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A Framework for Fog-assisted Healthcare Monitoring

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Abstract. In order to tackle some challenges in ubiquitous healthcare monitoring such as mobility, scalability, and network latency, a framework for Fog-assisted healthcare monitoring is proposed in this paper. This framework is composite of body-sensing layer, Fog layer (Fog-assisted gateway), Cloud layer (health Cloud). And then, this paper makes an intensive study in some key technologies of the proposed framework such as an IPv6-based network architecture, intelligent warning model based on subband energy feature, security framework of HL7 RIM-based data exchange, health risk assessment based on fusion of grey model and Markov model. Finally, results of experiment depict that the proposed intelligent warning model can make immediate distinction abnormal signals. Moreover, the proposed health assessment model confirms its effectiveness with respect to 245 patients in Xiamen District of Jimei.

Keywords: Healthcare monitoring, Fog computing, IPv6, HL7 RIM, Health risk assessment.

1. Introduction

Population aging is happening faster than ever before. A report issued by the World Health Organization (WHO) stated that there was a shortage of about 7.2 million healthcare workers in 2013, and this is estimated to reach 12.9 million by 2035. The increase in population and chronic diseases as a result there is increasing pressure on quality and quantity of healthcare. According to the Chinese Cardiovascular Health Index (2017), the mortality of cardiovascular and cerebrovascular diseases is on the rise. The number of patients with vascular disease was 290 million, including 13 million of stroke, 11 million coronary heart disease, 5 million pulmonary primary heart disease, 2 million 500 thousand rheumatic heart disease and 2 million congenital heart disease. The prevention and monitoring of cardiovascular disease (CVD) is very important, especially for sudden heart disease. If it is possible to monitor the subtle signs and take effective measures in advance, the patients of 70%-80% can avoid death. Healthcare monitoring considered as an important means to reduce the cost of medical treatment, alleviate the shortage of medical resources and improve the overall level of medical treatment.

Recent technological trends such as WBAN (Wireless Body Sensor Network), Cloud computing and Bigdata provide an infrastructure for ubiquitous healthcare monitoring that can prevent cardiovascular disease (CVD) and respond to the occurrence of disease. These systems not only allow the elderly to live independently for longer but they also have potential to make e-health services more sustainable by reducing the pressure placed on the overall health clinics by patients. The general architecture of ubiquitous healthcare monitoring includes three main components: (i) WBAN, (ii) Internet-connected gateways, and (iii) Cloud and Bigdata support. Sensors and devices of WBAN provide real-time physiological information related to the health condition of the monitored subject. Interconnected gateways act as a hub between WBAN and Cloud services, which are responsible for the coordination between heterogeneous sensors and their connection to WAN. Cloud is responsible for Bigdata processing and analytics of physiological data and further personalized healthcare and treatments. However, the architecture faces following challenges:

(i) Sensors and devices of WBAN generate a huge amount of data and it is difficult for Cloud system to process it in real-time due to communication overhead. Cloud computing is not able to provide low latency, location awareness and high quality of service for real time applications. In pratice, healthcare applications often require expeditious analysis of health data and immediate decision. The delay of data transfer and processing over Cloud is unacceptable.

(ii) The gateway is proficient to maintain reliable and secure network connectivity between Sensors and Cloud. However, some advantageous services that can be potentially offered by a smart gateway will be limited if the gateway is deployed in a standalone and independent fashion. Smart gateway should provide more intelligence at the edge of the network and facilitates the interplay between WBAN and Cloud system.

In Healthcare a little delay can cost a patient's life therefore, to enhance services and applications, Fog Computing has came in to picture. Fog computing enables the architecture to support low-latency response, efficient scalability, location awareness, and developing applications offered by gateways. By utilizing geographically distributing Internet-connected gateways, a Fog-assisted intermediary layer between WBAN and Cloud can be formed to provide efficient healthcare services. The objectives of our paper include: (i) proposing a framework for Fog-assisted healthcare monitoring; (ii) enabling underlying network to provide mobility of patients with different protocols; (iii) giving intelligent warning model based on subband energy feature; (iv) proposing security framework of HL7 RIM-based data exchange; (v) providing health risk assessment on fusion of grey model and Markov model.

The remainder of the paper is organized as follows: Section 2 gives a brief overview of related works. Section 3 presents a framework for Fog-assisted health monitoring. Section 4 discusses some key technologies of proposed framework. The experiments for showing effectiveness of proposed frameworks are setup in Section 5. Section 6 concludes the paper.

2. Related Works

2.1. Cloud Computing in Healthcare System

In Cloud Compting domain, in 2014, Hua-Pei Chiang et al. [5] proposed a green cloud-assisted healthcare service on WBAN, and considered the sensing frequency of the physiological signals of various body parts, as well as the data transmission among the sensor nodes of WBAN. Transmission in WBSN is coordinated according to the number of sensor nodes worn by each user and the detection frequency of the various sensor nodes; personal physiological signals are regularly and efficiently transmitted to the cloud network for processing. PhysioDroid [3] used a wearable chest belt with sensors for ECG, heart and respiration rates, skin temperature, and body motion. It shows the severity of health vital signs using different colors and generates an emergency call according to them. In 2015, Shu-Lin Wang et al. [23] proposes a framework which integrates Cloud Computing Wireless Communication, and Wireless Sensor Networks technology, and applies a Collaborative Filtering (CF) technique to develop a Mobile Health Information Recommendation service to help users to obtain their preferred health information more efficiently. In 2016, Rasha Talal Hameed et al. [10] developed health monitoring system based on wearable sensors and cloud platform. The sensors measure various parameters, such as a glucometer, airflow and patient position which are transmitted via microcontroller by a gateway to a cloud storage platform. In 2018, Prabal Verma el al. [22] proposed cloud-centric IoT based disease diagnosis healthcare framework consists of three phases. In phase1, users' health data is acquired from medical devices and sensors. The acquired data is relayed to cloud subsystem using a gateway or local processing unit (LPU). In phase 2, the medical measurements are utilized by medical diagnosis system to make a cognitive decision related to personal health. In phase 3, an alert is generated to the parents or caretakers in context of person's health.

2.2. Fog Computing in Healthcare System

In 2016, C. S. Nandyala et al. [17] proposed architecture for IoT based u-healthcare monitoring with the motivation and advantages of Cloud to Fog(C2F) computing which interacts more by serving closer to the edge (end points) at smart Homes and Hospitals. M. Ahmad et al. [1] proposed a framework of Health Fog where Fog computing is used as an intermediary layer between the cloud and end users. The design feature of Health Fog successfully reduces the extra communication cost that is usually found high in similar systems. In 2018, B. Negash et al. [18] focuses on a smart e-health gateway implementation for use in the Fog computing layer, connecting a network of such gateways, both in home and in hospital use. Home-based and in hospital patients can be continuously monitored with wearable and implantable sensors and actuators. A. M. Rahmani et. al [19] proposed to exploit the concept of Fog Computing in Healthcare IoT and the strategic position of such gateways at the edge of the network to offer several higher-level services such as local storage, real-time local data processing, embedded data mining, etc., presenting thus a Smart e-Health Gateway. Sandeep K. Sood [21] designed a Fog assisted cloud-based healthcare system to diagnose and prevent the outbreak of chikungunya virus. The state of chikungunya virus outbreak is determined by temporal network analysis at cloud layer using proximity data.

In summary, Fog computing is a paradigm extending Cloud computing and services to the edge of the network, and thus to reduce the latency of decision making. Local decision making not only reduces the latency but also network traffic resulting in a much more energy-efficient system than cloud-assisted solutions. Many researchers have proposed Fog-assisted healthcare monitoring systems but have not laid emphasis on location awareness, intelligent warning for real time applications (e.g., heart disease, cerebral infarction), health risk assessment for forecasting health conditions (e.g., heart attacks) before they occur.

3. Proposed Framework

In this paper, we proposed a framework for Fog-assisted healthcare monitoring, which is composite of body-sensing layer, Fog layer(Fog-assisted gateway) and Cloud layer (Health Cloud). In body-sensing layer layer, wearable and implantable physiological sensors of body-sensing layer generate physiological data. Fog-assisted gateway provides protocol conversion, data preprocessing and local analytics and services, located at the network edge. Health cloud implements data warehouse, bigdata analysis and provides health services. A Framework of Fog-assisted health monitoring is shown as Fig. 1.

3.1. Body-sensing Layer

Body-sensing layer is composed of a series of intelligent physiological sensors, including fingertip oxygen sensors, blood-glucose sensors, ECG sensors, implantable sensors of blood pressure, to measure some basic physical vital information of the patients, like temperature, blood pressure, blood sugar, pulse rate, heart condition, respiration etc. Each sensor is equipped with the physiological signal conditioning circuits, a microcontroller, and a short distance protocol interface. According to demands of a patient's disease, these sensors can be selectively configured to monitor the respective physiciological signal. Consequently, they provide a continuous flow of physiological information related to real-time health conditions of the monitored subject.The physiological information initially processed by these sensor nodes is then transmitted to the gateway via wireless or wired communication protocols such as Bluetooth, Wi-Fi, ZigBee or 6LoWPAN.

3.2. Fog-assisted Gateway

Physiological sensors select the nearest Fog-assisted gateway to send physiological data. Multiple geographically distributed Fog-assisted gateway forms the fog. Each Fog-assisted gateway supports different communication protocols, acts as a dynamic touching point between WBAN and the local switch/Internet. It receives data from different subnetworks, performs protocol conversion, and provides other higher-level services such as data preprocessing, local analysis and services, including intelligent alarm, on-line real-time monitoring, and notification service. And then, selected data is sent to Health Cloud for further analysis based on security framework of HL7 RIM-based data exchange. According to framework of Fog-assisted health monitoring, Fog-assisted gateway requires to continuously handle a large amount of sensory data in a short time and response appropriately with respect to various conditions. Consequently, Fog-assisted gateway also enhances location awareness and high quality of service for real time applications.

3.3. Health Cloud

Health Cloud holds health monitoring archives and electronic medical records in Cloud data center. Combined with patient's physiological monitoring data, Health Cloud provides intelligent classification and risk assessment of chronic disease, which helps the individuals to have a comprehensive understanding of health conditions. Intelligent classification based on cascaded deep learning helps individuals to predict the potential disease with its level of severity [12]. Health risk assessment model based on fusion of grey model and Markov model is applied to predict relative risk and absolute risk of individual's health status. Health Cloud provides some healthcare services and health intervention with doctors, nutritionists and other medical team.

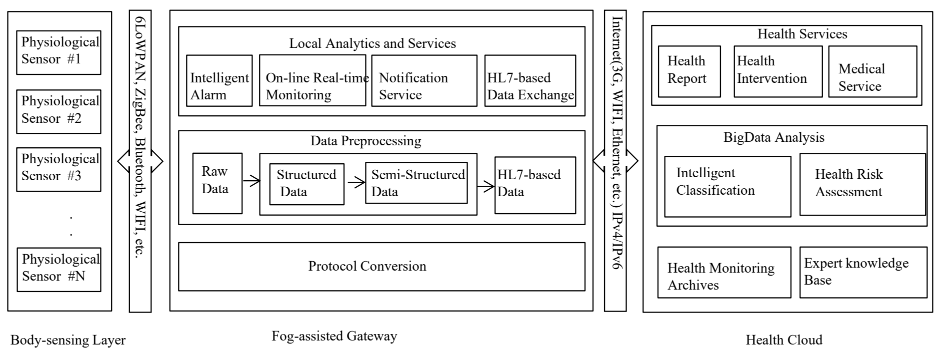

Fig. 1. A framework for Fog-assisted health monitoring

4. Some Key Technologies of Proposed Framework

4.1. Protocol Conversion for Enhancing Sensor Node Mobility

As shown in Fig. 1, intelligent physiological sensors are connected to Fog-assisted gateway using different standards (e.g., ZigBee, 6LoWPAN, Bluetooth, Wi-Fi). Thus, Fog-assisted gateway plays very important role in providing interoperability for the various sensors connected via distinct network interfaces, enabling them to exchange information wand work seamlessly. For example, ECG sensor integrates ECG sensor module, data conversion module, power module, storage unit, wireless transceiver and other major functional modules. ECG sensors are responsible for collecting ECG parameters. The wireless transceiver is responsible for the communication between sensor node and Fog-assisted gateways. IPv6 (Internet Protocol Version 6) is one of the most important connectivity of the IoT, as it is not possible to add billions of devices to the IPv4 (Internet Protocol Version 4) Internet. IPv6 is an Internet Layer protocol for packet-switched internetworking and provides end-to-end datagram transmission across multiple IP networks. In this approach each device on the network has a unique address globally reachable directly from any other location on the Internet. Therefore, protocol conversion is responsibile for uniformed mapping from different standards (e.g., ZigBee, 6LoWPAN, Bluetooth, Wi-Fi) to IPv6.

Protocol conversion method for sensor network access Fog-assisted gateway comprises the following step: (i) initializing a gateway: respectively establishing a mapping relationship between a sensor address and the gateway. For example, ECG sensors have unique IPv6 addresses, which are configured automatically by global routing prefix, subnet ID and interface ID. Each sensor has EUI-48 bit Bluetooth device address, so the interface ID can be obtained by the IEEE EUI-64 translation mechanism. To convert an EUI-48 Bluetooth device address into an EUI-64, the interface appends the two octets FF-FE and then copy the organization-specified extension identifier. The interface ID plus the routing prefix FE80::/64 and automatically configures the 128 bit local link address. (ii) simultaneously starting two processes: receiving and analyzing periodic data packets of the sensor network by using the sensor network monitoring process, and saving the periodic data packets in a local memory according to the mapping relationship; updating a corresponding memory by using the received new sensing data. The method finishes communication protocol conversion at the gateway.

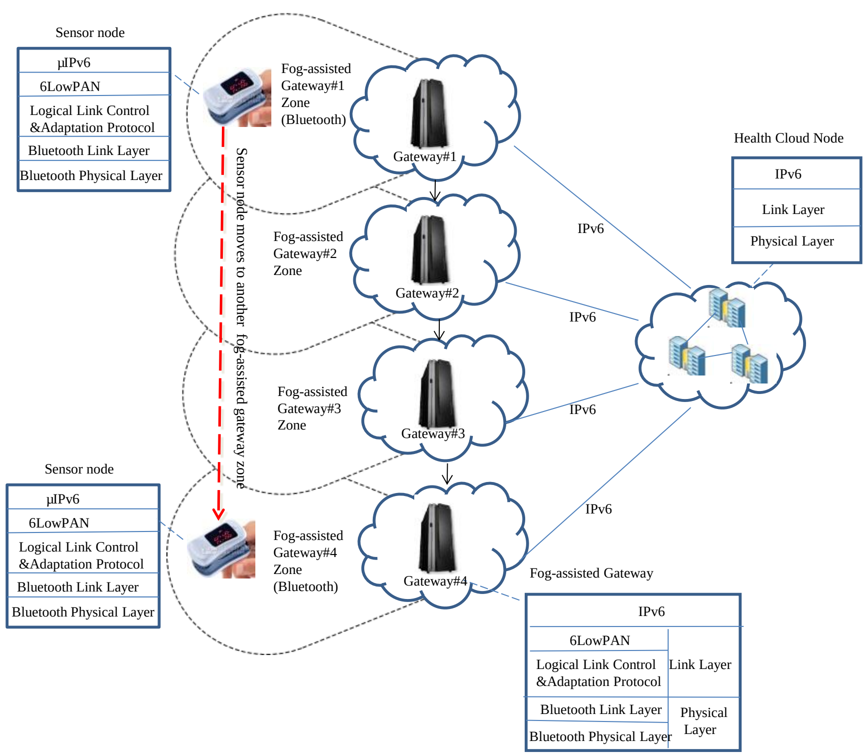

Fig. 2. An IPv6-based network architecture

Based on protocol conversion method, we proposed an IPv6-based network architecture (see Fig. 2). Some characteristics of this architecture are as follows:

(i) The protocol stack of sensor node from bottom to top includes: Bluetooth Physical Layer, Bluetooth Link Layer, Logical Linking Control and Adaptation Protocol, 6LowPAN, μIPv6.

(ii) The protocol stack of Fog-assisted gateway from bottom to top includes: Bluetooth Physical Layer, Bluetooth Link Layer, Logical Link Control and Adaptation Protocol, 6LowPAN and IPv6. It also supports Physical layer, Link layer, and IPv6 in dual protocol stack.

(iii) The protocol stack of Health Cloud from bottom to top includes: physical layer, link layer, and IPv6.

Based on protocol conversion and IPv6-based network architecture, Fog-assisted gateways are used to support sensor nodes during mobility from one geographic location to another domain. Mobile IPv6 [13] allows sensor nodes to move within the Internet topology while maintaining reachability and ongoing connections between mobile and correspondent nodes. In practice, each gateway utilizes discovery and mobility support module to provide uninterrupted service for sensor node. For example, as sensor node moves from Fog-assisted gateway$\#1$ zone to Fog-assisted gateway$\#4$ zone, it receives a broadcast message from the Fog-assisted gateways regarding its identity. When sensor node receives broadcast message, it replies with a discovery request to the respective gateway, which is processed by the device discovery and mobility support module in the gateway. Each sensor is always identified by its home address, regardless of it is situated away from its home geographic location.

4.2. On-line Real-time Monitoring and Processing

As a key feature of Fog computing, one-line real-time monitoring and local data processing are implemented to provide intelligence at the Fog-assisted gateway, which requires to continuously handle a large amount of sensory data in a short time and response appropriately with respect to various conditions. Physiological signal analysis plays a significant role in the on-line real-time monitoring and processing. Takes ECG monitoring for example, ECG signal is the recording of the electrical activity of the heart which provides the clinical information about the condition of heart. The signal is characterized by electrical activity during a cardiac cycle named as QRS complexes, P and T waves. Detection of QRS complex and R-peak is one of the most important parts of the ECG signal analysis. Till now, differentiation methods and digital filters, including neural networks (NNs)[24], Hilbert transform [14] [20] , are used for detection of QRS complex or the R-point in the ECG signal processing. However, robustness and high detection accuracy still remain open problems. In this paper, we exploit wavelet transforms and average-absolute difference threshold to detect more accurately the morphology of QRS complex.

Definition 1 (Wavelet Transform) The wavelet transform decomposes non-stationary signal into a number of scales having different frequency component and analyses each scale with a certain resolution for getting accurate features of the signal.

$$H(a,b) = \int_{-\infty}^{+\infty} x(t)\varphi_{a,b}(t)\,dt \tag{1}$$

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi^*(\frac{t-b}{a}) \tag{2}$$

Where, $x(t)$ is the original signal, * denotes the complex conjugation, $\varphi_{a,b}(t)$ is the window function of the mother wavelet and $\varphi^*(\frac{t-b}{a})$ is its shifted and scaled version.

Definition 2 (Hilbert Transform) A real valued time function is $y(t)$, and the Hilbert transform of the given signal is

$$z(t) = H[y(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} y(\tau)\frac{1}{t-\tau}\,d(\tau) \tag{3}$$

Hilbert Transform exhibits the property of time dependency because the independent variable is not changed in accordance with the transformation.

Definition 3 (Absolute Difference Threshold) Discrete wavelet transform decomposes a signal at decomposition level n, the time axis is recursively divided into halves at the ideal cut-off time $\frac{1}{2^{n+1}}t_s$, where is sampling time. Let absolute difference be $\Delta y_i = |y_i - y_{i-1}|$, where amplitude (mV) y_i, y_{i-1} respectively is the at the time (second) of t_i, t_{i-1} .

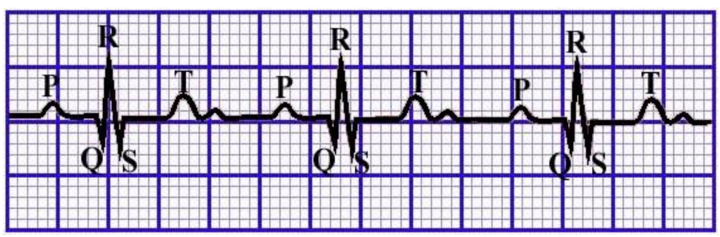

Fig. 3. ECG signals extracted by Fog-assisted gateway

QRS complex comprises of **Q** wave, **R** wave and **S** wave generated due to ventricular depolarization ((see Fig. 3). Detection of QRS complex is the entry point of almost all ECG signals analysis technique. In most of the ECG signals **R** wave appears as a sharp peak in between **Q** and **S** waves, which are of lesser amplitude and duration with respect to **R** wave. QRS complex is the region between **Q** wave onset and **S** wave offset. The detection of the R-peak algorithm is summarized as:

ECG sensors record the signals of physiological in real-time mode, and Fog computing node extracts original ECG signal. ECG signal is de-noised by wavelet transform. The enhanced signal undergoes to the differentiation to maximize the R-peaks with zero-crossing on x-axis. The differentiated signal is processed by Hilbert transform to provide a region of finding real QRS complex. Absolute difference threshold $|\Delta y_i|$ is calculated in real QRS complex and set its average as set the threshold ξ . Let difference sequence be $\Delta y_i = |y_i - y_{i-1}|$,i=1,2,. . . ,n, if $|\Delta y_{i_0}| > \xi$, then y_{i_0} the maximum point of y_{i_0} region is determined as the R-peak.

4.3. Intelligent Warning Model Based on Subband Energy Feature

Fog-assisted gateway collects physiological data from physiological sensor nodes. One of goals in healthcare monitoring is detecting health changes and asses health states. In particular, drastic health changes result from abrupt changes in process dynamics. Fog-assisted gateway collects physiological monitoring data in real-time from physiological sensor network. Furthermore, it needs to effective to distinguish and find the cause of the abrupt changes, as far as possible to remind the deviation type and avoid false alarm. In general, the process of intelligent warning is as follows:

(i) Fog-assisted gateway collects the signal under normal condition and establishes sample library of feature parameters.

(ii) Based sample library, Fog-assisted gateway establishes and holds knowledge base and inference rule base.

(iii) The physiological sensor keeps continuous monitoring patient, and Fog-assisted gateway receives signals and compares with the standard sample library of feature parameters to determine the current health state.

(iv) If the current state is "Red" state, Fog-assisted gateway starts alarm and finds out the reasoning from knowledge base.

Takes ECG monitoring for example, abrupt signal in ECG waveform is a sharp ridge. The feature of subband energy distribution is extracted by discrete wavelet transform. ECG waveform can be decomposed into high-frequency subbands and low-frequency subbands. So it needs to design perfect reconstruction filters to extract the vector of numerator coefficients of subbands energy feature. Subband analysis algorithm is summarized as:

(i) By using Orthogonal wavelet packet decomposition of ECG signal sequence, the coefficients of high frequency and low frequency are

$$c_{j,k} =< f(t), 2^{j/2}\phi(2^j t - k)|j, k \in Z > \tag{4}$$

$$a_{j,k} =< f(x), 2^{j/2}\phi(2^j x - k)|j, k \in Z > \tag{5}$$

where $\phi(t)$, $\phi(x)$ are orthogonal scaling functions,j is a scale parameter, k is a time-locationzation parameter, and wavelet function $\phi(t), \phi(x) \in L^2(R)$.

(ii) Let $f_{i,j}(t_j)$ be ECG signal in node (i, j) of wavelet packet decomposition tree (the j^{th} node of level i) which is reconstructed by wavelet packet decomposition. Sequences of subband energy areobtained by

$$E_{i,j} = \sum_{k=1}^{m} |x_{j,k}|^2 \tag{6}$$

where $x_{j,k}$ (j=0,1,2,...,2^j-1;k=1,2,...,m) is the ampltude of discrete point of $f_{i,j}(t_j)$, m is the number of sampling point in node (i, j).

(iii) The feature vector $[\lambda_0, \lambda_1, ..., \lambda_{(2^i-1)}]$ of i level is constructed as

$$\lambda_j = \frac{E_{i,j}}{\sum_{j=1}^{2^i-1} E_{i,j}} \qquad j = 1, 2, ..., 2^i - 1. \tag{7}$$

(iv) Fog-assisted gateway calculates deviation between ECG feature vector and sample library of feature parameters under normal condition, and determines abrupt signal caused by sensors fault(sensor periodic fault, sensor blockage fault, sensor bias fault) or heart disease.

4.4. Security Framework of HL7 RIM-based Data Exchange

Fog-assisted gateway should realize the data exchange with Health Cloud which generally adopts SaaS mode. Because the monitoring data models are different, and only by adopting uniform standards, barrier-free transmission can be solved and interpreted unambiguously by different receivers. HL7 (Health Level 7) [6] standard is an international standard for data transmission of medical and health institutions and medical instruments and equipment authorized by the National Standards Agency (ANSI) of the United States. HL7 International specifies a number of flexible standards, guidelines, and methodologies by which various healthcare systems can communicate with each other. Such guidelines or data standards are a set of rules that allow information to be shared and processed in a uniform and consistent manner. The HL7 RIM data model [11] can clearly express the timing, hierarchy and logic. The purpose is to solve the inconsistency of information standards developed and formulated by different developers and provide a reference model at the highest level for standard developers and formulators. For example, following HL7 RIM, HL7 aECG (the HL7 Annotated Electrocardiogram) [4] is a standard medical record data format for storing and retrieving electrocardiogram data for a patient.

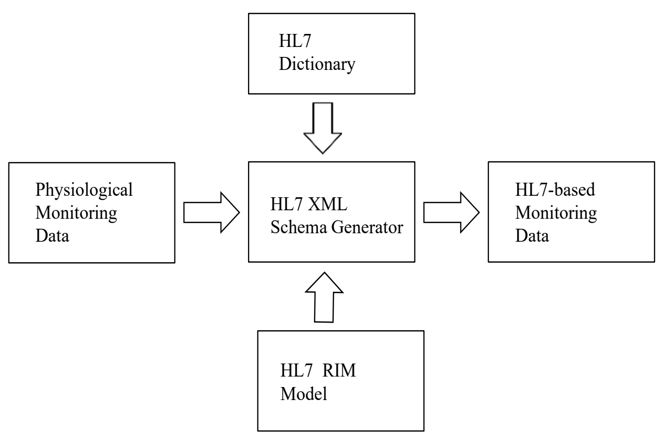

Fig. 4. HL7 RIM-based data transformation framework

Fig. 4 shows a unified data transformation framework based on HL7 RIM, including HL7 dictionary, HL7 RIM model and HL7 XML schema generator. Each data element is either composed of simple attributes into composite data, or a list of data elements, i.e. each is a composite data type attribute. HL7 RIM uses any element, data type, and vocabulary in the HL7 dictionary deriving from RIM specifications to ensure consistency. HL7 XML schema generator transforms physiological monitoring data into unified data format following HL7 standards. Consequently, physiological monitoring data is to easily share clinical information.

HL7 RIM-based data transformation framework is conducive to realize data exchange between Fog-assisted gateways and health cloud, further support personal health record management and health risk assessment. Theoretically, this ability to exchange information should help to minimize the tendency for medical care to be geographically isolated and highly variable. HL7 RIM-based data is encapsulated as XML request, and sends to receiver through Simple Object Transfer Protocol (SOAP).

Aiming at the characteristics of security requirements of HL7 RIM-based data exchange, combing the existing security models (e.g., Web Services Security specification [2]), a security framework of data exchange is presented (see Fig. 5). The XML SOAP request processing is composed of a series of message handlers as follows: security attribution handler is responsible for adding security attributions including time stamp, period of validity and sender into original SOAP message; digital signature handler puts the digital signature to the message based on XML-Signature specification[7][15]; encryption handler is in charge of encrypting SOAP message where cipher key is distributed according to XKMS specification[8]. Each handler provides the functionality for parsing XML SOAP requests and dispatching the calls to the appropriate methods[16].

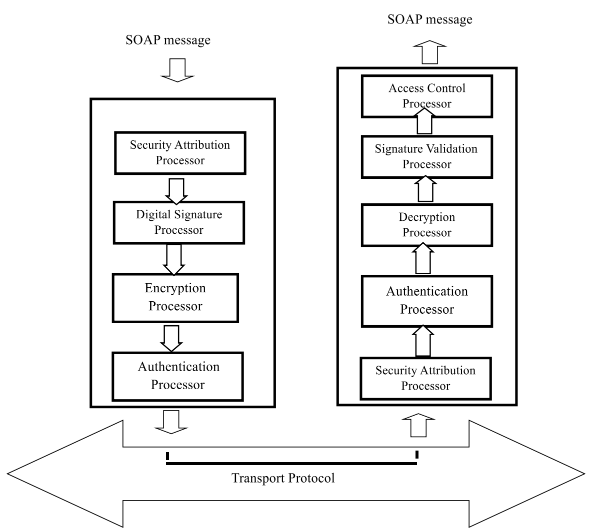

Fig. 5. Security framework of HL7 RIM-based data exchange

4.5. Health Risk Assessment Based on Fusion of Grey model and Markov Model

Health Risk Assessment (HRA) is used to provide individuals with an evaluation of their health risks and quality of life. The Framingham risk assessment (FRS) model [9] is a classic health risk assessment model, which is used to predict risk of individual cardiovascular disease in the next 10 years. Because of different countries and regions, people's living habits are different, FRS model is not universal. For example, RAWG (Risk Assessment Work Group) desired to build upon experience with prior Framingham 10-year CHD risk prediction equations and the more recent Framingham 10-year general CVD risk prediction equations. RAWG elected to capitalize on the extensive data from several large NHLBI-sponsored cohort studies to derive a more geographically and racially diverse database. Aiming at the limitations of Framingham model, we choose Chinese medicine recognized factors, including age, body weight, blood pressure, blood glucose and BMI, etc. Health Cloud holds health monitoring archives and electronic medical records in Cloud data center. In order to help patients to have a comprehensive understanding of health conditions, health risk assessment model based on fusion of grey model and Markov model is applied to predict "relative risk" and "absolute risk" of individual's health status. "Relative risk" refers to the possibility of certain chronic diseases compared with the same age group and the average level of other people. "Absolute risk" is the possibility of individuals suffering from certain chronic diseases in the next few years.

Definition 4 (Baseline Incidence) Let RR_i be the relative risk of a certain level of factors, P_i be the proportion of individuals who are exposed to a level of the total population, then the baseline incidence rate is $RR_i = \frac{1}{\sum_{j=0}^{n}(RR_i \times P_i)}$.

Definition 5 (Relative Risk) Risk Score=(Baseline Incidence) $\times$ (Relative Risk). Let P be the combination of m factors $P = (P_1 - 1) + (P_2 - 1) + ... + (P_n - 1) + Q_1 \times Q_2 \times ... \times Q_m$, where P_i be risk factors (greater than or equal to 1), Q_i be risk factors (less than 1).

There are many models which can be used in chronic disease forecasting in "Absolute Risk", such as Markov chain models, Grey Models, General Regression Models, Autoregressive Integrated Moving Average Class models (ARIMA) and Neural network. However, these models typically require large numbers of observations and complicated input factors to make sensible predictions. Physiological monitoring data has the characteristics of random fluctuation. For better forecasting performance, hybrid models which combined two or more single models for communicable disease forecasting have also been explored, and previous findings indicate that hybrid models outperformed single models. A hybrid approach combining Grey model GM(1,1) and Markov Model to forecast the prevalence of physiological monitoring data.

(i) GM(1,1) Model

Step1. Let original data sequence be $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\}$.

Step2. $X^{(1)}$ is obtained by 1-AGO (Accumulated Generating Operation)

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)\} \tag{8}$$

where $x^{(1)}(t) = \sum_{i=1}^{t} x^{(0)}(i)$, t=1,2,3…,n.

Step3. The grey differential equation of GM(1,1) of $x^{(1)}(t)$ is as follows

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = u \tag{9}$$

where a, u are obtained respectively by using least square method $x^{(1)}(t) = [x^{(0)}(1) - \frac{u}{a}]e^{(-at)} + \frac{u}{a}$.

Step4. Applying the Inverse Accumulated Generating Operation (IAGO), and then we have

$$\hat{x}^{(0)}(t+1) = (1 - e^{a})[\hat{x}^{(0)}(1) - \frac{b}{a}]e^{(-at)} \tag{10}$$

(ii) Residual Error Correction of GM(1,1) Model

Step 1. Let residual error sequence be

$$\varepsilon^{(0)}(t) = |x^{(0)}(t) - \hat{x}^{(0)}(t)| \qquad i = 1, 2, 3, ..., n \tag{11}$$

Step 2. $\hat{x}^{(0)}(t+1)$ is obtained by similar method as follows

$$\hat{x}^{(0)}(t+1) = (1-e^{a})[x^{(0)}(1) - \frac{u}{a}]e^{(at)} + sgn(t+1)(1-e^{a_1})[\varepsilon^{(0)}(1) - \frac{u_1}{a_1}]e^{(-a_1 t)} \tag{12}$$

where symbol function $syn(t)$ is obtained by the original residual errors.

(iii) Markov Model

Markov chain is a forecasting method which can be used to predict the future data by the occurred events. We can get the simulation sequence by Equation 13 as follows

$$\hat{y}^{(0)} = \{\hat{y}^{(0)}(1), \hat{y}^{(0)}(2), ..., \hat{y}^{(0)}(n)\} \tag{13}$$

We can divide $\hat{y}^{(0)}$ into n states. According to the relative error, any state can be denoted as $\Theta_j = [\Theta_{j-1}, \Theta_{j+1}]$, where $\Theta_{j-1} = \hat{y}^{(0)}(j) + a_j$, $\Theta_{j+1} = \hat{y}^{(0)}(j) + b_j$. Assume n_j is the number of original sequence, the transition probability from Θ_i to Θ_j can be established by Equation14 as follows

$$P_{ij}(k) = \frac{n_{ij}(k)}{n} \qquad i = 1, 2, 3, ..., n \tag{14}$$

Where $P_{ij}(k)$ is the transition probability of state Θ_j transferred from state Θ_i for k steps. Transition probability matrix can be expressed as $P(k) = (P_{ij}^{(k)})_{n\times n}$,where $P_{i1}^{(k)} + P_{i2}^{(k)}$+...+$P_{in}^{(k)} = 1$;$i$=1,2,...,$n$. The transition probability matrix $P(k)$ reflects the transition rules of the states in a system, which is the foundation of the Grey-Markov model.In order to confirm future state transition, after the relative residual error range $[\Theta_{j-1}, \Theta_{j+1}]$ is obtained, the median in range $[\Theta_{j-1}, \Theta_{j+1}]$ (i.e.,$\hat{y}^{(0)}(j) + \frac{a_j+b_j}{2}$) is selected as the relative error. Furthermore, forecasting value of original data sequence is obtained by combining with Equation12 and Equation14.

5. Experimental Setup and Analysis

5.1. Working Process of Fog-assisted Healthcare Monitoring System

In this section, experiments to test the framework of Fog-assisted Healthcare Monitoring are provided. We developed the prototype system of proposed framework, which is connected with Health Fog and Health Cloud[12]. Health Fog has 10 Fog computing servers. Each server is configured with Linux operating system, Xen VMM and 5 virtual machines, as Fog-assisted gateway. Health Cloud has cloud resource pool with 40 vCPU, 100G memory, 10T storage, support a variety of health archives management including physiological factors (such as “age”, “sex”, “height”, “weight”, “smoking”, “diabetes family history”, “ECG”, “SpO2”, etc.). Health Cloud has collected personal health records more than 50000 copies. Wireless body sensor network is composed of physiological sensors, including oxygen sensor, glucose sensor, accelerometer, and so on. IPv6-based network architecture is composed of wireless body sensor network, IPv6 transmission network, Health Fog, and Health Cloud, mobile intelligent device. Subsets of 2.4 GHz band wireless IEEE 802.11 and IEEE 802.15 family standards (Wi-Fi and Bluetooth) were needed. In order to determine the validity of the framework, we selected the 55-65 years old (male) in Xiamen District of Jimei from as the research object. Health monitoring data of patients was systematically generated for 30 days. The working process of the system is as follows (See Fig. 6):

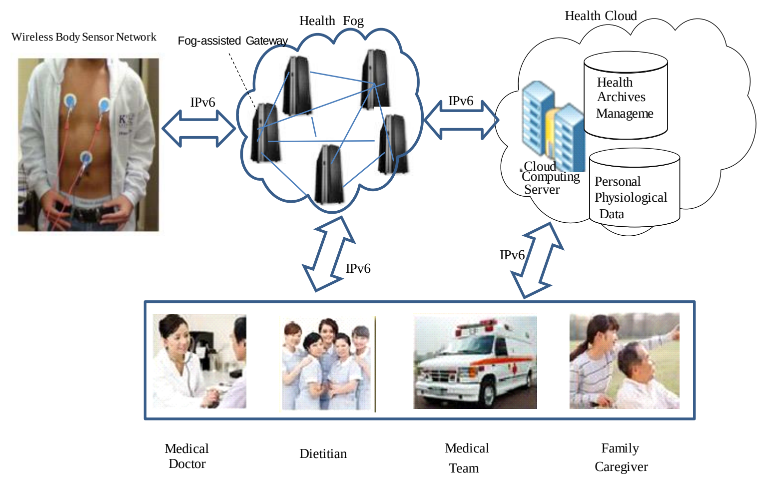

Fig. 6. Working process of Fog-assisted healthcare monitoring system

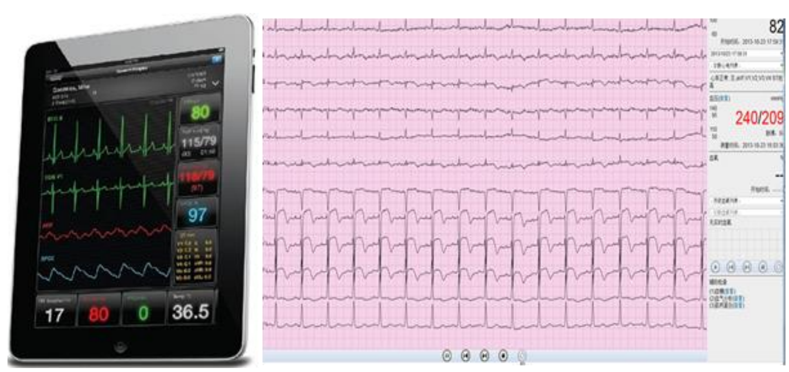

Fig. 7. Interface display of mobile intelligent device

(i) Mobile intelligent device connects Health Fog based on wireless IPv6 WIFI, and registers personal information, including personal data (“age”, “sex”, “degree of Education", "diabetes family history", etc.), life preferences ("smoking", "drinking", "physical exercise", etc.), routine physical examination data (BMI(Body Mass Index; "weight", "height", "waist circumference", "hip circumference"), WHR(Waist-to-Hip Ratio)).

(ii) Wireless Body Sensor network is composed of a series of intelligent physiological sensors which generate physiological data, including "systolic blood pressure", "SpO2", "fasting blood glucose", and "heart rate", etc.

(iii) Health Fog is composed of Fog-assisted gateway, which has a built-in Bluetooth gateway as boundary node of Wireless Body monitoring network, which receives data from different subnetworks, performs protocol conversion, and provides other higher-level services such as data preprocessing, local analysis and services, including intelligent alarm, on-line real-time monitoring, and notification service. Apart from that, Fog-assisted gateway also provides substantial connectivity and allows sensor nodes to move within the Internet topology while maintaining reachability.

(iv) Fog-assisted gateway in Health Fog sends physiological data to Health Cloud for further analysis based on security framework of HL7-RIM data exchange. Health Cloud implements health archives management and personal physiological data. Health cloud provides intelligent classification service and risk assessment service of chronic disease. Health cloud also provides some healthcare services and health intervention with doctors, nutritionists and other medical team.

(v) Mobile intelligent device receives health risk assessment and alarm messages as quickly as possible. Fig. 7 shows the interface display of mobile intelligent device for continuous monitoring of the patient's health.

5.2. Intelligent Alarm Service

Whenever, the "heart rate", "blood pressure", "body temperature" and "fasting blood glucose" exceed the normal values, mobile intelligent device receives alarm messages from Fog-assisted gateway as quickly as possible. Mobile intelligent devices can send an alert message with clinical value to the doctor and family caregiver using wireless network through Health Fog. Takes ECG monitoring for example, the abrupt signal may be caused by heart disease, sensor periodic fault, sensor blockage fault, sensor bias fault, which need to be distinguished in time. Table 1 shows some subbands energy characteristics of abrupt signals.

Table 1. Subbands energy characteristics of abrupt signals

Chronic diseases	High frequency signals (%)	Low frequency signals (%)
Heart disease	0-1%	99%-100%
Sensor periodic fault	98.1%-99.8%	0.2%-1.9%
Sensor blockage fault	0	0
Sensor bias fault	3.1%-7.2%	92.3%-96.9%

When the abrupt signal is judged to be the cause of the human disease, the prototype system detects and determines two adjacent R wave time according to the mean absolute differential threshold algorithm, and makes further five types of electrocardiogram types:

- Ventricular Tachy ($RR_i < 500ms$);
- Bradycardia ($RR_i > 1500ms$) ;
- Ventricular Premature ($HRV_i > 120ms$) ;
- Ventricular Parked ($RR_i > 3000ms$) ;
- Ventricular Leakage ($2.3RR < RR_i < 2.6RR$).

Under normal circumstances, if five consecutive times meet the above characteristics, prototype system sends out the alarm and messages to the relatives,the doctor,or caregivers. When it is determined that the abrupt signal is a sensor bias fault, the prototype system prompts the human body to take the correct posture to avoid device shaking.

5.3. Response Latency

In order to evaluate performance of protype system, we compared response latency of the system under IPv4-based Cloud-assisted environment or IPv6-based Fog-assisted environment. Response latency of the average system under IPv4-based cloud assisted environment is 118.43ms, and that under IPv6-based Fog assisted environment is 26.42ms. Mobile intelligent device received response latency in different environment are shown in Fig. 8. The main reason is as follows: (i) In IPv4-based Cloud-assisted environment, mobile intelligent device needs long-distance communication overhead with Health cloud. In cloud computing where raw data is transferred from sensor nodes to cloud, if network condition is unpredictable, it may cause uncertainty to response delay. However, in IPv6-based Fog-assisted environment, mobile intelligent device is close to Health Fog with short-distance communication. In Fog computing where implementing data analytics and making time-sensitive decisions within the local network makes the proposed system more robust and predictable. (ii) The efficiency of data preprocessing, on-line real-time mointoring, intelligent alarm and notification service are similar in two environments. Therefore, The IPv6-based Fog-assisted environment response latency proposed in this paper is much lower than that of IPv4-based Cloud-assisted environment.

5.4. Health Risk Assessment

The chosen factors in this case are comprehensive, including: “degree of education”, “smoking”, “physical exercise”, “heart Rate”, “BMI”, “systolic blood pressure”, “cerebral stroke”, “fasting blood glucose”. Table 2 shows the baseline incidences and Risk scores of different risk factors. According to personal physiological monitoring data and health archives in health cloud, we take one old people aged 61 for example, who has “primary education”, “no smoking”, “no physical exercise”, “BMI” (Obesity), “blood pressure”(140 mmHg/209 mmHg), “heart rate”(92), “no cerebral stroke”, “blood glucose” (super high). “Relative risk” of chronic disease is 15.666 (1.658+2.873+2.885+6.543 +1.778+5.325−6+0.952× 0.926 =15.666). The total incidence of Hypertension in Xiamen District of Jimei is close to 5%, so this old people’s current “absolute risk” of chronic disease is 15.666*5%=78.78%.

A hybrid approach combining Grey model GM (1,1) and Markov Model can be used to forecast absolute risk within 5 years. The working process of health risk assessment based on Fusion of Grey model and Markov Model is as follows:

Fig. 8. The result of response latency testing

(i) applying the inverse accumulated generating operation (IAGO) to forecast condition of personal physiological monitoring;

(ii) computing the residual errors of GM(1,1) Model;

(iii) relying on Markov chain to predict the future data by the occurred events. For example, states of blood pressure includes:

- Hypotension ("Systolic"<90mmHg, "Diastolic"<60 mmHg);
- Normotensive ("Systolic" 90-119mmHg, "Diastolic" 60-79mmHg);
- Prehypertension ("Systolic" 120-139mmHg, "Diastolic" 80-90mmHg);
- Stage I Hypertension ("Systolic" 140-159mmHg, "Diastolic" 90-99mmHg);
- Stage II Hypertension ("Systolic" 160-179mmHg, "Diastolic" 100-109mmHg);
- Hypertensive Urgency ("Systolic" >180 mmHg, Diastolic">110 mmHg);
- Isolated Systolic Hypertension ("Systolic" >160 mmHg, "Diastolic" <90 mmHg).

The transition probability matrix is obtained by Equation 14 and Markov Model is used to predict next state by the occurred states.

6. Conclusions

Fog computing nodes as smart gateways at the proximity of sensor nodes can tackle many challenges in ubiquitous healthcare monitoring such as mobility, scalability, and network latency. In this paper, a framewrok for Fog-assisted healthcare monitoring is proposed. This framework is composite of body-sensing layer, fog layer and cloud layer. The body-sensing layer measures physiological signals and Fog-assisted gateway collects these information. Fog-assisted gateway also provides protocol conversion, intelligent alarm, online realtime monitoring and notification service. Physiological monitoring data is transferred to cloud layer for further processing and analysis, including health risk assessment and intelligent classification. The contribution of the paper can be summarized as follows: (i) proposing a hierarchical framework for Fog-assisted healthcare monitoring; (ii)

Table 2. Risk factors and risk score of diabetic inpatients in Xiamen (55-65 years old)

Factors	Factor Values	Baseline Incidences	Risk Scores
Degree of Education	Primary and Secondary Education	0.952	0.952
	Middle School	0.901	0.754
	College Degree or Above	1.105	0.524
Smoking	NO	1.658	1.658
	YES	0.680	2.572
Physical Exercise	NO	0.926	0.926
	YES	0.926	0.784
Heart Rate	$<$90 Normal	0.658	0.765
	$>$90 Abnormal	1.043	2.873
BMI	Normal	1.265	1.625
	Overweight	0.961	1.307
	Obesity	0.984	2.885
Blood Pressure	$<$120 mmHg	0.123	0.223
	120-140 mmHg	0.771	0.771
	140-160 mmHg	0.976	2.521
	160-180 mmHg	1.383	4.654
	$>$180 mmHg	1.573	6.543
Cerebral Stroke	NO	0.978	0.978
	YES	0.978	1.778
Fasting Blood Glucose	Normal	0.926	0.926
	High	0.978	4.152
	Super High	1.548	5.325

enabling underlying network (i.e., IPv6-based Network Architecture) to provide mobility of patients with different protocols; (iii) giving intelligent warning model based on subband energy feature; (iv) proposing security framework of HL7 RIM-based data exchange; (v) providing health risk assessment based on fusion of grey model and Markov model. The next step is to improve the intelligent alarm based on CNN (Convolutional Neural Network) and reduce communication delay in the presence of large-scale data collection.

Conflict of Interest. Authors Jianqiang Hu, Wei Liang, Zhiyong Zeng, Yong Xie and Jianxun Eileen Yang declare that they have no conflict of interest.

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