A Wearable RFID System to Monitor Hand Use for Individuals with Upper Limb Paresis

Youngkyun Lee, Xin Liu, Jeremy Gummeson, Sunghoon Ivan Lee
College of Information and Computer Sciences
University of Massachusetts, Amherst
Amherst, USA
{youngkyunlee, xliu9}@umass.edu, {gummeson, silee}@cs.umass.edu

***Abstract*—Continuous monitoring of hand function in individuals with upper limb paresis, such as stroke survivors, could provide a quantitative assessment of their real-world functional performance, which has great potential to enhance the clinical guidance of rehabilitation interventions. In this paper, we explore a novel wearable approach to quantify the amount of hand use by leveraging Radio Frequency Identification (RFID) technologies. We introduce a prototype implementation of our wearable RFID system composed of a wrist-worn reader (antenna) and a small passive tag placed on a fingernail. Then, we discuss a machine learning-based data analytic pipeline that analyzes the backscattered RF signal to estimate the amount of hand use. The accuracy of the system is validated against an optoelectronic motion capture system – the gold standard for human movement analyses – using a dataset collected from five neurologically intact individuals. The proposed wearable RFID system could accurately estimate the amount of hand use with R^2 of 0.67 and Normalized Root Mean Square Error of 7.3%, and shows great potential for clinical applications.**

***Index Terms*—RFID, wearable system, remote monitoring, stroke, upper limb, paresis, rehabilitation**

I. INTRODUCTION

In the United States, stroke is the fifth most common cause of death. Approximately, 800,000 individuals suffer from stroke, and 60% of stroke survivors experience upper limb paresis [1]. Stroke is a leading cause of long-term disability in adults, significantly affecting their performance of essential activities of daily living (ADLs) such as eating, bathing, brushing teeth, and clothing [2]. Rehabilitation is the most effective treatment method to help stroke survivors with a paretic upper limb regain normal functioning capacity observed in the clinic [3]. However, research studies have shown that functional improvements assessed and observed in clinical settings may not always translate to patients' actual performance of ADL in real-world settings [4]. Thus, monitoring of functional performance in patients' home environments can serve as an important digital marker to evaluate the real-world impact of the prescribed rehabilitation programs and provide opportunities to facilitate personalized therapeutic interventions [5].

Wrist-worn accelerometers have been extensively studied as an effective means to monitor upper limb performance [6]. However, wrist-worn sensors primarily capture gross arm movements, which may introduce contextual noise in the assessment of purposeful, goal-directed use of the limbs and result in the overestimation of upper limb performance [7]. More recently, capturing the amount of fine hand use has been considered as an alternative, effective representation of upper limb performance, since the hand is the most distal part of the upper limb that individuals aim to control to perform goal-directed ADLs [8]. Our group has recently introduced a finger-worn accelerometer to capture the amount of hand use [9], but these sensors are quite bulky in size and not yet validated for long-term use. In a recent study by Friedman *et al.*, authors proposed a wrist-worn magnetometer with a finger-worn magnetic ring to capture hand movements [10], but the sensor measurement may suffer from ambient magnetic noise (e.g., environmental magnetic field) for the real-world deployment.

In this paper, we introduce a novel system based on Radio Frequency Identification (RFID) technology to monitor the hand use in ambulatory settings. The proposed system employs a wrist-worn Ultra High Frequency (UHF) RFID reader and a passive (batteryless) RFID tag embedded in an artificial fingernail that is attached to the middle finger. The system leverages the close proximity of the reader antenna which provides some guarantees that the tag's direct path component will be stronger than reflected multipath and other environmental interferences. Furthermore, our system captures movements from the most distal part of the hand (i.e., distal phalanx of the finger) which could provide more dynamic and sensitive measurements of hand function when compared to previously studied body locations, such as the wrist or the proximal phalanx of the finger. The system analyzes the physical layer characteristics of the backscattered RFID signal from the passive tag and estimates the amount of hand use based on a machine learning-based algorithm. We validate the accuracy of the proposed system using data collected from five neurologically intact, healthy individuals based on an optoelectronic motion capture system, which is the gold standard for human motion analysis.

II. SENSOR SYSTEM

A. Background

RFID is a technology that can identify and track proximate tags without clear line of sight by leveraging UHF electromagnetic waves. A notable characteristic of RFID technologies is that backscattered electromagnetic signals from the passive tags can be used to identify their position and orientation with

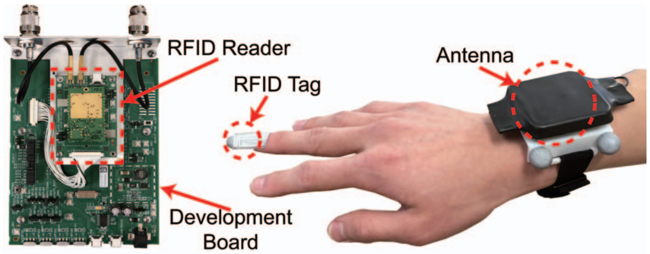

Fig. 1. A prototype implementation of the proposed wearable RFID system. *Left*: UHF RFID reader and its development kit (M6E-M, ThingMagic, USA). *Right*: an artificial fingernail with an embedded passive RFID tag and a wrist-worn apparatus to hold the antenna.

respect to the reader (antenna). Specifically, the location of the tags can be inferred by analyzing the Received Signal Strength Indicator (RSSI) and/or phase of the tag's response [11].

B. Sensor Device

This work hypothesizes that RFID technologies can be used as a wearable system to analyze various kinematic patterns of a passive tag placed on a fingernail, such as the velocity and acceleration of the tag (finger) movements. Specifically, we assume that the backscattered signal from the tag could be processed to estimate the amount and intensity of hand use. Figure 1 shows the prototype implementation of our wearable RFID system. The system contains three major components: the RFID reader, antenna, and artificial fingernail with an embedded passive tag. An off-the-shelf, miniaturized high-performance RFID reader (M6E-micro, ThingMagic, USA) developed for mobile or handheld devices was used in our system. For the prototype implementation, we used the development kit provided by the manufacturer. We used a standard UHF RFID carrier generated at 915 MHz with 30 dBm of transmit power; furthermore, the EPC Gen 2 protocol was optimized to read a single tag by assigning one inventory slot with the parameter Q set to 0. The antenna was placed on the wrist using a 3D printed enclosure and strap. The dimension of the RFID-tag was $1.1 \times 2.5\ cm^2$, which was small enough to be placed on the distal phalanx of different fingers.

We tested multiple configurations for the location and orientation of the antenna on the wrist and the tag on the finger in order to achieve the highest sampling rate and maximum signal coverage. We identified that the antenna placed on the top of the wrist, as shown in Figure 1, resulted in the optimal sensing performance. The intuition behind the selected antenna position is that the reader antenna has line of sight to the tag, mitigating multipath interference that would distort RSSI and phase.

III. Data Collection

In our study, five neurologically intact, able-bodied subjects, aged between 18 and 40, were recruited via word of mouth from the University of Massachusetts Amherst. Once subjects arrived at the laboratory and agreed to participate in this study, they were equipped with our RFID system on their dominant wrist and the passive RFID tag on the middle finger. Reflective markers for the benchmark analysis (i.e., ground truth measurement) based on an optoelectronic motion capture system (Miqus, Qualisys, Sweden) were also attached on the tip of the artificial nail and on the wrist-worn device (see Figure 1).

Subjects were asked to perform a total of six tasks, each of which took about 90 seconds to complete. The first four tasks were to perform random finger movements spanning the entire active range of finger motion, such that the system can be validated to support reliable performance for the entire anatomical space. Because subjects felt uncomfortable (fatigue) to continue moving their fingers for a long period of time, subjects repeated the 90-second random movement session four times, so that we could collect a sufficient amount of data for analyses. Then, subjects were asked to perform grasping movements for 90 seconds, which is one of the most important finger movements required for ADLs [12]. Subjects were also asked to move the finger up and down for 90 seconds, since straightening the finger is an important preparation action to perform the grasping movement; bending the finger is related to dystonia, a common motor symptom in elderly stroke survivors.

IV. Data Analytics

Figure 2 shows a graphical summary of the data analytic pipeline used for 1) constructing ground truth measurements of the amount of hand use, and 2) estimating the amount of hand use based on the data obtained from the proposed RFID system.

A. Construction of Ground Truth Measure of Hand Use

The amount of hand use was defined as the *Activity Count* of finger movements (i.e., acceleration), a clinically validated measure of movement intensity and overall quantity: 1 Activity Count $= 0.00166 \cdot g = 0.0163\ m/s^2$, where $g = 9.81\ m/s^2$ for gravity [13]. First, the position time-series of the middle finger in a 3D Cartesian coordinate system, obtained from the motion capture system at 100 Hz, was converted into acceleration time-series ($a_x[t]$, $a_y[t]$, $a_z[t]$) by taking double derivatives. A low pass filter at 6 Hz was applied to the time-series after each derivative to remove any non-human generated noise while retaining most of the real human motion [14]. The activity count for every data sample, denoted as $m[t]$, was computed using the following equation: $m[t] = \frac{1}{0.0163}\sqrt{a_x^2[t] + a_y^2[t] + a_z^2[t]}$. Finally, the times-series of $m[t]$ was segmented using a sliding window of 1 second with 50% overlap. Note that the window size of 1 second has been conventionally used to quantify the intensity of human movement [13]. The activity count values of each window were then averaged to produce a single measure of the amount of hand use within each second of movement.

B. RFID Signal Pre-processing

This section describes methods for pre-processing the RSSI and phase time-series data obtained from the backscattered

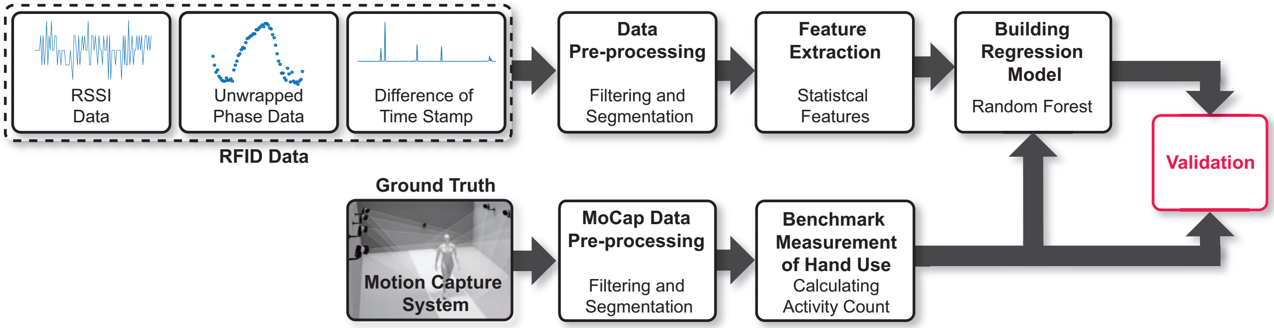

Fig. 2. The data analytic pipeline for estimating and validating the amount of hand use using data obtained from the proposed RFID system.

RFID signal, such that they could be used to estimate the amount of hand use at 1 Hz as we discussed in the previous section.

Phase unwrapping: The RFID reader provides RF phase information across one RF period ($0 - 2\pi$ radians), which created discontinuities in the time-series data. Thus, the phases were unwrapped by comparing each phase value to its immediately previous value. The current phase value was adjusted by +/-π to reduce absolute differences between the current and previous phases.

Filtering RSSI and phase: Since the sampling rate of our RFID system was subject to change based on the signal strength (i.e. dropped RFID query responses), the RSSI ($p[t]$) and the unwrapped phase ($\phi[t]$) time-series were first interpolated to yield a consistent sampling frequency of 100 Hz. Then, a low pass filter at $5Hz$, which was more stringent than the conventional 6 Hz for non-human noise elimination, was applied to yield information regarding coarse finger movements.

Additional time-series generation: Five additional time-series that we hypothesized to be relevant to the amount of hand use were generated: $\frac{d\phi[t]}{dt}$, $\frac{dp[t]}{dt}$, $\frac{d^2\phi[t]}{dt^2}$, $\frac{d^2p[t]}{dt^2}$, and $\tau[t]$. Four of these time-series are the first- and second-order time difference of $p[t]$ and $\phi[t]$. $\tau[t]$ represents the time difference between each adjacent data points before the missing data interpolation. We hypothesized that $\tau[t]$ would carry important information related to finger movement as the signal availability may be correlated to a specific region of motion.

Time-series segmentation: Similar to the activity count, the derived time-series were segmented using a sliding window of 1 second with 50% overlap.

C. Estimating the Amount of Hand Use

The following statistical features were computed from the seven aforementioned time-series: 1) mean, 2) max, 3) min, 4) std, 5) root mean square, 6) skewness, 7) kurtosis, 8) dominant frequency and 9) interquartile range. These features have been previously shown to be relevant to the intensity and smoothness of human movement [15]. A total of 63 features were extracted to train a machine learning model that estimated the amount of hand use.

Random Forest regression was employed to train the estimation model [16]. The model parameters of the algorithm (i.e., the number and maximum depth of trees) were optimized by maximizing the R^2 value of the estimation compared to the ground truth amount of hand use. The performance of the estimation model was evaluated using Normalized Root Mean Square Error (NRMSE) and R^2. NRMSE is an error measure representing the percentage of RMSE with respect to the value range of the benchmark measure spanned by the subject during the entire experiment. All the analyses were performed in a leave-one-subject-out cross validation manner to avoid overfitting and provide a generalized performance evaluation.

V. Results

A. Robustness of the System for Human Movement Analysis

Figure 3 shows a histogram of the RFID reader's data sampling rate for each window across all five subjects. This provides insights regarding the robustness of the wearable RFID device in capturing sufficient amount of data required for human movements; human movements are usually performed at less than $6Hz$ [14], the frequency that the proposed system should be able to support. The sampling rate was calculated based on how many data points were captured by the RFID reader during the duration of the sliding window (i.e., 1 second). As shown in Figure 3, the sample rate was not constant throughout the data collection. The median and the mean sample rates were 32.0 Hz and 30.2 Hz, respectively. 4.90% of the windows captured data points at less than or equal to 6 Hz, and 2.81% of the windows did not have any data points. In this study, we decided to consider windows of sampling rate less than or equal to 6 Hz as missing data.

B. Estimation Accuracy for the Amount of Hand Use

Figure 4 shows a scatter plot between the benchmark measurement (actual activity count) obtained from the motion capture system and the estimated amount of hand use obtained from our Random Forest model, evaluated in a leave-one-subject-out cross validation manner. The R^2 value was 0.67 and the corresponding NRMSE was 7.3%, indicating that the proposed wearable RFID system could accurately estimate the amount of hand use within the entire range of motion. It is noteworthy that the proposed algorithm underestimated the

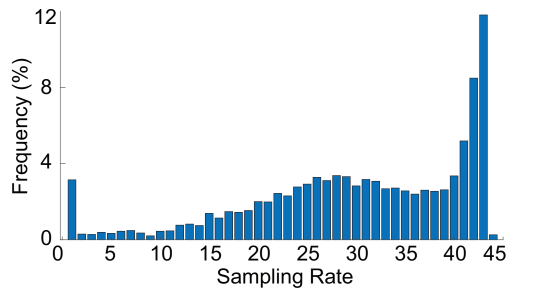

Fig. 3. A histogram of sampling rate generated by the proposed RFID system during the data collection across all the subjects.

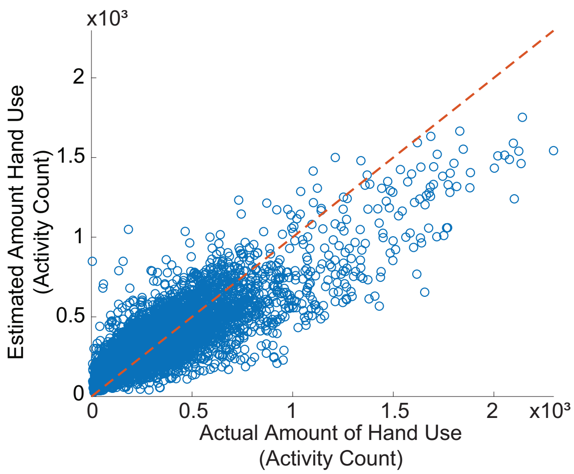

Fig. 4. A scatter plot between the benchmark measurement (i.e., actual activity count) and estimated amount of hand use. The R^2 value was 0.67 and NRMSE was 7.3%.

high-intensity hand use (i.e., activity count $> 1.5 \times 10^3$), as shown in Figure 4. We believe that the collected experimental data contained relatively small number of high intensity data points (approximately 1% of the data points had activity count greater than 1.5×10^3) and thus, the trained regression algorithm assigned higher priority on low-to-mid intensity movements.

VI. Discussion and Conclusions

This study demonstrated a novel wearable RFID approach to monitor the amount of hand movement in the ambulatory setting. The system is minimally obtrusive as it requires a single wrist-worn device (RFID reader) and a passive tag that can be attached to a fingernail. The minimal-obtrusiveness of the system is particularly important when deploying the sensor in stroke survivors as they need to go about their normal daily routines while wearing the system. Our system could provide an accurate estimate of hand use with R^2 of 0.67 and NRMSE of 7.3%. We believe that our system has great potential to be used in stroke survivors within their naturalistic settings to estimate the amount of goal-directed use of their stroke-affected limb (as well as the contralateral limb).

There is a limitation worth noting in our investigation of the proposed wearable RFID system. Currently, the RFID reader operates at $30\ dBm$ ($1W$) for transmitting the electromagnetic RF signal, which can serve as a bottleneck for the real-world deployment of the system. Future work includes finding the optimal transmission power by investigating the trade-off between the power requirement and data loss rate (currently at 4.9%). A custom antenna design with a more directive gain pattern could be used to further reduce the transmission power.

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