2017 IEEE International Conference on AI & Mobile Services (AIMS)

Activity Recognition as a Service for Smart Home

Ambient Assisted Living Application via Sensing Home

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***Abstract*—An aging population has inspired the marketing of advanced real-time ambient assisted living solutions. However, the accurate collection of behavior information, recognition of human activities and implementation of this scheme in a real living environment is a challenging task. In this paper, we propose a feasible extended framework which is compatible with common devices and protocols. Specifically, we treat activity recognition as a cloud service; thus, the application of home automation, environment and health management and advance warning of risk can be directly applied using this service. Finally, we evaluate our approach and show that it can achieve a theoretical accuracy of 93%, and can be run on cost-effective devices such as BeagleBone.**

Keywords*—*IoT; AAL; Integrated Learning; AI as a Service

I. INTRODUCTION

The Internet of Things (IoT) [1] and smart cities [2] have attracted attention from academia and industry for decades. By definition, IoT allows people to be connected any time, with anything and anyone, ideally using any path/network and any service [3]. This has enabled several critical services such as traffic, energy, education, health and crime management to be applied in many cities [4]. Some leading smart city projects include IBM's Smart Planet and Smart Cities, the Smart Dubai and Smart Amsterdam initiatives and Oracle iGovernment, as examples.

One of the typical applications of IoT is ambient assisted living (AAL), which aims to support independent living and is motivated by the worldwide trend towards an aging population. Advances in pervasive computing have resulted in the development of wireless, unobtrusive and cost-effective sensors for gathering information. With the popularity of networking and smart hardware, the application of AAL is now entering civil usage from the academic experimental stage. With continuous developments in technology and the popularity of networking, home-level electronic equipment has become plentiful in function with wallet-friendly prices. Both giant IT companies and start-ups provide a range of smart devices, such as Google Home and Amazon Echo, or release platforms, such as Apple Homekit [5] and Xiaomi [6]. From the point of view of communication, these devices and applications use heterogeneous networks which connect together hardware, smartphones and cloud services. However, due to considerations of design, security and the privacy issues of the vendors themselves, there is no unified communication standard or criterion for data formatting.

Although the Zigbee Alliance [7], Wi-Fi Alliance [8] and China Smart Home Industry Alliance (CSHIA) [9] have devoted much effort to this issue, it has been impossible to create any unified criteria for smart devices in recent years. For the short term, a message request via JSON for sensors to read and operate the actuation unit via a cloud service is one feasible solution.

The primary reason for the continued development of AAL is to assist disabled and elderly people, and especially those with chronic diseases, in order to enhance their wellbeing and enable independent living. To provide assistance for individual residents, a smart home with electronic medical equipment and telemedicine is one solution to the demand from the abovementioned aging population [10], the cost of health care [11] and the importance that individuals place on remaining independent and in their own homes [12]. In this field, the most challenging and well-researched issues are human activity monitoring, modeling and pattern recognition. There is a need for online activity recognition techniques which can remotely

978-1-5386-1999-5/17 $31.00 © 2017 IEEE
DOI 10.1109/AIMS.2017.29

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track the status or activities of the resident. Everything as a service (Xaas) [13] is a category of models introduced in the area of cloud computing [14], and this may help institutions to focus on their own areas of expertise. With the behavior of the resident as a service, vendors and service providers are able to offer various applications for assisted living.

The main purpose of this work is to develop an integrated machine learning as a service to achieve human activity recognition. In the interests of this goal, we use common sensors and controllers and put forward an extensible data framework which is compatible with a greater range of devices, protocols, manufacturers, in order to facilitate the implementation for consumers. The contribution distinguished our work from others lies in 1, A hybrid heterogeneous home network is proposed, which enables various devices to join into the intelligent system. 2, Three-layer sliding windows are adopted to achieve unsupervised classification of behavior. 3, Activity Recognition algorithm as a cloud service, let personal data stored locally to protect privacy, and cost-effective devices can be implemented, independent of the vendor.

The remainder of the paper is organized as follows. Section 2 outlines related work. Section 3 describes the proposed approach, including the architecture, the topology of the heterogeneous network and details of the hardware. The integration and implementation of various algorithms and applications are presented in Section 4, including the hidden Markov model for behavior prediction, a segmented time slide window with relative entropy for abnormal detection, a decision tree and a naïve-Bayes-based home automation. The implementation of various components and the results of the evaluation of the framework are discussed in Section 5. Finally, the conclusion, potential applications, extended activities of daily living (ADLs) and future work are given in the last section.

II. RELATED WORK

A substantial number of leading projects within the fields of smart environments and activity recognition, such as the CASAS project [15], MavHome [16], PlaceLab [17], CARE [18], Smart Umass [19],Duke University Smart House [20] and the Aware Home [21], stand testimony to the importance of this research area, as do medical approaches such as the Smart Medical Home [22], GETALP [23], U-health [24,25] and telemedicine [26], a health service especially suitable for chronic patients and elderly people living at home [27,28]. These approaches vary depending on the underlying sensor technologies used to gather the activity data.

A. Sensor

The recognition of human activities from video is one of the most promising applications of computer vision [29] and dense sensing [30,31]. Vision-based solutions are often used in security surveillance, but are unsuitable for in-home applications due to privacy and ethical considerations, while medical approaches, including connected health [32] and integrated care [33], require equipment such as electrocardiography (ECG) devices [34] which are not affordable for most users. Lightweight applications such as medication management [35] seem promising for the time being. A Wi-Fi signal-based solution [36] was one creative idea, but this suffers from certain drawbacks such as confusion generated by multiple targets, noise and interference [37]. Currently, smart devices with wearable sensors [38,39] or wireless sensors[40] are surging into the civilian market, which has enabled heterogeneous home-level AAL implementations [41], and has created the problem of complexity and competition between vendors and standards.

B. Methodology

Symbolic approaches require rules, logic and events, inspired by logical modeling and reasoning based on ontology [42]. These use logic-based knowledge representations to model activities and sensor data, even to infer activities. In contrast, data-driven approaches uses machine learning techniques that elicit activity models from existing datasets. In probabilistic learning or statistical reasoning, the hidden Markov model (HMM), conditional random fields (CRF) [43] and other state-of-the-art algorithms are used to recognize the activities occurring and to perform activity inference. In addition, evidence theory is gaining increasing attention in the area of behavior recognition, and is suited to the capturing of context uncertainty, including Dempster-Shafer theory, known as belief functions [44]. There are also a number of unsupervised activity discovery methods which can be used to mine for frequent sensor sequences [45] or discontinuous patterns [46].

C. Data Setting

One common type of experiment is to ask subjects to perform a set of labeled activities, one at a time, within a laboratory setting [47]. In this case, the activities are well segmented, which allows the researchers to focus on the task of mapping the pre-segmented sensor sequences to activity labels. Individuals need to be able to complete ADLs and instrumental ADLs (IADLs) [48] such as eating, grooming, cooking, drinking and taking medicine with instrument status, in order to lead a functionally independent life. Thus, the automated recognition and tracking of these datasets is an important step towards monitoring the functional health of a smart home resident. This is the primary motivation behind much of the activity recognition research in smart environments [49]. However, these approaches indicate an offline annotation process that takes advantage of pre-segmented and scripted data, leading to confusion when a new event, or behavior not in the historical statistics, occurs [50].

In view of the discussion above, we contend that capturing features of sensor data and wearable devices and by extension instrumental status with human behavior. We thus construct a private smart space based on the resident's house, with sensors and heterogeneous wireless sensor networks (WSNs) gathering promoted dimension and precision data from sensors and other devices (not specific to any vendor or dataset) for use in real-time activity recognition as a cloud service. The primary features that distinguish the work presented in this paper from other related work are: 1) the design of an extended ADL framework for compatibility with a diversity of vendors, combined with iADLs to enhance data variety; 2) the proposal of an integrated learning scheme using a hidden Markov model to establish the probability model, and a time slide window with Kullback-Leibler divergence to detect real-time deviant behavior; 3) the introduction of the Dempster-Shafer theory to eliminate conflicts and confusion, in order to offer the integrated algorithm as a cloud service, and 4) the implementation of a local cost-effective embedded device with a lightweight decision tree algorithm for the control of electric appliances.

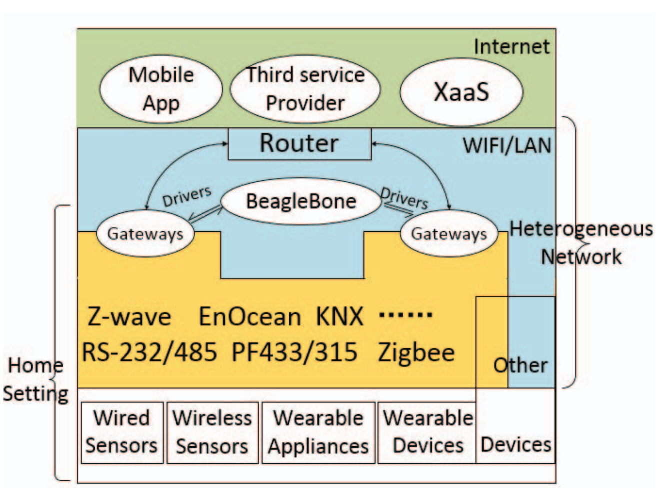
III. FRAMEWORK AND ARCHITECHTURE

Everything as a service (XaaS) [51] is a category of models introduced with cloud computing. With IoT based infrastructure, challenges in Smart Cities has been addressed partly. Today, large varieties of different sensors are available. They are capable of measuring a broad range of phenomena, which made context aware computing and advanced application of smart home possible [52]. In this section, we explain the sensing as a service framework in a generic conceptual form. In Section 4, we present a real world scenario based on this model. At the end of Section 5, we map the real world scenario into the conceptual model in order to provide a practical understanding

We present AR as a service for smart home, in part of the cloud service providers. Four layers as functional abstraction throughout the deployment process for application. 1. Hardware vendors, as sensor or appliance supplier, detects, measures or sense a physical phenomenon such as humidity, temperature and so on. 2. Integrator, as smart home solution provider, major with APP and cloud service attached. 3. Other cloud service providers, like weather, traffic. 4. Data Consumers, professional or institution with both online and offline services.

Let smart home hardware sample and send the sensor data of a smart home, AR as a service, return computational results. With this help, AAL applications could be independent of devices, just like AI and NLP services provided by Microsoft Cortana.

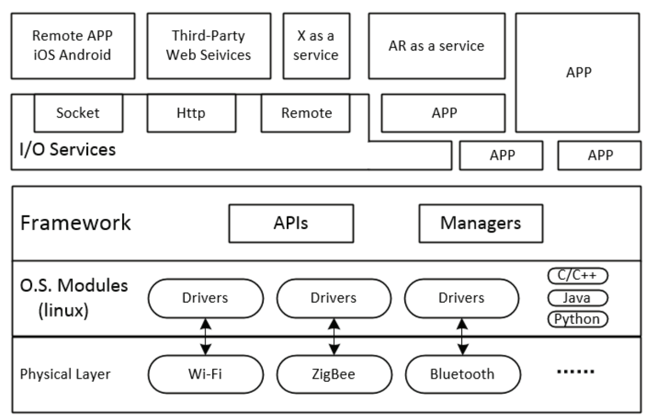
Fig.1. Architecture of Heterogeneous System



In the deployment process, majority prefer to renovate old buildings instead of fabricating them from scratch. Aiming at reduce cost, take advantage of integration and enhance the value of existing domestic systems, with configuration, maintenance, heterogeneous communication solution satisfy these requirements. Indeed, multiple incompatible standards, competition in vendors exists. However, with the popularity of the Internet, smart devices tend to banding with mobile APPs, which made data synchronization possible via JSON format. Besides, onboard communication conversion module or USB based convertors are available. In this way, the interconnection between different manufacturers could be implemented as software integration. The architecture of the heterogeneous network smart home system with cloud services described in Fig 1.

As shown in Fig.1, common intelligent devices in smart home with mainstream communication protocols are compatible at three levels: 1. Direct communication. Take Bluetooth as an example, we use the open sourced Beagle-Bone [53] with on board Bluetooth module to design data interface and drivers. 2. Gateway communication. Take Xiaomi[54] suit as an instance, data interaction through WLAN. 3. Cloud interaction. We use homebridge [55] to interact with the APPLE Homekit [5] and Siri. Thus, a feasible software stack for our solution with clear layers division is presented in Fig.2.

Fig.2. Software stack of Heterogeneous System



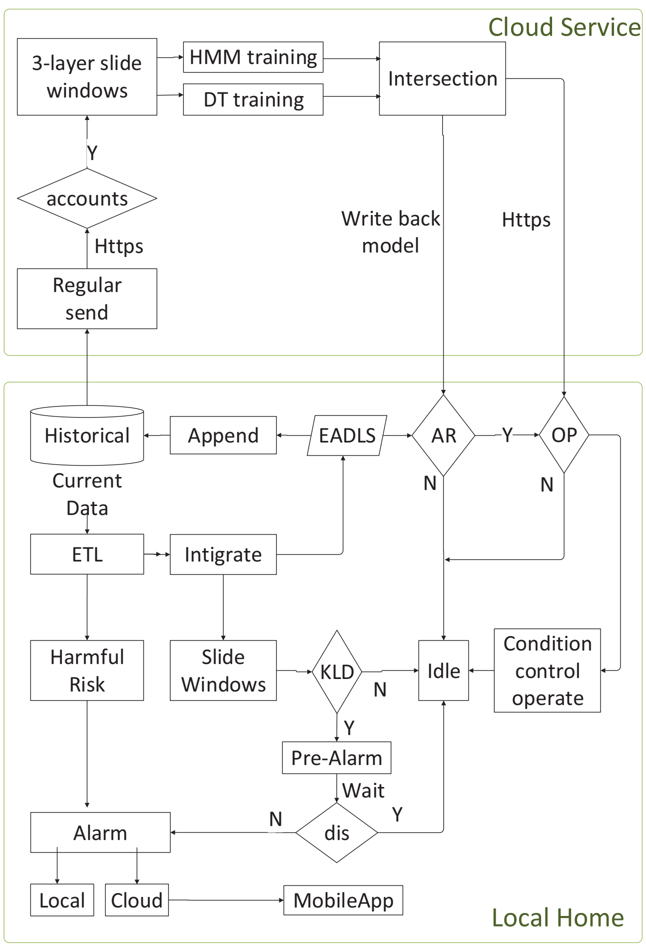
In order to unify the data of each manufacturer into a centralized table, we use ADLs, iADLs and Specification of Zigbee Alliance[] and VillaKit Specification of CSHIA[] for reference, put forward a temporary extended ADLs (EADLs) format. To simplify the complexity of compatibility and integration, we use a large sparse matrix. The first column is the digital parameter of time axis, each of the rest columns represents the functional state of a sensor or a household appliance. Except for temperature and humidity, formaldehyde, PM2.5 content and other numerical parameters, most of the table functionally expressed "1" as "ON", "Yes" or "Fired" status, leaving "0" as "OFF", "No", "Idle" or "Null". Redundant indeed, but it will not take up too much storage space when compressed, and it is more suitable for the training of machine learning algorithms. We provide a sample data at https://github.com/hustlxb/Sample in csv format. In this file, we defined the table as shown in table 1.

TABLE.1. EXTENDED ADLS FORMAT DEFINITION

Columns	represent
[0]	Float: Time Aix
[1-9]	Date parameters as holiday or not…
[11-60]	Weather parameters as Rain, Windy…
[61]	Smoke sensor or fire alarm
[62-111]	Motion detect
[112:161]	Appliance status
[162:181]	Float parameters as PM2.5…
[182-191]	Door Trigger
[192-255]	Preserved

The whole flow of this heterogeneous framework can be described by Fig 3. The current data as the real-time streaming format comes from various smart devices, we use ETL and JSON to transfer the data into EADLs. Then the current data segment compute the AR model to get current activity, and execute the following operations. Let the historical data and operation records be the training set to receive a user habit based training model.

Fig 3. Flow chart of the solution framework.



In this framework, the smart home in charge of sensor sample and storage, then regularly uploaded to the cloud to calculate the AR model. After the computational process, the AR model of the resident write back to local beagle-bone. Streaming sensor data come into tree based local light-weighted model to compute and return the corresponding operation.

IV. AR AS A SERVICE

Our approach reflects some complexities of unconstrained real-world data that cannot be observed in other datasets. The factor is that the inclusion of sensor events that may do not belong to any of the known activity labels for performance evaluation. This is a common problem that one faces when scaling the AR approaches to real-world settings. Thus, unsupervised learning is required. In this paper, we propose a location based 3 level sliding window clustering and classification scheme. Firstly, the behavior of households is abstracted and clustered. Secondly, according to the clustering results, we use hidden Markov model to calculate the predictable AR model, and the Decision tree (C4.5) algorithm to return the trigger entropy AR model. Finally, combine the two AR model as an intersection set and adjust with boosting and D-S theory to reduce the deviation.

A. Location based slide window cluster

We assume that the parameters of each sensor are orthogonal. Although there is a relationship between magnetic door trigger and passive infrared motion sensor, the sensors and controllers are functionally independent. Except for wearable devices, major smart home devices such as sensors and wall switches have fixed position. In a normal home, each room has a relatively fixed purpose, such as a kitchen, toilet, balcony and bedroom. In this way, the function of the room can be labeled during the initial configuration. In addition, the number of sensors and controllers in each room are finite in actual deployment. The number of clusters can be determined based on the number of devices in each room. In theory, if there are n devices, behavior can have 2 n sub species combination. Take a typical bedroom equipped with one door trigger, one PIR motion sensor, an Air Conditioner, one Table Lamp for instance. The theoretically combination has repetition meaning as shown in table 2.

We present the first application of the 3-layer sliding window method for dealing with discrete smart device events. The first layer is a large window based on date and weather, mainly used to determine the working days, holidays and weather have an impact on behavior. The second layer of sliding window is specified by the explicit device status “ON”. The third layer of the sliding window is a subdivision fragment, to detect the association between sensor devices. Statistical methods adopted to eliminate the small probability of occurrence in the same segment to determine the amount of abstract behavior in the room. Take environment like table 2 as an example, we illustrate how the 3-layer sliding window is clustered shown in Fig.4.

TABLE 2. SENSOR STATUS MAP

	Door	Motion	AC	Light	Actual meaning
Status	0	0	0	0	Idle
	0	0	0	1	Light on
	0	0	1	0	AC on
	0	1	0	0	In home
	0	1	0	1	In home with L on
	0	1	1	0	In home with AC on
	0	1	1	1	In home with AC&L on
	1	0	0	0	Door open
	1	0	0	1	Door open with L on
	1	0	1	0	Door open with AC on
	1	1	0	0	Open door
	1	1	0	1	Open door with L on
	1	1	1	0	Open door AC on
	1	1	1	1	Open door with AC&L on

Fig. 4. Approach of slide window clustering with streaming data.

As shown in Fig.5, simple actual activity with infinite devices in bedroom. The first layer of slide window, based on historical information, combined with the current date and weather, there is a preliminary rough judgment of AR environment. Then the device status based explicit segmentation of layer 2 detect longer chunks. "ON" status of Light or AC naturally to be good indicator of the activity fragments. As a result, inferred activities A1 and A2 confirmed. At the third layer of slide window, time is divided into fine fragments as T1-T18, to capture and statistic the fired sensor information. Pick the maximum information out of each time segment with 2n possibilities to represent the current behavior. In this way, actual activities of the resident could be abstracted into the limited status, and the number of clusters in each room could be determined.

B. Hybrid AR model training

We combine the hidden Markov Model (HMM) and Decision Tree (DT) C4.5 algorithm together, to generate a hybrid AR model. HMM, is a standard model of sequential production based on probability, describe the state of random sequence by a hidden Markov chain randomly generated, and the various production and produce a state observational process of random sequence. The sequence of Markov chain stochastic production state of the hidden state sequence and an observation for each state generated by the random sequence of the resulting observation, each location sequence can be seen as a moment, which match our slide window.

In our activity recognition model, the feature sequence is $\{x_1,x_2,\ldots x_{n-1}\}$ observed by sensors and smart devices. Behavior mode is a variable state $\{y_1, y_2, \ldots y_n\}$, represent the system state of the time. The generated model represents the most probable sequence of the behavior of the actor in the observation sequence.

Therefore the probability distribution is:

$$P(x_1, y_1, \ldots x_n, y_n) = P(y_1)P(x_1|y_1)\prod_{i=2}^{n} P(y_i|y_{i-1})P(x_i|y_i)$$

The probability of conversion between the states of the model, marked as $A=[a_{ij}]_{N\times N}$. The probability of obtaining the observed values in the current state as $B=[b_{ij}]_{N\times M}$. Let π be the initial state probability. Vitby algorithm can use dynamic programming (DP) method to efficiently solve the optimal path, that is, the maximum probability of the state sequence.

The advantage of decision tree is that it does not need any domain knowledge or parameter setting. Compared with the probabilistic model, the DT can directly determine the information entropy of the state transition and the actual sensing parameters. In order to eliminate the uncertain factors, we adopt the intersection results of HMM and DT as the final AR model. Both the two model results high in accuracy, to deal with uncertainty, we do not consider what the specific behavior is, use the boosting ideological to determine a higher degree of certainty vote.

C. Anomalies Detection

When the AR model has been trained, we imported the Kullback–Leibler divergence (KLD). Let p be the true distribution of the real time activity stream, and q be the trained AR model. The distance of distribution between p and q is:

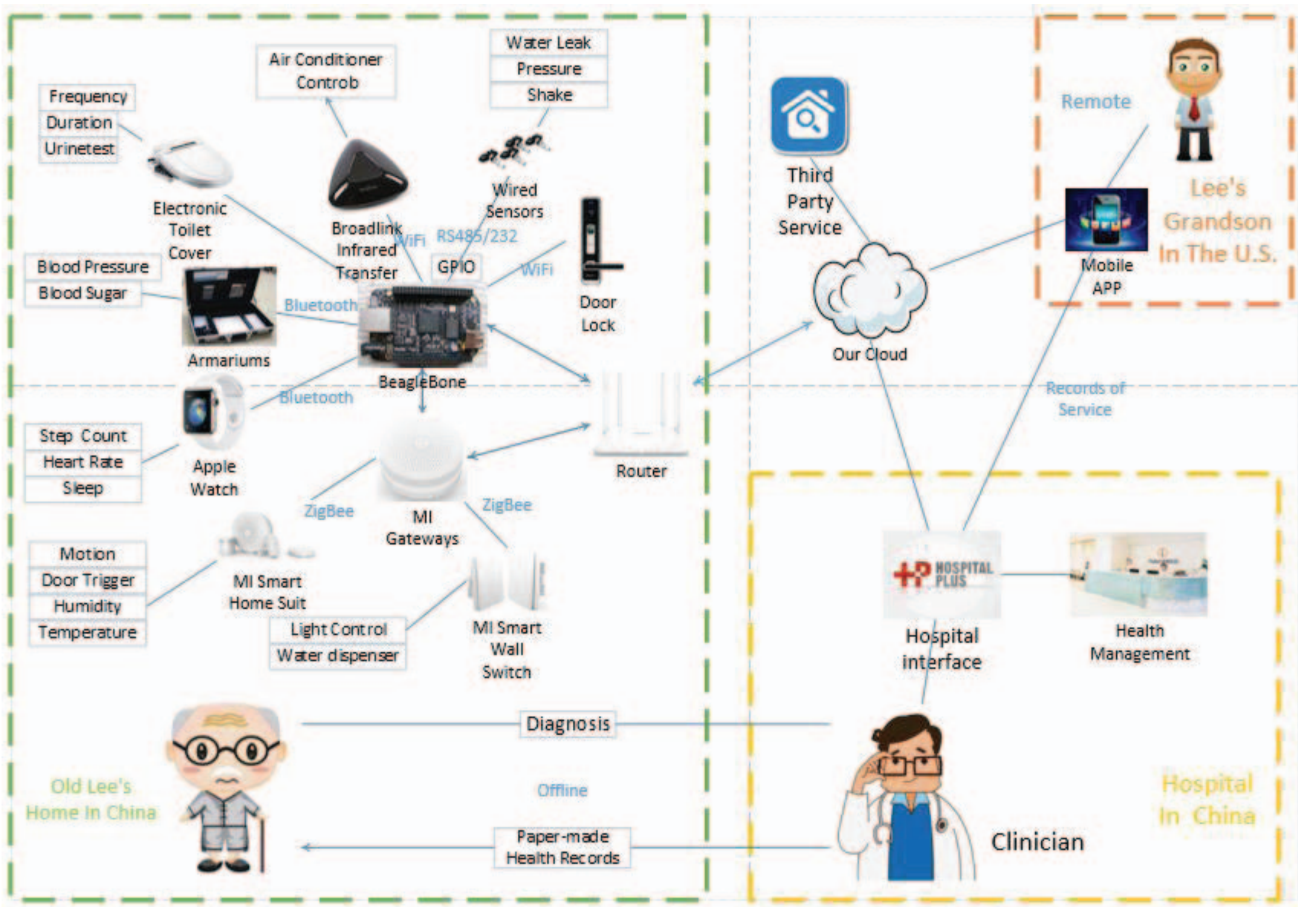
$$D(p\|q) = H(p,q) - H(p) = \sum_i p(i) * log\frac{p(i)}{q(i)}$$

The larger the difference is, the greater the relative entropy is, the smaller the difference is, the smaller the relative entropy. This comparison exists in both the historical model and the current sliding window of streaming data. If the difference is greater than the threshold of a few of our windows, it is possible that the anomalies occurs. Besides, there is a tricky setting: no matter how great the difference is, if any motion or door trigger sensor fired means the pre-alarm is dismissed.

V. IMPLEMENTATION AND EVALUATION

At present, the project has entered the pilot phase. In order to realize AAL for the elderly, especially to serve those living alone with chronic disease in Xi'an, China. Old Lee, one of our typical volunteer user, with heart and anorectal diseases, who lives alone in his home 1.3 miles away from the hospital and he is too old to get used to the mobile APP. We use MI suit and wired gas sensors to collect environmental and motion information, with armamentariums like electric blood pressure and toilet cover to obtain pathological information, we integrated all devices into a Beagle-Bone Black for implementation with our platform and applications. As shown in Fig.5, health and living routine will be synchronized to his contracted physician at regular intervals. Combined with professional medical examination report, the clinician would be able to provide guidance and help according to Old Lee's chronic disease and living status. Besides, when anomalies occurs, such as parameters of heart rate or blood pressure over the preset threshold, nurses can receive messages for the first time and take appropriate action. Health status, medical and service records are able to be checked by Lee's grandson via mobile APP, despite of the distance away from American.

Fig.5. Typical user scenario with medical service linkage.



We took three weeks of monitoring Old Lee, with interviews and feedback according to his living data to verify our idea. As an individual cases, on the one hand, Lee has many regular habits and living routines with small fluctuations, such as time to get up, meals, go out for a walk, and so on. Activity Recognition results above 93% of these behavior accuracy. On the other hand, unpredictable behaviors exist. Temporary motions like friend visit, toilet, shopping and return home, these activities are various and discrete. Sampled data of three week is difficult to find duplicate events recur. Longer period and more volunteers participate in data is required.

VI. CONCLUSION AND FUTUREWORKS

For the time being, we offer a temporary compatibility solution of AAL, with the features of easy to use, wallet friendly and effective. A hardware independent solution is provided by the Activity Recognition as a service model, which use heterogeneous networks to be compatible with more brands of smart equipment. In the practical application case study, our volunteer data show that some of the regular behavior are relatively easy to extract and identify by time series correlation model. Even the light weighted naïve Bayes or simple Decision Tree perform high in accuracy. The distribution of such behavior routine is suitable for the use of K-L distance to identify anomalies for the retired elderly, but may not fit for the irregular youth. Even though we took some tricky operation and used intersection set and boosting vote to reduce the false alarm rate, a reasonable weight adjustment should take in to consideration of the balance between user experience and security. For those Improvisation activities, requires observational data for a longer term and other creative approaches to solve in the future. We will deploy one hundred home in New City District in Xi’an, China soon. In order to serve more chronic elderly better, we will public some privacy preserving data set of our volunteers provided for peer research.

ACKNOWLEDGMENT

This work is co-funded by JCYJ20160531194457572, basic research project of Shenzhen science and Technology Innovation Committee, and 2015 R&D support foundation of Shenzhen Virtual University Park: Shenzhen branch of DSSL, project of research and platform construction, and in part by Independent innovation research foundation of HUST. The authors acknowledge support from Xi'an municipal government and cooperation from Mayinglong Group, co-funded by community service for home care of elderly project in Xi’an. The authors would like to thank their families for spiritual support and psychological understanding. Additionally, the authors thank the anonymous reviewers for their useful comments and suggestions, which are very helpful to improve the pilot project.

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