Sleep Disorder Evaluation Using Ambient and Wearable Sensor Technologies

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Abstract. This work describes a heterogeneous sensor platform for elderly people useful in Ambient Assisted Living context for sleep disorder evaluation. The platform integrates hardware (ambient and wearable sensors), as well as software components (data simulation tool, reasoning). Three sensors with different sensing principles are considered: a Time-Of-Flight camera, a MEMS wearable wireless accelerometer and an Ultra-Wideband radar. The inputs of the platform are the postural information, even simulated, in common to all involved sensors (i.e., Standing , Bending, Sitting, Lying down). Since they are extensively used both for analysis of Activities of Daily Living and human behaviour understanding. A posture simulator, calibrated on real experiments performed by each sensor involved in the platform, has been implemented in order to compensate the lack of wide datasets containing long-term data. Moreover, the platform integrates a reasoning layer for automatic sleep disorder evaluation by using an unsupervised learning technique. The effectiveness of the platform was demonstrated by preliminary results, exhibiting high accuracy in sleep disorder evaluation using the three aforementioned sensors.

Keywords: sleep disorder evaluation; ambient sensor technologies; wearable sensor technologies; ambient assisted living; time-of-flight 3D sensor; ultra-wideband radar sensor; wearable accelerometer ; unsupervised learning

1 Introduction

The demography distribution of the developed world is set to change dramatically over the coming decades. The world's older population continues to grow at an unprecedented rate. Today, 8.5 % of people worldwide (617 million) are aged 65 and over. According to a new report [1], this percentage is projected to jump to nearly 17 % of the world's population by 2050 (1.6 billion). This trend of population ageing is as a result of reduction in fertility combined with increases in life expectancy. Although the latter issue is a positive situation, a number of related effects require consideration. In this context, the need to explore new solutions is considered essential.

In the last years, two priorities in research are investigated: a) to establish novel and effective methods for assessment of activity levels at home, and b) to establish appropriate methods for the long term monitoring and management of chronic conditions with the purpose of alleviating the increased strain on healthcare resources. The use of sensor technologies within intelligent environments (IEs) is one such approach which has the potential to facilitate these needs. IEs can provide objective data describing behaviour and health status, facilitating the development of novel activity recognition, assisted living, or healthcare monitoring solutions. Moreover, the current technologies, such as smart sensors, allows to keep the privacy and let the end-users to live in their own homes reducing the need for assistance from medical staff or caregiver. Integrated platforms of heterogeneous smart sensors are becoming more and more a key technology player in Ambient Assisted Living (AAL) scenarios. Moreover, advancement in sensor technologies give us the opportunity to recognize ADLs [2] for a long-period of time. Continuous monitoring of ADLs is helpful for detection of lifestyle disorders. Irregular human sleep patterns, for example, may cause health problems, such as disorders of psychological or neurological nature. Consequently, early detection of sleep anomalies can be useful for the prevention of such problems. In literature many approaches have been proposed for only monitoring human behaviour, reporting information about user's health and life patterns [3,4]. On the other hand, in [5-7] some methodologies for the detection of anomalies in behaviour pattern are described, whereas in [8] is presented a platform for sleep monitoring and bedsores prevention. In the above systems set of features obtained from raw data provided by specific sensor technology are considered (e.g. pressure sensor, motion sensor, IR sensor, wearable sensor...). In these works, using probabilistic approach, the detection of sleep anomalies is reached with a good level of accuracy. However, these systems have some limitations. In fact, they do not have the ability to manage long-term data and in some circumstances a training phase is required.

This paper reports the description of a heterogeneous platform for human sleep disorders evaluation within AAL context. The input of the system is constituted by sequences of human postures generated using an activity simulation approach specifically designed and implemented within this work. The simulator provides sequences of postures according to a calibrated simulation based on real-life experiments conducted with three different sensors: a Time-Of-Flight (TOF) sensor, a Ultra-wideband (UWB) radar and a ST MEMS three-axial accelerometer (ACC). The use of postures is motivated by their extensive use in ADLs modelling [9], besides that ADL sequences allow to model human behaviour. The main contribution of this work is related to the design and development of a platform for automatic detection of anomalies in sleep patterns by using an unsupervised methodology. It is important to highlight the platform capability in providing a technology invariant interface abstract from any specific sensing technology. The preliminary results show the ability of the presented approach to detect with good accuracy sleep/wake phases for subsequent medical evaluation of sleep disorders.

2 Material and Methods

The platform architecture is organized, as shown in Figure 1, in three main layers: detection layer, simulation layer, reasoning layer.

The detection layer provides sequences of human postures detected by three different sensors: a Time-Of-Flight (TOF) sensor, a Ultra-wideband (UWB) radar and a ST MEMS triaxial accelerometer (ACC). The first two (TOF, UWB) approaches refer to ambient solutions, whereas the last one falls into wearable ones.

In the simulation layer, long-term posture sequences are generated according to a calibrated simulation, based on real-life experiments and conducted with the three aforementioned sensors.

The reasoning layer offers an automatic tool for the detection of anomalies in CR by using an unsupervised methodology.

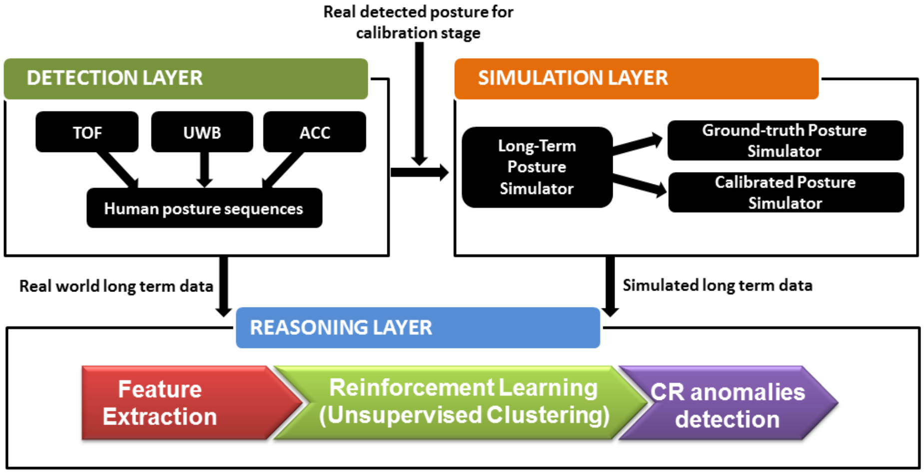

Fig. 1. Implemented logical modules overview.

2.1 Detection Layer

Human postures can be detected by using several sensing approaches implemented with either ambient or wearable solutions. In this paper, three different kind of sensing approaches are taken into account: (1) TOF 3D vision, (2) UWB radar and (3) ACC. All these posture detection approaches are differently characterized in terms of invasiveness, accuracy, robustness to object occlusion and cluttering and data richness, as summarized in Table 1.

For the assessment of the sensor's accuracy with respect to the posture recognition task, a common experimental framework has been used, in which eighteen healthy subjects (9 males and 9 females, age 38±6 years, height 175±20 cm, weight 75±22 kg) have been involved. The participants performed typical ADLs such as household tasks, meal preparation, feeding, sitting and watching TV, relaxing and sleeping.

Table 1. . Comparison of Three Posture Detectors

Characteristic	TOF	UWB	ACC
Invasiveness	Low	Very Low	Medium
Accuracy	Very High	Medium	Medium
Robustness to object occlusion and cluttering	Low	High	Very High
Data richness	Very High	Medium	Medium

During such experimental sessions, data were collected simultaneously by a TOF sensor, a UWB radar and a MEMS accelerometer worn by participants. For all approaches, the detection algorithms ran on a fan-less embedded-PC equipped with Intel® Atom™ processor. The following subsections describe each sensor in detail with specific focus on posture detection approach used.

Time-Of-Flight (TOF) sensor. This detector adopts the MESA SR-4000 [10] shown in Figure 2, a state-of-the-art TOF sensor having compact (65×65×68 mm) dimensions, noiseless (0 dB) working, QCIF (176×144 pixels) resolution, long (10 m) distance range, wide (69°×56°) field-of-view, and low power (9.6 W) consumption. The TOF-based posture recognition is inspired by the work of Diraco et al. [11]. At early processing level, the computational framework includes a self-calibration procedure to allow for easy installation of the TOF sensor, without requiring neither calibration objects nor user intervention. The self-calibration makes use of the popular RANSAC-based plane detector to identify the position of the floor, which is used to estimate the extrinsic calibration parameters. Moving foreground objects are extracted from calibrated range data by modelling the background with a mixture of Gaussian and segmenting the foreground with a Bayesian classifier. Finally, people are detected and tracked using the CONDENSATION (Conditional Density Propagation) algorithm. The remaining part of the computational framework focuses on feature extraction and posture classification. The intrinsic topology of a generic shape, i.e. a human body scan captured via TOF sensor, is graphically encoded by using the concept of Discrete Reeb Graph (DRG) proposed by Xiao et al. [12]. To extract the DRG, the Geodesic distance is used as invariant Morse function [13] since it is invariant not only to translation, scale and rotation but also to isometric transformations ensuring high accuracy in body parts representation under postural changes. The geodesic distance map is computed by using a two-step procedure. Firstly, a connected mesh, shown in Figure 3.a, is built on the 3D point cloud by using the nearest-neighbour rule. Secondly, given a starting point M (i.e. the body’s centroid) the geodesic distance between M and each other mesh node is computed as the shortest path on mesh by using an efficient implementation of Dijkstra’s algorithm suggested by Verroust and Lazarus [14]. The computed geodesic map is shown in Figure 3.b in which false colours represent geodesic distances.

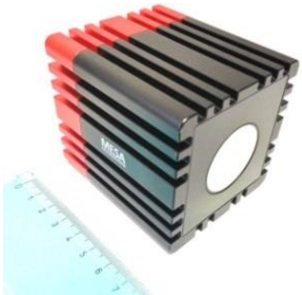

Fig. 2. MESA SR-4000 Time-Of-Flight sensor.

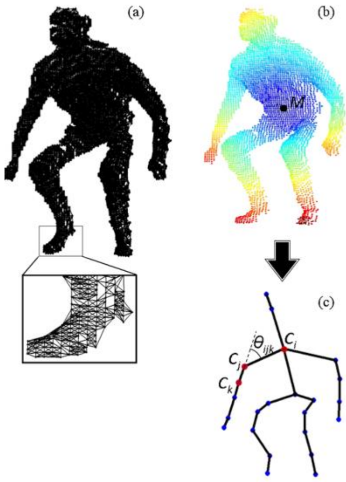

Fig. 3. TOF-based features. (a) Mesh; (b) Geodesic map; (c) DRG-based features

The DRG is extracted by subdividing the geodesic map in regular level-sets and connecting them on the basis of an adjacency criterion as described by Diraco et al. [10] that suggest also a methodology to handle self-occlusions (due to overlapping body parts). The DRG-based features are shown in Figure 3.c and represented by the topological descriptor that includes DRG nodes $\{C_i,C_j,C_k\}$ and related angles $\{\theta_{ijk}\}$. A multiclass formulation of the SVM (Support Vector Machine) classifier [15] based on the one-against-one strategy is adopted to classify (St, Be, Si, Ly) postures. Since interesting results have been reported with the Radial Basis Function (RBF) kernel for posture recognition [16], such a kernel is used and associated parameters, namely regularization constant K and the kernel argument γ, are tuned according to a global grid search strategy. The classification performance, estimated using the datasets previously discussed, are reported in Table 2 in terms of confusion matrix.

Table 2. TOF Confusion Matrix

		Predicted postures (%)			
		St	Be	Si	Ly
Actual postures (%)	St	99	1	0	0
	Be	0	97	3	0
	Si	3	0	97	0
	Ly	0	2	0	98

Ultra-wideband (UWB) radar sensor. This detector adopts the PulsON 410 manufactured by Time Domain Corporation [17] shown in Figure 4, a state-of-the-art UWB radar sensor, having a good wall penetration capability (2 GHz bandwidth), RF transmissions from 3.1 GHz to 5.3 GHz centered at 4.3 GHz, compact (76×80×16 mm) board dimensions, and it is able to operate in both mono- and multi-static configurations. UWB radar sensors find many applications ranging from vital signs detection to target localization and tracking, not only in contactless modality but also through the walls. In this study, the PulsON 410 sensor is used for recognition of human postures regardless to the presence of large occluding objects (e.g., pieces of furniture, walls, etc.) interposed between target and sensor. The computational framework includes three main stages: (1) the preprocessing for clutter reduction/removal, (2) the feature extraction, and (3) the posture classification. At the preprocessing stage, after band-pass filtering (Butterworth IIR 16th order) with a transition band of 3.1-5.3 GHz for filtering out frequencies outside the transmitter range, the clutter is removed by using the Running Gaussian Average technique for background subtraction [18]. Given the Time-Of-Arrival (TOA) corresponding to the component of the human body, the feature extraction stage is based on the estimation of the following quantities: normalized energy, variance, skewness, kurtosis, as defined in [19]. Finally, the feature vector is classified by means of ensemble classification technique based on Real AdaBoost [20]. The AdaBoost classifier was trained by using the 10% of posture sequences, instead the remaining sequences were used for testing. The classification performance was estimated either with and without large occluding objects, and the related averaged confusion matrix is provided in Table 3.

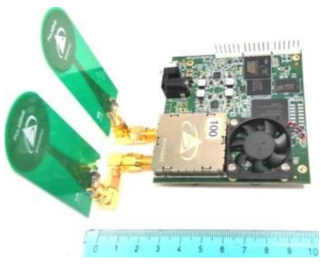

Fig. 4. MESA SR-4000 Time-Of-Flight sensor.

Table 3. UWB Confusion Matrix

		Predicted postures (%)			
Actual postures (%)		St	Be	Si	Ly
	St	82	13	5	0
	Be	18	75	6	1
	Si	11	8	79	2
	Ly	0	4	15	81

MEMS three-axial accelerometer (ACC) sensor. The wearable device used in this version of the platform is the Wearable Wellness System (WWS), produced by Smartex [21]. It made up of a sensorized garment and an electronic device (SEW) for the acquisition, the storage and the wireless transmission of the data. It has been designed to continuously monitor main vital parameters (ECG, Heart rate, Breathe rate) and the movements. The WWS garment is suitable and comfortable, reducing the well-known usability problems of the smart wearable devices. Moreover it can be washed and it can be in tight contact with the body without any creases. In Figure 5 the male version of the t-shirt is shown. It integrates a) two textile electrodes, b) one textile piezo resistive sensor and c) a pocket, placed on the chest, for the electronic device in which it is integrated a tri-axial MEMS accelerometer for the movement monitoring. The WWS can operate in streaming via Bluetooth up to 20 meters (in free space) or in off-line modality, storing the data on a micro-SD integrated in the SEW device. In streaming mode the duration of its rechargeable battery life is about 8 hours, while in off-line the duration is more than 18 hours. For the elaboration, the raw acceleration data have been sent to the embedded PC with a 25 Hz frequency, that it is enough to recognize the physical activity [22]. The data are in the decimal format and represent the acceleration values with full scale in the range of ±2g for an high sensitivity and a 10 bit resolution. The MEMS accelerometer is DC coupled, so it measures both static and dynamic acceleration along the 3 axes and allows to get information on the 3D spatial relative position (compared to the Earth gravity vector) of the person who wears it. Indeed, if the accelerometer relative orientation is known, the resulting data can be used to determinate the angle α of the user position with respect to the vertical direction. The main computational steps of the software architecture for the posture recognition are: data acquisition, data pre-processing, system calibration, feature extraction and classification. Data are converted into gravitational units to represent acceleration data in the range of ±2g, in order to make possible to extract the angle α and avoiding different orders of magnitude in the features. The samples coming from the device are filtered out by a low pass FIR filter to reduce the noise due to the electronic components, environment and human tremor. In order to correctly handle the pre-processed data, a calibration procedure was accomplished by recovering the initial conditions after the device mounting. The features extracted to detect the posture are: the Averaged Acceleration Energy (AAE), the mean and the standard deviation [23] over three acceleration axes by using a 5 sec sliding window. Moreover the features obtained in [24] have been used, they consider the variation of dynamic acceleration and the change of position during a sitting/lying/standing up actions with respect to an upright position. The classification of the (St, Be, Si, Ly) postures have been obtained by implementing the effective and robust semi-supervised k-means clustering algorithm and Euclidean distance [25]. The classification performance, estimated using the datasets previously discussed, are reported in Table 4 in terms of confusion matrix.

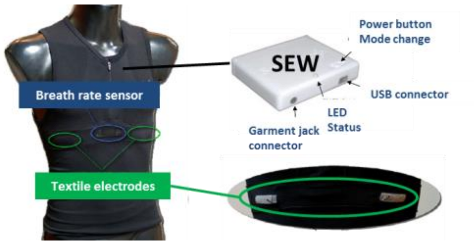

Fig. 5. Smartex WWS composed by a sensorized garment and an electronic device (SEW).

Table 4. ACC Confusion Matrix

		Predicted postures (%)			
		St	**Be**	**Si**	**Ly**
Actual postures (%)	**St**	92	2	6	0
	Be	2	84	2	12
	Si	11	2	87	0
	Ly	0	5	1	94

2.2 Simulation Layer

Since the availability of datasets for behaviour analysis is limited by difficulties associated with the collection of such data, and considered the lack of datasets containing long-term postural sequences, a simulator of ADLs/postures has been implemented. The simulator provides synthetic data with the ability to rapidly generate a large simulated dataset driven by different parameters which allow to reproduce different normal/abnormal behaviours (in particular human sleep patterns).

The simulator is composed by two stages; the first for simulation of long-term ADLs/postures, the last for a calibrated simulation of long-term postures referred to a specific sensing approach.

Long-term ADL/posture simulator. The general architecture of the simulator is inspired from the work of Noury et al. [26]. The authors assumed that the daily activities of a subject are almost regular. Thus, the simulator is based on a Markov model with homogeneous periods, while the time for transitions is ruled by a Finite State Machine (FSM) [27]. The Markov chains are frequently used to represent a Bayesian process with multiple states and their associated conditional probabilities. Thus the use of HMM seems a suitable probabilistic approach to model the whole system.

As shown in Figure 6, the day is segmented into seven periods (e.g., wake up, morning, lunch, afternoon, dinner, going to bed, sleep) and thus seven Markov models corresponding to well identified circadian rhythms were modelled. In this way, each period can be represented by a graph of the transitions (used for the translation in activity sequences that can occur during the specific daily period) that are controlled by their probabilities. The simulated data are structured in the following matrix expression: M = [Date, StartTime, EndTime, Activity], where Date, StartTime, EndTime and Activity are column vector representing respectively the date of the simulation day (expressed in the following format: dd/mm/yyyy), the start time, the end time of the simulated activity (expressed in the following format: hh:mm:ss) and the name of the latter.

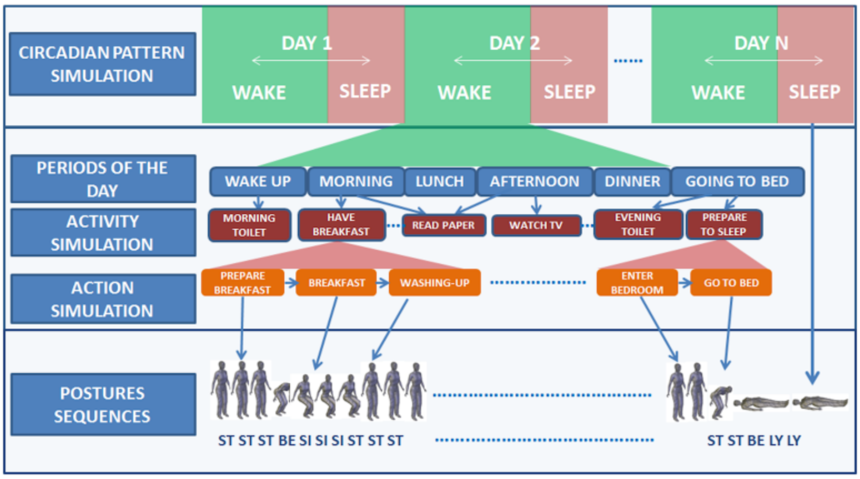

Fig. 6. Conceptual representation of the posture simulator (SI=Sitting, ST=Standing, BE=Bending, LY=Lying Down)

Each period of the day is modelled using a N-states HMM in which N represents the ADLs performed during the period itself. The next step of the simulator is devoted to translate activities in a sequence of actions. In this work, an action is an atomic element which provides the details of a specific activity. For example, the activity "have breakfast" is translated by the following sequence of actions: "prepare breakfast" - "breakfast" - "washing up". The assumption made in this version of the simulator is always to translate each activity with the same sequence of actions, only varying the time duration.

Finally, as described in the next subsection, the last layer of the simulator is addressed to model each action as a sequence of the postures (taking into account the only four postures previously mentioned).

Calibrated approach for long-term posture simulator. Starting from the sequence of actions provided by the ADL simulator, the posture sequence is generated by using a calibrated approach based on real observations conducted with real detectors (i.e., TOF, UWB, ACC). Such calibration consists in modelling errors introduced by each specific detector, starting from simulated ground-truth sequences. The Model Error Modelling (MEM) method [28] together with the Expectation-Maximization (EM) algorithm [29] are used to model detection errors. Furthermore, the parameters of the simulated detectors are obtained by minimizing a cost function based on the Prediction Error Method (PEM) [30].

2.3 Reasoning Layer

Given long-term posture sequences referred to the different sensing approaches, the platform includes a feature extraction procedure aimed to identify the starting point of sleep periods and their durations for each day. At this purpose, the most efficient solution is to recognize human actions from patterns of posture sequences, and more specifically to extract starting points of the actions: “going to bed”, “sleep in bed” and “wake up”. The approach implemented in this work allows ADLs recognition using the technique described below. Basically, human actions are recognized by considering successive postures over time periods. A transition action occurs when the person changes the current action to another action. Thus, a transition action might include several transition postures. Transition actions are merged together to form single atomic actions and global events are recognized by using Dynamic Bayesian Networks (DBNs) specifically designed for indoor application scenario, following an approach similar to Park and Kautz [31]. Designed DBNs have a hierarchical structure with three node layers: activity, interaction and sensor. The activity layer stays on top of hierarchy and includes hidden nodes to model high-level activities (i.e. ADLs, behaviours, etc.). The interaction layer is a hidden layer as well and it is devoted to model the states of evidence for interactions inside the home (i.e. appliances, furniture, locations, etc.). The detector layer, at the bottom of hierarchy, gathers data from detector sensors (postures). Each DBN is hence decomposed in multiple Hidden Markov Models (HMMs) including interaction and sensor layers, and trained on the basis of the Viterbi algorithm [32]. In this way, the detection of sleep start time can be derived from the recognition of the action “going to bed”, and the duration of sleep can be obtained evaluating the difference between “wake up” time and “sleep in bed” time.

The extracted features (start time of sleep and relative duration) are used for the detection of sleep periods and also to estimate human sleep trends evaluating their mapping into the two-dimensional space in which the x-axis indicate the start time of sleep and the y-axis its duration (expressed in hours and minutes). This step is explored with a reinforcement learning procedure; in particular, using an incremental clustering technique [33], the last step of the platform provides an unsupervised approach for real-time discovery of changes in a sleep patterns with respect to an initial pattern assumed as reference, namely Reference Sleep Pattern (RSP). This is achieved by incrementally clustering incoming features (extracted from the current day whose postures are simulated) in the aforementioned feature space. When a new cluster appears, a change in the sleep pattern is detected (and thus classified as normal or anomalous) if the features belonging to the new cluster are extracted from N consecutive days (not necessary adjacent), with N set according to physician’s indications.

3 Experimental Results

The robustness of the feature extraction step has been evaluated on a series of experiments in which synthetic data, obtained after calibrated simulation of real data generated by TOF sensor, were affected by different percentages of errors related to: (1) sensor noise and (2) fault situation which can occur in real contexts (e.g. wearable sensor not worn, vision sensor turned off or occluded, resulting in postures not available during a time period). The purpose to simulate situations close to reality has been reached by modeling the noise with two kinds of components: bias noise (uniform distribution) and posture transition noise (Gaussian distribution). Performances have been evaluated in terms of Mean Absolute Error (MAE) by measuring the misalignment between ground-truth sleep phases and detected ones, and also in terms of Mean Relative Error (MRE) related to the percentage of undetected sleep phases. The previous error measurements are estimated through 13 synthetic datasets constituted by different time periods, and characterized by an average length of sleep pattern equal to 8 hours. The duration of sleep is randomly perturbed by variance values between 0.5h and 1.5h. The number of simulated days for each experiment, the percentage of errors and relative performances are reported in Table 5.

Table 5. Experimental results of the feature extraction step

		# Days	Bias Noise	Posture transition Noise	Fault situation	Alignment MAE (minutes)	Detection MRE (%)
Experiment	1	120	0%	0%	0%	5	0
	2	90	20%	10%	0%	5,2	0
	3	150	20%	30%	0%	5,3	0
	4	90	30%	10%	0%	5,2	0
	5	90	30%	30%	0%	20,1	5
	6	120	20%	10%	15%	8,4	4
	7	120	20%	30%	15%	9,5	6
	8	90	30%	10%	15%	11,7	7
	9	90	30%	30%	15%	26,8	13
	10	150	20%	10%	30%	14,4	10
	11	120	20%	30%	30%	18,8	10
	12	150	30%	10%	30%	25,1	12
	13	120	30%	30%	30%	36,5	21

The results obtained reveal that a total noise level of about 60% can affect the accuracy of the detected sleep phases in terms of temporal misalignment compared with the ground-truth. Moreover, if a fault situation is added to the noise the percentage of undetected sleep phases grows and this happens more if the fault situation occurs during the sleep periods.

For the validation of the incremental clustering step, experiments that simulate different time periods have been carried out reproducing postural time series according to posture classification performance. Three time intervals (60, 120 and 180 days) have been taken into account as reference period M, followed by periods within which a change in the CR pattern was simulated (labelled with N). In Table 6, the detection rate of trend changes, at varying of both M and N, is reported for each detector. It is important to note that at the increasing of M, the incremental clustering achieves good performance if changes in CR pattern persist for a time period N. However, it is important to note that an acceptable detection rate (at least of 80%) is obtained for period N (in days) closely related to each detector: a greater amount of days N is required at the increasing of M.

Table 6. Detection rate (%) of deviations from the reference CR at varying of "M" and "N"

			N (days)						
		Detector	*7*	*14*	*21*	*28*	*35*	*42*	*49*
M (days)	*60*	*TOF*	76,4	**90,2**	90,7	94,6	95	95,8	96.5
		ACC	73,1	**84,6**	86,1	89,5	92,3	93,1	94,5
		UWB	69,7	73,5	77,2	**81,4**	84,5	87.7	90,2
	120	*TOF*	72,1	74,4	**80,3**	88,7	88,9	89,2	90,5
		ACC	69,8	70,1	73,9	76,8	**80,2**	83,6	86,7
		UWB	65,2	67,6	70,2	73,5	78,5	**81,4**	82,9
	180	*TOF*	60,4	73,7	79,7	**80,2**	87,4	88,9	90,4
		ACC	58,7	62,6	66,9	70,4	74,2	**79,7**	83,7
		UWB	56,4	60,1	63	67,9	72,7	77,5	**80**

4 Discussion and Conclusion

From the analysis of the obtained results, it is evident the platform ability in identification of changes in human sleep patterns with high accuracy. However, the performances are strictly related to the sensing technology involved; in fact, at varying of the detector, a different number of days N is required to reach a satisfactory detection rate. For example, if we consider a reference period of length M=120 days, a detection rate of about 80% is reached within N=21 days (TOF), N=35 days (ACC), N=42 days (UWB). The platform has been validated by using posture sequences simulated in a calibrated way (with calibration error less than 5%) and referring to common ADLs carried out by older people in their home environment. Furthermore, the solution was tested considering reference periods M very different in order to taking into account any deviation with respect to standard execution of ADLs.

This leads up to believe that the performances that can be reached using real monitoring systems should be included between M=60 and M=180, with N corresponding to the sensing technology used. From the usability perspective, the platform is consistent with the independent living context; in fact the detection of changes in sleep patterns can be automatically obtained allowing offline analysis by a caregiver/doctor for subsequent clinical evaluations. Finally, it is important to stress the versatility of the platform which can potentially operate with any kind of detector able to provide postural information.

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