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GerActive: Wearable App for Monitoring and Encouraging Physical Activity among Older Adults

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Abstract

The ability to monitor a person's level of daily activity can inform self-management of physical activity and assist in augmenting behavioral interventions. For older adults, the importance of regular physical activity is critical to reduce the risk of long-term disability. In this work, we present *GerActive*, an application on the Amulet wrist-worn device that monitors in real time older adults' daily activity levels (low, moderate and vigorous), which we categorized using metabolic equivalents (METs). The app implements an activity-level detection model we developed using a linear Support Vector Machine (SVM). We trained our model using data from volunteer subjects (n=29) who performed common physical activities (sit, stand, lay down, walk and run) and obtained an accuracy of 94.3% with leave-one-subject-out (LOSO) cross-validation. We ran a week-long field study to evaluate the usability and battery life of the *GerActive* system where 5 older adults wore the Amulet as it monitored their activity level. Their feedback showed that our system has the potential to be usable and useful. Our evaluation further revealed a battery life of at least 1 week. The results are promising, indicating that the app may be used for activity-level monitoring by individuals or researchers for health delivery interventions that could improve the health of older adults.

I. Introduction

Unhealthy behaviors are a leading cause of chronic diseases including hypertension, diabetes and obesity in all demographic groups, even in older adults [1]. Older adults with sedentary behaviors are at a higher risk of long-term disability and nursing home placement [2]. The American College of Sports Medicine (ACSM) and the Centers for Disease Control (CDC) recommend 30 minutes of moderate-intensity activity or 15 minutes of vigorous activity daily in this population [3].

Promoting health behavior change is difficult in the clinical setting, and the use of technology holds promise by engaging individuals in becoming aware of their physical activity levels and movement. In this work, we developed *GerActive*, a wrist-worn, energy-efficient system that uses a lightweight machine-learning algorithm to monitor and encourage physical activity among older adults. Our *GerActive* app monitors the activity level of older adults in real time using acceleration data recorded from the Amulet device, a low-power wrist-worn wearable device [4].

This manuscript advances the science of activity monitoring in three ways: first, we demonstrate the development, implementation and evaluation of an open-source wearable

app for real-time monitoring and encouragement of physical activity among older adults; second, we develop and implement an SVM-based activity-level model validated on older adults; and third, we provide a preliminary evaluation of the system's usability, which is essential in this population at risk for multiple sensory abnormalities that could affect the end-user's experience [5].

II. Background

In this section, we describe the challenges of older adults in using technology. Next, we describe the Amulet platform on which the *GeriActive* app runs and why it is suitable for running the app. Then, we describe the categorization of the physical activity levels we use in this work.

A. Older Adults and Technology

Despite the belief that older adults are averse to using technology, this group is the fastest growing segment of the population that is engaging in information and communication technology. This has led to an increasing interest in the adoption of emerging technologies by older adults for health monitoring [6]. Specifically, this population is eager to learn how to use and integrate devices into their everyday lifestyle. However, older adults cite various inconveniences with using health technologies that require physical and mental effort and consequently, ease of use and usefulness are significant factors in technology adoption by older adults [7]. These concerns make a case for developing technologies tailored for older adults that address usability and usefulness, by involving the end-user as part of the prototype development process.

B. Amulet Wearable Platform

The Amulet is an open-source hardware and software platform for writing energy- and memory-efficient sensing applications [4]. Its built-in sensors and peripherals include: accelerometer, buttons, capacitive touch slider, haptic buzzer, LEDs, micro-SD card, and low-power display. The energy-efficient Amulet platform is useful for creating and running mHealth applications that monitor the physiological and behavioral health of its wearer, often lasting weeks before needing to recharge.

C. Physical Activity Level Categorization

Physical activity levels are defined using the Compendium of Physical Activities, which capture the intensity of activities expressed in metabolic equivalents (METs): 1 MET corresponds the metabolic rate obtained during quiet sitting [8]. According to the CDC guidelines, activities can be categorized into three levels: *low* activities (METs < 3, e.g., sit, stand, lay down); *moderate* activities (METs between 3 and 6, e.g. walking at a moderate pace, walking fast); and *vigorous* activities (METs > 6, e.g., running) [9]. We use these example activities to categorize our activity levels and do not measure the METs. We chose mostly locomotive tasks because they are often used in related work [6]. For more information, see our Tech report [10].

III. Related work

There is a need for a real-time activity monitoring system that is tailored, validated and evaluated specifically for older adults. The app's algorithm needs to be validated using data recorded from older adults and should be simple to use by older adults at risk for sensory abnormalities. Research-grade gold-standard devices, such as ActiGraph (often used for measuring physical activity) cannot track activity levels nor provide real-time feedback, making it difficult for these devices to be used in a routine clinical setting [11]. Hence, they cannot be used to encourage older adults to meet the CDC's activity goal. Several commercial devices used for physical-activity monitoring, such as Fitbit and Apple Watch, can track real-time fitness parameters and the activity levels, and provide their wearer with immediate feedback [12]. The feasibility and acceptability of such devices in an older adult population was favorable, particularly in rural areas [6]. These activity trackers, however, are closed systems that use proprietary algorithms. As a result, it is not clear whether the algorithms were validated on older adults and their algorithms cannot be modified or customized for this population. For more related work, see our Tech report [10].

IV. Overview of System

GeriActive is an Amulet application that measures the daily activity levels of individuals (low, moderate and vigorous). The app continuously collects acceleration data, classifies the activity level, updates the day's accumulated time spent at that activity level, logs the data for later analysis, and displays the results on the screen as feedback to the wearer. The app consists of four components. The *data collector* samples data from a 3-axis accelerometer at 20Hz; previous studies have shown that a frequency of 20Hz is sufficient for capturing the frequency range of physical human activities for classifying activities [13]. The *activity-level detector* determines the activity level of the user by computing a vector of features from each 5-second window of accelerometer data. This feature vector is then fed to the classifier that determines the activity level as low, moderate or vigorous. The *activity-level monitor* is responsible for tracking and logging the number of minutes spent per day, for each of the three activity levels. This component also sets a daily activity goal of 30 minutes of moderate activity or 15 minutes of vigorous activity and tracks progress towards this goal. The user receives three encouragement alerts daily based on the progress made. The activity-level display presents information about the progress made towards the daily activity goal tracked by the activity-level monitor (Figure 1).

V. Activity Level Detection Model

We developed an activity-level detection model using a Support Vector Machine; SVM is a classifier that constructs a high-dimensional hyperplane and uses it to perform classification [14]. We chose linear SVM because its model is compact and is thus well-suited for low-memory platforms like the Amulet and hence we did not explore other algorithms. We trained a linear SVM model to distinguish low, moderate, and vigorous activity levels using the scikit-learn library [15].

A. Data Collection and Processing

We collected acceleration data from 29 volunteer subjects under a study protocol approved by our local Institutional Review Board. We had two cohorts: younger adults ($n=14$, college students 18–23 years old), and older adults ($n=15$, age above 65 years). Participants wore the Amulet on their left wrist, irrespective of their hand dominance, and performed each of the following physical activities for a duration ranging from 1 to 10 minutes: sit, stand, lay down, walk at a regular pace, walk fast and run. Four older adults were unable to perform the run activity and as a result no such data was available in these participants. We had 1,282 minutes of data.

From each 5-second non-overlapping time window of each subject's data, we extracted 6 temporal and 6 spectral features (using the Fast Fourier Transform) from the (x, y, z axes) and magnitude of the acceleration vector, features that previous studies have shown to be relevant for activity detection [13][16][17]. We used a total of $2 \times 6 \times 4 = 48$ different features. The temporal features are: mean, median, range, interquartile range, standard deviation and root mean square. The spectral features are energy, dominant frequency, dominant power, power ratio, coefficients sum and DC value.

B. Training and Evaluation

We trained different models and ran various experiments to evaluate the models with four common metrics: accuracy, precision, recall, and F1-score [13]. We performed our evaluation using leave-one-subject-out (LOSO) cross-validation since it reflects how well the model will perform on a new subject. We performed an experiment to find out how well a model trained on data from only younger adults would perform when tested on a dataset from older adults. The confusion matrix (Table 1) shows that the younger adult model misclassified 95% of older adults' vigorous activities as moderate and 35% of older adults' moderate activities as low, suggesting that a model trained using data from older adults is critical for good performance.

In another experiment, we compared feature subsets to evaluate their performance. In this experiment, we used data only from the older adults, to identify a small number of features that work best for older adults. Table 2 shows feature subsets along with the total number of features and accuracy metrics. The first observation is that all 48 features were not necessary to have good performance. In fact, the temporal features (24 features) outperformed the 'All' feature set in all the metrics, and the 'Magnitude Temporal' feature set (6 features) had comparable results. More surprising, the spectral features did not perform better than the temporal features. This result suggests that it is not necessary to use spectral features, which can be especially challenging to implement on a low-power device like the Amulet. In future work, it may be worthwhile to explore various subsets of spectral features – or others not included in this evaluation. For more details, see our tech report [10].

C. Model Selection and Implementation

We selected a model using only a subset of features and implemented the model on the Amulet. We used temporal features since they performed best and are less computationally intensive than the spectral features – all of which run in $O(n \log n)$ time for computing the

DFT components with the FFT algorithm. Next, we eliminated other features that ran in time more complex than $O(n)$: median and interquartile range, since they need the data to be first sorted before they are computed (sorting requires $O(n \log n)$ time). We then picked two of the remaining four cccc temporal features (mean and standard deviation) and extracted the features from the x , y , z accelerations, and magnitude of the acceleration, resulting in an 8-feature vector. We trained our linear SVM model with these features from the older-adult dataset and our model had a LOSO accuracy of 91.7%. We then implemented the model in the activity-level detector component of the *GeriActive* app. The component computed the 8 features from each 5-second window of accelerometer data. This 8-feature vector was fed to the activity-level classifier, which is an implementation of the decision function of a Linear SVM [17].

VI. Evaluation of system

We evaluated the *GeriActive* system by running a five-day field study and analyzing whether the system was easy to use (usability), and how long the battery might last before needing to be recharged (energy efficiency). In this five-day field study, five older adults (mean age: 80.4 and range 73–87 years) each wore an Amulet that tracked and logged battery life and the duration of time spent performing the three categories of activity. The app displayed to subjects how close they were to achieving the daily activity goal and gave them encouragement alerts three times a day.

A. Usability Evaluation

To evaluate the end-user experience, particularly in older adults who have sensory impairments, we sought to determine whether the *GeriActive* system was usable and whether this population group would be willing to use it for activity monitoring [7]. We asked subjects to react to various statements pertaining to the usability of the system; we summarize the mean responses in Table 3. Overall, there were high scores. These results suggest that the *GeriActive* system has the potential to be usable by older adults for activity monitoring.

B. Energy Efficiency Evaluation

All five Amulets were still running the *GeriActive* app upon return of the devices and none of the subjects had charged their Amulets, suggesting a battery life of at least 5 days. We computed a linear extrapolation of battery data (logged by the app) to estimate battery life and our results show that Amulet could run for at least 7 days (178 hours) before needing to be recharged, and in the best case, the system might last 14 days. This result demonstrates that the *GeriActive* system is sufficiently efficient for activity monitoring in older adults.

VII. Discussion and Limitations

The *GeriActive* system uniquely addresses the weaknesses of earlier work and results in a comprehensive monitoring system to encourage physical activity among older adults. First, the algorithm has been evaluated on older adults, and the above results provide a preliminary validation of this algorithm. Second, our system is easy to use by older adults as the app's

usage requires no interactivity and the long battery life results in infrequent charging. Third, our system monitors activity levels in real-time (unlike the ActiGraph) and provides immediate feedback to the wearer concerning progress towards the CDC's recommended daily goal. Fourth, our system, unlike Fitbit and other commercial devices, is open-source and could be modified to compute other statistics for exploring activity patterns of older adults and also include in-app messaging to facilitate engagement by the research/clinical team. Additional intelligence could be built into the system to encourage users to improve physical activity when they are falling short of the recommended daily activity goal like our encouragement alerts do. Finally, our system tracks three activity levels and provides a more granular (yet clinically practical) assessment of physical activity patterns than do other approaches.

This study has a number of limitations. Our field study had only five subjects and thus we can only draw preliminary conclusions from the data reported. Also, the accuracy of the system has not been validated in a free-living setting. Finally, the activity-level display currently does not show trends over the current week or previous weeks, which might be useful for older adults. We are currently running studies with a larger number of older adults to validate *GeriActive*'s algorithm in a free-living setting.

VIII. Conclusion

In this work, we developed a wrist-worn, energy-efficient system that uses a lightweight machine-learning algorithm (calibrated for older adults) to monitor and encourage physical activity among older adults. Our activity-level detection model obtained classification accuracy of 94.3%. Feedback from subjects showed that the *GeriActive* system is easy to use by older adults for monitoring their physical activity. Our energy-efficiency evaluation revealed a battery life of at least 1 week before needing to recharge. Our results demonstrate that it is worthwhile to adapt algorithms and interfaces for older adults, indicating that *GeriActive* is useful for research in health-delivery interventions that could improve the health of older adults. For more details about our work, see our Tech report [10].

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Figure 1.
Modes of *GeriActive* app

Table 1

Confusion matrix of younger adult model tested on older adult dataset

	Low (P)	Mod (P)	Vig (P)
Low (A)	99.7%	0.3%	0.0%
Mod (A)	35.1%	64.9%	0.0%
Vig (A)	2.3%	94.9%	2.8%

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Table 2

Classification results using various feature sets

Feature Sets	No of Features	Accuracy	Precision	Recall	F1-score
All	48	94.1%	94.4%	94.2%	93.4%
Magnitude All	12	91.2%	91.4%	91.2%	90.5%
Temporal	24	94.3%	94.7%	94.3%	93.6%
Magnitude Temporal	6	93.9%	95.8%	93.9%	93.7%
Spectral	24	92.1%	93.8%	92.0%	91.3%
Magnitude Spectral	6	92.4%	93.2%	92.5%	91.5%

Table 2

Summary of Usability Questionnaire Statements

Survey Statements	Mean (1–5)
My overall experience using Amulet was satisfactory	4.6±0.55
Wearing Amulet was enjoyable and interesting	4.2±0.45
The Amulet is comfortable to wear	3.2±0.45
I could easily feel the buzzer when it buzzed me	3.4±1.3
The display was easy to read, even in varying light conditions	4±0
The buttons were easy to use	3.6±0.55
I would consider wearing Amulet for a longer period of time	4.2±0.84
I think that Amulet can be used to help with activity monitoring in older adults	4.6±0.55