Chapter 11
Feature Extraction and Classification

ABSTRACT

In the previous chapter, the first stage for detecting the ECG noise removal was investigated. In this chapter, the second and the third stages are explained. The Second stage is to extract the effective features of the ECG signals. The final stage is to use MLP and PSO algorithms for classification of ECG signals to detect the 4 common heart disorders including the normal signals. Common disorders are Normal, Supraventricular, Brunch bundle block, Anterior myocardial infarction (Anterior MI), and Interior myocardial infarction (Interior MI).

1 INTRODUCTION

In previous chapters, it was described that the ECG signal and heart rate reflects the state of the heart. Important clinical information hidden in the ECG waveform helps as pointers to detect various types of heart disorders. The reflection may occur randomly in the time-scale, because bio-signals are non-stationary signals; the symptoms of disorder may not be shown up all the time. It would modify certain intervals during the day. Therefore, specialists have to observe the ECG signal over several hours for effective heart disorder diagnostics.

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From the literature, it is evident that there is a need for efficient classification of ECG signals for effective and robust heart disorder recognition. This chapter aims to use the PSO and BP, to train a neural network in the classification of ECG signals for the automated identification of heart disorders.

For classification, it is necessary that useful features of all ECG signals be extracted. Feature extraction is a module involves with forming a vector of features from each heart beat for classification process. In the classification stage of ECG signals, it is required to do the feature extraction module; because better performance for classification is achieved if smaller numbers of features are extracted as the inputs of classifier.

2 FEATURES OF DISORDERS

Consultation with heart specialists determined that 4 types of heart disorders, namely, bundle branch block, supraventricular tachycardia, anterior myocardial infarction (anterior MI) and inferior myocardial infarction (inferior MI) are common and would be detected in this work. Sample ECG signals for the 4 classes and normal ECG signals are given in Figure 1. Specialists detect these disorders by observing the PQRST waveform. For example, bundle branch block causes a widened and possibly jagged QRS waveform, while supraventricular tachycardia typically exhibits a narrow QRS complex on the ECG. The ST segment, which is normally iso-electric (flat and in line with the PQ segment) may be elevated or depressed due to myocardial ischemia or myocardial infarction. Table 1 shows the ECG classes and representation of outputs for each class.

One of the important steps in the classification process is feature selection. The objective in feature selection is to select the most efficient features for reducing their numbers, and retaining as much of their class discriminatory information as possible. Selecting the features with little discrimination power would lead to poor performance.

The extracted features for heart disorder detection are based on consultation with a heart specialist. The selected features are QRS duration, PR duration, QT duration, heart rate, RR duration and ST duration (Positive/Negative T; i.e. if the T is negative, then ST duration is 0). Appendix B shows the dataset of the 4 classes of heart disorders and the normal class. Figure 2-6 present each feature for a number of samples affected by each of mentioned disorders, including the normal human heart beat. In Figure 2, it is obvious that for bundle branch block, the QRS duration is wider than 0.12 seconds. Figure 3 shows lack of PR duration in supraventricular tachycardia. In Figure 4, it is clear that inferior MI causes a narrower QRS than

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