frail safe

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EXECUTIVE SUMMARY

The FrailSafe project aims to study all domains of frailty and to create new measures of assessments leading to a model which will be able to better understand, detect, predict, delay or even revert frailty. To achieve these aims plans are made to devise a comprehensive clinical assessment, to develop a real-life sensing and intervention platform, and to provide a digital patient model of frailty, sensitive to dynamic parameters. Recommendations will be provided to delay frailty, and all this through a safe, unobtrusive, acceptable system and cost effective system.

The aim of workpackage WP4 is to develop methods for the offline and online management, fusion and analysis of multimodal and advanced technology data from social, behavioral, cognitive and physical activities of frailty older people and apply them to manage and analyze new data. Results from the analysis of existing and new data will be also used to create user-profiling virtual models of elderly participants.

The main focus of the deliverable D4.4 is to report on the usage of existing and new techniques for real-time online data pre-processing and data reduction. The techniques must be suitable for FrailSafe's streaming sensor data, where efficiency, scalability and effectiveness issues are of main importance. Furthermore, results from the offline multimodal data fusion are examined here to make online data preprocessing possible in real time. This will be available by adopting dimensionality reduction methods to the streaming nature of the data. Online data fusion is focused on maintaining the desired accuracy, minimizing the overall processing time.

DOCUMENT INFORMATION

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Abstract (for dissemination)	The main focus of the deliverable D4.4 is to report on the usage of existing and new techniques for real-time online data pre-processing and data reduction.			
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1 Introduction

One of the FrailSafe project's aim is the real-time monitoring of the older persons towards detecting frailty risks and triggering alarms in case of emergency situations (e.g., fall, loss of orientation, or suicidal manifestations in electronic written text). In case of such an emergency situation, an alarm needs to be triggered updating the VPM (Virtual Patient Model) accordingly.

Towards this direction, a system that collects the data streams and processes them was developed. This system is built on the smartphone, as it is the device that is close enough to the participant in order to collect the sensor data and analyze them accordingly. The sensor data which are collected at the smartphone in a streaming fashion, are the GPS coordinates of the participant and the IMU signals of the vest the participant is wearing. These data are used in order to assess the balance of the older person and identify loss of stability, falls, and loss of orientation. Additionally, in the FrailSafe cloud there is a cluster running Apache Spark which has Spark Streaming module for real-time data processing. This cluster is used in order to collect the data streams from various sources and process them towards generating summaries and alerts.

The data analysis which has been identified as necessary to be performed in real-time for FrailSafe project, is targeted in the areas of Fall detection, Instability, Loss of orientation and Suicidal manifestations in text. The first three areas lie in the scope of this Deliverable, while the last one is in the scope of Deliverable D4.8 about the online mode of LingTester. Currently the online analysis algorithms are being developed and validated only in laboratory environment. In the final FrailSafe product any event identified in the smartphone will be transmitted in real-time to the FrailSafe cloud.

The most challenging aspect of fall detection is the distinction between falls and sudden movements that occur while performing Activities of Daily Living (ADLs). Such movements are usually activites that include high acceleration (e.g., walking or running) or transitions between activities (e.g., getting up from chair). We investigated the state-of-the-art on fall detection and evaluated whether it is feasible to detect falls using a single sensor. Then we extended our fall classification model and built an android application in order to detect falls in real-time. The initial developed app which used the sensors (accelerometer, gyroscope and magnetometer) of the smartphone managed to detect falls with high accuracy. In the final version, the app was modified in order for the smartphone to collect the sensor data directly from the WWBS and perform the fall detection algorithm on them.

Towards identifying loss of stability, we have developed an algorithm based on PCA (Principal Component Analysis) decomposition of the raw acceleration signals. The processing pipeline starts by filtering the raw data using a High-Pass Filtering. In the second step we use the PCA to eliminate the Principal Component and instead use the Secondary Gait Components. Then we reconstruct the decomposed secondary gait signals, from the separated Euclidean coordinates into a 3D timeseries signal that enables us to study secondary dynamics to the participant's gait.

Finally, we have analyzed the state-of-the-art on loss of spatial navigation and Loss of Orientation (LoO) which has gained much attention from both the research community and the industry lately. The majority of the systems proposed are based on tracking information, geo-fencing, i.e., predefined boundaries of where the participant is supposed to be, and alerting systems aimed to inform the caregiver that a participant is probably wandering. Towards this direction we have developed our Loss of Orientation application based on the current detection techniques.

2 Streaming Data Management and Processing

2.1 System architecture

One of the FrailSafe project's aim is the real-time monitoring of the older persons towards detecting frailty risks and triggering alarms in case of emergency situations (e.g., fall, loss of orientation, or suicidal manifestations in electronic written text). In order to be ready to provide real-time monitoring, a system that collects the data streams and processes them needs to be developed.

Data stream processing differs significantly from offline data processing (batch processing). Batch processing is used to compute arbitrary queries over different sets of data. It usually computes results that are derived from all the data it encompasses, and enables deep analysis of big data sets. In contrast, stream processing requires ingesting a sequence of data, and incrementally updating metrics, reports, and summary statistics in response to each arriving data record. It is better suited for real-time monitoring and response functions. We can summarize the differences in the following table:

	Batch processing	Stream processing
Data scope	Queries or processing over all or most of the data in the dataset.	Queries or processing over data within a rolling time window, or on just the most recent data record.
Data size	Large batches of data.	Individual records or micro batches consisting of a few records.
Performance	Latencies in minutes to hours.	Requires latency in the order of seconds or milliseconds.
Analyses	Complex analytics.	Simple response functions, aggregates, and rolling metrics.

The data processing which has been identified as necessary to be performed in real-time for FrailSafe project, is targeted in the following areas:

- Fall detection
- Instability
- Loss of orientation
- Suicidal manifestations in text

The first three areas lie in the scope of this Deliverable, while the last one is in the scope of Deliverable D4.8 about the online mode of LingTester.

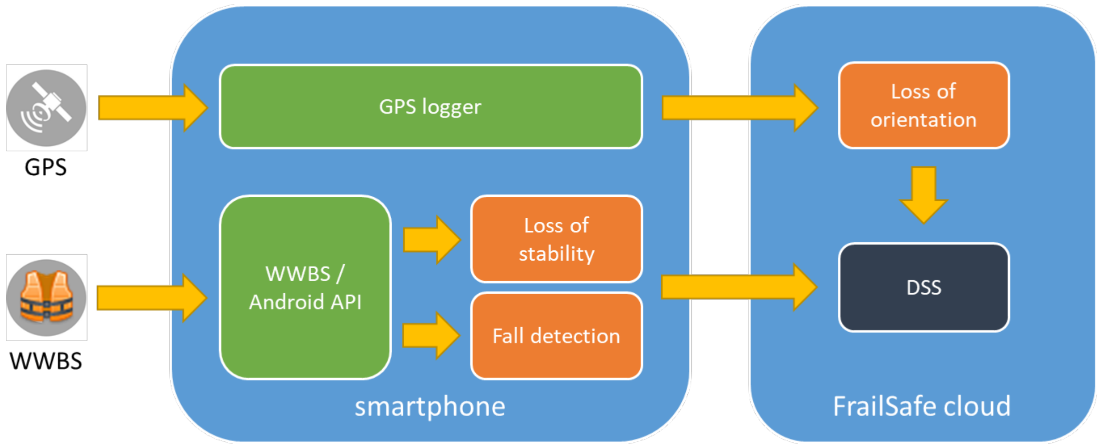

Figure 1: Streaming data management and analysis.

In Figure 1, we present the currect state of streaming data analysis in FrailSafe project. The data coming at streaming mode originate from two sources: GPS signals from the satellites and physiological signals from the wearable sensorized vest (WWBS). The device which is in charge to collect this data is the smartphone, and uses two different software modules developed by CERTH as part of Task T3.3:

- The **GPS logger** sends a request to the satellites to identify its location, and stores the reply with the specific details.
- The **WWBS-to-Android API** reads the signals generated by the WWBS sensors and transmitted by Bluetooth.

Then there are three components which use the acquired sensor signal streams and perform data processing. The *Loss of stability* and the *Fall detection* components use the WWBS signals to evaluate the instability of the older person and detect falls that might occurred during the monitoring period. These components run on the smartphone for various reasons. One of the most import is that by running the analysis close to the collection of data, we minimize the delay that is caused by data transmission. This way we can guarantee the timely detection of risky events (such as falls). We aimed to run the fall detection/loss of stability analysis even closer to the device which generates the data, i.e., the WWBS, but unfortunately the WWBS didn't have the necessary hardware requirements to do so. Additionally, running the analysis on the smartphone instead of transmitting data to the cloud gives us the advantage of being able to analyze the data and detect risks even when there is no internet connectivity available. Finally, the *Loss of orientation* component evaluates the sense of orientation of the older persons by processing the GPS signals. In comparison with falls and instability which are observed instantaneously, the loss of orientation that the older person might experience needs a larger time window in order to be detected. This is the reason that this component has been decided to run in the FrailSafe cloud. Finally, any event identified by the three components (such as a detected fall) is forwarded to the DSS.

Currently the online analysis algorithms are being developed and validated only in laboratory environment and thus are not used to monitor participants of the FrailSafe study. In the final FrailSafe product these algorithms will be used to monitor the older people and any event identified, will be transmitted in real-time to the DSS.

2.2 Streaming data description

GPS data

The GPS logger application for the smartphone collects measurements about the geographic location of the participants. The location is obtained by receiving a signal from GPS satellites, thus it is accurate only for the outdoor localization of the participant (in a macroscopic scale). The specific measurements obtained are the latitude, longitude, and elevation of each geographic location, together with the accuracy of the measurement and the orientation of the movement. Combining subsequent points of the location of the participant, we can derive other measurements with more clinical value such as the speed of movement, the distance covered etc. The GPS logger application additionally measures the number of steps the participant has made, using the phone sensors.

These measurements can be summarized in the following table:

Table 1: GPS logger recorded parameters.

Recorded parameter	Description	Sampling rate
Latitude	Satelite estimation of the latitude of the geolocation point	variable
Longitude	Satelite estimation of the longitude of the geolocation point	variable
Elevation	Elevation of the geolocation point (sea level)	variable
Speed	Indicative speed of movement	variable
Accuracy	Accuracy of the geolocation	variable
Bearing	Orientation of the movement	variable
Steps	Step counter (based on android sensor)	variable

Sensorized strap/vest

The sensorized strap/vest which is manufactured by our partner Smartex, is equipped with a series of sensors which provide useful measurements for FrailSafe participants. However not all of them are transmitted to the smartphone for analysis, because of real-time limitations. The data which are transmitted by the WWBS and captured by the API are the IMU measurements**.** These refer to the participant's specific force, angular rate, and the magnetic field surrounding the body in X-Y-Z axis measured using accelerometer, gyroscope and magnetometer, respectively. These measurements are needed in order to run Fall Detection and Loss of orientation algorithms.

Table 2: WWBS recorded parameters.

Recorded parameter	Description	Values (1 unit)	Sampling rate
AccX-Y-Z Value	Accelerometer in X-Y-Z axes	0.97 10-3 g	25Hz
GyroX-Y-Z Value	Gyroscope in X-Y-Z axes	0.122 °/s	25Hz
MagX-Y-Z Value	Magnetometer in X-Y-Z axes	0.6 µT	25Hz

2.3 Spark Streaming

A data stream could be defined as an unbounded sequence of data arriving continuously. Streaming divides continuously flowing input data into discrete units for processing. Stream processing is low latency processing and analyzing of streaming data. **Spark Streaming** is an extension of the core Spark API that enables scalable, high-throughput, fault-tolerant stream processing of live data. Spark Streaming is for use cases which require a significant amount of data to be quickly processed as soon as it arrives. Example real-time use cases are:

- Website monitoring, Network monitoring
- Fraud detection
- Web clicks
- Advertising
- Internet of Things: sensors

Spark Streaming supports data sources such as HDFS directories, TCP sockets, Kafka, Flume, Twitter, etc. Data Streams can be processed with Spark's core APIS, DataFrames SQL, or machine learning APIs, and can be persisted to a filesystem, HDFS, databases, or any data source offering a Hadoop OutputFormat.

Figure 2: Spark Streaming input and output streams.

Internally, Spark Streaming works as follows: It receives live input data streams and divides the data into batches, which are then processed by the Spark engine to generate the final stream of results in batches, as shown in the following figure.

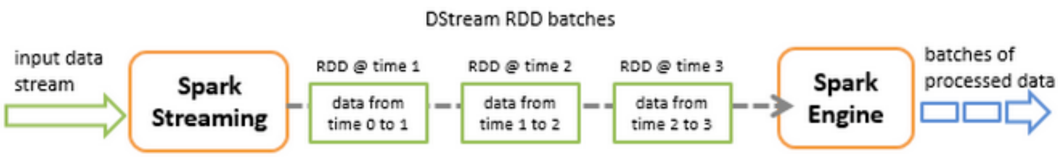

Figure 3: Spark Streaming data division to RDD batches.

Spark Streaming provides a high-level abstraction called discretized stream or DStream, which represents a continuous stream of data. DStreams can be created either from input data streams from sources such as Kafka, Flume, and Kinesis, or by applying high-level operations on other DStreams. Internally, a DStream is represented as a sequence of Resilient Distributed Datasets (RDDs), which are the basic abstraction in Spark and represent an immutable, partitioned collection of elements that can be operated on in parallel.

2.4 Frailsafe Spark Streaming Application

In the terms of Frailsafe project, Spark Streaming is planned to be used to store streaming data in the Frailsafe Database (HBase). More specifically, the sources of data that will be streamed in HBase, as described above, are the GPS and the WWBS shown in Figure 1.

The Spark-Streaming Application that has been designed and developed does the following:

1. Reads streaming data stored in CSV format in a directory in Hadoop File System (HDFS).
2. Processes the streaming data.
3. Generate alerts when abnormal data values (e.g. from WWBS) are detected.
4. Writes the processed data and alerts to an HBase Table.

More specifically, the aim of the application is to run permanently in FrailSafe Amazon Cloud, providing a continuous check for new data of the specified sources. When new data is inserted into the HDFS the application immediately starts processing it by transforming it into suitable form to fit HBase Schema that has been determined. After the completion of the processing, the storing procedure starts.

3 Real-time Data Analysis

3.1 Fall dectection

Falls are a common cause of injury among older people. According to the World Health Organization, 28–35% of people aged 65 and over fall at least once a year with serious consequences such as heavy injuries and even death. Additionally, the moments after a fall are very crucial. Many people experience what is called the "long lie," a long period of immobility after a fall that can have serious complications in a person's health. Unless precautions are taken, the number of injuries and the costs associated with fall-related trauma will double in the near future. Fall detection is therefore considered as an extremely important aspect of healthcare.

The most challenging aspect of fall detection is the distinction between falls and Activities of Daily Living (ADLs) such as sitting, standing or walking since falls typically occur while performing daily activities. In particular, ADLs with high acceleration are often confused with falls. Misinterpreting a fall as an ADL can have serious effects on the subject's health. Therefore, a fall detection system should be able to accurately distinguish falls from ADLs immediately when they occur. This requires falls to be automatically detected in real time. Another challenge is to make the system as simple as possible, with low false-alarm rates. Subjects using the system should feel comfortable and their quality of everyday life should not be affected. Accurate, reliable and real-time fall detection systems are therefore essential.

3.1.1 Current research state-of-the-art

Significant research has been conducted in this field and various fall detection systems have been proposed in the past years. (Noury et al, 2007) and (Yu et al, 2008) have investigated the principles of fall detection and reviewed early works on the subject. Fall detection approaches can be divided into two main categories: vision-based and wearable device (motion sensor)-based systems.

Several context aware systems that use devices such as cameras or infrared sensors to detect falls within an environment have been developed. (Rougier et al, 2007) used human shape deformation to track the person's silhouette in recordings taken from four cameras. Falls and ADLs were classified with 98% accuracy. In (Mastorakis and Makris, 2012), a human 3D bounding box was created and the Kinect infrared sensor was used to accurately detect falls without any prior knowledge of the environment. (Olivieri et al, 2012) used motion templates taken from a camera to recognize certain ADLs and detect falls, achieving 99% recognition rate. However, these approaches have certain limitations; the system can only monitor activities within the environment and thus, outdoor activities are excluded, restricting the mobility of the user. Also, other people moving within the same environment might also "confuse" the system and trigger false alarms in some cases.

The use of wearable motion sensors has been preferred by many researchers. With the advances in micro electro-mechanical systems (MEMS) technology, sensors such as accelerometers, gyroscopes and magnetometers have been integrated within small motion sensor units. Small devices that contain the above sensors can be used to collect movement data and detect falls. They are compact, light, inexpensive and have low power consumption. They can be placed in the subject's pockets or be easily attached at different body parts without making the subject uncomfortable; thus, they make the analysis of outdoor activities possible. Different body parts have been proposed for the sensor placement that improve the accuracy with minimum intrusion to the subject's everyday life. (Yang and Hsu, 2010) have examined the fundamentals of such sensors as well as the optimal position on the human body for sensor placement.

In fall detection studies, typically simple thresholding is used. A fall is detected when the acceleration suddenly increases due to the change in orientation from upright to lying position (Bourke et al, 2007). In (Bourke et al, 2010), the results of certain threshold-based methods that consider fall impact, velocity and posture have been assessed and tested on elderly subjects, achieving 94.6% sensitivity. Thresholding methods sometimes tend to miss "soft falls" meaning falls that might not exceed the threshold. Also, certain ADLs with high acceleration might exceed the threshold and get misclassified as falls.

The main classification problem is to distinguish falls from ADLs. Machine learning techniques have been used to achieve more reliable results. Every recorded movement in the fall and activity database (Özdemir and Barshan, 2014) has its own pattern. By extracting features from the raw data, these patterns can be classified by different classification methods. Before raw data are given to different classification algorithms, they must be pre-processed using a windowing technique. Such a technique divides the sensor signal into smaller time segments (i.e., windows) and a classification algorithm is applied separately on each window, producing a classification result. After pre-processing, features from the time or spatial domain are extracted to feed trained classifiers such as artificial neural (ANN) or Bayesian networks (BN), support vector machines (SVMs), decision trees, k-nearest neighbors (k-NN), etc. (Kaldegari et al. 2012) used statistical features such as maximum, minimum, mean, range, variance and standard deviation extracted from a waist-worn tri-axial accelerometer to investigate the performance of various classifiers on fall detection. The multilayer perceptron yielded the best sensitivity (90.15%). (Özdemir and Barshan, 2014) added autocorrelation coefficients and discrete Fourier transform (DFT) coefficients extracted from data acquired by sensors placed at different body parts. Six classifiers (k-NN, SVM, ANN, least-squares method, Bayesian decision making, dynamic time warping) were used to assign a fall or ADL class label to the feature vectors concatenated from all sensors. All methods achieved higher than 97.47% and 93.44% sensitivity and specificity, respectively. (Yuwono et al, 2012) obtained data from a single waist-worn tri-axial accelerometer and extracted features using the Particle Swarm Optimization (PSO) clustering method. Then, they proceeded to classify the data achieving above 98.6% sensitivity in detecting falls.

3.1.2 Sensor placement

Earlier studies report conflicting results on the best location on the human body to carry a single fall detection device. Some studies report that the waist is the best place, since it is close to the body's center of gravity (Bourke et al, 2010; Özdemir, 2016), while some claim that the chest or the head is better [9, 15-17]. Several studies consistently agree that the arms and the legs are not suitable parts of the body to carry a fall detection device since they are associated with higher accelerations (Kangas et al, 2007; Bianchi et al, 2010). Therefore, resolving this issue through experiments that follow standardized procedures will be a valuable contribution. (Özdemir and Barshan, 2014) acquired data from sensors placed on six body parts including head, chest, waist, wrist, thigh and ankle. In order to proceed with classification, the features extracted from each location are concatenated to a single feature vector leading to a high-dimensional feature space. However, fall detection often needs to be performed in real-time which requires lighter processing that can be achieved either through dimensionality reduction or selection of a single sensor unit located at the optimal position.

In our work (Ntanasis et al., 2016), we investigated whether placing a single IMU sensor on the body is sufficient for accurately detecting falls, and which is the optimal location for the sensor placement on the human body. To achieve this, we evaluate the activity and fall dataset created by (Özdemir and Barshan, 2014) with respect to several classification algorithms using only the data acquired from a single sensor location each time. The classification performance in terms of accuracy is used as the criterion to reveal the optimal sensor location. Since data from a single sensor unit are used, there is no need for dimensionality reduction, making the proposed methodology computationally efficient and thus, more capable of real-time fall detection.

3.1.3 Dataset

With Erciyes University Ethics Committee approval, seven males (24 ±3 years old, 67.5 ±13.5 kg, 172 ± 12 cm) and seven females (21.5 ± 2.5 years old, 58.5 ± 11.5 kg, 169.5 ± 12.5 cm) healthy volunteers participated in the study with informed written consent. Six wireless sensor units were tightly fitted with special strap sets to the subjects' heads, chests, waists, right-wrists, right-thighs, and right-ankles. Each unit comprises three tri-axial devices (accelerometer, gyroscope, and magnetometer/compass) with respective ranges of ±120 m/s2, ±1200o/s, and ±1.5 Gauss, and an atmospheric pressure meter with 300–1100 hPa operating range, which we did not use. Raw motion data were recorded with a sampling frequency of 25 Hz. Acceleration, rate of turn, and the strength of the Earth's magnetic field along three perpendicular axes (x, y, z) were recorded for each unit (Yuwono et al, 2012). A set of trials consists of 20 fall actions (front-lying, front-protection-lying, front-knees, front-knees-lying, front-right, front-left, front-quick-recovery, front-slow-recovery, back-sitting, back-lying, back-right, back-left, right-sideway, right-recovery, left-sideway, left-recovery, syncope, syncope-wall, podium, rolling-out-bed) and 16 ADLs (lying-bed, rising-bed, sit-bed, sit-chair, sit-sofa, sit-air, walking-forward, jogging, walking-backward, bending, bending-pick-up, stumble, limp, squatting-down, trip-over, coughing-sneezing). These are adopted from (Abbate et al, 2010) and lasted about 15 s on the average. The 14 volunteers repeated each test for five times. Thus, a considerably diverse dataset comprising 1400 falls (20 tasks × 14 volunteers × 5 trials) and 1120 ADLs (16 tasks × 14 volunteers × 5 trials) was acquired, resulting in 2520 trials. Many of the non-fall actions included in the dataset are high-impact events that may be easily confused with falls.

3.1.4 Feature Extraction

Before we train the classifiers, we need to identify and isolate the actual experimental events since raw data acquired from the sensors include several time points that correspond to immobility before and after the detected fall event. In order to identify the fall event, we detect the peak of the total acceleration vector is. Total acceleration is defined as:

$$A_T = \sqrt{A_x^2 + A_y^2 + A_Z^2} \qquad (1)$$

where Ax, Ay and Az are the accelerations along the x, y and z axis respectively.

In contrast to (Özdemir and Barshan, 2014), we measure the total acceleration on each sensor separately. For each sensor, we keep two seconds of the sequence before and after the peak acceleration, that is 50 values before and after the peak given the sampling frequency of 25 Hz. Therefore, for each test, we obtain six arrays of size 9x101, one for each of the six sensors.

We parameterize each one of the nine measured events using the features proposed in (Özdemir and Barshan, 2014): minimum, maximum and mean values, skewness, kurtosis, the first 11 values of the autocorrelation sequence and the first five frequencies with maximum magnitude of the DFT along with the five corresponding amplitudes, resulting in a feature vector of dimensionality 234 (26 features for each one of the nine measured signals) for each test.

3.1.5 Classification Results

We evaluate the ability of the above features to discriminate between falls and ADLs using several classification algorithms implemented by the WEKA machine learning toolkit [20] including J48 decision tree, k-nearest neighbors algorithm (IBk) [21], Random Forest (RF) [22,23], Random Committee (RC) and SVM [24] with RBF Kernel (SMO). The classifiers in our study were selected in an attempt to evaluate representative algorithms for each one of the main categories of machine learning classifiers including decision trees (J48), support vector machines (SMO), ensemble classifiers (RF, RC) but also simple methods such as k-NN (IBk).

We evaluated binary classification performance using accuracy, sensitivity and specificity. Evaluation was performed in a 10-fold cross validation setting.

Table 3: Evaluation all classification models.

Classification Model	Sensors	Accuracy	Sensitivity	Specificity
(a) J48	Head	96.48	91.06	95.76
	Chest	97.53	97.70	97.31
	Waist	97.96	97.99	97.94
	Wrist	93.71	94.78	92.37
	Thigh	98.24	98.71	97.67
	Ankle	97.45	97.49	97.40
(b) IBk	Head	93,70	92,84	94,77
	Chest	97,45	97,28	97,67
	Waist	98,61	98,85	98,30
	Wrist	89,74	84,13	96,77
	Thigh	96,42	94,20	99,19
	Ankle	95,58	93,34	98,39
(c) RC	Head	97,17	98,57	95,41
	Chest	98,61	99,07	98,03
	Waist	98,89	99,28	98,39
	Wrist	94,63	96,35	92,47
	Thigh	98,77	99,00	98,48
	Ankle	98,77	98,85	98,66
(d) RF	Head	96,77	99,36	93,51
	Chest	98,61	99,28	97,76
	Waist	99,28	99,64	98,84
	Wrist	95,62	98,28	92,29
	Thigh	99,20	99,43	98,93
	Ankle	98,77	99,07	98,39
(e) SMO	Head	97,29	97,92	96,49
	Chest	98,89	99,28	98,39
	Waist	99,36	99,50	99,19
	Wrist	96,78	97,71	95,61
	Thigh	99,48	99,21	99,82
	Ankle	98,57	98,85	98,21

Table 3 shows the achieved results in terms of accuracy, sensitivity and specificity for each sensor location for the J48, IBk, RC, RF and SMO algorithms, respectively. The position resulting in the best accuracy is highlighted in boldface font in the table. Figure 4 shows a comparative diagram across different body locations for each classification model.

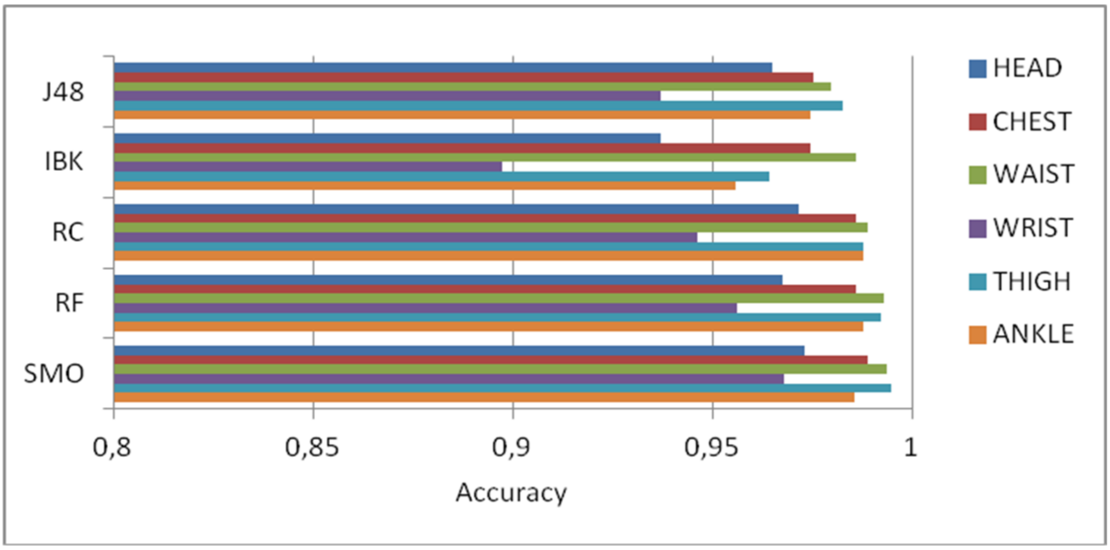

Figure 4: Bar graph showing the accuracy of all classification models for all sensors.

The accuracy, sensitivity and specificity of the classification shows high results for all classifiers. The overall highest accuracy (99.48%) for the thigh sensor location using the SMO classifier. For this case, the obtained sensitivity, i.e., the fraction of actual falls which are correctly identified as such is 99.21% and the specificity, that is, the proportion of ADLs, that were correctly classified as such is 99.82%.

Additionally, we observe that placing the sensors at the waist achieves the highest accuracy values for the RF (99.28%), RC (98.89%) and k-NN, IBk (98.61%) classifiers. Such results agree with our intuition for the superiority of waist location based on the fact that it is near the body's center of gravity. Finally, for the J48 classifier, the most accurate sensor location is the thigh, reaching 98.24% accuracy.

To summarize, the waist and thigh sensors achieve the highest accuracies for all classifiers, followed by the chest and ankle sensors. The wrist sensor is the one with the lowest accuracy for all classifiers. It is noteworthy, however, that placing a single sensor at any of the proposed locations achieves accuracy higher than 90% and there are cases where the differences among the sensors are not significant, especially when comparing the most accurate sensor locations such as the thigh and the waist.

3.1.6 Android app

In cooperation with CERTH, an Android app was developed that implemented the described fall detection algorithm towards detecting falls in real-time. The first version of the app used the sensors (accelerometer, gyroscope and magnetometer) of the smartphone purchased for FrailSafe project (Google Nexus 5X). When the sensorized vest (WWBS) was made available to the consortium by Smartex, the app was modified so that the detection of falls would be performed using sensor data from WWBS instead of the smartphone. This was made possible using the WWBS API for Android developed by CERTH, which is described in detail in D3.3 "WWBS Prototype". The API handles all Bluetooth communication with the WWBS and enables the easy consumption of the WWBS sensor and IMU data by the Fall Detector app. At the time of writing, the Fall Detector app has an option to switch between using the smartphone's internal sensor or detect and connect to a WWBS via Bluetooth. The final version of the app includes a "Stability Index" as well, which is described in the next section.

Since the input data come from a different source (the WWBS), the classification model had to be retrained. Under this premise, a new set of measurements were recorded by young volunteers, who performed ADLs and falls in controlled environment. The types and repetitions of the ADLs and falls are depicted in Table 4 and Table 5 respectively.

Table 4: Types of ADLs performed

ADL type	Number of trials
Sit-chair	5
Sit-sofa	5
Stand	1
Walk-forward	1
Walk-downstairs	1
Walk-upstairs	1
Lying	1
Lying-bed	5
Rising-bed	5
Bend-90 degrees	5
Bend-pick up	5
Jump	5
Limp	1

Table 5: Types of falls performed

Fall type	Number of trials
Back-sit	5
Front-knees	5

Front-left	5
Front-right	5
Front-knees lying	5
Front-protected lying	5
Syncope	5

The data collected from the volunteer were used to build a new classification model, according to the previously described methodology. The data of the input sensors are packetized in time windows and for each window the selected features are extracted. Then based on the extracted features each window is classified as “Fall” or “ADL”. The only difference in comparison to the first model is that magnetometer has now been excluded from the analysis, since many instances were misclassified when using this sensor, whereas after the exclusion the model outperformed the previous case. The retrained model has been tested in lab environment and performs well with high classification accuracy results. In order to validate our fall detection models using data obtained from older people, we plan to use recorded sessions of FrailSafe participants which include falls (that have been later verified using follow up calls).

3.2 Loss of stability

Falls, as analyzed above, are a common cause of injury among older people and one of the most frequent injury-inducing events as a result of ageing. While significant research had been done on the field of fall detection, and numerous systems have been proposed as a result, fall detection consists of a binary decision system, and there is a need for research on a continuous metric tracking the instability of an older person’s gait pattern in order to assess the risk of a fall event occurring. Failsafe aims to implement innovative strategies to accurately assess the Loss of Stability (LoS) of an older person, and estimate the risk falling.

3.2.1 Related Work – State of the art

Loss of Stability, as described above, overlaps with the general field of gait analysis, where significant research has been conducted for clinical applications, and specifically for assessing the state of ageing. Specialists assess participants’ health by using various methods that measure the parameters which most clearly represent the human gait. Literature research shows that the following parameters are estimated:

- Velocity
- Short step length (linear distance between two successive placements of the same foot)
- Long step or stride length (linear distance between the placements of both feet)

• Cadence or rhythm (number of steps per time unit)
• Step width (linear distance between two equivalent points of both feet)
• Step angle (direction of the foot during the step)
• Short step time
• Swing time for each foot (time from the moment the foot lifts from the floor until it touches it again, for each foot)
• Support time (time from the moment the heel touches the floor until the toes are lifted, for each foot)
• Distances travelled
• Gait autonomy (the maximum time a person can walk, taking into account the number and duration of the stops)
• Duration of the stops
• Existence of tremors when walking
• Record of falls
• Uneven terrain covered (height difference between drops and rises)
• Routes taken
• Gait phases
• Direction of leg segments
• Ground Reaction Forces
• Angles of the different joints (ankle, knee, hip)
• Electrical activity produced by muscles (EMG)
• Momentum and forces
• Body posture (bending, symmetry)
• Maintaining gait over long time periods

While several of the above parameters (e.g. Gait phases, body posture, assymetrical step time etc.) can provide an insight on the asymmetry/instability of an older person's walking pattern, most of the related literature makes use of systems available only in a controlled indoor scenario, i.e. Non Wearable Systems (NWS), such as body tracking systems (Vicon), 3D Cameras (Kinect) and other tracking equipment that can produce a very accurate reconstruction of a person's gait. Wearable Systems (WS), like the Frailsafe WWBS, do not offer so accurate measurements, but provide sustainability on long-term analysis, and can be applied to the outdoor scenario as well and evaluate gait during the participant's everyday activities outside the laboratory. One of the most promising and widely used wearable sensors in recent studies is the inertial sensor. In the following paragraphs, we present an account of studies that demonstrate the validity and wide range of applications of this type of sensor in recent researches.

Studies such as (Anna et al., 2013) in which they contrast gait symmetry and gait normality measurements obtained with inertial sensors and 3D kinematic measurements and clinical assessments, demonstrate that the inertial sensor-based system not only correlates well with kinematic measurements obtained through other methods, but also corroborates various quantitative and qualitative measures of recovery and health status. This type of sensor has also proven to be very useful to create fall-risk prediction models with a high degree of accuracy (62%–100%), specificity (35%–100%) y sensitivity (55%–99%), depending on the model, as shown in the study by (Howcroft et al., 2013). In the work of (Adachi et al., 2012) a walking analysis system was developed that calculates the ground reaction force, the pressure centre, reactions and movement of each joint and the body orientations based on portable force plates and motion sensors. They compared a 3D motion analysis system with their system and showed its validity for measurements of ground reaction force and the pressure centre (Adachi et al., 2012). (Novak et al., 2013) have recently developed a system based on inertial and pressure sensors to predict gait initiation and termination. They demonstrated that both types of sensors allow timely and accurate detection of gait initiation, with overall good performance in subject-independent cross-validation, whereas inertial measurement units are generally superior to pressure sensors in predicting gait termination (Novak et al., 2013).

Inertial sensors can be used to estimate walking speed by various methods, which are described in the review by (Yang and Li, 2012). With a view to improving the usability of these systems, studies such as (Salarian et al., 2013) focus on reducing the number of sensors that have to be placed on the body. They have also managed to estimate movements of thighs from movements of shanks to reduce the number of sensing units needed from 4 to 2 in the context of ambulatory gait analysis. Inertial Measurement Units (IMUs) are one of the most widely used types of sensors in gait analysis. Anna et al. developed a system with inertial sensors to quantify gait symmetry and gait normality (Anna et al., 2013), which was evaluated in-lab, against 3D kinematic measurements; and also in situ, against clinical assessments of hip-replacement patients, obtaining a good correlation factor between the different methods. In another recent study, Ferrari et al. presented an algorithm to estimate gait features which were compared with camera-based gold standard system outcomes, showing a difference in step length below 5% when considering median values (Ferrari et. al., 2013). In diseases where gait disorders are a symptom such as Parkinson's, we find several applications of sensors of this type (Salarian et. al., 2004): Tay et al. presented a system with two integrated sensors located at each ankle position to track gait movements and a body sensor positioned near the cervical vertebra to monitor body posture. The system was also able to measure parameters such as maximum acceleration of the participants during standing up, and the time it takes from sit to stand (Tay et. al., 2013).

Still, no significant work has been done on establishing a metric that indicates the gait instability, while complying with the light set of specifications needed for a wearable system to be as unobtrusive as possible. Considering the latter, we developed a technique in order to accurately estimate LoS by using only one (1) IMU, placed near the chest, as designed in the Frailsafe vest, by estimating the gait orientation asymmetry of the user.

3.2.2 LoS via Secondary Gait Component Analysis

Following the detailed literature review above, and the restrictions imposed by the specifications of the vest wearable system, we developed an algorithm based on PCA decomposition of the raw acceleration signals provided by the Inertial Measurement Unit of either a mobile phone, or the WWBS, communicated to the gateway smartphone device for processing. As can be seen in Figure 6, the processing pipeline consists of the following steps:

1. **High-Pass Filtering of the Raw data**: This step is necessary to eliminate any sensor bias imposed by the sensors or the environment (e.g. gravity) and study only the dynamic components of the acceleration.
2. **PCA**: Principal Component Analysis (PCA) is commonly used in signal processing algorithms because it accurately decomposes noisy multi-dimensional data into its principal and secondary components. Considering that we are analyzing gait asymmetry/instability, and the fact that a Kinematic measurement's principal component concerns the Kinematics regarding the gait orientation of the participant, we eliminate the Principal Component and instead use the Secondary Gait Components. Our main hypothesis is that these measurements should be considerably lower in a stable gait pattern, and their energy should increase as the gait becomes more unstable.

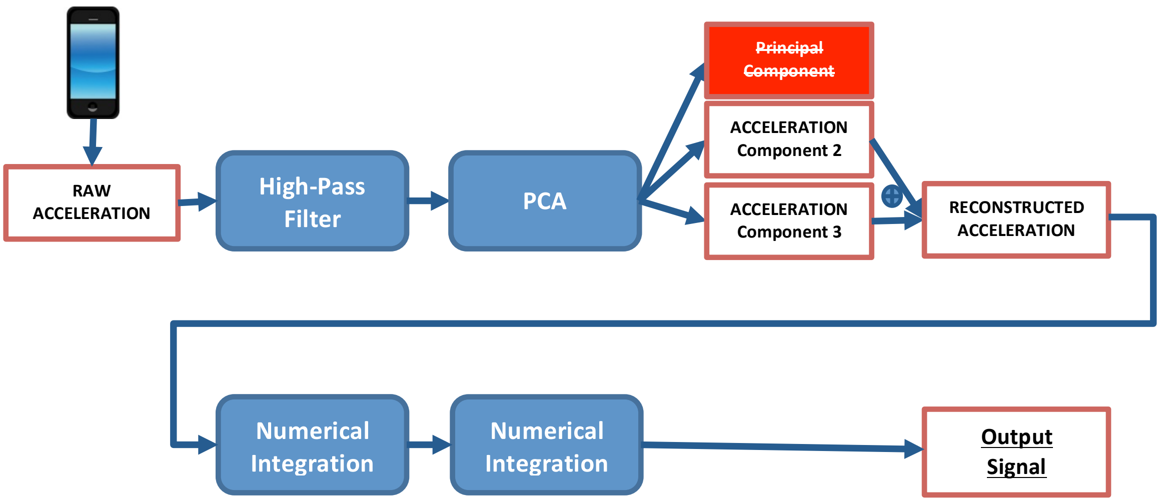

Figure 5. Loss of Stability estimation pipeline.

3. **Reconstruction & Integration:** In this steps, we reconstruct the decomposed secondary gait signals, from the separated Euclidean coordinates into a 3D timeseries signal that enables us to study secondary dynamics to the participant's gait (lateral movements, minor instabilities, staggering etc.).

3.2.3 Preliminary Evaluation

Since the detection system is in prototype-phase and all calculations are evaluated in an offline setup, we performed a preliminary test with 5 healty participants that were asked to perform 10 second walking sessions with increasing instability and staggering and studied the results. As can be seen in Figure 7, the techniques output signal, which should represent the gait's secondary motion dynamics, shows consistent increase in amplitude, which is encouraging for the viability of the estimator.

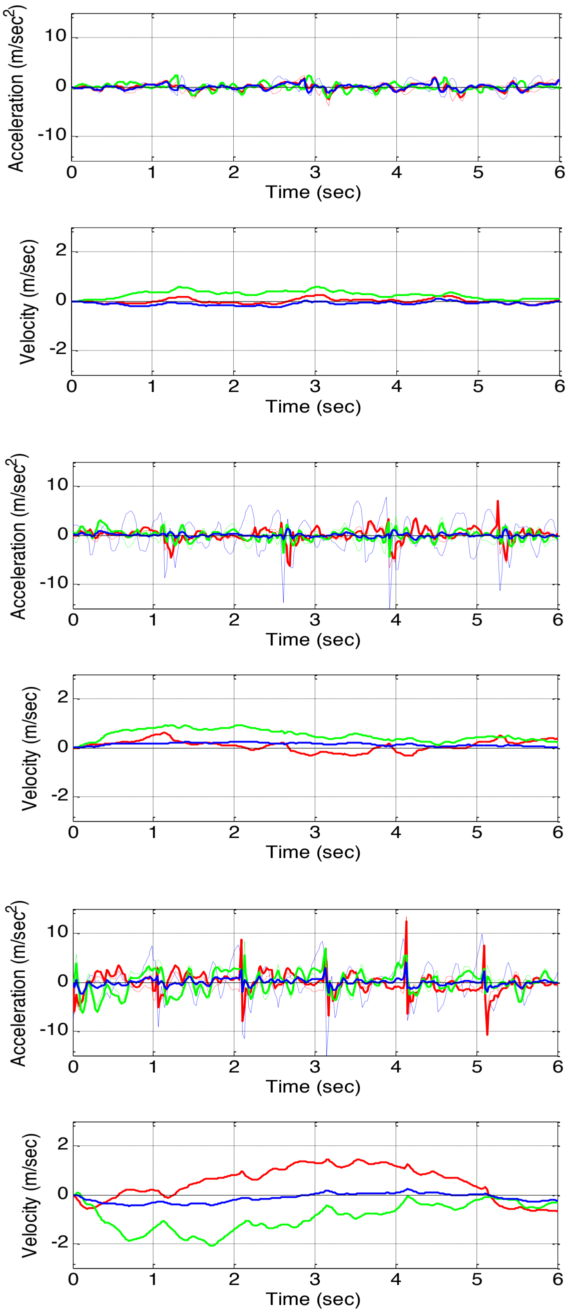

Figure 6. Output Signal color-labeled (x, y, z) for increasing state of severity (top to down).

Figure 8 shows the Signal Power corresponding to each subject (different slices), and each trial with increasing instability (blue-green-red). In each case, the signal power increased as the participant exhibited poorer gait stability.

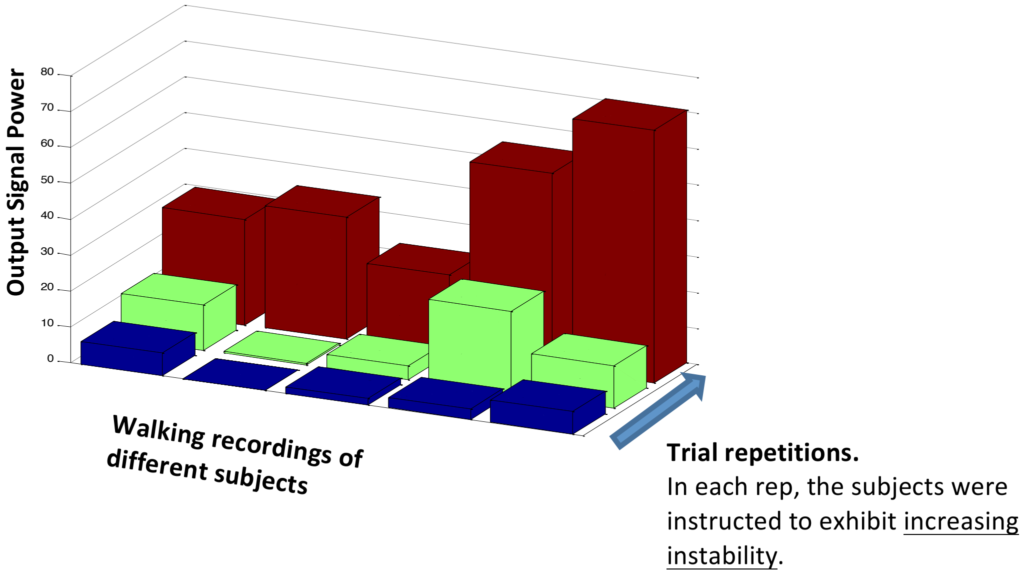

Figure 7. Results from our technique show a distinctive difference between different levels of instability severity.

Given the encouraging results, we proceeded to the implementation of the technique on the mobile device, in order to process live vest data, and perform the evaluation on a larger set of participants, that may exhibit non-induced instability and establish different severity thresholds, depending on the signal power's range for the participants, as well as also explore the possibility of establishing a dynamic treshodling mechanism that adapts to the participant's gait pattern.

3.2.4 Integration of LoS in the Fall Detector app

As described earlier in this deliverable, the above prototype implementation of the LoS algorithms were properly developed to be used in mobile devices and integrated in the Fall Detector app. As can be seen in Figure 9, by choosing the option to estimate the Stability Index, the main screen has been altered to show a live chart of the stability index, instead of that of the magnetometer.

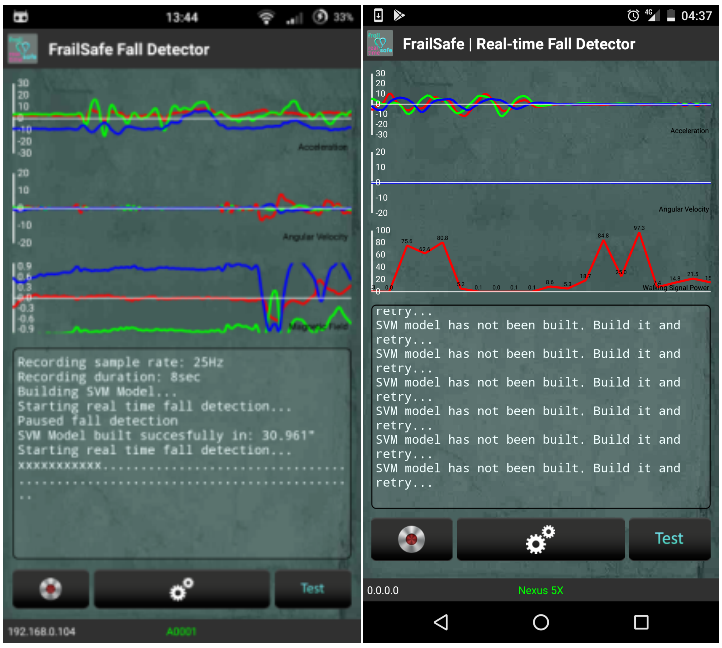

Figure 98. Main Screen of the Fall Detector app. Left: Plots showing the Accelerometer, Gyroscope and Magnetometer data. Right: Magnetometer chart has been replaced by the Stability Index chart.

3.3 *Loss of orientation*

Loss of Orientation is a potentially life-threatening and common behavior seen in the elderly, specifically Dementia and Alzheimer's patients. Between 60% to 70% of all patients with Alzheimer's will wander, and possibly get lost, at some point during the course of their disease, of these a staggering 50% will die if they are not found within 24 hours. Loss of spatial navigation, and more generally, Loss of Orientation (LoO) has gained much attention from both the research community and the industry, trying to explain the physiological reasons behind it, as well as develop necessary systems in order to detect it. The majority of the systems proposed are based on tracking information, geo-fencing, i.e. predefined boundaries of where the participant is supposed to be, and alerting systems aimed to inform the caregiver that a participant is probably wandering. However, these systems assume a higher level of severity, where the user is usually strictly monitored in a controlled manner, and doesn't qualify as an early warning system (EWS) for initial symptoms. We aim to explore LoO detection possibilities and implement a system that automatically detects a probable wandering episode using a combination of standard and novel detection techniques and serve as a EWS for the prefrail and detect early signs of dementia.

3.3.1 Related Work – State-of-the-art

Loss of Orientation is among the most problematic, frequent, and dangerous behaviors of people with dementia (PwD) and the frail, accounting for 15–60% of individuals with a clinical diagnosis of dementia and related impairments (Ballard et al., 1991). It includes a variety of behaviors, which are often originated from diverse factors (Chan et al, 2003). A lot of research has revealed that the frequent wanderers are more likely to experience adverse events such as falling, elopement, getting lost, and emotional distress. Furthermore, wandering is also the main reason of early institutionalization. Traditional methods to prevent the elderly from wandering include imposing physical restraints and medication. Because of the physical or psychological problems caused by physical restraints and the side effects of neuroleptic drugs, traditional methods are not always effective for protecting wanderers, especially for those who are prone to falling or unsafe wandering (Moore et al., 2009). Alternatively, nonpharmacological intervention has been recommended to manage rather than prevent wandering, highlighting a shift from prevention toward assisting safe walking. The main methods of nonpharmacological intervention include motion tracking, behavioral intervention, cognitive rehabilitation, and design/modification of living environments (Cohen-Mansfield and Werner, 1998).

3.3.1.1 Problem definition

Different attempts for the classification of wandering behavior exist (Algase et al., 2001, Algase et al., 2004). One of the most cited classification proposed by (Martino-Saltzman et al., 1991) categorizes wandering movement of the elderly into three different spatial categories: (1) Pacing: back and forth movement between any two points (i.e., physical locations); (2) Lapping: circuitous movement revisiting some points sequentially along a path; and (3) Random: haphazard movement without repeating points in a traveling sequence. Additionally, (Algase et. al, 1991) introduced temporal factor into the aforementioned spatial patters and represented wandering movement as spatiotemporal locomotion. The locomotion refers to the rhythmical movements consisting of two phases: walking and nonwalking. During the walking phase, the disoriented participant would wander following the pacing, lapping, and random pattern. After every walking phase, there will be a nonwalking duration, which may differ from person to person and be closely related to the environmental situations.

3.3.2 Detection techniques

There are two main research objectives pertaining to wandering of the PwD: wandering evaluation and wandering detection. Wandering evaluation targets recognition, evaluation, and testing of wandering movements to find new patterns and characteristics of wandering behavior based on offline analysis of trajectory data collected from sensors deployed in indoor environments. Wandering detection focuses on design, development, and deployment of assistive systems to provide the elderly safety assurance based on online observations of sensors deployed in indoor or outdoor settings. Three types of key techniques were applied in existing work for wandering research: event monitoring, trajectory tracking, and localization combined with Geo-fence technique. Frailsafe aims to exploit the GPS Tracker app to employ both the geo-fencing technique, and the trajectory tracking technique to explore the best possible strategy for a robust and stable Loss of Orientation System, as well to propose a new metric to detect random, but spatially relatively stationary patterns that elude detection from the abovementioned techniques.

3.3.2.1 Geo-fencing

Geofencing is one of the components in the wider spectra of Ambient Assisted Living related applications. Such applications are meant to provide support to persons with disabilities or to those impaired, as well as to their caretakers. Within this context, geofencing targets the safe mobility of such persons. A geofencing service monitors constantly the position of a person and automatically generates alerts and notifications when the person enters, leaves or moves within a specific geographic area, allowing the detection of being lost and generating appropriate intervention. The service can be addressed to elderly persons, being able to send an alert (such as a SMS message) to a caregiver when the participant has averted a predefined distance from a selected location. This type of service has become more popular in the modern society since it has the ability of increasing the quality of life for the elderly people, many of which are living independently. (Wong et. al., 2009), present a geofencing service application. They provide a complete system for tracking persons, especially elderly people, and their application can be extended to provide a geofencing solution. The system consists of a wearable AGPS (Assisted Global Positioning System) terminal with two-way communication capability and a GPS (Global Positioning System) assistance data server. This approach has a drawback because it forces the end-user to use a dedicated device for GPS based location acquisition and for the data transmission to the server. In their paper (Ryoo et. al., 2012) present a geofencing service solution which uses mobile devices for location acquisition and data transmission. They developed an energy-aware proactive framework that uses different communication technologies and sensors based on their energy usage, provided accuracy and availability. The proposed solution tracks the location of a person outdoor using the GPS sensor of the mobile device and indoor using 3G or WiFi interfaces. Frailsafe already employs these technologies in the outdoor monitoring app GPS Tracker, and we exploit existing mobility patterns of the older person to create geofencing boundaries, making it easier for the caretaker to deploy the system without needing to manually set predefined boundaries.

3.3.2.2 Trajectory tracking-based LoO detection

The trajectory tracking technique is used to acquire fine-grained motion trajectories, enabling the detection of spatiotemporal wandering trajectories based on the wandering patterns. (Martino-Saltzman et al., 1991) investigated travel patterns of wandering participants based on data acquired from electronic ankle tags worn by participants. In their experiments, an automatic detection system-activated video recording of travel activity in real time to record the ground truth, and four different patterns of direct, pacing, lapping, and random movement have been found from more than 10,000 recordings of 40 participants. Among these patterns, the direct pattern is normal and the remaining patterns link to wandering behavior. A similar work proposed by (Algase et al., 2003) uses commercial off-the-shelf biomechanical devices to capture movements of residents with dementia in nursing homes. Wandering behavior is determined by either counting the number of steps made by residents (StepWatch, National Institute of Child Health and Human Development, Rockville, USA and StepSensor, TippToes Ltd, Tippeary, Ireland) or measuring locomotion in three-dimensional spaces (Actillume, PHILIPS, Eindhoven, Netherlands and TriTrac-R3D, The Consortium to Lower Obesity in Chicago Children (CLOCC), Chicago, USA). The authors found that StepWatch sensor is particularly effective in assessing the amount of wandering behavior. A series of studies focused on path tortuosity has been performed by (Kearns et al., 2010) using RFID devices in common indoor living spaces. Path tortuosity is defined as the number of changes in directions of successive movement paths, and measured by leveraging fractal D (fractal dimension) technique. The value of fractal D ranges from 1, where a path follows a perfectly straight line, to a value of 2, where the path is tortuous (in line with the random pattern26). Their experimental results correctly classified all but two residents with dementia, and achieved a sensitivity of 0.857 and a specificity of 0.818.

The Escort system (Taub et al, 2011) is designed to protect wander-prone residents from experiencing negative events. The mesh-networked badges carried by users can sense location and communicate with a central server. Location data are obtained from a 'talking lights' optical location setup that uses ordinary light fixtures and other light sources as location beacons. Caregivers were responsible for keeping devices charged, attaching them to residents' clothing in the morning, and removing them at night. This iteration of the study ran for 12 weeks from September 1 until November 22, 2008. Focusing on outdoor wandering of the elderly, (Lin et al., 2012) investigated real-time detection of pacing and lapping movements from users' GPS traces. Based on the spatial wandering patterns, a data-driven method was proposed to examine and count turning points in any ongoing trajectory. The angular sum of the found turning points is chosen as a basis to determine whether a trace is lapping or pacing. Experimental results showed that the proposed method is workable in detecting lapping and pacing wandering locomotion investigated to detect deviations from traveling trajectories. We extended the above strategy, in combination with activity classification and frequent destinations, in order to perform real-time detection of a possible LoO event.

3.3.2.3 GPS Bearing deviation

Following the above assumptions of optimal trajectory, and the definition of LoO events by (Martino-Saltzman et al., 1991) about pacing and random pattern wandering, we explored a novel LoO detection technique to be used along the aforementioned ones, specifically designed to detect non-mobile LoO events. Assuming that an optimal route is desired, one can derive that the GPS bearing reading, i.e. the direction of facing of the user, has small-to-zero deviation when the user follows a relatively straight path to his destination. Therefore, we explored the properties of the bearing timeseries signal of both stationary LoO events, and trajectory-varying events, in a signal-processing manner, to develop a candidate criterion for the detection of random-patterned Loss of Orientation and wandering events, synergizing with abovementioned techniques in order to provide a complete early warning system of LoO events.

3.3.1 Loss of Orientation service

Using the preliminary research described above, and the problem definition of estimating a Loss of Orientation event, the Loss of Orientation service was developed, along with a Graphical User Interface front-end, the Loss of Orientation app. The LoO service is a set of implemented functionalities, addressing the problem definition of extracting a) geo-fencing alarm, b) estimating lapping patterns and c) estimating pacing patterns. The architectural modules of this application are described in detail in D1.4 "FrailSafe technical specifications and end-to-end architecture", along with its interactions with other modules of the Frailsafe system, its output parameters and its Data I/Os. The module requests daily localization logs from the FrailSafe Cloud, specifically the Outdoor Localization API, and provided a polygon of coordinates that act as geo-fencing boundaries for a selected user, the module processes the localization logs and after filtering them, extracts wandering patterns and triggers geo-fencing breaching alarms.

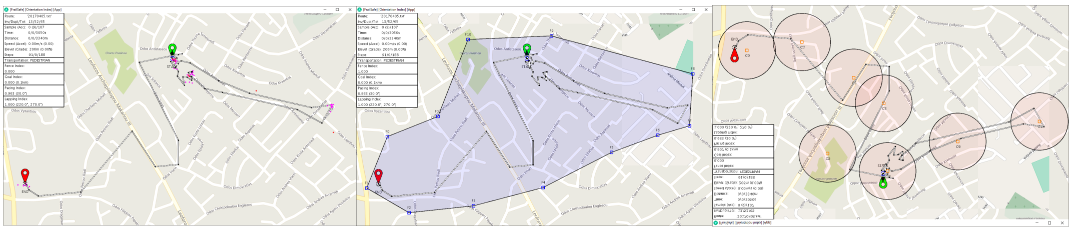

Figure 10 - The Loss of orientation app showing: a) GPS Log filtering, b) Geofencing (polygon), c) Geofencing (circular)

The core functionalities of the Loss of Orientation service are the following:

- *Filter* localization logs to extract walking paths, rejecting segments where the user is standing still or being transported in a vehicle (e.g. driving).
- *Trigger* a Geofencing alarm: An alarm triggered in case the user's logs indicate a cross in his geofencing boundaries
- *Extract* Lapping Index:An index value, indicating if the user's localization log contains looping circuit patterns.
- *Extract* Pacing Index: An index value, indicating if the user's walking path contains back and forth patterns.

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