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# IMU-based monitoring of discharged patients with COVID-19 for the assessment of in-home recovering

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## I. Introduction

The coronavirus pandemic (COVID-19), due to severe acute respiratory syndrome coronavirus-2, is a major current public health problem worldwide. It is crucial to recognize that recovery of patients with COVID-19 does not end with the hospital discharge but rather begins, and improving daily physical activity (PA) seems crucial to this recovery. Thus, characterizing PA in patients with COVID-19 after discharge should be a priority in public health. Furthermore, reporting the impact of COVID-19 on the functional status and PA in the long-running follow-up of patients would allow to understand the evolution and prognosis of the disease and develop a strategy of its management [1]. Hence, we aim to investigate PA and functional status in patients who suffered from COVID-19 across the severity of the disease. This paper describes the algorithm developed for the estimation of PA from data collected with an inertial measurement unit (IMU) and the preliminary results of the objective evidence of the improvement of activity level over time.

## II. Methods

We use the motion data in order to characterize patient's PA levels, to obtain activity features related with the time per activity level and the number of daily walked steps. The data used in this study are recorded while the volunteers perform their activities of daily living (ADL) through an IMU.

We record data from two different groups of people that differ in the information obtained during the recording. The first group, composed of 7 healthy volunteers, records the motion data together with the activity log, so we call them 'labeled data'. These data are considered as a reference in the validation of the proposed algorithm, therefore we ensure to capture resting time combined with different activities such as walking, running, cycling, and household chores. Conversely, the second group includes 69 patients who were affected by COVID-19 between March and June 2020. They were treated in the intensive care unit, hospitalized outside this unit or at home. Patients only record their daily activity data through the IMU, without any diary with extra information, so the obtained data are called 'unlabeled data'.

Monitoring is carried out by collecting data for one week, every three months, in three different periods, using an IMU-based system developed *ad-hoc* in the University of Alcalá. The system stores data into a micro SD card for further offline processing. Volunteers wear this device at the lower back strapped with a sport belt around their waist.

The data processing depends on the kind of data. The labeled data with $1\,\%$ of the unlabeled data are used to generate the activity level classifier, which is employed later to characterize the activity levels of the unlabeled data. Fig. 1 shows the flowchart of the proposed algorithm.

We relate the different activities of the volunteers to the MET values established in [3], defining four different activity levels: sedentary ($\leq 1.5\,$METs), light (between $> 1.5\,$METs and $\leq 3.0\,$METs), moderate ($> 3.0\,$METs and $\leq 4.5\,$METs) and vigorous ($> 4.5\,$METs). The data pre-processing methods include filtering, segmentation and feature extraction. The classification is based on a set of 21 time domain and 10 frequency domain features, from the filtered segmented signals and from the norm of the specific force, linear acceleration and turn rate corresponding to these segments.

We use a semi-supervised self-training model based on the Yarowsky algorithm [4] using a support vector machine learner with a polynomial *kernel*.The algorithm combines the labeled data and a portion of the unlabeled data to iteratively train a classifier and apply it to the following portion of unlabeled

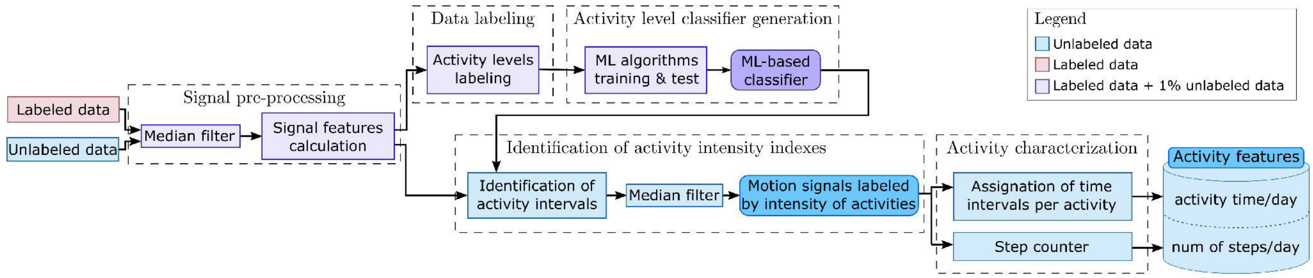


Fig. 1. Flowchart of the activity level characterization with inertial measurement units. This flow depicts the two processes followed by the different types of data. The purple color remarks the combination of the labeled data and 1 % of the unlabeled data. We use this data combination to generate the activity classifier based on a semi-supervised ML algorithm. This classifier is used to estimate the level of activity of the unsupervised data, depicted in blue, so the patients activity can be characterized. Finally, we obtain the activity features at the end of the flowchart by using the step counter presented in [2]

data. As inputs, we include the 90 % of the labeled data with a randomized order and 1 % of the unlabeled data. We use this set of the unlabeled data because of the amount of unlabeled data in this study, which consists in 80.1 GB. We reduce the number of data by selecting the first windows of each 100 windows. We test the method with the remaining 10 % of labeled data, obtaining an average error of 11 %.

We obtain the activity intervals along the recorded days using the classifier, which identifies the activity levels of the features of the segmented windows. In order to eliminate possible errors in the estimation, we use a slide median filter of 60 s over the temporal labels.

Using the daily motions recorded by the IMU, the algorithm identifies different levels of activity by time intervals and analyze the gait features. The gait analysis is based on the step counter proposed in [2]. The outputs of this data analysis are: 1) the duration of the activity per day, and its level from sedentary to vigorous; 2) the average number of steps per day.

## III. Results

In this study, we obtain the activity levels and relative duration per day and the number of steps of patients during their ADL using the motion data recorded by an IMU. To compare the results between the three recorded periods, we average daily data of each set. Fig. 2 shows an example of the results obtained for a patient who has been monitored during 6 days in the first recording set, 5 days in the second one and 6 days in the third one.

The analysis of the time intervals portions of the activity levels is useful to determine the PA levels of patients. In this way, Fig. 2 shows that the distribution of average time intervals with the same activity level remains similar during the three recording sets. The active time of the patient slightly increases along the recording sets. The results also show that the patient performs vigorous activities only during the second and third recordings, increasing their vigorous time during the third set. This trend is also consistent with the number of daily steps walked, shown in green in Fig. 2.

## IV. Conclusions

The activity levels are useful to health providers in order to infer relevant information of the sedentary or active lifestyle of patients. With data of long-term recordings, as the one designed for this study, they can also obtain information about their active trend and prescribe personalized therapies based on their lifestyle activity levels.

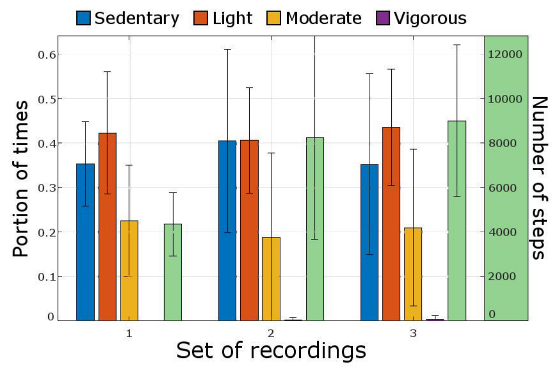


Fig. 2. Average and standard deviation of the portion of time of each activity levels and detected number of steps. The bars colors distinguish the activity levels: sedentary (blue), light (red), moderate (yellow) and vigorous (purple); the green bars depict the number of steps. The groups 1, 2 and 3 correspond to the recording sets.

## Acknowledgments

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