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An APN model for Arrhythmic beat classification

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ABSTRACT

Motivation: Changes in the normal rhythm of a human heart may result in different cardiac arrhythmias, which may be immediately fatal or cause irreparable damage to the heart sustained over long periods of time. Therefore, the ability to automatically identify arrhythmias from ECG recordings is important for clinical diagnosis and treatment. In this article, classification by using associative Petri net (APN) for personalized ECG-arrhythmia-pattern identification is proposed for the first time in literature.

Results: A rule-based classification model and reasoning algorithm of APN are created for ECG arrhythmias classification. The performance evaluation using MIT-BIH arrhythmia database shows that our approach compares well with other reported studies.

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1 INTRODUCTION

Heart disease is an umbrella term for a number of different diseases which affect the heart such as arrhythmia, myocardial ischemia and myocardial infarction (Miniño *et al.*, 2007). As of 2007, it is also one of the leading causes of death in the world, and especially according to the American Heart Association, One American is dying in every 34 s because of this disease (American Heart Association, 2008). Changes in the normal rhythm of a human heart may result in different cardiac arrhythmias, which may be immediately fatal or cause irreparable damage to the heart when sustained over long periods of time. Electrocardiogram (ECG) is an important routine clinical practice for continuous monitoring of cardiac activities. Since ECG signals vary greatly for different individuals and within patient groups (Hoekema *et al.*, 2001), ECG-pattern recognition is a difficult problem even with the aid of a computer. While normal sinus rhythm originates from the sinus node of heart, arrhythmias have various origins and indicate a wide variety of heart problems. Same symptoms of arrhythmia produce different morphologies due to their origins such as premature ventricular contraction (Minami *et al.*, 1999). For effective diagnostics, the study of ECG pattern and heart-rate-variability signal may have to be carried out over several hours. Thus, computer-based analysis and classification of diseases can be very helpful in diagnostics (Güler and Übeyli, 2005; Saxena *et al.*, 2002). A number of methods have been proposed to classify ECG-heartbeat patterns based on the features extracted from ECG signals. APNs have knowledge representation ability and could be translated into production rule systems. In addition, the APN formalism also is a graphical and mathematical tool for design, specification, simulation and verification of systems. Therefore, APN can be widely used in computer, knowledge-based systems, process control, decision making as well as other kinds of engineering applications. In this article, classification of ECG arrhythmias by using associative Petri net (APN) is proposed for the first time in the literature and is compared with several pioneering studies for arrhythmias detection.

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2 RELATED WORK

An ECG is a graphic produced by an electrocardiograph. A single normal cycle of the ECG represents the successive arterial depolarization and ventricular repolarization, and can be approximately associated with the peaks and other ECG waveforms, which labeled P, Q, R, S and T (McSharry *et al.*, 2003). Recently, different characteristic, such as P, T, U waves and PQ, QRS, ST segments, are also used for diagnostics (Singh and Tiwari, 2006). Automated classification of heartbeats has been previously reported by other investigators using a variety of features to represent the ECG and a number of classification methods. Features include RR-Interval features, heartbeat-interval features and ECG-morphology features (Philip *et al.*, 2004), ST-segment deviation, -segment slope (STS), -segment area (STA), T-normal amplitude (Exarchos *et al.*, 2006), STA, R–S interval (RSI), 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), auto-correlation coefficient (ACC), signal histogram (SH) (Gholam *et al.*, 2006), discrete Fourier transform coefficients (DFT) (Dokur and Ölmez, 2001), statistical features of the QRS complexes (Osowski and Linh, 2001), Hermite coefficients (Linh *et al.*, 2003), shift-invariant (Yeong *et al.*, 2006), continuous wavelet transform coefficients (Andreao *et al.*, 2006), QRS complex wave width (Homaeinezhad *et al.*, 2012; Martis *et al.*, 2013; Yeha *et al.*, 2012; Zhou *et al.*, 2005), amplitude value, DCT coefficients, DWT coefficients (Acir, 2006) and DWT coefficients (Abawajy *et al.*, 2013; Engin, 2004; Inan and Übeyl, 2005). In addition, the classification of heartbeats employed include linear discriminants (Philip *et al.*, 2004), association rules (Exarchos *et al.*, 2006), neural network (1 Dokur and Ölmez, 2001; Gholam *et al.*, 2006; Inan and Übeyl, 2005), fuzzy neural network (Engin, 2004; Linh *et al.*, 2003; Osowski and Linh, 2001; Yeong *et al.*, 2006), hidden Markov models (Andreao *et al.*, 2006), mirrored Gauss model (Zhou *et al.*, 2005), artificial immune-recognition system (Polat *et al.*, 2006), support vector machine (Acir, 2006) and dynamic time warping (Zhang *et al.*, 2009), cluster analysis (Yeha *et al.*, 2012), Neuro–SVM–KNN fusion (Homaeinezhad *et al.*, 2012), LibLINEAR, LibSVM (Abawajy *et al.*, 2013) and Principal component analysis, Linear discriminant analysis, Independent component analysis (Martis *et al.*, 2013).

Recent studies developed new feature-extracted and classification methods to detect various heart-related diseases and other complications by analyzing ECG characteristics. Ghaffari *et al.* (2010) use two innovative modified Hilbert transform-based algorithms to extracted QRS complexes and end-systolic end-diastolic pulses for detecting acute hypotensive episodes and mean arterial pressure dropping regimes. A new classification tree based on conditions combinations competition (T-3C) is proposed for the accurate diagnosis of cardiac ischemia and five measurements were considered in their study (Fayn, 2011). Vullings *et al.* (2011) use Bayesian framework to develop an adaptive Kalman filter. The adaptive estimation of the process and measurement noise covariance is performed by maximizing the Bayesian evidence function of the sequential ECG estimation. Sufi and Khalil (2011) use data mining techniques, to perform a real-time classification of cardiovascular disease. Lin *et al.* (2010) use Bayesian algorithm combined with a Markov chain Monte Carlo method to detection and delineation of ECG signals.

Recently, association rules have been utilized for the extraction of knowledge from medical history and for the analysis of medical signals (Bourien *et al.*, 2004; Konias and Maglaveras, 2004). An APN incorporated the concepts and operations of association algorithm of Apriori [3] and can represent the associative production rules of a rule-based system. Therefore, an adoption of APNs (Shih *et al.*, 2007) in reasoning and classification of ECG arrhythmias is straightforward in this article.

3 MATERIALS AND METHODS

This section is a brief description of methods used in this research such as a statistical sampling method, membership function generation by Minimize Entropy Principle Approach (MEPA) and reasoning process of ECG signals by proposed APN.

3.1 Dataset

PhysioNet's MIT-BIH Arrhythmia Database (PhysioBank, 2006) contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects (records 201 and 202 are from the same subject) studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Of these, 23 recordings were chosen at random from a collection of >4000 Holter tapes, and the other 25 recordings were selected to include examples of uncommon but clinically important arrhythmias that would not be well represented in a small random sample.

These groups comprise men and women between the ages of 23 and 89, and are analyzed by two independent cardiologists who use nomenclature to classify them by the types of beats and rhythms. Our selected heartbeat clusters are classified into the eleven heartbeat types including one normal and various abnormal types as shown in Table 1.

3.2 MEPA

In this section, an MEPA is adopted to provide the persuasiveness of determining the length of intervals and membership functions in heartbeat patterns. Assume that a threshold value is sought for a sample in the range between x_1 and x_2. An entropy equation with each value of x is written for the regions $[x_1, x_1+x]$ and $[x_1+x, x_2]$ which are defined as the first region f and the second region g, respectively. Entropy with each value of x in the region between x_1 and x_2 is expressed as (Christensen, 1980):

$$E(x) = f(x)E_f(x) + g(x)E_g(x) \tag{1}$$

Where

$$E_f(x) = -[f_1(x) + \ln f_1(x) + f_2(x) + \ln f_2(x)] \tag{2}$$

$$E_g(x) = -[g_1(x) + \ln g_1(x) + g_2(x) + \ln g_2(x)] \tag{3}$$

$$f(x) + g(x) = 1 \tag{4}$$

and $f_k(x)$ and $g_k(x)$ are conditional probabilities that class k sample in the region $[x_1, x_1+x]$ and $[x_1+x, x_2]$, respectively. A value of x that gives the minimum entropy is the optimum threshold value. The value estimates of $f_k(x)$ and $g_k(x)$, $f(x)$ and $g(x)$, are calculated as follows:

$$f_k(x) = \frac{n_k(x)+1}{n(x)+1} \tag{5}$$

$$g_k(x) = \frac{N_k(x)+1}{N(x)+1} \tag{6}$$

$$f(x) = \frac{n(x)}{n} \tag{7}$$

$$g(x) = 1 - f(x) \tag{8}$$

where

$n_k(x)$ = number of class k samples located in $[x_z, x_z+x]$, $n(x)$ = the total number of samples located in $[x_z, x_z+x]$, $N_k(x)$ = number of class k samples located in $[x_z+x, x_2]$, $N(x)$ = the total number of samples located in $[x_z+x, x_2]$, n = total number of samples in $[x_1, x_2]$, z = a general length along the interval $[x_1, x_2]$.

Table 1. Type of heartbeat

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

While moving x in the region $[x_1, x_2]$, we can determine the values of entropy for each position of x, as in Figure 1. The value in the region that holds the minimum entropy is called the primary threshold (PRI) value. If we denote a secondary threshold in one area such as SEC1 and the other secondary threshold in another area will be SEC2. In order to develop seven partitions, we need tertiary threshold values and denoted as TER1, TER2, TER3 and TER4. The induction is performed by the entropy minimization principle, which clusters most optimally the parameters corresponding to the output classes (Ross, 2000). By minimizing the entropy, we can find intervals in which the distribution of samples of any class is as relatively uniform as possible.

3.3 APN model

Classification using APN was applied for the detection of arrhythmia beats. APN is defined as follows (Shih *et al.*, 2007).

3.3.1 Definition of APN An APN is a directed graph, which contains three types of nodes: places, squares and transitions. Where circles represent places, squares represent thresholds of association degree and bars represent transitions. Each place may contain a token associated with a truth-value between zero and one. Each transition is associated with a certainty factor (CF) value between zero and one. Directed arcs represent the relationships between places. A generalized APN structure can be defined as a 13-tuple and the APN can be mathematically and graphically illustrated in Figures 2 and 3.

Let A be a set of directed arcs. If $p_j \in I(t_i)$, then there exists a directed arc a_{ji}, $a_{ji} \in A$, from the place p_j to the transition t_i. If $p_k \in O(t_i)$, then there exists a directed arc a_{ik}, $a_{ik}A$, from the transition t_i to the place p_k. If $W(s_m) = w_m$, $w_m \in [0,1]$, then the support sm is said to be associated with a real value w_m. If $G(t_i) = c_i$, $c_i, \in [0,1]$, then the transition t_i is said to be associated with a real value c_i. If $\beta(p_j) = d_j$, $d_j \in D$, then the place p_j is said to be associated with the proposition d_j. An APN with some places containing tokens is called a marked APN. In a marked APN, the token in a place p_j is represented by a labeled dot $\frac{\alpha(p_j)}{\bullet}$. The token value in a place p_j, $p_j \in P$, is denoted by $\alpha(p_j)$, where $\alpha(p_j) \in [0,1]$. If $\alpha(p_j) = y_i$ and $\beta(p_j) = d_j$, then it indicates that the proposition d_j is y_i. According to the antecedent portion or consequence portion of an APR contains 'and' or 'or' connectors, the APRs has five rule types (Shih *et al.*, 2007).

3.3.2 Associative transition function Let $\mathrm{IT} = \{i_1, i_2, \ldots, i_m\}$ be a set of items and DT be a set of database transactions. An association rule is an implication of the form $A \rightarrow B$, where $A \subset \mathrm{IT}$, $B \subset \mathrm{IT}$ and $A \cap B = \phi$. The association rule $A \rightarrow B$ holds in the transaction set DT with support s, where s is the percentage of transactions in DT that contain $A \cup B$. This is taken to be the probability $P(A \cup B)$. The association rule A→B has confidence c in the transaction set DT if c is the percentage of transactions in DT containing A that also contain B. This is taken to be the conditional probability $P(B|A)$ (Agrawal *et al.* 1993). That is,

$$\text{Support } (A \Rightarrow B) = P(A \cup B) \tag{9}$$

$$\text{Confidence } (A \Rightarrow B) = P(B/A) \tag{10}$$

Typically, association rules are considered interesting if they satisfy both a minimum support threshold $\tau_m, \tau_m \in [0,1]$, and a minimum confidence threshold $\gamma_i, \gamma_i \in [0,1]$. If the values of support and confidence are higher than their threshold τ and γ, the transition is enabled and the CF value of transition is corresponding to its confidence value ($\mathrm{CF} = c_i$) else the relationship does not exist ($\mathrm{CF} = 0$). A generalized formulation of the CF is shown in Equation (11):

$$G(t_i) = \begin{cases} c_l, & \text{if } s_m \geq \tau_m \text{ and } c_i \geq \gamma_i \\ 0 & \text{Otherwise} \end{cases} \tag{11}$$

where c_i is the confidence value, γ_i is a threshold of confidence, s_m is the support value and τ_m is a threshold of support.

3.3.3 Reasoning process An APN model can be expressed as a network structure. Each place in the network is denoted by a triple (p_k, $\alpha(p_k)$,

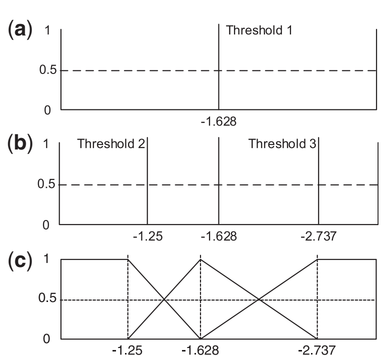


Fig. 1. Partitioning process of MEPA

$APN = (P, T, S, C, D, \Lambda, \Gamma, I, O, \alpha, \beta, G, W)$

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,

$S = \{s_1, s_2, \ldots\ldots s_m\}$ is a finite set of supports,

$C = \{c_1, c_2, \ldots\ldots c_i\}$ is a finite set of confidences,

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

$\Lambda = \{\tau_1, \tau_2, \ldots\ldots \tau_m\}$ is a finite set of thresholds of the supports,

$\Gamma = \{\gamma_1, \gamma_2, \ldots\ldots \gamma_i\}$ is a finite set of thresholds of the confidences,

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

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

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

$\alpha : P \rightarrow [0,1]$ 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,

$G : T \rightarrow [0,1]$ is an association function which assigns a real value between zero to one to each transition

$W : S \rightarrow [0,1]$ is an association function which assigns a real value between zero to one to each support.

Fig. 2. Definition of APN

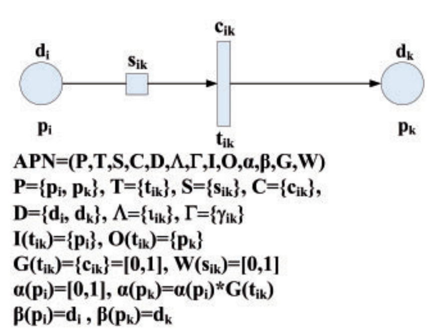


Fig. 3. A generalized APN structure

$\mathrm{IRS}(p_k)$), where $p_k \in P$ and $\mathrm{IRS}(p_k)$ is the immediate reachability set of p_k. $\mathrm{RS}(p_k)$ is the set of places which is reachable from place p_k and AP_{xy} denote a set of antecedent places of p_y. Let s_{xy} denote the support degree and c_{xy} denote the CF value associated with transition between place p_x and p_y. The degree of truth of proposition d_x is defined as $\alpha(p_x)$. The threshold of degree of truth of each proposition is given as λ. If $\alpha(p_x) \geq \lambda_x$, then the proposition d_x is existed. Assume that the thresholds of support and confidence degree are given with τ and γ. If $s_{xy} \geq \tau_{xy}$ and $c_{xy} \geq \gamma_{xy}$, then the transition is fired. A reasoning algorithm of APN can generate reasoning paths from starting place p_s, to goal place p_g as described below.

Reasoning Algorithm of APN

DEFINITION. Let V be a set of successful reasoning paths and v is a successful reasoning path, $v \in \mathrm{V}$. The proposition of goal place p_g is $d_g(v)$ and $\alpha(p_g(v))$ is the degree of truth of $p_g(v)$ if and only if there exist a successful reasoning paths from starting place to goal place.

INPUT. $P = \{p_1, p_2, \cdots, p_n\}$, $D = \{d_1, d_2, \cdots, d_n\}$, $S = \{s_1, s_2, \cdots, s_m\}$, $C = \{c_1, c_2, \cdots, c_i\}$, $T = \{t_1, t_2, \cdots, t_i\}$, $\Lambda = \{\tau_1, \tau_2, \cdots, \tau_m\}$, $\Gamma = \{\gamma_1, \gamma_2, \cdots, \gamma_i\}$ where P, D, S, C, T, Λ and Γ are a finite set of places, propositions, transitions, supports, confidences, thresholds of support and thresholds of confidence.

OUTPUT. The proposition $\beta(p_g) = d_g$ and the degree of truth of $\alpha(p_g)$ in a goal place.

//**Step 1:** From starting place p_s
    The starting place (p_s, $\alpha(p_s)$, $\mathrm{IRS}(p_s)$) is a non-terminal place, where
    (1) $\beta(p_s) = d_s$
    (2) $\alpha(p_s) \geq \lambda$, a transition be enabled to fire.
    (3) $\mathrm{IRS}(p_s) \neq \phi$
//**Step 2:** At descendant place p_i (from **s**tarting place p_s)
  For each place $p_i \in \mathrm{IRS}(p_s)$,
    IF $p_i = p_g$, $\alpha(p_i) \geq \lambda$, $\mathrm{CF}_{sg}{=}c_{sg}$, $s_{sg} \geq \tau_{sg}$ and $c_{sg} \geq \gamma_{sg}$ THEN
      An arc, labeled a_{sg} is directed from (p_s, $\alpha(p_s)$, $\mathrm{IRS}(p_s)$) to (p_g, $\alpha(p_g)$, $\mathrm{IRS}(p_g)$), where $\alpha(p_g) = \alpha(p_s) * c_{sg}$. The path is called a successful reasoning path.
    Else IF $p_i \neq p_g$, $\alpha(p_s) \geq \lambda$, $\mathrm{CF}_{si} = c_{si}$, $s_{si} \geq \tau_{si}$ and $c_{si} \geq \gamma_{si}$, THEN
      An arc, labeled a_{si} is directed from (p_s, $\alpha(p_s)$, $\mathrm{IRS}(p_s)$) to (p_i, $\alpha(p_i)$, $\mathrm{IRS}(p_i)$), where $\alpha(p_i) = \alpha(p_s) * c_{si}$.
    Else IF $\mathrm{AP}_{si} = \{p_a, p_b, \ldots, p_z\}$ and $p_g \in \mathrm{RS}(p_i)$ THEN
      Let $g = \mathrm{Min}$ $\{\alpha(p_a) * c_{ai}, \alpha(p_b) * c_{bi}, \ldots$ and $\alpha(p_z) * c_{zi}\}$.
        IF $g \geq \lambda$, $\mathrm{CF}_{si} = c_{si}$, $s_{si} \geq \tau_{si}$ and $c_{si} \geq \gamma_{si}$ THEN
        An arc, labeled a_{si}, is directed from (p_s, $\alpha(p_s)$, $\mathrm{IRS}(p_s)$) to (p_i, $\alpha(p_i)$, $\mathrm{IRS}(p_i)$), where $\alpha(p_i) = g * c_{si}$.
      End IF
    Else
        Mark place p_i as a terminal place.
    End IF
  End For
//Step 3: At descendant place p_k
  For each place $p_k \in \mathrm{RS}(p_s)$ and $p_k \in \mathrm{IRS}(p_i)$
    IF $p_k = p_g$, $\alpha(p_k) \geq \lambda$, $\mathrm{CF}_{ig}{=}c_{ig}$, $s_{ig} \geq \tau_{ig}$ and $c_{ig} \geq \gamma_{ig}$ THEN
        An arc, labeled a_{ig} is directed from (p_i, $\alpha(p_i)$, $\mathrm{IRS}(p_i)$) to (p_g, $\alpha(p_g)$, $\mathrm{IRS}(p_g)$), where $\alpha(p_g) = \alpha(p_i) * c_{ig}$. The path is called a successful reasoning path.
    Else IF $p_k \neq p_g$, $p_g \in \mathrm{RS}(p_k)$ and $\alpha(p_k) \geq \lambda$, $\mathrm{CF}_{ik} = c_{ik}$, $s_{ik} \geq \tau_{ik}$, $c_{ik} \geq \gamma_{ik}$, THEN
      An arc, labeled a_{ik} is directed from (p_i, $\alpha(p_i)$, $\mathrm{IRS}(p_i)$) to (p_k, $\alpha(p_k)$, $\mathrm{IRS}(p_k)$), where $\alpha(p_k) = \alpha(p_i) * c_{ik}$.
    Else IF $\mathrm{AP}_{ik} = \{p_a, p_b, \ldots, p_z\}$, and $p_g \in \mathrm{RS}(p_k)$ THEN
      Let $g = \mathrm{Min}$ $\{\alpha(p_a) * c_{ak}, \alpha(p_b) * c_{bk}, \ldots$ and $\alpha(p_z) * c_{zk}\}$.
        IF $g \geq \lambda$, $\mathrm{CF}_{ik} = c_{ik}$, $s_{ik} \geq \tau_{ik}$ and $c_{ik} \geq \gamma_{ik}$ THEN
        An arc, labeled a_{ik}, is directed from (p_i, $\alpha(p_i)$, $\mathrm{IRS}(p_i)$) to (p_k, $\alpha(p_k)$, $\mathrm{IRS}(p_k)$), where $\alpha(p_k) = g * c_{ik}$.
      End IF
    Else
        Mark place p_k as a terminal place.
    End IF
  End For
//**Step 4:** Successful reasoning paths determination.
    $\mathrm{V} = \{(p_g, d_g(1), \alpha(p_g(1))), (p_g, d_g(2), \alpha(p_g(2))), \ldots, (p_g, d_g(\mathrm{v}), \alpha(p_g(\mathrm{v})))\}$
    Let $z = \mathrm{Max}$ $\{\alpha(p_g(1)), \alpha(p_g(2)), \ldots, \alpha(p_g(v))\}$ be the degree of truth of proposition in p_g.
//**Step 5:** At goal place p_g
The proposition is $\beta(p_g) = d_g$, and the degree of truth is $\alpha(p_g) = z$.

4 EXPERIMENT

The experimental procedure for arrhythmia-beat detection is divided into ECG filtering and sampling, feature extraction, transfer function building and classification.

4.1 ECG filtering and sampling

First, we use a non-linear bilateral filter (Elad, 2002) to remove noise. The sampling size of our dataset has been estimated by the population ratio (Mendenhall and Beaver, 1994):

$$n = \frac{z^2_{\alpha/2} P(1-P)}{e^2} \tag{12}$$

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 in the estimation of an ECG beat will be the abnormal beat's probability. Therefore, we use non-constant number sampling to obtain the abnormal beat's proportion of population in ten time's trial, which is shown in Table 2. From Table 2, we can obtain an abnormal beat's estimator (population proportion expected value) as follow:

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

Table 2. Ten times non-constant sampling

Beat number	Abnormal number	Abnormal ratio (P_i)	Weight (C_i)
6628	4936	0.7447	0.0428
13 588	10 615	0.5000	0.0508
14 321	10 860	0.7583	0.0777
8886	5429	0.6109	0.0817
11 056	9417	0.3000	0.0578
9967	8584	0.8612	0.0668
15 476	12 867	0.8314	0.1605
10 392	8109	0.0900	0.0358
13 596	7680	0.5649	0.1425
9490	7537	0.7941	0.2831

where C_i is beat weight that is the sample proportion of sampling i time, P_i is abnormal ratio of sampling i time. C_i and P_i are shown in Table 2.

Substitute P-value, with 0.95 confidence levels and 0.02 sampling error in y sampling beat in different group, as shown in Table 3, we obtained 553 beat (with 120 normal and 433 abnormal) in our sampling data set. By randomly select, about two-thirds (67.5%) of the data set are used to training our proposed APN knowledge model and one-third (32.5%) of the data set are used to evaluate the proposed APN model.

4.2 Feature extraction

Selected features are important in enhancing the performance of ECG arrhythmia-beat detection. After detailed survey, we used the features listed in Table 4 for our prototyping.

The steps of detecting peaks are (i) calculating the moving average from original signal, and usually using the past ten records to calculate it; (ii) subtracting moving average from original signal, and getting a new signal; (iii) finding the peak of the signal; and (iv) setting the threshold to decide the detected peaks. As soon as the peak 'R' determined, we can obtain peaks P, Q, S and T through their relative position. In order to prevent possible error, peaks' amplitude would be measured from k line as shown in Figure 4 (Shih *et al.*, 2010). The definition of k line is in Equation (13).

$$k = \mathrm{Max}(\theta_i, i = 1, 2, \cdots, 11) + c \tag{13}$$

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

Table 3. Sampling number in clusters

Cluster	Beat number	Ratio (%)	Sample number
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 4. Features description

Variable	Feature	Description	Authors
x_1	RH	R wave amplitude.	Hosseini *et al.* (2006)
x_2	PH	P wave amplitude.	Acir (2006)
x_3	QH	Q wave amplitude.	Acir (2006)
x_4	SH	S wave amplitude.	Acir (2006)
x_5	TH	T wave amplitude.	Acir (2006), Exarchos *et al.* (2006)
x_6	PR	PR Interval.	Singh and Tiwari (2006)
x_7	QS	QRS wave duration.	Singh and Tiwari (2006), Zhou *et al.* (2005)
x_8	ST	ST Interval.	Singh and Tiwari (2006), Hosseini *et al.* (2006)

4.3 Transfer function building

Membership functions and thresholds are determined by MEPA (Christensen, 1980) in Section 3.2. Each of the features is partitioned into three states which are high, median, and low. For example, Figure 5 is the membership function of TH and the membership functions of some other features are shown in Appendix A.

4.4 APN model construction

The structure of our APN model for arrhythmia beat detection is constructed by using the construction algorithm from Shih *et al.* (2013) and is shown in Figure 6. Our APN model for the symptoms of heart-disease reasoning have eight variables, 11 middle states (one normal heart beat and 10 symptoms of heart disease), and one final state. All the degree of truth and states of the input places in the APN are gained by the membership functions calculated by Equation (11).

4.5 An example of arrhythmia-beat classification

An APN reasoning algorithm, in Section 3.3, is used to classify heart-beat symptoms into the following category: normal/abnormal heartbeat or 11 different types of arrhythmia beat. APN

Table 5. Confusion matrix of our APN reasoning

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1	34	2	1	1				2			
C2		24									
C3	5		2								
C4				20							
C5					9						
C6						6					
C7							8				
C8								6			
C9									11		
C10										25	
C11	1		0								28

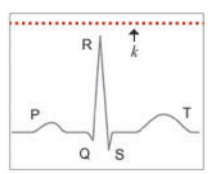
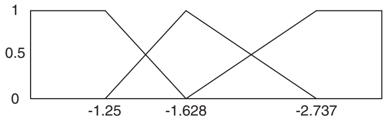


Fig. 4. A single ECG wave with k baseline



$$TH = \begin{cases} 1 & x > -1.25 \\ \dfrac{-1.6284 - x}{-0.3784} & -1.25 \geq x > -1.439 \\ \dfrac{x-(-1.25)}{-0.3784} & -1.439 \geq x > -1.628 \\ \dfrac{-2.7365 - x}{-1.1081} & -1.628 \geq x > -2.1824 \\ \dfrac{x-(-1.6284)}{-1.1081} & -2.1824 \geq x > -2.737 \\ 1 & x < -2.7365 \end{cases}$$

Fig. 5. Membership function of TH

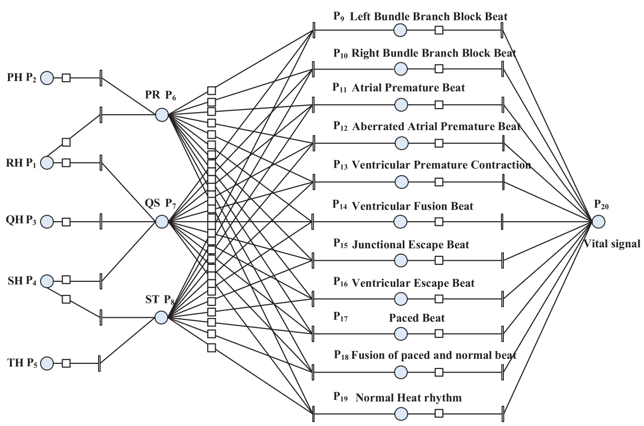


Fig. 6. An APN model for arrhythmia beat detection

model in Figure 6 is used for reasoning of arrhythmia-beat classification and has five inputs, three middle states, 11 outputs and one final state. For example, assume that five inputs characteristics $[x_1, x_2, \ldots, x_5]$ of an ECG-extracted signal from ECG wave are [−2.7162, −2.3648, −1.2864, −0.5810, −0.213]. From Appendix A, we can obtain the membership degree and the linguistic values of this ECG-extracted signal are [M, L, M, M, H] and [0.708, 1.0, 0.970, 0.791, 1.0]. Then $\alpha(p_1) = 0.708$, $\alpha(p_2) = 1.0, \ldots, \alpha(p_5) = 1.0$ are a mapping from places $p_1, p_2, \ldots, p_5$ to its real values by using membership function. The $p_1, p_2, \ldots, p_5$ are starting places, where $\lambda > 0$ shows that the proposition exists and $\lambda = 0$ shows that the proposition does not exist. Let $\beta(p_1) = d1$ and $\beta(p_2) = d2, \ldots, \beta(p_8) = d8$ and $d1, d2, d3, \ldots, d8$ are eight propositions of ECG signals is shown in Table 4. The propositions $d9, d10, \ldots, d19$ denote 11 clusters of heartbeat. Let place p_{20} be a goal place, $d_{20}(v)$ is the proposition of goal place p_{20} and $\alpha(p_{20}(v))$ is the degree of truth of $d_{20}(v)$. Assume that all the threshold values of τ_{ij} and γ_{ij} are set to 0.05 and 0.02, respectively. The reasoning example of our APN for the symptoms of heart-disease reasoning is as follow:

Step 1: From starting places $p_1, p_2, \ldots p_5$: places $p_1, p_2, \ldots, p_5$ are starting places and $\beta(p_1) = d_1$, $\beta(p_2) = d_2, \ldots, \beta(p_5) = d_5$ are 5 propositions of starting places. $\mathrm{IRS}(p_s) = \{p_6, p_7, p_8\}$

Step 2: In descendant place p_i, $p_i \in \mathrm{IRS}(p_s)$, $s = 1, 2, \ldots, 5$; i=6, 7,8.

$\mathrm{AP}_{si} = \{p_1, p_2, \ldots, p_5\}$ and all transitions are enabled, places $p_1, p_2, \ldots, p_5$ are exist since $(\alpha(p_s) \geq \lambda)$ and all the values of support and confidence are greater than threshold τ and γ, except c_{58} (i.e. $s_{si} \geq \tau_{si} = 0.05$ and $c_{si} \geq \gamma_{si} = 0.02$, $s = 1,2, \ldots, 5$; $i = 6, 7, 8$). Tokens are moved from $p_1, p_2, \ldots, p_5$ to p_6, p_7, p_8. Since the antecedent portion or consequence portion of APRs between $p_1, p_2, \ldots, p_5$ and p_6, p_7, p_8 belongs to type 3, the reasoning function is 'Max' operator (Shih *et al.*, 2007). The degree of truth of proposition of place p_6, p_7, p_8 are

$g = \alpha(p_i) = \mathrm{Max}\{\alpha(p_s) * c_{si} \mid s = 1, 2, \ldots, 5, i = 6, 7, 8\}$, then,

$$\begin{aligned} \alpha(p_6) &= \mathrm{Max}\{\alpha(p_1) * c_{16}, \alpha(p_2) * c_{26}\} \\ &= \mathrm{Max}\{0.708*0.2331, 1*0.3846\} = 0.3486 \\ \alpha(p_7) &= \mathrm{Max}\{\alpha(p_1) * c_{17}, \alpha(p_3) * c_{37}, \alpha(p_4) * c_{47}\} \\ &= \mathrm{Max}\{0.708*0.1955, 0.970*0.0513, 0.792*0.2623\} \\ &= 0.2077 \\ \alpha(p_8) &= \mathrm{Max}\{\alpha(p_4) * c_{48}, \alpha(p_5) * c_{58}\}, \\ &= \mathrm{Max}\{0.792*0.1492, 0\} = 0.1182 \end{aligned}$$

Therefore, $\alpha(p_i \mid i\text{=}6, 7, 8) = \{0.3486, 0.2077, 0.1182\}$.

Step 3: At descendant place p_j, $p_j \in \mathrm{IRS}(p_i)$, $i = 6, 7, 8$; $j = 9, 10, \ldots, 19$.

$\mathrm{AP}_{ij} = \{p_6, p_7, p_8\}$ and all transitions are enabled, places p_6, p_7, p_8 are exist since $(\alpha(p_j) \geq \lambda)$. Some paths are not discarded, since the values of support and confidence are less than threshold τ and γ, such as $p_6 \rightarrow p_{14}$, $p_7 \rightarrow p_{11}$, etc. (i.e. $s_{ij} \geq \tau_{ij} = 0.05$ and $c_{ij} \geq \gamma_{ij} = 0.02$, $j = 6, 7, 8$; $j = 9, 10, \ldots, 19$). Tokens are moved from p_6, p_7, p_8. Since the antecedent portion or consequence portion of APRs between p_6, p_7, p_8 and $p_9, p_{10}, \ldots, p_{19}$ belongs to type 1, the reasoning function is 'Min' operator (Shih *et al.*, 2007). The degree of truth of proposition at place $p_9, p_{10}, \ldots, p_{19}$ are

$g = \alpha(p_j) = \mathrm{Min}\{\alpha(p_i) * c_{ij} \mid i = 6, 7, 8; j = 9, 10, \ldots, 19\}$,

$$\begin{aligned} \alpha(p_9) &= \mathrm{Min}\{\alpha(p_6) * c_{69}, \alpha(p_7) * c_{79}, \alpha(p_8) * c_{89}\} \\ &= \mathrm{Min}\{0.3486*0.2941, 0.2077*0.0827, 0.1182*0.0889\} \\ &= 0.0105. \end{aligned}$$

$$\ldots$$

$$\begin{aligned} \alpha(p_{19}) &= \mathrm{Min}\{\alpha(p_6) *c_{6,19}, \alpha(p_7) * c_{7,19}, \ldots \alpha(p_8) * c_{8,19}\} \\ &= \mathrm{Min}\{0.3486*0.3529, 0.2075*0.2857, 0.1182*0.3278\} \\ &= 0.0387. \end{aligned}$$

Therefore, $\alpha(p_{\mathrm{j}} \mid j = 9, 10, \ldots, 19) = \{0.0105, 0.0112, 0.0319, 0.0105, 0.0047, 0.0085, 0.0085, 0.0066, 0.0063, 0.0072, 0.0387\}$.

Step 4: At descendant place p_k, since $p_k = p_g = p_{g20}$, places $p_9, p_{10}, \ldots, p_{19}$ are exist $(\alpha(p_{jk}) \geq \lambda)$ and all the values of support and confidence are greater than threshold τ and γ, all transitions are enabled (i.e. $s_{jk} \geq \tau_{jk} = 0.05$ and $c_{jk} \geq \gamma_{jk}$ =0.02, j=9,10, …, 19; $k = 20$). Assume that all the CFs linked to p_{20} are 0.9, and let $c_{j,20} = 0.9$,

$j = 9,10,\ldots, 19$. Tokens are moved from $p_9, p_{10},\ldots, p_{19}$ to p_{20} and their degree of truth are

$\alpha(p_{20}(v)) = \{\alpha(p_j) * c_{j,20} \mid j = 9,10,\ldots 19\}$, $v = 1,2,\ldots 11$, $c_{j,20} = 0.9$

$\alpha(p_{20}(1)) = \alpha(p_9)*c_{9,20} = 0.0105 * 0.9 = 0.0095$

$\ldots$

$\alpha(p_{20}(11)) = \alpha(p_{19})*c_{19,20} = 0.0387 * 0.9 = 0.0348$

There are eleven successful reasoning paths, $v = 1, 2,\ldots, 11$, $v \in \mathrm{V}$.

Step 5: There are 11 successful reasoning paths into goal place p_{20}, $\mathrm{V} \neq \phi$. Since the APRs between $p_9, p_{10},\ldots, p_{19}$ and p_{20} belongs to type 3, the reasoning function is 'Max' operator, we can select proposition d_{20} (v) and the degree of truth of d_{20} (v) at the place p_{20} as:

$\mathrm{V} = \{(p_{20}, d_{20}(1), \alpha(p_{20}(1))), (p_{20}, d_{20}(2), \alpha(p_{20}(2))),\ldots, (p_{20}, d_{20}(11), \alpha(p_{20}(11)))\}$

$z = \mathrm{Max}\ \{\alpha(p_{20}(1)), \alpha(p_{20}(2)),\ldots \alpha(p_{20}(11))\}$

$= \mathrm{Max}\{0.0095, 0.01, 0.0287, 0.0095, 0.042, 0.0077, 0.0077, 0.0059, 0.0056, 0.0065, 0.0348\}$

$= 0.0348$ (at $p_{19} \rightarrow p_{20}$)

Step 6: Obtain proposition d_{20} (v) and the degree of truth $\alpha(p_{20}(v))$ at place p_{20}.

Finally, we can obtain the belonged cluster (Cluster 11: Ventricular Premature Contraction) and degree of truth is 0.0348 in this example.

5 EXPERIMENTAL RESULTS AND DISCUSSION

The MIT-BIH arrhythmia database is used in our experiment. We use 368 cases in training and 185 cases for testing from sampled data in Table 3. After APN model construction, the testing result in confusion matrix of our proposed APN model is summarized in Table 5. Table 6 summarized the other reported results of heart-beat recognition with Fuzzy Petri net (Shih *et al.*, 2010), support vector machine (Acir, 2006), neuro-fuzzy network (Engin, 2004), fuzzy hybrid neural network (Osowski and Linh, 2001) and mirrored gauss model (Zhou *et al.*, 2005). Our proposed APN model can successfully recognize most of clusters since every cluster's accuracy are all greater than 90%.

In addition, our proposed APN model was further evaluated by the following performance measure such as: true positive rate (sensitivity) (TP-rate = TP/(TP + FN)), true negative rate (specificity) (TN-rate = TN/(FP + TN)), false positive rate (FP-rate = FP/(FP + TN)) and false negative rate (FN-rate = FN/(TP + FN)). Accuracy is defined with equation (TP + TN)/(TP + FP + FN + TN). *F*-measure combines precision TP/(TP + FP) and recall TP/(TP + FN) on the prediction of positive class (*F*-measure = 2 × precision × recall/precision + recall). A higher *F*-measure value indicates that the model performs better on positive class balancing of FP and FN. G-mean is the product of the prediction accuracies for both classes which is $\sqrt{\mathrm{TN}/(\mathrm{TN}+\mathrm{FP})\times\mathrm{TP}/(\mathrm{TP}+\mathrm{FN})}$. And, AUC is the area under ROC (receiver operating characteristic curve) curve calculated with MedCalc (http://www.medcalc.org/index.php). Higher AUC indicate a classifier has a better classification performance. Other data mining methods such as Naïve Bayes (NB), Decision tree (C4.5), Bayes Net, Support vector machine (SVM) and Fuzzy Petri net (FPN) running with Weka and MATLAB 2012 are shown in Table 7 for comparison. APNs and C4.5 have a higher TN-rate in detecting abnormal heartbeat. SVM and FPN have a good TP-rate in detecting normal heartbeat in our experiment. Generally, in Table 7, our APN have the best performance than other data-mining methods in sensitivity, *F*-measure and accuracy measurement. And, other measurements are great too. Therefore, we can conclude that our proposed APN model have a good result on classification of ECG arrhythmias.

Table 6. Comparison with other research

Heartbeat	APN (%)	Shih (%)	Acir (%)	Engin (%)	Osowski (%)	Zhou (%)
C1	93.51	92.9	89.8	93	98.1	93.9
C2	98.92	90.8	85.8	-	97	-
C3	96.76	96.7	-	99	94	-
C4	99.46	92.4	-	-	91.3	-
C5	100.00	97.8	-	-	-	-
C6	100.00	97.3	-	-	90	-
C7	100.00	95.6	-	-	-	-
C8	98.92	94.5	-	-	-	-
C9	98.92	95.1	-	-	-	-
C10	100.00	95.6	-	-	-	-
C11	100.00	93.5	90.3	100	96.5	93.9

-, Did not discriminate this heartbeat class.

Table 7. Performance measure of different approach

Methods	Sensitivity (%)	Specificity (%)	AUC	F-measure	G-mean	Accuracy
NB	85.0	83.4	0.842	0.694	0.842	0.838
C4.5	87.5	94.5	0.910	0.843	0.909	0.930
SVM	92.5	87.6	0.900	0.779	0.900	0.886
Bayes Net	85.0	92.4	0.887	0.800	0.886	0.908
APN	85.0	95.9	0.908	0.850	0.903	0.935
FPN	92.5	83.4	0.880	0.733	0.879	0.854

6 CONCLUSION

We have proposed a methodology for the detection of ECG arrhythmia using a generalized APN model in this article. The performance evaluation using MIT-BIH arrhythmia database in Table 7 shows that our approach compares well with other reported studies. The experimental results strongly suggest that our proposed APN model can help doctors in the diagnosis of ECG Arrhythmia and may applied to other symptom decision field. In the future, an applicable decision system for the clinical diagnosis of ECG arrhythmias can developed based on our provided APN model. And, the health care practitioners can be aware of types of cardiac arrhythmias and give early treatment to reduce deterioration.

APN is a powerful method for representing knowledge and logic reasoning in the domain of decision support systems. Unlike other Petri net model, APN model has a systematic procedure in model construction. The reasoning path of expert systems can be reduced to simple sprouting trees if APN-based reasoning algorithms can be applied. However, there still drawbacks exist in APN such as state explosion and no hierarchy concepts. We shall overcome all these drawbacks in the near future.

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REFERENCES

Abawajy,J.H. *et al.* (2013) Multistage approach for clustering and classification of ECG data. *Comput. Meth. Prog. Bio.*, **112**, 720–730.

Acir,N. (2006) A support vector machine classifier algorithm based on a perturbation method and its application to ECG beat recognition systems. *Expert. Syst. Appl.*, **31**, 150–158.

Agrawal,R. *et al.* (1993) Database mining: a performance perspective. *IEEE Trans. Knowledge Data Eng.*, **5**, 914–925.

Agrawal,R. and Srikant,R. (1994) Fast algorithms for mining association rules. In: *Proceedings of the International Conference on Very Large Databases (VLDB '94)*. Morgan Kaufmann Publishers Inc., Santiago de Chile, Chile, pp. 487–499.

American Heart Association. (2008) Heart disease and stroke statistics. [Online]. http://www.americanheart.org/presenter.jhtml?identifier=3000090 (18 March 2014, date last accessed).

Andreao,R.V. *et al.* (2006) ECG signal analysis through hidden Markov models. *IEEE Trans. Biomed. Eng.*, **53**, 1541–1549.

Bourien,J. *et al.* (2004) Mining reproducible activation patterns in epileptic intracerebral EEG signals: application to interictal activity. *IEEE Trans. Biomed. Eng.*, **51**, 304–315.

Christensen,R. (1980) *Entropy Minimax Sourcebook*. Vol. 1–4, Entropy Ltd., Lincoln, MA.

Dokur,Z. and Ölmez,T. (2001) ECG beat classification by a novel hybrid neural network. *Comput. Meth. Prog. Bio.*, **66**, 167–181.

Elad,M. (2002) On the origin of the bilateral filter and ways to improve it. *IEEE Trans. Image Process.*, **11**, 1141–1151.

Engin,M. (2004) ECG beat classification using neuro-fuzzy network. *Patt. Recog. Lett.*, **25**, 1715–1722.

Exarchos,T.P. *et al.* (2006) An association rule mining based methodology for automated detection of ischemic ECG beats. *IEEE Trans. Biomed. Eng.*, **53**, 1531–1540.

Fayn,J. (2011) A classification tree approach for cardiac ischemia detection using spatiotemporal information from three standard ECG leads. *IEEE Transact. Biomed. Eng.*, **58**, 95–102.

Ghaffari,A. *et al.* (2010) Parallel processing of ECG and blood pressure waveforms for detection of acute hypotensive episodes: a simulation study using a risk scoring model. *Computer Methods in Biomechanics and Biomedical Engineering*, **13**, 197–213.

Gholam,H.H. *et al.* (2006) The comparison of different feed forward neural network architectures for ECG signal diagnosis. *Med. Eng. Phys.*, **28**, 372–378.

Güler,I. and Übeyli,E.D. (2005) ECG beat classifier designed by combined neural network model. *Patt. Recogn.*, **38**, 199–208.

Hoekema,R. *et al.* (2001) Geometrical aspects of the interindividual variability of multilead ECG recordings. *IEEE Trans. Biomed. Eng.*, **48**, 551–559.

Homaeinezhad,M.R. *et al.* (2012) ECG arrhythmia recognition via a neuro-SVM–KNN hybrid classifier with virtual QRS image-based geometrical features. *Expert. Syst. Appl.*, **39**, 2047–2058.

Hosseini,H.G. *et al.* (2006) The comparison of different feed forward neural network architectures for ECG signal diagnosis. *Med. Eng. Phys.*, **28**, 372–378.

Inan,G. and Übeyl,E.D. (2005) ECG beat classifier designed by combined neural network model. *Patt. Recog.*, **38**, 199–208.

Konias,S. and Maglaveras,N. (2004) A rule discovery algorithm appropriate for ECG signals. *Comput. Cardiol.*, **31**, 57–60.

Lin,C. *et al.* (2010) P- and T-wave delineation in ECG signals using a bayesian approach and a partially collapsed gibbs sampler. *IEEE Transact. Biomed. Eng.*, **17**, 2840–2849.

Linh,T.H. *et al.* (2003) On-line heart beat recognition using hermite polynomials and neuro-fuzzy network. *IEEE Trans. Instrument. Measure.*, **52**, 1224–1231.

Martis,R.J. *et al.* (2013) ECG beat classification using PCA, LDA, ICA and Discrete Wavelet Transform. *Biomed. Signal Proc. Control*, **8**, 437–448.

McSharry,P.E. *et al.* (2003) A dynamical model for generating synthetic electrocardiogram signals. *IEEE Trans. Biomed. Eng.*, **50**, 289–294.

Mendenhall,W. and Beaver,R. (1994) *Introduction to Probability and Statistics*. Duxbury Press, USA.

Minami,K. *et al.* (1999) Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network. *IEEE Trans. Biomed. Eng.*, **46**, 79–185.

Miniño,M. *et al.* (2007) Deaths: final data for 2004. *Natl Vital Stat. Rep.*, **55**, 7.

Osowski,S. and Linh,T.H. (2001) ECG beat recognition using fuzzy hybrid neural network. *IEEE Trans. Biomed. Eng.*, **48**, 1265–1271.

Philip de,C. *et al.* (2004) Automatic classification of heartbeats using ECG morphology and heartbeat interval features. *IEEE Trans. Biomed. Eng.*, **51**, 1196–1206.

PhysioBank. (2006). [Online]. http://www.physionet.org/physiobank/database/mitdb/ (18 March 2014, date last accessed).

Polat,K. *et al.* (2006) A new method to medical diagnosis: Artificial immune recognition system (AIRS) with fuzzy weighted pre-processing and application to ECG arrhythmia. *Expert. Syst. Appl.*, **31**, 264–269.

Ross,T.J. (2000) Fuzzy logic with engineering applications. McGraw-Hill, USA.

Saxena,S.C. *et al.* (2002) Feature extraction from ECG signals using wavelet transforms for disease diagnostics. *Int. J. Syst. Sci.*, **33**, 1073–1085.

Shih,D.H. *et al.* (2007) A generalized associative petri net for reasoning. *IEEE Trans. Knowledge Data Eng.*, **19**, 1241–1251.

Shih,D.H. *et al.* (2010) An embedded mobile ECG reasoning system for elderly patients. *IEEE Transact. Inform. Tech. Bio.*, **14**, 854–865.

Shih,D.H. *et al.* (2013) Huang SC, an intelligent embedded system for malicious email filtering. *Comput. Standards Interfaces*, **35**, 557–565.

Singh,B.N. and Tiwari,A.K. (2006) Optimal selection of wavelet basis function applied to ECG signal denoising. *Digital Signal Process.*, **16**, 275–287.

Sufi,F. and Khalil,I. (2011) Diagnosis of cardiovascular abnormalities from compressed ECG: a data mining-based approach. *IEEE Transact. Inform. Technol. Biomed.*, **15**, 33–39.

Vullings,R. *et al.* (2011) An adaptive Kalman filter for ECG signal enhancement. *IEEE Transact. Biomed. Engineer.*, **58**, 1094–1103.

Yeong,P.M. *et al.* (2006) Intelligent classification of electrocardiogram (ECG) signal using extended Kalman Filter (EKF) based neuro fuzzy system. *Computer Meth. Progr. Biomed.*, **82**, 157–168.

Yeha,Y.C. *et al.* (2012) Analyzing ECG for cardiac arrhythmia using cluster analysis. *Expert Syst. Appl.*, **39**, 1000–1010.

Zhang,G. *et al.* (2009) Electrocardiogram data mining based on frame classification by dynamic time warping matching. *Comput. Meth. Biomech. Biomed. Engineer.*, **12**, 701–707.

Zhou,Q. *et al.* (2005) ECG beat classification using mirrored gauss model. In: *Proceedings of the IEEE Engineering in Medicine and Biology 27th Annual Conference, China*. pp. 5587–5590.