Data Fusion of Multimodal Cardiovascular Signals

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Computer technology has an important role in structuring biological systems. The explosive growth on high performance computing techniques in recent years with regard to the development of good and accurate models of biological systems has contributed significantly to the new approaches on the modeling transient behavior of biological system. Data Fusion is the process of combining data from several sources, inputs from sensors with information from other sensors, information processing blocks, data bases or knowledge bases into unified representational format [1, 2]. A data fusion system must identify when data represents different views of the same object, when data is redundant, and when mismatch occurs between data items. Data fusion deals with the synergistic combination of information made available by different measurement sensors, information sources and decision makers. Thus, sensor fusion is concerned with distributed detection, sensor registration, data association, state estimation, target identification, decision fusion, user interface and database management [3]. Various techniques involved in fusion are least square method, Bayesian method, fuzzy logic, neural network and so on, but they lack information on how they are applied [4,5]. Attempts have been made to relate these fusion techniques with fusion tasks in the fusion architecture framework. Data fusion [3,6] 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 but are now being employed in a wide range of applications [8–11]. Location of a moving object (such as an aircraft) using radar can be taken as an example [12]. Even tough data fusion methods were developed primarily for military applications, many non-military applications including in the area of biomedical engineering are emerging. They include applications to condition monitoring, monitor of machines, robotics and medicine [13–20]. A typical application in medicine is the detection of patient status based on the data obtained from the recording of multi channel electrocardiogram (ECG), arterial blood pressure (ABP) and respiration. Using of multimodal data can
improve disease detection in various ways. In the past, multisensor fusion for arterial and ventricular activity detection in coronary care monitoring was carried out. Alfredo et al [21] have presented multisensor and multisource data fusion skills to improve atrial and ventricular activity detection in critical care environments. Francisco et al [22] proposed a framework for fusion of structured and unstructured data based on case based reasoning concept. A novel approach for robust cardiac rhythm tracking based on data fusion has been described by Thoraval et al [13]. They have reported that their approach gives better detection of abnormal ventricular contractions. Hence, one can expect better results with regard to diagnosis by fusion of biological signals from various sources.

6.1 Approaches for Fusion

Patient monitoring systems are used in critical-care units (CCU) to detect, characterize, and automatically generate alarms for each potential life-threatening event. Data acquired about the patient consists of one or more measurements from different types of data gathering devices, such as electrocardiogram, blood pressure meters, transthoracic impedance and plethysmograph. After processing, this raw data is turned into information streams containing multiple measurements of heart rate, respiratory rate, systolic and diastolic blood pressure and SpO$_2$ [23–29]. These measurements can be fused to yield more accurate estimates of the actual patient parameters and status information such as the detection of sensor failures [13]. This can aid in the elimination of false-positive cases [4]. Fusion of multimodal data can be modelled as multi-dimensional process.

\[ Y(k) = [E(k)R(k)B(k)P(k)] \quad (6.1) \]

where \( k \) denotes the discrete time index, while \( E(k) \), \( R(k) \), \( B(k) \), \( P(k) \) refer, respectively to ECG, Respiratory, ABP, and PLETH channels in Eq. (6.1).

\[
E(k) = (e(k), e(k+1), e(k+2), \ldots \ldots \ldots) \quad (6.2)
\]

\[
R(k) = (r(k), r(k+1), r(k+2), \ldots \ldots \ldots) \quad (6.3)
\]

\[
B(k) = (b(k), b(k+1), b(k+2), \ldots \ldots \ldots) \quad (6.4)
\]

\[
P(k) = (p(k), p(k+1), p(k+2), \ldots \ldots \ldots) \quad (6.5)
\]

In Eq. (6.2) \( e(k) \) refers to ECG data, at \((k)^{th}\) instant of time, \( r(k) \) refers to respiratory data, \( b(k) \) refers to blood pressure data and \( p(k) \) refers to plethysmograph data at \( k^{th} \) instant of time respectively in Eqs. (6.3,6.4,6.5).

\[
E(k) = [(e_1(k), e_1(k+1), e_1(k+2), \ldots \ldots \ldots), e_2(k), e_2(k+1), e_2(k+2), \ldots \ldots \ldots)] \quad (6.6)
\]