An Embedded Mobile ECG Reasoning System for Elderly Patients

Dong-Her Shih, Hsiu-Sen Chiang, Binshan Lin, *Member, IEEE*, and Shih-Bin Lin

***Abstract*—With the increase in the number senior citizens and chronic diseases, the number of elderly patients who need constant assistance has increased. One key point of all critical care for elderly patient is the continuous monitoring of their vital signs. Among these, the ECG signal is used for noninvasive diagnosis of cardiovascular diseases. Also, there is a pressing need to have a proper system in place for patient identification. Errors in patient identification, and hence improper administration of medication can lead to disastrous results. This paper proposes a novel embedded mobile ECG reasoning system that integrates ECG signal reasoning and RF identification together to monitor an elderly patient. As a result, our proposed method has a good accuracy in heart beat recognition, and enables continuous monitoring and identification of the elderly patient when alone. Moreover, in order to examine and validate our proposed system, we propose a managerial research model to test whether it can be implemented in a medical organization. The results prove that the mobility, usability, and performance of our proposed system have impacts on the user's attitude, and there is a significant positive relation between the user's attitude and the intent to use our proposed system.**

***Index Terms*—ECG, embedded system, fuzzy Petri net (FPN), RF identification (RFID), telemedicine.**

I. Introduction

THE DEMOGRAPHIC shift of an aging population is a global phenomenon. Population ageing slows work forces and economic growth, and as health expenditure is the highest for the elderly, it puts increased demands on health and aged care systems [1]. In general, approximately 75% of the elderly have one or more chronic diseases, among which the cardiovascular disease is one of the most common diseases. Cardiovascular diseases are the greatest and serious health threat in an aging society [2]. The patients need more care from their family or friends. Unfortunately, more than 27% of the country's elderly population currently live alone [3]. Therefore, elderly health management is an important issue, especially with regards to cardiovascular disease.

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In the past, most of the patient monitoring devices were designed for hospital. Actually, a person may suffer from cardiovascular disease at any time and any place. Advanced developments in existing information technologies are making it possible to extend the range of treatment and health services available at the patient's home [4]. This kind of health care system can carefully monitor the health condition of the patient for a long time and within their familiar environment.

In most healthcare systems, the vital signals are widely used in the diagnosis and therapy of many diseases. Among these, the ECG signal is used for noninvasive diagnosis of cardiovascular diseases [5]. In the past decades, many successful healthcare applications of ECG have been presented. However, these currently available systems have some drawbacks [6], [7].

First, some developments of the healthcare system still focus on monitoring aspect and lack the focus on warning aspect. In case of an emergency, there are no predefined procedures that will help the patient quickly. Thus, it is extremely important to study new healthcare systems to achieve a true meaningful monitoring and alert system [8]. Second, sometimes the art devices for healthcare system are quite clumsy and uncomfortable for long-term use. Besides, most of them are usually designed for clinical professionals, losing the end-user viewpoint [9]. Third, there is a lack of real-time patient identification device. According to a report [10], more than 770 000 patients die or suffer injuries each year while in hospital due to medical errors such as the incorrect medication dosage. Aggregated across the U.S., the total cost of these mishaps is between \$1.5 and \$5 billion annually. This is mainly due to the lack of an efficient way to identify the patient being treated [11]. Therefore, a real-time patient identification technology plays an important role in the healthcare system.

In order to overcome all these drawbacks, we proposed a new mobile ECG monitoring and alert system architecture that integrates current network technology such as general packet radio service (GPRS), embedded system, and RF identification (RFID) technologies. When our proposed system detects an abnormal ECG activity, related hospitals will receive the alarm message. The prototype of our proposed mobile ECG monitoring and alert system enables continuous monitoring and identification of the elderly patient who lives alone.

II. Background and Related Works

An ECG is a graphic produced by an electrocardiograph, which records the electrical voltage in the heart in the form of a continuous strip graph. It is the prime tool in cardiac electrophysiology, and plays a vital role in screening and diagnosis of cardiovascular diseases. A single normal cycle of the ECG

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represents the successive arterial depolarization and ventricular repolarization, which occurs with every heartbeat. These can be approximately associated with the peaks and other ECG waveforms, which are labeled as P, Q, R, S, and T [12]. The P wave represents the both atria activations (depolarization). The Q wave represents early depolarization that causes a small downward deflection after the P wave. The R wave is a large deflection of the ECG when the ventricles are depolarized. The S wave is the first wave after the R wave that dips below the baseline. The T wave represents the ventricular repolarization. Recently, different characteristics, such as PR, QRS, and ST intervals, have also been used in diagnosis [13]. The QRS complex represents the ventricular activation. The PR interval is between the beginning of the P wave and the beginning of the QRS complex. The section from the end of the QRS complex till the end of a T wave is known as the ST interval.

Automated classification of heartbeats has been previously reported by other investigators by using a variety of features to represent the ECG and a number of classification methods. These features include RR interval, heartbeat interval, ECG morphology [14], ST segment deviation, ST segment slope, ST segment area (STA), T-normal amplitude [15], STA, R-S interval (RSI), ST slope (STS), R-T interval (RTI), QRS area (QRSA), Q-T interval (QTI), R-wave amplitude (RWA), heart beat rate (HBR), statistical features QRS energy (QRSE), mean of the power spectral density (MPSD), autocorrelation coefficient (ACC), signal histogram (SH) [16], discrete Fourier transform (DFT) coefficients [17], statistical features of the QRS complexes [18], Hermite coefficients [19], shift invariant [20], continuous wavelet transform coefficients [21], QRS complex wave width [22], amplitude value, discrete cosine transform (DCT) coefficients, and discrete wavelet transform (DWT) coefficients [23]–[25].

In addition, the classification of heartbeats is an important step toward identifying an arrhythmia. Classification methods employed include linear discriminants [18], association rules [15], neural network [16], [17], [25], fuzzy neural network [18], [19], [20], [24], hidden Markov models [21], mirrored Gauss model [22], artificial immune recognition system [26], and support vector machine [23]. Some widely used methods and features for classification are listed in Table I.

In traditional rule-based reasoning methods [27], [28], the causality relationship is described as a number of rules. However, since many rules are involved, a powerful inference engine is usually required to avoid cyclical causality to discover the connection between rules and derive the final decision. Obviously, such a rule-based method is time- and memory-consuming, and lacks self-learning ability [29]. Recently, some researchers adopt Petri nets (PNs) for inference and reasoning. PNs have the ability to represent and analyze a rule-based system in concurrent and synchronous phenomena. PNs also have an inherent quality in representing logic in an intuitive and visual way, and fuzzy PNs (FPNs) have all the advantages of PNs. Many results prove that an FPN is suitable for representing and reasoning misty logic implication relations [30]. Therefore, we use FPN as our reasoning process in our proposed embedded mobile ECG reasoning system.

TABLE I
SOME USED METHODS AND FEATURES FOR CLASSIFICATION

Method of classification	Feature
Linear discriminants (LDs)	RR-Interval, Heartbeat Interval, ECG Morphology [14]
Association rules	ST segment area, slope, and deviation, T-normal amplitude [15]
Neural network	STA, RSI, STS, RTI. QRSA, QTI, RWA, HBR, QRSE, MPSD, ACC, SH. [19] DFT [17] DWT [25]
Fuzzy neural network	Statistical QRS [18] Hermite [19] Shift– invariant [20] DWT [24]
Hidden Markov Models	wavelet transform [21]
Mirrored Gauss Model	QRS width [22]
Artificial immune recognition	- [26]
Support Vector Machine	Amplitude, DCT, DWT [23]

Many ECG-monitoring systems using mobile technologies for patients have been proposed. Hung and Zhang [31] present a wireless application protocol (WAP) based telemedicine system to monitor a patient. It utilizes WAP devices as mobile access terminals for general inquiry and patient-monitoring services. A wireless ECG subsystem was built for recording ambulatory ECG in an indoor environment and for storing ECG data into the database. The system shows how feasible WAP can be in remote patient monitoring and patient data retrieval. Zhu and Wang [32] present a PDA-based system. It comprises a designed ECG signal acquisition module, a pocket PC, and a GPRS communication module. This system can acquire ECG signals, display the ECG waveform on the liquid crystal display (LCD) screen of the PDA, and wirelessly transmit them to an authorized remote medical ECG management server. Salvador *et al.* [33] present a platform to enable patients with chronic heart disease to complete specifically defined protocols for out-of-hospital follow-up and monitoring. The patients belonged to one of four specific risk groups: arterial hypertension, malignant arrhythmias, heart failure, and postinfarction rehabilitation. They were provided with portable recording equipment and a cellular phone that supported data transmission of ECG and WAP. Fensli *et al.* [34] present a wireless ECG system for continuous monitoring of ECG activity, especially to diagnose arrhythmia. The patient is required to wear an ECG sensor, which is a smart electronic electrode, with wireless transmission of ECG signals to a dedicated handheld device.

All these systems can trace patient's ECG and display information on the specific devices. However, these systems can still be improved. In case of an emergency, the system sends a warning message, and also reasoning abnormal ECG signal to help medical personnel to diagnose remotely. Beside, since elderly do not necessarily stay in hospitals, we need to identify the elderly person precisely. In this paper, we will overcome the deficiencies and use RFID identification with FPN reasoning in our proposed embedded mobile ECG reasoning system for an elderly patient who lives alone.

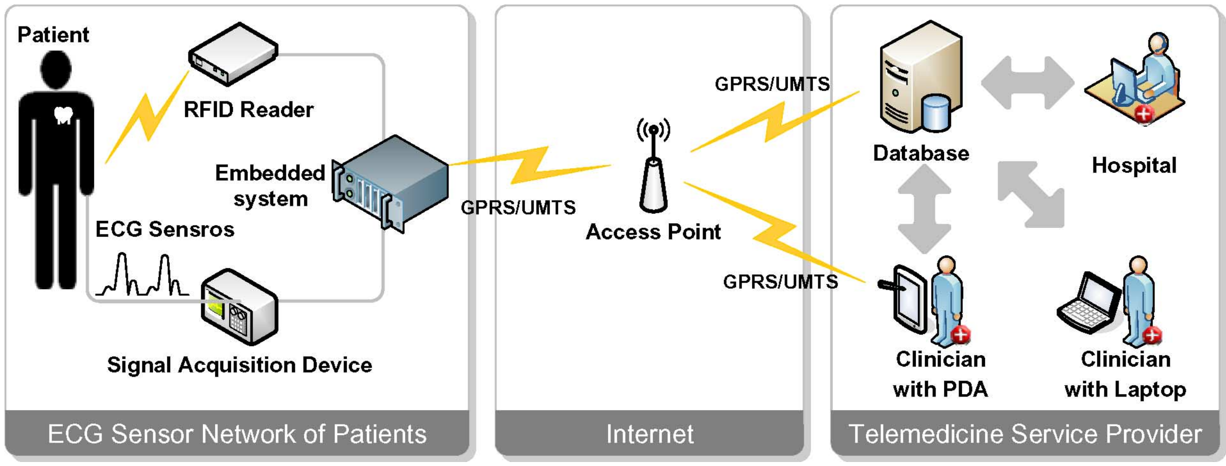


Fig. 1. System schematic of a mobile telemedicine system.

III. System Overview

The overall system architecture of the proposed telemedicine system is shown in Fig. 1. This telemedicine system combines wireless networks to build the environment for surveillance of critical patients. Our proposed telemedicine services are based on client–server architecture. There is a server (normally located in a hospital) that stores the incoming ECG signals from the clients and makes them available. The client, at an elderly or a patient's house, is responsible for acquiring data from the patient monitor or the RFID reader and transmitting it through the Internet.

At the patient's side, the elderly is connected to the patient monitor, which is used to acquire ECG signals. The RFID system contains a tag with an encoded form of the elderly patient's identification number, and is tied around the elderly patient's wrist. The RFID reader converts the elderly patient's information from a radio wave into a digital form. The output of elderly information is driven into an embedded system through the RS232 interface. The embedded system communicates between the medical sensor network and the mobile GPRS interface.

This mobile GPRS interface forwards the signals to the telemedicine service provider through GPRS/universal mobile telecommunications system network (UMTS). The server located in hospital stores data in a relational database. Then, health care providers monitor their patients by the application of the server. The transferred data format of our proposed system is shown in Fig. 2.

In addition, the overall telemedicine services, as shown in Fig. 3, consist of the following four units.

A. Patient Unit

The patient unit consists of the following modules.

1) *Module for acquiring elderly patient's ECG signals:* Most of the existing patient monitors are able to acquire traditional and reliable signals. In our prototype, the core module is an 8-bit microcontroller, PIC16F877, which has an on-chip, eight-channel, 10-bit, analog-to-digital converter (ADC). The three-lead ECG signals were amplified with a gain of 700, filtered (0.5–50 Hz), and fed into the inputs of the ADC in the microcontroller. In order to reduce the computation cost of the server, the ECG signals are processed at the client's end. After processing, only eight important extracted features will be sent to the management unit for reasoning.
2) *Module for elderly patient's identification:* Wristband RFID tag has been used to uniquely identify an elderly. Every elderly is assumed to have a wristband RFID tag tied around his/her wrist. For example, a PDC Smart Wrist Tag [35] is proposed in this prototype. Each RFID tag contains a unique number that identifies a specific item, called electronic product code (EPC); we use the EPC code to identify the elderly [36]. This tag stores the elderly patient's unique identification number. The RFID reader, DR1000 Dual Reader [35], reads the radio signal from the wrist tag. This wristband RFID tag's data are used to extract the elderly patient's information from the remote server.
3) *Module for data gathering:* The embedded system is used to communicate between the medical sensor network and hospital information system (HIS) interface. The input data of elderly patients, manipulated from the RFID reader and the patient monitor, are sent to the embedded system and transmitted to the server, as shown in Fig. 2. A WISCORE Enterprises' NET-Start! IXP embedded system [33] is chosen for this prototyping, which are shown in the lower part of Fig. 4.
4) *Module for Internet access:* The client application, using a EUPFIN Technology's EGD-01 GPRS module [35] and running over the Internet through GPRS module, is shown in the upper part of Fig. 4. It provides the core application functionality required by mobile applications.

B. Hospital Unit

The HIS consists of the hospital server and the hospital database system. The hospital unit is independent of the telemedicine project in almost all the hospitals. It already exists in the hospital or the private clinic that each pilot cooperates with.

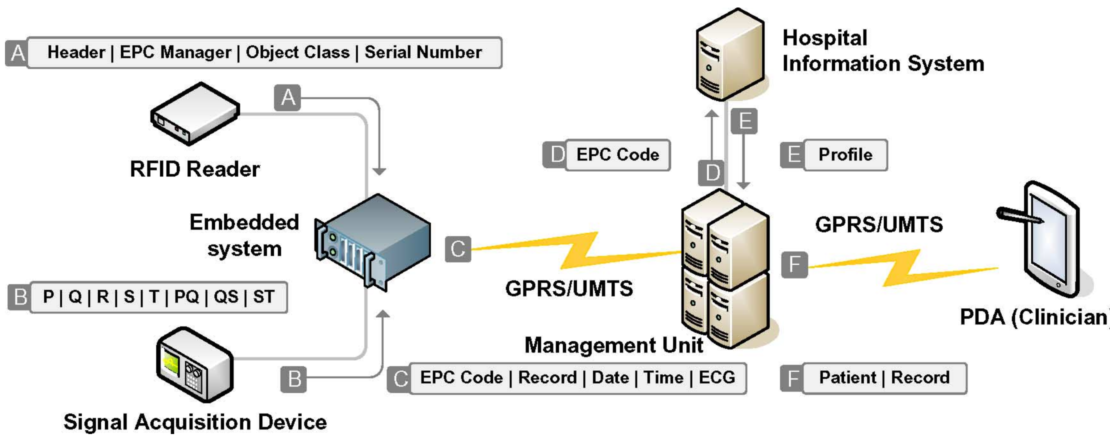


Fig. 2. Transferred data format of our proposed system.

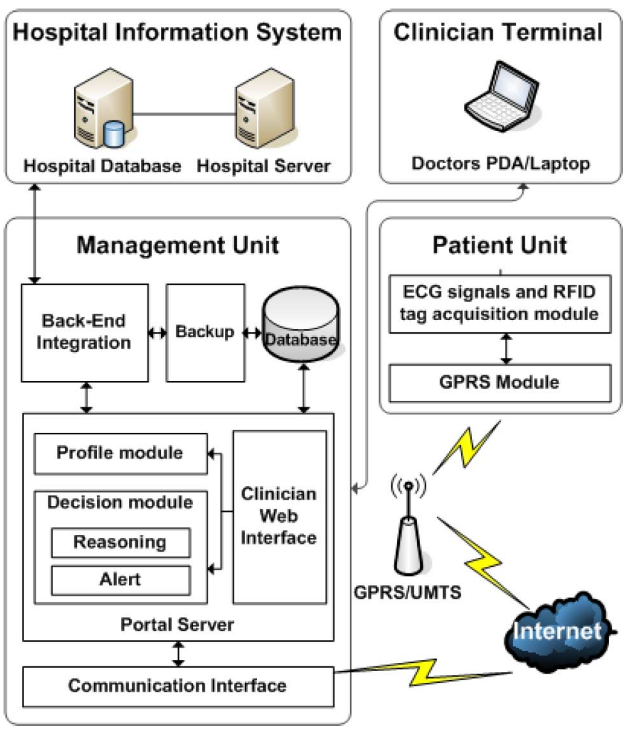


Fig. 3. Architecture of the proposed telemedicine system.

Fig. 4. Embedded system and GPRS module.

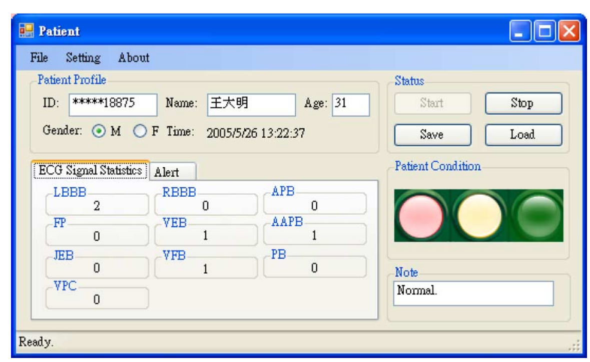


Fig. 5. Main control window of the management unit.

C. Clinician Unit

The clinical unit provides the clinicians with the means to use the telemedicine services. The clinician terminal can receive elderly patients' ECG data from the remote patient units via the GPRS/UMTS or the Internet. The clinical unit can provide a continuous monitoring of the ECG of elderly patients. Parameter values and monitor text messages, including alarm conditions, can also be displayed. Moreover, we also consider the confirmation mechanism in this unit. It ensures that someone will deal with the emergency event, and the emergency event will not be ignored. In order to intuitionally reflect the health condition, our system uses three colors to represent current condition of elderly. Clinicians can view the status of the elderly patient instead of reading the ECG signals. For example, if the elderly patient's ECG signal is abnormal, then a red signal is shown. Our system provides a PDA-based and smart-phone-based user interface. The upper area represents current condition of an elderly patient. Patients' profile is displayed in the middle area. Patients' ECG signal data are displayed in the lower area.

D. Management Unit

The management unit mainly consists of a fixed PC server and a management program. It is normally located in the nurse's or clinician's station, and provides a user-friendly interface for telemonitoring an elderly patient's ECG signals. The management program, as shown in Fig. 5, receives the data from the mobile unit, displays them on the screen, and stores them in a local database. Both the patient unit and the management unit have an alarm setting window, which enables the medical staff to set up an alarm according to the ECG status of the elderly.

In the management unit, the front-end integration service links to the clinician's Web interface. Also, a back-end integration service links to HIS, which manipulates medical records and other data/knowledge repositories. The profile module contains elderly patients' medical records and their requirements of the alert module. All elderly patients' ECG signals are encoded for the input of FPN. Reasoning detail of a patient's condition is shown in the next section.

IV. ECG Signal Reasoning

A correct and intuitive representation of the relationship between heartbeats not only makes diagnosis easier, but also helps in understanding the underlying correlation between ECG signals and the symptoms of heart diseases. Therefore, the FPN is used to identify different kinds of abnormal heartbeat. A reasoning example is illustrated in this section.

A. Dataset Description

PhysioNet [37] provides a set of databases that group records of one or more digitized ECG signals, as well as a set of their corresponding beat annotations. We used Massachusetts Institute of Technology (MIT)–Beth Israel Hospital (BIH) Arrhythmia Database [38] as the subdatabase to study different types of heartbeats.

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of four-thousand 24-h ambulatory ECG recordings collected from a mixed population of inpatients and outpatients at Boston's Beth Israel Hospital. The remaining 25 recordings were selected from the same set that had uncommon but clinically significant arrhythmias, which could not be well represented in a small random sample. These groups comprise men and women between the age of 23 and 89, and are analyzed by two independent cardiologists who classify them on the basis of the types of beats and rhythms. Our selected heartbeat clusters are shown in Table II.

1) ECG Filtering and Sampling: First, we use a nonlinear bilateral filter to remove noise. It can smooth the noise, but preserve the important features. In image-processing domain, some researchers use this filter to smooth images while preserving edges by means of a nonlinear combination of nearby image values [56]. A bilateral filter is given by

$$\hat{X}(k) = \frac{\sum_{n=-w}^{w} W(k,n)X(k-n)}{\sum_{n=-w}^{w} W(k,n)} \tag{1}$$

where $\hat{X}(k)$ is the original signal, $\hat{X}(k)$ is the smoothed signal, and w is the width of the filter $W(k, n)$. $W(k, n)$ is the kernel function of the bilateral filter, which is the product of two Gaussion smooth functions and can be expressed as

TABLE II
Type of Heartbeat and Its Description

Cluster		Description
Normal	C1	Normal heartbeat
Abnormal	C2	Left Bundle Branch Block Beat
Abnormal	C3	Right Bundle Branch Block Beat
Abnormal	C4	Atrial Premature Beat
Abnormal	C5	Fusion of paced and normal beat
Abnormal	C6	Ventricular Escape Beat
Abnormal	C7	Aberrated Atrial Premature Beat
Abnormal	C8	Junctional Escape Beat
Abnormal	C9	Ventricular Fusion Beat
Abnormal	C10	Paced Beat
Abnormal	C11	Ventricular Premature Contraction

TABLE III
Ten Times Nonconstant Sampling

	Beat no.	Abnormal no.	Abnormal ratio(P_i)	Beat weight (C_i)
1	6628	4936	0.7447	0.0428
2	13588	10615	0.5000	0.0508
3	14321	10860	0.7583	0.0777
4	8886	5429	0.6109	0.0817
5	11056	9417	0.3000	0.0578
6	9967	8584	0.8612	0.0668
7	15476	12867	0.8314	0.1605
8	10392	8109	0.0900	0.0358
9	13596	7680	0.5649	0.1425
10	9490	7537	0.7941	0.2831

$$W(k,n) = W_S(k,n)W_R(k,n) \tag{2}$$

where

$$W_S(k,n) = \exp\left(-\frac{n^2}{2\sigma_S^2}\right) \tag{3}$$

is the Gaussion kernel in the spatial domain, and

$$W_R(k,n) = \exp\left\{-\frac{[X(k)-X(k-n)]^2}{2\sigma_R^2}\right\} \tag{4}$$

is the Gaussion kernel in the intensity domain.

The sampling size of our dataset is been estimated by the population ratio [54]

$$n = \frac{z_{\alpha/2}^2 P(1-P)}{e^2}$$

where n is the sampling size, P is the estimator, e is the sampling error, α is the confidence coefficient, and z is the standard normal probability distribution. Since there is no further study on the estimation of an ECG, beat will represent the abnormal beat's probability (P will never be known exactly). Therefore, we use nonconstant number sampling to obtain the abnormal beat's proportion of population in a ten-time trial, which is shown in Table III. From Table III, we can obtain an abnormal beat's estimator (population proportion expected value)

$$P = \sum_{i=1}^{10} C_i * P_i = 0.0611844.$$

TABLE IV
SAMPLING NUMBER IN DIFFERENT CLUSTERS

	Beat no.	Ratio	Sample no.
C1	75041	21%	120
C2	8123	13%	72
C3	7336	4%	21
C4	2566	11%	60
C5	151	4%	23
C6	7171	16%	88
C7	886	6%	32
C8	259	3%	18
C9	224	3%	19
C10	7028	13%	74
C11	982	5%	26

TABLE V
FEATURES OF HEARTBEAT AND ITS DESCRIPTION

Number	Features	Description
1	RH	R wave amplitude.
2	PH	P wave amplitude.
3	QH	Q wave amplitude.
4	SH	S wave amplitude.
5	TH	T wave amplitude.
6	PR	PR Interval.
7	QS	QRS wave duration.
8	ST	ST Interval.

Substituting for the value of P, with 0.95 confidence levels and 0.02 sampling error, the sampling beat's size n is estimated to be 553. By sampling beat in different groups, as shown in Table IV, we obtained 553 beats (120 normal and 433 abnormal) in our sampling dataset. About two-thirds (67.5%) of the dataset are training data that are used to train the knowledge model and one-third (32.5%) of the dataset is used to evaluate the model.

2) Feature Extraction: The selection of suitable features is important in the automatic classification of ECG. Some researchers use different features in frequency domain, and others calculate the features in the time domain. From our experiences, we found that the features listed in Table V can better perform in our prototyping. Nevertheless, moving average method and the differential equation approach are used in our paper. The steps involved in detecting peaks are: 1) calculating the moving average from original signal, and usually using the past ten records to calculate it; 2) subtracting moving average from original signal, and obtaining a new signal; 3) finding the peak of the signal; and 4) setting the threshold to decide the detected peaks. As soon as the peak "R" is obtained, peaks P, Q, S, and T can also be found through their relative positions. In order to prevent possible error, the peaks' amplitude is measured from k line, as shown in Fig. 6. The definition of a k line is given as

$$k = \mathrm{Max}(\theta_i,\ i = 1, 2, \ldots, 11) + c \tag{5}$$

where k is a baseline, θ is the greatest amplitude of all peaks, i is the type of heartbeat, and c is a constant. Therefore, the amplitude of peaks P, Q, R, S, and T are all homogeneously negative.

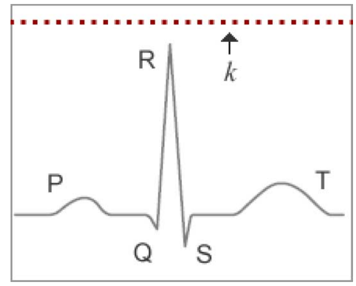


Fig. 6. Single ECG wave with k baseline.

$FPN = (P, T, D, I, O, f, \alpha, \beta)$

where

$P = \{p_1, p_2, \ldots\ldots p_n\}$ is a finite set of places,

$T = \{t_1, t_2, \ldots\ldots t_i\}$ is a finite set of transitions,

$D = \{d_1, d_2, \ldots\ldots d_n\}$ is a finite set of propositions,

$P \cap T \cap D = \phi, |P| = |D|$

$I : T \rightarrow P^{\infty}$ is the input function, a mapping from transitions to bags of places,

$O : T \rightarrow P^{\infty}$ is the output function, a mapping from transitions to bags of places,

$f : T \rightarrow [0,1]$ is an association function, a mapping from transitions to real values between zero and one,

$\alpha : P \rightarrow [0,1]$ is an association function, a mapping from places to real values between zero and one,

$\beta : P \rightarrow D$ is an association function, a bijective mapping from places to propositions.

Fig. 7. Definition of FPN.

B. Fuzzy Petri Net Model

FPN can be used to describe most of the relations and behaviors in a discrete-event dynamic system. As a mathematical tool, behavior properties and performance evaluation can be conveniently analyzed by using net theory and algebraic theory. Therefore, the reasoning path of expert systems can be reduced to simple sprouting trees if FPN-based reasoning algorithms are applied as an inference engine. Many results prove that FPN is suitable for representing and reasoning misty logic implication relations [30]. A generalized FPN structure can be defined as an eight-tuple in Fig. 7 [39], [40].

Fuzzy production rules (FPRs) are usually presented in the form of a fuzzy IF–THEN rule in which both the antecedent and the consequent are fuzzy concepts denoted by fuzzy sets. To effectively represent both the fuzziness and the uncertainty in FPRs, several knowledge parameters such as the values of certainty factor (CF) (μ_i) and threshold (λ) have been incorporated into the FPRs [39], [41], [42]. The composite FPR can be distinguished into the following rule types [39].

Type 1: IF d_j THEN d_k (CF $= \mu_i$). The fuzzy reasoning process of this type of rule can be represented by

$$\alpha\,(P_k) = \alpha\,(P_j) * \mu_i. \tag{6}$$

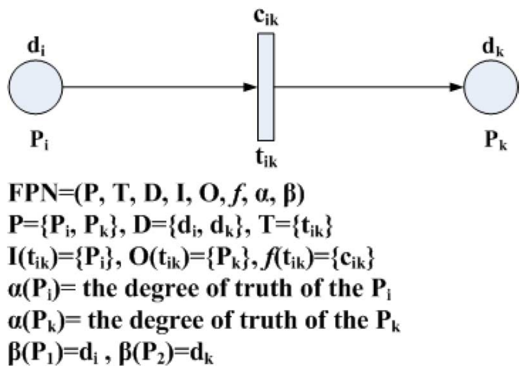


Fig. 8. Simple FPR.

Type 2: IF d_{j1} and d_{j2} and $\cdots$ and d_{jn} THEN d_k (CF $= \mu_i$). The fuzzy reasoning process of this type of rule can be represented by

$$\alpha\left(P_k\right) = \min\left\{\alpha\left(P_{j1}\right), \alpha\left(P_{j2}\right), \ldots, \alpha\left(P_{jn}\right)\right\} * \mu_i. \quad (7)$$

Type 3: IF d_j THEN d_{k1} and d_{k2} and $\cdots$ and d_{kn} (CF $= \mu_i$). The fuzzy reasoning process of this type of rule can be represented by

$$\alpha\left(P_{k1}\right) = \alpha\left(P_j\right) * \mu_i,\ \alpha\left(P_{k2}\right) = \alpha\left(P_j\right) * \mu_i, \ldots, \alpha\left(P_{kn}\right) = \alpha\left(P_j\right) * \mu_i. \quad (8)$$

Type 4: IF d_{j1} or d_{j2} or $\cdots$ or d_{jn} THEN d_k (CF $= \mu_i$). The fuzzy reasoning process of this type of rule can be represented by

$$\alpha\left(P_k\right) = \max\left\{\alpha\left(P_{j1}\right) * \mu_i,\ \alpha\left(P_{j2}\right) * \mu_i, \ldots, \alpha\left(P_{jn}\right) * \mu_i\right\}. \quad (9)$$

Type 5: IF d_j THEN d_{k1} or d_{k2} or $\cdots$ or d_{kn} (CF $= \mu_i$). The fuzzy reasoning process of this type of rule can be represented by

$$\alpha\left(P_{k1}\right) = \alpha\left(P_j\right) * \mu_{i1}, \alpha\left(P_{k2}\right) = \alpha\left(P_j\right) * \mu_{i2}, \ldots, \alpha\left(P_{kn}\right) = \alpha\left(P_j\right) * \mu_{in}. \quad (10)$$

A simple FPR is mathematically and graphically illustrated in Fig. 8. Given a set of FPRs and an observed fact, FPR reasoning is used to draw an approximate conclusion by matching the observed fact against the set of FPRs [39], [42]. The truth of each proposition is repressed by fuzzy membership functions and the CFs for the propagation of uncertain evidence from the antecedent of a production rule to its consequences [41], [55].

To subdivide our dataset into membership functions, we determine a threshold line with entropy-minimization screening method [43], and then start the segmentation process. We can gain the degree of truth of each feature under some states through the fuzzy membership function [40]. Each of the features is partitioned into three clusters: high, median, and low. For example, the value of the RH is in the range between -2.1284 and -2.8311, and this value meets two membership functions L_1 and L_2. Then, the maximum membership degree is chosen for RH. Fig. 9 is the fuzzy membership function of the RH, and the fuzzy membership functions of other features are obtained similarly.

In developing the CF model, Buchanan and Shortliffe [41] chose two basic measures of uncertainty: the measure of belief MB[*h, e*] that expresses the degree to which an observed piece of evidence *e* increases the belief in a hypothesis *h*, and the measure of disbelief MD[*h, e*] that expresses the degree to which an observed piece of evidence *e* decreases the belief in a hypothesis *h*. Each of these measures lies in the closed interval [0, 1]. The measure of belief MB[*h, e*] and the measure of disbelief MD[*h, e*] are defined as

$$\mathrm{MB}[h, e] = \begin{cases} 1, & \text{if } P(h) = 1 \\ \dfrac{\max\left[P(h \mid e), P(h)\right] - P(h)}{\max\left[1, 0\right] - P(h)}, & \text{otherwise} \end{cases} \quad (11)$$

$$\mathrm{MD}[h, e] = \begin{cases} 1, & \text{if } P(h) = 0 \\ \dfrac{\min\left[P(h \mid e), P(h)\right] - P(h)}{\min\left[1, 0\right] - P(h)}, & \text{otherwise} \end{cases} \quad (12)$$

where $P(h \mid e)$ and *P(h)* represent conditional and *a priori* probabilities, respectively.

In addition, a CF is definite, as shown in the following equation:

$$\mathrm{CF}[h, e] = \mathrm{MB}[h, e] - \mathrm{MD}[h, e] \quad (13)$$

and the function for combining two CFs $\mathrm{CF}(e_1, e')$ and $\mathrm{CF}(e_2, e')$ of two constituting pieces of evidence e_1 is

$$\mathrm{CF}(e_1 \text{ and } e_2, e') = \min\{\mathrm{CF}(e_1, e'), \mathrm{CF}(e_2, e')\}. \quad (14)$$

For the disjunction of two pieces of evidence, we have

$$\mathrm{CF}(e_1 \text{ or } e_2, e') = \max\{\mathrm{CF}(e_1, e'), \mathrm{CF}(e_2, e')\} \quad (15)$$

and the combination function for combining two CFs, $\mathrm{CF}(h, e_1')$ and $\mathrm{CF}(h, e_2')$, which have been derived from two coconcluding production rules, is shown in the following:

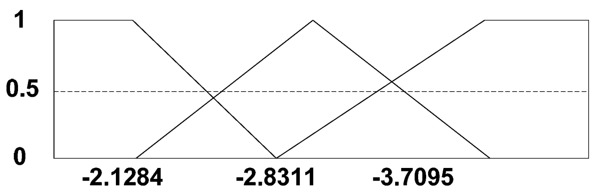
$$\mathrm{CF}(h, e_1' \,\mathrm{co}\, e_2') = \begin{cases} x + y(1 - x), & \text{if } x, y > 0 \\ \dfrac{x + y}{1 - \min\left\{|x|, |y|\right\}}, & \text{if } -1 < x, y \leq 0 \\ x + y(1 + x), & \text{if } x, y < 0 \end{cases} \quad (16)$$

where $\mathrm{CF}(h, e_1') = x$ and $\mathrm{CF}(h, e_2') = y$.

By combining the propositions and CFs, we can obtain a set of FPRs, and the structure of our FPN for the type of heartbeats reasoning is shown in Fig. 10.

C. FPN Reasoning

From Fig. 10, our FPN for heartbeats reasoning have eight inputs (eight features), 11 middle states (1 normal heart beat and 10 abnormal heartbeats), and one final state. All the degree of truth and states of the propositions in the FPN are gained by the fuzzy membership functions. All the values of CF in the FPN are calculated by (11)–(13). When the CF is used, the propagation of uncertainty in the inference network is accomplished by repeated application of sequential and parallel combination of CFs. According to the different antecedent of a production rule,



$$RH=\begin{cases}1 & x>-2.1284\\ \dfrac{-2.8311-x}{-0.7027} & -2.1284\geq x>-2.4797\\ \dfrac{x-(-2.1284)}{-0.7027} & -2.4797\geq x>-2.8311\\ \dfrac{-3.7905-x}{-0.8784} & -2.8311\geq x>-3.27\\ \dfrac{x-(-2.8311)}{-0.8784} & -3.27\geq x>-3.7095\\ 1 & x<-3.7095\end{cases}$$

Fig. 9. Fuzzy membership function of RH.

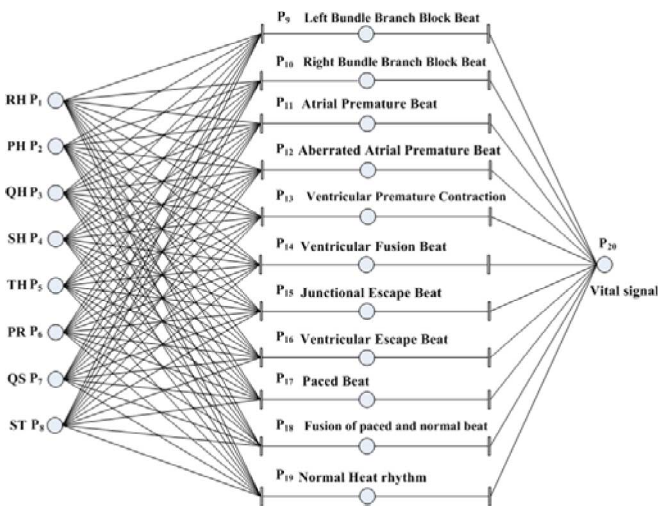


Fig. 10. FPN reasoning model.

different combination functions are used for the propagation of uncertain evidence. The knowledge base of our proposed system contains the following FPRs, R1–R12, as shown at the bottom of this page.

All the ECG samples acquire membership degree and linguistic variable themselves from the input of FPN by the fuzzy membership function. We can obtain the possible cluster and degree of an ECG signal by reasoning process.

For instance, given an ECG signal, the membership function returns the membership degree of eight characteristics as [0.84, 0.54, 0.73, 0.56, 1.00, 0.91, 0.63, 0.85], and the fuzzy linguistic variable of [$x_1, x_2, \ldots, x_8$] are [M, M, M, M, M, L, H, M]. Let $\beta(\mathrm{P}_1) = d_1$ and $\beta(\mathrm{P}_2) = d_2, \ldots, \beta(\mathrm{P}_8) = d_8$, where the places $\mathrm{P}_1, \ldots, \mathrm{P}_8$ are called the starting place and $d_1, d_2, d_3, \ldots, d_8$ are eight propositions of ECG signals. The variables $d_9, d_{10}, \ldots, d_{19}$ denote 11 propositions of ECG clusters, and the goal place and propositions are P_{20} and d_{20}, respectively. The reasoning example of FPN is as follows.

At first, the fuzzy linguistic variables and the degree of truth of place $\mathrm{P}_1, \mathrm{P}_2, \ldots, \mathrm{P}_8$ can be gained by fuzzy membership function.

Step 1: Starting places are $\mathrm{P}_1, \mathrm{P}_2$, and P_8: tokens are moved from $\mathrm{P}_1, \mathrm{P}_2, \ldots, \mathrm{P}_8$ to $\mathrm{P}_9, \mathrm{P}_{10}, \ldots, \mathrm{P}_{19}$

$$\alpha(\mathrm{P_j}) = \mathrm{Min}\,\{\alpha(\mathrm{P}_i) * t_{ij}\,|i = 1, 2, \ldots, 8\}, \quad \text{where}\quad j = 9, 10, \ldots, 19.$$

Therefore, the proposition of place $\mathrm{P}_9, \mathrm{P}_{10}, \ldots, \mathrm{P}_{19}$ are

$$\{d_9, d_{10}, \ldots, d_{19}\} = \{0.2532, 0.1674, 0.2646, 0.1953, 0.3136, 0.2352, 0.2961, 0.3584, 0.448, 0.42, 0.3456\}.$$

Step 2: Tokens are moved from $\mathrm{P}_9, \mathrm{P}_{10}, \ldots, \mathrm{P}_{19}$ to P_{20}. Assume that all of the CFs linked to P_{20} are 0.8, $t_{i,20} = 0.8$, and the proposition of place P_{20} is $d_{20}(k)$, the truth of $d_{20}(k)$ can be gained by FPR as

$$\begin{aligned}d_{20}(k) &= \{\alpha(\mathrm{P_i}) * t_{i,20}|i = 9, 12, \ldots, 19\},\quad k = 1, 2, \ldots, 11\\ &= \{\alpha(\mathrm{P}_9) * t_{9,20},\ \alpha(\mathrm{P}_{10}) * t_{10,20},\ \alpha(\mathrm{P}_{11}) * t_{11,20},\\ &\quad \alpha(\mathrm{P}_{12}) * t_{12,20},\ \alpha(\mathrm{P}_{13}) * t_{13,20},\ \alpha(\mathrm{P}_{14}) * t_{14,20},\\ &\quad \alpha(\mathrm{P}_{15}) * t_{15,20},\ \alpha(\mathrm{P}_{16}) * t_{16,20},\ \alpha(\mathrm{P}_{17}) * t_{17,20},\\ &\quad \alpha(\mathrm{P}_{18}) * t_{18,20},\ \alpha(\mathrm{P}_{19}) * t_{19,20}\}.\end{aligned}$$

Step 3: Since there are 11 success paths in final place P_{20}, we can select the degree of truth of place $\mathrm{P}_{20} = \mathrm{Max}\{d_{20}(k)\}$ and the proposition $\beta(\mathrm{P}_{20})$ by FPRs

---

$\mathrm{R1}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_9

$\mathrm{R2}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{10}

$\mathrm{R3}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{11}

$\mathrm{R4}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{12}

$\mathrm{R5}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{13}

$\mathrm{R6}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{14}

$\mathrm{R7}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{15}

$\mathrm{R8}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{16}

$\mathrm{R9}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{17}

$\mathrm{R10}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{18}

$\mathrm{R11}$: IF d_1 and $d_2 \cdots$ and d_8 THEN d_{19}

$\mathrm{R12}$: IF d_9 or $d_{10} \cdots$ and d_{19} THEN d_{20}.

TABLE VI
CONFUSION MATRIX OF OUR BEAT CLASSIFICATION

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1	33	2	1	1		1		2			
C2		23				1					
C3	5		2								
C4				17				3			
C5					6		1	1		1	
C6						6					
C7				5			3				
C8						3		3			
C9		6			1				4		
C10				5			2			18	
C11	1	8						1	2		17

as

$$
\begin{aligned}
d_{20} &= \mathrm{Max}\,\{d_{20}(k)\}, \qquad k = 1, 2, \ldots, 11 \\
&= \mathrm{Max}\,\{0.2026, 0.1339, 0.2117, 0.1562, 0.2509, \\
&\quad 0.1882, 0.2369, 0.2867, 0.3584, 0.3360, 0.2765\} \\
&= 0.3584\,(\text{at } \mathrm{P}_{17} \rightarrow \mathrm{P}_{20}).
\end{aligned}
$$

Thus, $\beta(\mathrm{P}_{20}) =$ cluster 9, and this ECG signal belongs to cluster 9 in Table II.

Therefore, we can obtain the cluster to which the ECG signal belongs to, and degree of high-risk heartbeats is 0.3584 from this example. If this degree exceeds a predefined range, the preconfigured red, yellow, or green light will be activated accordingly, and doctors will receive warning message and will immediately take care of the elderly.

D. Evaluation of FPN Reasoning

In order to evaluate the performance of our proposed method, the measuring criterion is defined as follows:

True positives (TP) number of correct beats classified as correct cluster;
True negatives (TN) number of incorrect beats classified as incorrect cluster;
False positives (FP) number of incorrect beats classified as correct cluster;
False negatives (FN) number of correct beats classified as incorrect cluster.

And, the overall accuracy is defined with equation (TP +TN)/(TP +FP + FN + TN).

In our evaluation, we use 368 cases to train our proposed FPN model and 185 cases for testing from sampled dataset of Table IV. Table VI summarizes the results of the confusion matrix that displays classification of beat recognition using our proposed FPN reasoning model. Table VII summarizes the comparative results of the accuracy of beat recognition with support vector machine classifier [23], neuro-fuzzy network [24], fuzzy hybrid neural network [18], and mirrored Gauss model [22]. We can successfully recognize most of clusters since every cluster's discriminate accuracy is greater than 90%. The comparison indicates good accuracy of our proposed method.

TABLE VII
COMPARATIVE RESULTS OF BEAT RECOGNITION

Heartbeat Name	Accuracy	[1]	[12]	[37]	[55]
C1	92.9%	89.8%	93%	98.1%	93.9%
C2	90.8%	85.8%	-	97%	-
C3	96.7%	-	99%	94%	-
C4	92.4%	-	-	91.3%	-
C5	97.8%	-	-	-	-
C6	97.3%	-	-	90%	-
C7	95.6%	-	-	-	-
C8	94.5%	-	-	-	-
C9	95.1%	-	-	-	-
C10	95.6%	-	-	-	-
C11	93.5%	90.3%	100%	96.5%	93.9%

–: This beat class was not discriminated.

V. SYSTEM EVALUATION AND DISCUSSION

When organizations decide to adopt a new technology or an information system, organizations have to address acceptance issues such as resistance to change, compatibility, and fear of adverse consequences [45], [46]. Social psychology literature includes the technology acceptance model (TAM) and the theory of planned behavior (TPB), which address the various problems that arise when a new information system or technological innovation in the information technology (IT) field is introduced in the workplace. These models have received significant attention in the research literature. The TAM, especially, has been applied in many usage scenarios and has performed consistently well. Based on social psychology, TAM is a parsimonious and powerful model for predicting the usage of an information system. TAM claims that ease of use and usefulness can predict usage of a system. Attitude and behavioral intention act as the mediating variables in TAM [47]. The TPB is a particularly well-established intention model that has been proved successful in predicting and explaining behavior across a wide variety of domains [48], [49]. The TPB posits attitude as an antecedent of intention to perform behavior. Previous research has found that when constructs of these or similar models are combined, they show better predictability compared to that of the each model alone [47], [50].

In order to understand the acceptance of our system and the drawbacks of the system, we propose a new research model, which modified constructs from the TAM and TPB, and includes "*mobility*," "*usability*," "*performance of the overall system*," "*attitude*," and "*intention to use*" in this context. In our research model, three important factors that impact individual's attitude are "*mobility*," "*usability*," and "*performance of the overall system*." Attitude toward using this system is the user's evaluation of the desirability of his\her using the system and the individual's positive or negative feelings about performing the target behavior. Based upon the empirical research of TAM constructs, the proposed model studies the impacts of these constructs on the consumer adoption patterns. Our research model is shown in Fig. 11. The hypotheses for the test are as follows.

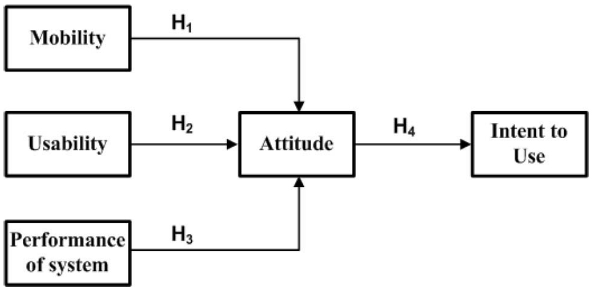


Fig. 11. Research model.

H_1: The mobility of the system and the attitude of users are positively correlated.
H_2: The usability of the system and the attitude of users are positively correlated.
H_3: The performance of the overall system and the attitude of users are positively correlated.
H_4: The attitude of users and intention to use are positively correlated.

The prototyping system was demonstrated at our laboratory. In the test scenario, 25 volunteers were asked to use our system, and eight interns stayed in a room in another building and observed the ECG signal of the elderly patient. The patient unit transmits the elderly patient's ECG signals and patient's ID to the management unit via GPRS, thus allowing medical staffs to monitor online.

According to the test scenario, a survey was conducted to elicit the operators' opinions on the mobile classification of the ECG reasoning system in five areas, which are mobility, usability, performance of the overall system, attitude of users, and intention to use. A questionnaire with a five-point Likert scale (from 5 = completely satisfied to 1 = completely unsatisfied) was used to rate the performance of the overall system. The satisfaction of mobility was evaluated in relation to statements of weight and size, and easy operation and easy monitoring estimated usability. The attitude of users and intention to use were also assessed.

Since the IT professionals and doctors are the major adopters in the medical organization, 25 volunteers and eight interns, including 22 males and 11 females, took part in the experiment and answered the questionnaire. All volunteers were undergraduates with the age ranging between 19 and 22 years. The age of the intent was within the range of 28–35 years (mean = 31.4, SD = 2.6).

The SPSS package was used to compute frequencies, means, percentage, reliability test, and Pearson correlation analysis. The Cronbach's coefficient was used to determine the reliability of questionnaire items. Table VIII shows the values of alpha. Since the values of Cronbach's coefficient are greater than 0.70, the recommended value is based on [44], and the reliability of construct for the sample in this study was considered to be sufficient.

We tested whether there was a positive correlation between mobility of the system, usability of the system, and performance of the overall system toward the attitude of users. We also examined whether there was a positive correlation between the attitude of users and personal intent to use the system. The hypotheses ($H_1 - H_4$) were tested using Pearson correlation procedure. The results of the correlations and their significances are shown in Table IX.

TABLE VIII
RELIABILITY ANALYSIS (CRONBACH'S ALPHA)

Construct	Cronbach's coefficient
Mobility	0.9093
Usability	0.8228
Performance	0.8368
Attitude of users	0.7657
Intent to usage	0.9728

TABLE IX
CORRELATIONS BETWEEN MAIN CONSTRUCTS

Hypotheses	Pearson' coefficient
H_1 **:** mobility and attitude of users	0.365*
H_2 **:** usability and attitude of users	0.545**
H_3 **:** performance of the overall system and attitude of users	0.529**
H_4 **:** attitude of users and intent to Usage	0.414*

*p<0.05, **p<0.01, ***p<0.001.

Based on the Pearson test, all four hypotheses ($H_1 - H_4$) were accepted, i.e., the user's attitude was significantly correlated with user's intent to use the system, and all factors ("*mobility*," "*usability*," and "*performance of the overall system*") were significant in affecting user's attitude toward using the system. The "*usability*" was the strongest variable that affected attitude toward system use, followed by "*performance of the overall system*" and "*mobility*."

Factor analysis can also be performed to confirm that the items are loaded according to the proposed model. According to [51], the acceptable value for factor loading is greater than 0.5. Thus, items with loading less than 50% were dropped from further analysis. Appendix A presents the results of factor analysis. Even more, we can employ a structural equation modeling (SEM) technique to analyze the research model we proposed. However, these data analyses are beyond our topic. They need further investigation and are not included in this paper. We will proceed with all the possible research in the near future.

Volunteers have lower mean values than doctors' in attitude and intention to use constructs. Roughly speaking, those interns highly rated the overall system for performance on our mobile classification of the ECG reasoning system. This study provided us an opportunity to express user's thoughts and feelings that they had experienced while using our prototyping system. Some of the suggestions for further improvement included that we make our system more complete, such as security and privacy consideration, the patient unit only periodically reports to the management unit, etc. In order to increase security and privacy in the future, we plan to incorporate encryption technology into our system such as hash function, asymmetric and symmetric encryption/decryption, key shadow, etc. Another major drawback was one-way communication between the embedded system and the HIS server. Only embedded system can send

TABLE X
COMPARATIVE RESULTS OF OTHER SYSTEMS

Function	Wireless technology	Identification device	Back-end system support	ECG diagnosis
Hung & Zhang [22]	GSM	No	No	No
Fensli et al. [15]	GPRS	No	Yes	Yes
Zhu & Wang [56]	GPRS	No	No	No
Salvador et al. [44]	GSM	No	No	No
Our system	GPRS	Yes	Yes	Yes

data to server; the server cannot send any message to control the embedded system. In the future, we will use the SMS service to interact with embedded system and server. For example, the command format is (#Time, ID, PassWd, Command, [Parameter $*$] #). All the instructions are enclosed within two "%" signs. The ID and PassWD stand for server ID and password; the instruction issued by Command and Parameter will be executed. Then, full duplex communication between the embedded system and the HIS server can be achieved.

VI. Conclusion

A monitoring system that performs a complete ECG analysis in a local device near the elderly patients is of great interest since it allows us to improve the quality of life of cardiovascular patients. By applying wristband RFID tag on an elderly, the medical data can be permanently attached to each elderly patient at all times. This art of composition greatly reduces the possibility of errors, and hence helps speed up the treatment in the hospital or at home. Our proposed system can allow much quicker treatment during emergency even before the elderly patient arrives at the hospital. Moreover, our FPN reasoning model can have accuracy rate on beat type from 90.8% to 97.8%. If system detects an abnormal ECG activity, related hospitals will receive the alarm message even more precisely. The comparison with other systems' environment is also shown in Table X. In addition, we surveyed 33 people to test whether there was a positive correlation between the attitude of users and personal intent to use the system. The results support that mobility, usability, and performance of our proposed system have impacts on user's attitude, and there is a significant positive effect between the user's attitude and the intent to use in our proposed system.

Mobile telemedicine is an emerging area that has the potential to change the way of health care provided today [52]. Although our proposed FPN model shows a good accuracy in beat recognition, however, it still suffers from self-learning capability and state explosion problem. In the future, we will try to investigate encryption technology and provide a collaborative framework that incorporates several different classification methods to improve our system's drawbacks, and further, it may incorporate EEG vital signal reasoning. Therefore, the system would provide a better quality of care for the elderly patient who lives alone. Another important research issue with health monitoring is the privacy and security aspect. Experts from Berkeley believe that security must be integrated into every component, as components designed without security are the vulnerable points where attacks start [53].

Appendix A

Rotated Component Matrix

	Component				
	1	2	3	4	5
M1	**.826**	.193	.077	.108	.119
M2	**.878**	-.056	.010	.273	.157
M3	**.881**	.047	.168	.016	.161
M4	**.827**	-.056	-.204	.266	.189
U1	.038	.129	**.878**	-.082	-.134
U2	-.193	-.110	**.869**	-.159	.032
U3	.236	.111	**.804**	-.038	.021
P1	-.201	**.829**	.136	.167	-.165
P2	.061	**.932**	-.069	-.118	.008
P3	.243	**.825**	.091	-.107	.006
A1	.218	.061	-.158	.329	**.819**
A2	.270	-.180	.060	-.019	**.887**
B1	.238	-.058	-.103	**.936**	.135
B2	.217	-.023	-.160	**.936**	.097

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