Power-Efficient Real-Time Approach to Non-Wear Time Detection for Smartwatches

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7 authors, including:

Anis Davoudi
University of Florida

Parisa Rashidi
University of Florida

Todd M Manini
University of Florida

Sanjay Ranka
University of Florida

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Matin Kheirkhahan, Hiranava Das, Manoj Battula, Anis Davoudi, Parisa Rashidi,
Todd M. Manini and Sanjay Ranka

Abstract— **There is a growing interest in the use of smartwatches to collect real-time physical activity and health care data. Much of this information is useful only when the person is wearing the smartwatch. Collecting data during other times consumes precious battery life and potentially communication bandwidth to relay the information. An approach that can correctly classify temporal regions during which the watch is not worn has the obvious advantages of both improving battery life and minimize communication bandwidth.**

There have been several methods proposed to determine wear time using passive devices such as accelerometers. However, they are offline procedures where data are collected continuously during data collection phase and non-wear times are excluded later and before analysis. Smartwatches' computational power allow us to perform several preprocessing steps instantly and concurrently with the data collection. We propose a power-efficient and real-time approach to non-wear time detection method which is capable of providing labels for 15-sec epochs accurately (accuracies for wear time and non-wear time are 97.68% and 96.78%, respectively). We also show that detecting non-wear periods in real-time ameliorates the battery requirements by as much as 50%.

I. INTRODUCTION

Physical activity (PA) has been shown to be strongly associated with health [1] and therefore, many works have focused on developing accurate PA assessment to describe and understand health-related outcomes [2]. For continuous PA monitoring and assessment, researchers have used wearable sensors and employed power-efficient communication means to measure the intensity, frequency, and duration of PA objectively [3]. With the rise of smartwatches' popularity, their variety of sensor monitors, and their nearly ubiquitious connectivity, there has been a major effort to use smartwatches for real-time PA monitoring and assessment [4].

Body-worn sensors collect data continuously and at a defined sampling rate. While continuous data collection is necessary for PA assessment and activity recognition [5] during wear-time, data collected during non-wear times are often not used for analysis. Non-wear times are defined as periods when participants detach the device from their bodies, such as during showering and sleeping. Detecting and excluding data collected during non-wear times enhances data analysis and yields better models describing association between PA and health outcomes [6]. To detect non-wear times, little or no registered activity plays an important role. However, in some cases, lack of activity during sedentary wear times (e.g., computer work) makes it difficult to distinguish non-wear periods.

There have been studies aiming to automate the non-wear time detection process using data obtained from a variety of sensors. Richardson et al. [7] use a threshold for the number of steps per day to identify days where the device is not worn. Moreover, several algorithms are proposed on the accelerometry count data to detect wear and non-wear times with a finer time resolution. Generally, these methods rely on defining bouts of consecutive zero activity counts as a non-wear period. However, these algorithms are unfit to detect non-wear periods that are shorter than the used threshold ($<$ 60 or 90 minutes) [8][9]. To achieve finer resolution for wear and non-wear time detection, some algorithms have been proposed to use raw sensor data. Rowlands et al. [10] use the standard deviation of the angle between the vertical axis and vector magnitude as the primary separator between the two classes. Their method is capable of identifying 8- to 60-minute wear and no-wear epochs when the accelerometer is worn on the hip or wrist. Zhou et al. [11] take body temperature into consideration to improve the classification of wear and non-wear epochs. However, to best of our knowledge, none of the existing approaches is capable of detecting wear and non-wear periods in real-time.

Unlike traditional, specialized devices, smartwatches are programmable which allows researchers to perform several preprocessing steps on the watch instantly. For example, they are capable of collecting data from a variety of sources (e.g., sensors and user-reported outcomes), constructing features, and handling missing values and outliers. The main challenges for using smartwatches in PA assessment studies are their limited memory sizes and short battery lives. Non-wear time detection in real time can result in an expedited data preprocessing step in the analysis pipeline. By real-time detection of non-wear period, data collection can be suspended by turning off the sensors [4]. Pausing data collection reduces the size of the data stored on the smartwatch's limited memory. It also has the added advantage of extending battery life as the power-hungry sensors (e.g., hear rate monitors) are

Matin Kheirkhahan, Hiranava Das, Manoj Battula, and Sanjay Ranka are with Department of Computer and Information Science and Engineering, University of Florida, Gainesville, FL 32601, USA. Emails: matin@cise.ufl.edu, hiranava@ufl.edu, mbattul1@ufl.edu, and ranka@cise.ufl.edu.

Anis Davoudi and Parisa Rashidi are with Department of Biomedical Engineering, University of Florida, Gainesville, FL 32601, USA. Emails: anis.davoudi@ufl.edu and parisa.rashidi@ufl.edu.

Todd M. Manini is with Department of Aging and Geriatric Research, University of Florida, Gainesville, FL 32601, USA. Email: tmanini@ufl.edu.

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In this paper, we present a two-step algorithm for real-time wear and non-wear time detection method. The proposed algorithm includes a feature construction step for 15−sec epochs followed by a classifier to label them as wear or non-wear. In our experiments, three main criteria are investigated: 1) accuracy of the proposed method, 2) feasibility of its implementation on the smartwatch, and 3) effect of detecting non-wear periods in real time and suspending data collection on the battery life.

The rest of the paper is organized as follows; in the next section, we describe the wrist model implemented and embedded in a smartwatch application and bring details on the experiments for wear and non-wear time detection. The third section provides the empirical results and highlights the impact of real-time wear and non-wear time detection on smartwatch's battery life. Finally, we summarize the findings and describe the best approach to utilize smartwatches in PA assessment studies in the presence of constraints.

II. METHODS

In order to detect the non-wear times of the smartwatch, we present a real-time approach which consists four main modules as shown in Fig. 1. First, the watch collects raw data using specified sensors and their defined sampling rates. Second, using raw sensor data, it constructs features for every epoch with specified length. Third, each epoch is labeled in real-time. Finally, the smartwatch enters battery saving mode upon non-wear time detection. If this is triggered, data collection is suspended for a certain period of time. We elaborrate on each of these steps in details in the following sections.

A. Data Collection

For developing our models, we use 15 hours of collected data. The implemented smartwatch application uses tri-axial accelerometer and heart rate monitors. Raw acceleration and heart rate data are collected at 10 Hz and 1/60 Hz (one sample per minute), respectively. The collected data include periods of non-wear (284 minutes) and wear times (476 minutes), as well as periods where the smartwatch was carried in the bag (141 minutes).

B. Feature Construction

The constructed features from accelerometer sensor data cover time and frequency domain aspects of acceleration, as well as the orientation of the watch. They have been effectively used for task identification [12] and non-wear time detection [10]. The constructed features are described as follows:

1) Time-domain features: These include the average and standard deviation of vector magnitude (mvm and sdvm). Vector magnitude for each point is calculated as
$$VM = \sqrt{x^2 + y^2 + z^2}$$
2) Orientation features: These are defined as the average and standard deviation of the existing angle between vector magnitude and the vertical axis (mangle and sdangle). The angle is calculated as
$$angle = \frac{180}{\pi} \times sin^{-1}(\frac{x}{VM})$$
3) Frequency-domain features: These consist of the dominant frequency (df), the fraction of power covered by the dominant frequency (fpdf), and the fraction of power explained by frequencies from 0.6 to 2.5 Hz (p625).

Table I shows the details of accelerometer features for each case. Furthermore, we also construct a boolean feature using heart rate monitor data indicating whether a pulse is sensed, which can be optionally used.

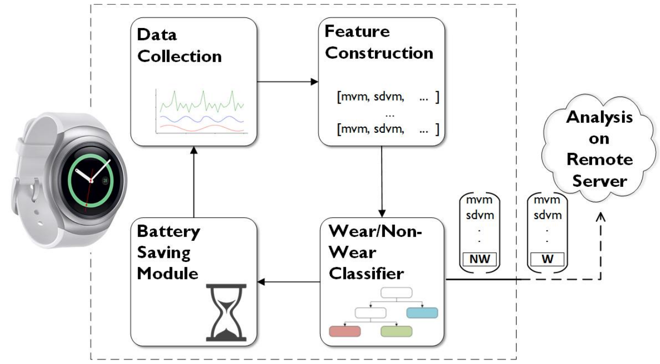

Fig. 1. Sensors collect data at a constant rate (10 Hz) and at every predefined interval (15 seconds) pass them to Feature Construction module to construct the accelerometer features. Next, feature vectors are fed into the trained classifier implemented on the watch to detect each epoch's label (e.g., wear or non-wear). Upon detection of a non-wear period, data collection is suspended for a specified amount of time before performing the next check.

C. Non-Wear Time Classifier

We developed machine learning based metods to determine if an epoch should be labeled as 'non-wear'. This component is implemented and embedded in the smartwatch application. Therefore, we consider classifiers which yield rules that are feasible to implement. Different classifiers are considered to find non-wear periods, including Linear Discriminant Analysis (LDA) [13], k-Nearest Neighbors (kNN) [14], Random Forest [15], Support Vector Machines (SVM) [16], and Decision Tree. The classifiers are evaluated based on their precision. The rule provided by the most accurate classifier is implemented on the watch to detect non-wear

TABLE I
ACCELEROMETER FEATURES DETAILS

	Wear (n = 1906)	In-the-Bag (n = 563)	Non Wear (n = 1136)
minutes (%)	476 (53)	141 (16)	284 (32)
mvm	10.03 (0.65)	10.03 (0.41)	9.74 (0.12)
sdvm	1.08 (1.55)	1.23 (1.73)	0.06 (0.25)
mangle	4.07 (25.84)	-5.35 (55.41)	-10.53 (52.11)
sdangle	10.27 (11.21)	6.7 (8.65)	1.03 (5.15)
p625	0.43 (0.08)	0.42 (0.07)	0.39 (0.04)
df	2.15 (1.23)	1.80 (1.41)	2.47 (1.48)
fpdf	0.05 (0.01)	0.06 (0.04)	0.01 (0.01)

Features are constructed for 15-sec epochs.
Values are presented as Mean (SD).

periods in real time. This component provides feature vectors with additional information of epochs' labels. The added information benefits the analysis and plays an important role in a more power-efficient data collection explained in the next section.

D. Battery Saving Module

To achieve a more power-efficient data collection, we implement the battery saving module which uses non-wear classifier's output. This module is responsible for halting the data collection after a non-wear epoch is detected. After a user specified period of time, the pause in data collection is lifted and data collection is resumed. Data collection continues if wear time is detected; otherwise, another gap in data collection is followed.

E. Power-Efficient Real-Time Non-Wear Time Detection

We consider two major aspects to using the main components in our framework to find the best algorithm for power-efficient real-time non-wear time detection:

1) Accuracy of the model: Accuracy in classifying epochs is the primary element in designing the final algorithm. This is due to the fact that incorrectly labeling epochs as non-wear results in a gap in data collection and loss of valuable data.
2) Addressing technological constraints: Among accurate models, we prefer the method which requires the least amount of resources (e.g., sensors and battery).

Ideally, we seek a model which rely on the least battery consuming sensors as sources of input and has power-efficient calculations for non-wear time detection.

III. Experimental Results

In our experiments, we developed an application for Samsung Gear S2 smartwatch for data collection. The application collected raw acceleration data at 10 Hz and constructed features for every 15-second epoch. We constructed feature vectors for each epochs and used them to train and evaluate the classifiers. We evaluated the performance of classifiers using leave-one-out-cross-validation on our dataset. We calculated the accuracy as the number of correctly classified epochs divided by the total number of epochs in that class.

Except for kNN, where scaled data (min = 0, max = 1) was used, all classifiers were applied to the original dataset without any modification. As a tuning parameter, $k = 5$ was selected for kNN. For Random Forest, we allowed 2 features for each try and used 100,000 trees for bagging. We used linear kernel for SVM and trained three sets of support vectors for each class and the greatest distance to the boundaries were used as the criterium for labeling. We also used heart rate monitor data as an additional feature.

TABLE II

Performances of Classifiers.

Classifier	Accuracy		
	Wear	In-the-Bag	Non-Wear
LDA	92.21	46.99	92.66
kNN	93.16	72.53	91.95
SVM	95.89	64.10	90.16
Random Forest	96.74	83.85	94.81
Decision Tree	94.42	76.62	94.27
Decision Tree HR[a]	100	90.12	97.69
Decision Tree MV[b]	97.68	82.89	96.78

a Heart rate monitor data were available.
b One-minute majority voting was applied.

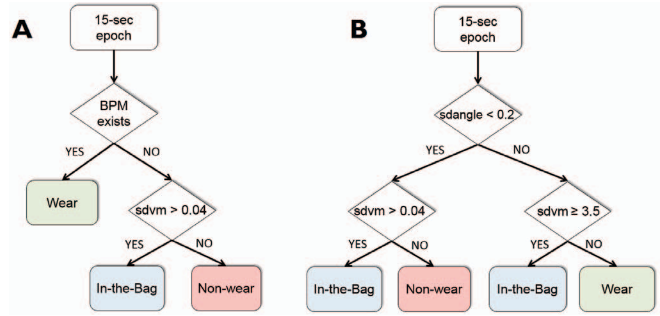

Fig. 2. Decision trees for datasets in presence (A) and absence of heart rate monitor data. If there for a 15-sec epoch beats per minute (BPM) is available it means the watch is worn. Otherwise (B), lack of variation in watch orientation (sdangle) and intensity (sdvm) contribute to distinguishing wear times from non-wear times.

Since heart rate monitor required at least one minute to provide beats per minute (BPM) value, we also considered one minute of accelerometer data to obtain a fair comparison. To this end, an one-minute majority voting mechanism was used, such that every epoch's predicted label was later refined based on the other epochs' labels within its one-minute interval. A two-minute window (containing eight 15-sec epochs) surrounding the epoch is used to confirm its predicted label and make it more consistent with its precedent and following epochs. Table II shows the accuracy of classifiers for different classes, i.e., wear and non-wear times, as well as in-the-bag periods. In-the-bag periods correspond to times where the smartwatch was not worn but carried in a moving bag.

We applied our proposed framework considering the two most accurate classifiers; i.e., the decision tree performing on accelerometer and heart rate monitor data, and the decision tree trained for accelerometer features with one-minute majority voting. For each case, the smartwatch application turned on the sensors for one minute, constructed feature vectors for each 15-second epochs, and labeled them using its implemented classification rule. The application performed the next check after an m-minute gap ($m \in \{5 \text{ and } 60\}$) during which the sensors were turned off. Fig. 2 (a) shows the decision tree learned for the dataset with heart rate monitor data. The presence of BPM was found as the top feature for wear time and it could distinguish this class from the rest perfectly (accuracy = 100%). For the dataset with only accelerometer features, distinguishing wear time from the case where smartwatch was carried in a bag was no longer trivial. Fig. 2 (b) shows the decision tree for such dataset. Although the absence of heart rate monitor's data resulted in constructing a decision tree with lower precision, applying one-minute majority voting yielded comparable accuracy with the case with BPM data. In this case, the accuracy for all classes was increased by more than 2.5% (wear: 97.68%, non-wear: 96.78%, and in-the-bag: 82.89%). Fig. 3

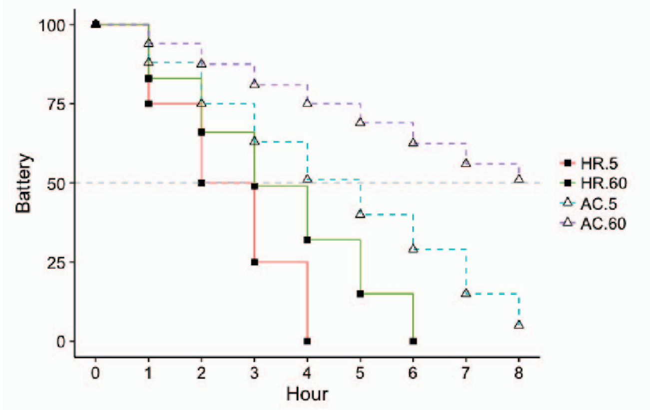

Fig. 3. Battery consumption by heart rate and accelerometer monitors for eight hours of non-wear time. Triangle points and dashed lines represent the experiments conducted using only accelerometers (AC) and square points and solid lines show the cases for heart rate monitor (HR). Using accelerometer results in less battery consumption compared to heart rate monitor. Moreover, increase in consecutive checks improves battery life. Therefore, it is not surprising to see the 5-minute gap for heart rate monitor (HR.5) results in the least battery life among all cases.

depicts the battery life for each decision tree and gap length. Checking heart rate monitor data (BPM) resulted in considerably shorter battery lives compared with the accelerometer-only decision tree (Fig. 3). Furthermore, longer suspension times between sensor data readings yielded higher battery preservance, at the expense of larger gaps in collected data.

The accelerometer sensor is the least battery consuming sensor and the classification rule obtained from decision trees require negligible power for their calculations. As a result, if heart rate monitor data is not required by study considerations, the ideal model to detect non-wear times in real-time and on the watch is the accelerometer-only decision tree coupled with the one-minute majority voting.

IV. CONCLUSIONS

In this paper, we have provided a power-efficient data collection approach for smartwatches which includes a feature set, a classifier, and an algorithm to combine and use them effectively. The proposed method is based on the smartwatches' capabilities of performing data collection, feature construction, and wear and non-wear time detection independently. We have shown that the best approach is to use a simple 2-level decision tree trained on accelerometer features. This choice is reinforced by its accurate performance on detecting wear and non-wear times and in the absence of power-hungry sensors.

Previously, lack of variation in the orientation of wrist-worn wearable was reported to be useful for non-wear classification rule [10][11]. This is aligned with the rule obtained from our two-level decision tree (Fig. 2 (b)). Equipped with a one-minute majority voting, the implemented classifier on the smartwatch is capable of detecting non-wear cases (i.e., non-wear and in-the-bag) with high accuracies.

We have also shown that detecting non-wear periods in real-time and stopping data collection increase the battery life. The results suggest that the improvement in battery life is more noticeable for longer gaps in data collection, which are more suitable for longer periods of non-wear time. Short battery life has been the biggest issue in using smartwatches in PA assessment studies as potential replacements of specialized devices (e.g., actigraphy accelerometers) [4]. Therefore, this method is an important step towards making smartwatches more applicable in practice.

REFERENCES

[1] B. H. Hansen, Y. Ommundsen, I. Holme, E. Kolle, and S. A. Anderssen, "Correlates of objectively measured physical activity in adults and older people: a cross-sectional study of population-based sample of adults and older people living in norway," *International journal of public health*, vol. 59, no. 2, pp. 221–230, 2014.

[2] N. F. Butte, U. Ekelund, and K. R. Westerterp, "Assessing physical activity using wearable monitors: measures of physical activity," *Med Sci Sports Exerc*, vol. 44, no. 1 Suppl 1, pp. S5–12, 2012.

[3] M. Ghamari, B. Janko, R. S. Sherratt, W. Harwin, R. Piechockic, and C. Soltanpur, "A survey on wireless body area networks for ehealthcare systems in residential environments," *Sensors*, vol. 16, no. 6, p. 831, 2016.

[4] S. Nair, M. Kheirkhahan, A. Davoudi, P. Rashidi, A. Wanigatunga, D. Corbett, T. Manini, and S. Ranka, "Roamm: A software infrastructure for real-time monitoring of personal health," in *2016 IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom) (IEEE Healthcom 2016)*, Munich, Germany, sep 2016, pp. 339–344.

[5] R. Nabiei, M. Najafian, M. Parekh, P. Jancovic, and M. Russell, "Delay reduction in real-time recognition of human activity for stroke rehabilitation."

[6] M. Kheirkhahan, C. Tudor-Locke, R. Axtell, M. P. Buman, R. A. Fielding, N. W. Glynn, J. M. Guralnik, A. C. King, D. K. White, M. E. Miller *et al.*, "Actigraphy features for predicting mobility disability in older adults," *Physiological Measurement*, vol. 37, no. 10, p. 1813, 2016.

[7] C. R. Richardson, L. R. Buis, A. W. Janney, D. E. Goodrich, A. Sen, M. L. Hess, K. S. Mehari, L. A. Fortlage, P. J. Resnick, B. J. Zikmund-Fisher *et al.*, "An online community improves adherence in an internet-mediated walking program. part 1: results of a randomized controlled trial," *Journal of medical Internet research*, vol. 12, no. 4, p. e71, 2010.

[8] L. Choi, Z. Liu, C. E. Matthews, and M. S. Buchowski, "Validation of accelerometer wear and nonwear time classification algorithm," *Medicine and science in sports and exercise*, vol. 43, no. 2, p. 357, 2011.

[9] L. Choi, S. C. Ward, J. F. Schnelle, and M. S. Buchowski, "Assessment of wear/nonwear time classification algorithms for triaxial accelerometer," *Medicine and science in sports and exercise*, vol. 44, no. 10, p. 2009, 2012.

[10] A. V. Rowlands, T. S. Olds, K. Bakrania, R. M. Stanley, G. Parfitt, R. G. Eston, T. Yates, and F. Fraysse, "Accelerometer wear-site detection: When one site does not suit all, all of the time," *Journal of Science and Medicine in Sport*, 2016.

[11] S.-M. Zhou, R. A. Hill, K. Morgan, G. Stratton, M. B. Gravenor, G. Bijlsma, and S. Brophy, "Classification of accelerometer wear and non-wear events in seconds for monitoring free-living physical activity," *BMJ open*, vol. 5, no. 5, p. e007447, 2015.

[12] J. Staudenmayer, S. He, A. Hickey, J. Sasaki, and P. Freedson, "Methods to estimate aspects of physical activity and sedentary behavior from high-frequency wrist accelerometer measurements," *Journal of Applied Physiology*, vol. 119, no. 4, pp. 396–403, 2015.

[13] C. R. Rao, "The utilization of multiple measurements in problems of biological classification," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 10, no. 2, pp. 159–203, 1948. [Online]. Available: http://www.jstor.org/stable/2983775

[14] M.-L. Zhang and Z.-H. Zhou, "A k-nearest neighbor based algorithm for multi-label classification," in *2005 IEEE international conference on granular computing*, vol. 2. IEEE, 2005, pp. 718–721.

[15] A. Liaw and M. Wiener, "Classification and regression by randomforest," *R news*, vol. 2, no. 3, pp. 18–22, 2002.

[16] J. A. Suykens and J. Vandewalle, "Least squares support vector machine classifiers," *Neural processing letters*, vol. 9, no. 3, pp. 293–300, 1999.