

Chapter 9

Classification and Feature Extraction

ABSTRACT

In this chapter, the proposed optimization algorithm, kinetic gas molecule optimization (KGMO), that is based on swarm behaviour of gas molecules is applied to train a feedforward neural network for classification of ECG signals. Five types of ECG signals are used in this work including normal, supraventricular, brunch bundle block, anterior myocardial infarction (Anterior MI), and interior myocardial infarction (Interior MI). The classification performance of the proposed KGMO neural network (KGMONN) was evaluated on the Physiobank database and compared against conventional algorithms.

9.1 INTRODUCTION

In previous chapters, it was described that the shape of ECG waveform and heart rate reflects the state of the heart. It may contain important pointers to various types of disorders afflicting the heart. Bio-signals are non-stationary signals; therefore, the reflection may occur randomly in the time-scale. The disease symptoms may not show up all the time, but would manifest at certain irregular intervals during the day. Therefore, for effective diagnostics, ECG pattern and heart rate variability may have to be observed over several hours.

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

DOI: 10.4018/978-1-5225-5580-3.ch009

aims to use the efficient Kinetic Gas Molecule Optimization (KGMO), to train a neural network in the classification of ECG signals for the automated identification of heart disorders. The proposed intelligent system is called KGMO neural network (KGMONN).

For classification, it is necessary that useful features of all ECG signals be extracted. The feature extraction module is concerned with forming a vector of measurements (feature vector) from each heartbeat, that is processed by the classifier. The feature extraction module is required because, although it is possible for the classification stage to process the ECG samples directly, greater classification performance is often achieved if a smaller number of discriminating features are first extracted from the ECG samples.

9.2 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 the desired neural network outputs for each class.

The feature selection is very important step in clustering process. The aim is to select the only most important features to reduce their number and at the same time, retain as much of their class discriminatory information as possible. If features with little discrimination power are selected, the subsequent cluster design would lead to poor performance.

The extracted features in this work 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. Figures 2-6 present each feature for

17 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-global.com/chapter/classification-and-feature-extraction/205182

Related Content

Clinical Decision Support System for Early Disease Detection and Management: Statistics-Based Early Disease Detection

Likewin Thomas, Manoj Kumar M. V. and Annappa B. (2019). *Pre-Screening Systems for Early Disease Prediction, Detection, and Prevention* (pp. 108-155).

www.irma-international.org/chapter/clinical-decision-support-system-for-early-disease-detection-and-management/215043

A Relational Perspective on Patient Engagement: Suggestions from Couple-Based Research and Intervention

Silvia Donato and Anna Bertoni (2016). *Promoting Patient Engagement and Participation for Effective Healthcare Reform* (pp. 83-106).

www.irma-international.org/chapter/a-relational-perspective-on-patient-engagement/150347

The Impact of Decline on Everyday Life in Alzheimer's Disease

Lovingly Quitania Park and Britt Busson (2019). *Chronic Illness and Long-Term Care: Breakthroughs in Research and Practice* (pp. 1-13).

www.irma-international.org/chapter/the-impact-of-decline-on-everyday-life-in-alzheimers-disease/213334

Healthcare System in Namibia: An Overview

Vistolina Nuuyoma and Daniel Opotamutale Ashipala (2020). *Biopsychosocial Perspectives and Practices for Addressing Communicable and Non-Communicable Diseases* (pp. 1-17).

www.irma-international.org/chapter/healthcare-system-in-namibia/252413

Creativity and the Arts

Richard L. Tietze (2018). *Applications of Neuroscience: Breakthroughs in Research and Practice* (pp. 1-39).

www.irma-international.org/chapter/creativity-and-the-arts/199627