ACRM
AMERICAN CONGRESS OF REHABILITATION MEDICINE

Archives of Physical Medicine and Rehabilitation

journal homepage: www.archives-pmr.org

Archives of Physical Medicine and Rehabilitation 2016;97:224-31

ORIGINAL RESEARCH

Using Wearable Sensors and Machine Learning Models to Separate Functional Upper Extremity Use From Walking-Associated Arm Movements

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Abstract

Objective: To improve measurement of upper extremity (UE) use in the community by evaluating the feasibility of using body-worn sensor data and machine learning models to distinguish productive prehensile and bimanual UE activity use from extraneous movements associated with walking.

Design: Comparison of machine learning classification models with criterion standard of manually scored videos of performance in UE prosthesis users.

Setting: Rehabilitation hospital training apartment.

Participants: Convenience sample of UE prosthesis users (n=5) and controls (n=13) similar in age and hand dominance (N=18).

Interventions: Participants were filmed executing a series of functional activities; a trained observer annotated each frame to indicate either UE movement directed at functional activity or walking. Synchronized data from an inertial sensor attached to the dominant wrist were similarly classified as indicating either a functional use or walking. These data were used to train 3 classification models to predict the functional versus walking state given the associated sensor information. Models were trained over 4 trials: on UE amputees and controls and both within subject and across subject. Model performance was also examined with and without preprocessing (centering) in the across-subject trials.

Main Outcome Measure: Percent correct classification.

Results: With the exception of the amputee/across-subject trial, at least 1 model classified >95% of test data correctly for all trial types. The top performer in the amputee/across-subject trial classified 85% of test examples correctly.

Conclusions: We have demonstrated that computationally lightweight classification models can use inertial data collected from wrist-worn sensors to reliably distinguish prosthetic UE movements during functional use from walking-associated movement. This approach has promise in objectively measuring real-world UE use of prosthetic limbs and may be helpful in clinical trials and in measuring response to treatment of other UE pathologies.

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The goal of upper extremity (UE) treatment is to increase use of the affected UE in the home and community. However, clinicians who rehabilitate these patients lack a practical method to directly measure functional use outside the laboratory.[1] Therefore, it is difficult to determine whether an intervention such as a new prosthetic limb, an improved motor training regimen, or an orthopedic procedure actually improves UE use. This inability has been a significant obstacle to advancements in UE treatment and restoration because clinical trials lack an objective and quantitative direct measure of the goal of intervention. It also limits the type and amount of UE treatment delivered because payers often require unambiguous evidence that treatments used are effective.

Supported by the MITRE Corporation of America, Veterans Affairs Rehabilitation Research and Development Merit Awards (award nos. A-6408 and A-6767).

Disclosures: none.

0003-9993/15/$36 - see front matter © 2016 by the American Congress of Rehabilitation Medicine
http://dx.doi.org/10.1016/j.apmr.2015.08.435

Clinical trialists generally address this problem using 2 approaches. They may evaluate changes in impairment using measures of UE movement and coordination, including the Action Research Arm Test,[2] Box and Blocks test,[3] or kinematics.[4] These measures are performance based, are sometimes objective and quantitative, and may be interval measures. However, as indirect measures of the variable of interest, they are assumed to correlate with the unmeasured domain of everyday functional use in the community. Moreover, these measures occur in a short time period in an artificial clinical or laboratory environment and may reflect fatigue, anxiety, distraction, or high motivation to please clinicians. The second approach is to assess the set of activities describing functional UE use. These activities are generally basic and instrumental activities of daily living (ADL) and leisure activities.[5-8] The predominant method of assessment of ADL is through self-report and interviews and questionnaires measuring assistance or equipment needed.[9-11] They do not directly measure performance in the home or community, they are ordinal rather than interval measures, and they do not specifically assess the use of the UEs to accomplish the ADL. Similar self-reports of UE use (eg, Motor Activity Log[12]) or UE satisfaction (eg, Stroke Impact Scale[13]) are other approaches which do address UE involvement in activities. Questionnaires are limited by recall bias,[1,14] the Hawthorne effect,[15] and difficulties in interpretation.[1,16]

Wearable technology[17] can directly measure the amount the UE is used in functional tasks of any sort. Patient-affixed motion sensors[16,18-20] present the opportunity to persistently analyze kinematic data. If these data could be analyzed to distinguish functional from extraneous UE movements using either onboard processing or via a handheld device (eg, smartphone), then UE use could be measured directly. Simply measuring the number of minutes the patient uses the affected UE in productive (predominantly prehensile) tasks would provide a measure with high face validity, continuous measurement properties, and unambiguous patient benefit.

Finding an unobtrusive sensor-based alternative suitable for community use is challenging.[21-23] Large sensor suites or those tethered to immobile equipment can restrict movement, alter behavioral patterns, and impede use.[19,24-27] Similarly, proximity sensors, usually radio frequency identification devices affixed to frequently used objects, can be used with a reader affixed to the patient's hand. Algorithms applied to the collected data estimate the type and duration of ADL performed.[28] The advantage over accelerometry is that no human annotator or subjective reference (eg, Motor Activity Log) is required. However, only a finite number of objects can be tagged, relevant objects vary across patients, and some relevant objects are outside of the home. There is a trade-off between intrinsic (ie, patient-mounted) sensors (eg, inertial measurement units [IMUs]) and extrinsic (ie, installed into the environment) sensors. Intrinsic sensors are more widely applicable because a single sensor suite is present to detect all activity, whereas extrinsic sensors typically have more easily interpreted data because of the added context gained from multiple sensors installed in multiple locations. For instance, it is much easier to infer that the patient is interacting with a box of cereal by detecting proximity to a radio frequency identification device tag on the cereal box, rather than inferring the same information from a wrist-mounted IMU.

List of abbreviations:

ADL **activities of daily living**
IMU **inertial measurement unit**
UE **upper extremity**

Much research toward automated UE functional use classification involves identification of the specific ADL being performed,[23,28-33] using data from both proximity and motion sensors. This research has had success primarily in the laboratory and has required multiple sensors on multiple body parts.[24,31,34-37] In particular, work by Patel et al[38] used random forests (an ensemble classifier) applied to accelerometry data from wrist-mounted IMUs; this was used to predict scores on the Functional Ability Scale.[39] Machine learners in these tests automatically gauged speed, smoothness of movement, task completion, and presence of compensatory movements. Ground truth was established by grading the motor tasks according to the Functional Ability Scale, and algorithm performance was evaluated in terms of deviation from human assessment. Giuffrida et al[27] also used clustering techniques to identify ADL motions from IMU and electromyography data combined (totaling 48 sensor channels), using sensors positioned at multiple points over the affected arm. Bailey et al[37] used bilateral wrist-worn accelerometers to quantify bilateral UE movements in healthy adults. Classification of lower limb activity via machine learners has also been studied.[22,24,40,41]

We set out to develop a prototype sensor and machine learning-based classification system with realistic potential for community use in the clinical and trial setting. Our goal was a system easily implemented using a single wrist-worn sensor, in both people with relatively normative UEs and those with a catastrophic injury (eg, UE prosthesis users). We apply basic classifier models to data taken from a body-mounted IMU, with the goal of separating functional use from the most common nonfunctional activity, arm swing while walking. Previous studies have been successful in classifying specific ADL in a laboratory setting using multiple sensor suites or require more computational power (eg, random forest system[38]). Our classifier models draw conclusions using a single poll from a 6 degree-of-freedom IMU. These models require less computational power because they do not contain temporal information and therefore do not require a segmentation step to identify sequences of sensor polls corresponding to a single, uninterrupted task. Giuffrida[27] showed that uncomplicated and computationally lightweight models similar to the ones we use can distinguish individual specific tasks using inertial and electromyographic data.

To tightly focus on the clinical goal of quantifying the number of minutes spent moving the UE in functional tasks, we restrict ourselves to a single wrist-worn IMU (increasing ease of use), but relax the classification task to simply separate all functional activity from the most common nonfunctional movements of walking. By applying these classification models to an intrinsically mounted sensor (eg, IMU), we show that streaming data from a wearable sensor can be used to evaluate upper limb impairments through analysis of functional use.

Methods

The study was approved by the local institutional review board; participants provided informed consent. Five regular users of UE prostheses and 13 healthy right-handed controls were tested.

Procedures

We used custom 9 degree-of-freedom IMU devices.[a] Each degree of freedom refers to a unique sensor: these were 3 orthogonally positioned linear accelerometers, 3 orthogonally positioned