Computational Intelligence and Sensor Networks for Biomedical Systems

Daniel T. H. Lai
Melbourne University, Australia

Jussi Pakkanen
Helsinki University of Technology, Finland

Rezaul Begg
Victoria University, Australia

Marimuthu Palaniswami
Melbourne University, Australia

INTRODUCTION

The growing demand for a better quality of life is now the major motivation behind the recent focus on health care research. Current worldwide shortages in medical personnel have placed immense strain on present health care systems in the presence of a growing global population. Alarming statistics from the recent WHO 2006 report[1] depict critical shortages in health care providers with 57 countries possessing less than 80% coverage of health care providers for their citizens. It is estimated that training the health care workforce to cope with these shortages by 2015 would incur annual costs of $1.6 to $2.0 billion per country depending on its size. This predicament makes it paramount to look at alternative avenues for more effective health care technologies to ensure the sustainability of worldwide health care systems.

Computational intelligence (CI) is the implementation of artificial intelligence in computer science allowing for the design of powerful decision systems capable of processing and interpreting large volumes of data. This discipline has recently been applied to biomedical engineering problems, specifically those in which human intervention can be replaced by some form of automated response. As will be seen later, supervised learning formulations such as artificial neural networks (Haykin, 1994), support vector machines (Schlkopf, Burges, & Smola, 1999; Vapnik, 2000), and fuzzy classifiers (Abe, 1997) have been recently applied to diagnostic and prognostic biomedical applications. These techniques learn nonlinear relationships between patient data and disorders which could not otherwise be captured with standard statistical analysis techniques. Moreover, CI techniques are cost effective to implement, being fundamentally software-based in nature and thus requiring only a processor with mathematical functions and adequate memory, for example, personal computers.

Sensor networks (SN) is an emergent technology which combines small sensors outfitted with wireless transmitters to form a network with more powerful sensing capabilities (Akyildiz, Su, Sankarasubramaniam, & Cayirci, 2002; Chong & Kumar, 2003). The primary application for SN technology is monitoring environmental changes making it ideal for deployment in patient monitoring systems. In contrast to other monitoring technologies such as video, SN offers a potentially cheaper solution consisting of cost effective interconnected sensors which cooperatively sense the surroundings. Individual sensor information is then fused to derive an instantaneous description of the environment.

In this article, we review briefly the recent applications of CI and SN technologies in health care, mentioning some of the challenges in deploying these technologies. This is followed by an example of a biomedical system incorporating both technologies in a single paradigm. The state of current systems and their advantages over existing methods are highlighted with examples focusing primarily on intelligent automated diagnostic systems to augment clinician diagnoses and health care monitoring systems for continuous patient observation.

COMPUTATIONAL INTELLIGENCE FOR DIAGNOSIS AND DETECTION IN HEALTH CARE

In recent times, intelligent biomedical applications incorporating CI techniques have been investigated for detection and diagnosis of pathologies. The objective is to replicate the diagnostic capabilities of a medical specialist based on patient data and where possible provide a more reliable diagnosis. In this endeavour, two trends have emerged: the first being pathology detection and the second being biological system modeling. The former has enjoyed cautionary clinician acceptance as pattern recognition is becoming common while the latter is less accepted due to the "black box" model which makes them difficult to be directly related to the pathology and thus remains a major issue to be addressed.
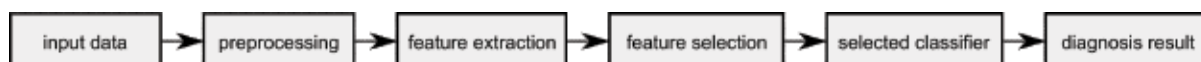
A general intelligent system incorporating CI consists of biosignal inputs, preprocessing, feature extraction, feature selection followed by pattern recognition (Figure 1). Biosignal inputs consist of measured signals from organs such as the heart or muscle. The signals are recorded, amplified, and filtered before feature extraction is performed. Proper feature extraction is essential for the later recognition stage as features should represent the unique pathological characteristics as much as possible. Feature selection is optional but functions to reduce redundant information which could confuse the detection process. The function of CI in this system lies in the final pattern recognition stage, where the task is to learn the implicit relationship between features and the respective pathologies given the finite set of data. It is important to note that the success of the system lies in its ability to perform well on new data and minimize the risk of misdiagnosis.

One of the more successful systems has been the diagnosis of cardiovascular diseases based on the QRS wave complex recorded from electrocardiograms (ECG) (Julian, Campbell, Cowan, & McLenachan, 2005). The average peak-to-peak voltage of the QRS complex is considerably larger than electrical activity from neighbouring organs making filtering simple and subsequent QRS detection algorithms sufficiently accurate (Friesen, Jannett, Jadallah, Yates, & Nagle, 1990). QRS information such as ST segment length (Edenbrandt, Devine, & Macfarlane, 1993), peak amplitudes, number of waveform turns, and peak to peak intervals (Kundu, Nasipuri, & Basu, 1998; Lin & Chang, 1989; Marques, Goncalves, Ferreira, & Abreu-Lima, 1994) have been effectively used as discriminating features. More advanced processing methods such as wavelet transforms, autoregression, and principal components analysis have also been applied to extract better features (Baxt,1993; Strauss, Steidl, & Jung, 2001). Classification of cardiovascular disorders using CI techniques, for example, ectopic beat detection (Chow, Moody, & Mark, 1992), arrhythmias (Coast, Stern, Cano, & Briller, 1990; Silipo, Zong, & Berthold, 1999), myocardial infarctions (heart attacks) (Fricker, 1997), and ischemia (Vladutu, Papadimithou, Mavroudi, & Bezerianos, 2001) has been sucessfully demonstrated. Tests performed on a variety of publicly available databases, for example, MIT-BIH[2] have yielded on average high accuracies with neural networks being the major applied technique (Table 1).

The classification of neuromuscular diseases has been more complex. Unlike the QRS waveform the motor unit action potential (MUAP), waveforms measured via electromyography (EMG) are composite waveforms derived from superposition of nerve signals emanating from adjacent muscle fibres (Emly, Gilmore, & Roy, 1992). Direct measurement of a single MUAP using needle EMG may not yield clear isolated waveforms either because motor units in the muscle fibers produce comparably smaller action potentials (-35mV to -70mV) making them easily corrupted by electrical noise. Even though muscle mechanics and action potentials are well understood, motor neuron firing is still thought to be random and nondeterministic. Research has examined the physical measurement of a single MUAP such as the number of turns and peak to peak amplitudes similar to QRS analysis (Park & Lee, 1998). This could be adequate provided a single clear MUAP waveform

Figure 1. General flowchart of intelligent detection biomedical system

input data → preprocessing → feature extraction → feature selection → selected classifier → diagnosis result

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