Hexagram Linkage: An Ambient Assistive Living System with Healthcare for Elderly People Living Alone

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Abstract. To handle the worldwide problem of aging, one of the most successful and cost-effective solutions is an ambient assisted living system. These systems integrate a collection of sensors, the Internet of Things, health management, human-computer interaction, offline medical entities and nursing services. The key technological component is a human activity recognition and anomaly detection system. We designed a platform framework that defines activity at three levels: atomic, basic and complex. Our framework process uses separate modelling with classical algorithms, so that four kinds of anomalies (point, set, scene and trend) can be detected. We implemented a real-world system and used it over two years within a scenario with nearly 200 users, thus proving the validity of the system and identifying certain deficiencies in the user's experience. Our system has the characteristics of practicability, compatibility, cost-effectiveness and robustness.

Keywords: Ambient Assisted Living · Daily activity monitoring · Abnormal behaviour pattern · Elderly healthcare

1 Introduction

The world's population of elderly people is increasing rapidly due to improvements in medical science [1], and the average life span and the proportion of older adults

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continues to increase. High-end nursing homes with advanced medical facilities are needed to solve problems arising from this situation, but due to limited social welfare and insurance resources, more than 90% of elderly people cannot afford care or medical costs. They have no choice but to live at home, and are more likely to suffer from depression and psychosomatic disorders than the general population [2], meaning that they may require emergency attention or cause social problems; in the worst cases, they may be found dead in their homes [3]. The problem of aging has posed many challenges to society, for example:

1. The increasing burden of medical expenses: More than 40% of the US health budget is spent on the elderly, who make up only 13% of the population, resulting in an unfair distribution of social resources. Most families cannot afford private doctors, nursing care or medical services.
2. Shortages of nursing staff: In China, the number of qualified nurses is lower than 1 million, while the demand for qualified people in the elderly care/nursing industry is about 38 million.
3. Social factors: Should the government or health insurance companies be responsible for the care of these elderly people? In most cases, relatives, friends and neighbours bear this responsibility.

In order to cope with the rapid aging of society, various technologies are developing rapidly in this field. Telemedicine [4], home monitoring [5] and video surveillance [6, 7] are relatively mature solutions and are widely used. These schemes monitor dangerous situations via sensors and cameras, and send the gathered data to neighbours, relatives and health care providers for response. Although the systems themselves are effective, the actual user experience is poor, since few people are willing to be monitored unless the situation is critical. Since about 89% of elderly people prefer to live in their own homes [4] where they are comfortable, and to maintain an independent and dignified lifestyle, the use of AI technology to replace some aspects of the caregiver labour force can solve these social problems in a relatively cost-effective way. Recently, a new paradigm has been developed that aims to enhance human capabilities through digital environments, involving an intelligent technology called ambient assisted living (AAL). These digital environments are sensitive, adaptive and responsive to human needs. This innovative vision of the everyday environment includes human-computer interaction technology, and is ubiquitous, inconspicuous, and very forward-looking. The following three factors should be considered in the design of such a system:

1. Maximisation of the user's privacy;
2. Development of a compact, robust, accurate and cost-effective sensing system;
3. The ability to detect abnormal patterns and generate alerts.

The main functions of an AAL system are to prevent, treat and improve the health status of elderly people. AAL tools such as drug management reminders can allow older people to manage their own health [8, 9]. AAL technology may also include a mobile emergency response system [10], a fall detection system [11] and a video surveillance system to provide more security for the elderly. Other AAL technologies are based on the monitoring of activities of daily life (ADLs) and generating alerts to help facilitate daily activities, as well as assisting elderly people in moving around and enabling the remote control of automated home appliances [12]. Finally, such technology can enable older people to contact and communicate with their peers, family members and friends more effectively [13].

Although it is in some respects similar to a smart home, an AAL system is more targeted toward healthcare and assistive functions, and needs the participation of relevant human and entity healthcare services. Sensors rely on wireless sensor networks (WSNs) to connect home gateways to medical application systems [14]. Many sensors that are used to monitor blood sugar, blood pressure and pulse rates can send vital signs to health monitoring systems, so that nurses or doctors can monitor patients remotely [15]. With the global development of cloud computing, mobile Internet and 4G and 5G communication, these applications will continue to increase in popularity. Research [16] shows that demand from individuals for medical equipment and AAL systems is increasing; citizens are gradually beginning to participate in personal health care, in order to continue living independently and to save on nursing expenses.

The motivation of this paper is to design an AAL system with health monitoring and anomaly detection functions that is characterised by ease of use, low cost, effectiveness and robustness. Our approach provides an ecosystem of medical sensors, computers, wireless networks and software applications for medical monitoring. The main objective is to prolong the independent and dignified life of elderly people within their home environment using the personal medical information and communication technology.

2 Related Works

The development of AAL systems is mainly based on the development and popularisation of the following technologies:

1. Giant health platforms: DACAR is based on Microsoft's HealthVault platform, which provides an interface allowing users to view, define, share and manage health data [17]. Apple has also launched its HealthKit [18] to provide users with solutions via a large number of WSNs, health devices and services.
2. Pervasive computing and wearable devices: These enable people to interact with these devices as part of their daily lives. Ubiquitous sensing is an active research field, the main purpose of which is to extract useful information from data acquired by sensors and the Internet of Things [19] to achieve specific purposes.
3. Mobile Internet: The popularity of online-to-offline systems has changed the way residents live and behave on the Internet, and the utilisation rate of resources within the society as a whole has increased.

2.1 Platform, Hardware Equipment and Applications

The CASAS [20] program at Washington State University uses a large number of sensor deployments to provide a non-invasive supporting environment allowing dementia patients to live independently at home. Besides, the CASAS project provides mobile internet applications. The University of Missouri's Aging in Place project [21] aims to provide a long-term health care model for the elderly, including monitoring the parameters of their daily lives, supporting the collection of health data close to the medical level, and thus providing remote protection for their health and safety. Elite Care [22] is an assistant living facility program equipped with a large number of civil-grade sensors for monitoring various indicators such as lay status, weight and sleep disturbance, to allow monitoring of the living and health status of households. In the Aware Home [23] project at Georgia Institute of Technology, a variety of equipment is used, such as floor sensors and assistant robots, to monitor and support elderly people.

Current projects in Europe include the Grenoble Health smart home [24], PROSAFE [25], and ENABLE [26]. The Ambient Assisted Living Joint Program (AALJP) [27], sponsored by the European Commission, aims to improve the quality of life of older people across Europe through the use of AAL technology. In Asia, AAL-related home health care projects include the early Welfare Technology House project [28] and the Ubiquitous Home project [29], which measures electrocardiogram data, weight, urine volume and other indicators. Any change in activity may be an indicator of cognitive or physical decline [30]. For example, indicators such as movement patterns, walking speed, number of discharges and changes in sleep rhythms have been identified as early signs of dementia [31].

Other projects focus on wearable devices and health surveillance systems at the medical level, and are more suitable for chronic patients with certain single diseases. These wearable medical devices expand the number of dimensions of the data and the application scope of AAL systems. For example, one project [32] developed equipment for indoor positioning and structured medical health monitoring; Health Vest [33] produced smart clothes for patients; the Cushionware project [34] developed pressure sensors to recognise when a patient is in a sitting position; and Wi-Sleep [35], which did not need to be worn, monitored respiration and heart rate via WiFi signals. Apple's iWatch, Huawei and Millet have also introduced wearable devices for health monitoring. BioHarness [36] developed a chest band for the monitoring of respiration and heart rate, and applied it to patients with heart disease. There are also other ancillary functions such as the outdoor location monitoring system OutCare [37], which is an anti-vagrancy system for Alzheimer's patients, and applications and tools biased towards cognitive orthodontics [38]. The sensors used in these devices are shown in the table below (Table 1).

Table 1. General subsidiary sensors in an AAL system

Sensor type	Measurement description	Sampling frequency
Accelerometer	Multiaxial acceleration measurement	High
Gyroscope	Directional state	High
Blood pressure	Blood pressure measurement	Low, trigger
Glucose	Blood glucose measurement	High, trigger
ECG	Electrocardiogram	Very high
EEG	Electroencephalogram	Very high
Temperature	Body surface temperature	Very low
Gas	Air pressure, harmful gas	Low
Muscle	Electromyography	Very high
Eyeball	Electrooculography	Very high
Pulse oximeter	Pulse oximeter oxygen saturation	Low

2.2 Anomaly Detection

Traditional detection focuses on disasters such as fires and gas leakages, and on triggering the corresponding alarm mechanism. An AAL system is different, as it involves the analysis of abnormal activities within households, and especially dangerous situations that may indicate that these households may need help. Many of the application algorithms for abnormality detection are the same as classification algorithms, and current research fields include inactive periods [39], fall detection [40] and disease prevention [41]. The function and value of these systems can be truly reflected. For example, patients with dementia and other mental illnesses can also be monitored for abnormal activities, enabling adverse consequences to be avoided [42].

Most of the more precise algorithms adopt data-driven approaches, but for anomaly detection, a knowledge-driven approach is needed in order to define the anomaly beforehand. The anomaly detection discussed in this paper mainly involves identifying the process of change in a household daily routine. Using supervised classification algorithms for machine learning, traditional modelling technology can still perform well in anomaly detection, in which anomalous activities are identified as new activities deviating from the norm. If there are no labelled training data, an unsupervised algorithm is needed. Cluster-based anomaly detection generally uses three approaches: (i) clustering; (ii) the vicinity of cluster centres; (iii) sparse clusters, using separate sizes and thresholds of clusters to determine an anomaly [43].

There are two main methods for detecting behaviour changes, and these involve profiling and discriminating. Normal behaviour is modelled using a method based on behaviour contouring, and an identified deviation is regarded as abnormal when it exceeds a threshold value. This method of identification involves learning abnormal data from historical data, and then identifying it directly when this abnormality appears. This is a common strategy in a knowledge-driven approach. However, in a real environment, historical data containing real anomalies are very scarce, meaning that a contour-based approach has greater practical significance for applications [44].

Feature extraction includes: (i) triggering times; (ii) triggering periods; (iii) the percentage of triggering activities of the total period; and (iv) the time difference between activities, from one location to another. Features may be related to the duration of events [45]. However, the features of persistent events are difficult to quantify, so it is adopted. A Gaussian normal distribution is used to calculate the average persistent events, and the positive and negative standard deviations ($u + 2\sigma$) are then used as boundaries, as these are more theoretically supported in a mathematical sense. Human behaviour will also be affected by several other factors, such as the weather, holidays, transportation, ball games, and other variations in behaviour, so a certain rate of error is still expected.

In order to solve this problem, a model scheme based on a probability graph can effectively reduce the number of false alarms [46], and can associate activities with health status to detect anomalies, collective anomalies and changes in health trends. A location-based scheme can also be used [47]. The best way to obtain user profile data is to define the most likely and frequent changes in location in order to detect changes in abnormal behaviour. Ordonez's scheme, proposed in 2014 [48], uses Bayesian statistics to model the distribution of follow-up features. Three probabilistic features in the wireless sensor network domain are analysed: (i) sensor activation likelihood (SAL); (ii) sensor sequence likelihood (SSL); and (iii) sensor duration likelihood (SDL), which detect abnormalities based on changes in the health context. Aztiria's Concept Drift

Table 2. Analysis and comparison of anomaly detection algorithms

Algorithm	Advantages	Disadvantages	Ref.
Artificial neural network	New rules can be added adaptively Mature application	Black box model Complex network architecture Unable to explain	[49]
Hidden Markov model	Processing sequence of data is simple and clear Accurate sequence of temporary actions Effective noise handling	Cold start Large training dataset required Data independent Manual pre-defined labels	[50]
Support vector machine	Linear or planar classification	Invalid outlier data samples	[3]
Conditional random field	No cold start Longer range Effective in dealing with noise	Computing overhead Manual labelling required Cooperation with other classifiers	[51]
Semantic rules	Lowest level heading text follows	Unable to handle undefined exceptions or noise	[52]
Profile/distance similarity	Simple calculation	Only binary data Unable to handle advanced logic Only one exception	[53]

scheme is based on the profile recognition of user behaviours [47]; it compares the latest data collected by sensors with historical contours of frequent activities in the user history data, and measures the amount of modification that would be needed to match behaviour computed based on the newly captured data with frequently occurring behaviour. Indicators or thresholds are used to determine whether the latest collected data is abnormal. All of the above schemes have certain advantages and disadvantages depending on the goal and scope of application. An analysis and comparison of several anomaly detection algorithms are given in Table 2.

3 Architecture and Preliminaries

3.1 Service Architecture

A typical AAL system is a people-oriented service system that has three main aspects: intelligent family, a remote health service and a physical care service. Based on the traditional architecture of big-data-related services and information communication platform, we expect that the service capability of an offline entity is crucial to implementation. Once the deployment and configuration of an AAL system is complete, continuous monitoring of sensors is carried out, thus making the household a private space. In addition to its own objective data attributes and the particular configuration, it also needs to synthesise external information from the Internet, carry out ETL and apply it comprehensively. Numerous types of data are produced by professional services, and together with the prior experience of the experts above are used to select the most appropriate intelligent service provider for matching and processing. Guardians far away from the elderly

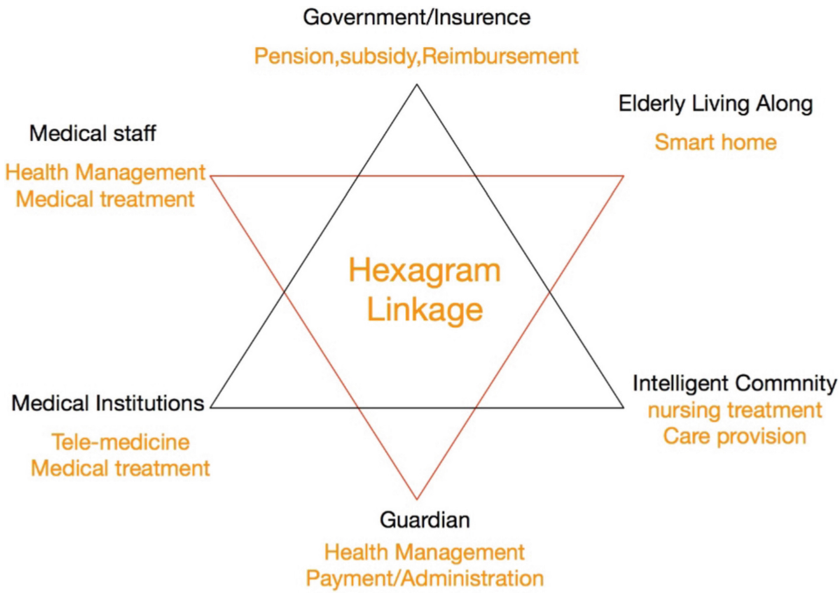

Fig. 1. Hexagram linkage: connected roles and services

person's home can purchase local or virtual services directly, anytime and anywhere, to protect their elderly loved ones living alone in their own home and to support their independent and dignified life. The architecture of these services is shown in Fig. 1. The hexagram framework connects each role with the corresponding services.

In this design framework, offline healthcare institutions provide long-term health services for residents, who are connected via telemedicine applications and the elderly person's smart home to form a complete AAL system via the Internet. With the gradual transition of the Internet to the era of mobile Internet, 4G networking and mobile computing have become available to every family, making XaaS (Everything as a Service) possible. Most computing and individual functions can remotely invoke cloud services and applications through RestFul's API. A guardian can check the status of the household anytime and anywhere via a mobile app. Based on the data shared by sensors, the Internet of Things, wearable devices and mobile medical equipment, guardians can determine a health status, price or other services that may be provided in the community or region, and can purchase entity services or third party services through mobile payment. The service can then be evaluated to promote a better experience for users. The AAL system therefore uses hardware as the carrier and entity services as support via the Internet, connecting the household and entity services together through the HAR system to facilitate automatic care. When an abnormal situation is identified, then take manual offline services, thus replacing some of the human labour in order to save costs. The abstract architecture of the overall system is shown in Fig. 2 below.

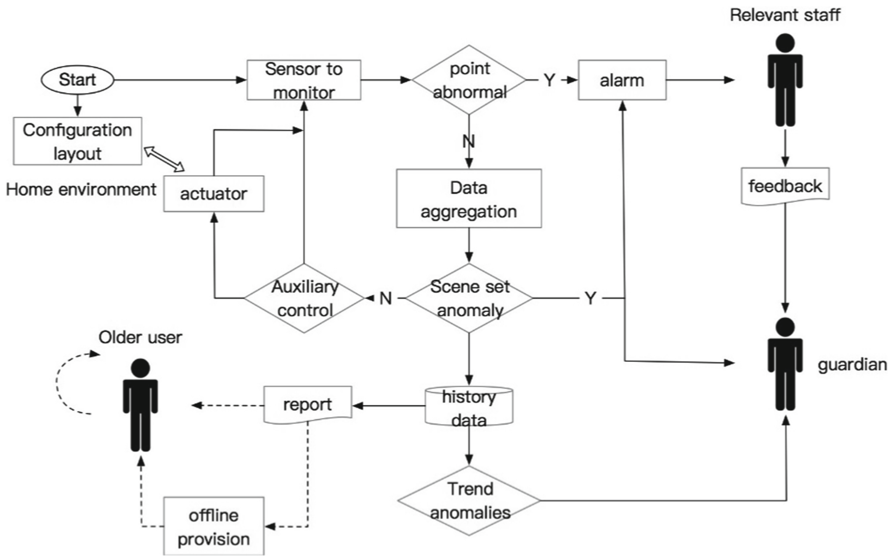

Fig. 2. Abstract flow chart for the AAL framework

3.2 Data Preliminary

In terms of equipment, we draw lessons from the deployment of the CASAS [54] project, since it has been running for five years and has been shown to be clinically effective. In terms of data attributes, we learn from MIT's PlaceLab [55], since each room has a fixed purpose within the home environment. Sensors collect basic behavioural activities, environmental parameters and corresponding timestamp information. Based on the goal of the application, we can add subjective knowledge and experience attributes, objective external data and environmental attributes to the position-aware scheme to enhance the dimensionality and validity of data. Apartment units in China are very standardised, and the living environments of most elderly people are shown in Fig. 3 below.

Fig. 3. Common living environments in China

An AAL system needs many different types of equipment, including MI equipment and medical equipment. These support the XML language to describe, define and link devices, provide data abstracts, and support the RESTful principle. After collecting data, we unified them via conversion to the ExADL data format, as used in our previous work [55]. The specific format is shown in Table 3.

Table 3.

Time axis	Objective attribute	Alarm	Active sensor	Subjective attribute	Behaviour description
[0]	[1:60]	[61:63]	[64:191]	[192:250]	[251:255]

The objective attributes of the data, including the device ID identification number, sensor type, timestamp, address code, data format, data sampling frequency, reading, sensor status information etc., reflect the parameter attributes of real data. In knowledge-driven schemes, subjective attributes require operators for configuration and to offer prior experience and knowledge. These attributes include: (i) ID; (ii) location, such as kitchen, living room and so on (enumerated values that machines may not necessarily understand, but human beings find very easy to understand); (iii) status and range (such as blood pressure or blood sugar values, normal range and threshold of early warning and alarms, which need professional knowledge combined with the situation in the particular household); (iv) associations (such as triggering of a smoke sensor due to an unknown fire) with the person who needs to be notified, which are solved by calling the processing module.

3.3 Data Pre-processing

The ExADL dataset is too large for the refined algorithms. In real applications, the selection of a subset of feature attributes related to the target can be used to complete the calculation and reduce the computational complexity. This is the process of selecting some data attributes from ExADL dataset to form a new dataset for different algorithms. This process is always accompanied by some simple calculations and data processing, including (i) time-related attributes, such as the time of occurrence, duration and repetitions; (ii) space-related attributes, such as the location of occurrence, room name, mobile data; (iii) complex attributes, such as events and interactions between people and objects; and (iv) state changes such as hidden attributes. The overall order of data processing is shown in Fig. 4.

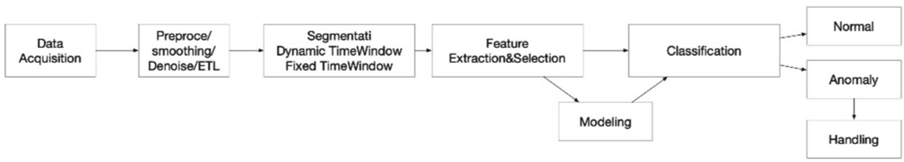

Fig. 4. Flow of data processing

We carried out the modelling of a resident's behaviour in our previous works [], in which we divided the user activity into three levels according to time granularity, corresponding to different modelling methods.

An atomic activity (AA) is the smallest unit of real human activity, i.e. one that cannot be monitored at a finer granularity. Sensor readings triggered by human activity such as swing, pressure, vibration, door opening and other attributes of active instantaneous trigger sensor, including ID, timestamp, data-driven attributes such as state readings, and the combination of knowledge-driven attributes such as the meanings and parameters of device state representation. The corresponding tags are specified in the configuration phase, and the classical ID3 algorithm is then used to model the atomic behaviour.

A basic activity (BA) is a basic unit that can independently represent possible human behaviours. It is a sequenced combination of all human-generated AAs and their attribute data within a small fixed time window (FTW). We use an unsupervised frequent pattern mining algorithm to carry out automatic labelling of black box BAs, and then use a classical hidden Markov model (HMM) to model the sequence.

A complex activity (CA) is an abstraction of real human activities. In the HAR field, it has the closest meaning to human behaviour. It refers to a sequenced set of all basic activities (BA) and other attribute information that is synthesised and formed within a specified time interval, which we call the dynamic time window (DTW). For long-term modelling of user routines, we use the classical conditional random field (CRF) model, which is generally based on a window of a day or week for offline modelling.

4 Anomaly Detection

The discovery of abnormal behaviour is of great significance in the application of AAL systems, since the living habits of the elderly are relatively routine. When abnormal behaviour occurs, it usually indicates a problem.

4.1 Definition of an Anomaly

In the actual feedback from deployment, a user's behavioural data typically obeys a normal distribution. Activity and data at each level correspond to different anomaly detection methods. We first define exceptions using four categories at the data level.

A point anomaly refers to an anomaly in data at the atomic behaviour level, including parameters exceeding a threshold range such as the time and position attributes of sensor triggering and normal habits, which have a greater statistical significance of deviation, for example a fire, getting out of bed at night or blood pressure that exceeds a standard value.

A set anomaly refers to the basic behaviour level data anomaly, including similarity matching between the sequence triggered by the sensor and the historical model exceeding the threshold. For example, when users are sick or depressed, many behaviours may deviate from historical habits.

Scenario anomalies refer to complex behavioural data anomalies, such as a user having a cold or diarrhoea, in which behavioural habits will deviate from the overall trend indicated by historical data.

Trend anomalies and others are usually calculated on the basis of specific parameters. The calculation period may be longer with fewer parameters.

The calculation process of each mode is shown in Fig. 5.

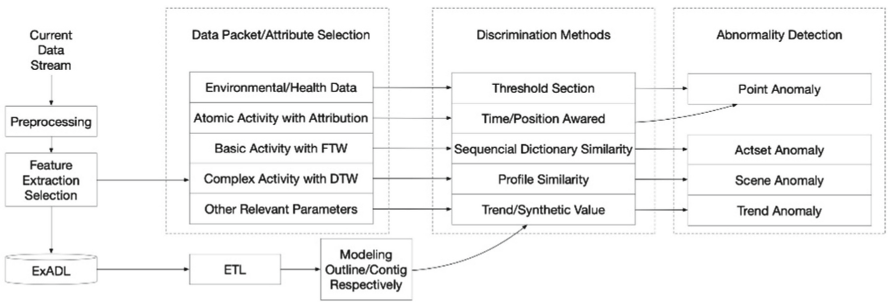

Fig. 5. Anomaly detection process at each level

4.2 Detection Methods

Point Anomaly Detection

When the system configuration is complete, we determine the alarm interval of the parameters, and start the alarm module when the data are abnormal. For abnormal behaviour, the main parameters such as the time and position of the trigger are inconsistent with the historical model, and the threshold is difficult to determine. We therefore use a simple Adaboost algorithm to carry out Boolean calculations, and beyond the part of the historical model we judge as anomalies. A detailed description is given below.

Input: Sample$(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)$
//Is the characteristic vector of K dimension, $\forall y_i \in \{-1,1\}$;
  Initial weight of n samples D0(i)=1/n;
  Weak classifier $g(x) \in \{-1,1\}$; Maximum number of iterations Imax
Output: All Weak Classifiers
1: For t =1 to Imax do
2: Looking for g(x) to minimise the weighting error
$g_t(x) = \mathrm{argmin}_{g_t^k(x)} \sum_{i=1}^{n} D_t(i) I[g_t^k(x_i) \neq y_i]$
$\varepsilon_t = \sum_{i=1}^{n} D_t(i)\, I[g_t(x_i) \neq y_i]$
3: Calculate the weight of gt(x):$\alpha_t = \frac{1}{2}\ln\left(\frac{1\text{-}\varepsilon t}{\varepsilon t}\right)$
4: Update sample weights;
  for i = 1 to n do
  $D_{t+1}(i) = \frac{D_t(i)\exp[-\alpha y_1 h_t(x_i)]}{\sum_i D_t(i)\exp[-\alpha y_1 h_t(x_i)]}$
  end for
5: end for
6: return $G(x) = \mathrm{sign}[\sum_{t=1}^{Imax} \alpha_t h_t(x)]$

Adaboost is a discriminant classifier, meaning that it needs to give a definite classification decision, and there is therefore a potential problem of uncertainty. Its statistical characteristics will select the largest number of classes in the sample as the prediction.

Set Anomaly Detection

We adopt a black box automatic marking behaviour method, based on frequent itemsets, and use an HMM to model the basic behaviour dictionary, which is composed of a series of vector matrices. In basic behaviour discrimination, we need to sample the sequence in the current time window and carry out a similarity discrimination with each behaviour in the behaviour dictionary. If the similarity is below a certain threshold, it is assumed to be normal behaviour, while if it is above this threshold, we need to start the processing mechanism.

However, in the actual processing of data inflow sequence, the original sensor data (a large number of noise and burrs) is not suitable, and needs to be smoothed before it can be used. An average smoothing method is generally used that defines the sensor attribute data sequence as $\boldsymbol{i}$, the behaviour dictionary as $\boldsymbol{Dic}$, and the time window as $\boldsymbol{w}$. The mean smoothing calculation is as follows:

$$F_w(i, Dic) = \frac{1}{w}\sum\nolimits_{j=i-w}^{i} SIM\left(Seq_j, Dic\right) \tag{1}$$

To calculate the distance, we adopt a cosine distance similarity. Assuming that the angle between two attribute vectors Seq_1 and Seq_2 is $\boldsymbol{\gamma}$, then the similarity between the two vectors is expressed by a cosine:

$$\cos(\gamma) = \frac{Seq_1 \cdot Seq_2}{\|Seq_1\| \cdot \|Seq_2\|} = \frac{\sum_{i=1}^{n} Seq_1 \times Seq_2}{\sqrt{\sum_{i=1}^{n}(Seq_1)^2} \cdot \sqrt{\sum_{i=1}^{n}(Seq_2)^2}} \tag{2}$$

The sequence similarity of behaviour attributes (such as trigger time, duration, location, state, etc.) can be calculated using the following formula:

$$SIM(Seq_i, Dic) = \max_{Seq_j \in Dic}\left\{SIM\left(Seq_i, Seq_j\right)\right\} \tag{3}$$

Scene Anomaly Detection

A set anomaly needs to traverse all the behaviours in the dictionary. However, a scene anomaly is relatively simple to calculate, and only needs to distinguish similarity by comparing a long-term historical contour model. We first need to determine the length of the time window, which can be expressed as a user profile in a long-term historical model trained using CRF over days, weeks or even months. Since the deployment and behaviour of users are uncertain, we use the algorithmic concept of self-organising maps (SOM) for reference in order to realise an unsupervised learning model to discriminate and to understand a user's behaviour as a hidden unknown state. If the user's behaviour deviates from the normal range, an abnormal occurrence is detected, which requires a guardian to confirm that the user is safe.

We assume that **s(t)** is the trigger time at which the user enters the room, **D(t)** is the duration, the hidden network node $\mathbf{M_i}$ is a weighted vector, and the latest data collected by the sensor are a combination of vectors $\mathbf{X(t) = [s(t), D(t)]}$.

In order to calculate the parameters of smooth iteration nodes, we let $\boldsymbol{\gamma}\mathbf{(t)}$ be a scalar parameter factor decreasing with time **t**, and $\mathbf{N_c i(t)}$ be a neighbourhood of $\mathbf{M_i(t)}$, representing the distance **X(t)**. Then, the value of $\mathbf{M_i}$ calculated after **I** iterations can be obtained by the following formula:

$$m_i(t+1) = m_i(t) + \gamma(t)N_c i(t)[x(t) - m_i(t)] \tag{4}$$

Input: **x(t)**，time limit **limT**
Output: Distance vector $\mathbf{m_i}$
1: m_1 = seed(); // Initialise random values
2: t=1；
3: while t < limT do
4: for each m_i in map do
5: d = diatance[m_i(t),x(t)]; // Computational cosine distance
6: track mi(t) with min(d); // Use the closest similarity
7: $m_i(t+1) = m_i(t) + \gamma(t)N_c i(t)[x(t)\text{-}m_i(t)]$
8: end for
9: end while
10: return m_i ;

Based on the return value and threshold value, the processing scheme is determined by prior knowledge or manual method.

Detection of Trends and Other Anomalies

Fluctuating trends in blood pressure, heart rate and respiratory parameters indicate an abnormal health status of a user. Some parameters do not have obvious threshold limits for alarms, such as daily use of a treadmill, sleep indicators and so on. We can therefore only use the user's own historical data as a normal profile contour and calculate the difference as a reference. Taking into consideration the influence of weather-related factors and holidays, we make a concrete judgment that the user's data primarily obey a normal distribution. When the difference exceeds twice the standard deviation, an early warning is triggered, prompting the remote caregivers to pay attention. The features selected in this way are relatively simple, but the time window used is relatively large, and is typically calculated in days or weeks. Since the data features are relatively small, the same configuration can tolerate larger computational time intervals. Offline computing is normally used to calculate each feature every day.

Input: **Single feature** extraction (motion detection, heart rate, blood pressure, sleep, etc.), **time interval** [T1, T2], and sliding window interval **W**
Output: **Characteristic matrix** (with statistical indicators)
1: Establish the computational time interval T1−T2//
2: while T1 < (T2 – W) do
for each feature do // Calculate for each feature.
// Starting with T1, a sliding window with a length W is established.
3: Process missing values ()；
4: Compute statistical indicators ();
// Include variance, skewness, kurtosis, correlation coefficient, etc.
5: Append(); // Write these values back to the eigenvalue matrix
6: T2=T1+1; //Move one day
7: end for
8: **return** average(feature matrix); // A smooth feature matrix is obtained.

This is handled manually when other logic or the threshold exceeds n times the standard deviation, where n = 1 or 2.

4.3 Anomaly-Handling Scheme

As described above, we define four kinds of data anomalies in AAL's information system. According to the degree of the emergency, we can divide the alarm and processing into four levels, which from high to low are as follows:

Disaster Level: For example, if a smoke alarm is triggered, this may lead to a fire, which should be dealt with by the nearest staff and 119 fire alarms.

Medical Level: Danger signs such as shortness of breath and sudden cardiac arrest are collected by mattress. It is necessary to call 120 for help from nearby medical staff and family members.

Nursing Level: Users are suspected to have health issues or danger signals, such as getting out of bed at night, instability in heart rate and blood pressure, insomnia/depression or other problems. There is a need to go to the scene to carry out a physical examination and confirmation, in order to ensure the user's safety.

Early Warning Level: Users show abnormal health trends or indicators, such as a slightly higher blood pressure, and need a guardian to contact them by telephone within a certain period of time, confirm the situation and decide on treatment. The overall exception handling process is shown in Fig. 2.

After the configuration and deployment of the AAL shown in the upper left, the system begins to monitor the data collected by sensors. According to the degree of abnormal danger and the level of the alarm, the alarm data can be distinguished from the pre-AAL gateway, which can identify abnormal data such as a fire, a gas leak, burglary, sudden respiratory arrest, rapid or slow heart rate, etc. The alarm module can then be started directly, and the relevant data can be dealt with by calling designated contact persons or emergency services such as 119 or 120. Questions, feedback on the problem and the results of the treatment are addressed by the guardian and the relevant handlers through consultation. When the gateway does not identify abnormal point data, it starts to calculate the similarity between the users and historical contours to see if there is any deviation in habits. If the distance similarity exceeds a certain threshold (that is, if it identifies an abnormal situation such as a cold or diarrhoea), it then confirms with the guardian whether this needs to be handled by the guardian. When data on a user can be accumulated for two weeks or more, trend anomalies can be calculated based on a historical weighted average. When assessing trends involving suspected insomnia, depression or forgetting to take medicine, the system should inform the guardian within a suitable period of time, and the guardian should confirm the situation as soon as possible and decide how to deal with it.

5 Case Study

In order to verify the applicability and validity of the anomaly detection methods proposed in this paper, as applied to helping elderly patients with chronic diseases, we established a demonstration base involving both medical and nursing care in Shaanxi Province, as a typical solution, with support from the government of the new urban area of Xi'an, Xi'an Mayinglong Hospital, Xi'an Mingzhong Community Service Co., Ltd., and the Information Storage Department of Wuhan Photoelectric National Laboratory. Our case study was run with 184 users for over two years, using the deployment specifications shown in Table 4 below.

Table 4. Equipment specification for the case study (per house)

Hardware	Description	Number
Temperature sensor	ZigBee, temperature and humidity at 10 min intervals	3
PIR sensor	ZigBee, motion detection at 1 min intervals	6
ECG band	BLE, steps, sleep, heart rate at 10 min intervals	1
SOS button	On demand	1
Toilet Cover	Wi-Fi, toilet time, frequency, duration	1
Leakage detector	Point alarm	1
Gas detector	Point alarm	1
Smoke alarm	Point alarm	1

With the continuous development of the electronic industry, the large-scale application of sensors makes the price of civil-grade sensors equipment wallet-friendly. Open-source hardware such as Raspberry pi and Arduino can connect different transmission

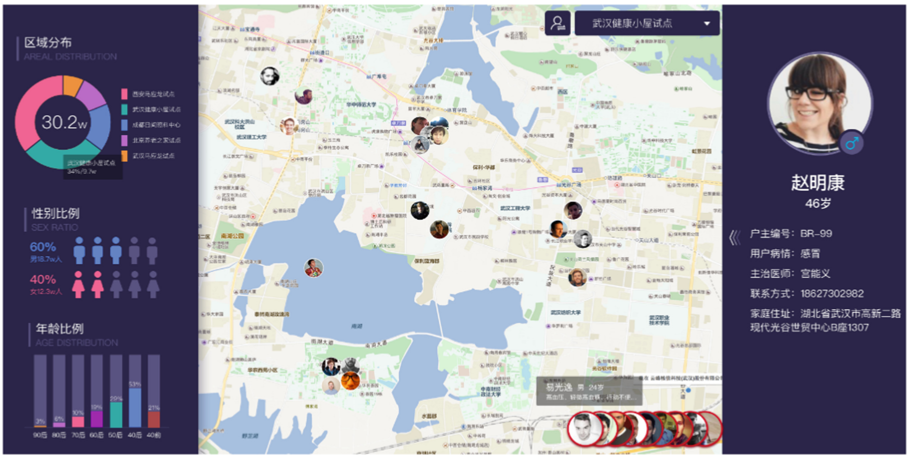

Fig. 6. Backstage management of our AAL system

protocols with various general IO interfaces. XML or JSON can quickly unify the data formats from different manufacturers, so a set of CASAS-like devices can be developed based on the above-mentioned devices, which can guarantee low cost, effective and robust (Fig. 6).

The average power consumption of the home-based part of the AAL system is about 1.8 W/h, as shown in the figure of other supporting software. The AAL project was generally effective. A total of 114 suspected safety hazards were found in time, and the guardian was notified to address these. No injuries or death occurred to the users. The warning and handling of exceptions is shown in Fig. 7.

Fig. 7. Blood sugar, blood pressure, sleep status and heart rate alerts

In total, we sampled 117 sets of abnormal alarms, five of which were false alarms, and the rest were caused by the user having a cold or diarrhoea, or changes in travel behaviour. Our detection algorithm is effective, but needs to be strengthened and improved in terms of the user's experience. A visual representation of this model checking is shown in Fig. 8.

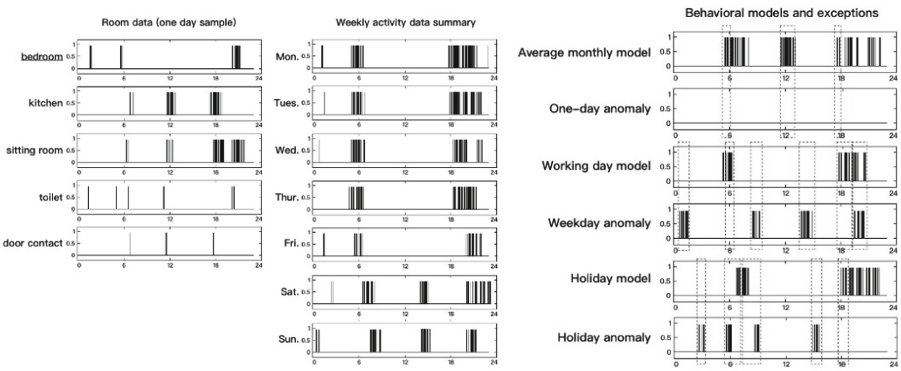

Fig. 8. Intuitive display of behaviour deviation

6 Discussion

Based on data feedback from 300 real users as part of the follow-up to this project, we conclude that the health status of working people is poorer than that of the elderly, although their physical functions are stronger. The work and rest patterns of retirees are relatively regular. Working users showed abnormal heart rates, blood pressure, sleep patterns and other aspects 20 times more frequently than the retired group. The performance of comprehensive satisfaction related to work stress and anxiety is acceptable. Some suggestions for improvement and user experience were received as feedback.

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