: Total duration of gross arm movements for paretic and non-paretic arm as well as forearm elevation histograms for paretic and non-paretic arm during activity.

Results: Duration of gross arm movements of the paretic arm correlates significantly better with the Box and Block Test than conventional activity counts when walking phases are included ($r = 0.95$, $p < 0.001$ vs. $r = 0.69$, $p = 0.029$; Steiger-Z=-2.58). Removing walking phases from the measurement period by means of a shank-mounted sensor resulted in a high correlation of both gross movements and activity counts with the Box and Block Test ($r = 0.97$, $p < 0.001$ vs. $r = 0.93$, $p < 0.001$; Steiger-Z=-1.11). Similar results were found when comparing ratios of paretic and non-paretic arms for gross movements and activity counts. Angular difference of the average forearm elevation of paretic and non-paretic arm highly correlated with the Box and Block Test ($r = 0.68$, $p = 0.031$).

Conclusion: The proposed gross arm movement metric is robust against passive arm movements during ambulatory activities and only requires a single sensor module placed at the paretic wrist for the assessment of functionally relevant arm use in stroke patients in the home environment.

Key words: Monitoring, ambulatory; Upper extremity; Activities of Daily Living; Rehabilitation; Stroke;

1 Introduction

Functional recovery and regain of independence following neurological injury are commonly assessed via clinical scores, comprising capacity and time measures, as well as subjective questionnaires[1]. Objective information on arm use in the home environment could provide a valuable complement to insights gained from clinical assessments, but is mostly limited to subjective feedback from the patients and relatives.

Wearable sensor technology has enabled unobtrusive monitoring of arm movements in the natural environment, with accelerometry representing the most established approach. Activity counts derived from the acceleration signals provide quantitative information about arm activity, such as total duration and intensity of movements [2, 3, 4, 5]. In the home environment, temporal synchronization of two wrist sensors also allowed to quantify bilateral arm use during activities of daily living (ADL), demonstrating that bilateral activity was less intense and more lateralized in stroke survivors than in non-disabled adults [6].

A drawback of accelerometry in wrist worn applications is its sensitivity to any kind of movements, especially passive arm swinging during ambulatory activities, which leads to an overestimation of real-world arm activity [7, 6]. Ambulatory activities can be detected by means of accelerometry [8, 9], but this requires additional, temporally synchronized sensors which negatively impact patient compliance. To reject the influence of ambulatory activities, which may involve involuntary arm movements such as passive arm swing, the ratio between paretic and non-paretic arm is commonly used [10, 3, 11, 12, 13, 14]. However, ratios are a relative measure of activity, and therefore are unable to capture potential increases/decreases in absolute activity.

Whereas clinical tests assess function and impairment, accelerometry measures only the effects of impairment in the form of reduced activity levels or reduced duration of arm use. Nevertheless, inertial sensors (accelerometers and/or gyroscopes) worn in a clinical setting during assessments such as the Functional Ability Scale of the Wolf Motor Function Test [15, 16, 17, 18] or the Fugl-Meyer Assessment [19], have allowed the reconstruction of these scores based on the recorded signals, demonstrating that qualitative information of arm movements can also be extracted. Still, there is a need for a metric motivated by the characteristics of typical grasping and object manipulation movements, complementing the quantitative measures of accelerometers with qualitative measures of functional arm use. Single-sensor setups are preferable because there is no risk of swapping sensors, no need for sophisticated synchronization and compliance in patients as well as clinicians is increased.

We propose a novel method to qualitatively assess arm use in the home environment, relying on only a single wrist-worn sensor module. To evaluate this method, we collected 48h recordings including acceleration and angular velocity in 10 chronic stroke survivors in their home environment using five sensor modules placed on wrists, shanks and waist and propose a novel method to qualitatively assess arm use relying only on one wrist worn sensor module. We compare our method against setups involving sensors worn at multiple anatomical locations and investigate its ability to reject influence of ambulatory activities on arm use. Performance measures are compared with clinical measures for gross manual dexterity.

2 Methods

2.1 Rationale

The goal of this work is to identify functional use of the arm, as in the case of reaching to and manipulating an object, with a single wrist-worn IMU. IMUs are subject to drift, especially in the horizontal plane, and measurement of absolute wrist orientation can therefore not be guaranteed. The use of magnetometers could add an absolute reference in the horizontal plane and reduce drift, but these are *"difficult to use in the vicinity of ferromagnetic metals"* [20], which are often encountered in daily settings (doors, elevators, speakers). However, when considering only short time windows of sensor recordings, the effects of drift can be neglected, and angular displacements can be measured reliably.

Reaching and manipulation movements performed during ADL typically involve grasping objects placed on a table or shelf and displacing them by moving the arm over a certain angle in the horizontal or vertical plane, or a combination of the two. During ambulatory activity, in return, the forearm is oriented towards the ground and swings passively. It has been shown that, during ADL, wrist position is mostly constrained around the sagittal plane [21] and above the waist [22], and thus absolute orientation with respect to the trunk, which could be influenced by sensor drift in the horizontal plane, is not essential. is not essential. We assume that forearm elevation (the angle between the forearm axis and a horizontal plane) and/or yaw (the angle between the forearm axis and the sagittal plane) change significantly during functionally relevant tasks. Based on these assumptions, we propose to infer functional arm use by measuring the relative angular change in forearm orientation induced by such movements.

To derive a metric based on these assumptions, thresholds for forearm elevation and lateral movement have to be determined. By observing reaching and manipulation tasks we defined a threshold of $30°$ for angular change in elevation and/or yaw in order to identify such movements (Figure 2). Further, by constraining the elevation of the forearm to a range of $-30°$ to $+30°$, the influence of pro- and supination movements of the forearm on the proposed metric (e.g. at $\pm 90°$ elevation, changes in yaw cannot be distinguished from pro-/supination movement) can be reduced and problematic singularities at $\pm 90°$ can be avoided. Additionally, by excluding forearm elevation lower than $-30°$ from the analysis, the influence of ambulatory activities can be reduced.

From clinical observation it follows that stroke survivors show reduced arm activity in ADL and have difficulties in lifting the arm against gravity. We therefore hypothesize that forearm elevation of left and right arm differ in stroke survivors, and that average forearm elevation is lower compared to the unaffected arm. We assume that this discrepancy is also reflected in a reduction of gross arm movements performed during ADL. We further hypothesize that the proposed metric describes meaningful arm function as assessed through the Box and Block Test (BBT) and is robust against the influence of ambulatory activities.

2.2 Subjects

10 subacute/chronic stroke survivors were enrolled in this study after providing written informed consent. The study was approved by the local ethics commission. A detailed list of subject demographics can be found in Table 1. All subjects were independent walkers. Subjects' gross manual dexterity was assessed with the BBT [23] by a trained clinician either at their homes or during a therapy session in the clinic.

Subjects wore five wearable sensor modules (Section 2.3) for 48 hours, one on the dorsal side of each wrist, one on the lateral side of each shank right above the ankle and one around the waist. Subjects were equipped with the sensors by the clinician either at their homes or during a therapy session in the clinic. The modules at wrist and shanks were fixed with silicone straps while the waist sensor was fixed with an elastic band. Subjects were instructed to wear all sensor modules during all activities and to keep them donned for bathing or showering in order to eliminate the risk of swapping the modules or placing them at a different location. The sensors were returned to the clinic by surface mail. Data from the waist sensor was excluded from the analysis.

Table 1: Demographics and Box and Block Test (BBT) scores of the 10 subacute/chronic stroke survivors who participated in this study.

#	Gender	Age	Weeks since stroke	BBT par.	BBT non-par.
1	m	61	24.2	11	41
2	m	52	47.8	6	42
3	m	70	22.1	23	42
4	m	47	8.5	55	65
5	m	61	26.0	7	52
6	m	63	21.0	35	51
7	m	31	14.4	65	62
8	m	33	14.2	58	70
9	m	44	20.1	41	60
10	m	65	17.6	23	41
		52.7 ±13.6	21.6 ± 10.6	32.4 ± 21.8	52.6±11.0

2.3 Sensors

For the purpose of precisely recording human posture and motion data over a period of 48 hours we used ReSense, a low-power 10-degrees-of-freedom (DOF) inertial measurement unit (IMU) comprising a 3-axis accelerometer, a 3-axis gyroscope, a 3-axis magnetometer and a barometric pressure sensor [24]. This sensor module can record continuously for at least 24 h at a sampling rate of 50 Hz and by means of an intelligent power management this timespan can be doubled. Multiple sensor modules can be synchronized temporally via a base station prior to the measurement and the calibrated clock in each unit guarantees less than 90 milliseconds drift per day between sensor modules. This sensor system (Figure 1) was specifically designed for use by clinical staff and self-use by patients.

Figure 1: ReSense sensor modules and base station [24]. The base station allows data readout, battery charging and temporal synchronization of up to 5 sensor modules simultaneously via a USB 2 port.

2.4 Data processing

All data processing steps described in the following were performed in Matlab (2014a, The MathWorks, Natick MA, USA).

2.4.1 Preprocessing

Prior to all processing steps, the recordings from the wrist and shank worn sensors were resampled at exactly $50Hz$ and gaps due to sensor standby during inactive time periods were filled by means of zero order hold interpolation for acceleration. Angular rate was set to zero during these periods. Resampling was necessary because of the inaccuracy of the onboard clock of the low-cost MEMS sensors, which, according to our experience, may differ by up to 2%. Correction of residual zero offset and drift of the recorded gyroscope data was then performed based on linearly interpolated averaged signals from still phases. These phases were identified by means of a moving variance filter. Data from barometer and magnetometer were excluded from the data analysis.

2.4.2 Walking identification

Identification of walking phases was based on acceleration signals from the shank-worn sensor module at the unimpaired leg [25]. Data streams were segmented into windows of 7.5 seconds (375 samples) with no overlap and fed into a support vector machine (SVM) classifier previously trained on data from 12 stroke survivors [25]. The output of the classifier was further processed by morphological filters which filled gaps (non-walking) of ≤ 4 windows (30 seconds) and removed small walking bouts of only 1 window (7.5 seconds).

2.4.3 Manual labeling

Manual labeling of corrupted/faulty segments and nightly sleeping phases was then performed by visual inspection of the raw data of wrist and shank sensors and the identified walking phases. Faulty segments could occur when subjects did not wear their sensor modules for some time or when they accidentally swapped or inverted them, even though they were clearly instructed not to do so. These periods were manually identified and were excluded from the analysis. Nightly sleeping phases were defined manually from the time point where activity marginally dropped, after the last walking bout, and mostly static signals were visible until the time point where activity increased and the first walking bout could be identified. Active phases during nightly bed time were labeled as sleep phases even when they clearly included walking. Inactive periods during daytime were only labeled as sleep in case the duration exceeded one hour.

2.4.4 Activity counts

Acceleration from the wrist worn sensors was high-pass filtered at 0.3Hz in order to remove constant offsets due to gravity. Activity counts (AC) for epochs with window size of 1 minute (3000 samples) and no overlap were calculated by means of equation 1 adapted from [26].

$$AC = \frac{1}{f_s \cdot Epoch} \sum_{n=1}^{N} \sqrt{a_x[n]^2 + a_y[n]^2 + a_z[n]^2} \tag{1}$$

where $N = f_s \cdot Epoch \cdot 60$

$Epoch$: duration of an epoch in minutes

f_s = sampling frequency in Hz

$a_{x/y/z}$ = acceleration in direction $x\ y\ z$.

A threshold of $0.05g$ was applied on the acceleration magnitude to suppress very low sensor excitation mainly due to sensor noise.

AC were calculated during awake time including and excluding walking phases. To exclude walking phases from AC, the acceleration of wrist-worn sensors was set to zero during the periods where walking was detected by means of the shank sensor. The final outcome is the average number of counts per minute during awake time. When excluding walking phases from AC, the average was calculated over the duration of awake time minus walking time.

2.4.5 Forearm elevation

Acceleration and angular rate from wrist-worn sensors were used to estimate the forearm orientation relative to the earth referential frame. For this purpose the gradient descent orientation filter proposed by Madgwick et al. [27] was selected. Raw sensor measurements of gravity and angular rate were fused into an optimal orientation estimate. The filter also assures convergence from initial conditions and compensates for eventual drift in a vertical plane. A single adjustable parameter β is required to tune the filter and, in this work, the optimal value of 0.03 as proposed by [27] was used. The filter outputs orientation in a quaternion representation $\mathbf{q} = [q_0,\ q_1,\ q_2,\ q_3]$, which can be transformed into a 3x3 direction cosine matrix $\mathbf{R}$ [28]. To calculate the forearm elevation (Figure 2), the forearm vector $\vec{a_s} = [1\ 0\ 0]^\top$ was expressed in the earth fixed referential e: $\vec{a_e} = R^\top \vec{a_s} = R^\top [1\ 0\ 0]^\top$. The elevation Θ of the forearm vector $\vec{a_e} = [a_{ex}\ a_{ey}\ a_{ez}]$ can then be computed as:

$$\Theta = arctan\left(\frac{a_{ez}}{\sqrt{a_{ex}^2 + a_{ey}^2}}\right) \tag{2}$$

The normalized probability distribution of forearm elevation Θ during daily routines was established in a polar representation between $-90°$ to $90°$ with a histogram bin-size of $1°$ (Figure 3). Phases of inactivity were detected by means of a threshold of $0.05g$ on the acceleration magnitude and were excluded from the probability distribution. Probability distributions were established for both forearms during awake time, including and excluding walking phases. The sum of the absolute error between left and right distribution and center of mass (COM) were extracted from the distributions and served as performance metrics.

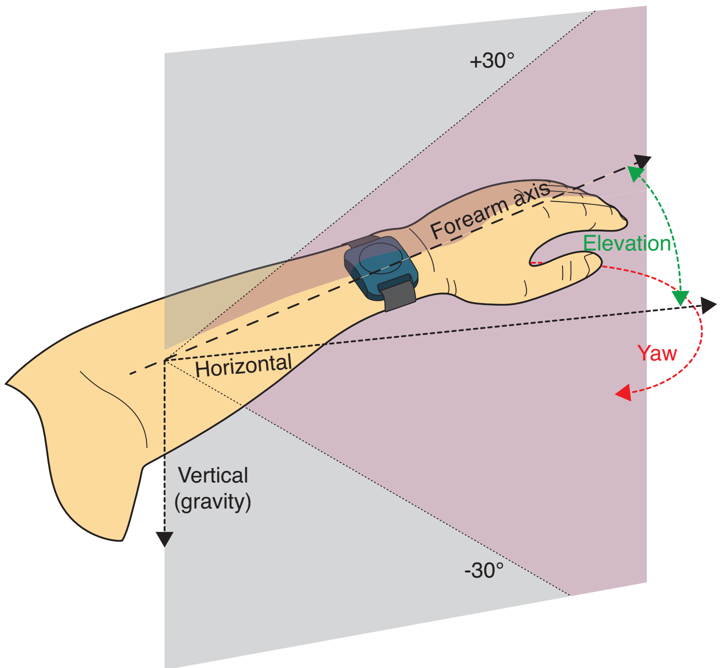

Figure 2: Illustration of the forearm angles extracted from the IMU. Elevation is the angle between the horizontal and the forearm axis and yaw is the angle covered in lateral movements. The red area in the vertical plane illustrates the region where gross arm movements are identified and movements outside of this area are not captured by the algorithm. It has to be noted that shoulder abduction, flexion and rotation as well as elbow flexion can influence elevation and yaw.

2.4.6 Gross movement identification

Gross movement (GM) identification is based on the orientation estimate determined for forearm elevation. In addition to elevation Θ, the rotation around the vertical axis in the earth referential (collinear with gravity), i.e. the yaw, was calculated and also considered (Figure 2). Yaw (Φ) was computed by numerically integrating the angular rate ω_{ez} over time:

$$\Phi[k] = \frac{1}{f_s}\sum_{n=1}^{k}\omega_{ez}[n] \tag{3}$$

where $\vec{\omega_e} = [\omega_{ex},\ \omega_{ey},\ \omega_{ez}] = R^\top \vec{\omega_s}$

f_s is the sampling frequency in Hz

$k = [1 \ldots N]$ where N is the total number of samples to be integrated.

Elevation and yaw were then segmented into windows of two seconds with 75% overlap. An overlap was introduced to increase the probability of capturing movements within a window that match the defined heuristic rules. In each of the windows, the following heuristic rules were tested

$$|\Theta| \leq 30^\circ \ \textbf{and}\ range(\Theta) + range(\Phi) \geq 30^\circ \tag{4}$$

where $range(x) = max(x) - min(x)$

and *true* was assigned for valid conditions, *false* otherwise. Drift in the horizontal plane was negligible as only the range of the angle within short windows of two seconds was analyzed. Angular ranges were defined based on the assumptions listed in Section 2.1. The final output was the total amount of windows labeled *true* multiplied with the difference of window size minus window overlap, thus resulting in the total duration of GM during the recording period.

2.4.7 Statistical analysis

Pearson's correlation coefficients were calculated for the BBT of the paretic arm with: the difference of forearm elevation probability distribution COM between impaired and unimpaired arm (excluding walking), AC of the paretic arm (including and excluding walking), the ratio of AC paretic/non-paretic arm (including and excluding walking), GM of the paretic arm (including and excluding walking) and the ratio of GM paretic/non-paretic arm (including and excluding walking). Correlations of AC and GM were compared with the Steiger's Z-test for dependent correlations [29] in order to identify significant differences in correlation strength.

3 Results

Forearm elevation distributions of two representative subjects are depicted in Figure 3. The distributions of paretic and non-paretic forearm elevation differed in a subject with a low BBT score of 6, with the COM of the paretic forearm, displaying a lower elevation during activity. In return, distributions of paretic and non-paretic forearm elevation matched for a subject with a high BBT

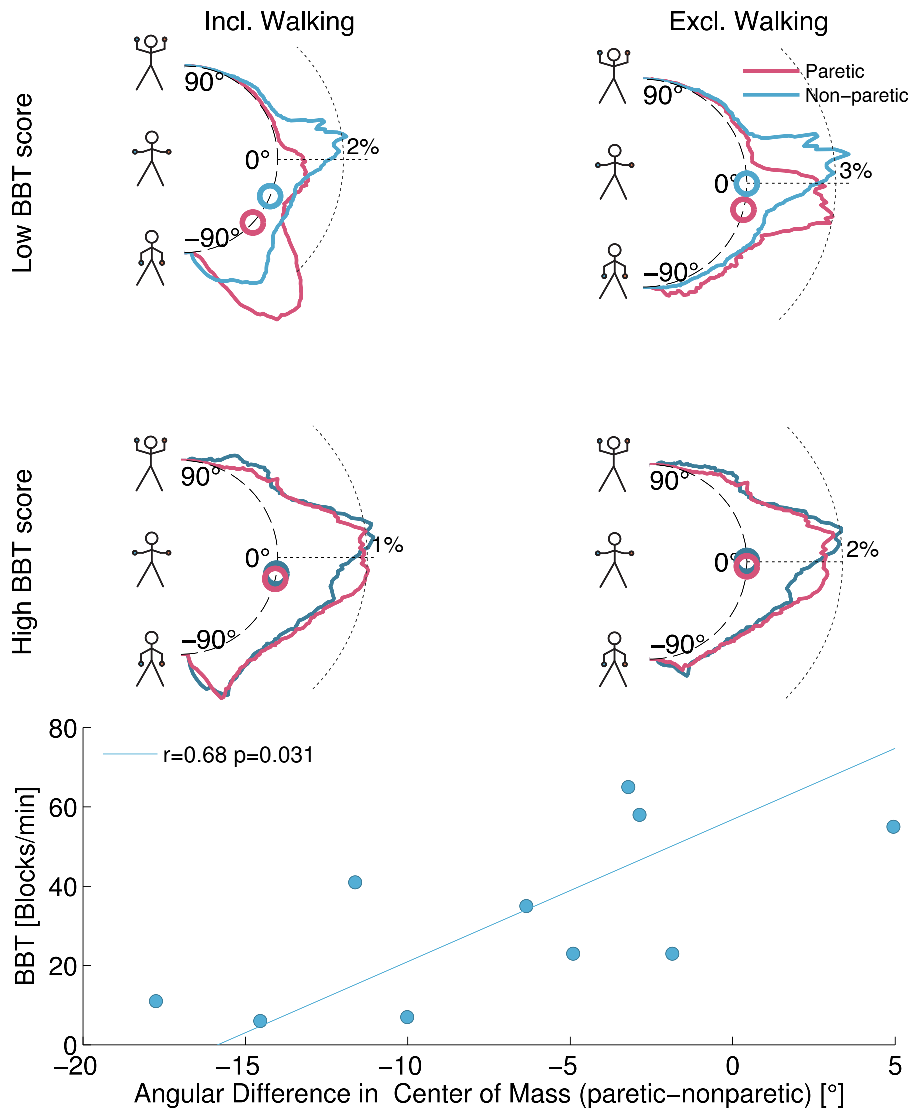

Figure 3: Top: Polar representation of the probability distribution of the forearm elevation of subject 2 (top, BBT score of 6) and subject 7 (bottom, BBT score of 65) during activity of paretic (red) and non-paretic (blue) arm, including (left) and excluding (right) walking phases. The bold circles mark the center of mass (COM) of the distributions. 90° means the forearm points upward against gravity, while −90° means the forearm points downward along gravity. The forearm angle is independent of upper arm orientation. Bottom: Scatter plot of the difference of forearm elevation probability distribution COM between impaired and unimpaired arm (excluding walking phases) with the Box&Block Test, showing a high correlation.

score of 65. Removing walking phases from the recordings resulted in less activity with an elevation lower than $-45°$ and thus raised the COM. Similar results were found in all 10 subjects. Pearson's correlation coefficients of BBT score correlated with the difference of COM ($paretic - nonparetic$) of ten chronic stroke survivors is $r = 0.68$ ($p = 0.03$) (Figure 3).

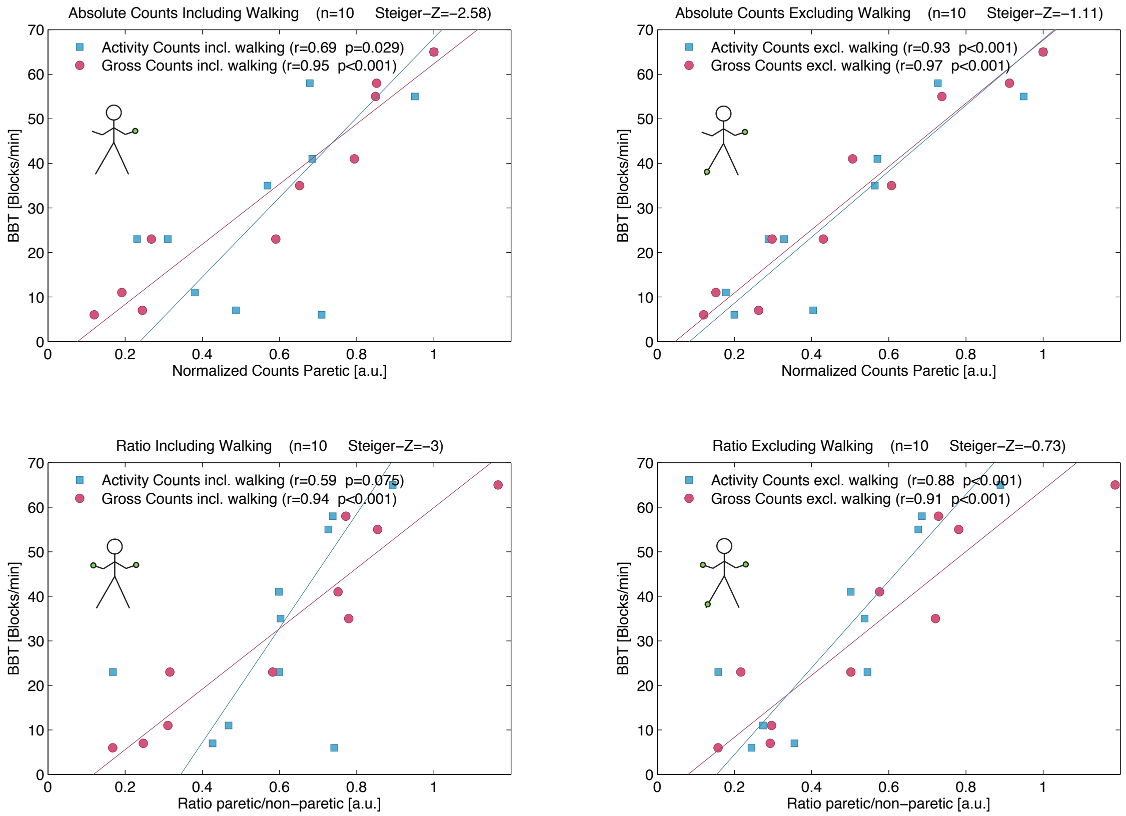

Figure 4: Scatter plots of activity counts and the Box&Block Test (blue squares) and gross movements and the Box&Block Test (red dots). Absolute counts on paretic arm including walking (top left) and excluding walking (top right) and ratios between paretic and non-paretic arms including walking phases (bottom left) and excluding walking phases (bottom right). The lines represent the total least squares fit. The correlations of activity counts (AC) and gross movements (GM) were compared using the Steiger's Z-test.

Correlations of arm AC and arm GM with the BBT are shown in Figure 4. Correlation of total paretic arm AC including walking with BBT was $r = 0.69$ ($p = 0.029$) and total paretic arm AC excluding walking with BBT was $r = 0.93$ ($p < 0.001$). Steiger's Z-test on the two latter correlations was $\bar{Z} = 2.99$ and this value, when compared to the normal curve rejection points of ± 1.96, is significant. Correlation of the ratio of paretic/non-paretic arm AC including walking with BBT was $r = 0.59$ ($p = 0.075$) and the ratio of paretic/non-paretic paretic arm AC excluding walking with BBT was $r = 0.88$ ($p < 0.001$). Steiger's Z-test again showed a significant difference ($\bar{Z} = 2.56$). GM correlated significantly better with BBT than AC with BBT when walking phases are included. This applies to the ratios ($\bar{Z} = -3.0$) and absolute values ($\bar{Z} = -2.58$). Correlation coefficients increased in the case of AC with BBT when walking phases are excluded and no significant difference compared to GM with BBT could be identified using Steiger's Z-test. In all four tested conditions, the correlation of GC with BBT resulted in high correlation coefficients $r \geq 0.91$ ($p < 0.001$) and no significant difference could be identified by means of the Z-test.

4 Discussion

Absolute AC of the impaired arm during awake time and excluding walking phases show significantly better correspondence with clinical scores than when including walking phases. Ambulatory activities can lead to overestimation of AC and consequently weaker correspondence with clinical scores. This is supported by previous findings [13, 6]. Removing walking phases from the datasets resulted in more representative measures and ACs (total paretic and ratio paretic/non-paretic) highly correlated with clinical scores.

In contrast to AC, our results demonstrate that measuring GM is robust against movements during ambulatory activities. This can be attributed to the fact that movements with forearm elevations of $< -30°$, which can mostly be attributed to an arm hanging down and swinging passively during gait, are not captured. Also, oscillations in the forearm elevation due to walking are typically below the amplitude threshold we have set and remain undetected in case the forearm elevation should fall within the span of $[-30°,\ 30°]$. We conclude that the method of GM qualifies for a single-sensor-setup with one 6-DOF IMU worn at the wrist. Such a single-sensor-setup is highly beneficial as it may improve user compliance and ease usability. We saw that patients removed and accidentally swapped sensor modules even though they were instructed not to do so. Such a risk could be minimized in a single-sensor setup.

While GC correlated strongly with the BBT score, the latter is sensitive to both arm and hand function (e.g. difficulty in grasping a block) whereas our proposed method only assesses arm use. Nevertheless, similar correlations could also be found with other clinical tests such as the Chedoke Arm and Hand Activity Inventory ($r \geq 0.91$ ($p < 0.001$)). The strong correlation of the proposed metric with the BBT suggests that it may provide valuable insights into the true use and performance of the impaired arm in stroke survivors in the home environment.

Previous research could identify good correspondence of activity ratios with clinical scores [2, 5], which we could not reproduce. Besides employing different clinical tests, these studies were performed in a clinical environment, where subjects may have more similar daily routines and walking activity, which causes a constant overestimation of AC and thus will not be reflected in correlation coefficients. Compared to previous studies, our setting differed with subjects being in their homes and showing distinctive behavioral patterns, with some subjects going for walks of three hours duration and others being extremely passive in terms of ambulatory activities.

From the forearm elevation distributions including and excluding walking phases we can deduce that ambulatory activities increase activity when the forearm points towards the ground. In case of a paretic arm with a low BBT score, this may constitute a substantial part of captured overall activity. This motivated the rejection of movements with an elevation of less than 30°. To the best of our knowledge none of the previous studies [10, 3, 11, 12, 13, 14, 6] corrected for this passive activity resulting from ambulation by means of an additional shank sensor, thus likely distorting the arm activity levels of severely impaired subjects. Visual inspection of the distribution can also give insights into the recovery of stroke survivors. Difference of COM of paretic and non-paretic forearm could be identified as clinically relevant parameter as it strongly correlated with the BBT. These findings are in accordance with measurements of vertical wrist position [30], where stroke survivors showed a reduced amount of activity with their affected wrist when located above mid-trunk level.

Results show that forearm elevation, which we assume to be linked to arm function, can be monitored during daily life by means of wrist-worn 6-DOF IMUs. By using gyroscopes, the precise orientation of a sensor module could be reconstructed, even during fast movements, and also changes in orientation in the horizontal plane could be captured, which is impossible with accelerometers only.

In order to consolidate our findings further validation needs to be performed with a larger sample size as the sample used in this study was rather small with only ten subjects. Nevertheless, the proposed method promises more detailed and qualitative insights in to functional arm use in the home environment beyond what is possible with pure accelerometry.

5 Conclusion

We performed 48h measurements with IMUs in a temporally synchronized body sensor network using five sensor modules in stroke survivors in their home environment. Excluding walking phases by means of a shank worn sensor can be beneficial to calculate activity counts in a home environment where patients show more distinctive behavior patterns than in a clinical environment. Further, we demonstrated that the addition of gyroscopes to sensor modules is useful for forearm elevation measurement, despite the increased energy demand of such sensors.

Finally, an unobtrusive approach to measure functionally relevant arm use in stroke survivors, which is robust against passive arm movements during ambulatory activities, was presented. The proposed algorithm requires only one wrist-worn IMU, thus simplifying system complexity and increasing user compliance and acceptance. The algorithm can be implemented on nearly any IMU to run in real time and could thus be used to provide online feedback about absolute impaired limb use to the user.

Acknowledgment

This work was supported by the National Center of Competence in Research in Neural Plasticity and Repair (NCCR Neuro) of the Swiss National Science Foundation, as well as by a private foundation. The authors would like to thank Prof. Dr. med. Jürg Kesselring for his support at the Rehabilitation Centre Valens, and all the patients who volunteered for the study.

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