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Learning & decision making algorithms in pervasive environments

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Contents

Glossary of terms used

Acronym/terms	Definition
ADL	Activities of Daily Living
AR	Assistive Robotics
COPD	Chronic Obstructive Pulmonary Disease
ER	Emergency Room
FEV1	Forced expiratory volume in 1 second
FVC	Forced expiratory vital capacity
GOLD	The Global Initiative for Chronic Obstructive Lung Disease
HCI	Human Computer Interaction
HRI	Human Robot Interaction
iADL	Instrumental Activities of Daily Living
ICF	International Classification of Functioning
KSERA	Knowledgeable Service Robots for Aging
KSERA-system	A smart home environment and a mobile platform, i.e. Nao
KSERA ubiquitous home environment	A smart home environment
Nao	Humanoid Robot
UCD	User Centred Design
Scenario	Usage narrative
Use case	Describe the functional requirements
WHO-ICF	See International Classification of Functioning
WP	Work package

Executive summary

This report provides an overview of the state of the art algorithms and the KSERA approach.
KSERA is the system expected to operate in real life conditions in a house in which one person with COPD is living. The house is a non-deterministic environment generating events over time. The events are acquired from ubiquitous sensors and processed by the artificial cognitive component of KSERA in order to recognize activities and estimate room occupancy.
The most useful learning algorithms for activities recognition and room occupancy estimation are based on probabilistic inference (such as hidden Markov models and conditional random fields) and fuzzy logic. The decision making algorithms can be split in different classes of decisions depending on their complexity: instantaneous responses are suitable for high priority events, medium term analysis is suitable for detecting trends, and more complex scenarios require both the history of the managed events and the current monitoring acquisition. With these algorithms KSERA integrates a wider range of contextual and environmental data using more sophisticated algorithms than commercial solutions, so that more complex scenarios can be processed.

Purpose of this deliverable

This document is a report about learning and decision making algorithms, aiming to evaluate the possible solutions that may be implemented in the KSERA system.

Suggested readers

This document is public and it might be used by those willing to know more about sensor acquisition and data processing in a system used for AAL purposes.
It is specifically recommended to all KSERA partners and in particular to those involved in the KSERA system design, development and evaluation.

Relationship to other documents

This document inherits information from the task T1.1 (D1.1), scenarios and use cases description, T1.4 (D1.2), basic rules for ubiquitous monitoring, and T2.1 (D2.1), the architecture design.
This document describes the state of the art in senior patient monitoring and COPD treatment approach. The KSERA approach is then described, based not only on critical event detection, but also on learning algorithms. Both information from the pervasive environment and benefits from an ambient assisted living are exploited, in order to best suite the system response to the actual needs of the monitored user.

1 Introduction

Homecare and tele-monitoring solutions available on the market are able to detect ***critical events*** and manage ***alarm situations***. This is generally done by means of an immediate triggering based approach using the known a-priori heuristics and thresholds.
The triggering of the situations is possible using crisp or Fuzzy comparisons. Typically, the AAL situations are Fuzzy categories requiring the Fuzzy reasoning.

The purpose of the KSERA research activity is to implement an advanced homecare service using robotics, particularly aimed at COPD patients. Its efficiency is maximized by extracting as much information as possible from the acquired data and using such information in order to perform the most suitable action towards the user.
Therefore, the KSERA approach (Figure 1) is based on the deployment of one network of heterogeneous sensors, composed by three main sensing categories (fixed sensors, mobile devices, and intelligent house's ones), the acquisition of data, and the processing of the situations [28]. This feeds advanced processing algorithms that are able to extract deeper information, which is used to integrate and extend the standard monitoring approach.

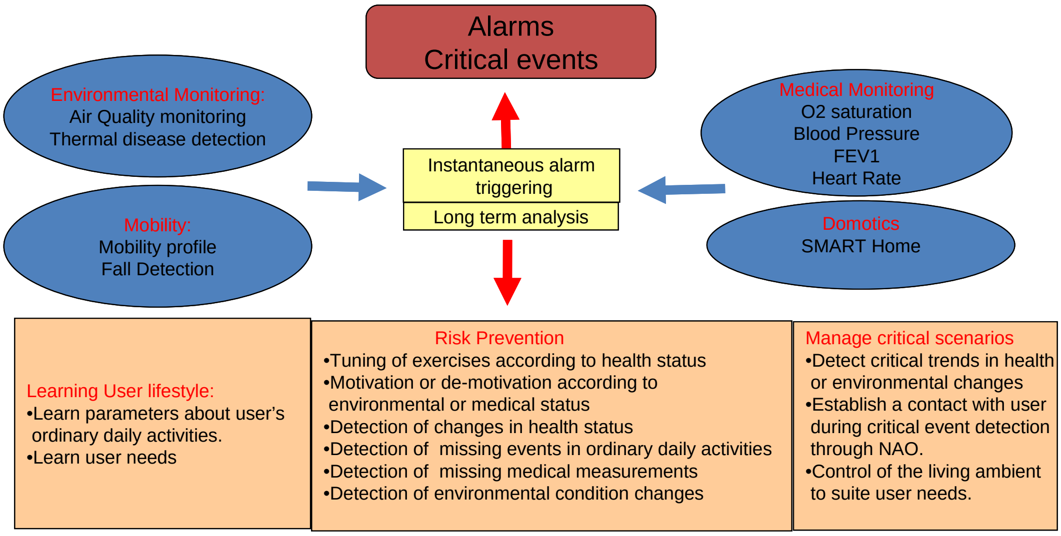

Figure 1: KSERA ubiquitous monitoring based homecare approach

The document is organised as follows:

- Chapter 2 describes what is currently the state of the art in monitoring and health care services. Which devices are usually employed and what kind of approach is employed treating COPD patients.
- Chapter 3 describes the KSERA approach, its ubiquitous monitoring system and the desired approach in data processing.
- Chapter 4 describes the actual state of the art in learning and decision making algorithms, in which solutions are reported compliantly with the KSERA approach implementation.

2 State of the art in KSERA target scenarios

This section is intended to give an overview on the available tools and services that nowadays are employed to remotely assist old and physically less able people, providing the care and reassurance needed to allow them to remain living in their own homes.
A brief focus is given to the particular class of users affected by COPD, which is the main target for the KSERA application, considering the state of the art in approaching such issue. This is, in other words, the KSERA starting point.

2.1 State of the art in senior monitoring

Nowadays several solutions are available on the market aiming at providing remote care services to older people. The simplest services consist of giving the user a device that can be used to trigger an emergency call towards a caregiver. Moreover, the availability of reliable short range radio protocols allows the deployment of wireless devices that can be used to gather more information about the user and his/her needs, thus providing the base for more specialised services. Finally domestic medical instruments are used.

2.1.1 Homecare

Typically, the ***Homecare on-demand services*** are based on the use of radio devices (Figure 2), able to transmit an alarm signal upon pressing a dedicated emergency button. The home user can ***express the need of care*** at a certain moment using the specialized nomadic device: the service is asked by pushing the “emergency call” button.
A receiver unit acts as a gateway towards the telecommunication networks (very often just the PSTN network), forwards an emergency call to a call center, and activates a speakerphone system, allowing the communication between the caregiver and the user.
Such remote controllers are small sized devices that can be worn as a necklace or brought as a key-ring.

Figure 2: Remote emergency button [20]

2.1.2 Telemonitoring

Simple homecare devices are able to undertake an emergency call only when the “emergency button” is pressed. More complex situations remain unmanaged in this scenario hence.
By means of devices deployed at the user’s domicile, or worn by the user, many other parameters can be monitored, and critical situation can be triggered. Some examples [20] are:

- Bed/Chair Occupancy Sensor: provides an early warning by alerting that the user has left his/her bed or chair and did not return within a preset time period, indicating a potential fall.
- Enuresis Sensor: Placed between the mattress and sheet, this sensor provides immediate warning on detection of moisture, allowing effective action to be taken.
- Epilepsy Sensor: This state of the art sensor monitors the user's vital signs including heart rate and breathing patterns to detect a range of epileptic seizures.
- Fall Detector: fall detectors can provide valuable peace of mind by automatically detecting a serious fall and raising an alert to the caregiver.
- PIR (Movement Detector): a movement detector can be used for both activity and inactivity monitoring.

- Pressure Mat: monitors movement in a specific area, for example if someone got out of bed or left the house.
- Property Exit Sensor: As people with dementia are prone to walking about, this sensor specifically monitors for people leaving a building at unusual times of day or night. It can also detect if a main exit door has been left open.
- Pull Cord: raises alerts in areas where personal triggers are unlikely to be worn e.g. positioned next to the bed or in the shower.
- Natural Gas Detector: provides an early warning of dangerous levels of gas. Can be linked to the Gas Shut off Valve to automatically cut off the gas supply, if a leak is detected.
- Smoke Detector: provides early warning in case of fires.
- Heat Detector: provides additional warning in case of fires in rooms where smoke detectors are unsuitable e.g. kitchen.
- Temperature Extremes Sensor: monitors low and high temperature extremes in addition to rate of rise of temperature.

All the above sensors can give the chance to detect one occurrence of the above event and react upon it. However, the context of the non-deterministic environment remains still unmanageable. The complex events, such as aggregations of the elementary events, remains unmanaged requiring more complex systems with cognitive capabilities, those capable to do some inferences about happenings in real life.

2.1.3 Telemedicine

In Telemedicine scenario, the remote monitoring, also known as self-monitoring/testing, enables medical professionals to monitor a patient remotely using **various** technological devices. This method is primarily used for managing ***chronic diseases or specific conditions***, such as heart disease, diabetes mellitus, or asthma. These services can provide comparable health outcomes to traditional in-person patient encounters, supply greater satisfaction to patients, and may be cost-effective.
Some dedicated telemedicine systems are nowadays available on the market allowing controlling and managing different chronic diseases and avoiding the patient the need of frequent visits to medical centres.

Devices capable of assessing lung function / oxygenation (directly or indirectly) are specifically relevant to KSERA, because COPD disease affects breathing and lung function and therefore tissue oxygenation. For example, Pulse Oxymeters (measures O_2 blood saturation and heart Rate) [22], blood pressure monitoring systems [21], glucose monitoring systems, and ECG systems [23] are all devices that can be deployed (Figure 3) in KSERA context, according to the needs specified in the rules (D1.2).

Figure 3: Wireless medical devices: a blood pressure monitoring system [21], a pulse-oxymeter [22] and an ECG monitoring system [23]

2.2 State of the art in COPD patient treatment

KSERA aims on the patients suffering from the Chronic Obstructive Pulmonary Disease (COPD). The natural course of COPD is characterized by occasional sudden worsening of symptoms called “acute exacerbations”, for instance caused by infections or the consequence of air pollution. COPD symptoms have a direct effect on the activities of daily living because shortness of breath limits vitality and thus the extent to which activities can be performed without problems.

Medical knowledge helps to define the technical devices that are useful for the remote management of the COPD patients.

Preventing hospitalization by signaling the early stages of exacerbations is only possible if sufficient information about the patient and its daily living parameters are made available. In this case a remote monitoring approach with the data analysis aimed on the relevant event’s triggering can be useful.

Vital signs can be observed by sensors and recorded. Vitality signs fluctuate on a daily basis and are influenced by weather and by specific events, injuries, etc. As a result, daily living activities will be affected in some way. For example irregular sleeping patterns might emerge, and/or less time being spent outside by the patient can be recorded.

KSERA monitoring sub-system offers the possibility to detect and record the above parameters, while the triggering rules are set up by healthcare professionals in order to make triggerable the events and the relevant situations from within the real life of the COPD patients.

It is therefore clear that automatically assessing a patients' health situation by measuring activity in the home and correlating this data with a validated measurement for COPD complaints may offer considerable advantages and improvements to the caregivers’ quality of service.

Consequently one of the KSERA impacts comes from the system capacity to detect and trigger the above situations, relevant to the remote management of the COPD patients.

3 KSERA approach

In KSERA project there are several Use Cases defined to describe the real life situations of the “living with COPD”. As defined in D1.1, the considered monitored user group (Persona) consists of older people in different stages of (risk of) COPD development, which are: GOLD 0 (no COPD, yet), GOLD I stage (not recognized COPD, as is common among older persons), GOLD II (moderate COPD, housebound because of co-morbidities), GOLD III (severe COPD), and entering the GOLD IV stage of very severe COPD, but without requiring regular oxygen administering.
The monitoring task is faced by the deployment of a complex network of devices. Homecare, telemonitoring and telemedicine solutions, as described in the previous section, shall be integrated with environmental sensors thus providing a pervasive monitored environment.

At least two different options are considered by KSERA:
a)
- the direct measurement of the sensor **values** for triggering appropriate actions of the KSERA system using a-priori known sets of rules and/or thresholds;
- the acquisition of a time **series of values** that can be screened against the patterns for triggering actions;
b)
- the discovery of the correlations between the **current values** in order to discover trends;
- the discovery of the relationships between the **series of values** over time in order to discover the changes, motifs and trends.

Certain data can be analyzed using direct comparisons, using the IF THEN ELSE rules. The above comparisons might be ***crisp*** (Boolean) or ***Fuzzy***. Let us exemplify a possible rule mapping using case A3 from D1.2 describing the actions to be taken based on measurements of Relative humidity (RH) outdoors in the shade, and shielded from wind (Table 1).

Table 1: Rule based on Relative humidity (RH) outdoors in the shade, and shielded from wind

Patient		>30°C + High RH	Advised not to venture outdoors	Yes	0800-2000	In proximity to patient/caregiver at home

The crisp Boolean will be:
IF (Temperature > 30°C) ***AND*** (RH>85%) ***AND*** (VENTURE_OUTDOOR) ***THEN*** GiveAdvise();

The more generic and simple Fuzzy equivalent of the same rule would be:
IF (OutdoorCondition ***IS*** Adverse) ***AND*** (ApproachingTheDoor) **THEN** Do MoveNAO(“nearby patient”); Advise(“Not venture Outdoor””) END;

The remaining acquired data should be elaborated using more sophisticated methods. For instance, the rules might postulate that the “comfortable” temperature for COPD patient is 20°C, but Mr. Smith might prefer the lower value reducing regularly the value set by HVAC. In this case it is essential to learn that the appropriate value for Mr. Smith is different one, for instance 18°C. It can be done applying the observation followed by self-learning stage. Such learning can only be done using soft computing methods.

The discovery of the long lasting trends should be also done using the analysis of the time series. The same or similar techniques of soft computing might be applied.

Certain data being acquired by KSERA will be processed by means of the learning algorithms then. Finally Decision making algorithms will be performed in order to provide the user a suitable service or action.

This section is intended to briefly describe which kind of network is considered and, therefore, which kind of data will be processed for the implementation of the learning and decision making algorithms.

3.1 KSERA ubiquitous monitoring

A large amount of data is needed to train and assess learning and decision making algorithms. Such data is provided by a complex network of sensing devices, implementing KSERA Ubiquitous monitoring system described in the deliverable about the architecture and will be developed in more detail in the D4.2. We report some details about this sub-system (Figure 4).
A system is defined as ubiquitous when it is not bound to a particular location. Examples of such systems are:

- mobile devices, like smart phones, laptops, tablets, ...
- wearable devices, incl. the multi-sensorial wearable monitoring devices (wrist watch is an example)
- implanted devices and,
- smart home sensors.

Other important features of a ubiquitous system must have are:

- context awareness and,
- decision support capabilities.

An ubiquitous system must be able to work without any human intervention and the processing device may employ middle and long-range wireless communication in order to enable the delivery of rich content and feedback between the patients and their remote carers.

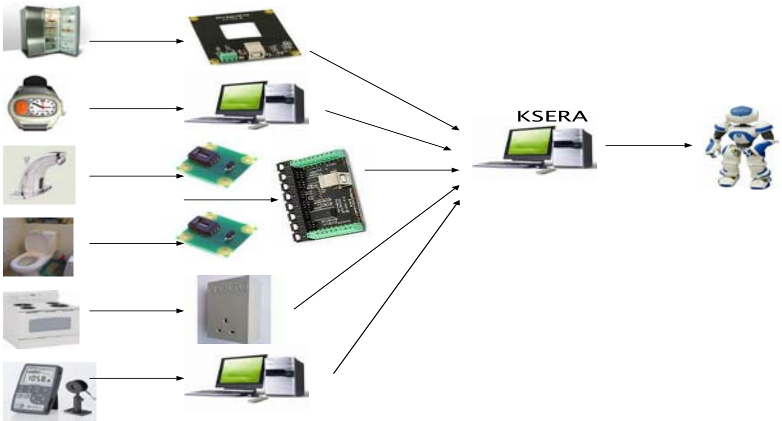

Figure 4: KSERA ubiquitous monitoring architecture

Data from such pervasive environments is used to trigger elementary alarm scenarios.
These data sources can also be used by more complex algorithms which deduce contextual information by merging and combining multi-modal data sets.

3.1.1 Ambient Assisted Living (AAL)

Some of the most common applications that an AAL system should have are:

- monitoring of vital data,
- detection of emergencies such as falls,

- prediction of an upcoming exacerbation or disease based on the monitored vital data collected by the system and,
- memory aids applications such as reminders, calendars, etc.

The core of an AAL system is a sensor network, possibly unobtrusive and easy to install. According to such requirements, wearable devices will be taken into account, integrating an emergency button, mobility detection and fall detection. Solutions like a care watch (Figure 5) are interesting because they can be directly integrated into ordinary object, thus maximizing user's acceptance and usability.

Figure 5: Example of wearable device: a care watch [19]

3.1.2 Sensor Network

A sensor network will be deployed composed of an environmental, medical and wearable system sharing some common properties like being wireless and low-power consuming.
Such sensors must be coordinated in order to achieve efficient acquisition of relevant information.
There are several classes of sensors that will be integrated into the KSERA sensor network:

- Outdoor environmental sensors: Temperature, relative humidity, windspeed, inhalable particles. Both real and "virtual" (based on web services) solutions shall be envisaged in order to maximize efficiency and minimize deployment costs.
- Indoor environmental sensors: temperature, relative humidity and air quality monitoring solutions shall be considered.
- Wearable Sensors: solutions will be envisaged, acquiring mobility, heart rate, and providing emergency call activation control.
- Medical Sensors: used irregularly or twice a day, give information about the user's health condition. ECG monitoring systems, FEV1 meters, pulse oxymeters and blood pressure monitoring systems shall be envisaged.

Such a sensor network shall be integrated with a powerful processing unit, able to run the learning and decision making algorithms, thus managing the whole AAL, by means of the actuation subsystems, such as the robot NAO and the integration within a domotic environment.

3.2 Learning user lifestyle and needs

This learning issue is focused on researching the heuristics (for instance probabilistic or fuzzy approaches) being able to extract information about the user's lifestyle and needs (Figure 6).
As a matter of facts, the information acquired by means of the ubiquitous monitoring system can be used to extract activity profiles characterizing daily habits, thus detecting abnormal behaviors and optimizing exercise tuning.

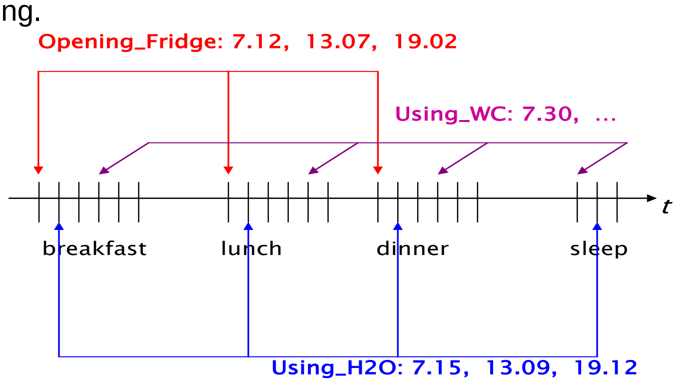

Figure 6: Sensor pulses correlated with daily activities

Such algorithms are needed to recover information, which is impossible to acquire with direct monitoring. Most real life events cannot be measured and sensed directly. In order to react

appropriately in a particular situation, indirect measures are needed to assess the events and the event chains. For example, to avoid dehydration, it is important that the seniors drink enough water during a hot summer. This involves monitoring of environmental conditions, learning user habits (how much water he/she is used to drink) and motivating through the robot NAO.
The amount of water being consumed cannot be measured directly. A possible technical workaround is the indirect measurement of the water consumption (learning user habits) and the evaluation of its consequences on the user's health status by means medical measurements.

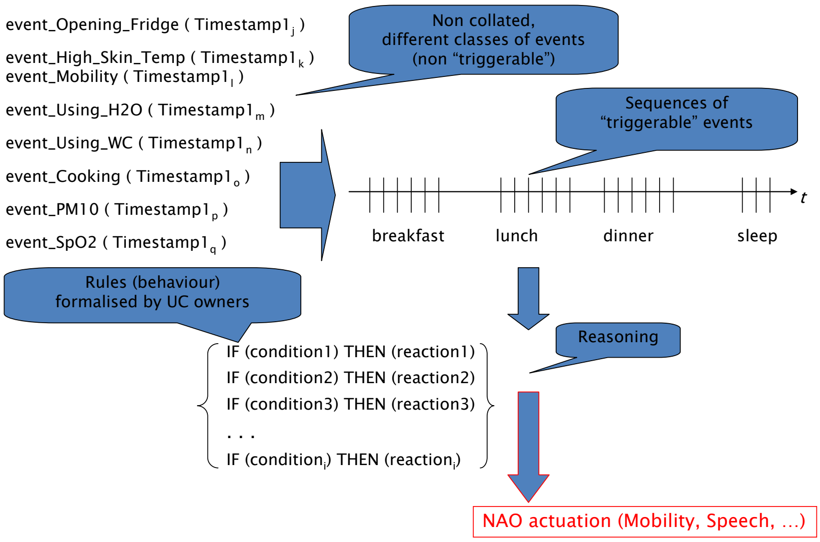

Figure 7: Decision making rules

This drives towards a system of conditional rules like IF "hot summer" AND "health status is getting worse due to dehydration" then "issue warning" (Figure 7).

In other words the KSERA approach is focused on the fusion of data from a sensor network (environmental conditions, air quality, motion detection) with deeper information about the user's habits and activities, extracted from a medium/long term database, mainly by means of soft computing methods, and specifically combining data warehousing and pattern matching techniques.

3.2.1 Advantages from merging learnt information and environmental/health status

Learning algorithms provide complementary information that integrates data from ubiquitous monitoring. It is possible to continuously monitor the user and the environment in which he/she lives, but also to detect abnormal changes in daily activities and in the ordinary monitored profiles.
Moreover such complementary information can be used to re-model the priority requirements of the decision in order to best suite the real needs of the user.

For instance, considering a potential critical environmental condition, the standard approach could be warning the user from going out. However, an additional information about different needs, for instance that the user is not going out for several days and there's a positive trend in health status, may lead to a different choice. In other words, a learning algorithm based approach is much more dynamic and prone to adaptively follow the needs of the user.

3.2.2 KSERA approach

KSERA has the capability to process the data using dedicated monitoring functions. This choice is made because KSERA can combine different modules being included incrementally in the

deployable framework, dynamically tailoring the final solution being deployed in concrete AAL conditions. From the research perspective it is also compliant with the incremental prototyping.
Let us assume the business model in which several assistive levels are offered. The cheapest one might be minimal, using the simplest monitoring functions (low cost, only direct comparisons for example). More sophisticated KSERA versions might include the advanced knowledge elicitation functions, soft computing machine learning techniques, exploiting the additional modules.

There are several approaches in implementing learning and decision making algorithms. This document, in particular chapter 4, reports the state of the art in advanced approaches like probabilistic or Fuzzy models. Such advanced solutions have been investigated and their integration into the KSERA system has been considered. Even though all these envisaged solutions can add flexibility to the system, their integration appears still complex with respect to the approach based on strict rules.

To achieve the capability to ***trigger the events*** in everyday life of COPD patients, and to face the issues which could come from the non-deterministic living environment, KSERA needs the capability to compare the series of data and to take the decisions by learning the rules, not known a-priori. For these reasons the KSERA approach will be based on:

- Direct matching of single measurements with fixed thresholds. Crisp and Fuzzy categories comparison will be used.
- Pattern matching of multiple simultaneous measurements by means of “if – then - else” based rules
- Pattern matching of multiple non-simultaneous measurements – or timed series - using pattern matching and data warehousing techniques
- Analysis of the stored acquired measurements in order to detect trends and changes using data warehousing approach.
- Analysis of the appropriateness of the values set by rules for the classes comparing the instances recorded in the real life conditions using observational study and self-learning techniques.

4 KSERA: Learning and decision making algorithms

In this chapter state of the art approaches are considered coping with two main issues: learning information by processing all the acquired data and using such information in order to perform the most suitable action. Considering the first task different approaches are analyzed. In the literature solutions and approaches are available based on probabilistic models [4], fuzzy techniques [2] or hybrid solutions.
Concerning the second issue, different classes of decision making algorithms are considered, from a complexity point of view, starting from instantaneous triggering approaches to more complex solutions based on approaches available in literature.

4.1 State of the art in learning algorithms

KSERA system uses algorithms that allow the main server to ***understand*** and evolve the ***user behaviour***. KSERA uses empirical data, such as the data coming from KSERA sensors and KSERA database. The learning system takes advantage of the examples (data) to capture characteristics of their unknown underlying probability distribution. Data can be seen as examples that illustrate relationships between observed variables. It brings in the machine-learning domain. A major focus of machine learning research is to automatically learn to recognize complex patterns and make intelligent decisions based on data.

The main difficulty lies in the fact that the set of all possible behaviours - given all possible inputs - is too large to be covered by the set of observed examples (training data). Hence the learning system must generalize from the given examples, so as to be able to produce a useful output in new cases.
The approaches useful in this context are first of all statistics, data mining, pattern recognition, data warehousing, adaptive control, and some other techniques. Machine learning algorithms are typically taxonomy-organized, based on the desired outcome of the algorithm.

Soft computing in general is a collection of methodologies to apply synergistically in order to obtain flexible information processing means to ***handle real-life ambiguous situations***. Unlike conventional ***hard computing***, soft computiing exploits the tolerance for imprecision, uncertainty, approximate reasoning, and partial truth categories in order to achieve robustness, low cost, and human-like decision-making. Soft computing components are: Fuzzy Logic, Artificial Neural Networks, Evolutionary Algorithms (including Genetic Algorithms), Genetic Programming, Evolutionary Strategies, Support Vector Machines, Wavelets, Rough Sets, Simulated Annealing, Swarm Optimization, Memetic Algorithms, Ant Colony Optimization, Tabu Search, and some others.

Among the learning techniques, there are

- Decision tree learning; it uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value. Decision trees are commonly used in robotic environments.
- Association rule learning; it is a method for discovering interesting relations between variables in large databases. The non-deterministic environments are likely producing the large datasets.
- Artificial neural network (ANN); it is a mathematical model or computational model to simulate how biological neural networks work. Using an interconnected group of artificial neurons, it processes information in a non-linear manner. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. This technique is similar to the natural cognition.
- Genetic programming (GP); it is a methodology inspired by biological evolution to find computer programs that perform a user-defined task. Each individual is a computer

program. Machine learning technique optimizes a population of computer programs according to a fitness landscape determined by a program's ability to perform a given computational task. Has a strong optimisation potential to find a solution which appears invisible, e.g. gives the capability to discover hidden patterns.

- Cluster analysis; it is the assignment of a set of observations into subsets or similarity clusters. Clustering is a method of unsupervised learning, and a common technique for statistical data analysis. In the context of nomothetic events in AAL it might bring benefits.
- Bayesian networks; Directed Acyclic Graphical (DAG) model is a probabilistic graphical model to represent a set of random variables and their conditional independencies. In telemedicine domain Bayesian networks are useful because could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. Efficient algorithms exist that perform inference and learning.

In KSERA ***events*** are recorded using the internal sensing capabilities (Ubiquitous Monitoring sub-system) and made persistent in KSERA database. This results in an ***event flow***, which is defined as:

$E(t_i) = \{E_1(t_i), E_2(t_i), \ldots, E_i(t_i), \ldots\}$ events might happen simultaneously giving a “snapshot”
$E'(t) = \{E(t_0), E(t_1), E(t_2), \ldots, E(t_i), \ldots, E(t_{i+k}), \ldots\}$ history of events, event flow, sequence of events

Each element $E_i(t_i)$ is an event in the event space. Each $E(t_i)$ is a set. The $E'(t)$ is a collection of sets. We can use the term “string” to indicate the sequence of events.

The event flow stored in database is the multi-dimensional ***dataset***, which should be processed against the known a-priori heuristics, or those not yet known revealing the conditions of “normality”, “abnormality”, “disease progression”, “exacerbation of disease”, “danger”, and similar categories.
Certain categories should be recognized and triggered by KSERA because of the triggering rules set for the Telemedicine or Ambient Assisted Living purposes.

In human live there are many repetitive events: eating, sleeping, walking, taking medicine, and many others, all of which happen at a certain frequency. These frequencies typically vary over time as well, which might be known or not known a-priori. In normal healthy circumstances there should be at least three daily events “having meals”, but there should not be events like “taking pills”. The above knowledge might be encoded in some way to be used by the system.

Being “digitized” by a collection of the various classes of sensors, the above sequence might show the nomothetic events, such as “preparing meals”, “having meals”, “taking pills”, “doing something” etc., e.g. it might happen that two ***sets*** (or ***sub-sets***) are identical or repetitive:

$$E'(t_i) = E'(t_k),$$

or it might happen that certain ***elements of the set*** are repetitive:

$$E_i(t_i) = E_i(t_{i+k}).$$

This discussion sheds some light on algorithms that are of interest to KSERA. The following are currently considered the most important algorithmic trends:
1. Finding similarities among sequences (such as “meals”, “walking”).
2. Detecting certain patterns within sequences (such as “breakfast”, “taking pills”).
3. Finding similarities among parts of temporal sequences (such as repetitions, nomothtics, motifs).

4. Constructing trees (expressing the evolution of days with their daily activities whose are currently known).
5. Classifying new data according to previously clustered sets of annotated data.
6. Reasoning about microarray data and the corresponding behavior of pathways.

The first three trends can be viewed as instances of pattern matching. The pattern itself may not be exactly known, because it may involve inserted, deleted, or replacement events.

Regular expressions are useful for specifying a multitude of patterns in AAL. KSERA need is to be able to infer these regular expressions from typical sequences and establish the likelihood of the patterns being detected in new sequences.

Multiple alignments is an useful technique, which helps align several sequences of events, so identical events become properly lined up vertically, with gaps allowed within events.
The sequences may represent variants of the behaviour in various AAL scenario. The goal is to find conserved parts of the pattern that remain unchanged along the time. Finding conserved behavioural parts also provides hints about a normal or abnormal behaviour.

Classification and machine learning are used to sort out new data based on a human-annotated set of examples. Among the machine learning (soft computing) techniques applied to ALL are the ubiquitous Hidden Markov Models, which are essentially probabilistic finite-state machines that use computed branching probabilities from a learning set and that establish the likelihood that a new string is processed through certain states with pre-established properties.

The AAL data collected from the non-deterministic environments, such as residential homes, is vast and noisy, calling for new heuristic based techniques (such as Bayesian nets, SVM, Fuzzy logic and evolutionary algorithms). KSERA is the first attempt to apply the cognitive system to AAL in COPD case. The additional difficulty is that the information about the relationships among events in COPD living are tacit. In the current state-of-the-art there are no references in the literature about the attempts to conceptualise the above disease, its progression and the implication on the daily life, useful to program the robot from scratch. There is the ample information about other AAL sub-domains instead.

Data processing techniques are applied to the information gathered by means of the available environmental, wearable and medical sensors. It is possible to apply learning algorithms in order to recognize users daily activities, to characterize their common patterns and finally to detect activities performed by the user. This section is intended to describe the state of the art approaches in this research field, which represent the KSERA starting point.

In the current state of the art there are several options in implementing decision making options in software. An overview of recent applications is contained in [29].
Another collection is available in [30].

4.1.1 Learning Activities of Daily Living

Daily living brings a ***collection of events*** coming from the non-deterministic environment, with little chances to apply the crisp rules because of the complexity. The medical knowledge about COPD is tacit and typically Fuzzy. There are many reasons to sustain the application of the soft computing approaches to AAL practice in general and specifically to KSERA.

1. Traditionally, an expert system is built by eliciting knowledge from domain experts (medical knowledge about COPD in KSERA). The experts state what factors they use to assess relevant situations (D1.2). However, KSERA experts are imprecise about the rules they use for COPD disease analysis and control. This problem can be resolved by soft computing

mechanisms because they are capable of extracting the description of the hidden situation in terms of those factors and then elicit the rules replicating the expert's behavior.
2. Real life systems often produce results, which are very different from the desired ones. It happens because of unknown properties, functions of inputs, or other factors set during the static design of the system. This situation always occurs in the Health/AAL domain because of the complexity and non-deterministic real-life conditions. Bringing the dynamic improvement capability, soft computing brings a solution of the above problem.
3. In AAL context, because of the real life complexity, new data (unforeseen in the static model) and situations will be generated every day, and those new data will unavoidably update or replace the old known instances. Soft computing adapts to a changing environment. The above features brings an invariant solution, keeping the validity even when environment changes.
4. Incomplete, missing, or data with the noise is the real life operational condition. The conventional hard computing technique fails to handle it. Soft computing keeps the capacity to deal with missing and noisy data.
5. In real life, huge volumes of data and events are generated. In addition, the important hidden relationships and correlations we are not aware about because of the complexity exist in the data. Soft computing handles very large data sets, and can be used to extract such relationships.

Recognizing the activities performed in a monitored environment, for instance an apartment or a house is an approach widely used within the healthcare domain. The common activities that people tend to do every day, such as eating, bathing and toileting are considered as activities of daily living (ADLs). The activity recognition task typically is faced by processing data from simple sensors deployed inside the user's house.
Through these data sources it is possible to build a person's daily activity model. Such model is used by the system in order to generate signals according to specific alarm scenarios.

To achieve this task, processing techniques based on well known probabilistic models are usually employed, such as Bayesian statistics and Markov chain and hidden Markov Chain models.

Considering the use of the robotic artifact to actuate the feedback delivery, the state machine (ROS) is already one architectural component in the project middleware, suggesting paying better attention to the use of the above modeling of the events happening in the daily life of COPD patients.

4.1.2 Activity pattern discovery

Instead of focusing on a specific activity recognition, it is possible to consider patterns recognition (Figure 8). In this way, the insights that pattern analysis can provide are taken into account.
The human activity is a sequence of actions over space and time. Moreover, humans tend to have a daily cycle and in particular older people living alone tend to have a set of daily routines.
As a consequence, it is possible to predict an activity and, consequently prepare the suitable aid action (performed, for instance, using the robot), or to detect an unusual or abnormal activity and alert family or medical personnel.

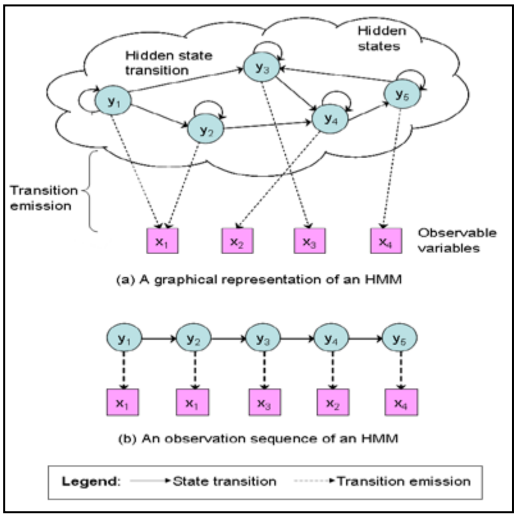

Figure 8: Activity pattern discovery [4]

Some of the most used approaches available in literature are based on probabilistic models. A detailed analysis of such approaches is available in [4], where solutions are considered, such as:

- Hidden Markov Model,
- Conditional Random Field,
- Skip Chain Conditional Random Field and,
- Emerging patterns.

Authors in [4] give the references for the probabilistic model approaches. The following sections summarizes some of these approaches for convenience.

4.1.2.1 The Hidden Markov Model

Complex activities are difficult to model. An interesting approach is based on the observation of signals from such complex activities. Then a model can be built upon these observations. This approach is called Hidden Markov Model (HMM). The activity model is defined by the observations of the effects of an activity, and then gradually tuned and reused.

As stated in [4], the HMM approach consists in determining the hidden state sequence ($y_1, y_2, \ldots y_t$) that corresponds to the observed output sequence ($x_1, x_2 \ldots, x_t$). As an example in Figure 8 a graphical representation of an HMM is shown, characterized by 5 hidden states and 4 observable variables.

HMM relies on two assumptions:

- The hidden variable at time t, y_t, depends only on the previous hidden variable y_{t-1}.
- The observable variable at time t, x_t, depends only on the current hidden state y_t. In other words, the probability of observing x while in hidden state y is independent of all other observable variables and past states.

Activities are considered as the hidden states and observable output is sensor data. The most probable hidden state sequence from an observed output sequence, is estimated by looking for the state sequence which maximizes a joint probability p(x,y) of the transition probability between state y_{t-1} and y_t and the observation probability, that is the probability that x_t is observed in state y_t.
The following picture (Figure 9) is an example of HMM for eating activity

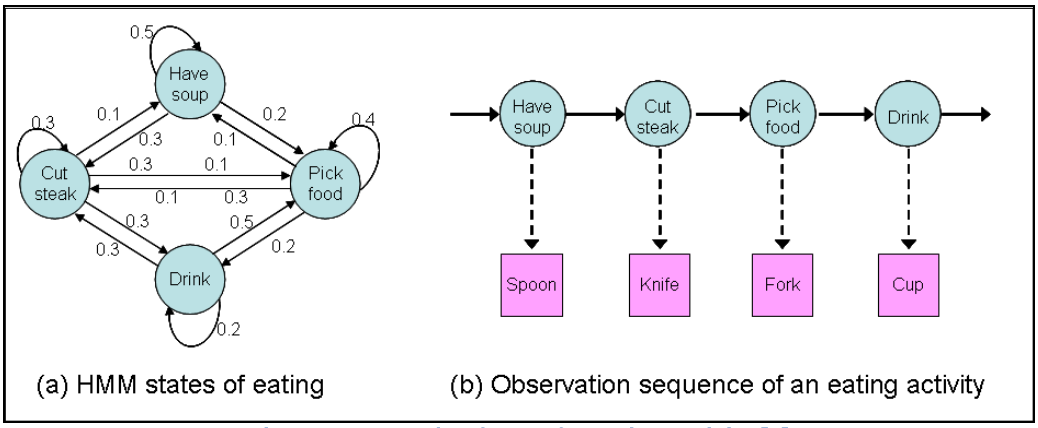

Figure 9: Example of HMM for eating activity [4]

4.1.2.2 The Conditional Random Field (CRF)

HMM approach has serious limitations, in particular when coping with interacting or concurrent activities. This is because of the very strict independence assumptions on the observations. A more flexible approach is called conditional random field (CRF).
CRF is defined as “a discriminative and generative probabilistic model for the dependence of a hidden variable y on an observed variable x”, as stated in [4].

Both HMM and CRF are used to find a hidden state transition from observation sequences. However, instead of finding a joint probability distribution p(x,y), the CRF approach attempts to find only the conditional probability p(y|x). In other words, CRF allows non-independent relationships among the observation sequences, hence adding flexibility and relaxing the independence assumptions.
A CRF is modeled as an undirected acyclic graph, able to model the relations between an observation variable and a hidden state. The following picture (Figure 10) shows the CRF equivalent of the eating activity already considered in the HMM description.

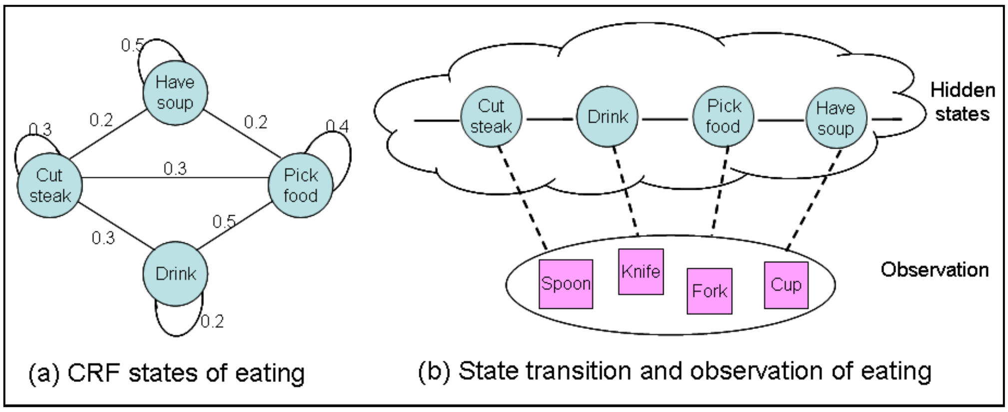

Figure 10: CRF equivalent of the eating activity [4]

A more detailed analytical description of the CRF approach is available in [4].

4.1.2.3 The Skip Chain Conditional Random Field (SCCRF)

Both CRFs and HMMs approaches share the limitation of being suitable only for activities that are sequential in nature. To model concurrent and interleaved sub-activities, more sophisticated functions are needed, such as Skip Chain CRF (SCCRF). A Skip Chain is essentially a Linear Chain with a larger distance between two variables. From a mathematical point of view, they may be defined as products of multiple Linear Chains.

4.1.2.4 Emerging Patterns

This approach consists in defining feature vectors, called emerging pattern (EP), which describe significant changes between two classes of data. Considering several observed instances, each having a set of attributes and their corresponding values, some of them may be associated to a particular class more than the others. For example observations related to “motion activities in the kitchen” and “burner on” may be related to the class “cooking activities”.
To find these attributes, “support” and “growth rate” functions are computed for every attribute X. The analytical description is again found in [4].

4.1.3 Human Activity Recognition

Most used architectures rely on sensors placed at well-defined locations or wearable sensors allowing a continuous recording of human activities. Recognizing human activities based on sensor readings can capture many useful low-level features of human users, their living environments and human-to-environment interactions. Data received from the sensor network can be used to detect variability and trends, rather than acquire absolute values. In such way caregivers can capture events, which are very difficult for the patients to report. Data collected through these technologies could increase the likelihood of early detection of an illness.

Almost all such works focus mainly on recognition of a single-user activity. However in real life, activities are often performed with the interaction of more users. Most of the existing work on multi-user activity recognition only used video data. The reason is that it is rather hard to determine hidden parameters of HMMs in the case of multimodal group action or activity recognition, where features from each model are concatenated to define the observation mode
Some studies propose advanced probabilistic models, often derived from HMM, able to recognize multi-user activity recognition from sensor readings in a smart home environment, such as Coupled Hidden Markov Model (CHMM).

Another interesting approach is based on a Fuzzy Bayesian network. Examples are available in literature, showing that it is more efficient than the discrete model when using continuous data for recognizing the user's activity.

Motion detection sensors or cameras can collect log data about the user's activities in an abstract way, and require large computational complexity.
Other sensors may be employed like accelerometers or physiological sensors, like for instance, the Meijer approach [15], the Ravi approach [16] and the Parkka solution [17].

A Fuzzy logic has advantages to represent continuous data in symbolic states for preprocessing, and a Fuzzy Bayesian network, which is compromised with the preprocessed fuzzy data, may solve the problem between ambiguous measurements.

With the restriction on the number of patients living in the home - in KSERA we assume one patient only - the field might be restricted. The sensors used for the measurements carry also some semantic information about the class of sensor, the operational conditions, and the time. In these conditions an Artificial Neural Network (ANN) can be applied because it is able to capture and represent complex input-output relationships. The motivation for the development of the ANN technique comes from the desire for KSERA that information is processed in ways similar to the human brain.

4.1.4 Fuzzy Rule Based Prediction

Fuzzy logic technique can be used to implement simple, small, embedded systems up to large networked ones. It can be implemented in either software or hardware. Fuzzy logic uses a simple and easy way in order to get the output(s) from the input(s). The outputs are related to the inputs using IF - THEN statements giving the easy readability of this technique. Fuzzy logic respects the uncertainty, which is normal in real life.
The realistic inputs in AAL bring uncertainty, which is transformed by Fuzzy Logic in precise outputs enabling the triggering of real life events by KSERA. Fuzzy Logic really simplifies complex systems which will make KSERA cheaper: Fuzzy Logic reduces the design steps and simplifies complexity that might arise since the first step is to understand and characterize the system behavior by using existing knowledge and experience.

A predictive ambient intelligence environment is intended to "predict the next state of consecutive interactions with the use of the knowledge it has learnt from previously observed interactions" [2]. For instance, it can predict the favorite light intensity of different occupants in a specific area of the environment at a specific time of a day.
The key challenge of predictive ambient intelligence environments is a learning problem in distributed sensor networks. Prediction consists of extracting patterns in order to identify sequences of actions, and then matching such sequences in order to predict the next action.

4.1.4.1 Reinforcement learning

The approach called “reinforcement learning” [2] is a method to estimate the relation between input and output with a “trial and error” approach. A “reinforcement signal” function must be maximized. When the difference between input and target is significant, a “punishment” is applied decreasing the value of the reinforcement signal. On the other hand, when input and target signal are quite similar, a “reward” is applied; increasing the value of the reinforcement signal.

In its fuzzy version (Figure 11), “knowledge is represented by fuzzy rules and the learning process is an unsupervised algorithm” [2]. The learning process consists of sampling, inputs from sensors and transforming the samples to fuzzy sets in a “fuzzification” phase. Then the fuzzy inputs with stored fuzzy rules are compared and the reinforcement learning is applied. Any significant difference between fuzzy inputs and stored fuzzy rules is considered as a punishment. On the other hand, a slight difference between fuzzy inputs and fuzzy rule is a reward to the fuzzy rule

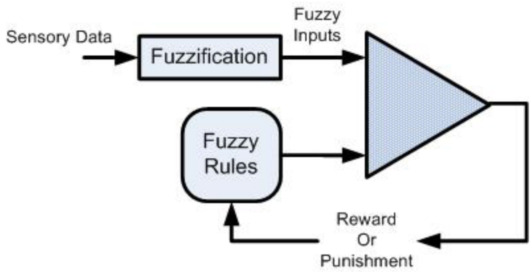

Figure 11: Fuzzy rules based reinforcement learning [2]

For example, assuming that a rule states that “If time is 8pm and John is in the dining room, then set the light intensity to 8”, and the system recognizes that John is in the dining room at 8pm but the light intensity is set to 4, the application of the reinforcement learning leads to give a significant punishment to the stored rule.
The most significant advantage of fuzzy rule-based learning is the reduction of raw data by applying the fuzzification mechanism.

4.1.4.2 Fuzzy approach: prediction techniques

Stochastic models and dynamic-based techniques are classical techniques which are found to underperform in predicting the behavior in complex systems. Alternative approaches have been investigated using computational intelligence techniques such as Neural Networks, Neuro-Fuzzy and Evolutionary Fuzzy Systems.
The goal of the prediction task is to use past values of time series to the time t to predict the values at some point in the future $(t + \delta)$.

To minimize the difference between the predicted time series and actual time series, the error generated from all data must be minimized. The mean square error function (Eq. 1) is the classical approach for the minimization of the prediction error.

$$E(\Theta) = \frac{1}{2}\sum_{k=1}^{s}\left(x(t+\delta) - \hat{x}(t+\delta)\right)^2 \qquad \textbf{Eq. 1}$$

Now the main problem widely discussed in the literature is related to the application of the steepest descent technique in fuzzy inference systems. It is reasonable to take large steps down the gradient at locations where the gradient is small and small steps where the gradient is large [2]. If the second derivatives are used, then the error will be minimized faster and more accurately.
The gradient descent is too slow for real-time adaptation. A solution available in literature to increase the speed is the Levenberg-Marquardt (LM) learning mechanism.

4.1.4.3 Fuzzy approach application

Examples are available in literature in which such fuzzy approaches are employed in learning and predicting the rooms’ occupancy in a smart home environment. In this case the data source is represented by a network of PIR sensors deployed all over the monitored area. The output from the sensor is then processed in the form of a linear combination and feeds the fuzzy engine. The output may be used to drive the light system or to manage any actuation subsystem related to the occupancy of the user in the monitored area.

4.1.4.4 Genetic programming

Genetic algorithms [31] gives a technology biologically inspired observing the evolution. It is a randomized search and optimization technique guided by the principles of evolution and natural genetics, which are notably efficient, adaptive, and robust search processes, producing near-optimal solutions. GA have a good implicit parallelism. Therefore, the application of GA appears to be appropriate and natural. The errors generated in experiments can be handled with the robust characteristics of GA. GA are executed iteratively on a set of coded solutions, called population, with three main operators: selection, crossover, and mutation. They use only the objective function information and probabilistic transition rules for moving to the next iteration. Of all the evolutionarily inspired approaches, the GA is the simplest one, capable to release the readable set of rules understandable by human being, those perfectly usable in the decision support systems because explicitely showing the triggering rules. This is because GA are generally based on manipulating populations of ***bit-strings*** (events in our context) using both crossover and point-wise mutation.

4.2 Decision making algorithms

A large amount of data is collected in KSERA by means of the ubiquitous monitoring system, both fixed sensors and wearable ones, and medical devices. Data processing is performed and new information is acquired also by means of the employed learning algorithms. Finally, "decision making algorithms" are used in order to assess actions performed by the system by means of its actuation components.
The capability to assess the situations and analyse the data is offered by dedicated monitoring functions, which are implemented and called on-demand basis.
Different monitoring functions will implement the different techniques accordingly the needed features and the capabilities.

A first, the simplest, class of decision making algorithms is represented by immediate triggering of values. It is not necessarily requiring any soft computing (learning) capability.
Besides, more and more complex algorithms are considered, depending on the rules stated in D1.2. There are dedicated functions dealing with the "snapshots", the aggregated series coming from the same time slot, and the series along the time bringing the changing trends and triggerable patterns, if any.
The following section is intended to scout among implementable solutions.

4.2.1 Immediate triggering

Some kinds of actions have to be decided and performed on direct request, either by the user (an emergency button use to summon rescue calls) or by the system by means of automatic alarm scenarios, based on data check compliant with "a priori" defined rules. Several examples of those are reported in KSERA D1.2 document.

4.2.1.1 Emergency calls

Emergency calls have to be summoned (to the remote care centre) right after the triggering the relevant event, which can be detected manually pushing the alarm button or automatically by the cognitive system triggering the "dangerous" conditions or events. Such event may be either the activation of an emergency button, or the detection of a critical event, such as fall detection. An example is depicted as follows (Figure 12):

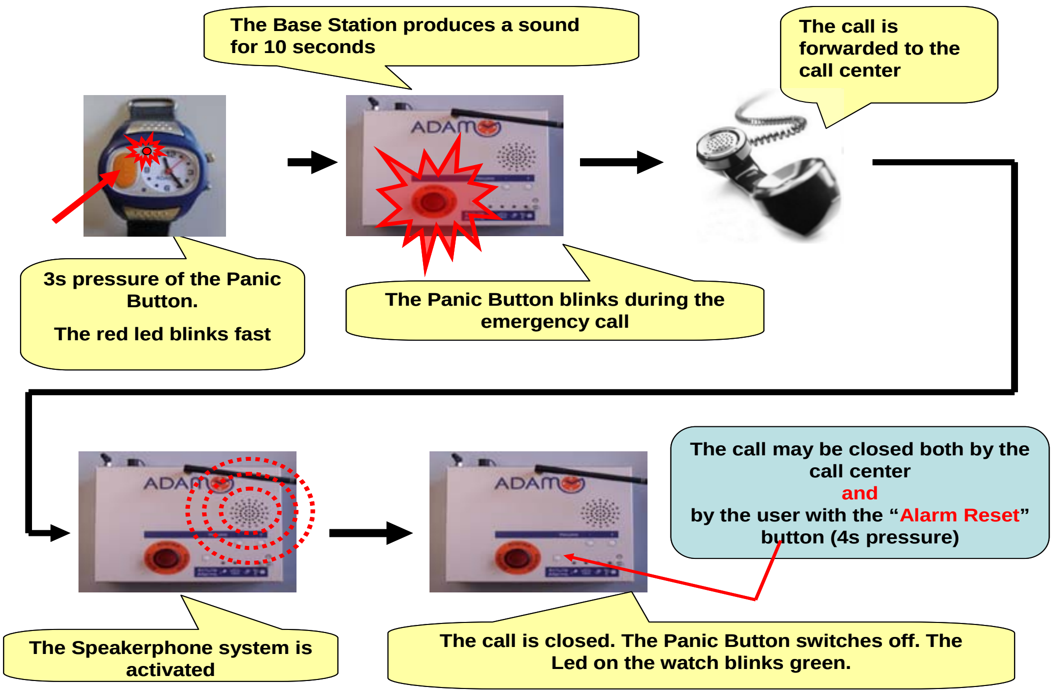

Figure 12: Emergency call flow diagram

Right after the triggering event (an emergency button has been pushed on a wearable device), the system starts a series of routines aimed to transfer the alarm notification to an operational center (for instance a medical centre), activates a speakerphone system and let the remote operator talk directly to the user, in order to assess the actual level of emergency and perform the most suitable actions.

The enumeration of the cases implying the "emergency" call to the call centre being performed in KSERA is specified in D1.2 (rules for ubiquitous monitoring).

4.2.1.2 Fall detection

Fall detection is one of the cases in which the alarm is raised in ALL systems.
Fall detection algorithms are mainly based on the principles of acceleration change characteristics during the process of a human body falling. According to this approach [4] the process is divided into 4 successive phases (Figure 13):

- weightlessness,
- impact,
- inactivity and,
- difference to initial status.

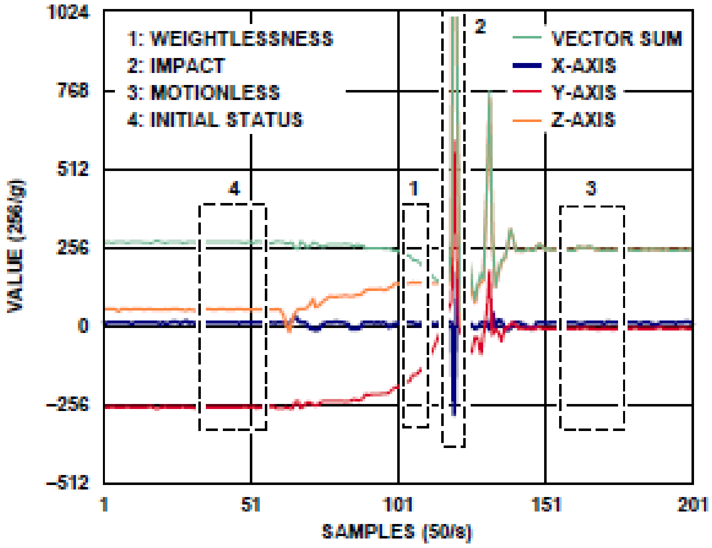

Figure 13:Human body fall process [18]

Weightlessness is a phenomenon, which always occurs at the start of a fall. Even though weightlessness during an ordinary fall is not as significant as that during a free-fall, during this phase the vector sum of acceleration is also less than 1 *g* (while generally, under normal conditions is greater than 1 *g*). Therefore, this could the first basis for detecting a fall.

After experiencing weightlessness, the human body impacts at the ground; the acceleration curve shows this as a large impulsive shock. This is the most easily detectable element for determining a fall status.

Generally, after falling and impacting, the human body cannot rise immediately, but it remains in a motionless position for a short period. This is shown on the acceleration curve as a segment of a flat line and can be detected as an inactivity interval. This is the third basis for determining a fall situation.

After a fall, the human body turns over, so the acceleration in three axes is different from the initial status before the fall. Therefore, the fourth basis for determining a fall may be monitoring if the difference between sampling data and initial status exceeds a certain threshold (for instance 0.7 *g).*

The combination of these four bases of determination form the entire fall detection algorithm, and then the system can raise an alert accordingly for the fall status.

The ideal position for a wearable device aimed to fall detection is a barycentric location, for instance on a belt.
Object like a watch are subjected to continuous motion, thus are not the most suitable device. However they have some advantages:

- they are experienced by the user (mainly elderly people) as ordinary objects and the refusal is minimal. This psychological aspect is very important since the detection device is useless if refused by the user and consequently not worn.
- A watch is easily reachable to summon an alarm via a dedicated button if a fall happens but is not recognized.

Finally there's an energetic aspect that must be taken into account. A trade-off must be found between algorithm performances and computational charge for the monitoring device, in order to optimize not only the complexity onboard, but power saving as well, thus avoiding batteries consumption.

4.2.1.3 Critical medical measurement result

Medical measurements have to be taken periodically more than once a day by the user. After each acquisition, the measurements value is checked accordingly to a set of medical rules. If a critical value is detected, an action has to be performed, such as an emergency call or a more precise monitoring, accordingly to the actual degree of severity.
In KSERA, the monitoring rules set by D1.2 are enumerating all the cases in which the system will react.

Also the environmental monitoring could be managed in a similar way. Medical rules involve environmental conditions too, for instance the air quality. Compliantly to such rules and to the actual environmental condition actions, the system has to perform the most suitable action.
The same deliverable D1.2 lists the above cases.

4.2.1.4 Daily activities

Some activities have to be performed daily by the user, such as taking medical measurements or performing training exercise. The KSERA monitoring function will be set up to give the ability to detect missing activities. For instance, a check on the timestamp of each recorded medical measurement provides an instrument to detect a missing medical measurement.
Such events can be used to perform a "motivation" action towards the user.

4.2.2 Medium term history analysis

Immediate triggering can be used only in critical situations or when missing activities are detected. There are many situations that have to be managed in an AAL that do not necessarily require an instantaneous action, but may lead to a deeper analysis on the acquired data history.
This class of algorithms is more complex than just a threshold comparison, and involves the computation of monitoring parameters dependant on a medium term acquisition and on a heterogeneous set of data. That is applying data warehousing tecniques, trying to extract information from the stored history of acquired measurements

4.2.2.1 Check health status

Data from medical devices can be used to track the health status of the user. While instantaneous triggering is used whenever a critical situation is detected, slight changes in medical measurements (O2 saturation, blood pressure, heart rate) could be monitored and could lead to an action only if suspect, but not critical conditions persist along a period of time.

4.2.2.2 Check environmental status

Changes in environmental condition could be monitored as well and lead to an action if uncomfortable conditions persist over a certain period of time.
This can be done considering air quality markers, for instance O_2, O_3, CO, CO_2, NO_2 or estimating relative humidity and temperature.
Merging such data, t is possible to compute several monitoring parameters that can be tracked. For instance, e well know approach in monitoring thermal condition is the Steadman table (Figure 14), used to merge temperature and relative humidity values in order to compute the apparent temperature, that is an index invented in the late 1970s, designed to measure thermal sensation in indoor conditions.

Apparent temperature (AT) from temperature and relative humidity - after Steadman 1994

Relative Humidity (%) \ Temperature (°C)	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
0	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46
5	16	17	18	19	20	21	22	23	24	25	26	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	44	45	46	47	48
10	17	18	19	20	21	22	23	24	25	26	27	28	29	31	32	33	34	35	36	37	38	39	41	42	43	44	45	46	48	49	50
15	17	18	19	20	21	22	24	25	26	27	28	29	30	31	33	34	35	36	37	38	40	41	42	43	45	46	47	48	50		
20	17	18	20	21	22	23	24	25	26	28	29	30	31	32	33	35	36	37	38	40	41	42	43	45	46	47	49	50			
25	18	19	20	21	22	24	25	26	27	28	29	31	32	33	34	36	37	38	40	41	42	44	45	46	48	49					
30	18	19	21	22	23	24	25	26	28	29	30	31	33	34	35	37	38	39	41	42	43	45	46	48	49						
35	19	20	21	22	23	25	26	27	28	30	31	32	34	35	36	38	39	40	42	43	45	46	48	49							
40	19	20	21	23	24	25	26	28	29	30	32	33	34	36	37	39	40	41	43	44	46	48	49								
45	19	21	22	23	24	26	27	28	30	31	32	34	35	37	38	40	41	43	44	46	47	49									
50	20	21	22	24	25	26	28	29	30	32	33	35	36	38	39	41	42	44	45	47	49	50									
55	20	22	23	24	25	27	28	30	31	32	34	35	37	38	40	42	43	45	46	48	50										
60	21	22	23	25	26	27	29	30	32	33	35	36	38	39	41	42	44	46	48	49											
65	21	22	24	25	27	28	29	31	32	34	35	37	39	40	42	43	45	47	49				AT above 50°C								
70	21	23	24	26	27	28	30	31	33	35	36	38	39	41	43	44	46	48	50												
75	22	23	25	26	28	29	31	32	34	35	37	38	40	42	44	45	47	49													
80	22	24	25	27	28	30	31	33	34	36	38	39	41	43	45	46	48	50													
85	23	24	26	27	29	30	32	33	35	37	38	40	42	44	45	47	49														
90	23	25	26	28	29	31	32	34	36	37	39	41	43	45	46	48	50														
95	23	25	26	28	30	31	33	35	36	38	40	42	43	45	47	49															
100	24	25	27	29	30	32	33	35	37	39	41	42	44	46	48	50															

Figure 14: Steadman table for apparent temperature computing [24]

Besides, information about wind speed can be used to assess outdoor thermal conditions and detecting uncomfortable or disease condition, computing a wind chill index (Figure 15).

Apparent temperature (AT) as a Wind Chill - after Steadman 1994

Wind Speed (km/h) \ Temperature (°C)	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	-8	-7	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6	8	9	10	11	12	14	15	16	17	19	20	21
2	-9	-8	-6	-5	-4	-3	-2	-1	0	1	2	4	5	6	7	8	10	11	12	13	15	16	17	18	20	21
4	-9	-8	-7	-6	-5	-4	-2	-1	0	1	2	3	4	6	7	8	9	10	12	13	14	15	17	18	19	21
6	-9	-8	-7	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6	8	9	10	11	12	14	15	16	18	19	20
8	-10	-9	-8	-7	-5	-4	-3	-2	-1	0	1	2	4	5	6	7	8	10	11	12	13	15	16	17	19	20
10	-10	-9	-8	-7	-6	-5	-4	-2	-1	0	1	2	3	4	6	7	8	9	10	12	13	14	16	17	18	20
12	-11	-9	-8	-7	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6	8	9	10	11	13	14	15	16	18	19
14	-11	-10	-9	-8	-7	-5	-4	-3	-2	-1	0	1	2	4	5	6	7	8	10	11	12	13	15	16	17	19
16	-11	-10	-9	-8	-7	-6	-5	-4	-3	-1	0	1	2	3	4	6	7	8	9	11	12	13	14	16	17	18
18	-12	-11	-10	-8	-7	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6	8	9	10	11	13	14	15	17	18
20	-12	-11	-10	-9	-8	-7	-6	-4	-3	-2	-1	0	1	2	4	5	6	7	9	10	11	12	14	15	16	18
22	-13	-11	-10	-9	-8	-7	-6	-5	-4	-3	-1	0	1	2	3	4	6	7	8	9	11	12	13	15	16	17
24	-13	-12	-11	-10	-9	-7	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6	8	9	10	12	13	14	15	17
26	-13	-12	-11	-10	-9	-8	-7	-6	-4	-3	-2	-1	0	1	2	4	5	6	7	9	10	11	12	14	15	16
28	-14	-13	-12	-10	-9	-8	-7	-6	-5	-4	-3	-1	0	1	2	3	5	6	7	8	9	11	12	13	15	16
30	-14	-13	-12	-11	-10	-9	-7	-6	-5	-4	-3	-2	-1	1	2	3	4	5	7	8	9	10	12	13	14	16
32	-14	-13	-12	-11	-10	-9	-8	-7	-6	-4	-3	-2	-1	0	1	3	4	5	6	7	9	10	11	13	14	15
34	-15	-14	-13	-12	-10	-9	-8	-7	-6	-5	-4	-3	-1	0	1	2	3	5	6	7	8	10	11	12	13	15
36	-15	-14	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	-1	1	2	3	4	5	7	8	9	10	12	13	14
38	-16	-15	-13	-12	-11	-10	-9	-8	-7	-6	-5	-3	-2	-1	0	1	3	4	5	6	8	9	10	11	13	14
40	-16	-15	-14	-13	-12	-11	-9	-8	-7	-6	-5	-4	-3	-1	0	1	2	3	5	6	7	8	10	11	12	14
42	-16	-15	-14	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	-1	1	2	3	4	5	7	8	9	11	12	13
44	-17	-16	-15	-14	-12	-11	-10	-9	-8	-7	-6	-5	-3	-2	-1	0	1	3	4	5	6	8	9	10	12	13
46	-17	-16	-15	-14	-13	-12	-11	-9	-8	-7	-6	-5	-4	-3	-1	0	1	2	3	5	6	7	9	10	11	13
48	-18	-16	-15	-14	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	-1	1	2	3	4	6	7	8	9	11	12
50	-18	-17	-16	-15	-14	-12	-11	-10	-9	-8	-7	-6	-5	-3	-2	-1	0	1	3	4	5	6	8	9	10	12
52	-18	-17	-16	-15	-14	-13	-12	-11	-10	-8	-7	-6	-5	-4	-3	-1	0	1	2	4	5	6	7	9	10	11
54	-19	-18	-17	-15	-14	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	-1	1	2	3	4	6	7	8	10	11
56	-19	-18	-17	-16	-15	-14	-13	-11	-10	-9	-8	-7	-6	-5	-3	-2	-1	0	2	3	4	5	7	8	9	11
58	-20	-18	-17	-16	-15	-14	-13	-12	-11	-10	-8	-7	-6	-5	-4	-3	-1	0	1	2	4	5	6	8	9	10
60	-20	-19	-18	-17	-16	-14	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	-1	1	2	3	5	6	7	8	10
62	-20	-19	-18	-17	-16	-15	-14	-13	-11	-10	-9	-8	-7	-6	-5	-3	-2	-1	0	2	3	4	5	7	8	9
64	-21	-20	-19	-17	-16	-15	-14	-13	-12	-11	-10	-8	-7	-6	-5	-4	-2	-1	0	1	2	4	5	6	8	9
66	-21	-20	-19	-18	-17	-16	-14	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	0	1	2	3	5	6	7	9
68	-21	-20	-19	-18	-17	-16	-15	-14	-13	-11	-10	-9	-8	-7	-6	-4	-3	-2	-1	0	2	3	4	6	7	8
70	-22	-21	-20	-19	-17	-16	-15	-14	-13	-12	-11	-10	-8	-7	-6	-5	-4	-2	-1	0	1	3	4	5	6	8
72	-22	-21	-20	-19	-18	-17	-16	-15	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	0	1	2	3	5	6	7
74	-23	-22	-20	-19	-18	-17	-16	-15	-14	-13	-12	-10	-9	-8	-7	-6	-4	-3	-2	-1	1	2	3	4	6	7
76	-23	-22	-21	-20	-19	-18	-16	-15	-14	-13	-12	-11	-10	-8	-7	-6	-5	-4	-2	-1	0	1	3	4	5	7
78	-23	-22	-21	-20	-19	-18	-17	-16	-15	-13	-12	-11	-10	-9	-8	-6	-5	-4	-3	-2	0	1	2	4	5	6
80	-24	-23	-22	-21	-19	-18	-17	-16	-15	-14	-13	-12	-10	-9	-8	-7	-6	-4	-3	-2	-1	1	2	3	5	6

Apparent temperature with no radiational heating and relative humidity fixed at 70%
Formula from *Norms of apparent temperature in Australia*, **Aust. Met. Mag**, Vol 43, 1994, 1-16.

Figure 15: Wind chill reference table [24]

4.2.3 Decision making approach

In KSERA, the data is acquired by the means of the Ubiquitous Monitoring Systems saving the data locally in the database.
KSERA main server undertakes the immediate triggering and the scheduled one accordingly the frequency set in D1.2 (instantly and every X seconds/minutes).
tionary
KSERA undertakes the medium-term history analysis which goes to be performed directly on the acquired data, after being stored in the database.

KSERA will undertake the invocation of the dedicated monitoring functions. Some of the above functions makes the pattern matching aiming to detect the occurrences of the already known apropri patterns. Some of the dedicated functions will assess the data against the “normality” in the present time, looking for the correlations. Some of the dedicated monitoring functions will check for the evolutionary changes along the timeline.
The remaining functions are those affected by the application of the self learning techniques to learn the appropriateness of the instances defined in the general rules, but likely personalised by certain patients.

Therefore a lot of information is got from learning algorithms application. Based on such approach, new automatic alarm scenario may be considered and more complex decision making approach may be implemented.

KSERA will embed the use of the above self-learning techniques in the dedicated monitoring functions invoked on demand by the main server in order to perform the dedicated calculations. The specification of the above functions is based on the rules set by D1.2.

4.2.3.1 Suspect change in daily activities

Information about daily activities being performed is gathered by means of the sensors giving the elementary data (information), which is stored in KSERA database. The above data make sequences, e.g. temporal series holding the history of the daily activities performed by the patient along the time. KSERA event flow is:

$E(t_i) = \{E_1(t_i), E_2(t_i), \ldots, E_i(t_i), \ldots\}$ events might happen simultaneously giving a “snapshot”
$E'(t) = \{E(t_0), E(t_1), E(t_2), \ldots, E(t_i), \ldots, E(t_{i+k}), \ldots\}$ history of events, event flow, sequence of events

Each element $E_i(t_i)$ is an event in the event space. Each $E(t_i)$ is a set. The $E'(t)$ is a collection of sets.

The above sequence might show the nomothetic events, such as “preparing meals”, “having meals”, “doing something” etc., e.g. it might happen that two ***sets*** are identical or repetitive:

$$E'(t_i) = E'(t_k),$$

or it might happen that certain elements are repetitive $E_i(t_i) = E_i(t_{i+k})$.

The concentration of the above events might remain stable or might be varying, e.g. the time slot of “having breakfast” might remain constant or be changing. The number of meals might be constant or be changing etc. The above consideration about the event “taking pills” gives the treatment compliancy. KSERA wants to discover the changing patterns happening along the time.
To undertake this kind of data processing, there are several steps. One step is about the classification of the aggregated events. Other steps are: discovery of the patterns and the discovery of pattern’s dynamics.
The above information is processed by KSERA server applying the above learning techniques. Such information can be used to monitor user activities, detecting suspect and sudden changes in what can be recorded as an ordinary sequence of activities.
As mentioned before such events do not necessarily lead to an instantaneous alarm condition, but can be used to activate some pre-alarm routines or to feed more complex decision algorithms.

4.2.3.2 KSERA efficient reasoning approach

The final purpose of the implementation of decision making algorithms is the establishment of a rule model scheme for efficient reasoning.
Such rule model scheme, based on the set of rules described in KSERA WP1, is the core of the monitoring engine. Depending on the input from the physiological and environmental sensors and based on medical knowledge base developed by means of the above described learning algorithms employment, the system shall be able to advise the elderly with COPD in their decisions and activities matching their lifestyle.

There are two approaches in such challenging task.

The first one is based on the application of a hard logic, that is the application of “if / then / else” rule schemes on the acquired database and knowledgebase. For instance:
Scenario 1:

- IF the input from motion sensor reveal that the user is performing few activities (based on learnt activity patterns) AND
- IF the health status of the user requires more physical activity (based on medical rules and database) AND
- IF the environmental conditions are compliant (based on medical rules and database) THEN
- Motivate the user to perform some activity outside, maybe a walk.

Scenario 2:

- IF the environmental conditions are critical (based on medical rules and database) AND
- IF the health status of the user is getting worse (based on medical rules and database) THEN
- Motivate the user to stay at home and rest.

The events happening in real life operate likely with the Fuzzy categories. An event “having the breakfast” is Fuzzy because of the possible interpretation of the events belonging to. The use of the heater, microwave owen, fridge, and so on might be variable, depending of the meal to prepare. It might occur in the same time slot but will have the different timing. Having the breakfast in “Early morning” typically followed by “waking up later” will provoke “having breakfast” occurring not in “Early morning” but in “Late morning”. A second approach may be based on a soft “fuzzy” logic then. Non-linear fuzzy rules application may be an interesting solution to solve more complex scenarios.
The hard logic is based on the assumption that a certain threshold is crossed or not, but it cannot give information about “how much” a certain threshold is crossed. On the other side, fuzzy rules scheme may be applied to cope with scenarios characterized by a certain level of ambiguity. For instance:
Scenario 3:

- IF the environmental conditions are not so bad (based on medical rules and database) AND
- IF the health status of the user is getting worse, but is not quite critical (based on medical rules and database) AND
- The user has been at home for several days
  THEN
- Motivate the user to have a short walk outside.

The second approach is quite interesting for its flexibility, but is quite complex considering its implementation and integration into the KSERA system. Therefore the hard logic based approach will be considered for the KSERA application.

5 Conclusions

KSERA project is intended to provide assistance to COPD patients by means of a ubiquitous monitoring network. The rules for monitoring are fixed in D1.2. Heterogeneous data are continuously acquired using sensorial framework and made persistent in the database. This environmental and medical information is used to detect critical situations and automatically and transparently provide services to the user.

First class of the monitoring functions deal with the “situations” expressed by the measured values/parameters. The immediate triggering of the above situations is possible using the “snapshots”, which is applied by KSERA server in real-time. This is needed to keep the interoperability with the mobile artefact (NAO robot). AN example: IF Hot THEN ReduceTemperature;

Second class of monitoring functions deals with the aggregated entities or sets. Dealing with sets is more complex task. Monitoring functions operating with the sets are present in KSERA. The task is achieved with the employment of data processing techniques aimed to learn as much knowledge as possible from the acquired raw data (learning algorithms) and to provide the most suitable response to the current needs of the user (decision making algorithms). The classification of the situations based on the certain events happening during a given timeslot gives a capability to trigger the events like “taking pills”, “having a meal” ertc.

Third class of monitoring functions deals with the historical entities. Dealing with sequences of sets gives a chance to elaborate the historical behaviour, e.g. to detect the changing patterns or trends. COPD patient might reduce gradually the quantity of the physical activities being performed during the day, which might indicate the disease progression.

Concerning the learning algorithms, the most used solutions based on probabilistic and fuzzy approaches have been envisaged in sight of a possible application in user activities recognition or room occupancy estimation. However the implementation and integration complexity leads to the employment of more “classic” solutions:

- Pattern matching techniques, based on traditional computational algorithms, and “if-then-else” rules.
- Analysis of the stored history of acquired measurements by means of a data warehousing approach.

Concerning the decision making algorithms, different classes of decisions have been envisaged according to their complexity. Instant responses are employed to high priority triggered events. A medium term analysis is suitable for instance for environmental information, or for events which require the analysis of a history of collected data. Finally, more complex scenarios are envisaged. They involve the history of the managed events and the current monitoring acquisition in order to provide responses to the user being compliant to the current needs and his/her usual habits.

5.1 Expected advantages

Nowadays, commercial homecare services rely on the employment of devices, both - fixed (wall mounted sensors, emergency buttons and so on) and wearable (remote controllers), able to trigger instantaneous events and summon emergency calls.
Furthermore telemedical services rely on the delivery of medical measurements (blood pressure, heart rate, O_2 saturation) by means of the available telecommunication networks. Such measurements are then checked by professional operators.

KSERA is aimed to merge these kinds of services, providing a more complete and efficient one, able not only to automatically trigger emergency alarms like commercial homecare solutions, but also to take into account a wider set of data (including both environmental and medical data) and process more complex scenarios. All these can be performed by implementing advanced processing algorithms, based on probabilistic and fuzzy approaches, which have been described in this document.

Integrating different classes of data processing approaches into KSERA is a crucial issue. Especially creating a system which is able to create a pervasive “AAL” environment, in which all the components (sensor, actuation and processing unit) not only operate as separate monitoring agents (like the available commercial solutions), but also as an integrated monitoring system is a big challenge.

5.2 Learning and decision making algorithms in KSERA

Given the above considerations, the KSERA approach is based on three main classes of solutions: immediate triggering, pattern matching activity monitoring and data warehousing based medium/long term analysis. These solutions are accompanied by soft computing techniques, when needed, from within the body of the dedicated monitoring functions.

5.2.1 Immediate triggering solution

This solution is used when applying hard if/then rules to single measurement values. For instance when dealing with fall detection or critical medical measurements.

<u>Example 1: from D1.2, “Rules for potential risk situations - Possible fall recognised”</u>
A wearable device is worn by the monitored user.
IF (PossibleFall **IS** detected) **THEN** (Send_the_alarm). KSERA system will notify the alarm the predefined receivers and a call will be established.

<u>Example 2: from D1.2, “Blood pressure measurement”</u>
IF (the diastolic pressure drops below 50 mmHg) OR (diastolic pressure increases above 120 mmHg) **THEN** request to asses heart rate, to perform ECG and send measurements to the specified call center.

5.2.2 Pattern matching activity monitoring

Information from the sensors deployed in the monitored area is stored continuously in a database, providing the recording of the monitored parameters along the time. Set of parameters are used to identify the user’s activities, by means of data classification and event aggregation. After a training phase, for instance one month, the system can record the dynamics of the repetition of the detected activities. It is then possible to perform pattern matching in order to detect sudden or suspect changes in the typical learnt series of actions.

<u>Example 3 from D1.2; “Rules for potential risk situations – unusual activity patterns”</u>
“If abnormal activity patterns occur, the robot Nao approaches the user and asks if the user is fine. If no appropriate reaction of the user takes place then a phone / videophone connection to predefined receivers will be established.”

5.2.3 Data warehousing based medium/long term analysis.

While the pattern matching based algorithm relies on the analysis of different measurement values acquired at the same time, medium/long term analysis considers the history of a specific monitored

parameter, that is, the values recorded over a defined interval of time of one only kind of measurement.
This is performed in order to detect trend changes in a particular monitored parameter. Soft computing processing will be performed in order to compute statistical and probabilistic indexes, based for instance on different order averages and derivatives.

Example 4 from D1.2, “Rules to motivate for outdoor activities”
IF Weather is fine and outdoor environmental condition are good and stable (positive trend in acquired values)
AND
Low activity at home (negative trend in mobility)
AND
Time is in-between preferred time for outdoor activity (Pattern matching)
THEN
Use the Robot NAO in order to suggest and motivate the user for having a walk outdoor.

5.2.4 Final considerations

The overview is based on the rules reported in the D1.2 and those normally used in the AAL scenario. The computational techniques being described are those needed to implement the triggering rules in the KSERA prototype 1. More sophisticated operations might be included in the stage 2 prototype, amending this document if necessary.

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