2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Accuracy comparison of machine learning algorithms at various wear-locations for activity identification post stroke: A pilot analysis*

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Abstract— **Objective and accurate activity identification of physical activities in everyday life is an important aspect in assessing the impact of various post-stroke rehabilitation therapies and interventions. Since post-stroke hemiparesis affects gait and balance in individuals with stroke, activity identification algorithms that consider stroke-specific movement irregularities are needed. While wearable physical activity monitors provide the means to detect activities in the free-living, algorithms using their data are specific to the wear location of the device. This pilot study builds, validates, and compares three machine learning algorithms (linear support vector machine, Random Forest, and RUSBoosted trees) at three popular wear locations (wrist, waist, and ankle) to identify and accurately distinguish mobility-related activities (sitting, standing and walking) in individuals with chronic stroke. A total of 102 minutes of data from two lab visits of three-stroke participants was used to build the classifiers. A 5-fold cross-validation technique was used to validate and compare the accuracy of classifiers. RUSBoosted trees using data from waist and ankle activity monitors, with an accuracy of 99.1%, outperformed other classifiers in detecting three activities of interest.**

Clinical Relevance— **One of the major aims of post-stroke rehabilitation is improving mobility, which may be facilitated by understanding the structure and pattern of everyday mobility through real-world, objective outcomes. Accurate activity identification, as shown in this pilot investigation, is an essential first step before developing objective outcomes for monitoring mobility and balance in everyday life of these individuals.**

I. Introduction

About 7 million Americans suffer from stroke annually [1]. With the advancement in health-care, the majority of these individuals survive a stroke but live with prolonged disability in the community [2]. Globally, stroke is the third leading cause of disability, and 65% of stroke survivors report restrictions in activities associated with community reintegration even during the chronic phase (> 6 months) of stroke [3]. Mobility and balance limitations persist in the chronic phase post-stroke, which limits the activity and participation of post-stroke individuals in the community [3-5]. One of the major goals of post-stroke rehabilitation is known to help improve mobility and balance [6-7] and improve functioning in everyday life in the community. Many rehabilitation interventions are being developed with an aim to improve mobility in individuals with stroke as mobility is a critical aspect of community integration [8]. The goal of improving mobility may be best understood by, first, understanding the structure and pattern of everyday mobility in the community, and second, evaluating the true impact of any clinical intervention on mobility outside the clinic, i.e., in the community. However, both of the aforementioned approaches require objective and accurate detection of mobility-related activities (sitting, standing, physical activity, etc.) in everyday life.

With technology advancing tremendously over the last decade, wearable devices have provided the means to accurately, objectively, and continuously track mobility [9]. Various signal processing and machine learning (ML) algorithms have been developed to identify activities of everyday life using the raw data from wearable devices [10]. However, these algorithms are specific to the movement patterns of individuals and, therefore, are population-specific [11]. Individuals with stroke suffer from hemiplegia, which affects their balance and mobility patterns. Mechanisms of walking after stroke are often characterized by reduced speed, kinematic, temporospatial, and neuromuscular asymmetry, and postural instability [12]. As stroke-gait is different from healthy individuals, the algorithms developed for other populations are not accurate for slow speed and asymmetrical gait, as is typical in individuals with stroke [13]. Therefore, activity identification algorithms specific to individuals with stroke are needed. There is limited research for activity identification in individuals with stroke, with research primarily focusing on identifying upper extremity movement or identifying step count during walking [14, 15]. Further, the accuracy of activity identification algorithms using raw data from the wearable devices is also specific to the wear location of the device [15]. However, neither a popular wear location chosen by the users nor an accurate wear location identified through research for activity identification in post-stroke individuals is provided in the literature.

The goal of this investigation is to accurately and objectively identify the three basic activities related to mobility - standing, sitting, and walking, in everyday life using raw data from wearable devices in a laboratory setting. The

*Research supported by pilot study grant from Kessler Foundation.

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second objective is to compare the accuracy of activity identification algorithms at three popular wear locations – ankle, waist, and wrist, for individuals with chronic stroke. We hypothesized that the waist would be a better wear location in terms of accuracy for activity identification compared to the wrist and ankle locations. The rationale is that the waist is closer to the center of mass of the body, and therefore, the measurements from the waist may be more stable and reflective of total body movement.

II. Methods

A. Participants

All study procedures presented in this paper involving human subjects were approved by the Institutional Review Board. Three participants who were in the chronic phase post-stroke (>6 months) and were medically stable (defined as no changes in medication) for at least three months prior to the start of the study were recruited. All participants had hemiplegia affecting one side of their body but were able to walk at least 10 meters with minimal or no support. Hemiplegia was defined as paralysis affecting only one side of the body and was diagnosed by the subjects' treating physician at the time of injury.

Two female participants and one male participant aged 60, 63, and 64 years respectively were recruited for the study. The 64-year-old male and 60-year-old female participants had right hemiplegia, while the 63-year-old female participant had left hemiplegia. Participants' demographics and functional assessment scores at visit 1 are presented in Table 1 and reflect on the functional ability of each participant.

TABLE I. Participant Demographics and Functional Assessments

	Participant 1	*Participant 2*	*Participant 3*
Age	60	63	64
Gender	Female	Female	Male
Affected	Right	Left	Right
BBS	51	46	54
TUG (sec)	9.7	15.6	10.8
10 MWT (sec)	8.8	12.1	7.8
CBMS	36	27	45
TIS score	22	18	14

B. Assessments

During two in-lab visits which were one week apart, participants wore three ActiGraph GT9X Link (ActiGraph, Inc., FL, USA) physical activity monitors (PAM), one each on the non-affected ankle, non-affected wrist and waist. The ActiGraph GT9X Link is a popular research-grade PAM and FDA-approved class II medical device in the United States. It is worn using accessories (i.e., Velcro ankle straps, a waist belt with buckle, and a wrist band). The PAM collects movement (accelerometer) data without any identifiable information. The three wear locations (ankle, waist, and wrist) selected in this study are popular PAM wear locations in stroke research [16, 17]. All three PAM (ankle, waist, and wrist) were set-up to record tri-axial accelerometer data at 30 Hz. While wearing the PAM, participants performed a battery of functional assessments and completed a mobility course consisting of standing, sitting, walking, and going up/down stairs. Functional assessments included Berg Balance Scale (BBS)

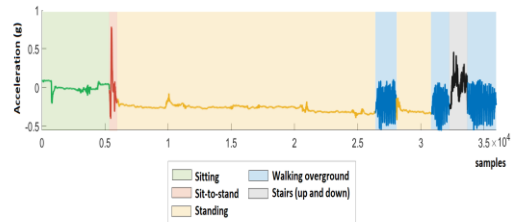

Figure 1. Raw acceleration patterns for different activities from the anterior/posterior axis of the waist PAM the mobility course.

[18], Timed-Up-and-Go (TUG) score [19], 10-meter walk test (10MWT) [20], 6-minute walk test (6MWT) [20], community balance and mobility scale (CBMS) [21] and Trunk Impairment Scale (TIS) [22]. The BBS assesses static and dynamic balance, the TUG assesses mobility and risk of falls, the 10MWT assesses walking speed, the 6MWT assesses endurance, the CBMS assesses postural instability that limits community engagement in ambulatory individuals, while TIS assesses motor impairment of the trunk. All these functional assessments are clinical standards and validated measures that are typically used to assess mobility and balance in individuals with stroke. All assessments and activities were video-recorded for both visits for all participants.

C. Data Analysis

Feature Extraction - To identify activities of interest (AoI), the PAM data corresponding to walking, standing and sitting activities was extracted. Each of these activities has a distinct pattern as seen from the accelerometer data in Fig 1. A total of about 102 minutes of data which included 10 minutes of walking, 5 minutes of standing and 2 minutes of sitting for each visit from each participant, was extracted and used to build and validate ML classifiers for activity detection. The data from each PAM (wrist, waist, and ankle wear locations) was divided into windows of 5-second intervals (total 1229 windows) and a criterion activity label was assigned to each window based on the video recordings. A window size of 5-second was selected so that a window for walking activity will include at-least 2 gait-cycles for all post-stroke limited community ambulators (walking speed > 0.4 m/s) [8]. Features were extracted from each 5-second window data from each PAM (ankle, waist, and wrist). Features extracted from each 5-second window from each PAM included time-domain variables (mean, standard-deviation, range, the correlation coefficient between each pair of three axes), for all three accelerometer axes as well as the resultant vector magnitude signal (calculated as $\sqrt{(x^2+y^2+z^2)}$). The frequency-domain features included the three most prominent frequencies and their corresponding energy in the fast fourier transform spectrum for all three accelerometer axes.

Classifiers - Once the features from each window for all three PAM were calculated, the choice of ML classifiers to build and validate was based on literature. Linear support vector machine (SVM) and Random Forest classifiers are popular ML algorithms for activity identification in individuals with stroke and, therefore, were selected to build and validate. This study's data set consisted of more data windows of walking compared to that of sitting. To account for this imbalance in the data set, apart from the linear SVM and RF classifiers, we also chose to build and validate the Random Under Sampling Boosted (RUSBoosted) trees classifier. The three chosen classifiers were built and validated using data from each PAM (each wear location- ankle, waist, and wrist). In order to avoid over-fitting, the default values of the hyper-parameters for each classifier were used. The ML classifiers (SVM, Random forest, and RUSBoosted trees) were trained, and a 5-fold cross-validation technique was used to validate the classifiers. The classifier-predicted activity was compared to the criterion activity label (manually assigned using video recording) for each window to determine the accuracy of the classifier.

Performance Evaluation - To evaluate the performance of the classifiers, confusion matrices were plotted. Sensitivity, or true positive rate, was computed as the ratio of the number of true positive data windows to the number of real positive data windows for each activity category. Specificity, or true negative rate, was computed as the ratio of the number of true negative data windows to the number of real negative data windows.

III. Results

TABLE II. ACCURACIES OF DIFFERENT ML CLASSIFIERS AT EACH WEAR-LOCATION

	SVM (linear)	*Random Forest*	*RUSBoosted trees*
Ankle	94.1%	98.5%	98.8%
Wrist	97.7%	97.6%	98.5%
Waist	93.7 %	96.5%	99.1%

A total of 36 features were extracted from the raw data of the PAM at each wear location. The features included time and frequency domain outcomes extracted from each axis of the PAM. The range of each feature value was different for each PAM wear-location. Fig. 2 (A-C) shows visual representation of some of the features calculated from each PAM wear-location. Different features plotted on the Y-axis (standard deviation, correlation, energy) against a common feature (mean) on X-axis for all data shows a visual representation of how different AoI (sitting, standing and walking) vary based on extracted features and how the same feature varies based on the wear-location of the PAM. Fig. 2 (D-F) show the confusion matrices for the RUSBoosted trees classifier built using data for each wear-location. For each wear-location, confusion matrices show the accurately classifies windows and misclassified windows for each AoI.

While all classifiers had very good accuracy (>90%), the RUSBoosted trees classifier performed better than other classifiers for all PAM wear-locations as shown in Table 2. While the overall accuracy for the RUSBoosted trees was similar for all PAM, the RUSBoosted trees classifier built using the waist PAM data had the least misclassification of activities across the three different activities of walking, standing, and sitting, with the highest accuracy of 99.1%. The RUSBoosted trees classifiers had a sensitivity and specificity of 100% and 100% (for ankle data), 99.3% and 99.2% (for wrist data), 100% and 100% (for waist data), respectively for identifying 'walking' activity as seen for Fig. 2 (D-F). The RUSBoosted trees classifiers a sensitivity and specificity of 95.3% and 99.3% (for ankle data), 98.0% and 99.3% (for wrist data), 97.3%, and 99.3% (for waist data), respectively for identifying 'sitting' activity. The RUSBoosted trees classifiers from the ankle, wrist, and waist data had a sensitivity and specificity of 97.8% and 99.2% (for ankle data), 96.9% and 99.1% (for wrist data), 98.0% and 99.5% (for waist data), respectively for identifying 'standing' activity.

IV. Discussion

This pilot investigation compared three ML algorithms built using data from PAM worn at three different wear-locations. All the three ML algorithms showed a high accuracy (>90%) at each wear location. Particularly, RUSBoosted trees classifier for the waist wear-location had the highest accuracy (99.1%), closely followed by the classifier for the ankle (98.8%) wear-location. This may be due to the stability (reduced variability) in the waist and rhythmicity in the ankle accelerometer data compared to the wrist during the AoI. Especially during walking, ankle and hip joints tend to follow cyclic and rhythmic trajectories for healthy individuals. For individuals with stroke, such patterns may be distorted

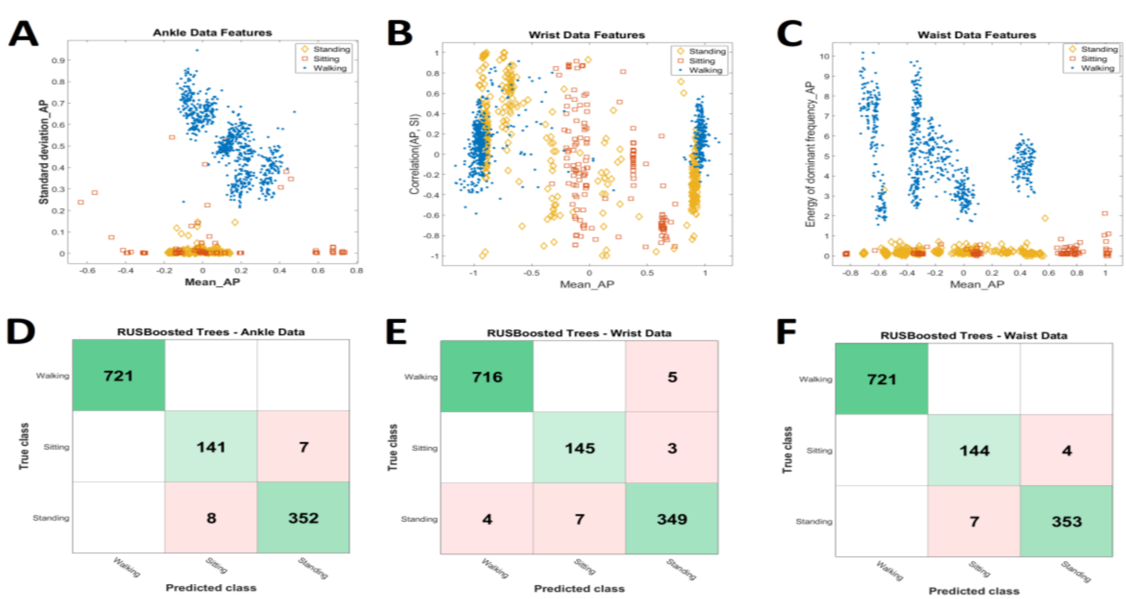

Figure 2. (A-C) show some of the features from each PAM that help visually distinguish between the different activities. (D- F) show the confusion matrix for the RUSBoosted trees classifier for each PAM wear-location

compared to the healthier limb but the rhythmicity and repeatability of motion still exist. The placement of sensors on the non-affected side may have contributed to the enhanced accuracy in detection of AoI. PAM worn on the wrist is known to pick up random hand movements that may not reflect or correlate with the voluntary movement during the AoI.

The accuracy of the RUSBoosted trees classifier presented in this study is higher compared to accuracy of activity detection algorithms previously reported by O'Brien et al. [15]. O'Brien et al. used single accelerometer based sensor and reported accuracy similar to that reported by Laudanski et al. using two inertial measurement units (IMUs). The gyroscope sensors which are part of the IMUs drain the battery life of IMUs much faster compared to accelerometers and hence, currently they are not best-suited for long-term data collection. The RUSBoosted trees classifier presented in this paper also accounts for the imbalance in time spent in different activities and hence might be more suitable for activity identification in the community where time spent in activities is imbalanced as well. However, due to the limited sample size, the results of this pilot study need to be interpreted cautiously.

Although the data presented in the current pilot investigation included data from two-different visits from three stroke participants only, the current analysis had more than 102 minutes of data with 1229 5-second windows. The three participants in the current pilot had varied functional abilities as seen in Table I which brought the inherent variability in the data that is typical to stroke individuals. The number of windows used in the current pilot is much greater than that used by Laudanski et al. (240 2-second windows). The features used in the current study are standard features that have been previously used in activity recognition in individuals with stroke.

Identifying mobility-related activities accurately is an important first step before individuals with stroke may be continuously monitored in everyday life to assess the impact of rehabilitation. Therefore, as a next step, we will collect more data from a larger sample and test the algorithms on an out-of-sample data-set to establish external validity. Upon further validation, these algorithms could be used to determine the total time spent by individuals post-stroke in AoI in the community and to study the community based mobility characteristics of post-stroke individuals.

Acknowledgment

The authors would like to thank Amanda Krantz for her help during data collection.

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