Lifestyle analysis of a female group of university workers: Do they reach recommended levels of physical activity?

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***Abstract* — Maintaining appropriate levels of Physical Activity (PA) and healthy lifestyles produces several health benefits. The U.S. Department of Health and Human Services recommended from 150 minutes to 300 minutes a week of moderate PA to obtain substantial health advantages. To promote well-being and healthy lifestyles, digital technologies play a very important role, since they can give a real-time feedback about the performed activities. In this study, we analyzed the lifestyle of a female group of university workers. We asked 23 healthy women belonging to the community of Politecnico di Torino to wear a device during a typical working day. The device was able to classify the activities performed by the subject in six classes: "resting" (i.e., sitting and laying), upright standing, walking, ascending stairs, descending stairs and "other activities" (comprising all the activities not included in the previous classes). We analyzed the time spent on each activity during the day and found that subjects spent, in average, almost one hour on dynamic activities (walking and stair climbing), that is in line with the recommendations. However, subjects did not carry out these activities continuously, but they split them into relatively short intervals whose maximum duration was approximately 10 minutes.**

Keywords—physical activity, wearable sensors, human activity recognition, decision tree

I. Introduction

Benefits of daily Physical Activity (PA) are well known and widely demonstrated. Wu *et al.* proved that 30 minutes of physical exercise five times a week reduce hospitalization in overweight and obese adults suffering from diabetes [1]. In a recent study by Schneider *et al.* [2], authors found that patients affected by Chronic Obstructive Pulmonary Disease (COPD) performing PA in combination with a non-sedentary lifestyle present markedly better clinical conditions than sedentary ones. Moreover, PA produces several benefits from the psychologic point of view [3]. These are only a few examples among numerous recent works demonstrating the benefits produced by a correct lifestyle.

In 2018, the U.S. Department of Health and Human Services published the "*Physical Activity Guidelines for Americans, 2nd edition*" [4] to help people improving their health by a regular PA. This report recommends from 150 minutes to 300 minutes a week of moderate PA to obtain substantial health benefits. Moreover, the same report highlights a difference of the PA levels in American adults between men and women: only 26% of men and 19% of women met the guidelines in 2016.

In the broad contest of promoting well-being and healthy lifestyles, Digital Behavior Change Interventions (DBCIs) can play an essential role. The term DBCI identifies "an intervention that employs digital technology to promote and maintain health" [5]. The technologies suitable to this purpose can range from smartphones, personal computers, and tablets to wearable devices able to give a real-time feedback on the performed activities [6]. Wearable devices [7], [8] usually rely on a) a set of sensors acquiring signals that describe the activity accomplished by the subject, and b) a processing unit, responsible for signal recording and activity classification.

As previously mentioned, women are more critical than men in maintaining appropriate levels of PA (19% of women vs 26% of men that met the guidelines [4]). The aim of this study is to analyze the lifestyle of a female group of university workers during a typical working day by using a wearable device**.** In particular, we monitored the time spent by each subject in performing different daily activities, to understand if their level of PA was in line with the current recommendations.

II. Materials and Methods

A. Population and Experimental Protocol

Twenty-three healthy women (age: 33 ± 11 years; age range: 24 - 60 years) were involved in this study. All the subjects were part of the community of Politecnico di Torino.

A wearable device by Medical Technology, Torino, Italy, based on a magnetic and inertial measurement unit, acquired the signals. The sensor consists of a tri-axial accelerometer, a tri-axial gyroscope and a tri-axial magnetometer allowing for acquiring acceleration, rate of turn, and Earth-magnetic field, for a total of 9 signals. The measurement range was ± 4 g for the accelerometers, ± 2000 °/s for the gyroscopes, and ± 4 G for the magnetometers. The sampling frequency was equal to 80 Hz. The device was supplied with a 32-bit microprocessor equipped with a fixed point processing unit (ARM 4 Cortex).

The wearable device was fixed on the lateral side of the right thigh, using an elastic band. The y-axis was oriented in down-top vertical direction, x-axis was aligned to the antero-posterior direction, and z-axis was aligned to the medio-lateral direction. All subjects were asked to wear the device during a typical working day, from the morning to the evening. Each subject signed an informed consent form.

The device was able to recognize five different kinds of activities: "resting" (i.e., sitting or laying), upright standing, walking, ascending, and descending stairs. Moreover, a further class of activities called "other activities" was considered, comprising all the activities not included in the previous categories. The details of the signal processing and classification algorithms implemented on the microcontroller are described below.

B. Signal Processing

To avoid bias due to magnetic disturbances on the magnetometer, only inertial signals (i.e., accelerometer and gyroscope signals) were used for the activity recognition. Each signal was segmented using a 5 s sliding window with an overlap of 3 s between subsequent windows.

C. Activity Recognition

The microcontroller analyzed every window to recognize the type of activity performed by the subject.

First of all, since static ("resting" and upright standing) and dynamic activities (walking, ascending and descending stairs) show very different signal characteristics, a first recognition step based on two rules was implemented to discriminate these two classes of movements:

- if the variance of gyroscope signal in *z* direction is below 600 deg·s^{-1}, then the time window represents a static activity, otherwise it represents a dynamic activity.

Static activities were further separated in "resting" and "standing" according to the following rule:

- if the mean value of acceleration in the *y* direction is below 8.5 m·s^{-2}, then the window is classified as "resting", else the window is classified as standing.

Thresholds used in this first rule-based recognition step were identified by analyzing the characteristic of the signals during static and dynamic activities, with the support of an expert in movement analysis. In particular, the first threshold (variance of gyroscope signal in *z* direction is below 600 deg·s^{-1}) was due to the fact that during static activities the inertial signals are stable and almost constant, and thus they present a lower variability with respect to dynamic activities. The second threshold (mean value of acceleration in the *y* direction is below 8.5 m·s^{-2}) was set taking into account the value of the gravitational acceleration. In fact, during static activities the mean value of the accelerometer signal in vertical direction is almost equal to the gravitational acceleration, while in the other directions it is almost 0. During upright standing, the *y* axis is oriented in top-down vertical direction and, thus, its signal is centered around 9.8 m·s^{-2}. On the contrary, during resting (sitting or laying) the *y* axis is quite horizontal, and the corresponding signal has a mean value substantially lower (around 0 m·s^{-2}). For this reason, we set a threshold to 8.5 m·s^{-2} that allows to separate the two situations, admitting a certain degree of variability in the signals due to noise, small

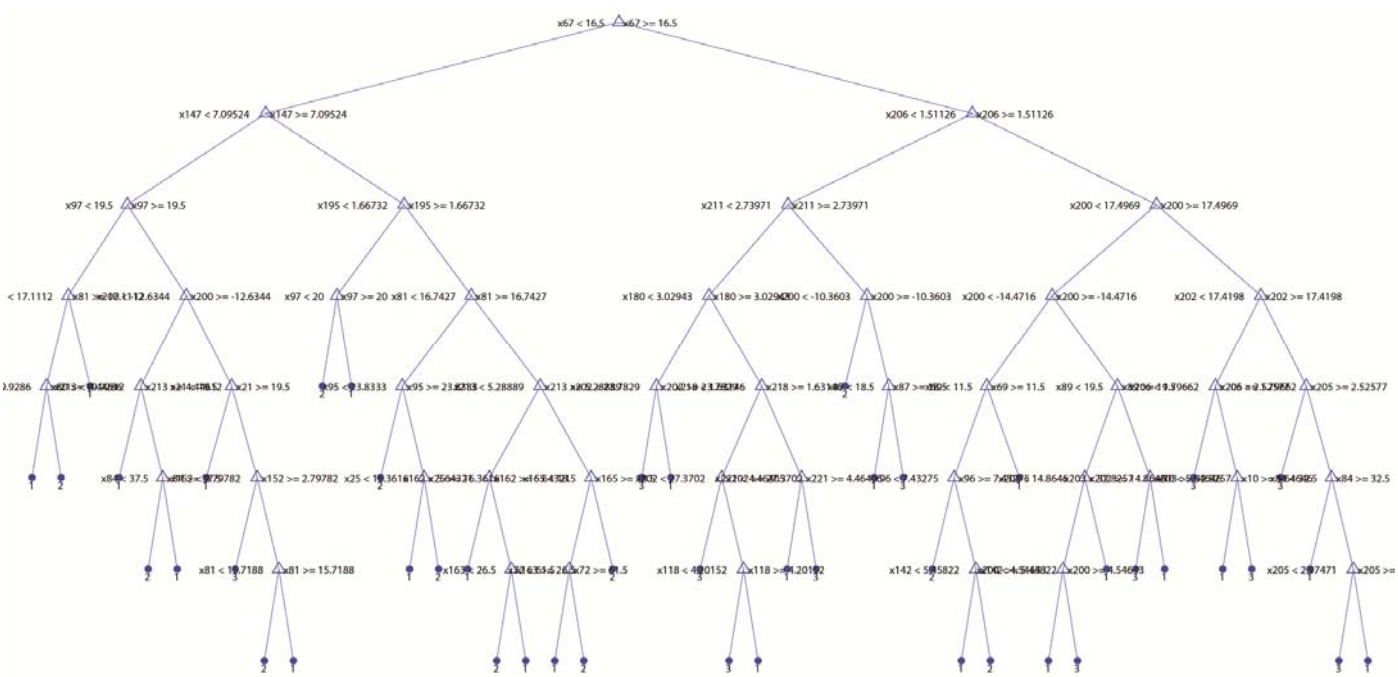

Fig. 1. Decision Tree (DT) classifier implemented on the wearable device for recognizing dynamic activities. Each node is associated to a variable (identified as 'x' with the corresponding identification number) and a corresponding threshold. The leaves represent the class assigned to the window (1: walking; 2: ascending stairs; 3: descending stairs).

movements, …

All the windows recognized as dynamic by the application of the first rule were then fed into a Decision Tree (DT) classifier that separates the windows belonging to the remaining three classes (walking, ascending and descending stairs). The selection of this classifier emerged from a previous study, in which we demonstrated that DT can be easily implemented on a microcontroller and allows to reach very high recognition performances (> 90 %) [9].

A DT is a tree-like graph that, once constructed, is able to perform classification using a set of nested *if… then* rules based on specific variables and thresholds. In this case, the DT used a set of 32 variables, which were computed for each time-window by the microcontroller. These variables, all belonging to the time-domain, were automatically selected during the construction of the DT, from an initial set of 221 features. Briefly, for each signal we extracted information about zero crossings and number, position, and duration of positive and negative peaks (33 features x 6 signals). Moreover, we computed single and double integration of the acceleration in the anteroposterior and vertical directions, and the single integration of the rate of turn in mediolateral direction. Other 23 features were extracted from these signals. A detailed description of the initial set of features can be found in [6]. Only 32 variables were used by the DT: from the accelerometer signal, 1 feature was calculated in *x* direction, 6 features in *y* direction and 2 features in *z* direction; from the gyroscope signal, 3 features were calculated in *x* direction and 11 features in *z* direction; the remaining 9 features were calculated from the integrated signals.

Fig. 1 shows the DT implemented on the device. In the tree, each node is associated to a variable (identified as 'x' with the corresponding identification number) and a corresponding threshold. The leaves represent the class assigned to the window (1: walking; 2: ascending stairs; 3: descending stairs).

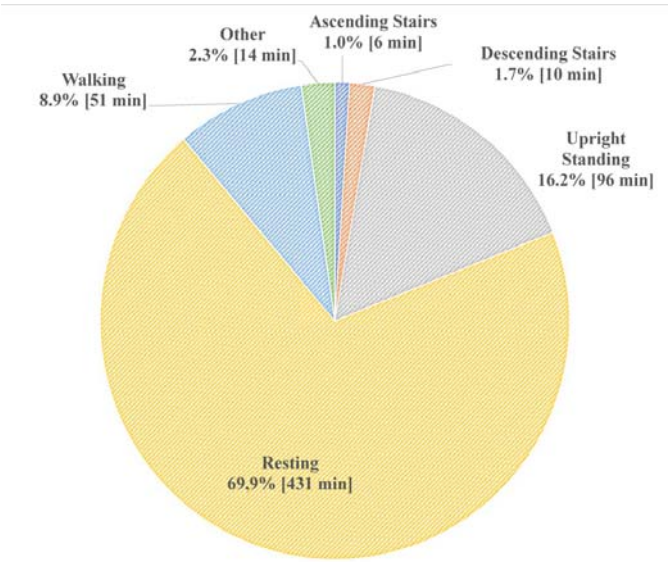

Fig. 2. Percentage of time spent in each activity during the day (the corresponding mean time, in minutes, is reported in brackets).

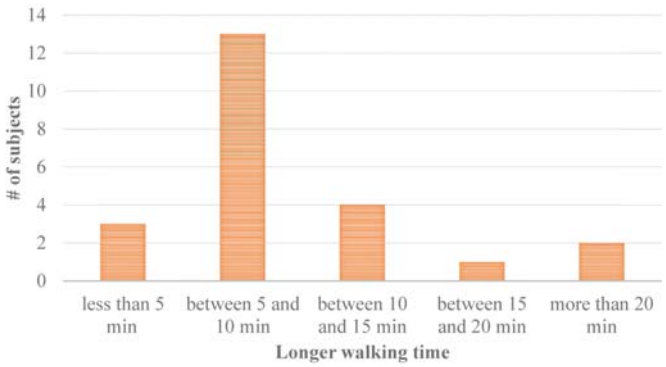

Fig. 3. Distribution of the longest continuous walking time for each subject.

D. *Post-processing*

Finally, we implemented a post-processing step based on majority voting on the activity assigned to each window, to reduce isolated classification errors: considering five subsequent windows, the most frequently recognized activity was assigned to the entire group of windows. In case of no prevalent activity in the group of 5 windows, all windows were assigned to the class "other activities".

III. Results and Discussion

The average recording time over the group of subjects (mean ± standard deviation) was 10.2 ± 1.7 hours.

Fig. 2 shows the percentage of time spent in each activity during the day (the corresponding mean time, in minutes, is reported in brackets). Fig. 2 demonstrates that most of the time (about 70%) is spent "resting", in particular in the sitting position. Almost 90 minutes are spent, on average, in upright standing (16.2% of the recording time). Dynamic activities, such as walking and stair climbing, take up only the 11.6% of the time, in average approximately one hour.

Fig. 3 shows the distribution of the longest continuous walking time for each subject. As it can be observed, only two subjects out of 23 walked continuously for more than 20 minutes. On the average, the longest walking time without interruption is 10 minutes.

Analyzing these results in light of the recommendations of the U.S. Department of Health and Human Services, we can state that our population reaches the required levels of PA. In fact, our findings show approximately 60 minutes of dynamic activities in a typical weekday, corresponding to 300 minutes a week (considering only the working days). However, from an in-depth analysis of these activities, in particular walking, it is evident that this activity is not continuous, but it is divided into numerous intervals.

IV. Conclusions

This study analyzed the lifestyle of a female group of university workers during a typical working day, to verify if their level of PA was in line with the current recommendations. Our results show that the average time spent in dynamic activities (approximately one hour) reaches the requirements of

the U.S. Department of Health and Human Services. However, these activities are not carried out continuously, but they are split into shorter activity intervals whose average duration is 10 minutes. Although the calories spent for carrying out a specific activity do not depend on the fact that the activity is carried out continuously, to obtain a benefit from a cardiopulmonary point of view it is generally recognized that sessions of at least 20 minutes continuous of walking are required. It follows that only a minority of the subjects that participated in this study (2 out of 23) really reaches the prescribed levels of PA.

However the use of wearable devices, able to return a real-time feedback about the performed activities, could help people to increase awareness about their health and pushed them to reach suitable levels of PA.

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