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Abbreviations

Short	Long
EC	European Commission
EU	European Union
WP	Work Package
KOA	Knee Osteo Arthritis
OA	Osteo Arthritis
HAR	Human Activity Recognition
DOF	Degree of Freedom
IMU	Inertial Measurement Unit
RNN	Recurrent Neural Networks
CNN	Convolutional Neural Networks
AE-CNN	AutoEncoder Convolutional Neural Networks
MD	Mahalanobis Distance
PCA	Principal Component Analysis
SDK	Software Development Kit

1 Executive Summary

This deliverable relates to the activity performed, during the reporting period, within OACTIVE WP 5: Behaviour Modelling and Environmental Biomarkers. In particular, the report refers to Task 5.2, led by CERTH.

The following document describes the activity carried on to implement a behavioural model of KOA (Knee OA) patient. The main aim was to gather the data which are necessary to the generation of the behavioural model, from direct measurement of patients by the means of wearable platforms developed within OACTIVE frame

With respect to the methodological part, we particularly focus on the design of a complete methodology that can take advantage of collected sensor data to generate a behavioral model that can be supportive in predicting future development of Knee Osteoarthritis or even in the individual's rehabilitation after knee surgery for Osteoarthritis. More precisely, we estimate uncommon behaviors within daily activities as an indication for further examination. Based on accelerometer sensor data, the proposed framework utilizes state-of-the-art Machine Learning models for Human Activity Recognition and Deep Hybrid Models for outlier detection suggesting a solid basis for further developments and wider applicability.

Following project evolution, the activity related to sensor development in the OACTIVE frame has been extended in order to complement the data set coming from a controlled environment (motion lab) developed in the first phase (D5.1), with data obtained in an uncontrolled environment. For this reason, the set of sensors available in OACTIVE has been expanded with a device, always IMU based, able to be used autonomously by the patient directly at home. This approach allows to provide two complementary data set for the development of the behavioural model of OA patient: the first provides information on how OA affects patient's movement, the second on how OA influences patient's habits and behaviour. Both versions of the developed electronic board include an IMU sensor (MPU 9250 by Invensense) with 9 DoF, an M3 micro-controller, Bluetooth transmission and a LiPo battery of 660 mAh. The case and package have been designed to optimize handling and comfort when worn. Different textile accessories, developed internally at Smartex, have been provided for easy don and doff of the devices.

2 Introduction

Osteoarthritis (OA) is one of the most diffused forms of musculoskeletal disorders and the most prevalent chronic rheumatic diseases worldwide (Bortoluzzi *et al.*, 2018). OA is considered as a complex disease in both treatment and rehabilitation processes, with some cases such as the knee OA there is not a sufficient cure (Taylor *et al.*, 2010). Recent advancements in IoT technologies have shifted part of the OA research on behavioral monitoring using wearable devices (Belsi *et al.*, 2016). Many wearable devices as smartwatches, smart bands and smartphones have seen an increase in use, as they are widely available, low-cost, they have high computational power and can be used by people of all ages and education profiles. Additionally, these devices can be easily used for continuous daily monitoring, as they are small and with long battery life and autonomy. Using daily continuous monitoring along with a robust human activity classification system we can model a personalized activity profile which can be later used in data mining tasks (profile grouping, prediction etc). Weight, height, gender, age, physical and overall health condition, but also everyday habits like exercise, nutrition and smoking combined with the personal daily activity profile of an individual, may play an important role in the prediction of future development of knee Osteoarthritis or even in the individual's rehabilitation after a knee surgery for Osteoarthritis (White *et al.*, 2014).

Both aforementioned documentations could be used to make personalized Osteoarthritis prediction, activity recommendation system and many other knee Osteoarthritis related systems, as a long-term activity monitoring of individuals with high variability of personal characteristics can be documented and combined with the outputs' provided information. Another recent example showing the usefulness of a Human Activity Recognition (HAR) Behavioral Model could be the analysis of the influence of very specific situations, like the quarantine for COVID-19 in the profile of the daily activities of people (D'Angelo & Palmieri, 2021).

Towards this direction, there is a remarkable progress related to wearable-based studies for OA and more specifically for knee OA (Saida *et al.*, 2020; Burrows *et al.*, 2020; Chen *et al.*, 2015). More specifically, the effect of total knee arthroplasty (TKA) on trunk fluctuation and regularity of gait in patients with knee osteoarthritis has been recently classified successfully through an analysis using accelerometers (Saida *et al.*, 2020). It has been shown that several factors influence the association between physical activity and pain from knee OA while the increased levels of daily physical activity are related with reduced onset and progression of knee OA (Burrows *et al.*, 2020). An indicative study for knee OA along with wearable-based analysis is the work of Chen *et al.* (2015) where the authors developed a system that can identify the type of exercise movement the user performed and detect deviations from the correct exercise movement. Using three wearable accelerometers as signal source, the experimental results demonstrate the feasibility of the proposed mechanism, which can help patients perform rehabilitation movements and progress effectively. Although the promising results given by the previous studies, the increase in OA-related available data as well as the improvement of wearable-based technologies and mining tools offer us the opportunity for exporting more reliable OA signatures.

In the OACTIVE project, we particularly focus on adapting HAR for Behavior Modelling within OA's prognosis-prevention and/or to the rehabilitation of OA patients, slowing down OA progression. In detail, we propose a complete methodology based on the combination of Supervised and Unsupervised Learning. Initially, we focus on identifying daily activities such as walking, jogging, going upstairs/downstairs and sitting, as they are the most usual physical activities in a person's daily life, and they involve knee movement. For this purpose, we focus on the utilization of accelerometer data while, we employ pre-trained Deep Learning models incorporating open-source labelled activity databases. HAR based only on accelerometer data retrieved from a single device remains a challenging task, motivating us to utilized state of the art models for this purpose. Once the HAR process is complete, we take one step further, trying to identify abnormal behaviors of one's activity in an unsupervised manner. To this end, we focus on a hybrid methodological framework, usually referred as "Deep Hybrid Model" where a Deep Learning method such as the Autoencoders is utilized for feature extraction, followed by a conventional Machine Learning algorithm or statistical process. We interestingly observe that even for non-OA patients' databases we are able to identify persons with uncommon walking behavior. Through our proposed model we aim to provide an additional critical marker on top of current Behavioral Modelling/Monitoring methods.

3 Behavioural Model

3.1 Human Activity Recognition

In Human Activity Recognition (HAR), various daily human activities such as walking, running, standing, sitting, drinking, eating, driving, etc. are recognized, in controlled or uncontrolled states. Recently it has become one of the trendiest research subjects in academia for numerous applications, mainly due to its applications in Healthcare and Eldercare where it is combined with advancements in Machine Learning, Big Data and Internet of Things (IoT). HAR can be done with data, collected by different means such as 1) ambient sensors and/or well-placed cameras in labs or smart houses and 2) inertial sensors of wearable devices like specialized harnesses placed anywhere on the body, smartphones and even wrist-worn smartwatches and smart-bands (Stisen *et al.*, 2015).

Inertial sensor- based HAR systems still face many challenges, including 1) complexity and variety of daily activities, 2) intra-subject and inter-subject variability for the same activity. Consequently, as a user's movements drift from the generic, the system error increases. So, the method for activity classification should have the ability to generate adapted results for each different user, 3) the trade-off between performance and applicability, 4) the fact that small difference in sensor placement/specifications may give dramatically different data, 5) computational efficiency in embedded and portable devices and most critically 6) difficulty of data annotation (Lana & Labrador, 2012).

The typical structure of a HAR system involves a training phase where a classifier learns how to identify specific activities. In more detail, classifying data points created by tri-axial accelerometers and gyroscopes, falls to the area of classifying time-dependent sequences into known well-defined movements. Traditional approaches involve hand-crafting features extracted from the time series data, corresponding to time windows of fixed-size (Suto *et al.*, 2017). Unfortunately, feature extraction requires deep expertise in the field and even then, derived models may have limitations in generalizability. Recently, Deep Learning methods such as Recurrent Neural Networks (RNN) and most precisely their LSTM variation, along with the one-dimensional Convolutional Neural Networks (CNN), have been shown to provide impressive results on activity recognition tasks by automating the data feature engineering process. The former takes care of time dependence, keeping in memory previously gained information and the latter tends to uncover hidden patterns in a time window, utilizing a convolution step (Ordóñez & Roggen, 2016).

3.2 HAR in Behaviour Monitoring

In Behaviour Monitoring, usually a system analyses patterns such as destinations, frequency and periodicity of specific identified incidents which indicate whether the behaviour exceeds a specified baseline or threshold (Amor *et al.*, 2014). Regarding the observation of people’s lifestyle, behaviour changes, possible progresses constitutes the obtained knowledge that can be utilized by computer-based models in plenty of important applications, solving individual and social problems. For example, the development of an Osteoarthritis patient’s Behaviour Model, requires daily monitoring and analysis of his/her physical activities (Williamson *et al.*, 2015). The utilization of the provided information like the frequency and duration of every activity performed daily for a specific time-period, supportively contributes towards the development of predictive models that are capable to understand the onset and progression of OA. Such models could be utilized by expert physicians in prognosis and/or diagnosis of the disease, developing personalized treatment plans, or evaluating the rehabilitation after an OA surgery (Semanik *et al.*, 2015).

To this end, it is important to notice, that activity classification accuracy is not of critical importance, as even if there are a minor portion of mis-classifications, the impact on the reliability of the finally created behaviour model is expected to be insignificant. In general, a fuzzy activity prediction that monitors generic activity behaviour is combined with information provided by medical history and demographics such as age, gender, weight-height and lifestyle of an individual, in order to provide the tools for a complete person-adapted model (Song *et al.*, 2010).

Here we take one step further, to adapt HAR for Behaviour Modelling within knee OA's prognosis-prevention and/or to the rehabilitation of knee OA patients. In detail, we propose an additional supported Anomaly Detection step, which could be used to evaluate if a subject executes some basic physical daily activities normally, or not. We are particularly interested in examining daily activities such as walking, jogging, going upstairs/downstairs and sitting, as they are the most usual physical activities in a person's daily life and they involve knee movement.

The anomaly detection task could be dealt as a supervised classification problem, utilizing an individual pretrained algorithm for every activity towards a binary classification task ("normal" and "abnormal"). However, in this case we would require either data created within a lab environment or study participant annotation during daily life cycle, leading to impractical circumstances in both cases. Limited availability and time requirements in the first case and subjective view of individuals in the second respectively.

Subsequently, we proposed a hybrid model, utilizing straightforward annotation of daily activities and open databases to train a model for typical HAR and then an unsupervised Anomaly detection methodology to identify uncommon behaviours within specific activities.

3.2.1 Anomaly Detection in HAR

Anomaly detection (AD) is a data mining process which identifies data points, events, and/or observations that deviate from a dataset's normal behaviour and typically occur rarely. Types of Anomalies can be separated to Point Anomalies, Pattern Anomalies, Change Points or Trend Anomalies. Anomalous data can indicate critical incidents, which may be interesting for many different reasons and detecting them can be a solution for a variety of problems. Machine learning is progressively being used to automate AD. Semi-supervised approaches to anomaly detection aim to utilize labelled samples, but most proposed methods are limited to including samples labelled as normal (Ruff *et al.*, 2019).

Unsupervised techniques that do not require manually annotated training data, presume that most samples are normal and only a small percentage of them is abnormally characterized by some statistical differentiation. Groups of frequent similar instances, based on these assumptions, are assumed to be normal and the infrequent data groups are categorized as malicious. The most popular unsupervised algorithms include K-means, Auto-encoders, PCA, GMMs, and hypothesis tests-based analysis (Thudumu *et al.*, 2020). Auto-encoders, which found an explosive rise of interest in the recent years for many applications (Sakurada & Yairi, 2014), constitutes an unsupervised type neural network, mainly used for automated feature extraction and dimension reduction. An Auto-encoder consists of encoding and decoding parts. In the encoding part, main features are extracted representing the data's patterns, and then each input sample is reconstructed in the decoding part. The final output must be recreated from the input and the reconstruction error must become as small as possible.

Here we specifically investigate the Anomaly Detection amongst time series using a specially designed Autoencoder to automatically extract features from time-series data that have been already characterized as a particular daily activity. We follow a hybrid deep anomaly detection process where a distance- based statistical technique is applied to the feature space to detect the anomalies. We take advantage of the non-linear transformations that can be performed by the autoencoder using their non-linear activation function and multiple layers.

3.3 Proposed Methodology

The proposed hybrid deep learning methodology can be summarised into the following steps:

- Daily, recording of Accelerometer Signal in uncontrolled states.
- Segmentation of the Time Series into Time Windows.
- Classification of every Time Window, using a pre-trained 1D-CNN classifier, deciding which activity is currently performed.
- Recovering small Time Periods, consisting of Sequential Time Windows characterized by confident predictions for each activity performed by every individual.
- Automated feature extraction through a CNN Auto-encoder, deriving the feature vectors of each activity performed by every individual.
- Utilising a statistical Anomaly Detection method on the feature space for outlier detection.
- Incorporate the obtained information to complement the Behaviour Model.

Notice that, besides the specialized equipment' sensors, a smartphone's accelerometer can be used. The mobile device can be placed preferentially somewhere near to the centre of gravity of an individual's body, giving more accurate information for its movement. The use of mobiles has the advantages of practical use and wide availability, which subsequently provides the ability to generate a large-scale database, and develop robust generalized models. Given the sensor data, we perform a typical time series data preprocessing step, in order to train an 1D-CNN classifier utilizing data points of fixed size time windows. The time window length is set according to the minimum time-period, during which, physical activity can be performed.

In practice, in order to test the quality and normality of the execution of those physical activities with the prospect of developing a human behaviour model, we only need a small daily sample for each of them. A good arbitrary selection of the duration of this sample is 2-3 minutes, as this seems to be long enough time for an abnormal pattern in an activity to appear (Hemmatpour *et al.*, 2018). To this end, we only need to retrieve a sequence of time windows that belong to the same class (activity) according to our classifier. Preferable we want to minimize error rate for these particular samples, as such we threshold this sequence selection by requiring high prediction confidence. This way, we expect to avoid minor kinetic variations within the activity that would affect our anomaly detection process.

At the next step, having secured a short time series for each daily activity and for each individual, we proceed to the anomaly detection process. Initially, for every activity we train a specialized Auto-Encoder to extract representative features. Then, the anomaly detection algorithm operates at the extracted feature space to identify individuals with uncommon behaviour.

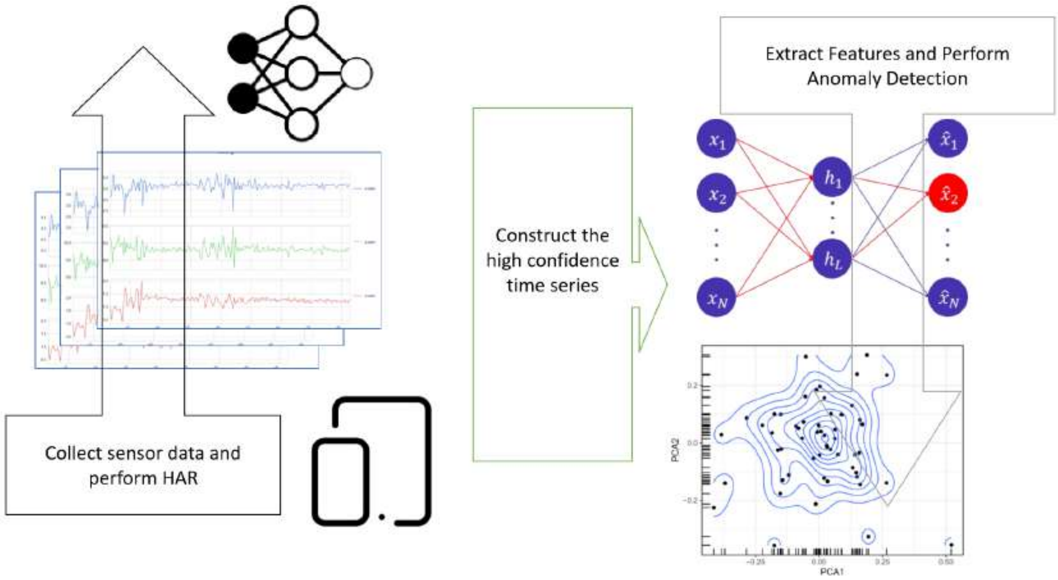

Figure 1 The workflow of the proposed methodology

3.4 Experimental Study and Results

3.4.1 Data Description

The dataset utilized here is the publicly available dataset, named "WISDM - Actitracker" (Lockhart *et al.*, 2011). The Actitracker dataset is the real-world equivalent of the WISDM dataset. It consists of tri-axial accelerometer data samples, recorded by an Android Smartphone, carried in the subjects' front pocket. Gender and age balanced, 563 volunteer subjects performed a set of physical activities, in an uncontrolled environment, for specific periods of time. In all cases, the sampling rate of the accelerometer was 20Hz, collecting data every 50 ms, so there were 20 samples per second. The raw time series data resulted in 1.098.207 samples, with a class distribution of Walking: 424,400 (38.6%), Jogging: 342,177 (31.2%), Upstairs: 122,869 (11.2%), Downstairs: 100,427 (9.1%), Sitting: 59,939 (5.5%) and Standing: 48,395 (4.4%).

3.4.2 Activity Classification

A crucial part of the proposed methodology constitutes the classification of the time-intervals signal samples, since the most representative ones will be used to produce the human activity feature. Convolutional Neural Networks (CNN) are state-of-the-art classification algorithms with high usage in the last years on signal classification tasks and problems of activity recognition from wearable sensors. CNN are multistage trainable architectures and used to classify human activity from accelerometer signal data. In order to classify the signal the proposed CNN utilize batches of raw accelerometer signals in the form of time windows with dimensions w × 3, where w corresponds to the number of (x, y, z) signal samples per time window. The model is trained using the three signal channels learns their local patterns applying a layer of convolutional operators, forwarding the discovered information to a feed-forward layer. The basic CNN components are the convolutional layers which are combined with a pooling layer functioned as a sub-sampler of their outputs, significantly reducing their dimension. The output of a convolutional layer produces ten feature maps. The information of feature maps is flattened and feed one fully connected layer with fifty neurons and then forwarded to the output layer with a number of neurons equal to the number for human activities. In the convolutional part of CNN to extract the local pattern among the three signal channels a 1-dimensional kernel with size three is deploy among channels, producing the aforementioned feature maps. In feed-forward part due to large values that some signals occurs (maybe from sensors falt) and in order to achieve convergence of the training process of the model the sigmoid function is utilized on full-connected layer. Finally, the training of the model achieved by minimizing of the error function that is utilized on the last layer of the network. The differences between the network's output for each specific input data and the original label of this data are propagated backward to the network, adjusting the connection weights at every iteration. The softmax loss function it is utilized as error function.

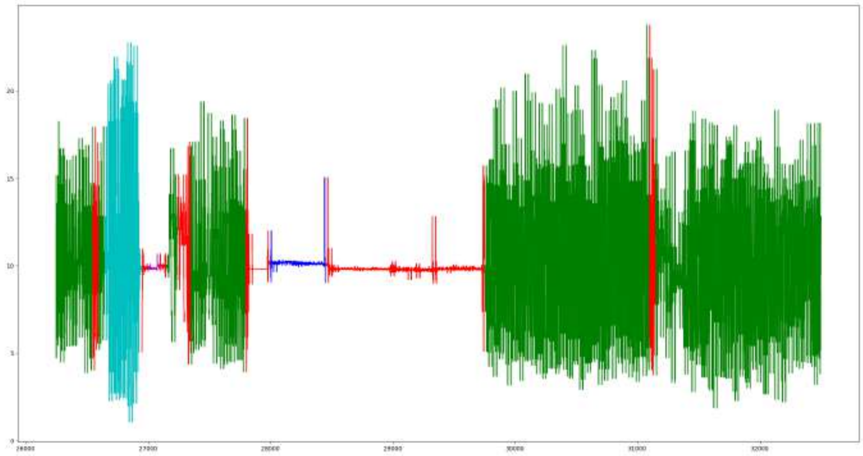

Figure 2: An example of the prediction results with respect to the total acceleration.
Red areas correspond to misclassification.

In figure "Figure 2: An example of the prediction results with respect to the total acceleration.

Red areas correspond to *misclassification.*" We observe an indicative example of the classification process. Red areas correspond to misclassifications. We observe that these mostly regards static activities. In "Figure 3: Confusion Matrix of the HAR *process*" we have a much clearer view observing the resulting confusion matrix for the full dataset. As shown the walking activity, which constitutes the majority class of the dataset has been accurately predicted.

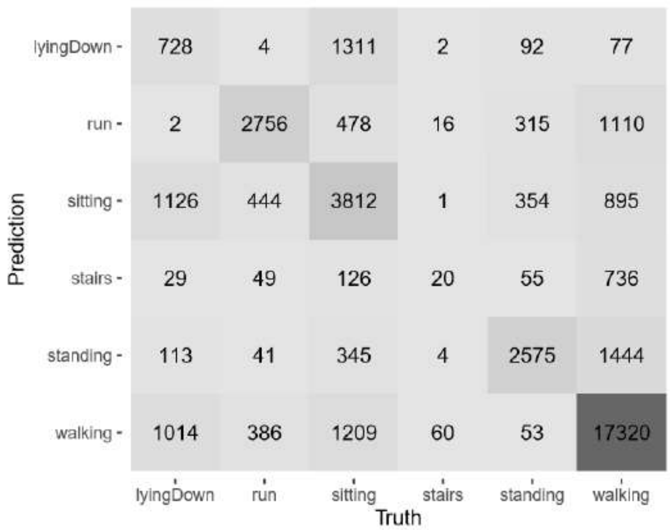

Figure 3: Confusion Matrix of the HAR process

For this reason we continue our analysis emphasizing on the anomaly detection regarding the "walking" category. To this end we need to construct the time series for each individual from the walking class that will be used to extract features in the next step. To ensure that there are enough samples that have been predicted with high accuracy we observe the following histogram where we conclude that this assumption holds. By setting threshold value for prediction confidence to 95% the classification accuracy for the walking classing is increasing from 85% to 94%.

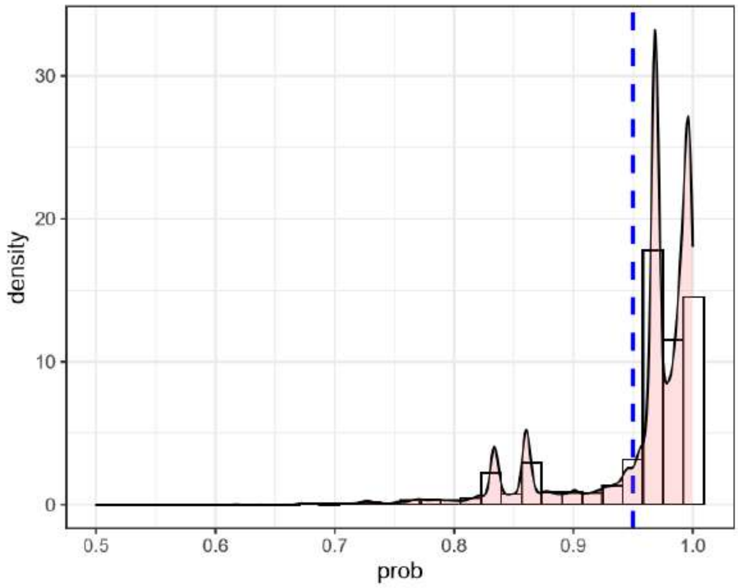

Figure 4: The prediction probability distribution for the "walking" class and the corresponding threshold utilized

3.4.3 Feature Extraction

The feature representation is produced by a non-linear semi-supervised method, the well-known AutoEncoder Convolutional Neural Networks (AE-CNN). AE-CNN is a type of CNN that does not require the labelling of data, and therefore it is an unsupervised learning algorithm. The aim is to learn an input function to reconstruct the input to an output of lower dimensions. Autoencoder approximates the identity function to make an output that is similar to the input of the network. Mathematically, considering x as an input, passing through a number of convolutional layers where the number of their feature maps is gradually decreasing, called encoder part, following a identical number of layer that operate the deconvolutional operator, called a decoder part, where the output tend to be similar to the input. The layer that enclose between the encoder and decode parts is the code source and it is represents the feature production, called also as feature representation, of encoding procedure of the network. The proposed AE-CNN consisted of two layers in encoding part with 80 and 40 feature maps with the first layer deploy 2-dimensional kernel size 3×3 and the second one an 1-dimensional with size 4. The output of the second layer mapping to the feature representation layer which consisted of ten dimensional neurons. The decode part of the networks consisted of the 2 deconvolutional layers with 40 and 80 feature maps and the related to the encoded part kernel size and dimensions.

3.4.4 Anomaly detection

In this part of our anomaly detection analysis we utilize the produced matrix from the feature extraction step. Now our dataset A_n^p is constituted by the n individuals (samples) and the p extracted features for each one of them. Keep in mind that this is a data matric constructed for the "walking" class specifically. To this end we are interested to visually investigate the data at hand and possible visually identify potential outliers. To achieve this we utilize two popular Dimensionality Reduction techniques, namely Principal Component Analysis (PCA) and t-SNE. The results are presented in the following figure.

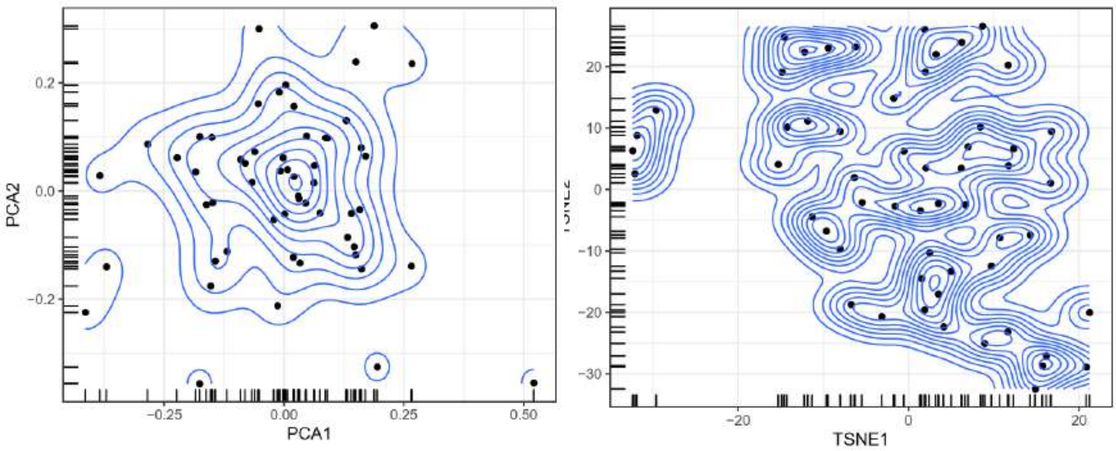

Figure 5: Two dimensional Visualizations of the extracted feature space (PCA left and tSNE right).

As shown in both cases we are able to identify samples that are relatively different from the general population. At the PCA representation we observe isolated far away instances while for tSNE we observe a structure that can be identified as a separate minority cluster.

In the next step, we focus our analysis upon a popular way to statistically identify and deal with multivariate outliers. Mahalanobis Distance (MD) calculates the distance of each case from the central mean. Larger values indicate that a case is farther from where most of the points cluster. In what follows, we calculate and visualized MDs versus the quantities of a chi-square.

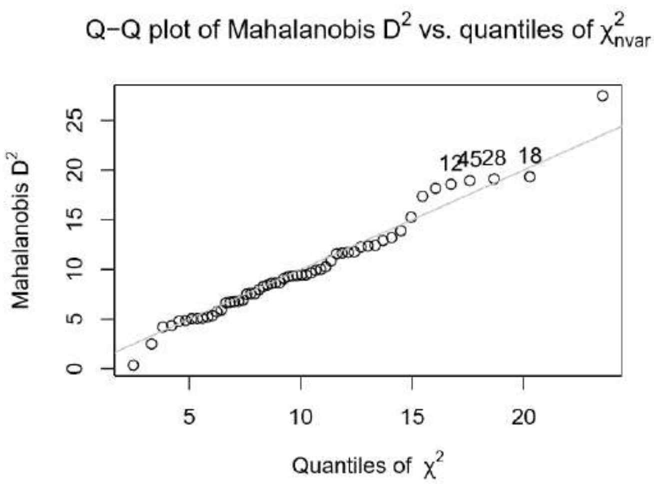

Figure 6: MDs versus the quantities of a chi-square for the extracted features

As shown, most of the points appear to follow in line, but few don't, while we observe a particular one being almost isolated in the upper right corner. We continue our analysis by employing a more formal test for outlier detection, utilizing a cut-off score for MD. We identify as outliers the observations that fall above the cut-off score for a chi-square test with p degrees of freedom, where p is the number of variables. For the alpha value set to 0.01 we identify one outlying point. Not surprisingly, it's the case with a huge MD relative to the others. Although, we could conclude our analysis here we take one step further since the author Leys *et al.* (2018) argue that MD is not a robust way to determine outliers. The problem lies with the fact that MD uses the means and covariances of all the data - including the outliers - and then the individual scores are calculated according to all these values. Since we are mostly interested in identifying cases that stray from the typical behavior, we decide to base the criteria for outlier detection using a subset of the data that is the most central. That is the code idea of the Minimum Covariance Determinant, which calculates the mean and covariance matrix based on the most central subset of the data. Here we employ this concept to calculate new distance scores from a 75% subset of the data that is highly central. We follow a similar approach for calculating the distance scores, and we use the same cut-off score as before. We have now identified 13 outliers in contrast to the 1 identified with the traditional MD. To this end we may claim that the Minimum Covariance Determinant version of MD allowed as to identify outliers that would otherwise go unnoticed with traditional MD.

4 OACTIVE Wearable sensors

4.1 IMUs platforms

During the second reporting period, following Oactive evolution, further requirements have been defined in order to collect the data necessary for building the behavioural model. Indeed, in the first phase the attention was more focused to analyse the relation between KOA and patient's mobility. More in detail the aim was to observe how, KOA effect on patient's capability to move, could affect consequently user habits and thus his/her behaviour. To collect such data, it has been considered useful to start with measuring sessions in a controlled environment, like a motion laboratory, and acquire data on patient's gait and his lower limbs movement. For this reason, it has been designed and developed an integrated wearable platform, composed by 6 IMUs devices, capable of providing high-resolution signals from human lower limbs (for details see D5.1). However, in a second phase it appeared essential to generate the behavioural model the opportunity to gather data from the patient for longer periods and directly during normal daily living activities in order to observe how KOA influences Patient's habits and behaviour. To achieve this result, it has been necessary a supplement of activity in sensor development. Since task 5.1 was formally closed, this activity is reported in the following paragraphs. A second wearable system has been developed, based on the same technology of the integrated platform but composed of a single IMU device. This solution allows to collect, besides the raw data, also information on the posture, the intensity of the activity and step frequency of the subject who is wearing it.

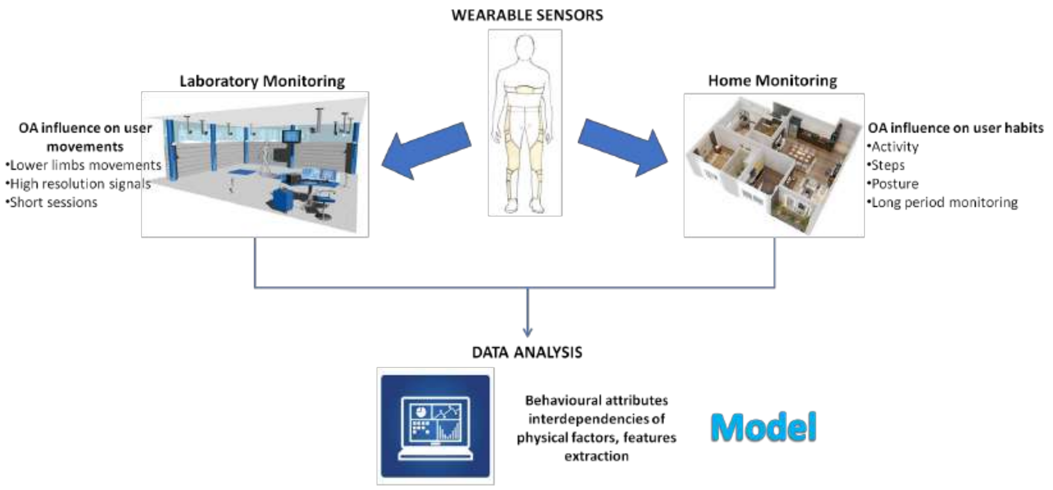

Figure 7: wearable sensors for behavioural model

For both versions the developed electronic board includes an IMU sensor (MPU 9250 by Invensense) with 9 DoF, an M3 micro-controller, Bluetooth transmission and a LiPo battery of 660 mAh. The case and package have been designed to optimize handling and comfort when worn. Different textile accessories, developed internally at Smartex, have been provided for easy don and doff of the devices.

In the Oactive frame Smartex produced two different wearable systems: one designed for monitoring and acquire data in controlled situation (motion lab), and the second to be able to be used autonomously by the patient and capable to provide data from daily living activity in an uncontrolled environment. This approach allows generating two complementary data set for the development of the behavioural model of OA patient: the first provides information on how OA affects patient’s movement, the second on how OA influences patient’s habits and behaviour.

Figure 8: kit for integrated platform (left) kit developed for remote monitoring system (right)

Following the outcomes of T5.1, during this reporting period it has been conducted a research to individuate a cost-effective alternative for the smart shoe described in D5.1. The sensorized insole produced by MOTICON has been considered the most suitable solution and has been purchased and provided to WP 7 partners.

4.1.1 Controlled condition monitoring: Integrated Platform for multiple devices acquisition

In its former version, the integrated wearable platform for controlled condition monitoring was able to connect via Bluetooth to the host up to six IMU devices simultaneously with a sampling frequency of 100 Hz (as described in D5.1). Several efforts have been applied to increase the connectivity of the integrated platform to expand the connectivity of the whole platform up to 8 devices. To achieve this result, indeed, it was necessary to overcome 2 main limits: the first one is due to the maximum number of Bluetooth connections to a single receiver. This limit is nominally 7, but test done during the development, showed that it was not possible to connect more than 6 devices without significant degradation of the performance of the system. This implies the necessity to use more than one Bluetooth dongle to connect further IMUs, but as second limit, Windows based systems do not allow the use of more than one Bluetooth receiver with the same functionality at the same time. To solve these issues it has been explored the possibility to use a Bluetooth hub exploiting a Linux based system (Raspberry Pi 3). This bridge device, connected via Ethernet socket to the central host (Windows PC) allows the connection of multiple Bluetooth dongles (2 Bluetooth adapters for Oactive) and the connection to 7+ devices.

Figure 9: IMUs devices and the Raspberry Pi bridge

Consequently the App has been updated to offer the possibility to select the receiver to which each device must connect. Moreover it has been completed also a revision of the app to correct some bugs identified in the version released in the previous reporting period.

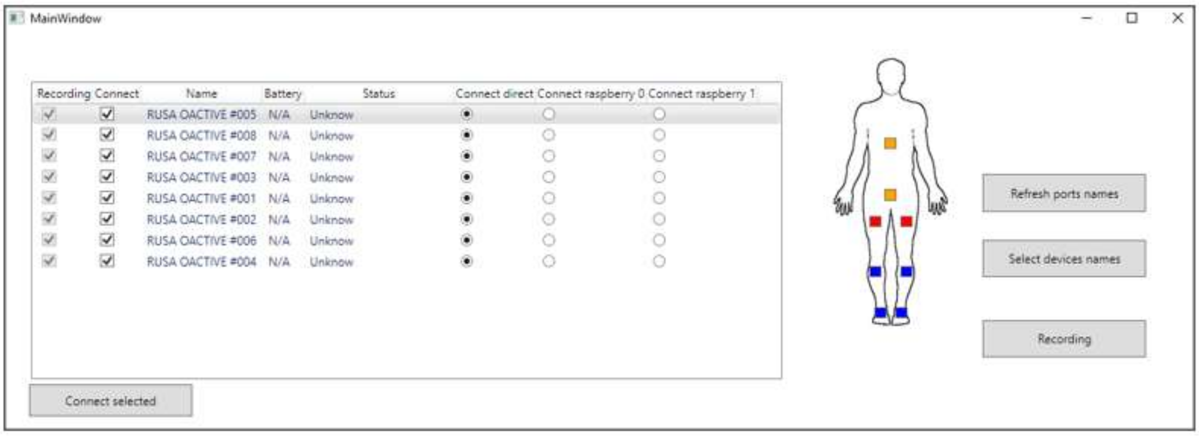

Figure 10:APP screenshot, is possible to see the option for connection to Rasberry Pi Bluetooth dongles

Each device acquire data form IMU sensor (Quaternion, 3 Accelerometer, 3 Gyroscope,3 Magnetometer) with a sampling frequency (fs) of 100Hz. The data are saved on the local host, is possible to record up 8 files per session (one for each device) in the following format:

- timestamp_n*reg_prog_position_dev_name_device.bin
- timestamp: year, month, day, hour minutes
- n*reg_prog: serial number of session on PC
- position_dev: position of the device on the human body
- name_device: name label on bluotooth card

Anyway, the introduction of this intermediate level, and the augmented complexity of the platform introduced serious issues to the stability and the reliability of the integrated platform. Due to Oactive requirements, reliability of the platform has been privileged and the platform has been released in its 6-device version.

4.1.2 Remote monitoring: single device acquisition

The second line of study was dedicated to the development of a system capable to collect data and get measurements in a not-controlled environment. This class of devices has been considered necessary to extract features and information on patients' behavior from observations and measurements taken directly at patient's home during his daily living activities. The electronic is based on the same hardware developed for the "integrated system" with a sampling frequency reduced to 25 Hz in order to decrease power consumption. Data provided by the devices include data coming directly from the IMU (MPU 9250 by Invensense), quaternion and raw signals from 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer. Moreover, this version of the system provides a set of extrapolated parameters more linked to patients behaviour: activity classification (laying/standing, walking, running), activity intensity, pace counter.

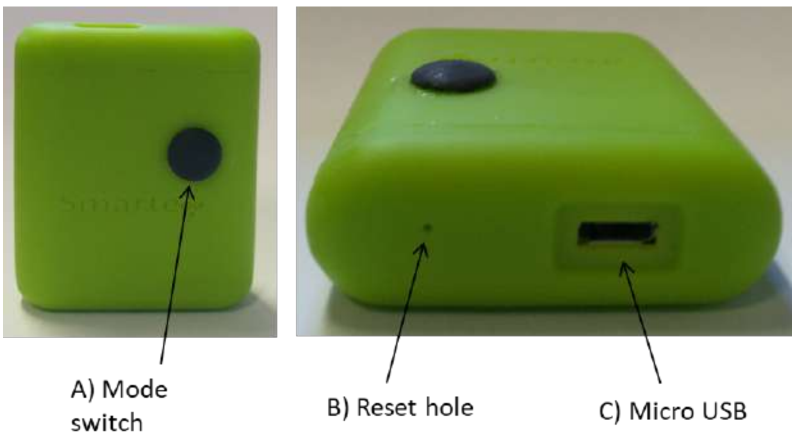

Figure 11:device for remote monitoring

In normal conditions of use the system covers up to 8 hours of continuous recording in order to guarantee long measurement session. The data acquired are saved on an internal SD card and can be easily downloaded via USB for post-processing and offline analysis. The file are saved in a proprietary format to compress data and anonymize the information.
The platform has been designed to facilitate as much as possible autonomous operation by the final user. The system is distributed in kit with two textile accessories of different size.

Four main steps are required:

- Wear the device on the chest by the means of the elastic band provided with the system
- Start recording
- Stop recording at the end of measurement session
- Put device on battery recharge

Once completed the measurement sessions, an operator will get back the devices and proceed to collect the data acquired.
A software suite has been provided to visualize the recorded sessions, download and convert data from proprietary format to CSV format.

Figure 12: screenshot of the visualization software

4.2 Sensorized Insole

Following the outcomes of T5.1 Smartex agreed, with the other partners involved, to invest resources on the selection and purchase of a system to evaluate forces generated under feet.

Research on products available on the market has been conducted and in close collaboration with WP7 (UPAT)

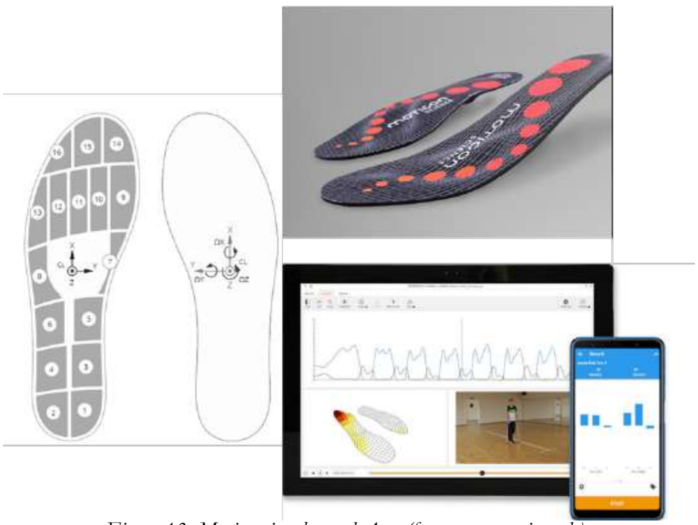

Figure 13: Moticon insoles and App (from www.moticon.de)

Each insole includes:

- 16 pressure sensors
- 6-degree of freedom IMU
- In factory calibration
- Selectable sampling frequency from 10 to 100 Hz and
- BLE transmission

2 pairs of insoles have been purchased together with the Software Development Kit (SDK) and the sensors' mobile app.

5 Conclusions

Recent developments in wearable devices allow us to design specialized equipment for data retrieval and simultaneously utilize large public access databases. The accelerometer data that is most frequently retrieved can be used for Human Activity Recognition and through a Behavioral Modelling process, subsequently provide a solid basis for the prediction of future development of Osteoarthritis or even in the individual's rehabilitation after a surgery for Osteoarthritis. Towards this direction, here we propose a complete framework able to extract information that can be critical in decision making regarding personalized knee Osteoarthritis prediction, activity recommendation for rehabilitation and many other Osteoarthritis related systems. The proposed framework is based on the utilization of state-of-the-art Machine Learning models for signal processing and Deep Hybrid Models for outlier detection suggesting a solid basis for further developments and wider applicability.

The second part of the document describes the activity conducted in sensor development (started in T5.1). The research followed two main directions: improvement and the optimization of the integrated system for controlled condition monitoring**,** the development of a system for remote monitoring to be used autonomously by the OA patient. This strategy allows to provide two complementary datasets one capable to observe how KOA affects patient's motility and consequently his habits and thus his behaviour, the second, obtained monitoring of the patient for longer periods directly during normal daily living activities, in order to observe how KOA influences Patient's habits and behaviour. Several efforts have been applied to increase the connectivity of the integrated platform. to 8 devices simultaneously. A Bluetooth hub has been developed exploiting a Linux system (Raspberry Pi 3). The App has been updated to offer the possibility to select the receiver to which each device must connect. Anyway, the introduction of this intermediate level, and the augmented complexity of the platform introduced stability and reliability issues. Due to Oactive requirements, reliability of the platform has been privileged and the platform has been released in its 6-device version. A complete review of the app was performed to correct some bugs identified in the version released in the previous reporting period. To observe and measure patients' behavior directly at patients' home, a second class of wearable platform has been developed. The system, designed to facilitate as much as possible autonomous operation by the final user, provides raw data coming from the 9 DOF IMU (MPU 9250 by Invensense) plus quaternion, and data extrapolated, which are activity classification (laying/standing, walking, running), activity intensity, pace counter. In normal conditions of use the system can guarantee up to 8 hours of continuous recording. Data, saved on an internal SD card in proprietary format to compress and anonymize the information, can be visualized and converted by a software suite provided with the system

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