# Measuring Upper-Extremity Use with One IMU

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Abstract: Discharge home from hospital can be a critical stage in the rehabilitation of patients with central neurological disorders such as stroke. The new skills and early recovery achieved in the hospital may be difficult to transfer to the home environment. This work addresses the monitoring of arm usage and proposed a new metric called Weighted Activity Counts (WAC) based on a sensing system that consists of only one inertial measurement unit (IMU). The proposed metric combines activity counts and the smoothness of the movement. This work defines Normalized Gross Energy Expenditure (NGEC) as the reference metric. WAC shows good performance under the validation protocol we designed (correlation coefficient $r > 0.90$). The optimal placement for the single sensor which can sufficiently and reliably describe arm usage is also explored in this work.

## 1 INTRODUCTION

The main goal during stroke and central neurological disorder rehabilitation is to achieve optimal motor performance enabling patients to live independently. Researchers use standardized clinical tests and functional motion tasks to assess the capacity of stroke patients, for example, Fugl-Meyer Assessment (Sanford et al., 1993) and the Action Research arm test (ARAT) (Lyle, 1980). In the home environment, it's hard for the physicians to access necessary information about the intensity and quality of a patient's daily-life activities (Klaassen et al., 2016). Therefore, it is of interest to build an unobtrusive and modular system for objectively monitoring the patient's upper or lower extremity motor function in daily-life activities. Since the upper extremity function is a key Activities of Daily Living factor and seen as a high research priority in rehabilitation (Klaassen et al., 2016), the main focus of this study is on upper extremity movement.

The use of an IMU is a potential method for the minimal assessment of body movements in a daily life setting (Van Meulen et al., 2015), (Xu et al., 2016), (van Meulen et al., 2017). IMUs combine accelerometers, gyroscopes, magnetometers and also do not require an external physical reference system to estimate movement which makes the use of IMUs suitable for measurements in a daily life setting (van Meulen et al., 2017).

Several IMUs based metrics have been used to describe upper extremity movements. In the arm usage coach (AUC) system (Klaassen, 2015), (Klaassen et al., 2016), researchers put forward the difference acceleration vector (DAV) which calculates the 3D norm value of the vector difference between the movement acceleration and the gravity vector in a predefined resting position. Another commonly used metric is the integral of the absolute value of acceleration (IAA/IMA). This method takes the integral of the absolute values of the acceleration measured by the accelerometer (Bouten et al., 1994). Another most widely used method has been put forward by Hale et al., who use the mean acceleration (in $m/s^2$) for each of the three axes across set 1-second or 1-minute intervals called as activity counts (AC) to measure the amount of the arm usage (Hale et al., 2008). However, Leuenberger et al. (Leuenberger et al., 2017) suggested that AC provides quantitative rather than qualitative information. This holds for the other metrics as well.

Smoothness is a characteristic of coordinated human movements. According to Rohrer et al., patients' movements seem to become smoother with recovery (Rohrer et al., 2002). During rehabilitation, motion quality especially the smoothness can be different which consequently requires the changes of treatment programs. Thus, smoothness is an important indicator of the quality of the movement. This work proposes a new metric called Weighted Activity Counts (WAC) that fuses the smoothness of upper extremity move-



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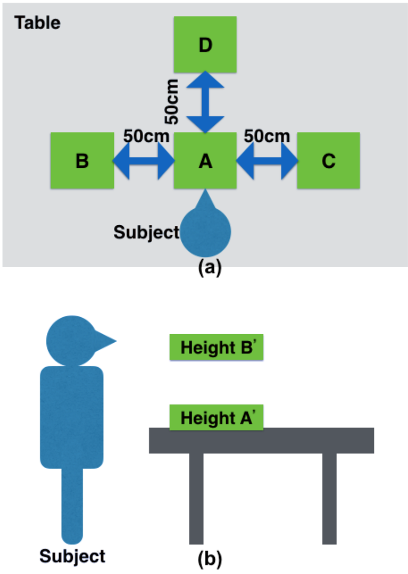


Figure 1: Protocol Phase One. (a) is the top-down view of the different position on the table with a participant seated on a stool. (b) is the overview of the different heights above the table with the subject standing in front of the table.

ments with the conventional AC. To investigate the new metric, an experiment with healthy subjects has been conducted.

This work defines a reference metric Normalized Gross Energy Consumption(NGEC) based on the law of conservation of mechanical energy: the mechanical energy is defined by the sum of the potential and kinetic energy. NGEC is also based on one sensor, and able to evaluate the gross arm usage. In this study, we validate the proposed metric as a measure of arm usage and compare it with other four state-of-the-art metrics.

The remainder of the paper is organized as follows: Section 2 describes the experiment protocol that was used to evaluate the metrics, the rationale of the WAC metric and the reference metric we proposed, and Section 3 provides the results of comparison among different metrics, Section 4 presents the discussion based on the experiments, and finally, conclusions are given in Section 5.

# 2 MATERIALS AND METHODS

This section comprises of the measurement configuration, two-phase experimental protocol and the processing procedure (including pre-processing, the calculation of the metrics and thereference metric).

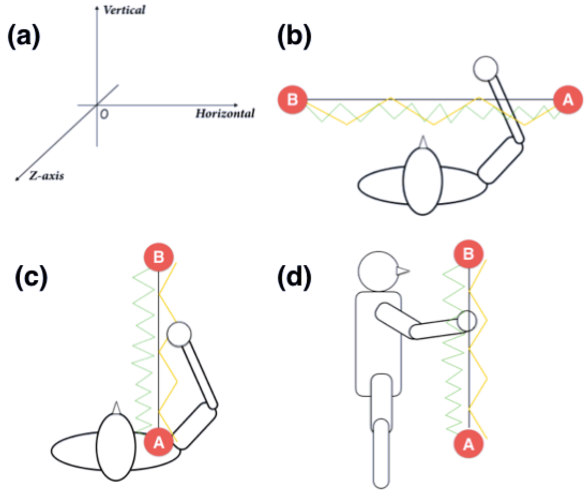


Figure 2: Protocol Phase Two. (a) is the coordinate frame of all the experiments, (b) is the top view of horizontal task, the subject was in stable sitting position, and (c) is the top view of front & back task(z-axis), the subject was in stable sitting position. The black, yellow, green line in the figures represent the normal, light tremble and heavy tremble motion traces separately. Finally, (d) is the side view of vertical task, the subject was in stable standing position to avoid bending their upper body.

## 2.1 Measurement Configurations

The device we used in our experiment is the Xsens MVN suit (Roetenberg et al., 2009). IMUs are placed over the entire body on different body segments. First, the body length, shoulder width, arm span and foot size of the subject are measured. Sensors are placed on the hands, wrists, upper arms, forearms, shoulders, sternum, chest, pelvis and head. Each sensor consists of a 3D accelerometer, gyroscope and magnetometer. Those data are collected and bundled with the use of MVN Studio at a frequency of 60 Hz. The Xsens Awinda protocol ensures real-time sending and receiving of data and handles data packet loss.

## 2.2 Experimental Protocol

A total of 12 healthy subjects ($24 \pm 4$ years old) volunteered to participate in the study. The data was collected in two phases as part of two separate studies. The first seven subjects were given the protocol Phase One and the other five were asked to perform Phase Two. The proposed protocol in our research has been approved by the ethical committee in University of Twente. All subjects filled in an informed consent before doing the experiments. The participants are asked to perform the following movements as seen in figure 1 (a):

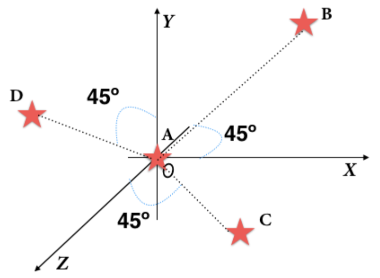


Figure 3: Complex task. Subjects were asked to move the object from A to B, C, D separately with three different motion types (normal, light tremble, heavy tremble).

- A–B–A–C–A–D–A;
- B–C–D–B–D–C–B;
- pick up the object from ground and place it at A and then pick up object from A and move it to ear, finally put it back to A.

Then based on figure 1 (b), the motion sequences can be grouped into the following three sections:

- Lift the object to height B' and lower it back to height A'– Move object from height A' to height B' (place it at height B') – Move object from height B' to height A';
- at height A', move object A–B–A–C–A;
- Move object from A to D at height B'– Move object back to A– Use the dust cloth to clean the table by going forth and back once.

The second phase of our protocol is as shown in figure 2. This part consists of a horizontal task, vertical task, front& back task and complex task. In the first three tasks, subjects were asked to move a small ball from point A to point B along different routes (black, orange, green line in figure 2) in order to mimic different smoothness degree of movements (motion types). In the fourth task, subjects were asked to move the ball along the diagonal of all three planes, as seen in figure 3 and also with three motion types (normal, light tremble and heavy tremble). The routes in the fourth task were selected by the subjects. All tasks were done three times. Before each task, there was a short break before starting.

## 2.3 Weighted Activity Counts

Decomposition of the complicated motion makes it possible to use euler angles to estimate the position during the arm movement. Based on IMUs system, acceleration and angular rate from 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. (Madgwick et al., 2011) was selected. The algorithm fuses sensor measurements of angular rate and gravity into an optimal orientation estimate. It also assures convergence from initial conditions and compensates for drift in a vertical plane. In this algorithm, the weighting of the accelerometer measurements in the error correction $\beta$ according to the definition in (Madgwick et al., 2011). We set $\beta$ to 0.03 as proposed by Madgwick (Madgwick et al., 2011). After that, the algorithm calculates the orientation value by numerically integrating orientation change rate. Then, the estimated orientation change rate is computed as the rate of change of orientation measured by the gyroscope, and the magnitude of the gyroscope measurement error $\beta$, which is removed in the direction based on accelerometer and magnetometer measurement (Madgwick et al., 2011). The filter outputs orientation in a quaternion representation $q = [q_0, q_1, q_2, q_3]$. The euler angles $\phi$, $\theta$ , and $\psi$ can then be computed from these quarternions. Variance reflects the average distance from each point to the average value in the whole motion procedure. In that case, we use all the three angles' variances to describe the smoothness of the movement. Here,

$$N = f_s \cdot Epoch \tag{1}$$

where $f_s$ is sampling frequency in Hz; Epoch is duration of each movement in second, and the preparation time of the movement should not be counted in Epoch. Then, we define the Smoothness Degree (SD) of the data points in the observation period as:

$$SD = \frac{variance(\phi) + variance(\theta) + variance(\psi)}{3} \tag{2}$$

According to equation 2, when the movement shows large variance in $\phi$, $\theta$ , and $\psi$ then, the SD value will also be large, which shows that the movement contains certain degrees of tremble on one or more directions. The estimated SD is combined with the weight of conventional Activity Counts (AC). AC for epochs are calculated by equation 3 adapted from (Janz, 1994):

$$AC = \frac{1}{N} \sum_{n=1}^{N} \sqrt{a_{x,n}^2 + a_{y,n}^2 + a_{z,n}^2} \tag{3}$$

Here $a_{i,n}$ is the acceleration at time 'n' for the i-th axis, and 'N' is the total number of samples. Using the above, the Weighted Activity Counts(WAC) is defined as:

$$WAC = SD \cdot AC \tag{4}$$

In this equation, WAC combines the movement's quality SD and the intensity AC together to capture the smoothness degree of the movement.

### 2.4 Difference Acceleration Vector

Difference Acceleration Vector (DAV) is used to detect movement of the arm by using 3D accelerometers. The length of the DAV is calculated by subtracting a reference gravitational acceleration vector **g(n)** from the current acceleration vector **a(n)** and taking the norm of the resulting vector. DAV is defined as:

$$\frac{1}{N}\sum_{n=1}^{N}\sqrt{(a_{x,n}-g_x)^2+(a_{y,n}-g_y)^2+(a_{z,n}-g_z)^2} \tag{5}$$

DAV takes the difference of the acceleration vector compared to a reference position which already reduces the influences of gravitational acceleration and possibly noise. In that case, no filter is applied to the acceleration data when calculating the DAV (Klaassen et al., 2016).

### 2.5 Integral of Absolute Value of Acceleration

The Integral of Absolute value of Acceleration (IAA) was firstly described by Bouten et al (Bouten et al., 1994). Another known abbreviation of this method is IMA, the integral of the modulus of the acceleration. This method takes the integral of the absolute values of the acceleration measured by accelerometer, as the formula:

$$IAA=\int_{t_0}^{t_n}|a_x|\,dt+\int_{t_0}^{t_n}|a_y|\,dt+\int_{t_0}^{t_n}|a_z|\,dt \tag{6}$$

The IAA metric is estimated by filtering the acceleration with a fourth order Butterworth zero phase low-pass filter with a cut-off frequency of 20Hz to attenuate the effect of frequencies that don't arise from voluntary movement as proposed by Bouten et al (Bouten et al., 1994).

### 2.6 Root Mean Square

Schasfoort et al., describes the usage of the upper-limb activity monitor (ULAM) (Schasfoort et al., 2002), combined with the calculation of the root mean square (RMS) (Bussmann et al., 2001). The RMS of the signal was calculated after the band-pass filtering (FIR, $0.3-16$ Hz). Bussmann et al. (Bussmann et al., 2001), proposed this metric to measure upper-limb use from accelerometer data of the upper limb and intensity.

### 2.7 Reference Metric (NGEC)

Estimate of energy of the movement using IMUs was proposed by Aleshinsky et al. (Aleshinsky, 1986) and Zaman et al. (Zaman et al., 2014). In order to simplify the system and make it possible to be used in obtrusive monitoring, we proposed Normalized Gross Energy Consumption (NGEC) as the reference metric. NGEC is based on the work done by Aleshinsky et al. (Aleshinsky, 1986) which calculates the kinetic energy consumption by using:

$$E_{kin}=\frac{1}{2}\cdot m\cdot\sum_{n=1}^{N}\left|v_{2n}^2-v_{1n}^2\right| \tag{7}$$

Where the absolute value means the energy consumption should always be positive during the movement and $v_{2n}$ and $v_{1n}$ represent the final and start velocity respectively. In order to evaluate the gross energy consumption, we derive $E_{tot}$ as $E_{kin}+E_{pot}$, giving

$$\begin{aligned}E_{tot}=\sum_{n=1}^{N}(&\frac{1}{2}\cdot m\cdot\left|v_{2n}^2-v_{1n}^2\right|\\&+m\cdot g\cdot(h_{2n}-h_{1n}))\end{aligned} \tag{8}$$

where $h_{2n}$ and $h_{1n}$ represents the final and start sensor position in global frame at adjacent points during the movement.

In the calculation of both of these energies, the mass is needed. This mass includes the mass of the participant's arm and the object that is being moved. Since this mass is unknown and differs per subject, it is also possible to calculate the specific energy in $J/kg$, giving $NGEC=E_{tot}/m$.

Before estimating the NGEC, the acceleration data from the sensors was high-pass-filtered at 0.3Hz in order to reduce the influence of gravity. Please noted that the rotational kinetic energy during the movements is not counted. In the following section, we compare the WAC with the other four metrics (IAA, RMS, AC, DAV).

In this section, data was processed and analyzed using MATLAB (MathWorks Inc., Natick, MA).

## 3 RESULTS

### 3.1 Metrics Comparison

Using equation 3 and 4, combined with the acceleration data, we can get the value of AC and ultimately, WAC. Figure 4 presents the different WAC values among different motion types in each task.

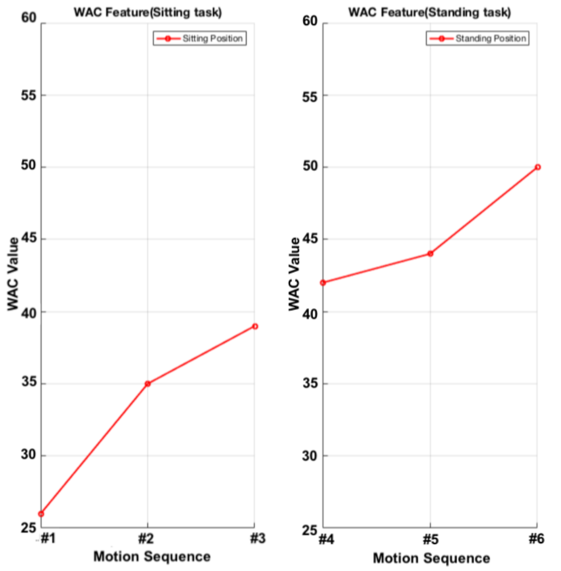


Figure 4: WAC value from hand worn sensor for different motions: left panel showing sitting and right panel showing the standing task.

Table 1: Comparing correlations among different metrics, based on NGEC for the hand worn sensor in Phase One, $r > 0.7$ is boldened.

| Seq1 | #1 | #2 & #3 | #4 | #5 | #6 |
|---|---|---|---|---|---|
| WAC | **0.82** | **0.90** | **0.90** | **0.90** | **0.95** |
| AC | 0.44 | 0.39 | 0.46 | 0.51 | 0.47 |
| DAV | 0.10 | 0.57 | 0.56 | 0.19 | 0.21 |
| IAA | **0.93** | **0.73** | **0.83** | **0.93** | **0.92** |
| RMS | 0.15 | 0.07 | 0.13 | 0.06 | 0.04 |

Two phases of the protocol are validated separately. In Phase One, we compare the proposed metric WAC with the other four state-of-art metrics, including AC, DAV, IAA, RMS, as shown in Table 1. Based on the difficulty of the motions, six sequences are made. Sitting position: (#1) short distance, simple; (#2) a little bit difficult, long distance and (#3) up and down, more difficult; Standing position: (#4) up and down; (#5) horizontal motion, short distance and (#6) forth and back motion, short distance.

For the Phase Two of the protocol, the correlation value when doing different tasks are compared in Table 2 with high correlation coefficient value ($r > 0.7$) marked in bold. The performance of the other four conventional metrics is presented in Table 2. Finally, we compare the correlation value (WAC and NGEC) among different motion types (normal, light tremble, heavy tremble) in Table 3. And Table 4 shows the SD value of the three measurements. The trend between WAC and motion type is seen in Figure 5.

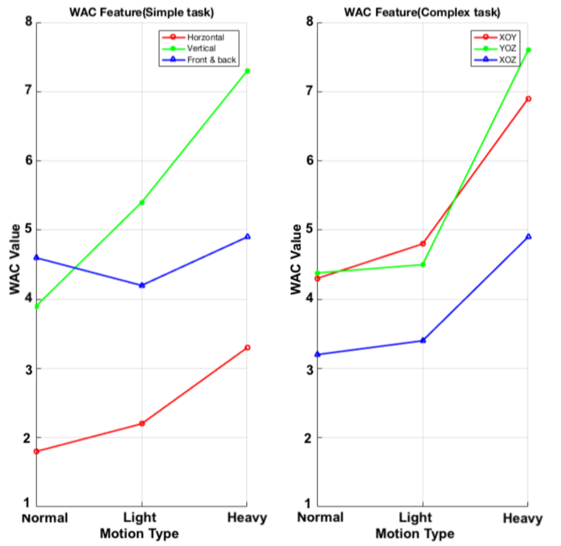


Figure 5: WAC value from hand worn sensor for different motions: left panel showing simple and right panel showing the complex tasks.

## 3.2 Optimal Sensor Placement

To explore the optimal position of the sensor, the same processing procedure was done by using the data from forearm and upper arm respectively. The results are provided in Table 5.

# 4 DISCUSSIONS

## 4.1 Summary of Assessment Results

This paper focuses on the assessment of arm usage in remote rehabilitation system by using wearable sensors. Since the multi-sensor systems maybe unsuitable for daily life (Burke et al., 2009), WAC is developed based on a single sensor. This metric combines the activity count metric for upper extremities with a smoothness metric. Based on the results of our experimental protocol, the following three main discussion points are focused in this paper:

- The performance of the proposed metric WAC under different tasks.
- The comparison among state-of-the-art metrics.
- The optimal placement for the sensors to assess the movements.

A two-phase protocol are designed to investigate the assessment capability of WAC. In the first phase of the protocol, subjects were asked to move an object along the fixed path to mimic the simple movements of patients. While in the second phase of the protocol,

Table 2: Comparing correlations among different metrics, using NGEC as reference for the hand worn sensor, for Phase Two. $r > 0.7$ is boldened.

| – | **Horizontal** | **Vertical** | **Front & Back** | **XOY** | **YOZ** | **XOZ** |
|---|---|---|---|---|---|---|
| WAC | **0.72** | **0.87** | **0.82** | **0.99** | **0.96** | **0.93** |
| AC | 0.01 | 0.25 | 0.38 | 0.05 | 0.10 | 0.14 |
| DAV | 0.53 | 0.68 | 0.13 | 0.26 | 0.16 | 0.18 |
| IAA | **0.84** | **0.87** | **0.98** | **0.94** | **0.94** | **0.92** |
| RMS | 0.01 | 0.50 | 0.02 | 0.18 | 0.21 | 0.06 |

Table 3: Comparing correlation among tasks and motion types. $r > 0.9$ is boldened.

| – | **Normal** | **Light** | **Heavy** | **Total** |
|---|---|---|---|---|
| Horizontal | **0.97** | 0.73 | 0.33 | 0.72 |
| Vertical | 0.88 | 0.45 | 0.53 | 0.87 |
| Front & Back | **0.98** | 0.86 | 0.61 | 0.82 |
| XOY | **0.96** | **0.92** | 0.76 | **0.99** |
| YOZ | **0.93** | **0.96** | **0.96** | **0.96** |
| XOZ | **0.95** | 0.87 | **0.94** | **0.93** |

Table 4: Variances of Euler angles for the horizontal test.

| **Motion Type** | $\phi$ | $\theta$ | $\phi$ | **Average SD** |
|---|---|---|---|---|
| Normal | 4.10 | 6.36 | 0.05 | 3.50 |
| Light | 1.23 | 28.32 | 0.26 | 9.93 |
| Heavy | 8.65 | 35.47 | 0.65 | 14.92 |

a 3D task was assigned to mimic the movements of stroke patients in their daily life.

## 4.2 Task Assessment

In Table 1 and 2, we compared WAC with the other existing arm usage metrics under the two phases separately. The results of the first experiment show that WAC and IAA have the highest correlation with selected reference NGEC for all movements (Table 1). For the Phase Two, the comparison among different metrics is shown in Table 2, in which the WAC is compared with IAA, DAV and AC. Both the IAA and WAC have better performance (correlation value is higher). Moreover, when taking a close look at the value, we can find IAA is better when assessing simple movements. For example, in Table 2, during the XOY, YOZ or XOZ task, WAC shows higher correlation than IAA, whereas during the Horizontal, Vertical or Front & back tasks, IAA is better. Meantime, the RMS metric show the lowest correlation for all experiments. For DAV, the highest value (0.68) appears when doing Vertical tasks in phase two and the poorest value appears when doing sequence 1 (#1) tasks. Based on the principle of WAC, the smoothness (or variance from it) of the motion adds weights on AC and improves the influence of motion quality on the metric. Hence, from Table 2, conventional AC and WAC show large differences in correlations with NGEC. The average correlation value of AC is 0.16, which is almost six times less than WAC. Also, in Table 1, when doing simple tasks, the difference between the two is down 1.96 times. Overall, WAC shows advantages when assessing arm usage in the complicated tasks.

The same conclusion can be summarized from Table 3. We divided the Phase Two tasks into different groups (Horizontal, Vertical, Front & back, XOY, YOZ, XOZ). The result shows that when doing more complicated tasks (XOY, XOZ, YOZ), the correlation value between the metric and NGEC is higher than the other tasks. Especially, the highest value (0.99) appears at XOY tasks and the least value 0.71 is seen for Horizontal tasks. Also, here we considered three types of motion (Normal, Light, Heavy tremble). When doing normal tremble movements, all the tasks except Vertical tasks are able to get great results (correlation value more than 0.98). The lowest value of 0.33 appears when the subjects do the heavy tremble during Horizontal tasks to mimic the patients, in which only the starting and ending points of the whole motion trace are fixed. While for the multi-type motion (the mixture of Normal, Light, Heavy tremble), the result shows higher correlation ($> 0.7$).

Next, we focus on the metric WAC and our reference metric NGEC. Firstly, to see the relationship between WAC and motion types more clearly, we generate the line graph for both the two phases. In figure 4 (Phase One), we group the six sequences by the degree of difficulty of the motions. As the motion becomes more complicated, the WAC value increases. Also, in figure 5 (Phase Two), the motion type changes from normal to heavy tremble, the WAC value increases. In both simple tasks (Horizontal, Vertical, Front & back) and complex tasks (XOY, XOZ, YOZ) cases, WAC is available to show the difference when the motion type is changing.

The difference between NGEC and WAC should also be noted. WAC combines the typical feature of AC and motion smoothness which addresses the question of arm quality during the rehabilitation. The al-

Table 5: Comparing correlations between sensor placement and task, for all five subjects, and all kinds of motion types. $r > 0.9$ is boldened.

| Placement | Horizontal | Vertical | Front & Back | XOY | YOZ | XOZ |
|---|---|---|---|---|---|---|
| Hand | 0.72 | 0.87 | 0.82 | **0.99** | **0.96** | **0.93** |
| Fore Arm | **0.90** | **0.96** | **0.99** | **0.98** | 0.86 | **0.91** |
| Upper Arm | 0.83 | 0.78 | **0.99** | **0.98** | 0.79 | **0.99** |

gorithms used on the WAC do not require a full body biomechanical constraint, such as that needed for the NGEC. The NGEC requires transformation of accelerations measured in the sensor frame to body frame, and estimation of positions, which is complex and requires more than one IMU. Therefore, NGEC, though easy to interpret, is more computationally intensive than WAC.

### 4.3 Optimal Sensor Placement

In Table 5 we compared the influence of sensor location on the correlation with the reference metric. Hand-worn sensor has better correlations when doing the complex task, while the forearm-worn sensor is better when doing the simple task ($r > 0.9$). This suggests that the hand worn sensor is a preferable option in daily life. However, from the perspective of user friendliness, the forearm or wrist could be the preferred location.

### 4.4 Future Work

Following from the discussion above, recommendation for the future research can be done. No feasibility study on stroke patients has been done in our work. We collected the data from healthy subjects and assigned typical tasks to mimic the stroke patients. Further validation with patients is required. Besides, both the two phases experiments require the subject to do the tasks without any ambulatory activities, either in standing or sitting position. The hand-worn sensor is sensitive to any kind of movements, e.g. the arm swinging during the ambulatory. These movements are inevitable for the patients during their daily life. Further exploration on this topic should is also worth to pay attention.

## 5 CONCLUSIONS

Daily-life monitoring for stroke patients is essential for the rehabilitation therapy. Efficient and convenient remote rehabilitation system is necessary for the patients in the home environment. One of the challenges in the analysis of patients' daily-life performance, compared to the assessment through standardized clinical tests in the hospital environment, is the development of metrics for quantifying the movements at home. In this work, we proposed a metric that combines both the motion's smoothness and the quantity together to describe arm usage. In order to validate the metric, we put forward normalized gross energy consumption to evaluate the physical energy during the movement. WAC uses a single sensor setup and is desirable as the convenience and usability it provides to the stroke patients. The results of both the simple 2D task and complex 3D task show good performance (>0.9) when compared to NGEC. WAC value also has relationship with motion types, which provides possibility for detailed monitoring of patients' daily rehabilitation.

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## REFERENCES

Aleshinsky, S. Y. (1986). An energy 'sources' and 'fractions' approach to the mechanical energy expenditure problem–i. basic concepts, description of the model, analysis of a one-link system movement. *Journal of Biomechanics*, 19(4):287–293.

Bouten, C. V., Westerterp, K. R., Verduin, M., and Janssen, J. D. (1994). Assessment of energy expenditure for physical activity using a triaxial accelerometer. *Medicine & Science in Sports & Exercise*, 26(12):1516–23.

Burke, J. W., Mcneill, M. D. J., Charles, D. K., Morrow, P. J., Crosbie, J. H., and Mcdonough, S. M. (2009). Optimising engagement for stroke rehabilitation using serious games. *Visual Computer International Journal of Computer Graphics*, 25(12):1085–1099.

Bussmann, J. B., Martens, W. L., Tulen, J. H., Schasfoort, F. C., Hj, B. E., and Stam, H. J. (2001). Measuring daily behavior using ambulatory accelerometry: The activity monitor. *Behavior Research Methods Instruments & Computers*, 33(3):349–356.

Hale, L. A., Pal, J., and Becker, I. (2008). Measuring free-living physical activity in adults with and without neurologic dysfunction with a triaxial accelerometer. *Archives of Physical Medicine & Rehabilitation*, 89(9):1765–1771.

Janz, K. F. (1994). Validation of the csa accelerometer for assessing children's physical activity. *Medicine & Science in Sports & Exercise*, 26(3):369–75.

Klaassen, B. (2015). A system for monitoring stroke patients in a home environment. In *Biostec Healthinf*, pages 125–132.

Klaassen, B., Bartels, P. G. H., Beijnum, B. J. F. V., and Hermens, H. (2016). The development and evaluation of an arm usage coach for stroke survivors. In *International Conference on Sensing Technology*.

Leuenberger, K., Gonzenbach, R., Wachter, S., Luft, A., and 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.

Lyle, R. C. (1980). A performance test for assessment of upper limb function in physical rehabilitation treatment and research. *International Journal of Rehabilitation Research*, 4(4):483–492.

Madgwick, S. O., Harrison, A. J., and Vaidyanathan, A. (2011). Estimation of imu and marg orientation using a gradient descent algorithm. In *IEEE International Conference on Rehabilitation Robotics*, pages 1–7.

Roetenberg, D., Luinge, H., and Slycke, P. (2009). Xsens mvn: Full 6dof human motion tracking using miniature inertial sensors. *Xsens Motion Technologies Bv*.

Rohrer, B., Fasoli, S., Krebs, H. I., Hughes, R., Volpe, B., Frontera, W. R., Stein, J., and Hogan, N. (2002). Movement smoothness changes during stroke recovery. *Journal of Neuroscience*, 22(18):8297–8304.

Sanford, J., Moreland, J., Swanson, L. R., Stratford, P. W., and Gowland, C. (1993). Reliability of the fugl-meyer assessment for testing motor performance in patients following stroke. *Physical Therapy*, 73(7):447–54.

Schasfoort, F. C., Bussmann, J. B. J., and Stam, H. J. (2002). Ambulatory measurement of upper limb usage and mobility-related activities during normal daily life with an upper limb-activity monitor: A feasibility study. *Medical & Biological Engineering & Computing*, 40(2):173–182.

Uswatte, G., Foo, W. L., Olmstead, H., Lopez, K., Holand, A., and Simms, L. B. (2005). Ambulatory monitoring of arm movement using accelerometry: an objective measure of upper-extremity rehabilitation in persons with chronic stroke. *Archives of Physical Medicine & Rehabilitation*, 86(7):1498–1501.

Uswatte, G., Miltner, W. H., Foo, B., Varma, M., Moran, S., and Taub, E. (2000). Objective measurement of functional upper-extremity movement using accelerometer recordings transformed with a threshold filter. *Stroke*, 31(3):662–667.

Van Meulen, F. B., Klassen, B., Held, J., Reenalda, J., Buurke, J. H., Van Beijnum, B.-J. F., Luft, A., and Veltink, P. H. (2015). Objective evaluation of the quality of movement in daily life after stroke. *Frontiers in Bioengineering and Biotechnology*, 3(210):1.

van Meulen, F. B., van Beijnum, B. F., Buurke, J. H., and Veltink, P. H. (2017). Assessment of lower arm movements using one inertial sensor. In *International Conference on Rehabilitation Robotics*, pages 1407–1412.

Xu, J., Wang, Y., Barrett, M., Dobkin, B., Pottie, G. J., and Kaiser, W. (2016). Personalized, multi-layer daily life profiling through context enabled activity classification and motion reconstruction: An integrated systems approach. *IEEE J Biomed Health Inform*, 20(1):177–188.

Zaman, K. I., White, A., Yli-Piipari, S. R., and Hnat, T. W. (2014). K-sense: Towards a kinematic approach for measuring human energy expenditure. In *Wireless Sensor Networks: 11th European Conference*, volume 8354, pages 166–181.