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Cardiac health diagnosis using data fusion of cardiovascular and haemodynamic signals

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ARTICLE INFO

Article history:
Received 25 August 2005
Received in revised form 24 December 2005
Accepted 18 January 2006

Keywords:
Multiple sensor systems
Data fusion
Fuzzy logic
Electrocardiogram
Arterial blood pressure
Pulmonary oedema

ABSTRACT

The electrocardiogram (ECG) is a representative signal containing useful information about the condition of the heart. The shape and size of the P–QRS–T wave, the r–r interval, etc., may help to identify the nature of disease afflicting the heart. However, human observer cannot directly monitor these subtle details and it is difficult to evaluate the cardiac health using ECG alone. Hence, the fusion of ECG, blood pressure, saturated oxygen content and respiratory data for achieving improved clinical diagnosis of patients in cardiac care units. In this study, a computer based analysis and display of the heterogeneous signals for the detection of life threatening states is demonstrated using fuzzy logic based data fusion. And to evaluate the severity of the disease a new parameter, deterioration index is proposed and results are tabulated for various cases.

1. Introduction

Computer technology has an important role in structuring biological systems. The explosive growth of high performance computing techniques in recent years with regard to the development of good and accurate models of biological systems has contributed significantly to new approaches to fundamental problems of modeling transient behavior of biological system. Data fusion is the process of combining data from several sources, inputs from sensors, information processing blocks, data bases or knowledge bases into unified representational format [1,2]. A data fusion system helps to identify the data of different views from the same object, the redundant data, and the mismatch between data. Data fusion is synergistic combination of information made available by different measurement sensors, information sources and decision makers. Various techniques involved in fusion are least square method, Bayesian method, fuzzy logic and neural networks [3,4]. Data fusion [5,6] architecture has gone through various developmental phases and gradually has evolved into two techniques, the rule based decision-making and fuzzy logic decision-making [7].

Multiple sensor systems were originally motivated by their applications in military surveillance and these days it is used in a wide variety of applications [8–11]. New data fusion methods developing in the area of biomedical engineering include applications like monitoring of machines, robotics and medicine [12–20]. A typical application in medicine is the

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doi:10.1016/j.cmpb.2006.01.009

detection of patient status based on the data obtained from the recording of multi-channel electrocardiogram (ECG), arterial blood pressure (ABP) and respiration. These multi-modal data can help in the accurate diagnosis of the hidden abnormalities. In the past, Alfredo et al. have presented multi-sensor and multi-source data fusion to improve atrial and ventricular activity detection in critical care environments [21]. Also, Azuaje et al. proposed a framework for fusion of structured and unstructured data based on case-based reasoning concept [22]. A novel approach for robust cardiac rhythm tracking based on data fusion has been described by Thoraval et al. [12]. Recently, Wasserman et al. have proposed a new approach for the generation of a mathematically optimal tumor boundary by the integration of MRI, CT and PET imaging data [23].

In this work, we have proposed the fusion of ECG, blood pressure, saturated oxygen content and respiratory data with rule based and fuzzy logic for achieving improved clinical diagnosis of patients in cardiac care units.

2. Materials

The Multi-modal data is acquired from the Physiobank's Multi-parameter Intelligent Monitoring for Intensive Care (MIMIC) database. The MIMIC Database directory contains records of periodic measurements of physiologic variables obtained from bedside Intensive Care Unit (ICU) monitors. The required data in MIMIC are stored in the numeric form of heart rate, blood pressure (mean, systolic and diastolic), respiration rate, oxygen saturation, etc. Data is acquired using PhysioToolkit Waveform Database (WFDB) library, a set of functions (subroutines) for reading and writing files in the formats used by Physiobank databases. We have tested the system with records 211–216, 218 and 219. The data information along with the patient's sex, age, duration of the recording and the number of classifications are given in Table 1. Two hours of data from the set from third to fifth hour is used for training and the rest is used for testing. All the signals are recorded continuously in an ICU environment. The data from the database contains the annotations of normal (true negative, TN) and the corresponding clinical class (true positive, TP). The details of the records are given below.

The software for rule based probability distribution, fuzzified probability distribution and heart rate calculation is written in MATLAB 6.1. To visualize the snapshot of the system to detect the fusion status, deterioration index, determination of heart rate, the program is coded in 'Visual C++' programming.

3. Method

3.1. *Preprocessing and analysis of signals*

QRS complexes in the ECG signal are detected in a chronologically sorted list by the time of their occurrence. The interval between two successive QRS complexes is defined as the r–r interval (t_{r-r} seconds) and the heart rate (beats per minute) [24–27] is given as:

$$HR = \frac{60}{t_{r-r}} \tag{1}$$

A respiratory impedance signal is used to acquire information about respiratory inspiratory volume, expiratory volume and respiratory rate. The impedance is measured in ohms and varies closely with the volume of air in the lungs. The peak and trough detectors detect four values, the global peak, the global trough, the local peak and the local trough. The global peak and trough are the largest and smallest values over the range of the entire data. The local peak and trough are the largest and smallest pieces of data until the respective local maximum or minimum is left. The respiratory rate is defined as a certain number of respirations or time period between the local peaks in which breathing occurs, normalized to a rate in respirations per minute. A list of times at which respiratory peaks occurred is kept, and this list is used to calculate respiratory rate (RR) and change in respiratory rate.

Arterial blood pressure is used to acquire information about systolic and diastolic pressures. Peaks and troughs are detected based on the local maxima and local minima. Lowest value is stored in the local trough and is compared with the next data. If data is greater than trough threshold then value stored in local trough gives the diastolic. Then the next incoming data is compared with local peak. If data is greater than local peak then data value is assigned to local peak and if the data is smaller than peak threshold then values stored in local peak gives systolic pressure.

PLETH is a signal from fingertip plethysmograph, used by the ICU monitor to determine oxygen saturation and the SpO_2 is determined from this signal.

Table 1 – Range of gender, age, gender, duration of clinical class and the number of classifications for each category

Record no	Clinical class	Subject details (sex, age (years))	Duration (h)	Actual number of classifications		
				Total	TP	TN
211	Respiratory failure	Female, 67	21.6	1806	575	1231
212	CHF/pulmonary edema	Male, 84	41.3	3284	882	2402
213	CHF/pulmonary edema	Female, 82	50.6	4769	2257	2512
214	CHF/pulmonary edema	Female, 72	25.6	2585	1479	1106
215	CHF/pulmonary edema	Female, 72	24.1	2531	1589	942
216	Respiratory failure	Male, 67	39.4	3231	1599	1632
218	Respiratory failure	Male, 67	26	1849	858	991
219	Respiratory failure	Male, 67	27.5	2032	869	1163