Cloud-Assisted Home Health Monitoring System

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***Abstract*—A new generation of home healthcare monitoring system strives to have such characteristics as low-cost, low-power and low-volume etc., and furthermore, it needs to quickly adapt to the development of national medical information based Cloud computing in China. In response to this trend, a Cloud-assisted home health monitoring system was designed in this paper. Sensors can be selectively configured to monitor the respective physiological signal depending on the diagnostic demands of a patient's disease. This system uses smart phones to receive physiological signals and cloud platforms (such as Xiamen Health Cloud) to storage physiological monitoring data. Combined with these data, health cloud provides risk assessment of chronic disease. Clinical application of the system shows that it has positive significance for patients with hypertension and diabetes who can enjoy health monitoring and the services of health could at home.**

Keywords—health monitoring; intelligent physiological sensors; hierarchical framework; risk assessment of chronic disease; WBAN

I. INTRODUCTION

The ageing of the population is the major force driving the epidemic of chronic diseases. In 2000, 7% of the Chinese population were aged 65 years or older, and more than 400 million Chinese adults are now aged 20-39 years. If current trends continue, by 2040 the group aged 65 years and older will have increased to almost 20% of the population. The ageing of the population alone is predicted to produce a 200% increase in deaths from cardiovascular disease (coronary heart disease, hypertension, diabetes) in China between the years 2000 and 2040. Medical informatization is 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. At present, there are two trends of medical informatization as follows:

(1) The rapid development of medical information service platform based Cloud computing. According to a 2013 survey by McKinsey, the healthcare expenditure of the United States has increased approximately $600 billion more than the expected benchmark [1,2]. Electronic Health Record Systems of HHS (Health and Human Services) of U.S Department, Google Health and Microsoft HealthVault began to be widely used in the United States and achieved great economic and social benefits. Fujitsu launched Fujitsu Healthcare Solution HOPE Cloud Chart, a cloud-based service that integrates an electronic medical record system and a medical billing and accounting system. Chinese Academy of Sciences (SIAT-CAS) developed key technologies of Sea Cloud Data System and launched low-cost health services. This service lets patients manage their own health records to share in cloud environments. This allows different health systems to access and manage these Personal Health Records.

(2) The new generation WBAN is expected to change the traditional healthcare system by providing reliable and robust health-monitoring service. In particular, wearable sensing technologies are combined with WBAN, as the healthcare system gradually evolves into a ubiquitous mode. WBAN provides a useful method to remotely acquire and monitor the physiological signals without the need of disrupting the patient's normal life, thus improving life quality. Patient healthcare data are collected from a number of sensors, analyzed, delivered through a network and shared with healthcare professionals for evaluation of patient care. PhysioDroid [3] used a wearable chest belt with sensors for ECG, heart and respiration rates, skin temperature, and body motion. Jara et al. [4] present a remote monitoring framework using IoT by proposing a protocol, called YOAPY, to create a secure and scalable fusion of multi-modal sensors to record vital signs. Gelogo et al. [5] tried to introduce an idea of a combination of wearable sensors and Android mobile applications for ubiquitous health monitoring system through a wearable belt consisting of several sensors for some vital physiological data, which transmits them to his phone via Bluetooth.

The development and implementation of long-term healthcare monitoring that can prevent or quickly respond to the occurrence of disease and accidents present an interesting challenge for WBAN in computing power and energy limits. Fortunately, WBAN can benefit from the virtually unlimited capabilities and resources of Cloud to compensate its technological constraints (e.g., storage, computation, and communication). In response to this trend, Cloud-assisted home health monitoring system was designed. It tries to introduce an idea of combination of wearable sensors, health could and Android mobile applications for ubiquitous health monitoring system, in which several sensors collect some vital physiological data, and transmits them to smart phone via Bluetooth; smart phone connects with health Cloud to solve storage and computation problem; health cloud provides risk assessment of chronic disease. Clinical application of the system can see this health in his phone and can enjoy health monitoring and the services of health could at home.

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II. HIERARCHY FRAMWORK

In this paper, we proposed a hierarchical framework for Cloud-assisted home health monitoring system by combining with WBSN, which can effectively overcome limitations of conventional home health-monitoring system in data storage capacity and computation limits. This framework is composed of Healthcare monitoring network, Health smartphone and Health cloud. This is shown in Figure 1.

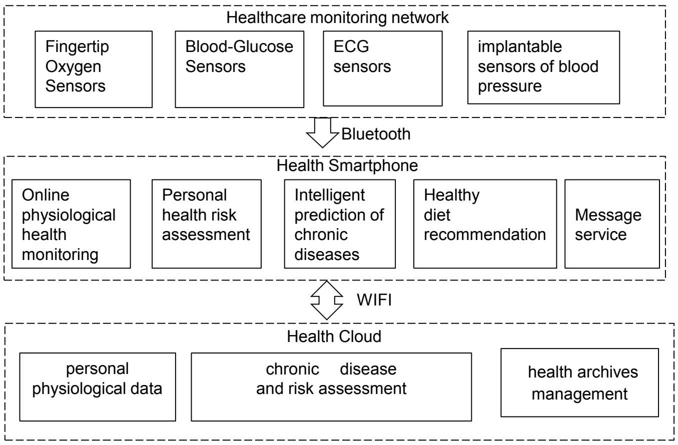

Fig.1 Hierarchical Framework for Cloud Cloud-assisted home health monitoring

(1) Healthcare Monitoring network

Healthcare monitoring network 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 Bluetooth interface. These sensors can be selectively configured to monitor the respective physiological signal depending on the diagnostic demands of a patient's disease. The patient's physiological signals are collected by the medical sensors, initially processed by these sensor nodes at the patient end, and then, the preprocessed data are transmitted to the coordinator node (Bluetooth module), which is a part of gateway module, via Bluetooth connection. Healthcare monitoring network brings together the abundance of existing specialized medical technology with pervasive, wireless networks, and low-cost, miniature, lightweight, intelligent physiological sensor.

- Blood-glucose sensor: This sensor will measure the level of glucose in patient's blood for monitoring purpose.
- ECG sensor: ECG sensor is a device that monitors electrical activities of the heart by using clips or electrodes placed on the skin.
- Implantable sensor of blood pressure: This unit can measure the blood pressure level (both Systolic and Diastolic) of the patient's.
- Fingertip oxygen sensor: It is a medical device that observes the oxygen saturation level of patient's blood and the level of volume change of blood [6].

Integrating intelligent medical sensors into wireless communication network makes it possible to remotely collect physiological signal of a patient, release the patient from being tethered to monitoring medical instrumentations, and facilitate the patient's early hospital discharge. This can further improve life quality by providing continuous observation without the need of disrupting the patient's normal life, thus reducing the risk of infection significantly, and decreasing the cost of the hospital and the patient [7] .

(2) Health Smartphone

Health smartphone collects different types of physiological values (temperature, blood pressure, blood sugar, pulse rate, heart condition, respiration etc.) from Bluetooth module with Bluetooth. Health smartphone is configured as a part of gateway module, the gateway module communicates with sensors via Bluetooth connection, and communicates with Health Cloud based WIFI.

Take ECG signal for example, once health smartphone receives the digital signals from the Bluetooth, the average absolute difference threshold algorithm is used to detect and determine the R wave, and the QRS waveform is extracted. If the digital signal contains the abrupt information, the intelligent warning model is used to distinguish the reason of abrupt signal and alarm.

Due to the limitations of storage space and computation, health smartphone connects with Health Cloud. On one hand, health smartphone can display physiological monitoring data in real-time and upload healthcare data to Health Cloud. On the other hand, health smartphone can show health assessment of chronic disease, and health archives management. Health smartphone can help individuals to know more about their health status and chronic diseases through the exchange of data with Health cloud.

(3) Health Cloud

Health Cloud (Xiamen Healthcare Cloud) holds health records and electronic medical records in Cloud data center. Combined with individual physiological monitoring data, health cloud provides chronic disease and risk assessment, which help the individuals to have a comprehensive understanding of health and disease type. 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.

III. RISK ASSESSMENT OF CHRONIC DISEASE

The Framingham risk assessment model FRS 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 cultural background and living habits are different, different people have different accuracy of filtering and classification by FRS model. Aiming at the limitations of Framingham model, we choose Chinese medicine recognized factors, including age, body weight, blood pressure, blood glucose and BMI, etc. Combined with individual physiological monitoring data, health cloud provides chronic disease and risk assessment (including "relative risk" prediction and "absolute risk"), which help the individuals to have a comprehensive understanding of health and disease type. "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.

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 artificial 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.

① GM(1,1) Model

Step1: Assume original data sequence to be:

$$X^{(0)}=\{\mathrm{x}^{(0)}(1),\mathrm{x}^{(0)}(2),...,\mathrm{x}^{(0)}(n)\} \tag{1}$$

Step2: $X^{(1)}$ is obtained by 1-AGO (one time accumulated generating operation):

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

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

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

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=u \tag{3}$$

Where a,u are obtained respectively by using least square method

$$x^{(1)}(\mathrm{t})=[x^{(0)}(1)-\frac{u}{a}]\mathrm{e}^{-at}+\frac{u}{a} \tag{4}$$

Step4: Applying the inverse accumulated generating operation (IAGO), and then we have

$$\overset{(0)}{x}(\mathrm{t}+1)=(1-e^{a})[\overset{(0)}{x}(1)-\frac{b}{a}]\mathrm{e}^{-at} \tag{5}$$

② Residual Error Correction GM(1,1) Model

Step 1: Assume residual error sequence to be:

$$\varepsilon^{(0)}(\mathrm{t})=|\mathrm{x}^{(0)}(\mathrm{t})-\overset{(0)}{x}(\mathrm{t})| \tag{6}$$

Step 2: $\overset{(0)}{x}(\mathrm{t}+1)$ is obtained by similar method as follows:

$$\overset{(0)}{x}(\mathrm{t}+1)=(1-\mathrm{e}^{a})[\mathrm{x}^{(0)}(1)-\frac{u}{a}]\mathrm{e}^{at}+\mathrm{sgn}(\mathrm{t}+1)(1-\mathrm{e}^{a_1})[\varepsilon^{(0)}(1)-\frac{u_1}{a_1}]\mathrm{e}^{-a_1 t} \tag{7}$$

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

③ 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 (8) as follows:

$$\overset{(0)}{x}=\{\overset{(0)}{x}(1),\overset{(0)}{x}(2),\overset{(0)}{x}(3),...,\overset{(0)}{x}(\mathrm{n})\} \tag{8}$$

Then $\overset{(0)}{x}$ is a Markov chain, we can divide it into n states according to the relative error, its any state can be denoted as:

$$\otimes_{\mathrm{j}}=[\otimes_{\mathrm{j-1}},\otimes_{\mathrm{j+1}}],\ \otimes_{\mathrm{j-1}}=\overset{(0)}{x}(\mathrm{j})+\mathrm{a}_j,\ \otimes_{\mathrm{j+1}}=\overset{(0)}{x}(\mathrm{j})+\mathrm{b}_j \tag{9}$$

Assume n_j is the data number of original sequence, the transition probability from $\otimes_{\mathrm{i}}$ to $\otimes_{\mathrm{j}}$ can be established

$$\mathrm{P}_{\mathrm{i,j}}(\mathrm{k})=\frac{n_{ij}(k)}{n_i} \qquad \text{i=1,2,3,….n} \tag{10}$$

Where $\mathrm{P}_{\mathrm{i,j}}(\mathrm{k})$ is the transition probability of state $\otimes_{\mathrm{j}}$ transferred from state $\otimes_{\mathrm{i}}$ for k steps. Transition probability matrix can be expressed as $\mathrm{P(k)}=(\mathrm{P}_{ij}^{(k)})_{n\times\mathrm{n}}$. The transition probability matrix $\mathrm{P(k)}$ reflects the transition rules of the states in a system, which is the foundation of the Grey-Markov model. After confirming future state transition, the relative residual error zone [$\otimes_{\mathrm{j-1}}$, $\otimes_{\mathrm{j+}}$] is obtained, the median in [$\otimes_{\mathrm{j-1}}$, $\otimes_{\mathrm{j+}}$] is selected as the relative error, so forecasting value of original data sequence is obtained according to the above explanation.

$$\hat{y}(j)=\frac{\otimes_{j-}+\otimes_{j+}}{2}=\overset{\wedge(0)}{x}(j)+\frac{a_j+b_j}{2} \tag{11}$$

Markov Model is concerned with state and state transition probabilities. Let prediction object have n states (E_1, E_2 ,…, E_n), and P_{i1}, P_{i2} ,…, P_{in} be the transition probability of state $\otimes_{\mathrm{i}}$ transferred from state $\otimes_{\mathrm{j}}$ (j=1,2,3,…n), $P_{i1}+P_{i2}+...+P_{in}=1$.

Take blood pressure (BP) for example, states includes Hypotension (Systolic<90mmHg, Diastolic<60mmHg), Desired (Systolic 90-119mmHg, Diastolic 60-79mmHg), Prehypertension (Systolic 120-139mmHg, Diastolic 80-90mmHg), Stage1 Hypertension (Systolic 140-159mmHg, diastolic 90-99mmHg), Stage 2 Hypertension (Systolic 160-179mmHg, Diastolic 100-109mmHg), Hypertensive urgency (Systolic >180 mmHg, Diastolic >110 mmHg), Isolated Systolic Hypertension (Systolic >160 mmHg, Diastolic <90 mmHg). Therefore, $syn(t)$ in Equation (7) is obtained by Markov Model.

IV. Cloud-Assisted Home Health Monitoring System

A. *The Workflow of Cloud-assisted Home Health Monitoring System*

We developed cloud-assisted home health monitoring system Called Cloud-Health, which connected with Xiamen Health Cloud. Xiamen Health Cloud has cloud resource pool with 400 vCPU, 1000G memory, 60T image storage and 32.7T pool of computing resources and storage resources, cyber source pool, and support a variety of health archives management including 14 physiological factors (such as “age”, “gender”, “ethnicity/race”, “height”, “weight”, “pre-diabetes”, “diabetes family history”, “physical activity”, “blood cholesterol”, “ECG”, “SpO2”and “smoking”. It has collected personal health records more than 300million copies, and provides a good environment to meet the needs of residents treatment of chronic disease and intelligent early warning emergency. The working process of the system:

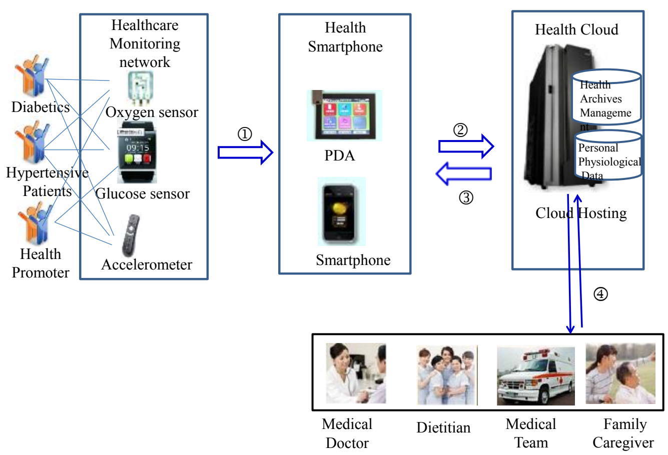

Fig.2 The workflow of Cloud-assisted Home Health Monitoring System

①Healthcare monitoring network is composed of a series of intelligent physiological sensors. Health smartphone receives physiological data in real time from Healthcare monitoring network.

②Health smartphone uploads the physiological monitoring data and implements health archives management in health cloud.

③Health cloud holds health archives and Personal physiological data. 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 smartphone can show health assessment of chronic disease.

④ Health cloud provides some healthcare services with doctors , nutritionists and other medical team. Diabetics, Hypertensive patients and health promoters can enjoy health monitoring and the services of health could at home.

B. *Experimental results*

TABLE I. 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
Blood Fat	Normal	0.926	0.926
	High	0.978	4.152
	Super High	1.548	5.325

In cooperation with the Xiamen City Heart Center, combining with the Xiamen Health cloud, We selected the 55-65 year old (male) in Xiamen District of Jimei as the research object. The chosen factors in this case are comprehensive, including: Degree of Education, Smoking, Physical Exercise, Heart Rate, BMI, Blood pressure, Cerebral Stroke, Blood Fat. Logistic model was used to obtain the baseline incidences and Risk scores of different risk factors (See TABLE I).

Body mass index (BMI): It represents the body mass of an individual which is derived from dividing the body mass by the square of a person's height:

$$BMI = \frac{Weight(lb)}{Height^2(in)} \times 703 \quad (12)$$

According to personal physiological data and health archives in health cloud, we take 1 old people aged 61 for example, who has primary school culture, not smoking, no exercise, blood pressure 140 mmHg /209 mmHg, heart rate 92, no cerebral stroke, super high blood fat. His 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 sugar diabetes in Xiamen District of Jimei is close to 5%, so this old people's 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.

V. CONCLUSION

Cloud-assisted home health monitoring system was presented in this paper. This system introduces an idea of combination of wearable sensors, health could and Android mobile applications for ubiquitous health monitoring. The objective was to detect the abnormal data, which help the individuals to have a comprehensive understanding of chronic disease and risk assessment.

The contribution of the paper can be summarized as follows. A hierarchical framework for Cloud-assisted home health monitoring system was presented. Then, using the proposed framework, we provide a scalable storage with health cloud, to solve storage and computation problem. Finally, 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. The proposed framework has been studied and applied in Xiamen Health Cloud. Ongoing work on this topic includes applying the MapReduce infrastructure and IPv6 in Health Cloud in order to improve the performance of processing delay, and integrating the communication delay with the proposed model in the presence of large scale data collection.

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