# Intelligent classification of electrocardiogram (ECG) signal using extended Kalman Filter (EKF) based neuro fuzzy system

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## Introduction

Electrocardiogram (ECG) reflects activity of the central of the blood circulatory system, i.e. the heart. An ECG signal can provide us with a great deal of information on the normal and pathological physiology of heart activity. Thus, ECG is an important non-invasive clinical tool for the diagnosis of heart diseases. For more than four decades, computers have been used in the classification of the ECG resulting in a huge variety of techniques [1,2] all designed to enhance the classification accuracy to levels comparable to that of a 'gold standard' of expert cardiology opinion. Included in these techniques are multivariate statistics, decision trees, fuzzy logic, expert systems and hybrid approaches. The recent interest in neural networks coupled with their high levels of performance has resulted in many instances of their application in this field [2,3].

The hybrid system of neural network and fuzzy logic has been widely accepted for pattern recognition tasks. Neural network and fuzzy logic abilities to learn from examples and extract the statistical properties of the examples presented during the training sessions, make it an ideal choice for an automated process that imitates human logic. Several efforts have been made to apply neural network and fuzzy logic for the purpose of ECG beat detection and classification [4,5]. In previouswork, they had proved that neural network and fuzzy system had better performances than the traditional clustering and statistical methods.

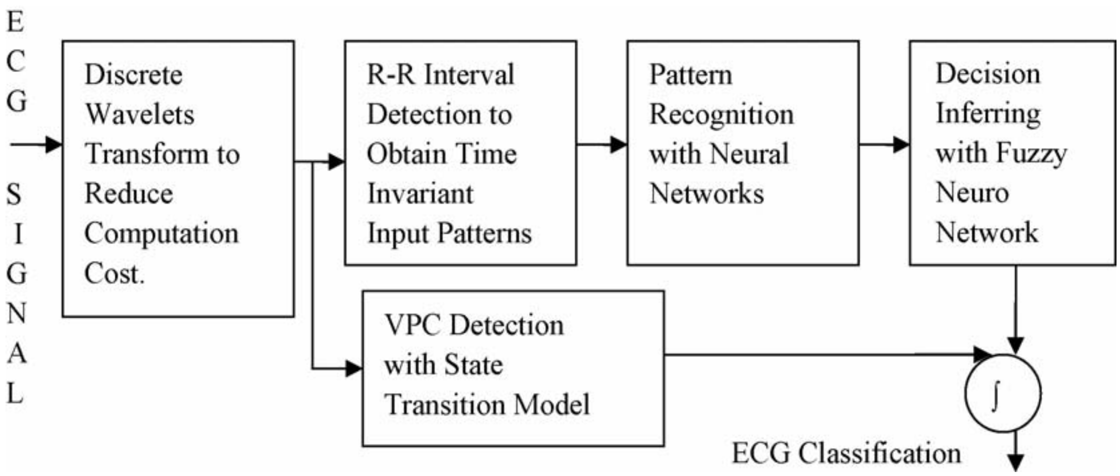


**Fig. 1 – Block diagrams of the ECG classification system.**

Interestingly, most of these technologies have their origins in biological or behavioural phenomena related to humans or animals, andmany of these technologies are simple analogues of human and animal systems. Hybrid intelligent systems generally involve two or more of these individual technologies that are either used in series or integrated in a way to produce advantageous results through synergistic interactions.
In data and information processing, the objective is generally to gain an understanding of the phenomena involved and to evaluate relevant parameters quantitatively. This is usually accomplished through “modelling” of the systems, either experimentally or analytically. Most hybrid systems relate experimental data to systems or models. Once a model of the system is obtained, various procedures such as sensitivity analysis and statistical regression can be carried out to gain a better understanding of the system.

There are many situations in which the phenomena involved are very complex and often not well understood. The nonlinear analytical modelling can be effective but it is time-consuming and will rely a lot on data richness. These difficulties lead us to explore the use of alternative powerful interpolators and generalisers such as neural networks and fuzzy logic system as a way of obtaining models based on experimental measurements.

This study presents the development of a hybrid system consisting of an ensemble of Extended Kalman Filter (EKF) based Multi Layer Perceptron Network (MLPN) and a one-pass learning Fuzzy Inference System using Look-up Table Scheme for the recognition of electrocardiogram (ECG) signals. This system can distinguish various types of abnormal ECG signals such as Ventricular Premature Cycle (VPC), T wave inversion (TINV), ST segment depression (STDP), and Supraventricular Tachycardia (SVT) from normal sinus rhythm (NSR) ECG signal.

## Methodology

In order to obtain high recognition accuracy, two feature extraction methods have been proposed. The method of unconstrained optimisation is applied for the detection of peak R in an ECG cycle. This hybrid recognition system is designed to emulate human intelligent in the field of ECG signals classification. Hence, the types of ECG signals used in the training and testing of the hybrid system are suitable for visual recognition by human expert without the aid of any signal processing tools except plain filtering of noises. The ECG signals such as Sinus Arrhythmia, ST segment elevation and Atrial Fibrillation are not included for the testing of this hybrid system due to the difficulty in determining the peak R in an ECG cycle. For the special case of ECG signal with VPC, a state transition model is devised for the detection of VPC based on the duration of R–R intervals.

Several methods are combined to classify ECG signals based on the features extracted. The tools utilized in the classification system are artificial neural networks and rule-based decision making with fuzzy system. These tools are further integrated with the VPC detection system to give the final classification result as shown in Fig. 1.

In this study, the ECG waveforms were taken from the MIT-BIH Database [6]. For each patient, there are one to two channels of ECGwaveforms available in the database and comparison is made between using one channel of samples only.

### *Subject and study protocol definition*

The data sets consist of 24 patients' ECG signals. Each ECG signal has been recorded for approximately 16.67 min and subdivided into segments of 6.4 s, which consists of 1600 samples at sampling rate of 250 Hz. The number of samples in each segment was taken to be even for the discrete wavelet transform (DWT) to reduce computation cost. Twelve patients' ECG signals were used for training purposes while the others were reserved for the testing and simulation of the system.

### *Features extraction*

The notion of invariant recognition of information has long been of interest in the areas of pattern recognition and signal processing. Generally, shift-invariant (SI) recognition may apply to shifts in time or spatial coordinates. Thus, SI recognition is common to problems in signal processing. The neural network that we are going to develop in Section 4 typifies the static multi layer (ML) feed-forward (FF) structure. The fact that inputs are time-varying is, insofar as this network is concerned, irrelevant. The network has no memory of past inputs.

The location in time of certain input information may vary over a class of inputs. Assuming that the time period of observation is larger than the event that is to be detected, the

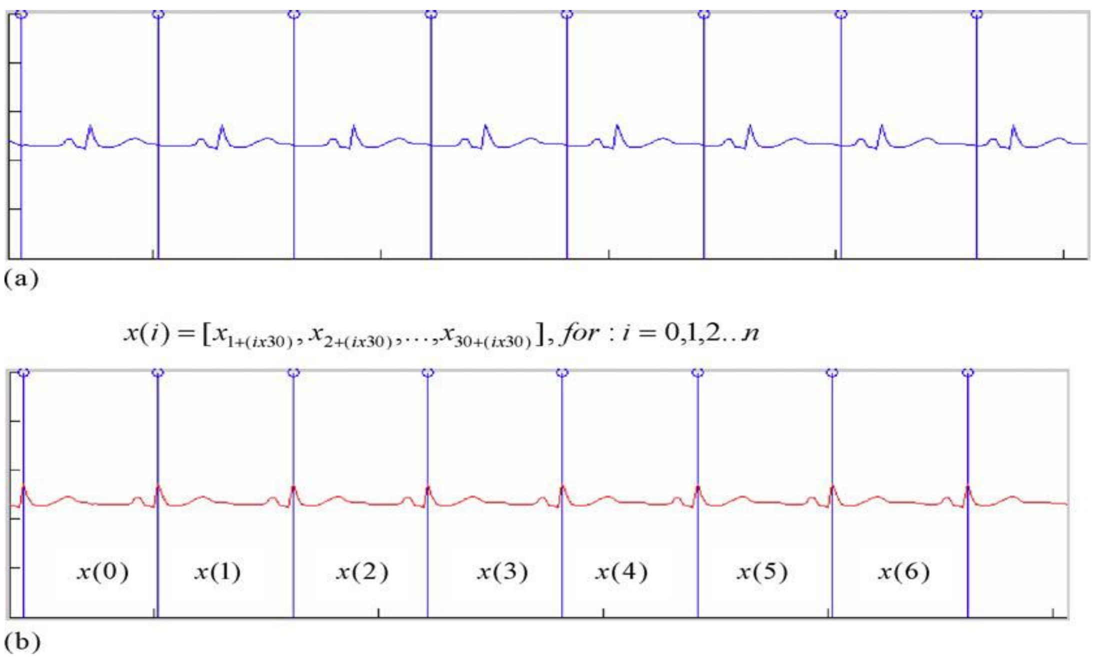


**Fig. 2 – (a) The time-varying spatial input patterns. (b) The time invariant spatial input patterns**

starting and ending times of the event may be random. One desirable characteristic of the recognizer is that the event be recognized independently of starting time. However, unless additional elements are incorporated into FF structure network design and training, the resulting network is shift sensitive. Thus, generalization to input shift invariance is not inherent in the FF structure network.

In order to make SI recognition possible for the neural network, we use a simple R–R interval detection algorithm as shown in Fig. 2, based on locating the peaks of two consecutive QRS waves

***Detection of Ventricular Premature Cycle (VPC)***

The absence of Pwave is significant in a Ventricular Premature Cycle (VPC). The QRS wave of the VPC signal follows immediately from the ST segment of its previous cardiac cycle. The QRS wave is inverted in a VPC signal. The size of the QRS wave is also significantly greater than its neighbouring QRS waves. VPCmay be presented in both normal sinus rhythm ECG signal and abnormal ECG signals as shown in Fig. 3a–c.

In order to detect these VPC signals, we need to extract the common features of the VPC signals. The absence of P wave will cause the R–R interval duration between the preceding normal cardiac cycle and the VPC becomes shorter and the R–R interval duration between the VPC signal and the following normal cardiac cycle becomes longer as shown in Fig. 4a. By plotting the duration of R–R intervals versus time as shown in Fig. 4b, the recognition of VPC signal is reduced down to merely recognition of the state transitions marked by the vertical lines in pink.We introduced a simple state model in Fig. 5 for the recognition of VPC signal. Let S1, S2 and S3 represent the states of medium, low and high duration of R–R interval, respectively. We therefore concluded that the transition from state S1 to S2 and then to S3 will result in VPC. However, there are other premature signals such as Atrial Premature Cycle (APC) that will produce the same state transitions as the VPC signal. Hence, we included the detection of QRS wave inversion that is presented in VPC signal only as shown in Fig. 5.

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