33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Development of a Triage Engine Enabling Behavior Recognition and Lethal Arrhythmia Detection for Remote Health Care System

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Abstract— **For ubiquitous health care systems which continuously monitor a person's vital signs such as electrocardiogram (ECG), body surface temperature and three-dimensional (3D) acceleration by wireless, it is important to accurately detect the occurrence of an abnormal event in the data and immediately inform a medical doctor of its detail.**

In this paper, we introduce a remote health care system, which is composed of a wireless vital sensor, multiple receivers and a triage engine installed in a desktop personal computer (PC). The middleware installed in the receiver, which was developed in C++, supports reliable data handling of vital data to the ethernet port. On the other hand, the human interface of the triage engine, which was developed in JAVA, shows graphics on his/her ECG data, 3D acceleration data, body surface temperature data and behavior status in the display of the desktop PC and sends an urgent e-mail containing the display data to a pre-registered medical doctor when it detects the occurrence of an abnormal event. In the triage engine, the lethal arrhythmia detection algorithm based on short time Fourier transform (STFT) analysis can achieve 100 % sensitivity and 99.99 % specificity, and the behavior recognition algorithm based on the combination of the nearest neighbor method and the Naive Bayes method can achieve more than 71 % classification accuracy.

I. INTRODUCTION

NOWADAYS, medical institutions are facing serious difficulties such as growing elderly population and doctor shortage. Realization of shorter hospital stay and substitutive home health care is expected to cope with such difficulties, and indeed due to remarkable advance in wireless information communications technology (ICT) and signal processing technology, several health care systems trying to replace in-hospital monitoring by remote home monitoring for patients' body conditions have been proposed. Typical vital data wirelessly and non-invasively obtainable from a person in such systems include electrocardiogram (ECG), body surface temperature, blood oxygenation level and three-dimensional (3D) acceleration, and among them, ECG and 3D acceleration are considered to be essential. This is because the occurrence of an abnormal event in ECG is directly related to a sudden death and the urgent level on the detected event depends on his/her behavior status when it occurs. Therefore, the requirements of such health care systems are the accurate detectability of the occurrence of an abnormal event in ECG data and the quick transmittability of the detail on the event to medical doctors.

We have so far developed a remote health care system. It is composed of commercially available wireless vital sensor which can monitor ECG, 3D acceleration and body surface temperature, several receivers and a desktop personal computer (PC) where a triage engine is installed. In this paper, after presenting the outline of the middleware of the receiver and the human interface of the triage engine, we introduce the lethal arrhythmia detection algorithm and the behavior recognition algorithm as two core techniques of the triage engine.

II. REMOTE HEALTH CARE SYSTEM

A. Usage Model

Fig. 1 shows the usage model of the proposed remote health care system, where a person (patient) wearing a wireless vital sensor can do normal daily activities such as walking, exercising, sleeping and so on at his/her home. The sensor continuously senses his/her vital signs and broadcasts the sensed data by wireless, and several receivers put on different places in his/her home receive then forward them to a desktop PC where a triage engine is installed. The triage engine is connected to the receivers by HyperText Transfer Protocol (HTTP), so it can be placed anywhere; the same home or even a near-by hospital for the home health care case (the system is applicable for the remote monitoring of a patient in a patient room or an intensive care unit (ICU). In this case, it can be placed in a nurse station).

The triage engine analyzes the received vital data and classifies them into three classes such as "normal," "low urgent" and "highly urgent." In "the highly urgent class" detecting the occurrence of an abnormal event, such as lethal arrhythmia, high body surface temperature and high heartrate beyond preset values, the triage engine immediately sends an e-mail containing the ECG image when the abnormal event is detected to a pre-registered medical doctor's mobile phone.

Manuscript received on March 25, 2011. This work was supported in part by the Strategic Information and Communications R&D Promotion Programme (SCOPE, No. 092307004) of the Ministry of Internal Affairs and Communications of Japan.

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978-1-4244-4122-8/11/$26.00 ©2011 IEEE

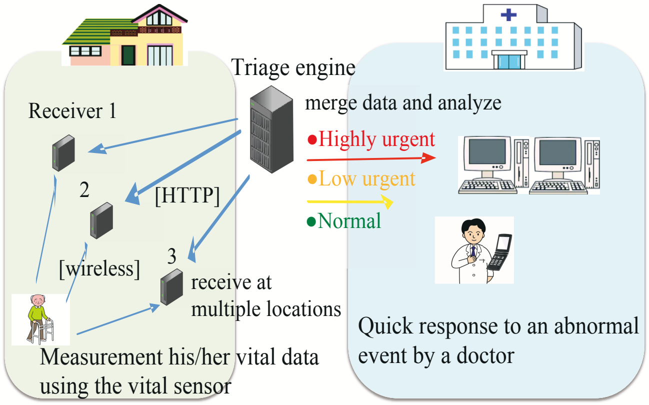

Fig. 1. A remote health care system using the wireless vital sensor.

(a) Body (b) A person wearing the sensor

Fig. 2. Pictures of the wireless vital sensor.

B. Middleware of Receiver

Figs. 2 (a) and (b) show the body of the wireless vital sensor and a person wearing the sensor. The sensor, which is commercially available in Japan, can continuously measure ECG, body surface temperature and 3D acceleration and send the data by wireless for more than forty eight hours. The receiver is a USB dongle attachable to a PC and the receiver software is installed in the PC. We reported that, from the result of the clinical test with 67 healthy subjects, the ECG sensing capability is satisfactory in terms of arrhythmia detectability and calculated RR50 accuracy [1]. However, since the wireless link between the sensor and the receiver is frequently and easily blocked by the body of a person wearing the sensor, the data loss rate is relatively high, that is, around 20 %. To improve the data loss rate, we proposed a receiver diversity technique in which multiple receivers locating at different places compensate for lost data each other. For the case of diversity with two receivers in a patient room, the data loss rate improved from 20 % to 1 % [2].

For the wireless vital sensor, the RF receiver software-driver is not manipulable, but the software development kit (SDK) is provided as a Windows application, so using the SDK, we developed the middleware which reliably and efficiently handles the measured vital data to the ethernet port of the PC. Fig. 3 shows the concept of the developed middleware of the receiver. The middleware, which was developed with C++, is workable as a Windows application. It is equipped with a ring buffer composed of eight sub-threads, so we can evaluate the effect of diversity for at most eight combinations of receivers.

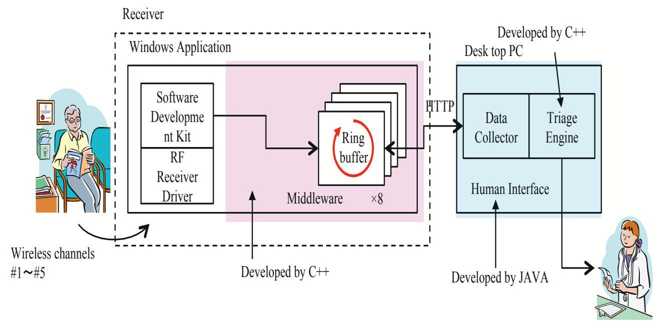

Fig. 3. Concept of the developed middleware of the receiver.

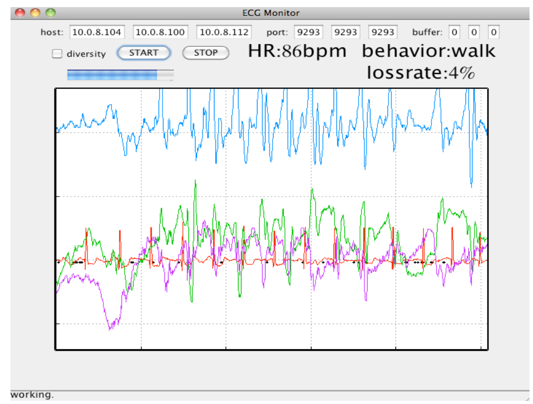

Fig. 4. Screenshot of the triage engine. The red curve and the other colored curves show the ECG and the 3D acceleration, respectively. The lost samples are depicted as black dots.

C. Human Interface of Triage Engine

We developed the triage engine with multiple functions to automatically classify input vital data. The application program was developed with the Java programming language and it can work on either a note PC or a desktop PC in UNIX environment. It can get any receiver's data with an appropriate IP address or their merged data up to three receivers, shown in Fig. 4. The main functions of the triage engine are

- to visualize the measured ECG and the 3D acceleration waveforms in the GUI every 10 seconds
- to calculate the heart rate based on R-R intervals and the data loss rate
- to classify behaviors by the 3D acceleration analysis
- to inform pre-registered medical doctors of an emergency alarm by e-mail when the occurrence of an abnormal event is detected.

The methods of the behavior recognition and the lethal arrhythmia detection are elaborated in the following sections.

III. Triage Engine

A. Behavior Recognition

For an accurate diagnosis, it is important to get the information on the bodily movement of the person when an arrhythmia occurs at a person. For instance, a patient during the Holter ECG measurement is requested to keep

TABLE I

ACCURACY COMPARISON (MEAN±DEVIATION) AMONG THE 4 CLASSIFIERS WITH A CONSTANT WINDOW WIDTH FOR THE 7 SUBJECTS' BEHAVIORS.

Classfier	Accuracy (%)		
	5 seconds	10 seconds	20 seconds
Decision Tree	75.18±8.39	76.51±7.43	71.88±13.85
KNN	70.71±11.82	70.70±10.64	71.17±11.37
Naive Bayes	75.14±8.29	**78.27±5.71**	78.01±5.20
SMO	73.34±9.05	74.52±9.59	75.34±7.37

TABLE II

RESULTS USING THE NAIVE BAYES WITH WINDOW WIDTH OF 10 SECONDS FOR THE 8 BEHAVIORS.

Behavior	Classified As (%)							
	W	R	Si	St	L	B	U	D
walking (W)	**80.2**	0	0	0	0	0	17.9	1.7
running (R)	2.7	**72.4**	0	0	0	0	19.8	5.2
sitting (Si)	0	0.5	**92.2**	7.3	0	0	0	0
standing (St)	0.5	0.5	20.9	**71.3**	0	6.3	0.5	0
lying (L)	0	0	0	0	**100**	0	0	0
bike (B)	6.4	0	0	0.4	0	**77.6**	15.6	0
upstairs (U)	27.9	12.7	0	0	0	8.9	**31.7**	19
downstairs (D)	11.3	9.3	0	0	0	0	28	**51.3**

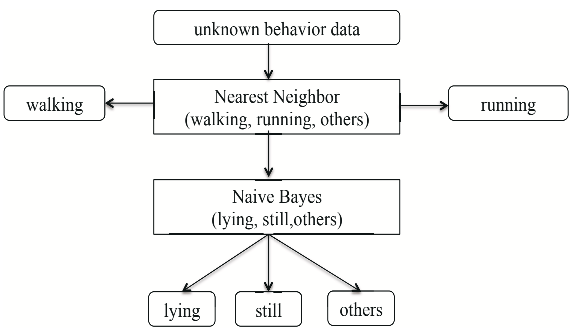

Fig. 5. Flowchart of the behavior recognition algorithm.

a diary on his/her behaviors of the day. This is because an arrhythmia may appear for a healthy person during a heavily-loaded activity such as running, walking and so on, and the arrhythmia is ignorable for diagnosis in these cases. Therefore, we carried out an experiment to find out an optimal method for the behavior recognition [3].

In the experiment, 7 subjects with the wireless vital sensor performed 8 behaviors, such as "walking," "running," "riding on a bike," "standing," "lying," "walking upstairs" and "walking downstairs." Using their 3D acceleration data, we calculated the mean, variance, energy, and frequency spectrum entropy in a constant time interval and applied 4 classification algorithms such as Decision Tree, k-nearest neighbor (KNN), Naive Bayes and Sequential Minimal Optimization (SMO) methods. The experimental results of the behavior recognition are shown in Table I. From the results, the method using the Naive Bayes method with window width of 10 seconds has the highest accuracy among the 4 classifiers. Table II shows the detailed result of the Naive

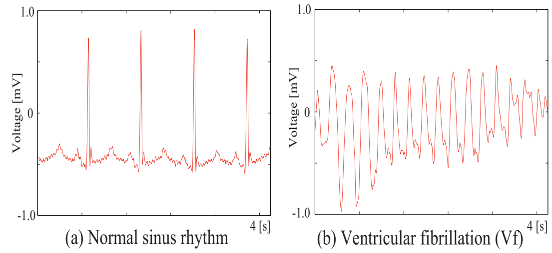

Fig. 6. A normal sinus rhythm signal and a Vf signal.

Bayes method.

Fig. 5 shows the flowchart of the behavior recognition algorithm in the triage engine. First, the input unknown behavior (3D acceleration) data are classified into "walking," "running" and "others" using our previously proposed algorithm based on the nearest neighbor method [4], where "walking" and "running" are distinguished in terms of the differences of their movement cycle and intensity. Second, the unknown data classified into "others" are furthermore classified into "lying," "still" and "others" using the Naive Bayes method. We can see from Table II that more than 71 % classification accuracy is obtainable for the main behaviors except for "bike riding," "upstairs" and "downstairs."

B. Lethal Arrhythmia Detection

Lethal arrhythmias such as ventricular fibrillation (Vf) and ventricular tachycardia (VT) causing a sudden cardiac death, might arise even in a person without heart disease. Figs. 6 (a) and (b) show a normal sinus rhythm signal and a Vf signal, respectively. We can see an apparent difference between the two signals in terms of their cycles, and the difference is most obvious on their frequency domains. That is, many peaks appear over a wide frequency band for the sinus rhythm signal, whereas a dominant peak appears in the frequency band from 3 to 7 Hz for the lethal arrhythmia signal [5]. Therefore, time-frequency analysis must be effective to distinguish the lethal arrhythmia from others.

The detection algorithm is based on the short time Fourier transform (STFT), which is well known as a time-frequency analysis tool. The STFT is defined as

$$STFT(t,f) = \int_{-\infty}^{\infty} x(\tau)w(\tau-t)e^{-j2\tau f\tau}d\tau \qquad (1)$$

where $w(t)$ is a window function and we selected the Kaiser window from the comparison results among several window functions. First, an extracted signal by the window is transformed into the frequency domain using the STFT, and the number of peaks over a threshold is counted. When the number is less than n, the signal is determined as a suspected lethal arrhythmia. The threshold can be calculated as

$$threshold = \alpha \arg \max_{f} P(f) \qquad (2)$$

where α is an empirically determined coefficient and $P(f)$ is the power spectrum density in the frequency domain from 3 to 7 Hz. Second, the above process is repeated by

TABLE III
OPTIMIZED PARAMETERS AND THE RESULTS ON THE DETECTION ALGORITHM OF THE LETHAL ARRHYTHMIA.

Optimized parameters	
n	5
α	0.0825
kaiser window coefficient	2.0
window width	5 seconds (500 samples)
sliding window width	1 seconds (100 samples)
Results	
Sensitivity	100 % (19 / 19)
Specificity	99.99 %

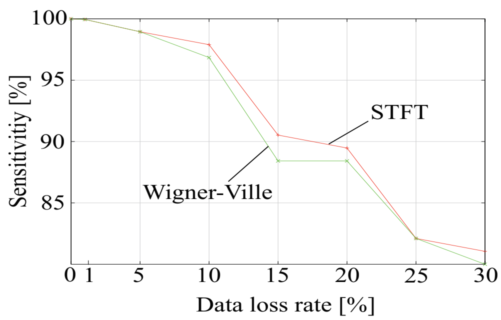

Fig. 7. Sensitivity versus the data loss rate.

sliding the window along the signal. Finally, when more than half of extracted signals are determined as suspected lethal arrhythmias in a certain time interval, the signal is determined as a lethal arrhythmia.

No lethal arrhythmia signal could be measured in our clinical test using the wireless vital sensor, so we used the sudden cardiac death Holter database (http://www.physionet.org/pn3/sddb/). In the database, the occurrence time of the lethal arrhythmia is annotated by medical specialists and 19 subject data containing Vf signal or VT signal were used as test data. After data acquisition, the AD resolution and the sampling rate of the acquired signal were converted from 12 bits and 250 Hz to 10 bits and 100 Hz, respectively, for construction of the pseudo environment using the wireless vital sensor. In addition, we intentionally lost some of the constructed data in accordance with the data loss pattern of the clinical test data for the wireless vital sensor.

Results were assessed in terms of the following four measures:

- True Positive (TP) : a lethal arrhythmia is detected as a lethal arrhythmia
- True Negative (TN) : a non-lethal arrhythmia is detected as a non-lethal arrhythmia
- False Positive (FP) : a non-lethal arrhythmia is detected as a lethal arrhythmia
- False Negative (FN) : a lethal arrhythmia is detected as a non-lethal arrhythmia.

Using the four measures, sensitivity and specificity are respectively defined as

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP}. \tag{4}$$

We optimized all parameters of the algorithm. The values and the results are shown in Table III. The algorithm is reliable enough for detection of lethal arrhythmias with sensitivity of 100 % and specificity of 99.99 %. Fig. 7 shows the sensitivity versus the data loss rate. For comparison purpose, this figure also contains the curve for a Wigner-Ville analysis [5] where parameters are also optimized. We can see that the proposed STFT method always outperforms the Wigner-Ville method. For the data loss rate of 20%, corresponding to the average data loss rate for the clinical test with a single receiver, there is some possibility in missing the transient lethal arrhythmia. However, for the data loss rate of 1%, corresponding to the data loss rate for the case of diversity with two receivers, the result is satisfactory because it is almost the same as that for no data loss case. Therefore, we can conclude that the receiver diversity technique is indispensable to a reliable diagnosis for lethal arrhythmia.

IV. CONCLUSIONS

In this paper, for the remote health care system which we have so far developed, after outlining the middleware of receiver and the human interface of triage engine, we introduced the behavior recognition algorithm and the lethal arrhythmia detection algorithm in detail. The developed triage engine has the following outstanding features:

- typical behaviors such as "walking," "running," "lying" and "still" can be classified with more than 71 % accuracy
- lethal arrhythmias can be detected with high accuracy (i.e. sensitivity of 100 % and specificity of 99.99 %)
- an urgent e-mail on the occurrence of an abnormal event and related information such as body surface temperature and behavior status at that time is automatically sent to a pre-registered medical doctor.

For realization of a truly reliable remote health care system, it is necessary to evaluate the capability of the triage engine by clinical tests and to improve it by tuning parameters and adding more functions. The research is still going on.

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