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Forecasting the behavior of an elderly using wireless sensors data in a smart home

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ABSTRACT

In this paper, the ability to determine the wellness of an elderly living alone in a smart home using a low-cost, robust, flexible and data driven intelligent system is presented. A framework integrating temporal and spatial contextual information for determining the wellness of an elderly has been modeled. A novel behavior detection process based on the observed sensor data in performing essential daily activities has been designed and developed. The developed prototype is used to forecast the behavior and wellness of the elderly by monitoring the daily usages of appliances in a smart home. Wellness models are tested at various elderly houses, and the experimental results are encouraging. The wellness models are updated based on the time series analysis.

1. Introduction

The age span of elderly people is increasing, and this trend set to continue in future (United Nations (UN), 2011). A normal elderly person is assumed to be well if he/she performs basic daily activities at regular intervals of time. This implies that the wellness of a person can be assessable and can be quantified in terms of wellness indexes. The elderly people prefer to live independently, but the self-regulating way of life involves with risks. In particular, the daily home activity involving basic functions like preparing food, showering, walking, sleeping, watching television, reading books etc., is a key indicator in determining the performance of home activities of an elderly and consequently their wellness. Thus an intelligent, data driven engineering system is needed to record the basic activities of elderly at home. The analysis of data in real-time will determine whether any change of regular activities have taken place and if any preventive action is required. This precautionary measure may help in reducing the future health-care cost.

A variety of sensing systems for monitoring and assessing functional abilities of elderly behavior in a smart home have been developed (DeSilva et al., 2012; Dan et al., 2011; Cook, 2012). Behavior prediction methods relating to abnormal behavior with temporal rules have been proposed (Tibor et al., 2011; Noury and Hadidi, 2012). Nouri and Hadidi (2012) have "demonstrated the feasibility to produce simulated data which mimics the data gathered by presence of sensors in field conditions"; and "imagined to raise an alarm whenever the real collected data becomes significantly different from the simulated data". Tibor et al. (2011), have introduced a generic ambient agent-based model to study the dynamic patterns of human. Simulation experiments have been conducted with the generic ambient agent-based model and the outcomes have been formally analyzed. However, these methods will lead to a high number of false alarms when their behavior prediction techniques do not satisfy the conditions of the knowledge base. It is useful, to be able to determine an event on certain conditions using predicting techniques. Thus, Predictive Ambient Intelligence (PAI) techniques are used in a smart home environment in order to forecast the behavior of inhabitant under a monitoring environment.

A Predictive Ambient Intelligence environment gathers information from Wireless Sensor Networks (WSN) including environmental changes and occupants' interactions with the objects within the monitoring environment. Collected data are used to determine the behavior of inhabitant at different times by using prediction methods. The prediction involves the extraction of patterns related to sensor activations. This is then used to classify the sequence of activities and match it to predict the next activity (Das and Cook, 2005). Healthcare specialists believe that the best procedures to recognize health conditions of elderly before they become sick is to look for the changes in the actions of everyday

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life such as activities of daily living (ADLs), Instrumental ADLs (IADLs) (Tapia et al., 2004; Lawton and Broody, 1969; Rogers et al.,1998; James, 2008). Effective classification of ADLs is an important factor for detecting the changes in the routine habits of the elderly to determine their health conditions. There have been a momentous research activities in activity recognition and anomaly detection subdomains of a smart home monitoring system (Tapia et al., 2004; Dan et al., 2011; Cook, 2012; Hu and Yang, 2008; Zhongna et al., 2009; Marie et al., 2012).

The general structure of a Smart Home Monitoring System (SHMS) involves smart devices, a communication system and an intelligent system. In general, “Smart Home” is an expression utilized for dwellings outfitted with technologies that enable proper scrutiny of residents promoting autonomy and upholding of better health. A wide range of smart home research is carried out in the world and is reported in (e.g., Tapia et al., 2004; Dan et al., 2011; Cook, 2012; Hu and Yang, 2008; Zhongna et al., 2009; Marie et al., 2012). The focus of researches is quite different as every researcher has distinct requirements with varied research objectives. However, from the government point of view they would like to cut cost on healthcare by using technology in healthcare.

One of the main objectives towards the development of a smart home monitoring system is to have a minimum number of sensors and perform intelligent data analysis (Okour et al., 2012). “Networks cannot be deployed massively, if they are not affordable”. Moreover, healthcare providers will not use them in a clinical routine, if they are not cost-effective or do not have important benefits over the traditional health care delivery (Romero et al., 2008). A home monitoring system based on a minimum number of sensors will lead to the development of a low-cost system. A low-cost system will be affordable to the elderly who are mostly retired or possibly a low-income earner. Though a significant amount of research has been done already and is continuing, there is still a need for an effective technique and a low-cost solution for elderly care in smart home monitoring. The problem is not simple as human behavior is quite complex and is not possible to define by computer algorithms guided by associated rules. The patterns of sensor values must be able to provide information related to the identification of elderly activities to determine the wellbeing of elderly at a macro-level.

The wellness monitoring system for an elderly is confined to monitoring the performance of daily activities and decides whether the behavior is regular or irregular. A key element in the success of a well-being monitoring systems depends on understanding of the normal lifestyle and the degree to which the behavior of the elderly has deviated from that norm. There are several research works related to ambient monitoring systems like CASALA (Brain et al., 2011), BT Care (Nick et al., 2005), and other related works using different approaches such as validation concepts for short and long term ambient health monitoring (Chiriac et al., 2012); and analyzing the behavioral patterns through health status monitoring (Barger, 2005). In this paper, we propose the big picture of measuring the overall wellness level of an elderly and also the micro scale level of behavior recognition, activity annotation and so on. The research findings discussed in this paper can be deemed to provide a solution to a question raised in the paper (Dan et al., 2011) on real-time data analysis of sensor technology for smart homes. Dan et al. (2011) have expressed their concern on the technical issue to be addressed before sensor technology can be successfully deployed into real-world residential settings. The application of the proposed prototype will provide sufficient evidence for detecting changes in daily routines associated with functional activities using sensor data.

The most difficult task in an ambient intelligence environment is the prediction of behavioral patterns from the sensory observations. The accumulated data from sensory devices in a Wireless Sensor Network can become huge and complex if many sensor devices are used in a smart home. It is extremely difficult to find the correct number of sensors required for a smart home monitoring. The reported literature suggests a large number of sensors for monitoring the elderly behavior; subsequently the systems are very expensive and are unattractive to the elderly (Okour et al., 2012). The sensors should be invisible and have wider acceptance to the elderly (Alemdar and Ersoy, 2010). The current research targets the transformation of an existing-home to a smart home using the WSN based home monitoring system. The sensors data analysis to extract knowledge and adapt to changes in elderly behavior can provide a solution to the wellness determination of the elderly problem.

The remainder of this paper is organized as follows: Section 2 discusses some related works. Section 3 describes the developed system and the implementation details. Section 4 provides the results of verification of the methods on a publicly available data set and consequently testing the system at different elderly houses. Finally, Section 5 provides conclusions.

2. Prognostic practices in ambient assistive living Environments

Forecasting in smart home environments equipped with sensor networks is a learning task. A major task for the intelligent home monitoring system is to have the ability to perceive, understand and realize the new situations. This will support an interpretation of sensory information in order to represent, understand the environment and perform correctly based on the prior knowledge when there is a situational change. For execution of these tasks, a variety of methods such as Analysis of Knowledge Discovery, Soft Computing Techniques and Statistical Modeling methods were introduced.

2.1. Analysis of knowledge discovery

A major task of this analysis is an attempt to learn the daily activity patterns from a large data set to realize a new situation for predicting the abnormal behavior of the elderly. Some of the existing methods are context-aware case-based reasoning as proposed in Ohbyung et al. (2012). The objective of this work is on the activity-based context-aware services; the contextual information is presented in terms of environment, temporal and inhabitant identification. The context prediction method is proposed to improve the accuracy of diagnosing a person's state of health with a single activity sensor. The shortcoming of this technique is that when the sample data are incomplete and somewhat inconsistent due to sensor conditions, the reasoning process will not be accurate. The authors of this work have mentioned that if the quality of sensors and sensor networks is improved, then the performance in terms of activities interpretation accuracy will be enhanced.

Similarly, knowledge-driven approaches to activity recognition in a smart home using contextual information with large repositories are proposed (Liminh et al., 2012). Formulating the description logic based on a trial system may not be apt, as human behavior is complex. Also, the specified ontology concepts and their corresponding rules may not match in a real situation over a long run of the system execution. Aggregating sensor observations along a time line requires complex procedures to be incorporated for effective activity recognition. There are methods for recognizing sequential, interleaved and concurrent activities using emerging patterns (Tao et al., 2009). The proposed idea is to differentiate daily activities accurately. But, the quantitative wellbeing assessments of the inhabitant in a smart home related to the daily activities have not been explored.

2.2. Soft computing techniques

Study on inhabited intelligent environment, (iDorm) performed a test bed using the Adaptive Online Fuzzy Inference System (AOFIS) mechanism for prediction in various phases for learning, controlling and adaption. Different techniques of clustering approach and quantification of fuzzy membership functions are used to extract the fuzzy membership function for the collected information on the observation of interactions by the inhabitant. Accordingly, fuzzy rules were extracted from the documented data and a control agent approximates the likelihood of the activity by adjusting with the current situation (Doctor et al., 2004).

Several methods including neural networks, heuristic and machine learning techniques are used to extract ADL patterns from observed daily activities and these patterns are used later as predictive models (Brdiczka et al., 2009). However, these techniques need alternating solution (i.e. the activities learning model need regular updates), if the execution environment is changed and there can be issues of data inadequacy for adapting to a new system. There are methods for deriving abnormal activity models from a general normal model via a Kernel Nonlinear Regression (KNLR) and Support Vector Machines (SVM's) and Hidden Markov Models to reduce the false positive rate in an unsupervised manner, however these methods were applied for wearable sensors on the body (Marie et al., 2012).

2.3. Probabilistic and statistical analysis

Probabilistic prototypes are more suitable than the above mentioned two techniques. It has increased its importance, as sensor observations are noisy and human activities are performed in a complex nondeterministic mode. There are several investigations on activity recognition aiming on the use of probability concepts, and statistical analysis procedures such as (Noury and Hadidi, 2012; Sanchez and Tentori, 2008; Bao and Intille, 2004). Some of them are Markov representations (Noury and Hadidi, 2012) and their variants Conditional Random Fields (CRFs). The methods require large training data for acceptable reasoning with no guarantee for detecting an appropriate abnormality condition.

Thus, there is a huge demand for an electronic system with intelligent mechanism for monitoring basic ADLs behavior of elderly living alone, so that care can be delivered at the right time by providing the right information to the caregiver. Human activity recognition and determination of the behavior as 'regular' or 'irregular' are two important functions to be performed. One of the major tasks in a smart home environment is to quantify the well-being of elderly by monitoring object usages. In order to detect behavioral changes and for better prediction of object usages in a smart home; a new framework termed "wellness determination" in smart home has been devised and extensive work is being performed (Suryadevara and Mukhopadhyay, 2012; Kaur et al., 2012). The next section describes the development work done for wellness determination of an elderly in a smart home.

3. Description of the developed system

The overall structure of the system consists of two important modules: (i) Wireless Sensor Network (WSN) and (ii) intelligent home monitoring software system to collect sensor data and perform data analysis for detecting behavioral changes of an elderly. Fig. 1 depicts some of the household appliances equipped with fabricated sensing modules for monitoring their usage.

The household objects regularly used by the elderly are attached with fabricated sensing units. The fabricated sensing units consist of different types of sensors based on the electrical and non-electrical functionalities. The system is developed based on the principles of the developed prototype as mentioned in Suryadevara and Mukhopadhyay (2012). The electrical sensing systems intelligently detect which particular electrical appliance is ON and how long it is used. Electrical sensing devices operate on the detection of current flow connected to household objects. The objects such as microwave, water kettle, toaster, room heater and television are monitored as they are regularly used by the elderly at home. The non-electrical functional objects such as bed, chair, toilet and sofa are monitored using an ultra-thin, flexible and non-obtrusive Flexi Force sensor (Flexi Force Sensor, 2013). The input signals from the sensing units are integrated and connected through radio communication interface XBee modules (XBee RF Module, 2013). Thus, the sensor information of the objects is wirelessly transmitted through the XBee module.

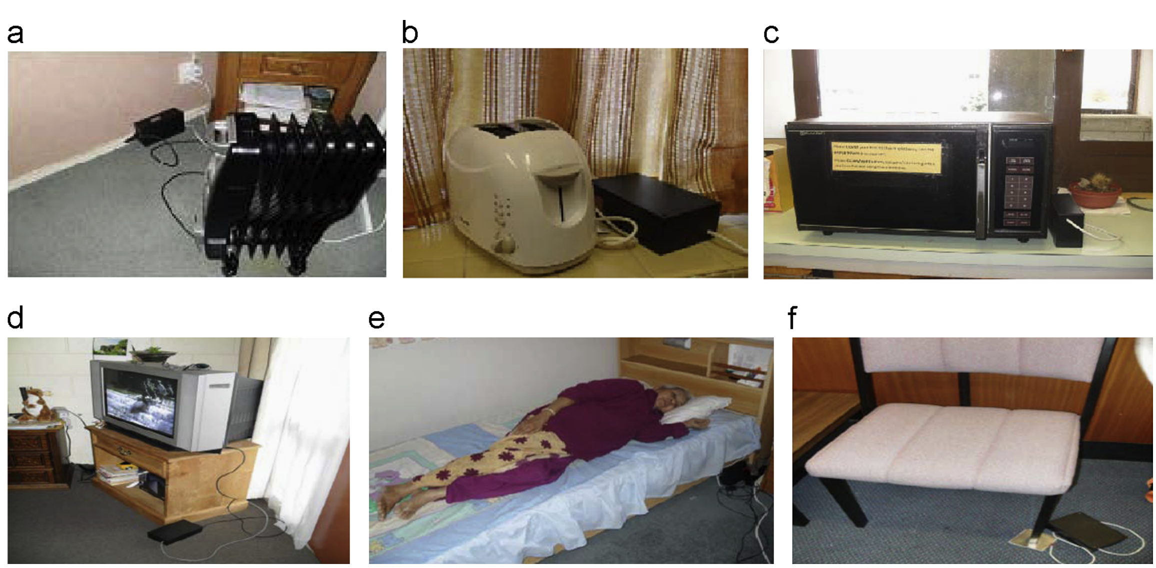

Fig. 1. Wireless sensing units developed to monitor household appliances. (a) Room heater, (b) toaster, (c) microwave, (d) tv, (e) bed and (f) chair.

WSN is designed according to the IEEE standard 802.15.4 of ZigBee using XBee devices. Communication is established and managed by the functional set of the XBee modem configuration with appropriate values for network, security, serial and *I*/*O* interfacing of XBee modules. The power supply for the fabricated sensing units is through direct supply from an electric power outlet. Instead of connecting a household object to a power outlet the household object is connected to the fabricated sensing unit. The fabricated sensing units are configured in the form of mesh topology so that reliable data communication is achieved. The Quality of Service (QoS) in the configured mesh topology in terms of reliability and delay in transmission of sensing information is given in Table 1. The statuses of the appliances (Active/Inactive) are collected by a coordinator of the WSN. The XBee coordinator has been connected through the USB cable of the host computer, which stores the data into a database of the computer system as shown in Fig. 2. The programs for Data Acquisition, Activity Recognition and Wellness Determination are written in C# and are executed simultaneously for effective behavior recognition.

The developed sensing system is noninvasive, flexible, low-cost and safe to use. The system does not use any motion and/or vision based sensor. The rationale for the observing usage of household appliances is based on the fact that these are regularly used by the elderly in various situations like preparation of food, relaxing, toileting, sleeping and grooming activities. They are useful to determine the wellness of the person in performing these basic daily activities. In addition to the fabricated sensing units, emergency help and deactivate operations are developed with Xbee modules to facilitate the corresponding operations during the real-time activity monitoring of the elderly. Since, we are concerned with how "well" elderly is able to perform their basic ADLs, required number of sensing devices that correspond to the daily object usages are used in the present system. The importance of the system is that it has been designed and developed for using in an existing elderly home rather than a newly constructed house or a test bed scenario.

3.1. *Wellness determination process through monitoring daily activities*

Fig. 3 shows the schematic representation of the determination of wellness of elderly in a smart home. The recognition of basic ADLs and determination of wellness of the elderly are described in the following steps.

Steps:

1. The sensing data for different events are collected with temporal information. The data are stored in a file for further processing.
2. Activities are annotated by applying conditional probabilistic method as given below: The best activity identification for the stream of sensor events is given by the maximum likelihood estimate as the conditional probability which is the relative frequency of sensor (t) in the stream of sensor pattern belonging to activity (c).

$$P(t|c) = \frac{N_{ct}+1}{\sum_{t' \in V}(N_{ct'}+1)} = \frac{N_{ct}+1}{\sum_{t' \in V} N_{ct'} + K'} \quad (1)$$

where N_{ct} is the number of times a particular sensor id occurs in activity 'c'. V is the set of sensor ids. $K' = |V|$ is the number of unique sensor ids.

The activity identification process is as follows:

2a. Ascertain different activities with unique letters such as Preparing Tea (PT)=A, Preparing Coffee (PC)=B, Preparing Toast (TS)=C.
2b. If the Water Kettle sensor is active then the following stream of letters A, B will be considered, indicating it may be used for preparing tea or preparing coffee. Similarly, if the Fridge sensor

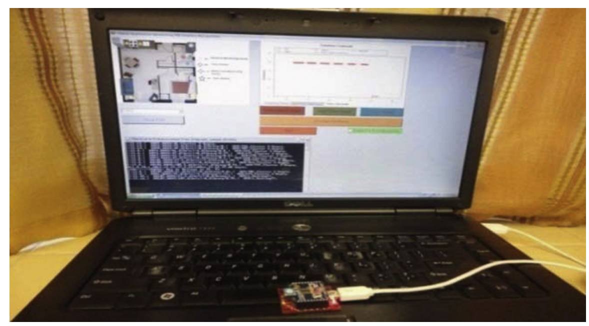

Fig. 2. ZigBee coordinator receiving sensors data.

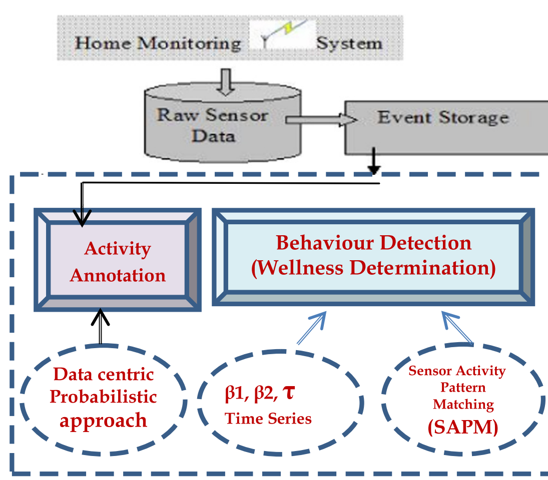

Fig. 3. Block diagram of the wellness determination of the smart home.

Table 1
Reliability of data transmission through mesh topology in HMS.

# Hops	Sensor_ID	Router/ End_Device	Range from coordinator (m)	Obstacles	Period between packets '*T*' (s)	Expected packets	Incorrectly received packets	Correctly received packets	Reliability (%)	Delay
0	407C602B	End_Device	8	2 Walls	10	7854	46	7808	99.4	
	4079CDD6	End_Device	3	No walls	10	8338	26	8312	99.6	
1	407C602B	Router	8	2 Walls	10	8056	16	8040	99.8	
	4079CDD6	End_Device	12	4 Walls	10	8076	29	8047	99.6	10.50%
2	407C602B	Router	8	2 Walls	10	5561	15	5546	99.7	
	4079CDD6	Router	12	4 Walls	10	5575	64	5511	98.8	12.40%
	407C5C8D	End_Device	16	3 Walls	10	5566	102	5464	98.1	

unit is active then the stream of letters A, B, C will be considered, and if Teabag container Sensor unit is active then letter 'A' will be considered.

2.c If the inhabitant uses household appliances Water Kettle, Fridge, and Teabag container in any sequence then the letter stream generated will be either: A,A,B,C,A or A,B,C,A,B,A or A,A, B,A,B,C etc,. The objective of the activity identification process is to identify maximum probable activity from the sensor stream event letters.

2. d On applying Eq. (1), P (A, B, C, C|TS) = 0.0277 results maximum likelihood stream of "(A, B, C, C)" letters, which belongs to activity: preparing toast (TS).

Well-being of an elderly in smart home is determined by observing daily usages of different appliances. We introduced two functions to determine the wellness of the elderly in performing their daily activities under the object monitoring environment (Suryadevara and Mukhopadhyay, 2012). The first function (β_1) indicates about the non-usage or inactive duration of the appliances, and the second function (β_2) is about the over-usage of specific household appliances. The following are the details:

$$\beta_1 = 1 - \frac{t}{T} \tag{2.a}$$

$$\beta_2 = 1 + \left(1 - \frac{T_a}{T_n}\right) \tag{2.b}$$

where β_1 is the wellness function of the elderly based on the measurement of inactive duration of appliances, t is the time of inactive duration of all appliances (i.e.) duration time no appliances are used, T is the maximum inactive duration during which no appliances are used, leading to an unusual situation, β_2 is the wellness function of the elderly based on excess usage measurement of appliance, T_a is the actual usage duration of appliance and T_n is the maximum usage duration use of appliance under normal situation.

The wellness functions as presented above, determine their indices values based on the known duration values of the different activities of elderly under care. Initial activity information is obtained from the interview of a respective elderly during the installation of the system. The obtained sensor activity data are amended while the system is running. For example, if the person gets up from bed at different time in the morning, the latest time is taken as the normal time of rise in the morning. It did not take into account of the time duration the elderly is sleeping. The threshold values for β_1 and β_2 are set at 0.5 and have been considered as safe limit. The wellness function calculated in our earlier work did not take into account day of the week, weekly, monthly and seasonal variation (Suryadevara and Mukhopadhyay, 2012). Though the daily activities of an elderly are assumed to be remaining constant, but the variation of the seasonal weather can have a strong influence on these indexes. Moreover, with time the performances of daily activities of the elderly also get changed (i.e. with time there will be changes in the daily behavior and have strong impact on the well-being of the person). This implies there will be seasonal behavioral change in the lifestyle of the elderly. It is important to note of these changes and ensure they are included in the model. Thus there is a need to update the wellness functions as described in our previous work (Suryadevara and Mukhopadhyay, 2012). Instead of taking fixed maximum time of over-usage (T_n) and no-usage (T) as given in Eqs. (2.a) and (2.b) for calculating wellness functions, it will be more practical to use updated maximum time duration of the appliances including seasonal factors to determine β_1 and β_2 effectively. In order to determine the updated time parameters and record the past maximum durations, time series modeling is applied. This will also provide a trend on the usage of household objects and perform forecasts based on the past usages.

Tendency of the object usage duration (τ) is very much useful in prediction as well as in determining the behavior of the elderly. Potential advantage is to update the run-time duration usages of a particular household object in monitoring state. Consideration can then be given to the updated maximum usage duration of household objects as stated in Suryadevara and Mukhopadhyay (2012).

3.2. Time series modeling and forecasting

Time is a fundamental element in our daily life and will provide us a vital source of information for smart home monitoring system. Moreover, livelihood activities are cyclic and evaluation of daily activities will indicate performance behavior of an elderly. Hence, monitoring daily usage of household appliances (i.e.) object monitoring in a smart home will help us to recognize the habitual nature of the person and thereby we can know how "well" the elderly is able to perform his/her essential daily activities.

The changes in normal daily activities can be determined with respect to the time. Regular usage duration with allowable residuals of activities can indicate the regular behavior of the elderly. If there are any changes to the normal activity durations (i.e.) deviation from the allowable duration range then an irregular activity is detected.

Therefore, we model a system in terms of time series analysis for forecasting the usage duration of objects in a smart home monitoring environment. The time series data mining concepts are then applied to the observed series of daily activity durations to explore the temporal patterns existing in the activity durations. These patterns are formed into appropriate groups based on wellness parameters. After successful completion of steps 1 and 2 as discussed in Section 3.1, individual activity durations are recorded in separate files and the following time series forecasting strategy is applied.

Time series forecasting basically consists of three consecutive steps: Activity duration series constructing in terms of seasonal decomposition, deriving trend from the activity duration series by applying double exponential smoothing technique and forecasting.

Here, we illustrate the process of each step:

1) Activity duration series with seasonal decomposition: The seasonal decomposition is apt for data revealing a cyclical pattern as well as a trend. In this step, we implement a 1 week activity duration series as one cycle or season to identify the weekly activity pattern of the elderly. It also categorizes the periodic components in the historical data and uses them in a forecasting model.
2) Deriving trend using activity duration time series:
   To handle data exhibiting seasonality effectively we have applied double exponential smoothing strategy (Brockwell and Davis, 2001) recursively as given in Eq. (3) to determine the tendency of the activity. The advantage of this strategy is to minimize the mean deviation and capture the local (latest seasonal) trend of the series.

$$\begin{aligned} \tau = T_t &= \delta(L_t - L_{t-1}) + (1-\delta)T_{t-1} \\ L_t &= \alpha(x_t - S_{t-s}) + (1-\alpha)\,(L_{t-1} + T_{t-1}) \\ S_t &= \gamma(x_t - L_t) + (1-\gamma)S_{t-s} \end{aligned} \tag{3}$$

   where T_t is the trend (or slope) of the entire duration, L_t local level seasonal slope, S_t change in seasonal factor, x_t is the observation at the current time, s is the number of periods in one cycle (i.e. $s = 7$ in our case), α, δ, γ are the smoothing parameters ranging from 0 to 1, selected by minimizing mean square errors.

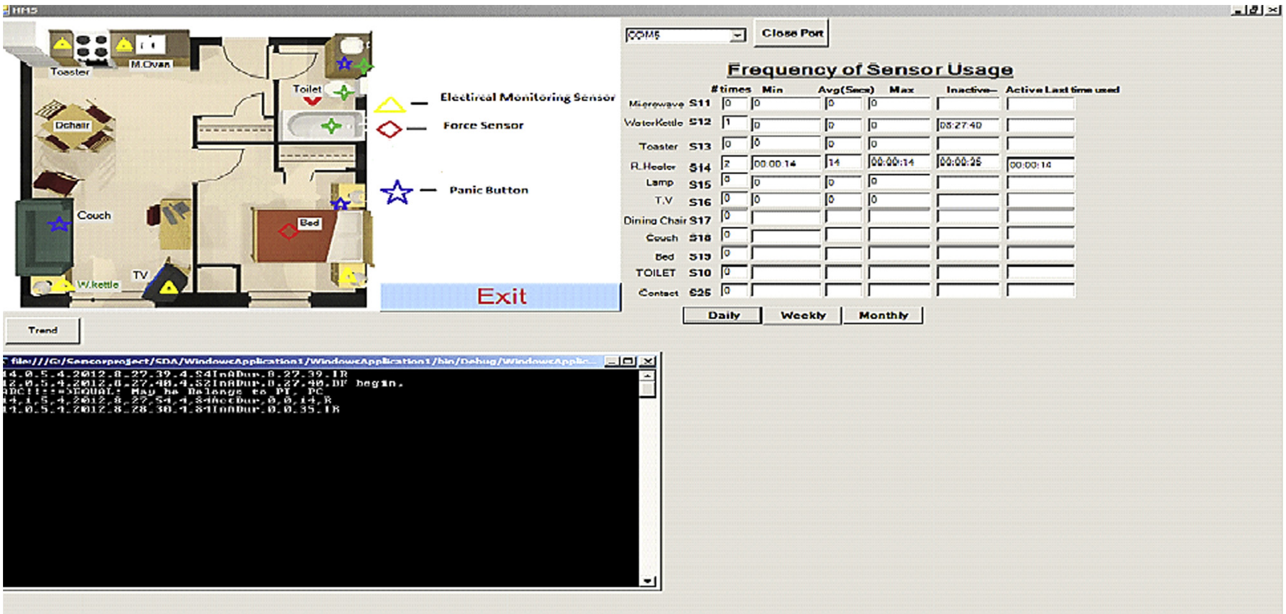

Fig. 4. Graphical User Interface of the system.

Starting values are:

$$L_t = (1/s)(x_1 + x_2 + x_3 + \ldots + x_s)$$
$$T_t = (1/s)((x_{s+1} - x_1)/s + (x_{s+2} - x_2)/s + \ldots + (x_{2s} - x_s)/s)$$
$$S_t = x_k - L_s, \quad \text{where} \quad k = 1,\ 2, \ldots,\ s.$$

3) Forecast the duration of activity by extrapolating the seasonal pattern as obtained in Eq. (3) and applying the following formulae:

$$F_{t+m} = L_t + T_{tm} + S_{t-s+m} \tag{4}$$

'm' is the required forecast period.

Once the forecasting process is completed, the behavior of the elderly is analyzed. The new method of behavior detection is described in the following section.

3.2.1. *Behavior detection*

In this process, we propose a mechanism for determining elderly behavior. The behavior of the elderly is categorized as regular or irregular based on the following conditions. The duration of the current activity is checked with the range of forecast. The forecast was estimated using Eq. (4). A 95% confidence level has been assumed in the forecasting. The allowable range of duration of any regular activity is given by Eq. (5)

$$\text{Allowable duration of regular activity} = \text{forecasted duration} \pm 2 \times \text{standard deviation} \tag{5}$$

If the actual duration is out of the range as given in Eq. (5), an irregularity flag is set. Additionally, the sequence pattern of the sensors with temporal constraint is analyzed by Sensors Activity Pattern Matching (SAPM) technique. In the SAPM technique the sequences of usage of sensors are analyzed to check any irregular behavior. The sequence of sensor stream on the basis of the day and time of the day are considered in analyzing the pattern. A lexicographic tree sequence is constructed in depth first traversal. Each sequence in the tree can be considered as sensor sequence extended. A sensor sequence extended is generated by adding new sensor_id at the end of the parent sequence in the tree. The SAPM process uses a priori pruning principle to reduce the search space for generating frequent set of patterns (Suryadevara et al., 2012). If there are no frequent set of patterns then the search space of the possible sequences of the sensor stream in the tree sequence will be less. Thus, the SAPM process will be able to predict the possible sequence of sensor ids on a particular day at a particular time period. If any irregularity is observed either in the sensor sequence pattern or with the usage duration of the objects then the wellness model will sets a flag indicating an anomaly. The corresponding wellness determination parameters are used in the model for future analysis.

4. Experimental results

Fig. 4 shows the front end of the developed software system indicating the status of sensors. The activity status of the sensors is stored in a computer. The data is used for activity annotation and wellness determination. The developed user interface shows the sensor status with their respective icons and information about individual sensor usage like: number of times used daily, minimum usage duration, average usage duration, maximum usage duration, last active time used and inactive duration since last used. The console window shows the sequence of sensors usage.

4.1. *Activity annotation:*

The 'sensor events' are used for labeling different activities. The 'sensor events' are based on real-time status of the sensor. Activities like sleeping, preparing breakfast or lunch or dinner, dining, toileting and self-grooming were recognized based on the spatial information (i.e. Sensor-ID) status and temporal information (Time of the Day). Activities like Watching Television, Preparing Tea are recognized with the help of active sensor ids sequence patterns and following statistical mathematical model as discussed in Section 3.1 (step 2). The activities recognized during run-time of the system are Toileting (TO), Preparation of Food (PF), Watching TV (WTV), Sleeping (SL), Relaxing (RE), Dinning (D) and Self-Grooming (SG).

Activity recognition as presented in Section 3.1 (step 2) is reliable, as the process is based on the data centric probabilistic approach. The reasons for considering this method are (i) maximum number of activities (ADL) can be recognized with less (minimum) number of sensors observations, (ii) activity annotation can be performed without huge training data and (iii) ascertain more probability for unseen(future) activities from the available sensor observations. The advantages of this approach when compared with Hidden Markov Models (HMM) and Bayesian probabilistic models are large training sets of data is not required to have accurate activity recognition. Moreover, aggregating different learning models such as (Patterson et al., 2007) require additional smoothing process in the interconnecting of HMM models for accurate recognition of activities. The ADLs are recognized from a multi-level structure of sensor events. Routine set of daily activities is recognized based on the parts of sensor events that correspond to an activity. The activity recognition method presented in Section 3.1 can also be considered for recognizing micro-level activities (i.e.) If preparation of food is considered as macro-level activity, then preparing tea, toast and coffee etc., are treated as micro-level activities. Since, we are interested in the overall wellness of the elderly; we consider mostly macro-level daily activities performed by the elderly, with a few micro-level activities.

The verification of the activity annotation is done with the information provided by the subject during the training phase. Whenever an activity is been performed, the elderly is asked to fill a timesheet with activities manually. After the trial run of the system, labeled activities were verified with the time sheet, and it was observed that 94% of the activities matched the timesheet. Some of the activities are not matched accurately because the elderly has not filled activity monitoring sheet. After correctly identifying these activities, we have applied time series modeling to forecast and determine the wellness of elderly.

4.2. Selection of sensors and using minimum number of sensors for monitoring basic ADL's

The selection of sensors is dictated by the lifestyle of the elderly. During the time series data mining training phase of the system different types of sensors attached to various household appliances are installed at the house. The elderly basic activities of daily living are monitored throughout the day (i.e. 24 h duration) and the life styles of the elderly are then reflected in its usage of the sensors. After 8 weeks of time series data mining training, the usages of the sensors are observed.

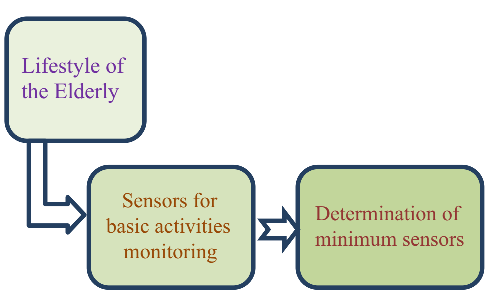

Fig. 5. Block diagram of finding minimum number of sensors required for monitoring basic ADLs.

Based on Eq. (6), frequency (η) of a particular sensor type locate data place in home is determined. Fig. 5 shows the corresponding block diagram.

$$\eta_T^c(loc) = 1 / \sum_{s \in S_c^l}^{|S_c^l|} fT(s) \tag{6}$$

where *loc* is the specific location in the house, *c* the sensor type, S_c is the set of sensors of a particular type *c*, and $f_T(S)$ is the frequency of sensors over a time period *T*.

From Table 2, it can be determined that the usage of contact sensor for the storage room is inadequate and can be ignored after the initial training stage of the elderly activity recognition.

4.3. Applying the forecast model to the WSU-CASAS smart home project Aruba test bed data for validation

The forecast model as discussed in Section 3.1 based on time series analysis has been applied to an off-line data set of the CASAS Project (Cook, 2012). The whole purpose is to validate the developed forecast model. This dataset contains sensor data that was collected in the home of a volunteer adult (Cook, 2012). The resident was a woman and the data collected over 33 weeks. We have considered only sleeping activity data of the test bed at this step for testing the developed forecasting model. Here, one pre-processing step was done (i.e.) multiple durations of sleeping activity on the same day are summed to consider the total sleeping duration of the resident on that day.

Forecast model was applied for two random scenarios of Aruba test bed: (i) Forecasting 9th week sleeping activity duration ranges by considering 8 weeks sleeping durations and (ii) Forecasting 30th week sleeping activity durations considering 29 weeks sleeping duration data. Computing the smooth trend curve and estimating the fitted curve (trend+seasonal factor) are performed according to the steps mentioned in Section 3.2, corresponding trend cycle and fitted curve for the 8 weeks sleeping activity durations of Aruba test bed data are depicted in Fig. 6.

Suitability of the fitted curve with respect to observation sequence is verified by implementing Kolmogorov–Smirnov test (KS-test) (Marsaglia et al., 2003) for normal distribution of the errors existing in the fitted curve. It was observed that the errors of the fitted curve have a mean, which is almost negligible, and a clear indication of fitted curve correctness with the observed sleeping durations. Extending the fitted curve of the sleeping activity from the obtained 8 weeks and adding seasonal adjusted factor with errors, the sleeping duration for the 9th week is forecasted. Table 3 shows the comparison of forecasted values with the actual 9th week sleeping durations. The same process is repeated for forecasting 30th week sleeping activity duration based on 29 weeks of sleeping sequences of Aruba test bed data. These results indicate the aptness of the forecasting procedure.

Except at two instances of 9th week and one instance of 30th week, the developed forecasting model has rightly predicted the range of sleeping activity durations of Aruba test bed data.

Table 2
Frequency of sensor usage.

Room type	Sensor type	Connected to device	η	
			Training	**Test**
Living	Force, electrical	Couch, chair, TV, heater	0.03, 0.05, 0.05, 0.1	**0.03, 0.04, 0.03, 0.1**
Kitchen	Electrical	Microwave, toaster, kettle	0.05, 0.05, 0.02	**0.04, 0.06, 0.00**
Bed	Force	Bed	0.29	**0.37**
Bath	Force	Toilet	0.35	**0.33**
Storage	**Contact**	**Cupboard**	**0.01**	**0.00**

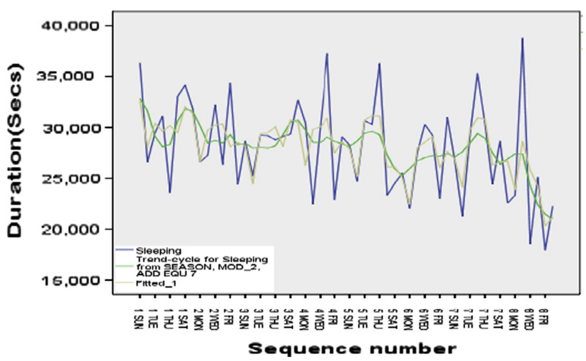

Fig. 6. Sleeping sequence, trend and fitting curve based on forecast model of 8 weeks Aruba test bed sleeping activity.

Table 3
Forecasting sleeping duration of Aruba test bed data.

9th week sleeping activity duration					
Forecast				**Actual**	
Max	(s)	Min	(s)	Duration	(s)
09:22:11	33,731	05:42:11	20,531	09:21:17	33,677
10:24:57	37,497	06:44:57	24,297	05:38:13	20,293
09:47:36	35,256	06:07:36	22,056	08:17:46	29,866
09:00:02	32,402	05:20:02	19,202	07:38:17	27,497
08:34:19	30,859	04:54:19	17,659	07:51:38	28,298
08:07:15	29,235	04:27:15	16,035	08:15:01	29,701
07:43:36	27,816	04:03:36	14,616	07:43:32	27,812

Considering 95% confidence interval, the errors prevailing in the fitted curve are computed by twice the standard deviation. This method was intelligent in not generating false alarms and was able to foresee the appliance duration usages. It was verified from the above mentioned two scenarios that the forecasting procedure is suitable for applying to daily activity durations. The following are the inferred statistical forecasting principle validations: Observed sleeping data closely match with fitted curve values. The trend is fairly smooth and steady. The errors in the fitted curve show normal distribution and have a mean much smaller than the observed mean.

4.4. Experimental results of the developed prototype model at trial home

A trial system was run in a smart home for collection of sensors data. It was attempted to learn the daily activity pattern from the collected data then the learning pattern was used to predict the irregular behavior of the elderly. The collected sensor data was stored in the appropriate files of the computer, and the sequences of steps as mentioned in Section 3.2 were implemented. Following are the three different illustrations of the forecasting implementation on three different objects used by the subjects at different locations. Fig. 7(a) shows the sequence plot and trend curve for 4 week sleeping durations at an elderly house. Fig. 7(b) depicts the generated fitted curve for the 4 week sleeping sequence.

In order to verify the error distribution prevailing in the derived fitted curve, Kolmogorov–Smirnov test is done on the obtained fitted curve values. Fig. 8 shows the errors of curve fitting as a normal distribution and mean almost zero. The system was successfully run at an elderly house. The system is currently in

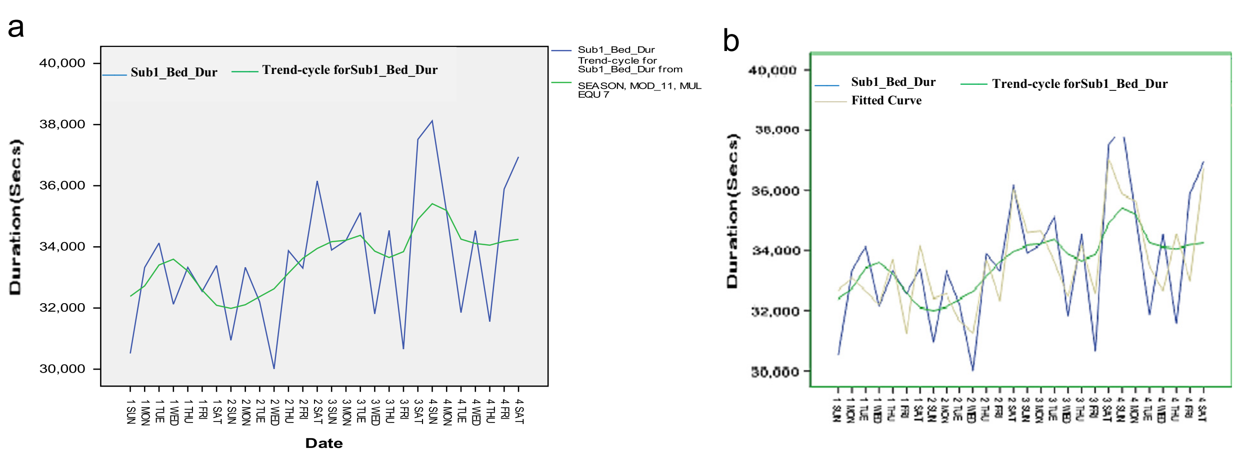

Fig. 7. (a) Bed sensor sequence, trend based on forecast model of sleeping activity of subject 1 elderly person for 4 weeks (blue color: sleep durations, green color: trend). (b) Bed sensor sequence, trend and fitting curve based on forecast of sleeping activity of subject 1 elderly person for 4 weeks (blue color: sleep durations, green color: trend, gray color). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

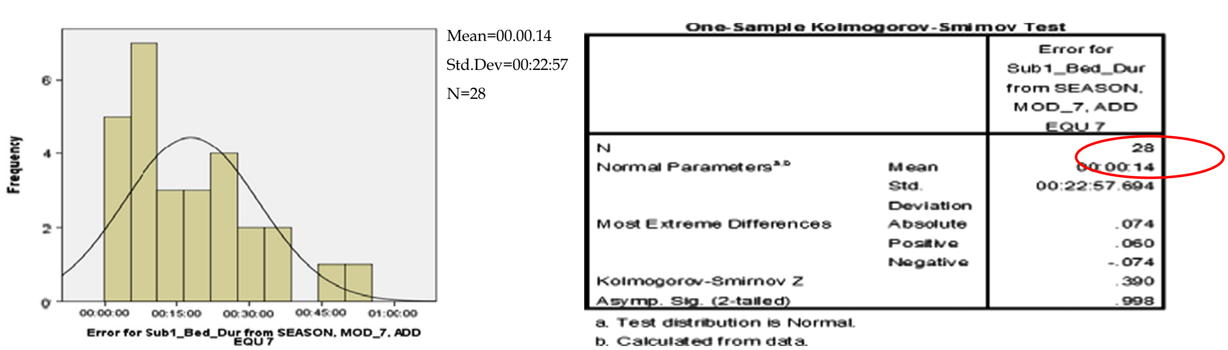

Fig. 8. Error normal distribution of the fitted curve for the subject 1 sleeping activity.

use at a few other homes for obtaining trials of the life-styles of a few other elderly people.

Based on the 8 weeks appliance usages, corresponding trend, seasonal adjusted and fitted curve values as mentioned in Section 3.2 are computed. Ninth and 10th week prediction of various appliances usages are derived and compared with the actual durations. Following are the illustrations about toilet and chair usages respectively. Fig. 9 is about the usage of toilet, its corresponding trend and 9th and 10th week predictions of an elderly at a subject house. Equivalent time durations are presented in Table 4.

Fig. 9(d) depicts the usage of dining chair by an elderly for a period of 10 weeks. Its corresponding trend, forecast for 9th week and 10th week are shown in Fig. 9(e and f). Equivalent time durations in seconds are given in Table 4.

Snapshot of the 9th week (Friday), estimated values based on the recorded 8 weeks are given in Table 4. Considering statistical inference of 95% confidence interval, the residuals in the fitted (predicted) curve are computed by twice the standard deviation. Accordingly, the forecast range with maximum and minimum duration's are computed according to Eq. (5). Forecast of an appliance is derived by applying Eq. (4) as discussed in Section 3.2.

It was observed that, two instances of irregularity at different subject houses were rightly predicted. These were related to the over usage of the appliances. In reality, the subject was using a chair for a longer time because he was sitting and talking with the guest on that day. In another instance, the duration of bed-use shows an over usage, because it was occupied by the elderly for a long duration as he was unwell. In order to have more précised behavior detection as discussed in Section 3.2.1, a novel strategy as presented in Suryadevara et al. (2012) integrating depth-first traversal of the activity search space with effective pruning mechanisms was augmented with the forecasting mechanism.

The a priori pruning mechanism is applied as mentioned in Section 3.2.1 in order to reduce the activity search space in the depth first traversal mechanism of SAPM process. Specifically, in this step we are interested in sensor activity pattern to determine how "well" the elderly is performing daily activities with the usage of regular household appliances. Accordingly, the status of the elderly in performing the daily activities as regular or not are derived. The recorded data values of the wellness functions and the forecast data at an instance of time are shown in Table 4. It contains the object usages wellness indices and their corresponding basic daily activities duration

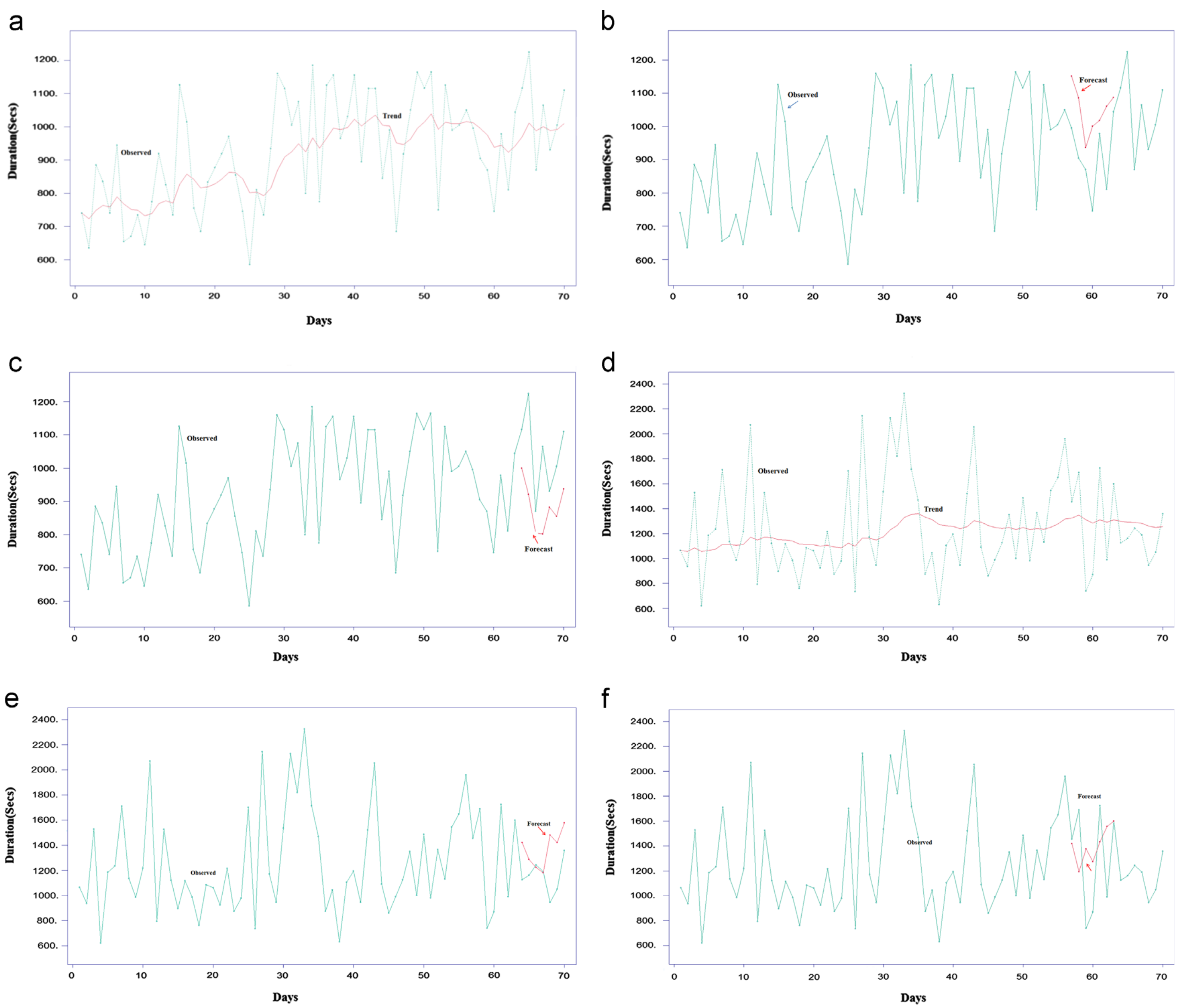

Fig. 9. (a) Toilet usage trend for 70 days. (b) Toilet usage (9th week forecast pattern). (c) Toilet usage (10th week forecast pattern). (d) Chair usage trend for 70 days. (e) Chair usage (10th week forecast pattern). (f) Chair usage (9th week forecast pattern).

Table 4
Wellness function indices of household appliances and forecast of the basic daily activities at a particular instance of time.

Sub	Activity	Sensor_ID	β_1	β_2	Forecasting for 9th week—(Friday)					Actual-duration (s)	Status
					Max-time (s)	Min-TIme (s)	α	δ	Γ		
#1	Sleeping	Bed	0.715	0.829	28,456	20,405	0.120	0.170	0.650	22,505	Regular
	Dining	Chair		0.865	1208	845	0.0200	0.1100	0.2100	1150	Regular
	Toilet	Toilet		0.785	1444	1028	0.1400	0.0900	0.3500	1353	Regular
	Relax	Couch		0.889	1457	840	0.150	0.130	0.540	1104	Regular
	Watching TV	TV		0.915	2806	2205	0.030	0.140	0.100	2608	Regular
#2	Sleeping	Bed	0.829	0.727	30,258	23,450	0.200	0.180	0.480	27,268	Regular
	Dining	Chair		0.504	14,545	10,425	0.140	0.170	0.300	15,580	Irregular
	Toilet	Toilet		0.576	1838	1426	0.160	0.130	0.200	1718	Regular
	Relax	Couch		0.614	2018	1487	0.150	0.040	0.250	1645	Regular
	Watching TV	TV		0.813	3804	2807	0.020	0.050	0.060	3045	Regular
#3	Sleeping	Bed	0.604	0.816	27,545	21,408	0.030	0.560	0.605	26,258	Regular
	Dining	Chair		0.713	16,250	12,350	0.400	0.600	0.010	15,145	Regular
	Toilet	Toilet		0.883	1628	1245	0.300	0.450	0.500	1465	Regular
	Relax	Couch		0.615	1845	1423	0.205	0.300	0.150	1628	Regular
	Watching TV	TV		0.715	4055	3605	0.100	0.650	0.750	3810	Regular
#4	Sleeping	Bed	0.758	0.445	28,235	22,035	0.205	0.600	0.700	29,701	Irregular
	Dining	Chair		0.914	1340	950	0.400	0.250	0.010	1205	Regular
	Toilet	Toilet		0.818	1123	885	0.100	0.200	0.650	1060	Regular
	Relax	Couch		0.756	1630	1245	0.300	0.200	0.250	1420	Regular
	Watching TV	TV		0.828	4838	4210	0.040	0.100	0.200	4506	Regular

predictions. The smoothing parameters (α, δ, γ) of the forecast process are tuned in relation to the 8 week past data. The maximum and minimum durations are recorded in seconds so as to facilitate the computation process effectively for some of the low duration activities. It was observed that subject #2 usage of dining chair and subject #4 usage of bed wellness indices were below the threshold limit (0.5). These indicate that the subjects are using the devices excessively. The β_2 (over usage indication) index data has rightly estimated the elderly performance with the corresponding devices.

Simultaneously, the forecasting procedure has indicated the active durations of the bed and chair are outside the forecast ranges. Accordingly, the behavioral detection process has set the status of the corresponding activities as irregular. Also, it was observed that forecast process and wellness functions are not estimated accurately in the initial trial period (i.e. upto 8 weeks). Data has been analyzed with the wellness determination process with four to 7 weeks. It was inferred that better estimation of wellness functions with time series modeling can be performed with minimum 50 observations of activity durations. Hence, forecasting process was accurate after 8 weeks of monitoring. As data gets accumulated over a longer period, determination of wellness function indices and forecast process will be more effective and accurate. If the variations in the activity durations are large, then it is obvious that the standard deviation of the fitted curve and forecast range values will also be large. This was observed in forecasting sleeping duration of Aruba test bed data as shown in Table 3. In general, a normal elderly person performs basic daily activities at regular intervals of time; behavior detection process can rightly estimate the wellness and will be a valuable contribution for the elder care.

Hence, the behavior detection process is more effective in this novel framework as it validates irregularity of the elderly behavior at three different points (object monitoring, activities recognition and forecast levels) of monitoring in smart home environment. The obtained results are compared with the inhabitant action prediction techniques as given in Das and Cook (2005). Prediction techniques involving weighted Markov models of different orders have converged up to 86% accuracy for data containing variations (Das and Cook, 2005).

The main objective of our data analysis by time series is to find a model which is able to forecast the statistical characteristics of the series, as the model will allow us to predict next values of the series from its past data. This is important as the behavior of the elderly changes with time and the changes should be taken into consideration in the model. The following steps are performed in the analysis of data using time series method, Time series of past data, suitable method for parameters estimation, best fitting model for diagnosis and forecasting of new values.

The wellness determination model acclimates and transforms data mining concepts to analyze time series data. Precisely, it notifies the hidden temporal patterns persisting in the time series data and predicts appropriate events. Conventional time series analysis approaches are restricted by the constraints of stationary series values and normality of the residuals. Also, outmoded time series analysis methods are unable to ascertain complex (nonlinear and irregular) characteristics of the human behavior. Time Series Data Mining (TSDM) overcame the above limitations of conventional time series analysis techniques in analyzing the complex behavior such as sleeping, toilet, dining chair usage patterns (which are completely non stationary) of the elderly person. Our wellness determination process involving time series data mining can resolve the behavior of the person as regular or irregular. Fig. 10 shows the block diagram of TSDM process.

The system is robust as it was successfully running at the elderly house without any hardware or software issues. The system is continuously running and collecting the data. Due to three different abnormal checking's during the knowledge exploration phase, generation of false alarms is reduced. The TSDM objective is to distinguish and forecast when important events will occur (events can be irregular). TSDM is expressed in terms of the wellness determination process as β_1, β_2 functions, and sensor activity pattern matching function, and forecasting formulation.

The steps in the Training Stage are as follows:

Initial values such as activity durations are fed into the system with the data provided by the elderly. The data are collected and trained to get the updated wellness parameters.

1. Evaluation of the basic wellness parameters.
   a. Computing the wellness indices.
   b. Verification of sensor sequence using SAPM process.
   c. Forecasting formulation, including the independent variables over which the value of the wellness function will be optimized and the constraints on the wellness function.

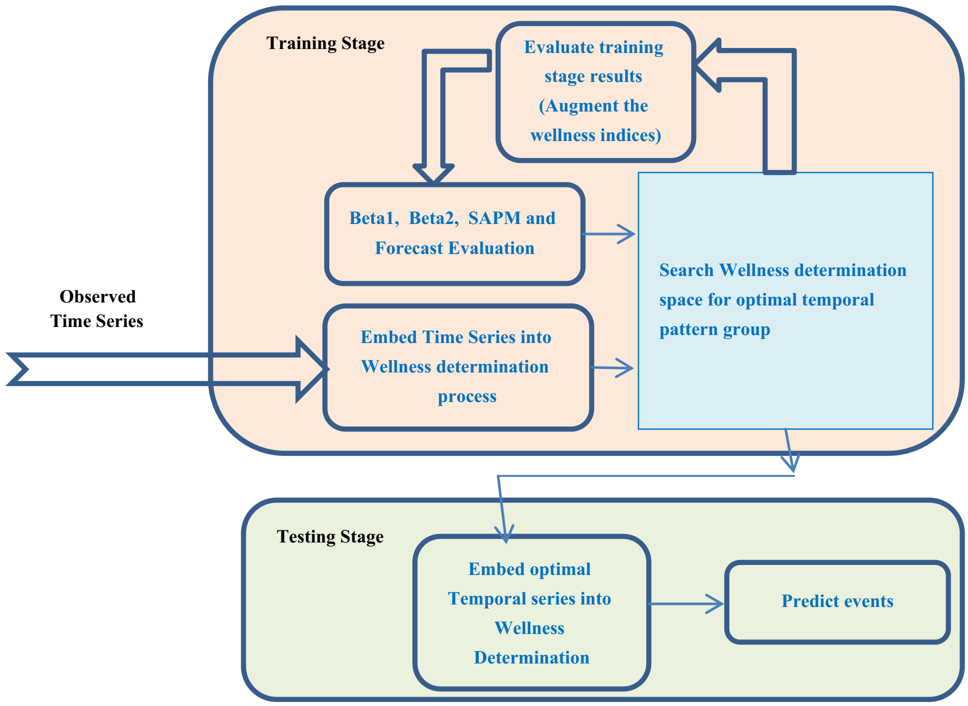

Fig. 10. Block diagram of Time Series Data Mining (TSDM).

2. Determine the trend of the time series activity durations (with minimum of 8 weeks training) and the length of the temporal pattern.
3. Based on step 1 computation, transform the observed time series into the optimal temporal pattern group of daily activities with appropriate statistical characteristics groups.
4. Associate each cluster with appropriate time index (such as weekdays and weekends in the training stage and augment the wellness indices.
5. In the training stage, search for the optimal temporal pattern group, which best characterizes the events (especially irregular events).
6. Training stage results will be updated continuously based on the elderly interactions with household appliances.

The steps in Testing Stage are as follows:
Data is analyzed from day 1, and the optimal temporal groups of wellness model are obtained after 8 weeks of training

1. Embed the testing optimal temporal group into the testing stage.
2. Use the optimal temporal pattern group for predicting events.
3. Update the testing stage results continuously based on the optimal temporal pattern groups of training stage variations.

The results exhibited in Das and Cook (2005) are achieved based on the test bed scenario. However, the wellness determination process presented in this paper was tested at four different elderly houses. In reality, the accuracy of activity recognition and the forecasting mechanism including variations was 94%, a significant improvement as compared to the works described in Das and Cook (2005). In addition, an anomaly detection process is more refined by considering the novel wellness indices (β_1, β_2, τ) in terms of object usages. The wellness determination process learns the daily activity durations and the corresponding patterns. This implies that, over a long period, the forecasting method can optimize wellness indices, thus supporting the behavior detection more accurately.

The potential advantage of the wellness determination technique is that prediction of the next action (daily activity using SAPM) with quantification in terms of usage duration is possible. This will be a promising achievement as compared to the existing research works.

5. Conclusion and future work

In this research, wellness is about well-being of elderly in performing their daily activities effectively at their home. A wellness determination process helps the healthcare providers to see the performance of the elderly daily activities. Data relating to the wellness indices and behavior recognition can guide the healthcare professionals to find out the starting variations of elderly activities quantitatively. This will recommend health professionals to provide precise elderly assistances.

The wellness determination process of an elderly living independently in a smart home environment has been presented in this paper. So far, determination of elderly wellness parameters like an excess usage of appliances, no usage of appliances (β_1, β_2) and irregular behavior detection through the usage duration of activities based on smart home object usages are derived.

An effective technique has been presented in the paper for analysis of data to monitor the daily activities of the elderly. The wellness determination process as presented in this paper is a novel framework as it verifies the behavior of elderly at three different stages of daily living (usage of appliances, activity recognition and forecast levels) in a smart home monitoring environment. This will help in not generating frequent false alarms.

The developed system including sensing and intelligent behavior detection subsystems are developed in-house and are used to recognize basic ADLs from the data analysis of sensor stream. The developed prototype is suitable for easy installation and maintenance in an existing elderly house. Also, it helps in easy transformation of an ordinary house to a smart home, so that aged community people can continue to live in their own home.

The system was stable in executing multiple tasks concurrently, such as data collection and analysis in real-time. If the system executes continuously for a longer time, an optimal, maximum utilization of the appliances used by the elderly are obtained. Thus, cumulative data for time series analysis will enable better prediction of the abnormal behavior of the elderly.

The developed system can be easily augmented with other co-systems such as physiological parameter monitoring sub-systems. This will supplement information about health parameters like body temperature and heart rate, so that elderly health perception and daily activity behavior recognition together can be assessed to determine the wellness of the elderly. In the near future, a few prototypes are planned to be developed and will be used continuously in homes of elderly located at different places. This will verify the robustness of the sensing system and wellness determination process to provide inputs for modification in design. The collected data can be uploaded to a website which can be accessed from a remote place.

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