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A Context-Aware mHealth System for Online Physiological Monitoring in Remote Healthcare

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Abstract: Physiological or biological stress is an organism's response to a stressor such as an environmental condition or a stimulus. The identification of physiological stress while performing the activities of daily living is an important field of health research in preventive medicine. Activities initiate a dynamic physiological response that can be used as an indicator of the overall health status. This is especially relevant to high risk groups; the assessment of the physical state of patients with cardiovascular diseases in daily activities is still very difficult. This paper presents a context-aware telemonitoring platform, IPM-mHealth, that receives vital parameters from multiple sensors for online, real-time analysis. IPM-mHealth provides the technical basis for effectively evaluating patients' physiological conditions, whether inpatient or at home, through the relevance between physical function and daily activities. The two core modules in the platform include: 1) online activity recognition algorithms based on 3-axis acceleration sensors and 2) a knowledge-based, conditional-reasoning decision module which uses context information to improve the accuracy of determining the occurrence of a potentially dangerous abnormal heart rate. Finally, we present relevant experiments to collect cardiac information and upper-body acceleration data from the human subjects. The test results show that this platform has enormous potential for use in long-term health observation, and can help us define an optimal patient activity profile through the automatic activity analysis.
Keywords: decision support systems, telemonitoring, Context-Aware application

1 Introduction

For patients with cardiovascular disease, physiological stress is an important index to measure their overall health status [1]. However, the daily physiological stress ration of a patient cannot be carried out through simple laboratory simulation due to the various factors that influence daily life; this makes the standardization work for measuring physiological stress difficult. Currently a large amount of research work in the field of preventive medicine is developed around physiological monitoring. With the development of communication and sensor technologies, the mode of (a) real-time physiological parameter acquisition and (b) automatic online analysis provides new technical solutions for effectively resolving long-term monitoring of a patient's daily activity. In previous work [2] [23] we reported about the potential relationship between cardiac information and physiological stress. A novel fuzzy modeling based HRV analysis method for stress assessment was proposed in [23]. The method of [23] extracts the features of HRV in time-frequency domain and fuzzy techniques are exploited to render robustness in HRV analysis against uncertainties arising from individual variations. This paper presents a wearable, remote-monitoring system based on patient context information. The monitor's purpose is to evaluate the physiological parameter combined with the human body status, and detect an anomalous event through the context information.

Patient context-aware information is an important concept in the mobile health environment. According to the descriptions of Dey, Abowd, et al., in their thesis's general definition of context [3], patient context can be defined as the information for a patient's medical situation, which can be roughly divided into the following categories: (a) patient's vital parameters, (b) medical symptoms (vomiting ...), (c) risk factors (cholesterol level ...), (d) activities (standing, walking ...), and (e) surrounding environment (room temperature ...)

Context-aware computing is an important research field in ubiquitous computing [4]. "Context-aware system" refers to a system which can perceive a change in the user's environment and make a corresponding adjustment. Under a mobile health environment, the context-aware system connects various medical and perception equipment via the network; access to various resources and information is more convenient for medical staff, thus improving their efficiency. The fusion of environment/position information, patient's health status, and physiological parameters can provide rich context information for doctors' decisions and provide an enhanced environment for more-informed medical service.

2 Related Work

In related work various types of relevant data have been collected individually or in some combination for a variety of healthcare purposes [5]- [6]. Physiological profile data has been used exclusively [7] or has been used in conjunction with activity profile data [8] and environmental information [9]. Among these papers, special note should be taken of the system described in [10]. This work presented an approach where vital parameter changes of patients are detected in the biosignal recording system in real-time, however, the users are prompted to provide additional input about their daily living activities. Therefore, user intervention is required in that system to provide additional context information [11]. In [12] systems are presented that analyze physiological function in conjunction with automated observation, wellbeing, and health status. In [13] a system is described that analyzes the relationship between an activity profile and physiological information.

Automatic recognition and quantification of human activities using wearable sensors during activities of daily living has been increasingly used in many research works [24]- [27].

3 System structure

This paper proposes a multi-sensor system which uses an inference decision support system with a basis of rules to improve the accuracy of discovering potentially dangerous heart rate variability. As shown in Figure 1, two different sensors at local site of patient are used for acquiring patient context information and physiological parameters. The sensors in the first category include environmental sensors used for monitoring interaction between a patient and the surrounding environment; meanwhile, a wearable acceleration sensor acquires the patient's activity status. The information acquired in this group of sensors can accurately reflect the time, location, and context of the patient's activity performing in the environment. The sensors in

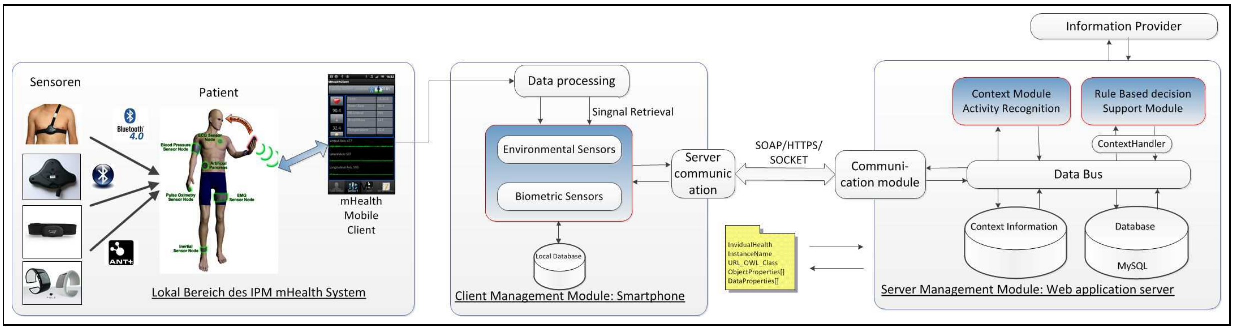

Figure 1: Institute for Preventive Medicine mobile Health (IPM-mHealth) System Structure

Figure 2: Hidalgo Equivital Muti parameter Sensor

the second category include vital signs sensors, which is a typical wearable sensor for measuring the patient's physiological parameters. Real-time accurate physiological parameter acquisition is the basis for data analysis; then we can combine the context information of physical activity to carry out more effective physiological status analysis. This paper has the focus on the two core elements of the framework: (1) automated activity recognition, and (2) knowledge-based decision module.

- Activity recognition can mainly be divided in two ways: visual-based and sensor-based [14] - [15]. The activity recognition method based on a 3-axis acceleration sensor belongs to the latter; this is the newly emerged branch of human body activity identification research. Compared with traditional activity recognition based on visual sense, it provides advantages such as the acquisition of movement data in a simpler and more human manner, etc. The algorithm designed in this paper focuses on the acceleration signal worn on a patient's body as a recognition basis.

- The Decision Module represents the intelligent core part of the system. For context processing, modeling should be carried out first for a patient's context information. (For example: the activity and position in an abnormal heartbeat situation can be included into one context). The experiments uses Web Ontology Language (OWL) to construct the model and process it using Sample Semantic Web Rule Language [16], which can also provide the higher level information about the overall health status of patients through its conditions based engine.

Figure 3: Equivital sensor chest belt

The system is tested by using the hardware devices: Equivital wearable-mutiparameter-sensor solution developed by Hidalgo [22]. One Equivital device was placed on the upper body of the participant (as shown in Figure 2 and 3). The sensor module with a special chest belt is an appropriate solution for recording the required measurands. It offers the possibility to acquire cardiac function (via three integrated fabric-based silver-coated electrodes), pulmonary function (via an integrated resistance strain gauge),activity function activity(via an integrated accelerometer ADXL330) and skin temperature (via an integrated thermistor).

The Equivital sensor solution, fully charged, offers 24 hours of operation. Due to the low overall weight of 175g (electronic module and the sensor 75g; belt 100g) and the dust/water resistance protection rating of IP 67 (0.4 m = 30 min.), the IPM-mHealth system allows subjects to move freely in their familiar work surroundings as an examiner continuously monitors their condition from any location.

4 System Design

4.1 Automatic Activity Recognition

Automated activity analysis is the essential component of the IPM-mHealth system which provides new opportunities for quality long-term studies of various vital functions. Activity identification can be defined as a classification problem in the machine learning field. The basic flow of activity identification is as follows. First, 3-axisacceleration sensor data should be acquired and sensor features (mean value, peak value, standard deviation, spectrum energy, etc.) should be extracted within the specific time window. Then, classification training for sensor data should be carried out under a different activity status. The activity recognition flow is shown in Figure 4:

1. First the accelerometer data will be collected and smoothed.

2. Specific sensor values will be extracted within a defined time window (average, maximum, standard deviation, etc.).

3. Then the WEKA tool will be used to classify the measured data relevant to the various states.

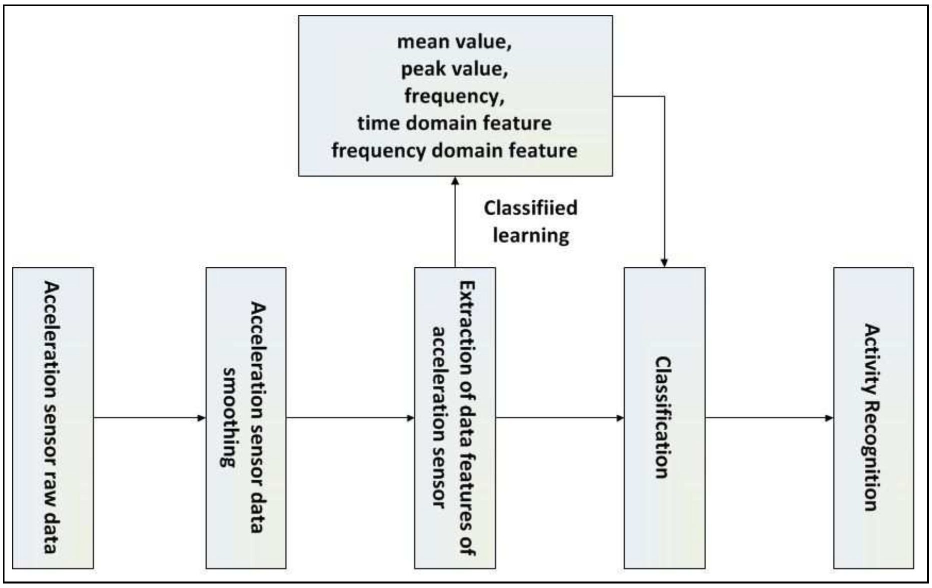

Figure 4: Flowchart for automatic activity recognition

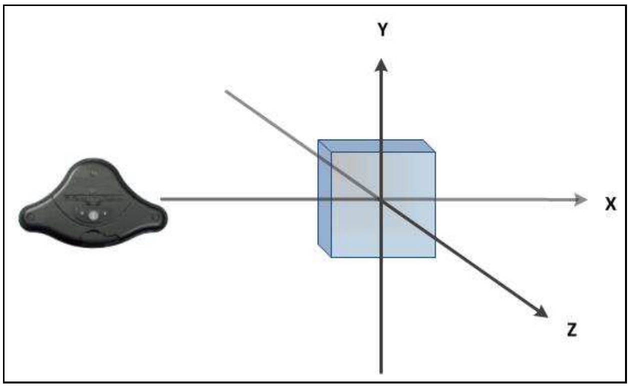

Figure 5: Direction of the Equivital 3-Axis Accelerometer

4. Finally, we use the 1-k-Nearest Neighbour (kNN) classifier to classify the activity status.

(1) Acceleration data acquisition

In this paper, we capture data for ten (10) volunteers performing six (6) different movements, including standing, walking, running, jumping, walking upstairs, and walking downstairs; for each action, the sensor data was collected five (5) times. A total of 300 samples of acceleration data are used as the original acceleration signal. The signals are collected by the Equivital sensor described above. The sensor module itself has an integrated three-axis accelerometer, ADXL330, and allows detection of orientation and body activity. The device's integrated 3-axis accelerometer was used at a sample rate of 100 Hz for each axis, providing synchronous acquisition of motion data.

The coordinate-system of the 3-axis acceleration sensors is defined relative to the front of the devicein its default orientation. As Figure 5 shows, the X-axis is horizontal and points to the right, the Y axis is vertical and points up and the Z axis points towards the outside of the front face of the device. In this system, coordinates behind the device have negative Z values.

All of these data (raw data, calculated data, and message data) can be transferred continuously and wireless from the sensor module, via a Bluetooth class interface, to the IPM-mHealth

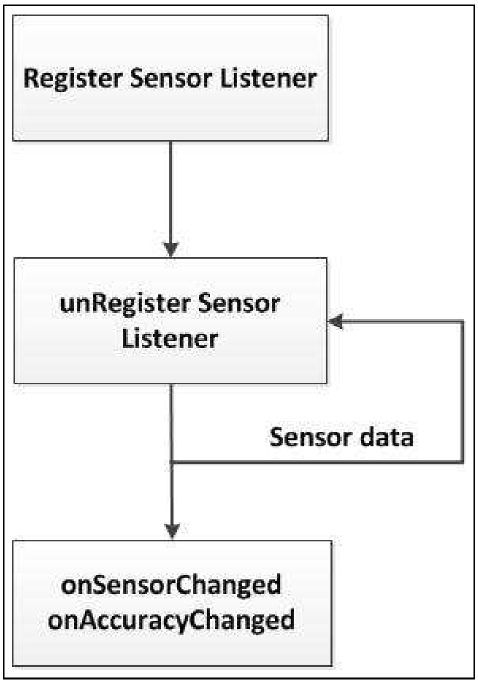

Figure 6: Data transmission process

client in realtime. By calling the Sensor Communication Module offered in the IPM-mHealth client, the raw data of Equivital acceleration sensors can be transferred and stored.

As shown in Figure 1, the IPM-mHealth client, running on the smart phones, is responsible for the collection of sensor node data and for sending the data to a remote data processing center. The data processing center, based on a Hadoop server cluster, is responsible for data collection, analysis, processing, and data mining. The communication between the IPM-mHealth client and server is implemented through HTTP/HTTPS, SOAP, and SOCKET. HTTP is used in synchronous XML workflow description; SOAP is used to transmit ontology instance information; the SOCKET connection is used in real-time high-demand, for example, transmitting ECG (1024 bytes/sec) and Acceleration (300 bytes/sec) data.

The acceleration data transmission process is shown in Figure 6.The Accelerometer EventListener Class is established to acquire the data; this class inherits the class Sensor EventListener of the Android API. It provides the following features: Registration of sensor services, Recall of sensor services, Acquisition of the sensor data, and Listening for real changes in the data.

After the sensor data is detected, the sensor data of the three directions can be obtained by calling the methods: onSensorChanged-DataX, onSensorChanged-DataY and onSensorChanged-DataZ. Since the direction has little influence to the following motion identification algorithm. Here we carried out a handling, i.e.: the vector sum of the acceleration data in each change should be calculated through the following equation:

$$\mathbf{D_i}=\sqrt{(\mathbf{A}cc\_\mathbf{X})^{\mathbf{2}}+(\mathbf{A}cc\_\mathbf{Y})^{\mathbf{2}}+(\mathbf{A}cc\_\mathbf{Z})^{\mathbf{2}}}$$

The data after each change of acceleration sensor status and the currently relative time (unit: millisecond) are respectively saved in two arrays, time-series[] and data-series[]. The original data time sequence after acquisition is shown in the following Figure, the horizontal axis is the time axis, i.e., time-series[], and the vertical axis is acceleration sensor data Di, i.e., data-series[].The motion order in the below figure is: (1) walk, then (2) a series of three times of jumps, (3) run,

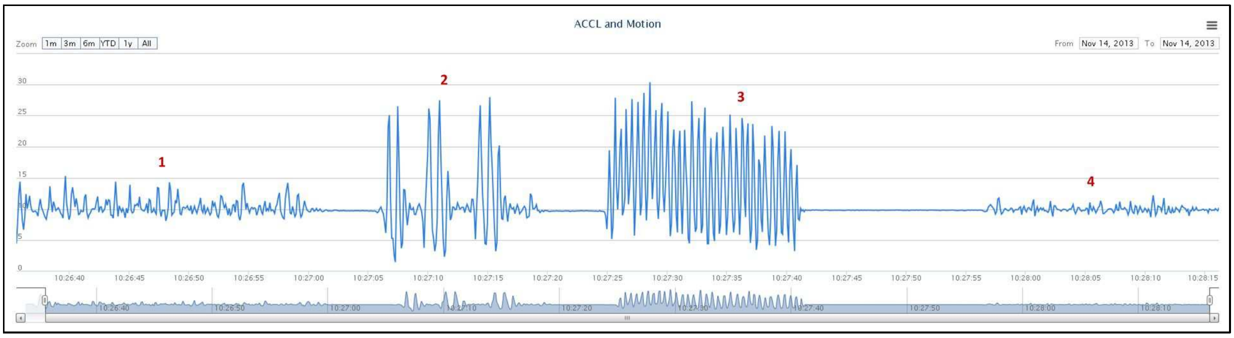

Figure 7: Time sequence diagram of acceleration raw data

and (4) slow walk. It can be seen from the original data that different motions differ in the data features of mean value, peak value, frequency, etc.

(2) Acceleration sensor data smoothing

The data acquisition interface of the Equivital sensor adopts a passive invoking method, where the data will be sent out only when the acceleration status changes. Therefore, the data acquired in the previous step are not evenly distributed at each time point. In order to equalize the time interval between each data point we used the following smoothing algorithm to calculate the mean data value at the time point with the an interval of 40 milliseconds based on the acquired original data time-series[] and data-series[].

The latest two time points in the time-series[] which is nearest to the time point T0 to be calculated are T1 and T2. Wherein: T1 <T0, T2 >T0 and the corresponding data on data-series[] are obtained to be D1 and D2. Assume that the acceleration speed of a mobile phone between T1 and T2 is linear, then the data value at T0 is D0, which can be calculated through the following weighted average method:

$$\mathbf{D_0}=\frac{\mathbf{D_1}*(\mathbf{T_2}-\mathbf{T_0})+\mathbf{D_2}*(\mathbf{T_0}-\mathbf{T_1})}{\mathbf{T_2}-\mathbf{T_1}}$$

New time-series[] and data-series[] can be calculated and set up through the above algorithm.

(3) Extraction of data features of acceleration sensor

In order to accurately capture and identify motions, the data set window can be set to 512*40, i.e., 20,480 milliseconds. Therefore, the data-series[] array can save 512 samples. When the array is full, re-save should be carried out from data-series[0] after emptying it. After filling in the array, data extraction with a time domain feature and frequency domain feature should be carried out for another time.

(a) Time domain feature

The time domain feature is the feature value of the data within a certain time window. Due to the smoothing of data carried out in the previous step, the acceleration sensor data is with the interval of 40 milliseconds Therefore, the time domain feature of the acceleration sensor, within 20,480 milliseconds (about 20 second), can be calculated directly via the mean value, maximum value, and minimum value of all the data within the data-series[] array. By extracting the various features of the acceleration signal within a single time window, several feature vectors can be constructed to characterize the behavior. In this paper, the following feature vectors are used.

1) Standard Deviation Formula: Standard deviation is defined as

$$\sigma=\sqrt{\frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{i=1}}^{\mathbf{N}}(\mathbf{X_i}-\overline{\mathbf{X}})^{\mathbf{2}}}$$

where N is the number of samples and X is the sample mean. Standard deviation, an often-used statistical characteristic. Standard deviation reflects the degree of dispersion of the acceleration sensor data. Since the acceleration data are unchanged when subjects are in the static state, standard deviation is near zero. When subjects are moving, the acceleration data are constantly changing and the standard deviation is always much greater than zero. Therefore, the standard deviation is an important feature to identify static operation and dynamic action.

2) Skewness: skewness is defined as formula

$$\mathbf{S}K=\frac{\mathbf{N}\sum_{\mathbf{i=1}}^{\mathbf{N}}\left(\mathbf{X_i}-\overline{\mathbf{X}}\right)^{\mathbf{3}}}{(\mathbf{N}-\mathbf{1})\,(\mathbf{N}-\mathbf{2})\sigma^{\mathbf{3}}}$$

where N is the number of samples, X is the sample mean (data), and σ is the sample standard deviation.In probability theory and statistics, skewness is a measure of the asymmetry of the probability distribution of the acceleration sensor data about its mean. The Skewness of the X axis can effectively distinguish between actions such as walking downstairs.

3) Kurtosis: kurtosis is defined as formula

$$\mathbf{K}=\frac{\sum_{\mathbf{i=1}}^{\mathbf{N}}\left(\mathbf{X_i}-\overline{\mathbf{X}}\right)^{\mathbf{4}}\mathbf{f_i}}{\mathbf{N}\sigma^{\mathbf{4}}}$$

where N is the number of samples, X is the sample mean (data) , σ is the sample standard deviation, and fiis the Sample Interval. Kurtosis is any measure of the "peakedness" of the probability distribution of acceleration sensor data, an important statistical characteristic. Kurtosis of the Y axis can effectively distinguish running and other actions.

(b) Frequency domain feature

The time domain feature alone cannot reflect the obvious characteristics in frequency domain of motion, therefore, characteristics in frequency domain should be obtained via Fast Fourier Transformation. Here, Fast Fourier Transformation should first be carried out on the data-series[] array. Fast Fourier Transformation (FFT) is a kind of fast algorithm of Discrete Fourier Transformation (DFT), which reduces the number of computations needed for N points from 2N2 to 2NlgN and the data can be efficiently changed from time domain into frequency domain. Fast Fourier Transformation should be carried out on data-series[] (FFT operation can be carried out directly if data-series[] array is 512and results in a complex number array in frequency domain space. Each complex number in the array includes real and image data. The corresponding Fourier component of each frequency within the frequency domain can be obtained through the following relationship, i.e., modulus of the complex number.

The energy of characteristics quality in frequency domain, which is required in this paper, is the ratio between the quadratic sum of Fourier components within a window and the window size. I.e., frequency domain energy reflected the data periodicity, as for the motion with high periodicity (such as running), the frequency domain energy is obviously high.

$$\mathbf{E}nergy=\int_{\mathbf{k=0}}^{\mathbf{w}}\frac{(\mathbf{M}od[\mathbf{k}])^{\mathbf{2}}}{\mathbf{w}}$$

In order to be convenient for feature extraction, this paper uses a windowing method to split the original acceleration signals. The single acceleration signal, after being windowed, includes 512 samples, which is enough for including a single complete motion of patient. If a shorter, rectangular window is adopted, it is not large enough to include information for identifying different motions. If the length of the rectangular window is too long, serious delay phenomenon will occur to the real-time system.

(4) Classified-learning

After above procedures obtain the feature values, data excavation tools should be used in the following step. This paper uses WEKA [18] to classify the learned test data, so as to lay a foundation for the following Activity.

(5) Classification

In the experiment, we used 45Training samples and 6-11 training samples of each action. Volunteers completed the following actions sequentially:(1) walking, (2) jumping, (3) standing, (4) walking up stairs, (5) walking down stairs, and (6) running. Every action lasted 30 to 50 seconds to make sure that, for every action, three (3) to five (5) groups of eigenvalues could be collected.

Finally, we use the 1-k-Nearest Neighbour (kNN) classifier to classify the obtained feature values based on the learning basis in the previous step. Its confusion matrix test results are shown as Table 1. We can see from the confusion matrix that the classification accuracy of 1-k-Nearest Neighbour (kNN) is high, and the overall accuracy is 95.56%, of which an example could be one jump motion wrongly included into running, and an example of one standing motion included into walking, which shows that these two groups of motions may produce slight confusion to sorting algorithms.

Table 1. Confusion matrix of knn results

Activity	**Classification**					
	Jump	**Walking**	**Standing**	**Down-stairs**	**Up-stairs**	**Running**
Jump	7	0	0	0	0	1
Walking	0	11	0	0	0	0
Standing	0	1	11	0	0	0
Down stairs	0	0	0	6	0	0
Upstairs	0	0	0	0	4	0
Running	0	0	0	0	0	4

4.2 Knowledge Representation

In order to detect an abnormal situation, the heart rate variability is particularly the most relevant parameter identified by cardiologists [20]. In this experiment, we used Equivital multi-parameter sensors to collect the ECG data. The changes in the beat-to-beat heart rate, the heart rate variability (HRV),calculated from the electrocardiogram (ECG), is a key indicator of an individual's cardiovascular condition. Assessment of HRV has been shown to aid clinical diagnosis and intervention strategies. An overview of some implemented production rules in the system is shown in the following Figure.

During the process of acquiring physiological parameters and activity identification an approach based on Context Information is used in the Physiological Decision Module to detect any abnormal cardiovascular events. It includes the basic medical knowledge required to identify potentially dangerous situations of patients in cooperation with the cardiologists and clinical experts. We first need to construct the Context Model before processing the Context Information [19]. The following forms are included in the context models: (Subject, Predicate, Value).

If the heart rate value is outside the scope regarded as "normal", or the heartbeat is not regular, we can simply identify HRV. Moreover, it can also determine HRV by means of the SDANN, the standard deviation of the average R-R intervals calculated over short periods, usually 5 minutes. However, according to the involved cardiologists, the HRV by itself may not have any meaning for identifying an anomalous situation; instead, it should be correlated with other information pertaining the patient, e.g. the physical activity and his/her posture. The following

```
if [ (RHRmax < measuredHeartRate <= HRmax)
AND (lying = true)
AND (elapsedTimeInterval > timeThreshold) ]
then
alertType = Alarm;
if [ (RHRmax < measuredHeartRate <= HRmax)
AND (walking = false)
AND (running = false)
AND (elapsedTimeInterval > timeThreshold) ]
then
alertType = Alarm;
if [ (measuredHeartRate > HRmax)
AND (elapsedTimeInterval < timeThreshold) ]
then
alertType = Warning;
```

physiological parameters are used by the implemented production rules on this aspect:

Cardiac information

- HRmax: patient's maximum heart rate calculated by Karvonen formula [21];
- measuredHeartRate: patient's heart rate measurement;
- restingHeartRate: patient's resting heart rate;
- timeThreshold: time threshold usually 10 sec;
- RHRmax : RHR+10;
- RHRmin : RHR-10;

Posture Information

- lying: datatype [boolean] property detecting whether the patient is lying or not;
- standingUp: datatype [boolean] property detecting whether the patient is standing up or not;

Physical Activity Information

- running activity: datatype [boolean] property detect whether the patient is running or not;
- walking activity: datatype [boolean] property detect whether the patient is walking or not;

Environmental Information

- room temperature: temperature of room where patient lives;

For example, we have a patient with HeartRate of 70 and ID 001, and physical activity was regarded as running, then the context information would be recorded as follows:

- (Patient001, HeartRate, 70), (Activity, Running, true), We can also define the specific conditions for the emergency task to be triggered: e.g. the Heart Rate of the patient drops below 40, or the blood pressure (systolic) exceeds 170. Reasoning may be carried out according to the rules of the language itself, for example:

- $(?a?p?b), (?prdf : subPropertyOf?q)- > (?a?q?b)$

User defined rules may also be used in the reasoning process, e.g.:

- (?patient, EquitalBloodPressure001, vl), GE(?vl, 170), (?patient, EquitalBloodPressure, vl), LE(?vl, 40) ->(?patient, healthStatus, "danger")
- (?patient, healthStatus, "danger"), (?Patient, healthStatus, "movementfail"), (EmergencyTask, taskState, "CLOSE") ->(EmergencyTask, taskState, "OPEN")

Some example rules are shown in Table 2, which are used by the system to predict an abnormal situation. When the heart rate is abnormally high, the HeartRateHigh rule assigns the alarm level. Abnormal heart rate in each instance of the HeartRate Class is specified in the hasMinRange and hasMaxRange properties. The system sets the Heartrate alarm if a patient's heart rate is greater than the specified normal maximum.

Table 2. Rules for the system's alarm management

Rule	**Description**
HeartRate-High	(?patient rdf:type HeartRate) , (?par1 hasCurrentValue ?v1) , (?par1 hasMaxRange?Max), greaterThan(?v1, ?Max) ->(?taskstate hasAlarmLevel "HES")
HeartRate-Low	(?patient rdf:type HeartRate) , (?par1 hasCurrentValue ?v1) , (?par1 hasMinRange ?Min), greaterThan(?v1, ?Min) ->(?taskstate hasAlarmLevel "LES")

5 Experimental results

In order to identify whether various functions of the IPM-mHealth system are effective or reliable in practical application, we designed an initial experiment. Its purpose was to carry out a test and verify the following functions: quality of physiological signals acquired by IPM-mHealth; comfort of sensor system; online activity recognition and alarm reliability; reliability of short-distance wireless communication; and reliability of remote wireless communication. Five healthy volunteers in the 21 35 age range without cardiovascular disease history participated in this test.

In the first test subjects with Equivital sensors carried out the motions for walking, jumping, running, standing, climbing the stairs, and walking down the stairs, in proper order; another observer recorded the test subjects' motions and corresponding times. In the second test, we simulated the abnormal heartbeat event and tested the reliability of the decision-making system under lying-flat and running conditions with the test subjects.

The relevant test data and statistical results are shown in Table 3 and Table 4. In the stability tests, we used ten (10) minutes to teach each volunteer how to put on and operate the system, then let them go home with the wearable device and keep the system running more than 24 hours. The sensor data was collected in real-time and sent to the central IPM-mHealth server; Table 4 lists the transmission packet loss rate for 24 hours' data. We can see that both, the short-distance wireless transmission and remote wireless transmission, operated normally. The expected real-time physiological data transmission was not lost. Illegal disconnection conditions did not occur in short-distance wireless transmissions during the entire test process. The acquired signal quality was satisfactory. In the automatic activity recognition experiment, volunteers completed totally 300 actions and 10 times for each action. In the abnormal alarm part, good effect was also received in the simulated anomaly detection, of which the conditions of over 150 heartbeats under 10 times of lying flat were correctly identified with alarms, while over 150 heartbeats under running state were included into the normal range. In the activity identification part, 90% motions were correctly identified by the system. The activity identification of standing and jumping had the best accuracy; the activity of climbing and walking down the stairs also had the better accuracy, while running, walking, etc. has misjudgement within 8%.

Table 3. Results of the automatic activity recognition and abnormal situation indicating

Activity	**Correct recognition rates**	**HR max**	**Alert (HR max)**	**Std**
Standing	97.8%	170	Alarm	10
Walking	91.6%	122	None	10
Running	92.6%	178	None	10
Jump	97.6%	150	None	10
climbing the stairs	96.6%	140	Warning	10
Walking down the stairs	95.2%	110	None	10

Table 4. Results of stability test

Parameter	**Acquisition frequency of sensor data**	**Packet-loss-rate**	**Data transmitted in a 24-hour period**	**Std**
Heartrate	0.3Hz	<0.1%	25,920 bytes	24
Respiratory	0.3Hz	<0.1%	25,910 bytes	24
Patient Temperature	0.3Hz	<0.1%	25,890 bytes	24
R-R Interval	1Hz	<0.1%	86,390 bytes	24
Acceleration X	100Hz	<0.1%	2,164,986bytes	24
Acceleration Y	100Hz	<0.1%	2,164,980bytes	24
Acceleration Z	100Hz	<0.1%	2,164,900bytes	24

We also find in the test results that the motions identified within the activity change duration may be misjudged when test subjects conducted multiple motions successively. The causes for this misjudging lie in the selection of the time window when the sensor test data was acquired. The time window selected in this paper is about 20 seconds, the data within 1 second may mix the corresponding acceleration data of two activities. Therefore, the data features and user activity did not mutually correspond, it could lead to misidentification between two activities. This problem can be solved by selecting a shorter time window, but the selection of an overly-short time window may create non-obvious problems for the corresponding data features of various activities.

6 Conclusion

A framework for context-aware physiological analysis with regard to daily activities is proposed in this paper for the detection of abnormal cardiac situations. OWL is used in the context-reasoning module to construct target medical tasks and circumstances. The IPM-mHealth system has been used in the Institute for Preventive Medicine at Rostock University Medical Center

Germany for remote monitoring research and about 60 subjects carried out 8-24 hour remote monitoring tests. In the questionnaire, over 90

However, this paper does not address how to process the context conflicts in the process of constructing ontology and reasoning conditions. The reliability and energy consumption problem of remote medical systems will be the focus in further research. As for the energy consumption problem, some new ultra low power transmission protocols that can greatly improve the sustainability of remote monitoring have appeared, such as ANT (ANT is a proven ultra-low power (ULP) wireless protocol that is responsible for sending information wirelessly from one device to another device, in a robust and flexible manner) and BLE (Bluetooth Low Energy). Other challenging tasks will include the system recovery mechanism and development of an intelligent error discovery to keep the stability of the system over time.

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