Classificatons of Electrocardiogram (ECG) Signals using Extended Kalman Filter (EKF) Based Neuro Fuzzy System

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ABSTRACT

Automatic electrocardiogram (ECG) recognition is a very important branch of biomedical signal processing. The ECG is a written record of the electrical activity of the heart, which is very helpful in the diagnosis of cardiac diseases. The demand for this non-invasive diagnostic procedure has stimulated a remarkable increase of advanced signal analysis techniques.

This study presents the development of Extended Kalman Filter (EKF) based Multi Layer Perceptron Network (MLPN) and Hybrid Fuzzy Neural System for the recognition of ECG signals. This system can distinguish various types of abnormal ECG signal 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.

In order to obtain high recognition accuracy, two feature extraction methods have been developed. The method of unconstrained optimisation for a function of one variable is applied in the detection of peak R for an ECG cycle. A simple state transition model is devised for the detection of VPC presence in ECG signals.

The data sets consist of 24 patients' ECG signals obtained from the MIT-BIH Database. Each ECG signal had been recorded for approximately 16.67 minutes. We subdivided these ECG signals into segments of 6.4 seconds, which consists of 1600 number of samples each, at sampling rate of 250 Hertz. The number of samples in each segment was taken to be even for the Discrete Wavelet Transform (DWT) to reduce computation cost. 12 patients' ECG signals were used for training purposes while the other 12 patients' ECG signals were used for the testing of the system. The overall average classification rate of the system is 91.8%. The two main objectives

guiding the research were met: 1) developing a novel ECG classification system based on online EKF learning and neuro fuzzy techniques and 2) implementing this novel approach in computer software.

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