Physiological Activity Tracker using Vitality Signatures

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Executive Summary

In this project, the effectiveness of the new patch developed by the Leibniz Institute of New Materials(INM) was evaluated. It is equipped with a vitality tracking sensor(Heart rate and SpO2). The goal was realized by differentiating the activities performed by subject using the vitalities recorded during the different activities.

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List of Abbreviation

SpO2: Oxygen saturation

MC: Mountain climbing

BPM: Beats per minute

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1 Introduction

Wearable medical devices have been increasing in popularity as they allow all medical professionals and researchers to collect important physiological data. Various devices have been developed both by commercial companies like AppleWatch, FitBit, MiBand or by researchers for specialized medical tasks. However, the commercial devices in use today are plagued with many issues today due to unstable skin-sensor contact. On the other hand, medical patches are notorious for leaving behind tissue damage while detaching the sensor patch. A new adhesive patch developed by the Leibniz Institute of New Materials(INM) aims to reduce these limitations by firmly fixing the sensor on our skin and further not leave tissue damage if detached. The patch was inspired by the adhesive properties of a gecko's feet. A gecko's feet has tiny hairs that are able to maximize the contact area with the surface and facilitates its ability to stick to walls. Van der waals forces are the core phenomenon that results in this ability to work. Currently, we were provided with a HeartRate and SpO2(Oxygen Saturation) sensor that fits inside the adhesive patch using a liftable slot. The sensor is connected to a microcontroller setup that displays real time information about one's HeartRate and SpO2. The sensor is calibrated to give values every 20 microseconds.
Using the adhesive sensor patch fixed to our skins, we investigate how different physiological activities change our HeartRate and SpO2 values. Next, we have tried various techniques to analyze the data and have plotted our findings in the subsequent sections. We have also tried to find clusters in the data and train an algorithm to predict whether a user is conducting a low-intensity or high-intensity workout.

2 Data Set

The adhesive patch with the sensor is connected to a microcontroller which gives out real time HeartRate and SpO2 values. The sensor gives out accurate values only when we place the patch on the skin, especially areas with a lot of capillaries close to the skin. Our experiments showed that the best places to attach the adhesive patch is on the fingertips and on the underside of our wrists.

Subsequently, we decided to test out how the HeartRate and SpO2 values change as we undergo certain physiological activities such as “climbing steps”, “walking briskly”, “squats”, “planks” and “mountain climbing(MC)”. To keep a reference to our original HeartRate and SpO2 values, we also recorded “resting” HeartRate and SpO2 for all the subjects.

Since the adhesive patch setup is connected to the microcontroller setup with a small wire, our approach was to collect the HeartRate and SpO2 values immediately after we finished the above mentioned activities. All the participants performed the above activities several times for a stipulated time period. We recorded the HeartRate and SpO2 values for the next 2 minutes. We decided on 2 minutes because we observed that HeartRate drops back to resting after about 2 minutes and SpO2 value returns to normal levels.

According to our observations, as shown in Figure 1, SpO2 values remained relatively stable all throughout our activities. Since the available features are only HeartRate and SpO2 (with limited variation for the activities considered) any kind of further evaluation was limited. To overcome this we considered adding three more features in the form of Acceleration in x,y,z directions. This was achieved using a free mobile application "Phyphox" available on both Android and IOS. We recorded additional features related to acceleration by keeping the phone in the participant's pocket and recording the acceleration while they performed the exercises. This data was extracted into a .CSV file and later merged with our original HeartRate and SpO2 values. One point to note here is that features related to acceleration are not recorded at the same time as HeartRate and SpO2 due to the limitation mentioned above.

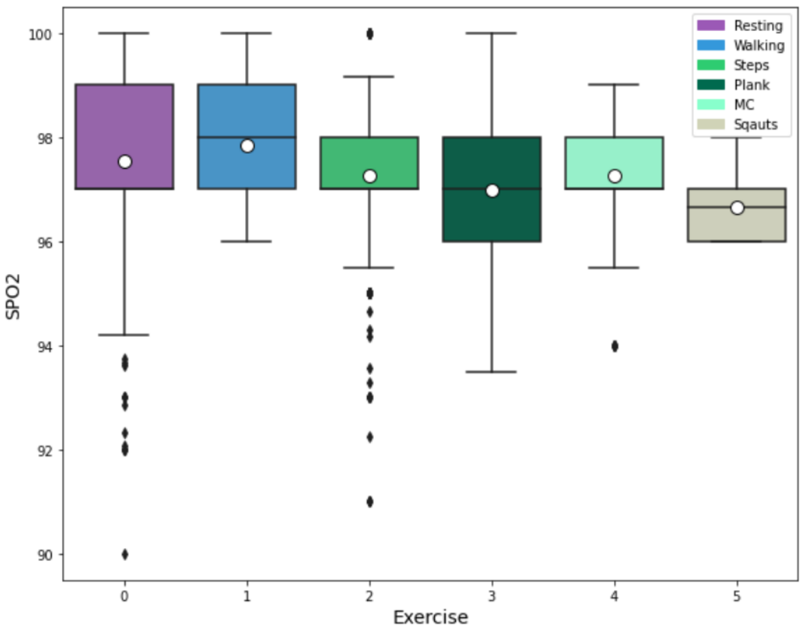

Figure 1. Box Plot chart of SpO2 for all activities

Further, in order to compare the sensor results with real world values, we utilized a commercial Oximeter device to check the HeartRate and SpO2 values of all participants while we were performing the recording of HeartRate and SpO2. The commercial fingertip Oximeter provided us a significant insight that is; there is a considerable offset in the "resting" HeartRate and SpO2 values. An important point to remember is that the values recorded from the adhesive patch sensor is "raw data" without any processing done in contrast to the commercial Oximeter as shown in Figure 3. As we can notice in Figure 2 the offset between the different methods of recording is not constant; it varies for every activity.

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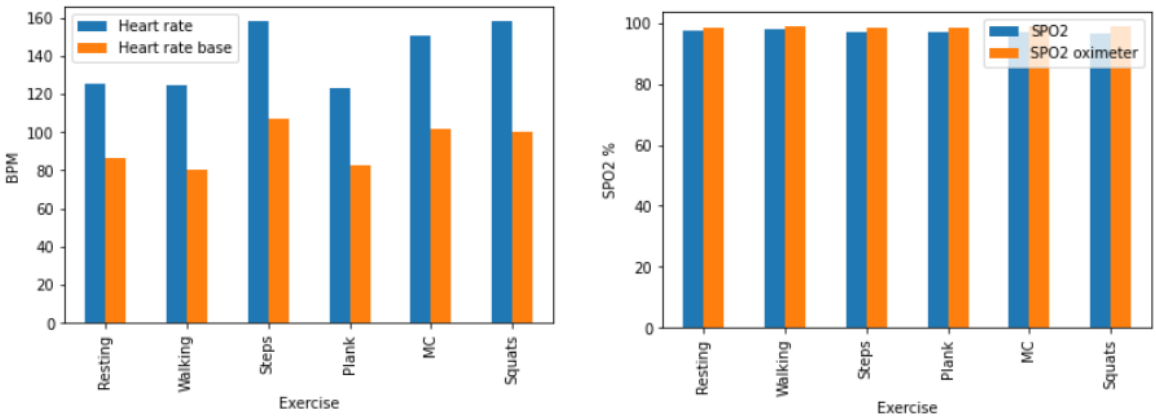

Figure 2. Patch HeartRate(blue) vs Oximeter Instrument HeartRate(orange)

Figure 3. Commercial Pulse Oximeter placed on Participant’s fingertip

Figure 2 shows a comparison between the HeartRate collected with the provided patch vs the HeartRate collected with the Oximeter instrument for each activity performed by every participant. The data used here is the compilation of all participant’s data. Whereas, Figure 4 shows the box plot of every activity. Looking at the mean of each activity, we can infer from the box plot that resting, walking and planks are closer together in terms of heart rates observed. On the other hand, steps, mountain climbing and squats have a more varied observed heart rate for all participants.

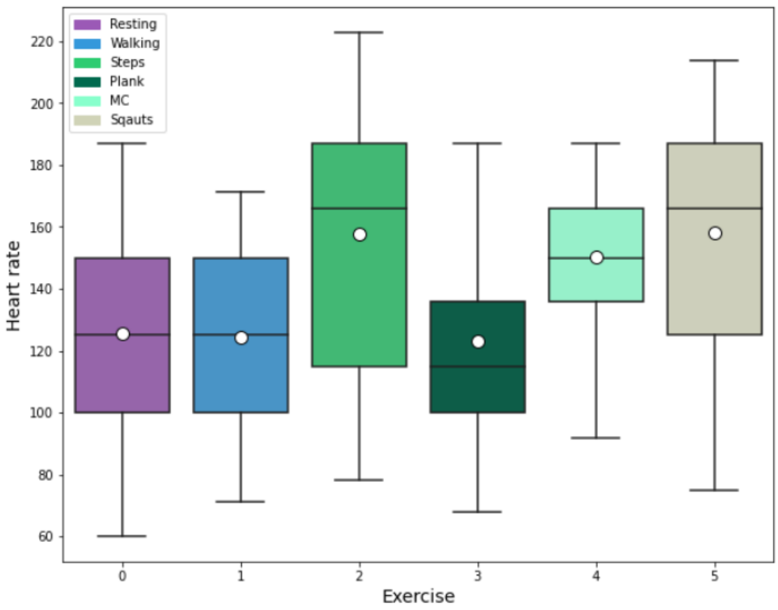

Figure 4. Box Plot chart of HeartRate for all activities

2.1 Data preparation:

Manual preprocessing:

From each data collection experiment we constructed an independent csv file containing SpO2 and heart rate. For each case, we manually cleaned any garbage data such as strings and added columns *person_id* (id of person doing the experiment), *exercise* (exercise type: 0-Resting, 1-Walking, 2-Steps, 3-Planks, 4-MC, 5-Squats), *spo_base*, *heart_rate_base* (measured using commercial Oximeter for further comparison). Finally, a new .CSV file was generated for each experiment.

Processing exercise subsets:

From the recording phase and manual inspection of the data, we noticed that the sensor constantly gave flawed values such as "-999". These data points were replaced by a mean value. The mean was calculated from the remaining SpO2 and HeartRate values after removing the flawed values.

Since the amount of data collected for each experiment differs, we took the same amount of data for each experiment, addressing different approaches:

- Getting the n-top samples from each recording session.
- Reducing file to n size by taking average of fixed samples from each recording session.
- Getting randomly selected 'n' samples from each recording session.

Afterwards we built "exercise subsets", that is; a subset for each exercise containing the information of the individual experiments.

Among all the above mentioned approaches, reducing the file to n size by taking average of fixed samples from each recording session gives better results for final classification of activities, the data distribution can be seen below.

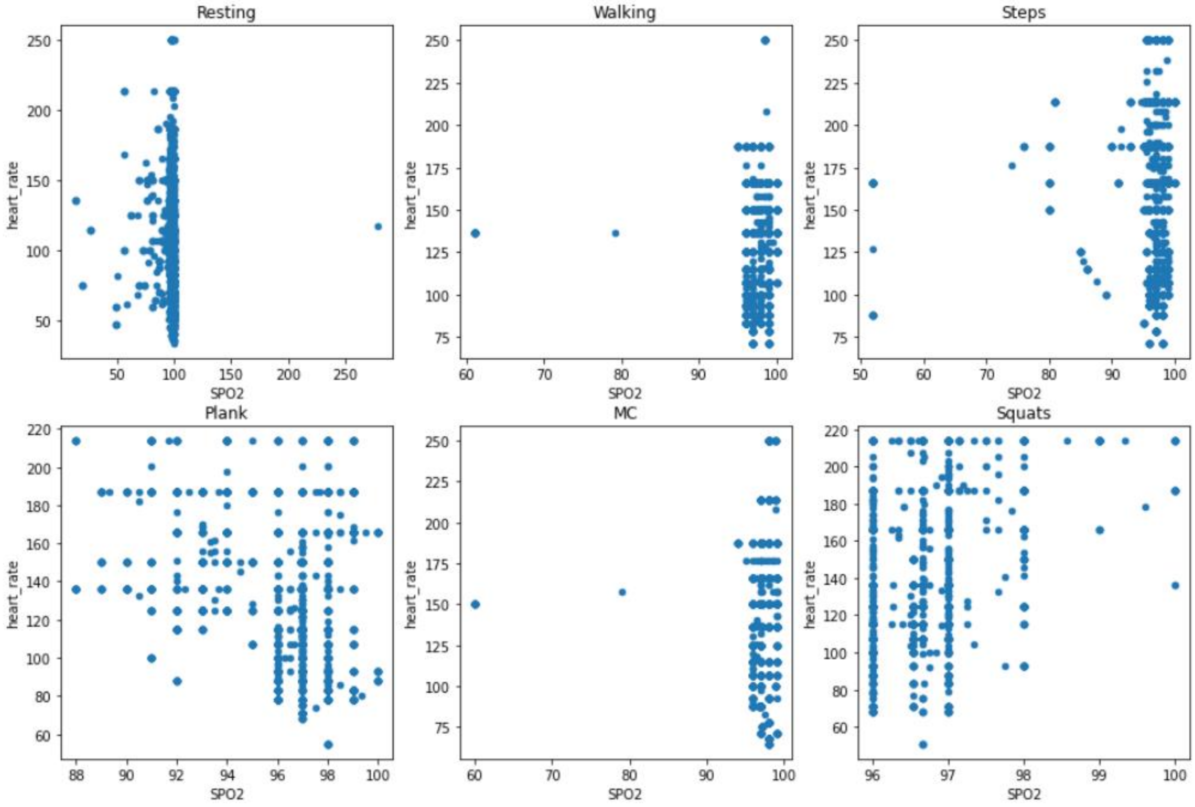

Figure 5. Comparison of SpO2 and heart rate for each type of activity

Figure 5 shows the distribution of SpO2 and HeartRate for each activity. Heart Rate lies in a wide range of values around 50 to 250, however the data is more concentrated in some regions. On the other hand, SpO2lies in a narrow range, approximately 90 to 100, but there are isolated samples.

Removing outliers:

From our data recording phase, we could observe that the sensor output varies drastically in consecutive outputs, for instance, during resting the sensor outputs heart rate 155 -> 71 -> 107 -> 136 within 5 seconds. Besides, we know that SpO2 values close to 60 usually indicate the need for supplemental oxygen, which is not the case of the particular people performing the experiment. That is why we consider those unusual values as outliers and not as exceptional cases.

Figure 6 draws the density distribution of the heart rate and SPO2 for each exercise. Even though the data is noisy and presents many peaks, we assume it is normally distributed and we address outlier removal using the Standard Deviation Method. For this approach, we compute lower and upper limits from data mean of each exercise and remove the points that fall outside 3, 2 and 1 standard deviations, which are not considered part of the distribution. As shown in Figure 7, if we take standard deviation = 3, the dataset contains many outliers, such as heart rate = 25. Whereas, standard deviation = 1 , only keeps values which are closer to the mean. Therefore, it might also discard significant values that are part of the distribution. As a result, we take standard deviation = 2 as an intermediate option.

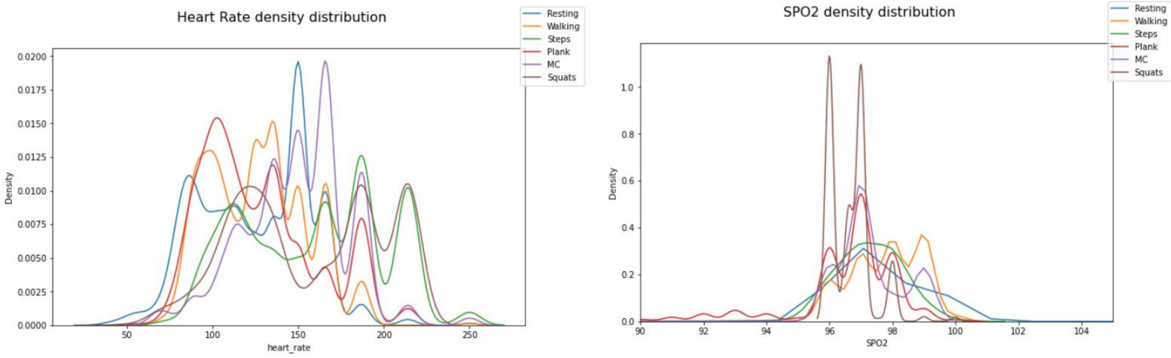

Figure 6. Density distribution of heart rate and SPO2 for each exercise.

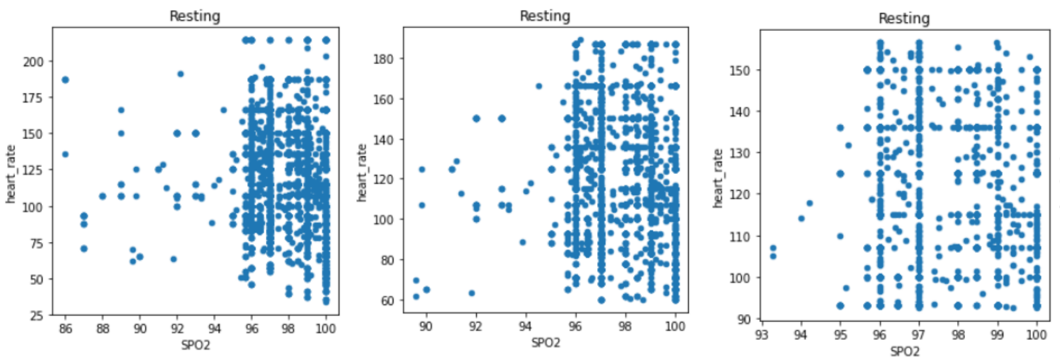

Figure 7. Resting subset after removing outliers with Sd = 3, 2, 1 respectively

On the other hand, we also considered the DBSCAN algorithm for outlier detection. The approach was to fit a model that is able to identify clusters of each subset by looking at the local density of the data points, and afterwards, remove those that were considered as outliers. The following Figure 8 shows the clusters found for Walking exercise, the black dots were considered outliers and were removed. However, one still can note big clusters with SpO2 close to 60, and heart rate around 250. Those points are clearly outliers, but since the sensor records many repeated flawed data, the algorithm groups them together. That is why we decided not to use this algorithm for handling the outliers.

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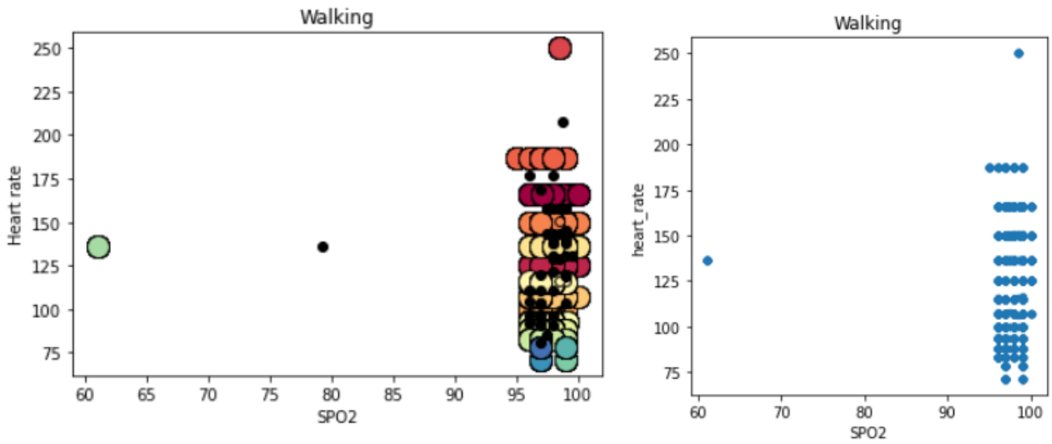

Figure 8. Walking subset: (left) DBSCAN clustering and (right) after removing outliers

For each activity the final dataset was created by having the same number of samples. Finally, we join the 6 activities subsets into one main dataset, including the records x, y, z acceleration for each corresponding activity.

3 Procedure and Analysis

The procedure involves taking in raw data and then preprocessing it by the methods mentioned above(Standard Deviation Method). After data preparation, Principal Component Analysis(PCA) was used to reduce 5 features (SpO2, Heart rate, x, y, z accelerations) into 3 principal components. As it is shown in Figure 4, there is a clear variation between Heart rate of activities Resting, Walking, Planks and Steps, Mountain climbing, Squats; therefore clustering these activities was considered, this task can be addressed in a Supervised and Unsupervised manner.

As the data collected is of time series data and iterations of experiments were limited, there was a possibility of overfitting to only training data, to prevent this and to capture the original distribution of data only Unsupervised clustering was considered. After it is done at the final stage, clusters were assigned with manual labels imitating the process of assigning activities to clusters by expert intuition. This can be seen as classification of High intensity and Low intensity tasks.

During testing, separate data was considered which was not used during training time. It involves the same procedure of data preprocessing as training, then the data was fed into the unsupervised model to predict the cluster which in turn indicates the activity performed.

As discussed above, only two clusters were considered(High intensity and Low intensity tasks). We tried different clusters for our ablation studies, and we found out that features like x, y, z acceleration boosted our clustering accuracy, however it also was noted that increasing the number of clusters in turn decreases the prediction accuracy of each cluster. This can be easily explained by pointing out that there is no clear separation between clusters. This has been further worsened by the fact that our data has very little features, besides, there was another aspect of data distribution shift between each person which hindered the clustering capabilities, as shown in the following Figure 9, we don't have the same baseline data for all the individuals involved in the experiment, indeed there are some participants that constantly have higher heart rate among all activities (see blue and green bars), whereas some others participants which heart rate is much lower (see purple bar).

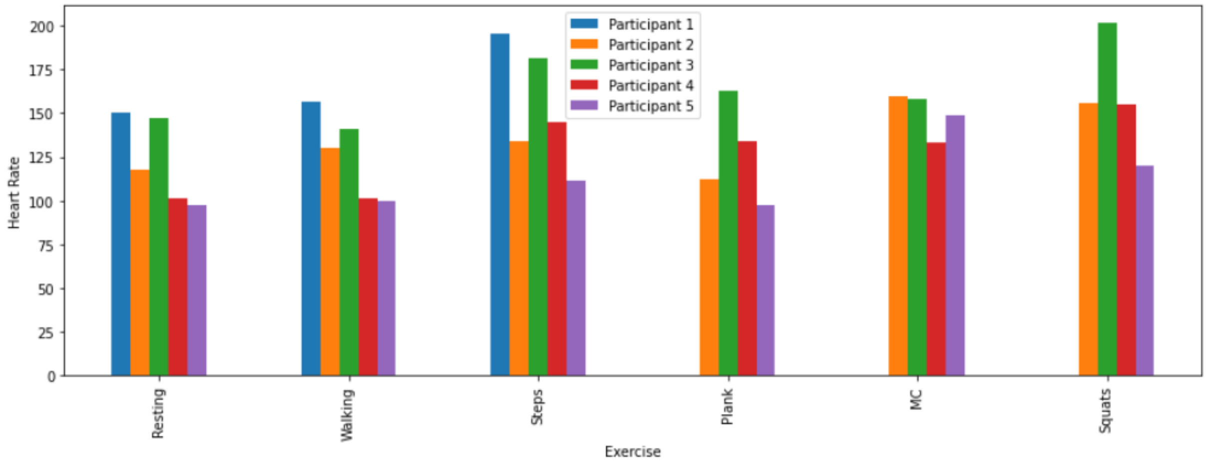

Figure 9. Heart rate variation per person in each activity

4 Results and Discussion

The main aspect of this project is to evaluate the effectiveness of the patch provided. This was interpreted as classification of different activities performed using the data provided by the adhesive patch with the sensor. We addressed this goal by performing Unsupervised learning on the available data, aiming to create differentiable clusters.

As we can see in the following table, we tried classifying the original 6 different physical activities, but a low accuracy was obtained, as the number of activities to classify increases, the model behaves poorly. At the end it has been decided to have classification of High intensity vs Low intensity activities where we got the best accuracy.

Number of clusters	Test Accuracy
2	**61.326%**
3	19.085%
6	17.21%

Table 1. Test accuracy for classification of different number of activities

Although the obtained clusters are not perfect, the final result was acceptable, providing the challenge of having limited data features and limitation of setup provided, which prevents accurate recording of data, given it was recorded after each participant performed the activity instead of during it.

Another observation relating to SpO2 is that it is hard to generate scenarios from a healthy subject which can affect SpO2 values, this can be realized if only a diverse set of subjects are available.

It is also observed that variability in data collected among individuals is high making the task harder. In future it can be further analyzed whether having similar subjects(in terms of vitals) can improve the final outcome, of course it can be only realized if the available dataset is big.

Appendix

Architecture of the data:

We start with the following file structure:

```
training
            |-- 0-Baseline
               |-- vitals
                        |-- experiment_person_1.csv
                        |-- experiment_person_n.csv
                        |-- ...
               |-- acc
                        |-- experiment_person_1.csv
                        |-- experiment_person_n.csv
                        |-- ...
            |-- 1-Walking
               |-- vitals
                        |-- ...
                |-- acc
                        |-- ...
            |-- ...
test
            |-- 0-Baseline
               |-- ...
```

The “vital files” have the structure*:*

person_id,exercise,spo_base,heart_rate_base,SpO2,heart_rate

Whereas “acc files” contain:

time,x,y,z,absolute

- *person_id:* classes 1, 2, 3, 4, 5 for each member of the team.
- exercise: classes 0 (resting), 1 (walking), 2 (steps), 3 (plank), 4 (mountain climbing), 5 (squats).
- *heart_rate_base:* beats per minute (BPM) obtained from commercial Oximeter.
- *spo_base*: Oxygen saturation percentage (SpO2) obtained from commercial Oximeter.
- *time:* Time record in seconds.
- *x:* Acceleration (m/s^2) along x-axis.
- *y:* Acceleration (m/s^2) along y-axis.
- *z:* Acceleration z (m/s^2) along z-axis.
- *absolute:* Absolute acceleration (m/s^2).

After data preparation phase, our training and test datasets merge the features previously mentioned:

person_id,exercise,spo_base,heart_rate_base,SPO,heart_rate,time,x,y,z,absolute

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spo_base and heart_rate are used only for data analysis purposes. Time and absolute acceleration are not used in our approach, however they are available for further work.

Description of the Code:

Our code is composed of 3 parts: Data preparation, Clustering and Demo Application.

Data preparation: In the notebook *data_preparation.ipynb* we read individual data from csv files obtained from each experiment (in the file structure stated at the Architecture of the data section), for every case the data is cleaned and outliers are removed. Finally, all data is joined together in a training and test dataset.

Clustering: In the file *process.py* we are taking preprocessed data and trained an unsupervised model to create clusters. Each cluster can be assigned to an activity. During test time the model predicts one of the clusters representing the activity. Three different csv files are available as input for different number of clusters(*sd2_avg_bal_data_set_group18_new_3,sd2_avg_bal_data_set_group18_new_6.csv,sd2_avg_bal_data_set_group18_new_2.csv*).

Demo Application: app.py file contains the source code for dashboard utility coded in Streamlit. This utility contains options to preview the raw data collected from the wearable device , as well as options to visualization. Finally, we report the training and testing accuracies for our model on 2 clusters.

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Declaration of Authorship

I affirm that I have produced the work independently, that I have not used any aids other than those specified and that I have clearly marked all literal or analogous reproductions as such.

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