One Inertial Sensor Based Upper Extremity Usage Measurement and Standard

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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. Recent years, with the development of wearable inertial sensor technology, the unobtrusive monitoring of patients becomes possible in the home environment. In order to make the monitoring system more suitable for clinical practice and daily life assessment, reduction of the number of sensors is also needed. In this article we address the monitoring of arm usage and proposed a new metric called Weighted Activity Counts(WAC) based on a sensing system which consists of only one inertial measurement unit (IMU). The proposed metric combines activity counts and the smoothness of the movement. The smoothness is defined by combining the angle variances of the motion. Because of the lack of a gold standard on arm usage, in this study, we define Normalized Gross Energy Expenditure (NGEC) as the standard. WAC shows good performance under the validation protocol we designed (r>0.90). In this research, we also found that the wrist is the optimal setting placement for the single sensor which can sufficiently and reliably describe arm usage.**

Index Terms—**arm usage, metric, smoothness, energy, rehabilitation.**

I. Introduction

THE main goal in the rehabilitation process of patients with stroke and central neurological disorders is to achieve optimal motor performance enabling patients to live independently with maximum freedom of movement. In current clinical practice of stroke rehabilitation, researchers use the standardized clinical tests and functional motion tasks to assess the capacity of stroke patients, for example, Fugl-Meyer Assessment put forward by Stanford et al. [1] and The Postural Assessment Scale for Stroke patients (PASS) [2]. To provide clues for patients' functional performance and formulate the arm usage when they back home, these tests are done regularly during the entire rehabilitation process [3]. However, after the patients returning home, it's hard for the physicians to master necessary rehabilitation information about the intensity and quality of a patient's daily-life activities [4]. Therefore, it's necessary for researches to build an unobtrusive and modular system for objectively monitoring the patient's upper or lower extremity motor function in daily-life activities, which is vital for the optimal guidance of rehabilitation therapy. The use of the upper extremity, especially arms and hands, is very important in performing activities of daily living. Therefore, upper extremity function is a key Activities of Daily Living(ADL) factor and seen as a high research priority in rehabilitation [8]. In this work, our main focus will be on the upper extremity motions of the patients and the optimal placement of the sensor.

In that case, metrics need to be used that quantify the movements in the home environment. The use of an inertial measurement unit (IMU) is a feasible method for the assessment of body movements in a daily life setting [5][6][7]. IMUs combine accelerometers, gyroscopes, magnetometers and also do not require an external physical reference system to estimate the movement which in particular makes the use of IMUs suitable for measurements in a daily life setting [7]. Several IMUs based acceleration vectors have been put forward as metrics to describe the upper extremity movements. In the INTERACTION project, a sensor system was developed, based on inertial, strain, goniometer, pressure and EMG sensors, for monitoring Stroke patients during daily life activities [19]. Klaassen et al. extended the project by developing an Arm Usage Coach, which stimulates the patients affected arm to be used more often at home. In the arm usage couch(AUC) system [8], 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). This method takes the integral of the absolute values of the acceleration measured by the accelerometer [9]. Both the two metrics have not been validated with the correspondent arm usage standards by using only one inertial sensor. Another most widely used methods has been put forward by Leigh et al., who use the mean acceleration (in m/s^2) for each of the 3 planes

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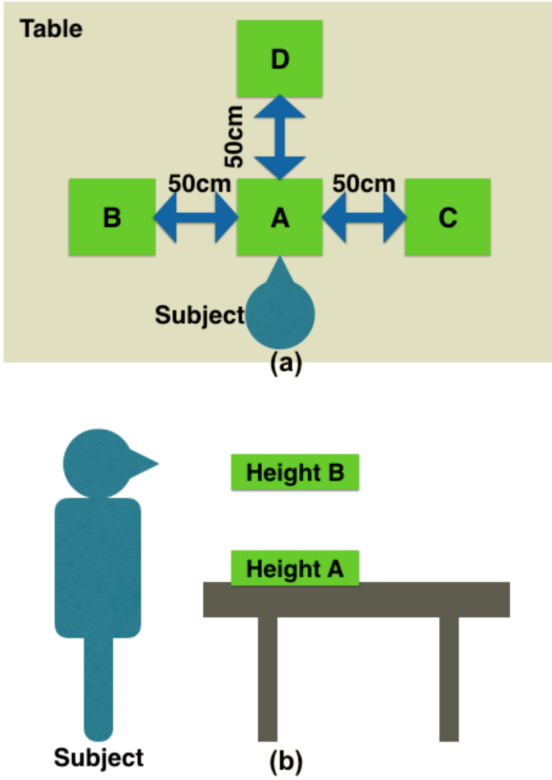

Fig. 1. Protocol Phase One. The figure (a) is the top-down view of the different position on the table with a participant seated on a stool. The figure (b) is the overview of the different heights above the table with the subject standing in front of the table.

(vertical (x), anteroposterior (y), and mediolateral (z)) across set 1-second or 1-minute intervals and present these data in a digital format which called activity counts(AC) as the metric to measure the amount of the arm usage [10]. However, Kaspar et al. suggest that AC provides quantitative rather than qualitative information [11]. Smoothness is a characteristic of coordinated human movements. According to Rohrer et al., patients' movements seem to grow smoother with recovery [13]. It has been proved that the smoothness is a result of learned coordination from the studies done by Rohrer et al. In the rehabilitation process, patients motion quality especially the smoothness can be different which consequently requires the changes of treatment programs. Thus, the smoothness of the movement is included in the proposed metric. In our work, we proposed a new metric called Weighted Activity Counts(WAC) to fuse the quality of the upper extremity with the conventional AC and also designed a 3D experiment protocol to prove the sufficiency of the metric.

In literature, no gold standards of arm usage have been put forward. Commonly there are few standards which are used by researchers, such as the travel distance of the arms. In our study, we use a reference based on the law of conservation of mechanical energy: the mechanical energy is defined by te sum of the potential and kinetic energy. we set the Normalized Gross Energy Consumption as the standard. The proposed standard is also based on one sensor, and able to evaluate the gross arm usage. In this study, we validate the proposed metric (WAC) as a measure of arm usage quality, and compare it with other four state-of-the-art metrics.

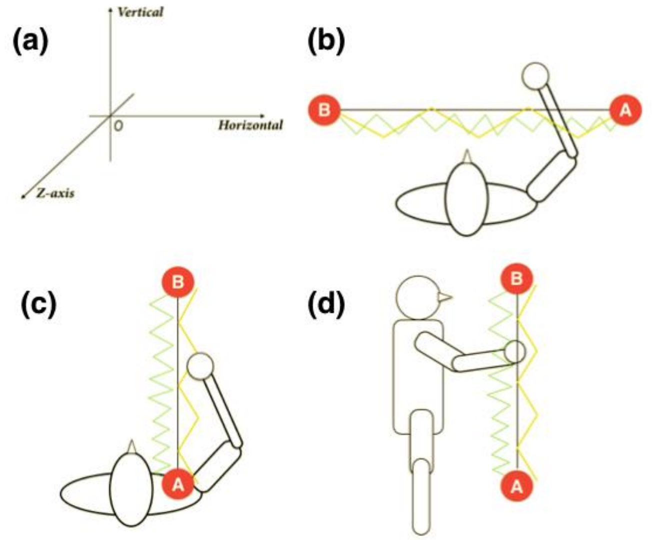

Fig. 2. Protocol Phase Two. The figure (a) is the coordinate frame of all the experiments. The figure (b) is the top view of horizontal task, the subject was in stable sitting position. The figure (c) is the side view of vertical task, the subject was in stable standing position to avoid bending their upper body. The figure (d) 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)

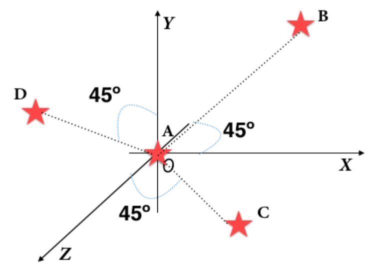

Fig. 3. Complex task. Subjects were asked to move the object from A to B, C, D separately with three different motion types (normal, light tremble, heavy tremble).

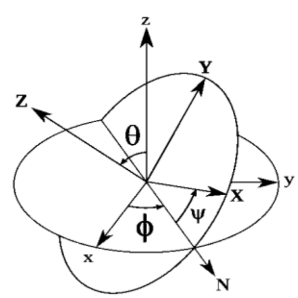

Fig. 4. The definition of φ, θ, and ψ in Euler angle.

The remainder of the paper is organized as follows. Section 2 discusses the rationale of the metric and standard we proposed. Section 3 describes the 3D experiment protocol which was used to evaluation the method. The comparison of results among different methods are given in Section 4. Section 5 presents the discussion based on the experiments result. Finally, conclusions are given in Section 6.

II. Method

In this section, the methods are described. This comprises the measurement configuration, two-phase experimental protocol and the processing procedure (including pre-processing, the calculation of the metrics and golden standards).

A. Measurement Configurations

The device we used in our experiment is Xsens MVN suit. 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. 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 [20].

B. Experimental Protocol

A total of 12 healthy subjects (24±4 years old) volunteered to participate in the study. We set two groups to take part in the two phases of our designed protocol separately to mimic the different motion types in the whole rehabilitation procedure. The first seven subjects were divided into group one and the other five were group 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.

Based on Fig.1 (a), the following motion sequences are performed:

(#1) A—B—A—C—A—D—A;

(#2) B—C—D—B—D—C—B;

(#3) pick up 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 Fig.1 (b), the motion sequences can be grouped into the following three sections:

(#4) Lift 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;

(#5) at height A, move object A—B—A—C—A;

(#6) 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.

For the second part of our protocol (Fig. 2), this part consists of a horizontal task, vertical task, front& back task and complex task (the direction can be seen in Fig. 3). In the first three task, subjects were asked to move a small ball from point A to point B along different routes (black, orange, green line in Fig. 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 (Fig. 4) and also with three motion types (normal, light tremble and heavy tremble). The routes in the fourth task were randomly selected by the subjects in order to mimic the patients. All the tasks were done three times. Before each task, there will be some rest time for the

subjects which the data is not counted during the calculation of metrics and energy consumption.

C. Weighted Activity Counts

We choose the smoothness of the movement as the quality indicator which can also reflect the patients' status of recovery. Meanwhile, Euler angle is commonly used in the description of the fixed-point motion, and also has been validated by Huiyu Zhou et al. in the upper limb motion tracking test [14]. Decomposition of the complicated motion makes it possible to use Euler angle 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. [15] 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 eventual drift in a vertical plane [11]. In this algorithm, we have to set the weighting of the accelerometer measurements in the error correction β according to the definition [15]:

$$\beta = \sqrt{\frac{3}{4}}\,\widetilde{\omega}_{max} \quad \textbf{(1)}$$

Where the $\widetilde{\omega}_{max}$ represents the maximum gyroscope measurement error of each axis which depend on the sensor's feature. In our work, based on Xsens sensor system, we set β as 0.03 according to the work done by Madgwick et al. where the optimal value of β was explored. 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 β, which is removed in the direction based on accelerometer and magnetometer measurement. [15] The filter outputs orientation in a quaternion representation $\mathbf{q} = [q_0, q_1, q_2, q_3]$. The Euler angle can then be computed as [15]:

$$\begin{bmatrix}\varphi\\ \theta\\ \psi\end{bmatrix} = \begin{bmatrix} arctan\dfrac{4(q_0q_1+q_2q_3)}{1-2(q_1^2+q_2^2)}\\ \arcsin(2(q_0q_2-q_1q_3))\\ arctan\dfrac{4(q_0q_3+q_1q_2)}{1-2(q_2^2+q_3^2)}\end{bmatrix} \quad \textbf{(2)}$$

The definition of φ, θ and ψ can be seen on Fig. 4.

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. To be specific, we define the Smoothness Degree (SD) during the movement period *N* (defined below) as:

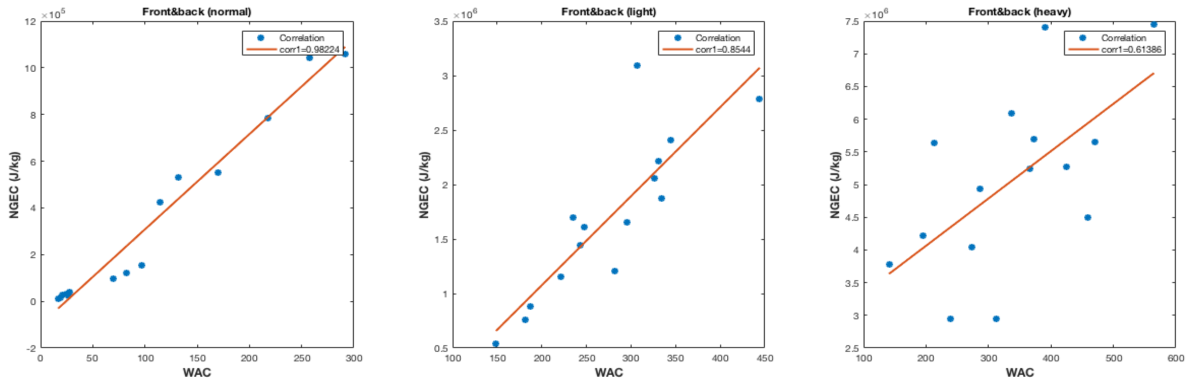

Fig. 6. Relationship between metric WAC and standard NGEC (front & back task, normal, light tremble, heavy tremble motion style). The data is from the hand-worn sensor.

$$SD = \frac{variance(\varphi)+variance(\theta)+variance(\psi)}{3} \quad \textbf{(3)}$$

According to Eq. 3, when the movement obtains huge variance value in of φ, θ or ψ then SD value can also be large correspondingly, which represents the movement contains certain degrees of tremble on one or more directions. The estimated SD will be added as the weight of conventional Activity Counts(AC). AC for epochs are calculated by Eq. 4 adapted from [16]:

$$AC = \frac{1}{N}\sum_{n=1}^{N}\sqrt{a_x[n]^2 + a_y[n]^2 + a_z[n]^2} \quad \textbf{(4)}$$

where in our research $N = f_s \bullet Epoch$; 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.

Using the above, the Weighted Activity Counts(WAC) is defined as:

$$WAC = SD \bullet AC \quad \textbf{(5)}$$

In this equation, WAC combines the movement's quality SD and the intensity AC together to capture the missed motion details (smoothness).

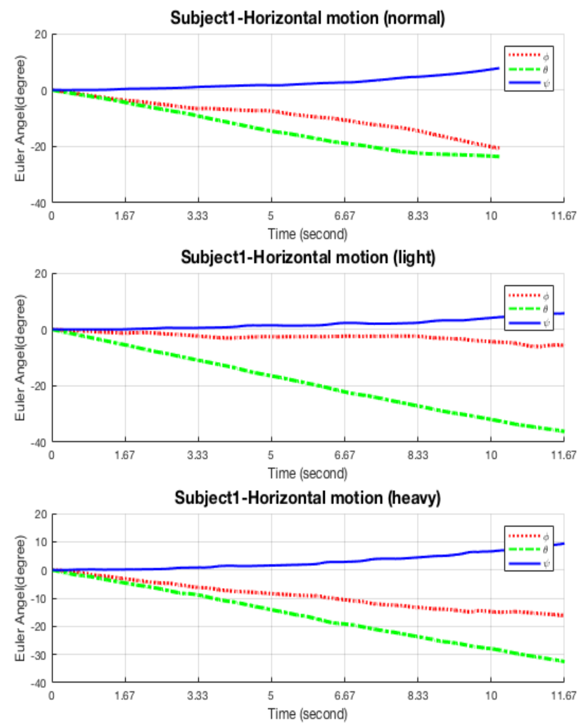

Fig. 5. Euler angle comparison when subject1 doing vertical test in three different motion types. The unit of the angle is degree. The data is from hand-worn sensor.

D. Difference Acceleration Vector

In order to detect movement of the arm by using 3D accelerometers, a certain metric has to be defined. Researchers created a new metric called the Difference Acceleration Vector (DAV). The length of the DAV is calculated by subtracting a reference gravitational acceleration vector *g(t)* from the current acceleration vector *a(t)* and taking the norm of the resulting vector. The length of the DAV, called "d(t)" is defined as followed:

$$d(t) = \frac{1}{N}\sum_{n=1}^{N}\sqrt{\left(a_x[n]-g_{x,t_0}\right)^2 + \left(a_y[n]-g_{y,t_0}\right)^2 + \left(a_z[n]-g_{z,t_0}\right)^2}$$

for more details about DAV, please refer to [6].

E. Normalized Gross Energy Consumption

Reduction of the number of sensors needed to evaluate arm movements, makes a system for the assessment of human body movements more suitable for clinical practice and daily life assessments [7]. IMUs based body motion energy calculation method has been put forward by Aleshinsky et al. [17] and Zaman et al. [18]. In order to simplify the system and make it possible to be used in obtrusive monitoring, we proposed Normalized Gross Energy Consumption (NGEC), which is based on the work done by Aleshinsky et al. [17] which calculate the kinetic energy consumption by using Eq. 6:

$$E_{kin} = \sum_{n=1}^{N}\frac{1}{2}m\left|v_{2n}^2 - v_{1n}^2\right| \quad \textbf{(6)}$$

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 separately. In order to evaluate the gross energy consumption, we expand Eq. 6 as:

$$E_{tot} = \sum(E_{kin} + E_{pot}) = \sum[\tfrac{1}{2}m|v_{2n}^2 - v_{1n}^2| + mg(h_{2n} - h_{1n})] \quad \textbf{(7)}$$

where h_{2n} and h_{1n} represents the final and end sensor position in global frame at each adjacent point during the whole movements, v_{2n} and v_{1n} represents the final and end sensor velocity at each adjacent point also, during the whole procedure.

In the calculation of both of these energies, the mass is needed. This mass is not only the mass of the object, but also the mass of the arm. Since this mass is unknown and differs per subject, it is also possible to calculate the specific energy in J/kg by dividing out the mass. The formula for this specific energy becomes thus:

$$NGEC = \frac{E_{tot}}{m} \quad \textbf{(8)}$$

In this work we choose to use NGEC as arm usage standard to measure the upper arm movements together with WAC as the metric. In the following section, we compare the WAC with the other four metrics (IAA, RMS, AC, DAV) under two different golden standards (travel distance and the NGEC)

F. Pre-processing

Since inaccuracies of an IMU such as noise, nonlinearity, bias is factored in the sensor unit [21], before calculating the metrics using the formula to calculate the metrics and the standards, we have to apply specific filter methods on the metrics respectively. The choice of the filter method depends on the feature being estimated. [22]

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. On the contrary, the root mean square (RMS) of the signal was calculated by after band-pass filtering (finite impulse response, 0.3–16Hz). Bussmann et al. [22], proposed this metric to measure upper-limb use from accelerometer data of the upper limb and intensity. 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 [23]. Finally, the NGEC is estimated after acceleration data from the sensors was high-pass-filtered at 0.3Hz in order to reduce the influence of gravity.

III. Result

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

A. Metrics Comparison

Fig. 5 shows an example of hand's orientation from subject one's first measurement while performing horizontal task in three different motion types by using gradient descent orientation filter method. And Table 6 shows the SD value of the three measurements.

Further, by using Eq. 5, combined with the acceleration data, we can get the value of AC and ultimately, WAC. Fig.7 is made in order to compare the different WAC value among different motion types in each task. To validate our proposed metric, we analyze the result by analyze the two phases in our protocol separately.

1. Phase One

In phase one, we compare the proposed metric WAC with the other four state-of-art metrics, including AC, DAV, IAA, RMS. First, we choose to set the proposed NGEC as the arm usage standard and calculate the correlation value. The result is shown in Table 1.

TABLE 1
CORRELATION COMPARISON AMONG DIFFERENT METRICS (BASED ON THE SAME STANDARD, NGEC), HAND-WORN SENSOR, R > 0.7 IS MARKED IN BOLD.

Seq	#1	#2 & #3	#4	#5	#6
WAC	**0,8204**	**0,8964**	**0,9049**	**0,9053**	**0,9489**
AC	0,4417	0,3925	0,4613	0.5122	0,4733
DAV	0,0975	0,5733	0,5637	0,1910	0,2144
IAA	**0,9302**	**0,7288**	**0,8340**	**0,9258**	**0,9213**
RMS	0,1527	0,0687	0,133	0,0584	0,0386

Besides, we compare the correlation values between WAC and the other two traditional golden standard (travel distance and mechanical energy). The results can be found in Table 2.

TABLE 2
CORRELATION COMPARISON AMONG DIFFERENT STANDARDS (BASED ON THE SAME METRIC, WAC), HAND-WORN SENSOR, R > 0.7 IS MARKED IN BOLD.

Seq	#1	#2&#3	#4	#5	#6
WAC_Energy	**0,7404**	**0,8513**	**0,8687**	**0,9062**	**0,9815**
WAC_Distance	0,1222	0,1231	0,1473	0.0567	0,5399

Finally, we group the six sequences by the degree of difficulty of the motions. 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. We calculate the WAC value separately and compare them in Fig. 8. During phase one, we are able to testify the performance of WAC under different golden standards. All the six motion sequence shows that WAC and RMS reach the highest correlation value among all the five metrics.

2. Phase Two

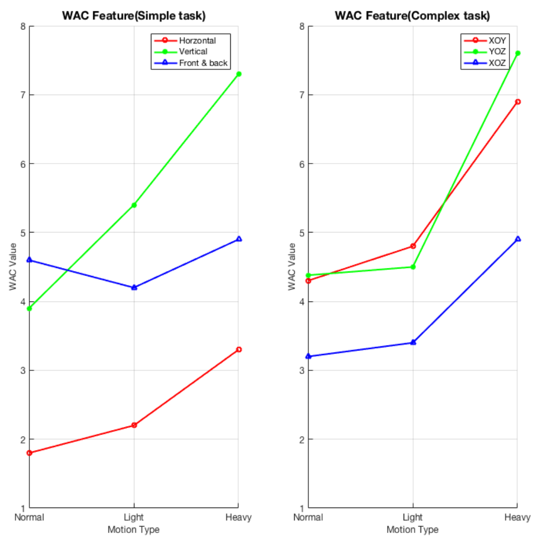

Fig. 7. WAC value comparison with the motion type. (left figure, simple task; right figure, complex task). The data is from the hand-worn sensor.

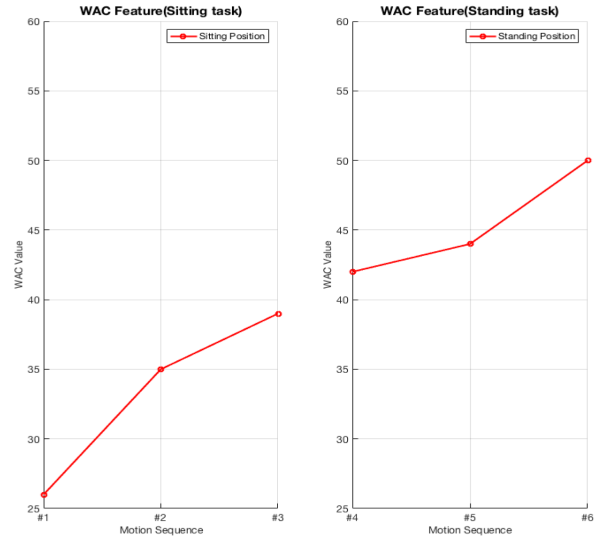

Fig. 8. WAC value comparison with the motion type. (left figure, sitting task; right figure, standing task). The data is from the hand-worn sensor.

In this phase, firstly, based on the metrics WAC and arm usage standard NGEC we proposed, we apply the novel method on all five subjects' experiments data. The relationships between WAC and NGEC for horizontal, vertical, front& back task can be seen in Fig. 6. The linear regression result can also be seen in the figures. The correlation value when doing different tasks are compared in Table 3 with the outstanding value (r>0.7) marked in bold. We also display the performance of the other four conventional metrics in Table 3.

TABLE 3
CORRELATION COMPARISON AMONG DIFFERENT METRICS (BASED ON THE SAME STANDARD, NGEC), HAND-WORN SENSOR, R > 0.7 IS MARKED IN BOLD.

Position	Horizontal	Vertical	Front& back	XOY	YOZ	XOZ
WAC	**0,7187**	**0,8722**	**0,8193**	**0,9910**	**0,9599**	**0,9295**
AC	0,0073	0,2489	0,3843	0.0483	0,1025	0,1423
DAV	0,5266	0,6835	0,1272	0,2612	0,1585	0,1770
IAA	**0,8419**	**0,8710**	**0,9748**	**0,9387**	**0,9357**	**0,9230**
RMS	0,0086	0,5037	0,0211	0,1779	0,2063	0,0589

After that, we compare the performance of WAC under two conventional standards (travel distance and mechanical energy). The results are summarized in Table 4.

Finally, we compare the correlation value (WAC under NGEC standard) among different motion types (normal, light tremble, heavy tremble) in Table 5.

TABLE 4
CORRELATION COMPARISON AMONG DIFFERENT STANDARDS (BASED ON THE SAME METRIC, WAC), HAND-WORN SENSOR, R > 0.7 IS MARKED IN BOLD.

Position	Horizontal	Vertical	Front& back	XOY	YOZ	XOZ
WAC_Ene	**0,7492**	**0,8345**	**0,7697**	**0,8432**	**0,8971**	**0,9460**
WAC_Dist	0,0566	**0,8728**	**0,7412**	0.6319	0,4284	**0,7068**

TABLE 5
CORRELATION COMPARISON AMONG TASKS AND MOTION TYPES. (R >0.9 IS IN BOLD)

Task	Normal	Light	Heavy	Total
Horizontal	**0,9713**	0,7339	0,3257	0,7187
Vertical	0,8807	0,4479	0,5267	0,8722
Front& back	**0,9820**	0,8635	0,6070	0,8193
XOY	**0,9617**	**0,9229**	0,7638	**0,9910**
YOZ	**0,9260**	**0,9553**	**0,9646**	**0,9599**
XOZ	**0,9481**	0,8733	**0,9428**	**0,9295**

TABLE 6
CORRELATION COMPARISON AMONG SENSOR PLACEMENTS AND TASK (ALL FIVE SUBJECTS, ALL KINDS OF MOTION TYPES), R >0.9 IS IN BOLD

Position	Horizontal	Vertical	Front& back	XOY	YOZ	XOZ
Hand	0,7187	0,8722	0,8193	**0,9910**	**0,9599**	**0,9295**
Forearm	**0,9005**	**0,9558**	**0,9883**	**0,9813**	0,8612	**0,9115**
Upper-arm	0,8309	0,7794	**0,9968**	**0,9772**	0,7983	**0,9882**

TABLE 7
VARIANCE OF EULER ANGLE (HORIZONTAL TEST)

status	**ϕ**	**θ**	**ψ**	**Average(SD)**
Normal	4.1024	6.3556	0.0545	**3.5041**
Light	1.2349	28.3200	0.2620	**9.9390**
Heavy	8.6496	35.4707	0.6467	**14.9223**

B. Optimal Sensor Placement

Finally, in order to explore the optimal position of the sensor, the same processing procedure were done by using the data from forearm and upper arm. The results can be seen in Table 6.

IV. Discussion

A. Validation of the metrics

In our research, we propose a novel metric named Weighted Activity Counts (WAC) which is an extension of conventional metric AC. The proposed metric WAC is able to tell us more information about the movement. The AC derived from the acceleration signals provide quantitative information about arm usage, such as the intensity of the arm use. However, AC is not able to reflect the quality especially the smoothness degree of the movements. Both the normal person and the patient may have the same AC value but with totally different movement quality. Consequently, it's impossible to use AC to describe the different when the patients are getting better. Even though we can use more sensors to detect the accurate position of the arms, it may negatively impact patient compliance. In that case, WAC is put forward to using SD as the index of the movements. According to Fig. 5 and Table 7 we can clearly see the huge different variance of different motion types.

When the SD is large, then the patient's movement may have a large tremble. Thus, when considering about different kinds of movement, from Fig. 7 and Fig. 8, we are able to find the trend of WAC with the movements become less smooth, the WAC will become large correspondently. Also, in Fig. 7, we are capable of detecting the motion type by WAC, for example, when the subjects are doing the horizontal test, the WAC value is less than 3. On the contrary, when WAC is more than 7, the subjects may probably do the front & back test. Therefore, WAC make it possible to detect or identify the movements and the motion type (normal, light tremble or heavy tremble).

From section III, we also compare the performance among the state-of-art metrics. When setting NGEC as the standard, in the first experiment (*Phase One*), the WAC and IAA reach the highest correlation values (Table 1). The conclusion is the same when setting the other two conventional golden standards. For the *Phase Two*, the comparison among different metrics is shown in Table 3, in which the WAC is compared with IAA, DAV and conventional activity counts. The outstanding value is marked in bold. Basically, both the IAA and WAC have good performance. IAA have been validated by Bouten et al. in 1994. The result is about the same as what we get here that IAA have good correlation with the energy expenditure. Moreover, when taking a close look at the value, we can find IAA is better when assessing simple movement. Howbeit, the real-world activities can be more complicated than the protocol we designed. Hence, WAC is still more proper for practical measurement based on the extraordinary performance in our research.

From Fig.8, in the *Phase One*, we divide the motions by their features (distance or difficulty). It's also able for us to classify the motion type when using WAC to describe the motion. Generally, when the motion is more complicated, the WAC value will be higher even in different tasks which shows great adaptive feature of the proposed metric. To end this part, WAC can reflect not only the motion features but also has been proved to be useful to describe the motion details. However, the limitation of WAC should be emphasized. From Table 7, WAC is able to give an indication of quality but cannot tell which axes the movement is largest. From the second row (light tremble), the mean value of the variance is only 10 where the largest value (theta) is missed. In this work, we proposed NGEC as the standards of the movements which in fact, reflects the energy changes during the movements. When the subject doing strenuous exercises, they will consume more energy. Compared with an automated respiratory gas analyzer, this method can only evaluate the gross energy expenditure. When we utilize the other two conventional standards, mechanical energy and travel distance, we are capable to find that WAC has good performance (>0.7).

B. Validation of the proposed method

When considering about both the metric and the standard, from Table 5, which is the comparison between different tasks and motion types in phase two, we can easily find that the average correlation value between the metric WAC and NGEC is more than 0.8. To be more specific, the highest value 0.99 appears when measuring the *xoy* plane movements while the lowest value 0.3257 when just considering about the horizontal task with heavy tremble. Overall, the 3D plane measurement is closer to the real life's motion so it can better test the performance of WAC and NGEC. From the table we can see that all the three-plane task show good correlation (>0.9) based on our method. In that case, the 3D result indicates the possibility of using WAC and NGEC to measure the daily life upper-extremity movements. In the simple task, it's more possible to appear low correlation value (<0.5) when measure single motion type. With the increase of complexity of the task, the result shows higher correlation. As we know, according to Brandon Rohrer et al.'s work, patients' movements seem to grow smoother with recovery [11], in that case, our proposed metric may perform well when describing the whole rehabilitation procedure. When comparing WAC and NGEC, WAC has lower computational complexity and higher interpretability. Different from WAC, which relies on only one sensor to be calculated, NGEC need extra sensor in order to estimate the distance travelled by the arms. Besides, WAC is able to combine the typical feature of AC and motion smoothness which makes it suitable to be set as the metrics in our methods.

C. Optimal position for the sensor placement

One sensor-based system makes the assessment of the patients' movements in the home environment more reliable and accessible. The optimal position of the sensor, therefore, is an essential problem for the researchers. According to Table 6, we compare the correlation value when putting the single sensor in different places of the subjects' strong arm. All in all, all the three positions can describe part of the movements. Hand-worn sensor has better performance when doing the complex task, while the forearm-worn sensor can do better when doing the simple task (>0.9). Common sense suggests that when doing the complex task, the whole upper extremity is going to change its position largely which can help us to understand the result showed in the Table 7. Both the WAC and NGEC are calculated by using the data from the same sensor, consequently, the correlation value represents the segment's movement but not the whole arm's movement. To consider about all kinds of movements (simple and complex), the better choice of the sensor can be the joint between the hand and the arm, which is actually, the wrist.

D. Limitations of our work

Following from the discussion above, recommendation for the future research can be done. Firstly, in our work, we choose to use Madgwick et al.'s gradient descent orientation filter to calculate the Euler angle. This algorithm is really sensitive to the error parameter β which will result in unreliable result of the experiments. Therefore, more algorithm should be explored in order to improve the performance. For example, Fokke et al. have put forward related algorithm based on single sensor [7] which is worth to try. Finally, the energy consumption of the whole system should also be evaluated before applying on the system on chip equipment.

V. Conclusion

In this work, we proposed a new metric which combines both the motion's smoothness and the quantity together to describe arm usage. Meanwhile, in order to validate the metric, we put forward normalized gross energy consumption to evaluate the expenditure during the movement. The results of both the simple 2D task and complex 3D task show good performance (>0.9) of the metric which indicates the sufficiency of the metric and the arm-usage standard. Besides, wrist-worn sensor is also an ideal choice for the placement of the single sensor.

Abbreviation

AC, activity counts; WAC, weighted activity counts; NGEC, normalized gross energy consumption; RMS, root mean square; AUC, arm usage couch; DAV, difference acceleration vector; IAA, absolute value of acceleration.

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