A machine learning technique for device non-wear detection in children with ADHD

Ibrahim Traore
University of Champollion - ISIS Castres
Toulouse INP, IRIT laboratory, University of Toulouse, France
0009-0002-8587-6054

Imen Megdiche
University of Champollion - ISIS Castres
IRIT laboratory, University of Toulouse, France
0000-0002-1331-8662

Jérôme Marquet-Doléac
Health Faculty
University Toulouse III - Paul Sabatier, France
0009-0002-6578-2309

Lotfi Chaari
Toulouse INP, IRIT laboratory, University of Toulouse, France
0000-0002-3590-0370

***Abstract*—Wearable devices dotted with accelerometers are widely used to study motor overflow in children with attention deficit/hyperactivity disorder (ADHD), as they provide accurate and reliable measurements of physical activity. To accurately determine the time spent in different intensities of physical activity (sedentary, light, moderate or vigorous), it is necessary to identify periods when devices are worn or not. However, this can be problematic because children's sedentary activities may be mistaken for periods when devices are not worn.**

In this paper we propose a machine learning approach to detect non-wear periods using data collected from 18 children with ADHD and 18 healthy children using the triaxial accelerometer Actigraph GT9X worn on the non-dominant wrist for one week. The objective is to reduce the overestimation of time spent in activities obtained after data reduction with algorithms using long non-wear time detection periods.

The agreement between real data and the classification performed by SVM model (Concordance Correlation Coefficient $>$ 0.95) supported the use of reduced time intervals for detecting non-wear periods.

***Index Terms*—Raw Accelerometer Data, Machine Learning, Non-Wear Time, Physical activity, Hyperactivity, ADHD**

I. Introduction

The use of accelerometers to objectively assess levels of physical activity (PA) has become common in research and health monitoring, especially in children and adolescents. These devices provide a reliable and non-intrusive method to assess the frequency, duration, and intensity of daily PA. However, the effectiveness of this method largely relies on accurately determining the wear and non-wear time of the accelerometer.

Previous studies [1]–[5] that the method used to determine wear time can lead to significant errors in assessing levels of physical activity.

Non-wear time refers to the duration when participants do not wear the accelerometer during a given measurement period. It should be typically excluded from further analysis, assuming that the time when the accelerometer is actually worn adequately represents the entire measurement period.

Algorithms have been proposed for detection of non-wear time. A first approach using activity count detects non-wear periods by counting consecutive zeros recorded by the accelerometer [3]–[6]. Another approach using raw data identifies these periods based on standard deviation and amplitude [7], [8]. These algorithms are defined over periods that are too long in estimating time spent in sedentary, light, moderate, and vigorous activities in children with ADHD.

In this article, we explored a machine learning-based approach tailored to shorter non-wear time detection intervals. Initially, we used 15 and 10-minute intervals, consistent with the literature, and aimed to minimize them while preserving crucial information. To improve the specificity in determining agreement for each wear and non-wear period, we compared the model's results with a real data reference.

The structure of this article is as follows: Section 2 presents the related works, in Section 3, we provide a detailed description of the proposed method. The results of our research, along with their analysis and interpretation, are presented in Section 4. In Section 5, we discuss the findings and their implications. Finally, in the conclusion section, we summarize the key points addressed and propose some perspectives for future research.

II. Related Works

The traditional method of validating wear and non-wear time involves the use of logs, where participants record the times they wear or remove the device. However, this procedure can be cumbersome and potentially prone to errors, especially when applied to large populations.

To automate this issue, algorithms have been proposed to identify non-wear periods and are grouped based on the type of data used : Activity Count (AC) or raw data.

AC data : algorithms defined using the summary measure AC are based on consecutive zeros recorded by the accelerometer. In the work of [9]–[15], different thresholds such as 10, 15, 20, 30, or 60 minutes of continuous zeros, have been used as indicators of non-wear.

The use of these algorithms carries the risk of confounding a genuine sedentary period with a non-wear period. It is difficult to differentiate sedentary behavior from true non-wear because in both cases, the accelerometer can record zeros.

Different studies have therefore been conducted to determine the appropriate threshold in children. J. Vanhelst et al. recommended using the 30-mn consecutive zeros algorithm to define non-wear time to improve the accuracy of assessing physical activity levels in youth [6]. Esliger et al. suggested using 20 mn of consecutive zeros as the criterion in children [5]. This finding is similar to another study involving 369,517 children aged 8 to 13 years [4]. Paw of China et al. estimated that the 20-minute algorithm was inadequate and recommended a minimum of 60 mn of consecutive zeros as the most realistic criterion for non-wear time [3]. Most of these studies compared multiple non-wear time algorithms to diary data and proposed the threshold they deemed most appropriate.

The main limitation of these studies lies in the difficulty of generalizing their approaches to raw accelerometer data. Indeed, these algorithms were defined based on the AC, which is a proprietary measure dependent on the device used.

Raw data : algorithms defined using raw data estimated non-wear time based on the standard deviation and range of values for each accelerometer axis. One variant [7] involved classifying consecutive 30-mn blocks as non-wear time if the standard deviation was less than 3.0 mg for at least two out of three axes, or if the range of values for at least two out of three axes was less than 50 mg. Another variant [8] relied on using 60-mn windows to reduce the risk of accidentally detecting short sedentary periods as non-wear periods. The windows overlapped (with 15-mn intervals and a 45-minute overlap between windows), which was done to improve the accuracy of detecting non-wear time boundaries compared to using non-overlapping time windows. In a study on motor overflow in children with ADHD, we measured their movements using activity thresholds based on raw data [16]–[19]. During the data reduction step, we applied we applied raw data 30 mn algorithm. The 30-mn non-wear period was too long as it tended to overestimate the time spent in sedentary, light, moderate, and vigorous activities. For example, with a log diary over a 7-day recording period that included school hours, an ADHD child spent an average of 2 853, 1 667, 830 and 259 minutes, respectively, in sedentary, light, moderate, and vigorous activities. After data reduction using raw data 30-mn algorithm, the results were 4 241, 1 763, 872 and 265 minutes, respectively, in sedentary, light, moderate, and vigorous activities.

The evaluation of non-wear time criteria accuracy proved to be robust through the use of these logs. However, there are inherent vulnerabilities in this approach, making it prone to errors. It is more appropriate to examine an automated approach over a shorter period that reduces overestimation of time spent in different intensities of physical activity in children with ADHD.

III. Experimental Methodology

The methodology (see Fig. 1) associated with the generation and evaluation of wear and non-wear time detection models is discussed in this section. This includes the data collection procedure, data segmentation method, feature extraction, dimension reduction, and the model development process.

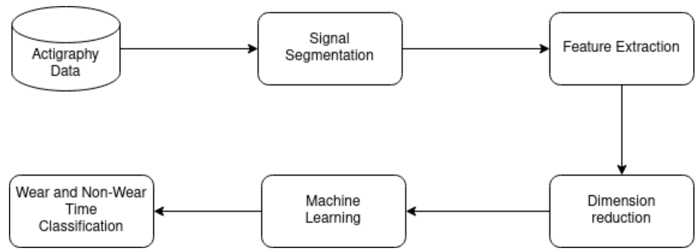

Fig. 1. The approach for wear and non-wear time detection.

A. Actigraphy Data Collection

1) Data Description: Physical activity data were collected from 18 healthy children (15 boys and 3 girls) and 18 children with ADHD (15 boys and 3 girls) aged 6.5 to 11.5 years (mean = 8.92 (+/- 1.42)) in normal living conditions using the Actigraph (model GT9X; ActiGraph, Pensacola, CA, USA).

The purpose of the study was carefully explained to all participants, and consent was obtained from their legal guardians prior to their participation.

The Actigraph GT9X is a tri-axial accelerometer that assesses physical activity by measuring mechanical movement in the three spatial dimensions: a vertical vector (x), an antero-posterior vector (y), and a medio-lateral vector (z).

This accelerometer has a dynamic range of ±8 g (where g represents the force of gravity) and offers a sampling frequency range from 30 to 100 Hz. In this study, the sampling frequency was set to 30 Hz with a recording duration of one minute using ActiGraph software support (ActiLife, v6.13.4, Pensacola, CA, USA).

Participants were instructed to wear the accelerometer for 7 consecutive days (including school days and non-school days) on their non-dominant wrist. The downloaded data from the device using ActiLife software represented between 17 and 18 million data samples per child.

2) Real Data Generation: Participants were asked to maintain a log diary for a period of 7 days in which they wore an accelerometer. Each day, they were required to note their waking and bedtime, as well as the times when they wore and removed the accelerometer, on a pre-printed standard recording sheet. The use of these diaries proved to be a robust method for assessing the accuracy of non-wear time criteria. However, this approach has vulnerabilities and is subject to errors. To establish real data, two distinct methods were employed. The first involved using log diaries. The second method was based on identifying non-wear periods using the algorithm based on standard deviation and range of values for each accelerometer axis, as described in [7]. The final result was based on data for which there was agreement between the information recorded in log diaries and algorithm's results, as illustrated in Fig. 2.

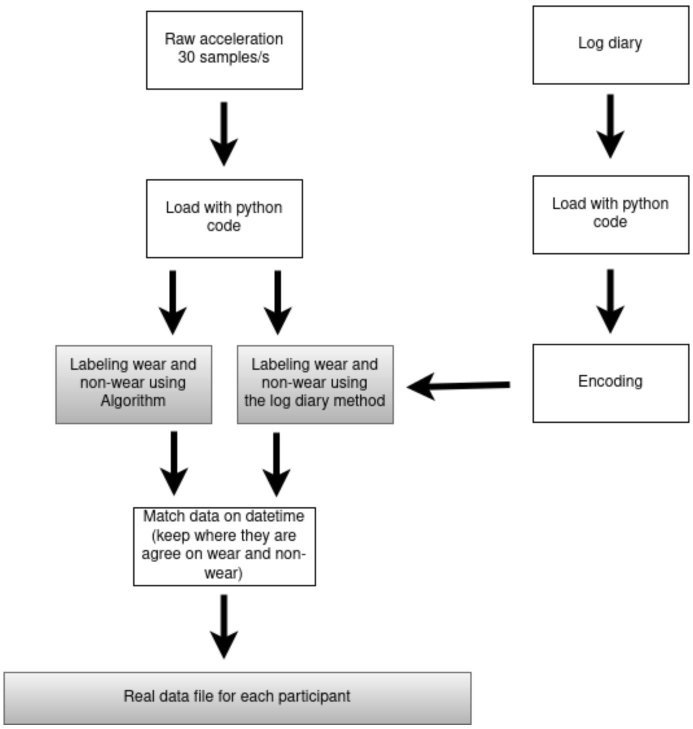

Fig. 2. Real Data Generation Process.

B. Signal Segmentation

Signal segmentation is a crucial step in our non-wear time detection process (see Fig. 1). Accelerometer produces a stream of raw, unprocessed signals representing the measured acceleration. To capture the dynamics of these signals, we divide them into smaller data segments. Segmentation involves dividing sensor signals into distinct data segments. There are different methods to perform this segmentation, and most of them can be classified into three categories: activity-defined windows, event-defined windows, and sliding windows [20].

The sliding window approach is the most commonly used segmentation technique in activity studies [20]. It is preferred due to its simplicity of implementation and lack of preprocessing, making it well-suited for real-time applications. In our study, we divided signals into fixed-size windows without overlap using the sliding window approach. Our goal was to reduce non-wear time detection period because longer non-wear times lead to an overestimation of time spent in different intensities of physical activity. Therefore, we experimented with different window sizes (2, 3, 4, 5, 10, and 15 minutes).

Since the accelerometer was set with a sampling frequency of 30 Hz (i.e., 30 samples per second), the number of samples in a 15-minutes window is 27,000 (30 Hz x 60 seconds x 15 minutes).

C. Features extraction and dimension reduction

Feature extraction helps to reduce the number of resources required to analyze a signal. Raw signals collected using wearable sensors during movement activities are typically sampled at discrete time intervals and contain a large number of data points or samples for analysis purposes.

TABLE I
FEATURE DESCRIPTIONS.

Feature	Description
1 - 3	Mean
4 - 6	Standard Deviation
7 - 9	Maximum
10 - 12	Minimum
13 - 15	Difference of maximum and minimum
16 - 18	Median
19 - 21	Number of values above mean
22 - 24	Number of values through mean
25 - 27	Covariance (x-y, x-z, y-z)

In many previous studies, machine learning methods have been used to detect the type and level of human activity from data collected using actigraphs [21]–[23]. The most commonly used features to characterize actigraphy signals were of a statistical nature extracted from the time and frequency domains.

In our study, we chose to use statistical features (see Table I) in the time domain due to their variability and reported good performance in the literature [24]. Most of the feature groups have three components in this order: x, y and z.

We used Principal Component Analysis (PCA) to reduce dimensionality and identify the most discriminative information. PCA involves replacing the initial set of data with a new reduced set constructed from the initial set of features. Out of the initial 27 features, we identified 15 principal components that effectively captured the variance in the data.

D. Classification of wear and non-wear time

The non-wear time detection algorithm needs to be able to recognize the accelerometer signal pattern corresponding to wear and non-wear time. We formulated non-wear time detection using two different approaches:

- Anomaly Detection Approach with One-Class SVM: The One-Class SVM (Support Vector Machine) algorithm is a machine learning method used for anomaly detection and classification of a single class of data [25]. The goal of this algorithm is to find the decision boundary that best encloses normal class data. Data points outside of this boundary are considered anomalies. In our case, we considered wear time as normal class and attempted to detect anomalies (non-wear time). The different steps of this approach can be defined as follows:
  - Step 1: Choose appropriate parameters (kernel = 'rbf', gamma = 'scale', nu='0.1').
  - Step 2: Use the data from normal class (70% of wear time) to train the model.
  - Step 3: Use the trained model to evaluate new samples (30% of balanced wear time with an equal number of non-wear time).

– Step 4: Evaluate algorithm's performance in terms of anomaly detection rate and false positive rate.

- Binary Classification Approach with SVM: The SVM (Support Vector Machine) algorithm is a supervised learning method used for classification and regression. Its main objective is to find an optimal hyperplane that separates data into different classes. In our case, we formulated non-wear time detection as a two-class classification problem: wear time and non-wear time. We tested this approach with SVM and KNN (k-nearest neighbors), and it was SVM that showed the best results among these two algorithms. The different steps of this approach with SVM can be defined as follows:
  – Step 1: Choose appropriate parameters (kernel = 'rbf', gamma='scale', C='1').
  – Step 2: Use training data (70% of the data) to train the model.
  – Step 3: Use the trained model to predict the class labels of new data (30% of the data).
  – Step 4: Evaluate algorithm's performance.

The principal components identified through PCA are used as inputs for machine learning algorithms (SVM and One-Class SVM) to build models capable of recognizing non-wear time from the accelerometer signal. Through this approach, we improved the performance of models by focusing on the most relevant information.

IV. Evaluation

A. Evaluation Methodologies

The performance of non-wear time detection algorithms based on acceleration can be evaluated using measures such as accuracy, recall, and F-measure. Accuracy (1) is calculated by comparing the number of instances correctly classified as wear time and non-wear time with the total number of instances.

- True Positive (TP) is The number of instances correctly classified as wear time.
- True Negative (TN) is The number of instances correctly classified as non-wear time.
- False Positive (FP) is The number of instances incorrectly classified as wear time.
- False Negative (FN) is The number of instances incorrectly classified as non-wear time.

$$\text{Accuracy} = \frac{\text{TP + TN}}{\text{TP + TN + FP + FN}} \tag{1}$$

Precision (2) is a performance measure that focuses on the proportion of correctly predicted wear time relative to all instances predicted as wear time.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Recall (3) is calculated by comparing the number of instances correctly classified as wear time with the total number of instances actually wear time, whether correctly classified or not.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

The F-measure (4) is a combination of precision and recall, and it is calculated using the following formula:

$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

To evaluate the agreement between detection algorithm results and real data, we used the Concordance Correlation Coefficient (CCC), which is a statistical test to measure agreement between two methods. CCC (5) values were interpreted as follows: poor concordance for values below 0.45, reasonably good concordance for values from 0.45 to 0.75, and excellent concordance for values above 0.75 [6], [26].

$$CCC = \frac{2\rho\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 + (\mu_1 - \mu_2)^2} \tag{5}$$

, where ρ is the correlation coefficient between the two variables, σ_1^2 and σ_2^2 are the corresponding variances, μ_1 and μ_2 are the means for the two variables.

B. Results

In this study, we used a sliding window approach to analyze raw acceleration data and extracted features for each window to classify them as wear or non-wear time. The number of windows for time intervals of 2, 3, 4, 5, 10, and 15 mn were 74 884, 49 921, 37 429, 29 943, 14 962, and 9 970, respectively, for children with ADHD.

The classification results of the acceleration data into wear and non-wear time are presented in Tables II and III for the two study populations. The classifiers were trained on their respective training sets, and the classification results in Tables 2 and 3 were obtained using their respective test sets.

We reported the accuracy, recall, and F-measure for each classifier and window size. The classification accuracies for One-Class SVM and SVM ranged from $65 - 94\%$ and $97 - 98\%$, respectively, for healthy children ($94 - 95\%$ and 99% for children with ADHD). The classification results of One-Class SVM were better in children with ADHD compared to healthy children. However, the best classification results were achieved using SVM, with an accuracy exceeding 98% for all window sizes and for both populations.

The confusion matrices for wear and non-wear time for the two groups of children using SVM with 5-minutes windows are presented in Tables IV and V. In the confusion matrix for children with ADHD (Table IV), we observed 8 misclassified wear time windows and 48 misclassified non-wear time windows, while in healthy children (Table V), 101 misclassified wear time windows and 37 misclassified non-wear time windows were observed.

V. Discussion

Accelerometers are a promising sensors for studying motor overflow in children with ADHD as they provide relatively accurate and reliable data on physical activity. However, to maximize data quality, it is essential to establish standard data

TABLE II
CLASSIFICATION RESULTS OF THE TWO ALGORITHMS IN CHILDREN WITH ADHD.

Windows size (mn)	One Class SVM				SVM			
	Accuracy	Recall	F-measure	CCC	Accuracy	Recall	F-measure	CCC
2	0.949	0.999	0.951	0.898	0.994	0.993	0.993	0.989
3	0.950	1	0.952	0.900	0.994	0.990	0.993	0.988
4	0.950	0.999	0.952	0.900	0.994	0.988	0.993	0.988
5	0.944	1	0.947	0.888	0.993	0.987	0.992	0.987
10	0.945	1	0.948	0.890	0.990	0.978	0.988	0.980
15	0.951	1	0.953	0.903	0.989	0.975	0.987	0.978

TABLE III
CLASSIFICATION RESULTS OF THE TWO ALGORITHMS IN HEALTHY CHILDREN.

Windows size (mn)	One Class SVM				SVM			
	Accuracy	Recall	F-measure	CCC	Accuracy	Recall	F-measure	CCC
2	0.651	0.399	0.533	0.302	0.981	0.994	0.971	0.957
3	0.657	0.410	0.545	0.314	0.982	0.992	0.973	0.960
4	0.781	0.660	0.751	0.562	0.983	0.988	0.974	0.961
5	0.741	0.578	0.691	0.483	0.983	0.986	0.975	0.963
10	0.944	1	0.947	0.888	0.982	0.970	0.973	0.960
15	0.941	1	0.945	0.883	0.978	0.960	0.966	0.950

TABLE IV
CONFUSION MATRIX FOR SVM WITH 5-MINUTES WINDOWS IN CHILDREN WITH ADHD.

	Predicted Wear Time	Predicted Non-Wear Tim
True Wear Time	5 205	8
True Non-Wear Time	48	3 720

TABLE V
CONFUSION MATRIX FOR SVM WITH 5-MINUTES WINDOWS IN HEALTHY CHILDREN.

	Predicted Wear Time	Predicted Non-Wear Tim
True Wear Time	5 640	101
True Non-Wear Time	37	2705

reduction procedures. The algorithm and estimation time for non-wear periods used can have a significant impact on the quantity and quality of data retained for analysis.

In this study, we explored two machine learning approaches to detect non-wear periods from triaxial accelerometer data collected from children with ADHD and healthy children. The aim was to propose an effective non-wear time detection approach specifically tailored to children with ADHD. To achieve this, we examined the performance evolution of the models as the detection period decreased.

The SVM algorithm demonstrated an accuracy exceeding 98% across different periods used for non-wear time detection in both populations. However, the One-Class SVM algorithm struggled to identify wear and non-wear periods in healthy children for 2, 3, 4, and 5-minutes windows. This may be due to the difficulty in differentiating non-wear periods from sedentary movements, as well as the fact that children with ADHD are generally more agitated than healthy children.

The comparison between real data and classification performed by the machine learning algorithms supported the use of shorter time intervals for non-wear period detection. Indeed, the agreement of SVM algorithm on each window

TABLE VI
TIME SPENT (MN) IN DIFFERENT INTENSITIES OF PHYSICAL ACTIVITY AFTER REMOVING NON-WEAR TIME WITH LOG DIARY, SVM (5-MINUTE WINDOWS), AND THE 30-MINUTE ALGORITHM BASED ON RAW DATA, FOR A CHILD WITH ADHD.

Intensity	Log diary	30 mn Algorithm (Raw data)	SVM (5 mn)
Sedentary	2 853	4 241	3 550
Light	1 667	1 763	1 732
Moderate	830	872	847
Vigorous	259	265	261

size was excellent for wear and non-wear period detection ($CCC > 0.95$).

The stability of both models in both populations begins from the 4 and 5-minutes windows.

The comparison between SVM, log diary, and the 30-minute algorithm based on raw data (Table VI) shows that our proposed approach has decreased overestimation and allows for correcting any reporting errors in the log diary.

This study has strengths and limitations. It is, to our knowledge, the first study to experiment with machine learning approaches and compare the results with real data obtained from a cross-reference between a diary and a raw data-based algorithm for non-wear period detection in children with ADHD.

Although the sample size is relatively small and primarily composed of male participants, we believe these results make a significant contribution to the study of accelerometer data collection and reduction and bring us closer to the goal of establishing standardized procedures for non-wear period detection for children with ADHD.

VI. CONCLUSION

In this article, we proposed a machine learning approach for detecting wear and non-wear periods using accelerometer data collected from children with and without ADHD. Our results demonstrate that wear and non-wear periods can be successfully distinguished using a machine learning algorithm, even with reduced time intervals compared to those typically used in the literature. Among the two classifiers tested, SVM classifier exhibited the best performance with a 5-minutes detection period, achieving an accuracy exceeding 98%. We compared the performance of our approach to real data, and we make evidence that our approach yielded satisfactory results. Based on these findings, we recommend using the SVM machine learning algorithm with 5-minutes windows in studies evaluating physical activity levels and wear time in children with ADHD. Our future work will involve applying this data reduction approach to optimally identify the intensities of physical activities in children with ADHD, focusing specifically on periods corresponding to moderate and vigorous intensity activities.

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