Sensor-Enabled RFID System for Monitoring Arm Activity: Reliability and Validity

Joydip Barman, *Member, IEEE*, Gitendra Uswatte, Touraj Ghaffari, Brad Sokal, Ezekiel Byrom, Eva Trinh, Michael Brewer, Christopher Varghese, and Nilanjan Sarkar, *Senior Member, IEEE*

***Abstract*—After stroke, capacity to complete tasks in the treatment setting with the more-affected arm is an unreliable index of actual use of that extremity in daily life. Available objective methods for monitoring real-world arm use rely on placing movement sensors on patients. These methods provide information on amount but not type of arm activity, e.g., functional versus nonfunctional movement. This paper presents an approach that places sensors on patients *and* household objects, overcoming this limitation. An accelerometer and the transmitter component of a radio-frequency proximity sensor are attached to objects; the receiver component is attached to the arm of interest. The receiver triggers an on-board radio-frequency identification tag to signal proximity when that arm is within 23 cm of an instrumented object. In benchmark testing, this system detected perfectly which arm was used to move the target object on 200 trials. In a laboratory study with 35 undergraduates, increasing the amount of time target objects were moved with the arm of interest resulted in a corresponding increase in system output ($p < 0.0001$). Moreover, measurement error was low ($\leq$2.5%). The results support this system's reliability and validity in individuals with unimpaired movement; testing is now warranted in stroke patients.**

***Index Terms*—Accelerometer, ambulatory monitoring in stroke survivors, proximity sensor, radio-frequency identification (RFID).**

I. Introduction

More than 650 000 individuals survive strokes annually in the United States [1]. Persistent impairment of the arm on the more-affected side of the body afflicts between 55% and 75% of the survivors [2] and is associated with diminished health-related quality of life [3]. Advances in methods to assess and treat the more-affected arm impairment after stroke, therefore, have the potential to improve the quality of life of a large number of people.

Well-known models of disability and data indicate that laboratory measures of function poorly index how stroke survivors actually use their more-affected arm in daily life [4]. Therefore, substantial effort has been spent on developing real-world measures of arm function. Most of these tests, however, rely on self-report [4]. Researchers have objectively measured amount of arm activity in the community by placing accelerometers on stroke survivors [5]. These techniques, however, cannot discriminate whether a given arm movement is functional or nonfunctional and cannot identify what tasks were performed. More complex activity monitors, such as inertial measurement units, hold promise for making such discriminations but to date have been shown only to index quality of arm movement after stroke on a standardized motor test in the laboratory [6]–[8].

This paper describes the design and testing of a prototype sensor-enabled radio-frequency identification (RFID) system, which consists of RFID tags paired with proximity and movement sensors for monitoring arm activity. In this system, movement sensors (i.e., accelerometers) are affixed to objects, along with one component of a RF proximity sensor. The other component of the RF proximity sensor is connected to an active RFID tag and worn on the arm of interest. Manipulation of instrumented objects with that arm produces synchronous signals from the movement and proximity sensors, permitting tracking of which objects are handled, when handling takes place, and whether handling is by the person and arm of interest. The proposed technology, thus, collects much richer objective data than possible with accelerometers or other physical activity monitors. Data are shared from benchmark testing of the system components (Study 1) and laboratory testing of a prototype system in healthy individuals (Study 2).

II. Background

A. Monitoring of Arm Activity With Accelerometers

To overcome the methodological limitations of self-reports, several researchers have employed accelerometers to objectively measure the amount of arm activity in stroke survivors in the community [5]. For example, Uswatte *et al.* [9] asked stroke survivors with mild-to-moderate impairment of their more-affected arm to wear an accelerometer above each wrist during all waking hours for two days before and after upper-extremity physical rehabilitation or a corresponding no-treatment period.

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J. Barman is with the Departments of Biomedical Engineering and Psychology, University of Alabama, Birmingham, AL 35294 USA (e-mail: joydip@uab.edu).

G. Uswatte is with the Departments of Psychology and Physical Therapy, University of Alabama, Birmingham, AL 35294 USA (e-mail: guswatte@uab.edu).

T. Ghaffari is with ActiveWave Inc., Boca Raton, FL 33487 USA (e-mail: touraj@activewaveinc.com).

B. Sokal, E. Byrom, E. Trinh, and M. Brewer are with the Department of Psychology, University of Alabama, Birmingham, AL 35294 USA (e-mail: bhsokal@uab.edu; zbyrom@uab.edu; evatrinh@uab.edu; mtbrewer@uab.edu).

C. Varghese is with the Department of Psychology, Marshall University, Huntington, WV 25755 USA (e-mail: chrisvargh@gmail.com).

N. Sarkar is with the Department of Mechanical Engineering, Vanderbilt University, Nashville, TN 37240 USA (e-mail: nilanjan.sarkar@vanderbilt.edu).

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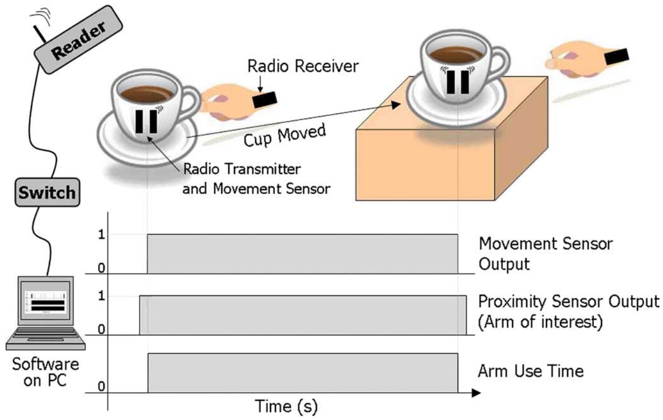

Fig. 1. Sketch of SERSMAA prototype.

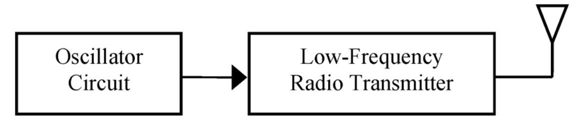

Fig. 2. Low-frequency radio transmitter circuit block diagram.

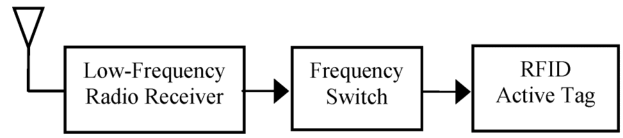

Fig. 3. Low-frequency radio receiver circuit block diagram.

The ratio of more-to less-affected arm accelerometer recordings was strongly correlated with amount of more-affected arm use in daily life ($r = 0.74$, $p < 0.001$). However, since all arm movements produce acceleration readings, this method cannot discriminate whether a given movement is functional or nonfunctional nor identify what tasks are performed.

B. Radio Frequency Identification Systems

RFID systems consist of small tags that transmit a unique ID using RF when interrogated by the RF reader that monitors the status of these tags [10]–[12]. Software on a PC connected to the reader processes the RFID signals. "Passive" RFID tags transmit their ID when they encounter the reader's radio waves [12], whereas "active" RFID tags, which are battery powered, transmit their ID independently from as far as 85 m [13]. Applications involve tracking whether tagged objects are within the range of the reader or not. Examples of commercial applications are monitoring when hospital equipment or patients leave designated areas or monitoring changes in inventory of merchandise in a warehouse [14]. However, RFID systems have not been used to remotely monitor upper-extremity activity in stroke survivors or other rehabilitation populations.

III. Apparatus

A. Sensor-Enabled RFID System for Monitoring Arm Activity (SERSMAA)

Fig. 1 shows the hardware setup of the prototype, and how the movement and proximity sensors operate together when an object is manipulated with the arm of interest.

A local area network (LAN) is setup between the PC and a RF reader using an Ethernet 10/100 Mb/s switch. The switch enables the reader and PC to communicate reliably over the LAN. A movement sensor (5 cm $\times$ 4 cm $\times$ 1.7 cm; 37 g) and proximity sensor transmitter (7.8 cm $\times$ 3.8 cm $\times$ 2 cm; 50 g) are placed on each object. The receiver component of the proximity sensor is connected to an on-board active RFID tag; this assembly (7.4 cm $\times$ 6.1 cm $\times$ 2.4 cm; 95 g) is attached to the arm of interest. Each movement sensor [15] and the RFID tag [13] possess a unique ID signature.

When the arm of interest approaches an instrumented object, the receiver component of the proximity sensor detects the radio transmitter's signals, triggering the RFID tag to broadcast an "ON" signal along with its ID. When the arm withdraws, the receiver no longer detects a radio signal, triggering the RFID tag to broadcast an "OFF" signal along with its ID. The RF reader relays the proximity status to the PC, which runs custom VB.NET software that processes the signals and stores the output in a text file. If the object is manipulated, the movement sensor records the changes in its acceleration, and stores these values in on-board memory for downloading into a text file that includes the movement sensor ID. Custom software processes the proximity and movement sensor text files offline. Synchronous "positive" values from the proximity and movement sensors indicate that an instrumented object is being moved by the arm of interest. Moreover, analysis of the proximity status and acceleration values, along with their ID and time stamps, permits tabulation of which objects are moved, when they are moved, for how long, and by which arm.

B. Proximity Sensor

Figs. 2 and 3 are block diagrams of the transmitter and receiver components, respectively, of the *prototype* RF proximity sensor. As described, transmitters are attached to objects, while the receiver is attached to the arm of interest.

The RF transmitter sends 30-Hz oscillator signals at a fixed low frequency of $\sim$10.7 KHz. The choice of a low-frequency is appropriate for sensing proximity of the receiver and transmitter over short distances of 1–23 cm, i.e., for detecting when the arm of interest is adjacent to an instrumented object. The RF receiver is tuned to the same frequency as the transmitter. The receiver output connects to a frequency switch circuit that turns ON when it reads the 30-Hz signal and turns OFF in its absence. Because the frequency switch output cannot be readily connected to the ActiveWave RFID tag [13], a jury-rigged solution is used in this prototype. The frequency switch output, instead of firing the tag directly, connects to an electromagnet, which produces a magnetic field when the frequency switch toggles ON. This magnetic field, in turn, activates an ActiveWave magnetic sensor active RFID tag, which sends a signal using a proprietary ActiveWave RF low power communication protocol to the RF reader indicating a change in sensor status. The power sources for both components are 3 V coin cell batteries.

C. Movement Sensor

The object movement sensors are ActiGraph GT1M activity monitors. These units, each of which has a unique ID, were chosen because previous studies have demonstrated that activity monitors with the same recording parameters track the arm movements of stroke patients, the first target population for the SERSMAA system, with high fidelity in real-world settings [9], [16]. The GT1M employs a biaxial accelerometer, which detects 1 g acceleration with a sensitivity of $\pm 10\%$. Acceleration is sampled at 60 Hz in each axis. These samples are integrated separately for each axis over a user-specified epoch, which in this case is 1 s, and are stored in 1 Mb flash memory [15]. To generate a single movement status signal for each epoch, OFF is recorded only if the integral values for *both* axes are ≤ 1; else, ON is recorded. The threshold of 1 filters out very small movements that are not likely to be functional [16]. Biaxial accelerometers are adequate for monitoring arm activity because manipulation of objects invariably results in movement components in all three axes [17].

IV. Study 1: Benchmark Testing

A. Methodology

Benchmark testing was performed under highly controlled conditions in the laboratory to determine whether the sensitivity and specificity of the SERSMAA prototype was adequate, i.e., $\geq 98\%$ and $>99\%$, respectively [18].

1) Proximity Sensor Testing: The proximity sensor transmitter was affixed to the outside of a coffee mug using Velcro. The proximity sensor receiver was attached with an elastic band to the right forearm of the experimenter just above the wrist. The mug was placed on a target at the center of several concentric circles drawn on a tabletop. Two hundred trials of each test were conducted, except for Test 1a, which had 100 trials. The start and end of trials were marked with beeps emitted by custom software on a PC.

a) To determine the range of proximity detection, the experimenter moved his hand along the tabletop in 1 cm increments every 5 s starting from a target 24 cm away from the mug and ending 20 cm away. Movement was parallel to the y axis of the mug. Sensor status was logged at each stop.

b) To evaluate how sensitivity varies with angle of approach, the experimenter placed his hand on a target >23 cm from the mug. The experimenter then grasped the mug handle with his right hand, released it, and returned his hand to the target. This movement was conducted parallel to the x, y, and z axes of the mug for separate sets of 200 trials.

c) To evaluate how sensitivity varies with interval between releasing and grasping an object, the y-axis test was repeated with inter-trial intervals of 1, 3, 5, and 7 s.

d) To determine how sensitivity varies with type of household object and hand size, the y-axis test was repeated with a telephone, book, hair brush, and television remote and with experimenters with hand sizes ranging from 18.5 to 21.5 cm (tip of middle finger to styloid process of radius).

e) To evaluate specificity, the proximity sensor receiver was set >23 cm away from any transmitters for 24 h.

f) To test robustness of the proximity sensor to distance from the reader and the effect of intervening walls, the y-axis test was repeated at varying distances from the reader and with a varying number of intervening walls.

g) To test robustness to interference from other electronic devices that emit RF waves, the y-axis test was repeated at varying distances from a loud speaker and television set.

2) Movement Sensor Testing:

a) To test how sensitivity varies with distance an object is moved, the movement sensor was attached to the mug. The experimenter moved the mug from one target to another on the table surface parallel to the x-axis of the mug. Two hundred trials each were conducted with the targets 2, 4, 6, 8, 12, and 16 cm apart. The experimenter had 1 s to complete each movement, i.e., trial, and a 3 s interval between trials.

b) To test how sensitivity varies with direction of movement, the 12 cm test above was repeated with movements parallel to the y and z axes of the mug.

c) To test how sensitivity varies with interval between movements, the 12 cm test for movement parallel to the mug's x-axis was repeated with a 2 s inter-trial interval.

d) To evaluate specificity, a movement sensor was turned on and left in one spot for 24 h.

3) Testing of System: To test the sensitivity and specificity of the entire system, proximity sensor transmitters and movement sensors were attached to two mugs (Mug 1, 2) set 43 cm apart. The ID of each movement sensor and the mug to which it was attached were recorded. The proximity sensor receiver was put on the experimenter's right arm. The experimenter placed his hands on separate targets each >23 cm from both mugs. When signaled, the experimenter grasped either Mug 1 or 2, moved it to a target 12 cm away with either his Right or Left hand, and returned the hand employed to its starting position. Two hundred trials were conducted, with 5 s between trials. This procedure was repeated with objects set 5 cm apart. The choice of which object to grasp and which arm to employ was determined by a random process on each trial.

4) Data Processing and Analysis: As noted, the proximity and movement sensor data were stored as text files. A custom-made VB.NET software algorithm combined the files offline by using the time and ID stamps therein as keys. The time stamp in the data files were automatically synchronized since the movement sensors were initialized on the same computer which recorded the status of the proximity sensor. The algorithm then calculated the number of following events for each test and object of interest: experimenter's right arm approached object (i.e., proximity status transitions from ON to OFF); object was moved (i.e., movement status transitions from ON to OFF); object was manipulated by the experimenters' right arm (synchronous transitions from ON to OFF status for the proximity and movement sensors). Changes in sensor status were deemed synchronous if the transitions in status from each sensor type were ≤ 2 s apart.

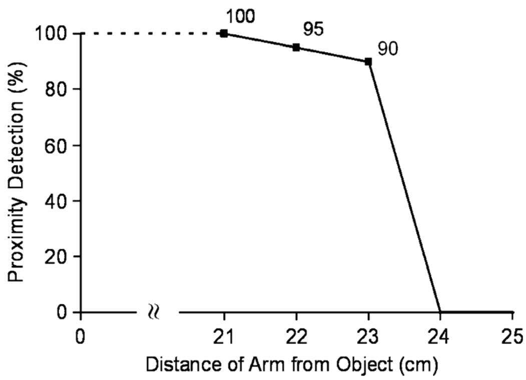

Fig. 4. Sensitivity of proximity sensor.

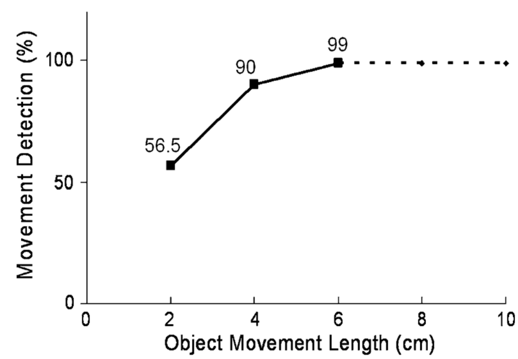

Fig. 5. Sensitivity of movement sensor.

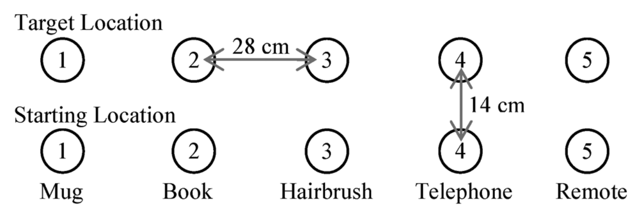

Fig. 6. Setup of objects for test 1 and 2.

B. Results

1) Proximity Sensor Testing: Fig. 4 shows how the sensitivity of the proximity sensor receiver varied with distance from an instrumented mug. When the mug was >23 cm away, i.e., outside of the intended range, the proximity sensor, appropriately, did not change status.

Sensitivity did not vary substantially with angle of approach. Out of 200 approach, grasp, release, and withdraw trials, proximity was detected 202, 198, and 204 times, respectively, for angles parallel to the x, y, and z axes of the mug. Nor did proximity detection vary substantially with interval between trials (1 s $=$ 194, 3 s $=$ 202, 5 s $=$ 198); type of object grasped (mug $=$ 198, telephone $=$ 203; book $=$ 198; hair brush $=$ 194, remote control $=$ 196); or experimenter hand size (18.5 cm $=$ 198, 19.6 cm $=$ 202, 21.5 cm $=$ 204).

Specificity was supported; no proximity detection signals were recorded when the proximity sensor receiver and transmitter were kept $\geq$23 cm apart for 24 h. In addition, proximity was detected during only 0.4% of inter-trial intervals during the above tests.

Proximity detection did not vary with distance of the sensor from the reader and the number of intervening walls. Proximity detection when the sensor and the reader were up to 25 m apart with five intervening walls was as good as when the sensor and reader were separated by 1 m with no intervening walls, which was the case for all the other tests of the proximity sensor. However, operation of a television and loudspeaker interfered with proximity detection; when the proximity sensor receiver and transmitter were within 20 cm of each other but $\leq$20 cm from these devices the sensor stopped detecting proximity.

2) Movement Sensor Testing: Fig. 5 shows how the sensitivity of the movement sensor varied with distance the instrumented object was moved.

Sensitivity did not vary substantially with direction of movement. For 12 cm movements parallel to the x, y, and z axes of the mug, detection was 99%, 99%, and 98%, respectively. Detection was poor when the interval between movements was $\leq$2 s. For a 12 cm movement parallel to the x axis of the mug, detection was 99% when the inter-trial interval was 3 s but only 48% when it was 2 s.

Specificity was supported; no movement was recorded when a movement sensor was turned on but kept in one spot for 24 h. In addition, for tests where the inter-trial interval was $\geq$3 s and movement was $\geq$4 cm, no movement was detected during the inter-trial intervals.

3) Testing of System: On the test in which the object to be moved and the arm to be employed were randomly selected, manipulation of the object of interest with the right arm was detected by the system with 100% sensitivity and specificity both when the objects were 43 and 5 cm apart.

V. Study 2: Reliability and Validity

A. Methodology

To evaluate whether SERSMAA reliably and validly measures manipulation of household objects, three tests were conducted in a 2.7 m $\times$ 1.5 m room in our laboratory. Participants were recruited from the introductory psychology subject pool at our university; 35 students with unimpaired upper-extremity movement were enrolled (27 women; median age $=$ 19 yr, range $=$ 17–46; 8 men; median age $=$ 19 yr, range $=$ 17–24). For all three tests, the proximity sensor receiver was fastened just above the wrist of the right arm of participants with an elastic band. A proximity sensor transmitter and an accelerometer were affixed with Velcro to five objects (Fig. 6). The ID of each accelerometer and the object to which it was attached were recorded. For Tests 1 and 2, the objects were handled in a fixed order. For Test 3, the objects to be handled by each participant in each experimental condition (low, medium, high) were selected randomly. For all three tests, order of the conditions was counterbalanced across participants, with breaks given between conditions of 10, 20, and 30 s in Tests 1, 2, and 3, respectively.

1) Test 1: The five household objects were placed 28 cm apart in a line on a tabletop. Fig. 6 gives the arrangement of the objects and starting and target positions.

Participants moved each object from its starting to target position and back, for 6 out of 18 s (low), 12 out of 18 s (medium), and 18 out of 18 s (high). As for Study 1, the movements were regulated by beeps controlled by custom software on a PC. The rhythm was set to 40 beats/min with one movement per beat, i.e., starting to target position by first beat, target to starting position by next beat. The Medium condition was repeated before proceeding to the next object.

2) Test 2: The procedure was similar to Test 1 except that instead of letting the object rest for 12 and 6 s in the low and medium conditions, participants moved it with their left hand. In addition, 5 s were given to switch from the right to left hand in these conditions.

3) Test 3: All five objects were placed at one end of the table. Participants, using their right arm, moved varying numbers of objects, one at a time, from the starting location to the target location 150 cm away. For low, medium, high conditions, participants moved 1, 3, and 5 objects, respectively. As for Test 1 and 2, the medium condition was repeated. So that the movements would be more naturalistic than in Test 1 and 2, the participants' behavior was not regulated in other way.

4) Data Processing and Analysis: Data processing was similar to Study 1. The summary variable (SV) calculated was time each object was handled with the right arm during each experimental condition. To evaluate reliability, measurement error was quantified for each target object and condition in Test 1 and 2 by expressing the difference between the actual duration of object handling and SERSMAA SV value as a percentage of the actual duration. In addition, the similarity of the SV values from the first and second iteration of the Medium conditions in Tests 1–3 was evaluated by calculating the mean difference in SV values between the first and second iteration and corresponding two-tailed, 95% confidence interval (*CI*). Correlational methods for evaluating test-retest reliability were not appropriate because successful implementation of the experimental manipulation, i.e., amount of time target objects were handled with the right arm, and low measurement error made the range of SV values for the first and second iteration of the medium condition very small. Construct validity was evaluated by testing whether increasing amount of time that objects were handled with the right arm (Test 1 and 2) or number of objects that were handled with the right arm (Test 3) produced a corresponding increase in SERSMAA SV values. For this purpose, separate analysis of variance (ANOVA) models were specified for Test 1 and 2 data with two repeated measures factors: amount of handling (low, medium, high) and object (1–5). The ANOVA model for Test 3 data had only one repeated measures factor: number of objects (low, medium, high). The Huynh–Feldt correction was applied to the p-values reported to account for any violations of the sphericity assumption. Data from one participant were missing because of technical issues with the system during data collection.

B. Results

Error for measuring amount of time objects were handled with the right arm was only 2.5% (Test 1: mean error $= 3.4\%$, $SD = 1.3$; Test 2: mean error $= 1.6\%$, $SD = 1.0$). SERSMAA SV values from the first and second iteration of the medium condition were highly similar (Test 1: mean difference $= 0.2$ s, $CI = -0.05$–0.4; Test 2: mean difference $= 0.05$ s, $CI = -0.1$–0.2; Test 3: mean difference $= 0.1$ s, $CI = -0.4$–0.6). In addition, when only one object was handled, SERSMAA erroneously reported handling of more than one less than 1% of the time (Test 1: mean $= 0.5\%$, $SD = 0.7$; Test 2: mean $= 0.8\%$, $SD = 0.6$). In Test 3, in which the objects to be handled in each condition were assigned randomly, SERSMAA correctly reported the objects handled on all trials.

TABLE I
TIME (S) OBJECTS WERE MANIPULATED WITH THE RIGHT ARM PER SERSMAA OUTPUT ($\mathrm{N} = 34$)

	Low	Medium 1	High	Medium 2
Test 1	6.2 (6.1–6.4)	11.6 (11.3–11.8)	17.1 (16.8–17.4)	11.8 (11.6–12.0)
Test 2	6.1 (5.9–6.2)	11.9 (11.7–12.1)	17.5 (17.3–17.7)	11.9 (11.6–12.1)
Test 3	3.8 (3.3–4.3)	10.8 (10.1–11.6)	16.8 (16.2–17.4)	10.7 (9.9–11.5)

Note. Values are mean, confidence interval (lower bound-upper bound). For Tests 1 and 2, participants were asked to handle objects with their right arm for 6, 12, and 18 s in the low, medium, and high conditions, respectively. For Test 3, the time that objects were handled was not regulated. Instead, the three conditions were differentiated by varying the number of objects handled, i.e., 1, 3, and 5 objects in the low, medium, and high conditions, respectively.

Increasing the amount of time the target object was handled (Test 1 and 2) or the number of target objects handled (Test 3) with the right arm resulted in a corresponding increase in system output (Test 1: $F[2, 324] = 1997$, $p < 0.0001$, Huynh-Feldt $\varepsilon = 0.87$; Test 2: $F[2, 328] = 4477$, $p < 0.0001$, $\varepsilon = 0.97$; Test 3: $F[2, 66] = 445$, $p < 0.0001$, $\varepsilon = 1.03$). Table I reports mean seconds target objects were handled with the right arm in each experimental condition for Tests 1–3. Data were collapsed across the second repeated measures factor, i.e., object, for Test 1 and 2 because there was no main effect for object or amount of time $\times$ object interaction.

VI. CONCLUSION AND DISCUSSION

The first application proposed for the SERSMAA system is remotely monitoring everyday arm activity after stroke. This system, unlike existing methods for ambulatory monitoring of arm activity, captures information about the movement and proximity of household objects. It does so by placing movement and proximity sensors on the arm and objects of interest. The results of the benchmark testing (Study 1) and laboratory study with individuals with unimpaired movement (Study 2) suggest that the SERSMAA prototype embodies a promising approach for monitoring arm activity of a single stroke patient at a time in the home.

The benchmark testing supported the sensitivity and specificity of the SERSMAA prototype for detecting proximity of the arm of interest to a household object, movement of the object, and handling of the object. When the proximity sensor receiver on the experimenter's right arm drew close ($\leq$21 cm) to an instrumented object, proximity was detected on $\geq$97% of trials, regardless of angle of approach, inter-trial interval, type of object, and hand size. When the experimenter's right arm was far ($\geq$23 cm) from an instrumented object, proximity, appropriately, was not signaled. The movement sensor detected $\geq$98% of instrumented object movements when they were $\geq$6 cm long and ≥ 3 s apart, regardless of movement direction. No movement signals were recorded when instrumented objects were at rest. When the object to be manipulated and the arm to be used were randomly selected, the conjoint proximity and movement sensor signals detected handling of the object of interest with the right arm with 100% sensitivity and specificity even when the objects were just 5 cm apart.

The laboratory study supported the reliability and construct validity of the SERSMAA prototype for measuring amount of time household objects were handled with the arm of interest. Amount of time objects were handled with the participants' right arm was measured with low error ($\leq$2.5%) and the SERSMAA output was very similar for two iterations of the same condition. The mean difference in output values between the first and second iteration was $<$1% of the time objects were handled. Increasing the amount of time household objects were handled, as predicted, produced a corresponding increase in SERSMAA output (p's < 0.0001). In addition, the prototype discriminated objects that were handled from those that were not with $>$99% accuracy.

These results suggest that future studies with stroke survivors in more natural settings are warranted. However, two modifications to the system are desirable. First, the size of the sensors needs to be reduced. An approach for doing so would be placing passive RFID tags [10]–[12], which are the size of a large stamp, on objects, while placing a RF reader with a short range and accelerometer on the more-affected arm of patients. Using a passive tag design will reduce the footprint of the sensors on the objects and also reduce the overall cost of the system, since only one accelerometer will be used to measure movement of the arm instead of using accelerometers on each household object. This approach would also overcome another limitation of the prototype tested, i.e., the inability to discriminate which patient is handling a tagged object if multiple patients are monitored simultaneously in the same setting. Since each patient would wear a RF reader with a unique ID on their more-affected arm, the passive tag approach would permit discrimination of who is handling what. A second modification that would be desirable is a capacity for real-time processing of the system signals.

Two other limitations of the prototype need further study before application of this approach to monitoring arm use by stroke survivors in natural settings. The frequency with which household objects in daily life are manipulated by the less-affected arm of patients when the more-affected arm is within 23 cm of the object, needs to be assessed, as the current system cannot identify which arm has manipulated the object under such conditions. In the case that both arms are used to handle the object, the current system only records use of the more-affected arm, which is of most interest for monitoring the effects of rehabilitation for that arm. In addition, the frequency of interference from electronic devices such as television sets in everyday environments needs to be assessed.

If these issues can be addressed successfully, this technology will be able to provide a much richer objective picture of everyday arm activity after stroke than possible now. Such an advance would permit more accurate measurement of real-world gains after upper-extremity rehabilitation. For this application, the patient's more-affected arm and a representative sample of household objects would be instrumented, and the RF reader and PC would be placed in the patient's home for several days pre- and post-therapy. Other rehabilitation applications are monitoring compliance with home exercise programs and therapeutic use of activity monitoring records. For example, the SERSMAA output could serve as input for software on the PC that controls a virtual therapist who reinforces patients immediately after they use their more-affected arm to manipulate instrumented objects in their homes. Business applications include tracking how often customers use a company's products (i.e., handle them) and monitoring which employees handle what on production lines.

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Joydip Barman (M'11) received the M.S. degree in electrical engineering and the Ph.D. degree in biomedical engineering from the University of Alabama, Birmingham, in 2004 and 2012, respectively.

He is currently a Senior Research Engineer with the Constraint-Induced Therapy Research Group, Department of Psychology, University of Alabama, Birmingham.

Gitendra Uswatte received the B.A. degree in economics from Princeton University, Princeton, NJ, in 1991, and the Ph.D. degree in clinical health psychology from the University of Alabama, Birmingham, in 2001.

He is currently an Associate Professor of Psychology and Physical Therapy at the University of Alabama, Birmingham.

Touraj Ghaffari received the B.S. degree in electrical engineering from Kansas University, Lawrence, in 1976, and the M.S. degree in electrical engineering from University of Missouri, Columbia, in 1978.

He is currently President and CEO/Founder of ActiveWave, Inc.

Brad Sokal received the B.A. degree in English and art history from Oberlin College, Oberlin, OH, in 1998. He is currently working toward the Ph.D. degree in clinical psychology from the University of Alabama, Birmingham.

Ezekiel Byrom received the B.S. degree in psychology from the University of Alabama, Birmingham, in 2012.

Eva Trinh received the B.S. degree in psychology from the University of Alabama, Birmingham, in 2012.

Michael Brewer is working toward the B.S. degree in psychology at the University of Alabama, Birmingham.

Christopher Varghese received the B.S. degree in psychology from the University of Alabama, Birmingham, in 2011. He is currently working toward the M.S. degree in psychology from Marshall University, Huntington, WV.

Nilanjan Sarkar (SM'92) received the B.E. degree in mechanical engineering from University of Calcutta, Kolkata, India, in 1985, and the Ph.D. degree in mechanical engineering from University of Pennsylvania, Philadelphia, in 1993.

He is currently a Professor of Mechanical and Computer Engineering at Vanderbilt University, Nashville, TN.