The Use of a Finger-Worn Accelerometer for Monitoring of Hand Use in Ambulatory Settings

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***Abstract*—Objective assessment of stroke survivors' upper limb movements in ambulatory settings can provide clinicians with important information regarding the real impact of rehabilitation outside the clinic and help to establish individually-tailored therapeutic programs. This paper explores a novel approach to monitor the amount of hand use, which is relevant to the purposeful, goal-directed use of the limbs, based on a body networked sensor system composed of miniaturized finger- and wrist-worn accelerometers. The main contributions of this paper are twofold. First, this paper introduces and validates a new benchmark measurement of the amount of hand use based on data recorded by a motion capture system, the gold standard for human movement analysis. Second, this paper introduces a machine learning-based analytic pipeline that estimates the amount of hand use using data obtained from the wearable sensors and validates its estimation performance against the aforementioned benchmark measurement. Based on data collected from 18 neurologically intact individuals performing 11 motor tasks resembling various activities of daily living, the analytic results presented herein show that our new benchmark measure is reliable and responsive, and that the proposed wearable system can yield an accurate estimation of the amount of hand use (normalized root mean square error of 0.11 and average Pearson correlation of 0.78). This study has the potential to open up new research and clinical opportunities for monitoring hand function in ambulatory settings, ultimately enabling evidence-based, patient-centered rehabilitation and healthcare.**

***Index Terms*—Finger-worn ring sensor, upper limb function, hand function, stroke, rehabilitation, remote monitoring.**

I. Introduction

STROKE is the third most frequent cause of death and a leading cause of disability in adults in the United States [1]. Approximately 50% of stroke survivors suffer from upper limb impairments in the chronic phase, which can be more prominent in one of the two limbs (affected vs. less affected limbs) [2]. Upper limb impairments after stroke often lead to limited ability to perform activities of daily living (ADL) and negatively impact the overall quality of life [3].

In conventional clinical settings, therapists periodically meet with patients in the clinic and prescribe appropriate rehabilitation exercise programs based on their evaluation of patients' functional capacity using clinically validated motor tests, such as Fugl-Meyer Assessment, Active Research Arm Test, or Wolf Motor Function Test [4], [5]. Unfortunately, scientific evidence shows that functional improvements observed and achieved in the clinic do not always translate to patients' home and community settings [6]. In other words, stroke survivors may show improvement in *capacity* (i.e., what they are capable of doing) without much change in *performance* (i.e., what they actually do) [6], [7]. Therefore, objective, ambulatory assessment of motor performance of the stroke-affected upper limb has been of paramount importance in estimating the real impact of rehabilitation, and to support patient-driven therapy and self-management of conditions [8].

Wrist-worn accelerometers have emerged as a potential solution to unobtrusively and continuously monitor patients' upper limb performance outside clinical settings for a long-term period [9]–[11]. Wrist-worn sensors focus on quantifying the duration and intensity (i.e., amount) of arm use based on the counts of the acceleration magnitude [12]. Although these metrics provide simple and intuitive quantification, they capture primarily gross arm movements, such as passive arm swings during walking, which are less relevant to the goal-directed use of the stroke-affected upper limb as part of patients' essential ADL [13]. Consequently, these measurements often result in inaccurate quantification of motor performance [8], [13]. This is considered as a major obstacle to translating research findings into clinically meaningful information and facilitating their widespread use in the therapeutic setting [8].

As an alternate approach to address this limitation of wrist-worn accelerometers and capture more goal-directed use of the upper limbs, researchers have proposed to monitor the hand function during ADL. Various wearable devices, such as instrumented gloves and goniometers, have been introduced to assess the hand function (i.e., amount of hand use) [14], [15]. However, these devices are usually difficult to don and doff, uncomfortable to wear, and socially unacceptable for long-term and continuous daily use, and thus, were mainly restricted to laboratory

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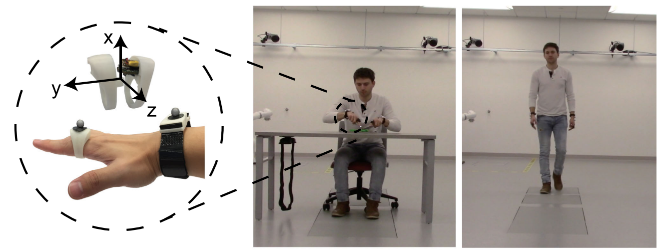

(a) (b)

Fig. 1. (a) The proposed body-networked sensor system composed of a finger-worn and a wrist-worn sensor. (b) A research staff member demonstrating a subset (e.g., cutting-putty and walking) of the 11 ADL that was performed during our data collection.

settings [16]. More recently, Friedman *et al.* proposed a wrist-worn device that can monitor daily use of the wrist and finger joints by measuring changes in the magnetic field produced by a magnetic ring [16]. Despite its feasibility of use in real-world settings, this sensor might be susceptible to ambient magnetic noise.

In this paper, we investigate the use of a miniaturized finger-worn accelerometer, combined with a wrist-worn accelerometer, to monitor hand performance in remote settings by measuring the amount of hand use. Our main contributions are two-fold. First, there exists no established quantitative measurement for the true amount of hand use during the performance of ADL, against which our sensing system needs to be validated. Hence, we introduce a new benchmark measure of the amount of hand use based on data obtained from an optoelectronic motion capture system, the gold standard for human movement analysis. We validate the test-retest reliability and responsiveness of the measurement during the performance of 11 motor tasks of ADL involving different intensity of hand use in a total of 18 neurologically intact, healthy individuals. Second, we introduce a machine learning-based analytic pipeline that processes the data obtained from the proposed sensing system to estimate the amount of hand use, and validate the accuracy against the benchmark measurement. We also provide a detailed discussion regarding the real-world deployment of the system, such as its ability to enable continuous operation under different network configurations.

II. Sensor System and Data Collection

A. Networked Wearable Sensor System

This study employed a body-networked sensor system composed of a miniaturized finger-worn sensor and a wrist-worn sensor developed by our research team (Arcus, ArcSecond Inc., USA) [see Fig. 1(a)]. The finger-worn sensor contained a nine-axis inertial measurement unit (IMU) that sampled data at 63 Hz, a Bluetooth communication module, a 40 mAh battery, and an ultra-low power 32-bit microcontroller. The wrist-worn sensor shared the same system architecture but in a different enclosure for its placement on the wrist.

We hypothesized that the wrist-worn sensor would mainly capture gross arm movements (e.g., arm swing or reaching for an object), whereas the finger-worn sensor would capture both gross arm and fine hand movements (e.g., object manipulation). Thus, we further hypothesized that we could extract information that is specifically relevant to hand use by analytically subtracting the wrist-worn sensor data from the finger-worn sensor data.

This work only leveraged the three-axis acceleration data while disabling the gyroscope and magnetometer because previous studies support that accelerometer data can provide accurate assessment of the amount of human upper limb movements [9], [17], [18], and the use of a gyroscope requires approximately 10 times more power than an accelerometer. For example, our finger-worn sensor with a 40mAh battery would support approximately 5 hours of continuous operation with a gyroscope. This is not practical for continuous monitoring of stroke individuals throughout their daily living. Thus, our work focuses on processing the imperfect data obtained from the two accelerometers within their own coordinate frames (i.e., the orientation of each sensor) using machine learning algorithms.

TABLE I
A List of Motor Tasks With Varying Levels of Fine Hand and Gross Arm Motor Involvement That Were Used in the Experiment

Task	Description	Type
1	Walking	Passive
2	Sit-to-stand	Passive
3	Stand-to-sit	Passive
4	Buttoning a shirt	Bimanual
5	Typing on a keyboard	Bimanual
6	Folding a towel	Bimanual
7	Tying shoelaces	Bimanual
8	Cutting a putty with a fork and a knife	Unimanual
9	Opening a screw-top jar	Unimanual
10	Taking the cap off of a bottle and drinking	Unimanual
11	Flipping pages of a magazine	Unimanual

B. Data Collection

A total of 18 healthy individuals between the ages of 18 and 40 years were recruited from the University of Massachusetts Amherst. All subjects had no major health issues that neglected their ability to follow instructions or independently perform motor tasks involving hand use. Once subjects arrived at the laboratory, they were bilaterally equipped with wearable sensors on the wrist and index finger as shown in Fig. 1. A reflective marker was placed on each sensor for a comparative analysis and to compute the benchmark measurement of the true amount of hand use by using an optoelectronic motion capture system (Miqus, Qualisys, Sweden).

Eleven motor tasks with varying levels of hand and gross arm motor involvement (e.g., passive, unimanual, and bimanual movements) were carefully selected to reflect ADL in real-world environments [19], [20] (see Table I). The motor tasks considered in our work can be categorized into two broad categories: motor tasks that mainly involved passive vs. goal-directed upper limb movements. Furthermore, this work considered two types of motor tasks involving goal-directed movements: movements that mainly involve bimanual vs. unimanual movements. Specifically, unimanual motor tasks were included in order to validate the proposed technologys responsiveness towards changes in the amount of hand use

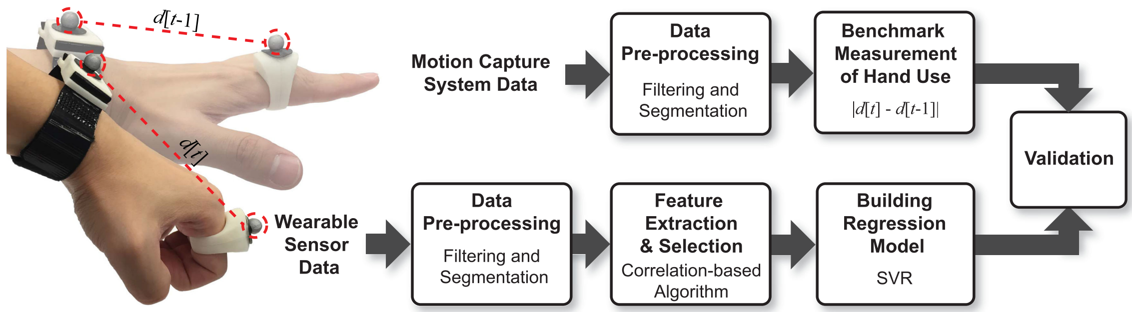

Fig. 2. Analytic pipelines to establish the benchmark measurement of the amount of hand use during the performance of ADL based on data obtained from a motion capture system, and to estimate the established benchmark measurement using data obtained from the proposed wearable sensor system.

due to a manual intervention (i.e., asking subjects to make use of their non-dominant and to complete the unimanual tasks). Subjects were asked to repeat each motor task three times in their most natural manner (i.e., as if they were to perform in their daily living). For the unimanual motor tasks specifically (Tasks #8–11), they were asked to perform the first two repetitions in a natural manner using their dominant hand (Repetition #1 and #2), and the last repetition by making their best efforts to use the non-dominant hand in order to validate our measurement's responsiveness to an intervention (Repetition #3).

III. Methods

A. Overview of Data Analysis

This section introduces analytic methods to 1) construct a new benchmark measurement of the amount of hand use based on data obtained from the motion capture system and validate its test-retest reliability and responsiveness to an intervention, and 2) to estimate the validated benchmark measurement using data obtained from the wearable sensors (see Fig. 2).

B. Establishment of the Benchmark Measure of Hand Use

The amount of comprehensive hand use (i.e., general use of the fingers and the palm) was defined as the average change in the distance between the proximal phalanx of the index finger (where the finger-worn sensor was placed) and the wrist. The three dimensional (3D) position time-series of the markers located at the wrist and finger, denoted as $\langle x_w[t], y_w[t], z_w[t]\rangle$ and $\langle x_f[t], y_f[t], z_f[t]\rangle$ respectively, were filtered using the sixth order Butterworth low-pass filter at a cutoff frequency of 8 Hz to remove high frequency and non-human generated noise. Then, the Euclidean distance $d[t]$ was computed between the two markers. The amount of hand use was then represented by computing the absolute difference of the distance $d[t]$ between each pair of adjacent samples:

$$m[t] = |d[t] - d[t-1]|. \tag{1}$$

A single representative value of the amount of hand use over the duration of each motor task was derived by computing the mean value of $m[t]$. The unit of the measurement is cm/s.

C. Validation of the Benchmark Measure: Reliability and Responsiveness

Test-retest reliability evaluates the ability of a metric to measure consistency in two tests under the same conditions [21]. In our study, the two tests were the first two repetitions of the motor tasks performed in a natural manner by the same subject (Repetition #1 and #2). This work hypothesized the observation of similar patterns of measurement. The level of test-retest reliability was quantified by using the intra-class correlation coefficient (ICC), whose value ranges from 0 to 1 [21]. The type of ICC used in this work was ICC (3,1). An ICC < 0.4 indicates poor, $0.4 \leq$ ICC < 0.75 indicates fair to good, and ICC ≥ 0.75 indicates excellent test-retest reliability [21].

Responsiveness examines the ability of a measurement to detect changes that are caused by a specific intervention [22]. In our study, the intervention was to make the best efforts to use the non-dominant hand to perform the unimanual motor tasks during Repetition #3 as discussed in Section II-B. The benchmark measurement of the dominant hand during Repetition #2 was compared against the following two measures using *two-sided Wilcoxon rank sum test* [23]: 1) the amount of the dominant hand use during Repetition #3 and 2) that of the non-dominant hand during Repetition #3. This work hypothesized to observe a statistically significant difference for the amount of the dominant hand use during Repetition #2 and #3, whereas the difference between the dominant hand use during Repetition #2 and the non-dominant hand use during Repetition #3 may depend on how differently (or similarly) subjects performed the same tasks with the two limbs.

D. Estimation of Amount of Hand Use Using Wearable Sensor

Fig. 2 shows the machine learning-based analytic pipeline that estimated the *validated* benchmark measurement of the amount of hand use using the accelerometer data obtained from the finger-worn and wrist-worn sensors. We also evaluated the estimation performance in different mobile network configurations that require different data throughputs.

1) Data Pre-processing: A sixth order Butterworth low-pass filter with a cutoff frequency at 8 Hz was again applied to remove any noise in the accelerometer time-series. A sliding window of

9 s with 50% overlap was used to segment the data in each motor task to support continuous computation of the amount of hand use; the impact of the length of the window on the estimation accuracy was also investigated. Each sliding window was considered as a data point containing 1) the three-axis accelerometer data obtained from the finger-worn $\boldsymbol{a}_f[t] = \langle a_f^x[t], a_f^y[t], a_f^z[t] \rangle$ and wrist-worn sensors $\boldsymbol{a}_w[t] = \langle a_w^x[t], a_w^y[t], a_w^z[t] \rangle$, and 2) the corresponding benchmark measurement of the amount of hand use (i.e., the mean value of $m[t]$ within the window).

2) Feature Extraction: Features were extracted from the filtered and segmented accelerometer data to capture the intensity, smoothness, and periodicity of hand use [24]. More specifically, the intensity was represented by the following features: 1) mean, 2) inter-quartile range (IQR), 3) minimum and maximum, and 4) root mean square of the acceleration time-series. The smoothness of hand use was captured by using 5) standard deviation and 6) the difference between the zero-phase filtered and original accelerometer time-series was computed. The periodicity of hand use was assessed based on 7) the dominant frequency and 8) ratio of the energy at the dominant frequency to the entire signal energy of the time-series. Besides the features mentioned above, we also computed the 9) skewness, 10) kurtosis, and 11) signal entropy of the time-series. The aforementioned features were derived from 1) signal magnitudes of acceleration time-series that were generated by both the finger- and wrist-worn sensors, 2) the difference of the two acceleration magnitudes, i.e., $a_d[t] = |\boldsymbol{a}_f[t]| - |\boldsymbol{a}_w[t]|$, 3) each axis of the acceleration time-series of the finger-worn sensor, and 4) signal envelopes of all the aforementioned time-series. Note that features were extracted from each axis of the finger-worn sensor but not from the wrist-worn sensor. This is due to the fact that conventional finger movements during both gross arm and/or fine hand movements are made within a confined space, whereas those of the wrist are less constricted. For example, finger movements during hand use (e.g., grasping or releasing) usually generated acceleration in the *x*-axis of the sensor, whereas gross arm movements (e.g., passive arm swing while walking) generated acceleration in the *y*-axis due to the centripetal force from pendulum-like arm swing behaviors [25]. Wrist movements, on the other hand, could be made relatively freely in all directions, and thus extracting features in individual axes of the wrist-worn sensor may overfit the regression model for the specific motor tasks considered in our experiment. In sum, a total of 271 features potentially relevant to the amount of hand use were extracted.

3) Feature Selection: Our study employed a Correlation-based Feature Selection (CFS) algorithm to identify data features that were particularly relevant to the amount of hand use [26]. CFS focuses on finding a subset of relevant features based on the evaluation of individual features' predictability and the degree of redundancy compared to others. The best-first search was used to construct the feature search space.

4) Regression Estimation: Support Vector Regression (SVR) was utilized to train a model that estimated the benchmark measurement of the amount of hand use based on the selected features. SVR is a supervised, nonparametric learning algorithm that could provide a computationally efficient estimation of the target variable [27], which is more suitable for resource-constrained computing environments such as our miniaturized wearable devices. We employed Radial Basis Function (RBF) as the kernel function to transform the feature space [28]. The hyperparameters were optimized based on work by Shevade *et al.* [29]. The performance of the model was evaluated using Normalized Root Mean Square Error (NRMSE):

TABLE II
FOUR DIFFERENT SENSOR NETWORK CONFIGURATIONS OF THE PROPOSED SYSTEM THAT ALLOW THE OPERATION OF THE SYSTEM BASED ON A TRADE-OFF BETWEEN THE AMOUNT OF POSSIBLE INFORMATION THAT CAN BE EXTRACTED (OR ESTIMATION ACCURACY) AND DATA THROUGHPUT (OR POWER CONSUMPTION)

Configuration	Description	Sensor(s)
#1	Accelerometer time-series data of the sensor nodes are transmitted to the mobile gateware in real-time	Finger and wrist sensors
#2	Accelerometer time-series data are processed to extract features on each sensor node, and relevant data features are transmitted to the mobile gateware at the end of each sliding window	Finger and wrist sensors
#3	Data features of the finger-worn sensor are transmitted to the mobile gateware in real-time	Finger sensor only
#4	Data features of the wrist-worn sensor are transmitted to the mobile gateware in real-time	Wrist sensor only

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(\hat{\alpha}_n - \alpha_n)^2}}{\max([\alpha_1, \ldots, \alpha_N]) - \min([\alpha_1, \ldots, \alpha_N])},$$

where $\hat{\alpha}_n$ and α_n respectively represent the estimated and benchmark measurements of the amount of hand use within a sliding window of index n. N represents the total number of windows (data points) within the testing dataset. Note that $\alpha_n = (1/T)\sum_t^T m_n[t]$, where T is the length of the sliding window, and $m_n[t]$ represents the measurement in (1). All the analyses were performed using leave-one-subject-out cross validation (LOSOCV) to provide a fair evaluation without individual bias and/or over-fitting.

5) Network Configurations: The proposed body sensor system can support different network configurations allowing the operation of the system based on a trade-off between the amount of possible information that can be extracted (or estimation accuracy) and data throughput (or power consumption). This study considered four different network configurations, which are summarized in Table II.

Configuration #1 investigated a network structure where raw accelerometer time-series from the two sensors were transmitted to the mobile gateware of our sensor network. The mobile gateware (e.g., smartphone or smartwatch) represents a node within the body network that collects data from the sensor nodes and pushes them to the cloud. This configuration would allow the maximum flexibility in sensor data processing and feature engineering as it provides access to the raw accelerometer time-series of both sensors. Configuration #2 investigated a more constrained network structure where the features were computed locally on the sensing node and then transmitted to the gateware at the end of each sliding window. This would substantially reduce the power consumption on the sensor nodes by eliminating the need for real-time data streaming. On the

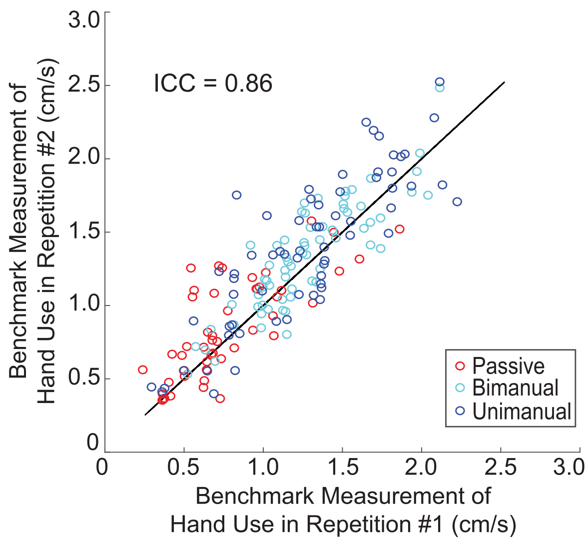

Fig. 3. Scatter plot for the average amount of dominant hand use during two repetitions of motor tasks (test-retest reliability). The black line ($y = x$) indicates the perfectly identical amount of hand use.

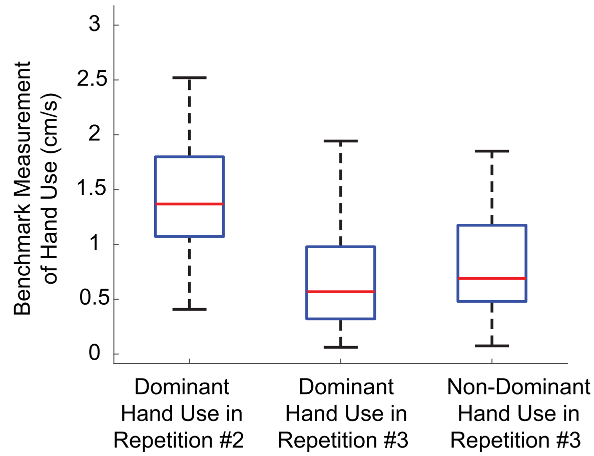

Fig. 4. Results of responsiveness when subjects were asked to use their non dominant hand to perform unimanual motor tasks. The plot shows the amount of dominant hand use during Repetition #2 and the amount of dominant/non-dominant hand use during Repetition #3.

other hand, it may also diminish the estimation accuracy as it prohibits the extraction of potentially important data features, e.g., features extracted from $a_d[t]$. Configurations #3 and #4 employ only a single sensor node (either the finger- or wrist-worn sensor) to estimate the amount of hand use. We investigated the estimation performance of these network configurations by eliminating features that were not possible within the corresponding configuration while keeping the rest of the analytic pipeline identical.

IV. Results

A. Validation of the Benchmark Measure of Hand Use

Fig. 3 shows a scatter plot of the proposed benchmark measure when subjects were asked to repeat the entire motor tasks in their natural manner (Repetitions #1 and #2). This yielded an ICC of 0.86, which indicates excellent test-retest reliability [21].

Fig. 4 graphically summarizes the responsiveness of the benchmark measurement when subjects were asked to perform the unimanual motor tasks 1) in a natural manner (Repetition #2) and 2) under an intervention to use their non-dominant hand (Repetition #3). The amount of the dominant hand use during Repetition #2 was compared against the amount of the dominant as well as the non-dominant hand use during Repetition #3. Two-sided Wilcoxon rank sum test showed statistically significant differences for the two comparisons: $p < 1.74 \times 10^{-13}$ for the amount of dominant hand use in Repetition #2 and #3, and $p < 2.91 \times 10^{-9}$ for the amount of dominant hand use in Repetition #2 and non-dominant hand use in Repetition #3. The significant difference between the amount of dominant hand use in Repetition #2 and the non-dominant hand use in Repetition #3 was caused by patients not performing the unimanual motor tasks naturally with their non-dominant hand. We observed that subjects used their dominant hand more actively in Repetition #2, with which they were more comfortable executing the motor task.

B. Estimation of the Amount of Hand Use

Fig. 5(a) compares the amount of hand use estimated by the proposed algorithm (y-axis) to the validated benchmark measurement (x-axis). A sliding window of 9 s was used to generate the data points in this figure; the effect of the window size on the estimation accuracy will be discussed later in this section. The average value of NRMSE computed over the LOSOCV (across all subjects' data) was 0.11 with a standard deviation of 0.024. The average Pearson coefficient was 0.78 with a standard deviation of 0.10. The estimated amount of hand use for all subjects showed statistically significant correlations to the benchmark measurement with the overall p-value $< 5.6 \times 10^{-204}$. The bias and limit of agreement of the Bland-Altman plot [Fig. 5(b)] were -8.7×10^{-3} and 0.67, respectively. The results presented herein support that our wearable system can produce a reliable and accurate estimation of the amount of hand use during ADL.

The size of the sliding window could affect the accuracy of the estimation algorithm based on SVR (see Fig. 6). A relatively short window size (e.g., 1 s–5 s) could provide estimations in near real-time, but the quality of data features extracted from such a short duration may not be sufficient to make an accurate estimation. For example, the estimation of the benchmark measure (i.e., a measure of changes in distance over a window, whose unit is in cm/s) by using the sensor data (i.e., a measure of acceleration in m/s^2) could not be performed effectively as the conversion from an acceleration to a distance measure fundamentally requires a sufficiently large number of data points – a process that resembles double integration. On the other end, a relatively long window (e.g., >15 s) may contain multiple activities of varying intensity of hand use, which makes it difficult to find unique patterns in data features that are associated with the amount of hand use, resulting in a lower estimation accuracy. Fig. 6 shows that a window size of 9 s could minimize

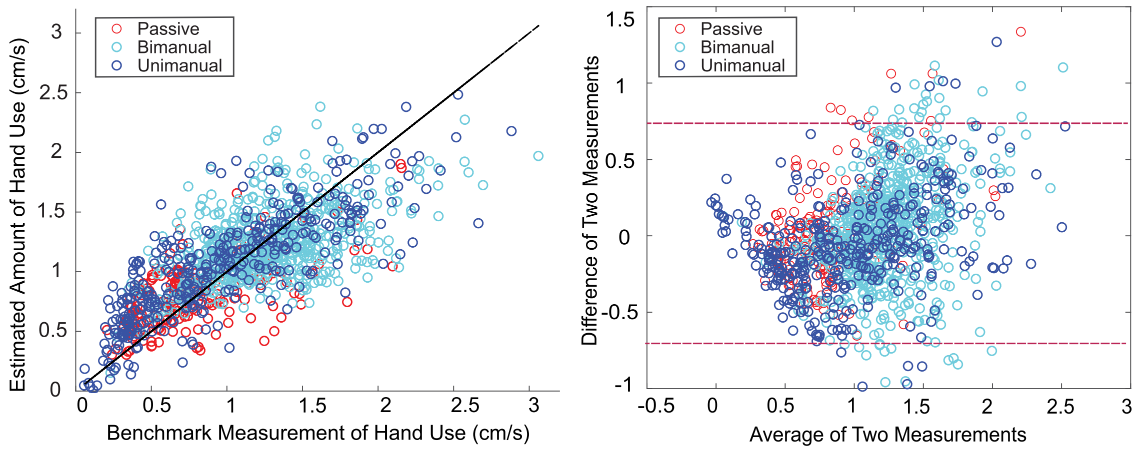

Fig. 5. (a) A scatter plot between the estimated amount of hand use based on our proposed work and the benchmark measurement (NRMSE of 0.11 and Pearson coefficient of 0.78), and (b) the corresponding Bland-Altman plot (bias of -8.7×10^{-3} and limit of agreement of 0.67).

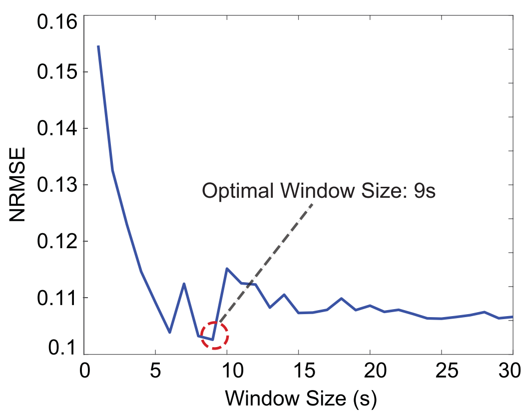

Fig. 6. Results of searching for the optimal window size. The plot shows that 9 s is the window size corresponding with the highest accuracy of estimation in terms of NRMSE.

TABLE III
A List of Eight Data Features That are Most Relevant to Estimating the Amount of Hand Use

Feature	Description	Sensor(s)
# 1	Difference in Inter-quartile range of $\|\boldsymbol{a}_w[t]\|$ and $\|\boldsymbol{a}_f[t]\|$	Wrist and Finger
# 2	Difference in standard deviations of $\|\boldsymbol{a}_w[t]\|$ and $\|\boldsymbol{a}_f[t]\|$	Wrist and Finger
# 3	Dominant frequency of difference between estimated velocity magnitudes of the two sensors	Wrist and Finger
# 4	Ratio of energy associated with high frequency movement to the signal envelope energy	Finger
# 5	Ratio of energy associated with high frequency movement to the entire signal energy	Finger
# 6	Inter-quartile range of acceleration in the x-axis of the finger sensor ($a_f^x[t]$)	Finger
# 7	Inter-quartile range of acceleration in the y-axis of the finger sensor ($a_f^y[t]$)	Finger
# 8	Ratio of energy associated with high frequency movement to the entire signal energy	Wrist

the overall estimation error in terms of NRMSE computed over the LOSOCV, i.e., an average NRMSE of 0.11 and an average Pearsons coefficient of 0.78.

Table III summarizes the eight most important features relevant to the amount of hand use. Since the evaluation was performed using the LOSOCV technique, the feature selection algorithm was performed on different training data and selected different feature subsets throughout the iterations of the LOSOCV. For example, in our analysis, 20 to 30 different features were selected (out of 271 features) in different iterations. Thus, we report the most frequently selected features from the iterations of the LOSOCV in order to summarize the important features [30]. The eight features in Table III were selected 100% in all iterations. It is not surprising that most of these features were derived directly from or partially involved the finger-worn sensor data, as we hypothesized that the finger sensor could capture information regarding the use of the hand. When we constructed the estimation model with these eight features, we obtained an NRMSE of 0.12 and Pearson coefficient of 0.74. This result shows that we can achieve near-optimal regression performance using only eight features when compared to using the entire feature set selected by the CFS algorithm (i.e., NRMSE of 0.11 and Pearson coefficient of 0.78). This is particularly important for the system's ability to support continuous monitoring – these features need to be computed for every sliding window.

Fig. 7 summarizes the estimation performance for the four sensor network configurations investigated in this work. Configurations #1 and #2 produced similar estimation accuracy (i.e., NRMSE and Pearson coefficient of $\langle 0.11$ and $0.78\rangle$ vs. $\langle 0.11$ and $0.77\rangle$, respectively). This result supports that the features extracted from the difference time-series of the finger and wrist accelerations $a_d[t]$ make minimal contributions to the overall estimation accuracy, which was also reflected on the feature selection results in Table III. Configuration #3, which employed only the wrist-worn sensor, showed significantly inferior performance compared to the other configurations. The achieved NRMSE and Pearson coefficient were 0.15 and 0.44, respectively. This observation suggests that wrist-worn

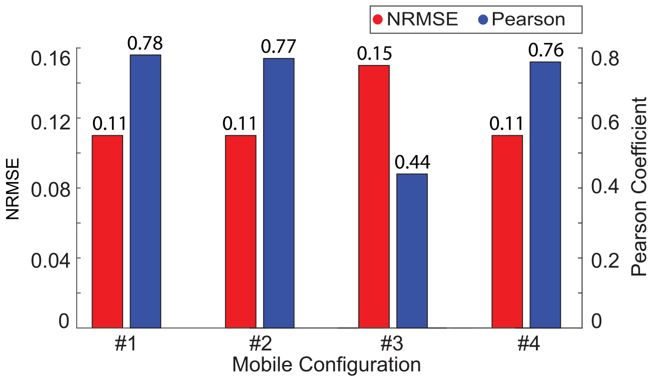

Fig. 7. The estimation performance of the proposed algorithm under different mobile configurations. Configuration #1, #2, and #4 provided a comparable estimation accuracy whereas Configuration #3 (wrist sensor only) showed significantly inferior performance.

accelerometers alone cannot capture important information regarding hand performance during ADL. On the other hand, Configuration #3, which employed only the finger-worn sensor, produced comparable estimation accuracy to Configurations #1 and #2. This result concurs with our feature selection summary (Table III) that shows important features contributing to the estimation involved data obtained from the finger-worn sensor.

V. Discussion and Conclusion

The results presented in this paper show that accelerometer recordings obtained from the proposed body-networked sensor system composed of a finger-worn and a wrist-worn sensor can be used to estimate the amount of hand use during ADL. The proposed machine learning-based analytic pipeline could provide an average error rate of 0.11 in terms of NRMSE and support continuous monitoring (e.g., producing estimations every 9 s). This paper also introduced and validated a new benchmark measurement of the amount of hand use based on data obtained from an optoelectronic motion capture system. The implementation and validation of this measurement can serve as robust ground truth for future studies that aim to quantify the amount of hand use using on- and/or off-body sensors.

A machine learning algorithm was necessary to process the body sensor data and make an accurate estimation of the amount of hand use. The most straightforward approach to estimate the amount of hand use without utilizing machine learning algorithms may be the computation of counts of the difference in acceleration magnitudes of the two sensors – a conventional approach to convert accelerometer data into a measurement of activity intensity in clinical research [11], [12]. This is intuitive since the wrist-worn sensor is assumed to capture mainly gross arm movement whereas the finger-worn sensor would capture both gross arm and fine hand movements. However, the estimation results based on this approach produced a poor estimation accuracy (NRMSE of 0.16) compared to the proposed machine learning-based mechanism. We believe that this is due the non-linear relationship between the accelerations measured by the finger- and the wrist-worn sensors during pendulum-like arm movement [25]. The sensor on the finger is more distal compared to the wrist and thus, the acceleration measured by the two sensors may vary significantly.

The proposed study validated the use of finger-worn sensors to estimate the amount of hand use based on a series of motor tasks associated with ADL. Thus, it is conceivable that the presented technologies could be translated to individuals' home settings to continuously monitor their abilities to function in daily life. The proposed system provides activity-independent quantification of the amount of hand use (i.e., does not require the classification of performed activities). Furthermore, the use of a machine learning algorithm (SVR with RBF kernel) capable of generating the estimations in a computationally efficient manner (with as few as 8 features) makes the system suitable for continuous monitoring in an environment with constrained resources, e.g., on the computing unit of our wearable sensors.

This study contains some limitations worth noting. First, our experiment involved a relatively small number of subjects (18 subjects) performing a set of 11 motor tasks. Thus, the results presented in this paper may not be generalized to the general healthy or stroke populations. However, all the analyses were performed in a LOSOCV manner, which produced an unbiased, fair evaluation rather an optimistic one. Second, the proposed method that estimates the amount of hand use does not provide information regarding the type of upper limb movements (e.g., passive vs. unimanual vs. bimanual vs. stabilization movements). Although accurate classification of upper limb movements based on machine learning algorithms could provide clinically relevant information regarding the functional level of patients with motor impairments (e.g., stroke survivors) [9], it is technically challenging to realize in practice. It is especially difficult to define the perfect classes of upper limb movements that could be performed in free living conditions based on a number of factors, such as the goal-directedness or whether it is unimanual or bimanual [8]. For example, the acceleration of the arm during sit-to-stand is mainly generated by the lower limb (standing up) and could be considered as a passive movement. However, reaching out both arms to balance on the armrest, could be considered an active (bimanual) movement. This also indicates that accurate classification would necessitate the understanding of the context of activities such that the accelerometer data could be properly segmented. Thus, the proposed work focused on quantifying the hand function (i.e., amount of hand use) that could capture relevant information regarding the goal-directed use of the upper limb, which also has been suggested by other work in the field [14], [15]. Lastly, the proposed technology cannot capture the use of the hands for stabilizing objects (e.g., holding a cup or stabilizing a piece of steak with a fork) as it focuses on estimating the amount of hand movement. Stabilization is an important category of hand function, however, we assume that capturing hand movements during ADL could provide more accurate information regarding the goal-directed use of the hands, especially for individuals with hemiparesis, when compared to conventional wrist-worn accelerometers.

We ultimately envision future scenarios in which stroke survivors can be continuously monitored in the free-living setting using the proposed wearable technology. The proposed technology supports a minimally obtrusive means to understand patients' functionality, which may reflect individual responses to rehabilitation. This would allow clinicians the opportunity to provide individually-tailored rehabilitation and therapeutic programs – potentially transforming the current stroke healthcare into evidence-based, person-centered care.

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