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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. Fracisco *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.

$$\mathrm{Y(k) = [E(k)R(k)B(k)P(k)]} \tag{6.1}$$

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).

$$\mathrm{E(k) = (e(k), e(k+1), e(k+2), \ldots\ldots\ldots)} \tag{6.2}$$
$$\mathrm{R(k) = (r(k), r(k+1), r(k+2), \ldots\ldots\ldots)} \tag{6.3}$$
$$\mathrm{B(k) = (b(k), b(k+1), b(k+2), \ldots\ldots\ldots)} \tag{6.4}$$
$$\mathrm{P(k) = (p(k), p(k+1), p(k+2), \ldots\ldots\ldots)} \tag{6.5}$$

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).

$$\mathrm{E(k) = [(e_1(k), e_1(k{+}1), e_1(k{+}2), \ldots\ldots\ldots), e_2(k), e_2(k{+}1), e_2(k{+}2), \ldots\ldots\ldots)]} \tag{6.6}$$

where $e_1(k), e_2(k)$ are two parameters heart rate and change in heart rate extracted from ECG signal E(k) at k^{th} instant given in Eq. (6.6).

$$R(k) = [(r_1(k), r_1(k{+}1), r_1(k{+}2), \ldots\ldots\ldots), (r_2(k), r_2(k{+}1), r_2(k{+}2), \ldots\ldots\ldots)] \tag{6.7}$$

where $r_1(k), r_2(k)$ are two parameters respiratory rate and change in respiratory rate extracted from respiratory signal R(k) at k^{th} instant given in Eq. (6.7).

$$\begin{aligned} B(k) = \ & [(b_1(k), b_1(k+1), b_1(k+2), \ldots\ldots\ldots), \\ & (b_2(k), b_2(k+1), b_2(k+2), \ldots\ldots\ldots) \\ & (b_3(k), b_3(k+1), b_3(k+2), \ldots\ldots\ldots)] \end{aligned} \tag{6.8}$$

where $b_1(k), b_2(k), b_3(k)$ are three parameters systolic pressure, diastolic and mean pressures extracted from blood pressure signal B(k) at k^{th} instant given in Eq. (6.8).

$$P(k) = [(p_1(k), p_1(k+1), p_1(k+2), \ldots\ldots\ldots)] \tag{6.9}$$

where $p_1(k)$ is the parameter oxygen saturation extracted from plethysmograph signal P(k) at k^{th} instant and is given in Eq. (6.9)

Multiple measurements of the same data are considered competitive data. For example, three measurements of heart rate must be fused to yield one estimate of the actual heart rate of the patient. If one sensor fails or is erratic, while the other two are very close, then the average of those two should be used as the correct estimate. Thus competitive integration yields two outputs. The first is the integrated data, in this case the heart rate. The second is status information, such as information about an erratic or failed sensor.

When multi-modal data is fused, it is considered complementary integration, which is defined as the integration of overlapping (partial) data. The data is partial because it only covers a certain aspect of the patient state. However, it is overlapping because the different types of data change together, as patient state changes. Complementary integration does not produce better estimates of the patient parameters as competitive data does. However, it does yield status information. The most obvious example is, if one type of sensor fails, the others continue to function normally.

In the model developed (Fig. 6.1), there are two heart rate measurements, one respiratory rate, blood pressure systolic, diastolic and mean pressures and one SpO_2 measurement. The relation between the two heart rate measurements is competitive, and can thus be used to yield a more accurate measurement and status information about the two sensors. The relationship between the heart rate, respiratory rate and respiratory volume measurements are complementary. Each of them partially cover the patient state, and can be fused to yield status information about the sensors. For example, if heart rate from lead 1, indicates zero but heart rate from lead 2 indicates some valid

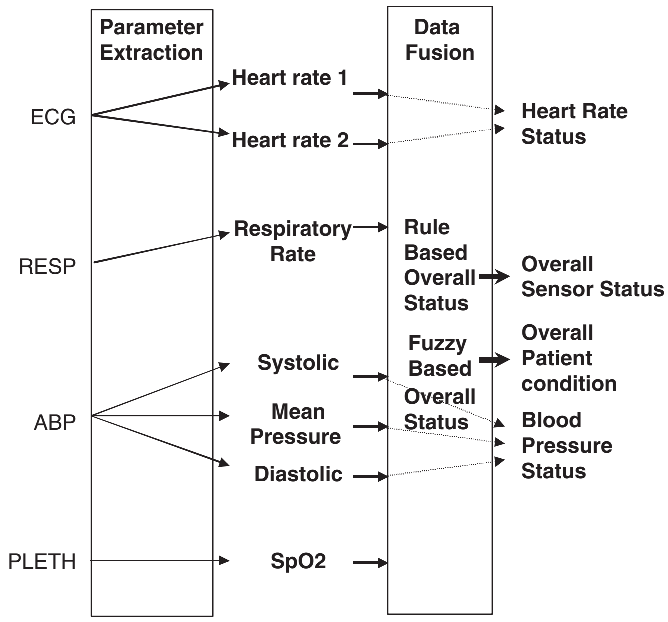

Fig. 6.1. Data Fusion Model of multi-modal signals

value, the ECG lead1 sensor has most likely failed. Similarly, the heart rate may indicate that the patient's heart has stopped beating, but the respiratory rate may show normal breathing.

It is unlikely that the patient's heart has stopped, and the heart rate sensor has failed [13]. These are the ways in which data fusion can provide better information to eliminate false-positive detections.

The rules used to create the heart rate status are as follows. If there is a difference of more than 5% between the two heart rate measurements, or if the status of the heart rate sensors differs, a "Heart rate discrepancy" is flagged. Otherwise, the heart rate is set to the average of the two values. To create the overall status, a tally is taken of the number of sensors that report a status of OK. If they do not indicate OK, they may indicate SENSOR_ERROR, which indicates a hardware failure, NO_DATA, which indicates that not enough data has yet been acquired to calculate patient parameters, or STALE_DATA which indicates no new data has been received within a certain time period. All of these results can be indicative of patient deterioration or sensor failures. However, if the problems are consistent between sensors, they are more likely to flag a problem with the patient rather than the sensors. The table on sensor discrepancy and the sensors reporting OK is shown in the Table 6.1. Parameters extracted from the multi-modal data are combined using rule based approach and fuzzy reasoning methods.

Table 6.1. Sensor discrepancies

Sensors reporting OK	Message Returned
Four (all sensors OK)	No sensor abnormalities detected
Three	Sensor discrepancy (one sensor)
Two	Sensor discrepancy (two sensors)
One	Possible acute patient deterioration; Sensor discrepancy (three sensor)
Zero (no sensors OK)	Highly likely acute patient deterioration

6.2 Rule Based Approach

Set theory has been found to be at the center of universe for the modern computing world. Every element in the world either belongs or doesn't belong to a set; either member or not a member of a set; either true or false. New rules can be derived from existing knowledge by using the true or false statements. Utilizing the information obtained from analyzing multimodal data, new rules can be formulated for detecting critical conditions of the patient. Rules can be developed such as: "If heart rate exceed 90 bpm" or "If respiratory rate exceeds 20" or "If mean Pressure has dropped by 20 bpm" and "Spo2 has decreased below 95%" then patient is diagnosed with left ventricular failure. A rule-based decision making system employs a series of Boolean result parameter tests, combined together with a series of Boolean operators such as AND, OR to indicate whether a particular condition is present or not.

There are many different categories of problems that could be detected by the rule-based approach, such as:

- A drop in heart rate over time is indicative of cardiac problem
- A drop in blood pressure combined with a rise in heart rate indicates that the heart is not pumping forcefully or low preload. The rise in heart rate occurs as the body attempts to increase blood flow.
- A drop in SpO_2 % indicates that oxygen content is reduced.
- Ventricular failures could be detected by a sudden change in heart rate to a very high rate.

The percentage mentioned above are just approximate test values and the clinician has choice of providing the accurate conditions and limits to the Table 6.3 based upon his clinical experience and clinical literature.

Some life-threatening episodes can be detected by using the rules documented in Table 6.2. These rules are not easily available in literature and are assigned based on the discussions with experienced cardiac surgeons. ECG, respiratory, blood pressure and plethysmograph signals were considered for fusion in Table 6.2, however if more parameters such as pressure signals from individual chamber of heart such as left atrium, pulmonary artery, right atrium if fused along with oxygen saturation, a more specific diagnosis can be made. Table 6.3 gives a general idea for fuzzification of parameters.

Table 6.2. Fusion Rules for Cardiovascular Condition Diagnosis

Condition	Constraints	Typical Test Values
Left Ventricular Failure	High Heart Rate	HR > 90 BPM and
	High Respiratory Rate	RR > 20 RPM/minute
	Drop in Blood Pressure	SBP < 80 mm/HG
	Low Oxygen Saturation	$SpO_2 < 95\%$
Right Ventricular Failure	High Heart Rate	HR > 95 BPM and
	Very high Respiratory Rate	RR > 25 RPM/minute
	Less drop in Blood Pressure	SBP < 110 mm/HG
	Very Low Oxygen Saturation	$SpO_2 < 90\%$
Pulmonary Oedema	Very high Heart Rate	HR > 120 BPM and
	Very high Respiratory Rate	RR > 25 RPM/minute
	Large drop in Blood Pressure	SBP < 80 mm/HG
	Very Low Oxygen Saturation	$SpO_2 < 90\%$
Tachycardia	Very high Heart Rate	HR > 120 BPM
Bradycardia	Very low Heart Rate	HR < 60 BPM

Table 6.3. Probabilistic rules assigned by the physician

(HR)		(RR)	(SBP)	(SpO_2)	Failure
			Single Constraint		
1–1	HR > 150	∈ all RR	∈ all SBP	∈ all SpO_2	80%
1–2	110 < HR < 130	∈ all RR	∈ all SBP	∈ all SpO_2	50%
1–3	90 < HR < 110	∈ all RR	∈ all SBP	∈ all SpO_2	30%
1–4	80 < HR < 90	∈ all RR	∈ all SBP	∈ all SpO_2	10%
			Double Constraints		
2–1	110 < HR < 130	RR > 20	∈ all SBP	∈ all SpO_2	80%
2–2	90 < HR < 110	15 < RR < 20	∈ all SBP	∈ all SpO_2	50%
2–3	80 < HR < 90	10 < RR < 15	∈ all SBP	∈ all SpO_2	15%
...	...	...	...	...	...
			Triple Constraints		
3–1	110 < HR < 130	RR > 20	SBP < 70	∈ all SpO_2	80%
3–2	90 < HR < 110	15 < RR < 20	70 < SBP < 80	∈ all SpO_2	60%
3–3	80 < HR < 90	10 < RR < 15	80 < SBP < 100	∈ all SpO_2	20%
...	...	...	...	...	...
			Four Constraints		
4–1	110 < HR < 130	RR > 20	SBP < 70	$SpO_2 < 90\%$	85%
4–2	90 < HR < 110	15 < RR < 20	70 < SBP < 80	$95\% < SpO_2 < 90\%$	70%
4–3	80 < HR < 90	10 < RR < 15	80 < SBP < 100	$90\% < SpO_2 < 99\%$	25%
...	...	...	...	...	...

6.3 Introduction to Fuzzy Based Decision Making

The world around us is very uncertain and unpredictable. No bivalent logic (also called Boolean or binary logic or law of excluded middle) can possibly solve real world problems without oversimplification. Many approximate

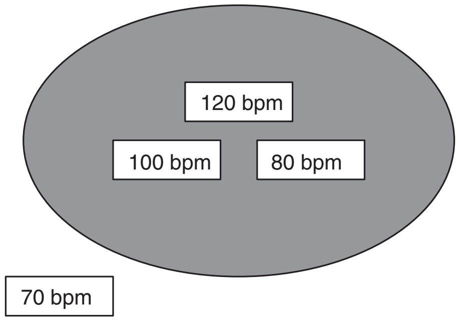

Fig. 6.2. Heart rates defined exactly by 72 bpm

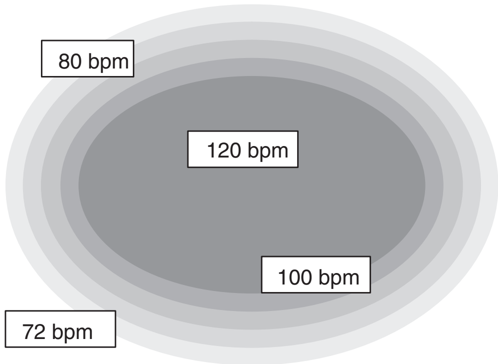

Fig. 6.3. Fuzzy Set of patients with high heart rates

reasoning (also called multi-valued, or continuous or fuzzy logic) methods have been proposed and applied to real world problems [4]. Fuzzy logic allows the representation of human decision and evaluation processes. In reality a crisp rule for certain case cannot be defined. These rules are discrete points in the continuum of possible cases and approximation is done between them. The full scope of human thinking, creativity cannot be mimicked by fuzzy logic. Solution can be derived for a given case by applying fuzzy logic techniques to the rules that have been defined for similar cases.

Most of the medical books describe that normal heart rate is 72 beats per minute, which doesn't mean that a patient with 71 bpm has abnormally low heart rate and a patient with 73 bpm has abnormally high heart rate. Figure 6.2 gives an example of the 'patients with high heart rate' (dark area), where the indicator function defines high heart rate as rates higher than 72 bpm. Figure 6.3 gives an example of a set, where certain elements can also be "more-or-less" members. The shades of grey indicate the degree to which the heart rate belongs to the set of high heart rate. This shades of grey which makes the dark grey area in Fig. 6.2 look "fuzzy" and gave Fuzzy Logic its name.

In Fig. 6.3, each heart rate is associated with a certain degree to which it matches the prototype for high heart rate. This degree is called the "degree of membership" $\mu_{\mathrm{HR}}(\mathrm{x})$ of the element $\mathrm{x} \in \mathrm{X}$ to the set high heart rate, where X is set of all high heart rates and heart rate is called a base variable 'x' with universe X. Different classes of events are specified, along with a membership function.

Fuzzy set is an extension of regular set in which for each element there is also a degree of membership associated with it. The degree of membership can be any value between 0 and 1. An element, whose degree of membership in a set is 0, doesn't belong to that set at all. An element whose degree of membership in a set is 1, belongs one hundred percent to that set. An element whose degree of membership in a set is 0.8, belongs eighty percent to that set and so on. Also an element can belong to more than one set to various degrees of membership. This provides a powerful scheme for representation of uncertainity. Thus this continuous or fuzzy logic includes conventional or binary logic as a special case and extends beyond that.

6.4 Fuzzy Logic Approach

In a rule-based system, a Boolean response is assigned to a condition. Thus a patient either has or does not have a certain condition. In contrast, a fuzzy-logic system attempts to assign a probability that a patient has a certain condition. Thus, a fuzzy-logic system may produce the response that a patient is 70% likely to have a Left Ventricular Failure, but only 8% likely to be having Pulmonary edema. This type of system has some advantages. Firstly, it rids the system of rigid thresholds, such as HR $>$ 90 bpm. A patient with high respiratory rate may be having respiratory troubles without crossing this threshold. In the rule-based system, this case would not be triggered. In contrast, the fuzzy-logic system would assign it a probability almost as high as for a patient with RR $>$ 20. It is for this reason the system is denoted fuzzy, as the boundaries become fuzzy rather than rigid. A second advantage of fuzzy-logic is it can be used to prioritize tasks. If one patient has a high probability of a serious state, while another patient has a lower probability of a less serious state, limited resources can tend to the highest risk group first. Fuzzy-logic is implemented using a decision function, as modeled in Fig. 6.4.

The inputs to the function are a set of patient parameters. The outputs are the probabilities that different conditions are occurring. For example, condition 1, Left Ventricular Failure may have a severity or probability of 70% while condition 2, Pulmonary edema, may have a probability of 5%. The challenge in fuzzy-logic is to create the decision function, as it may be a complex mathematical function. To partially automate the task, the method used is, for each condition, to create a closed object in n-space based on the Boolean rules for that condition, to fuzzify its boundaries, and finally to create a mathematical function to correspond to the fuzzified object.

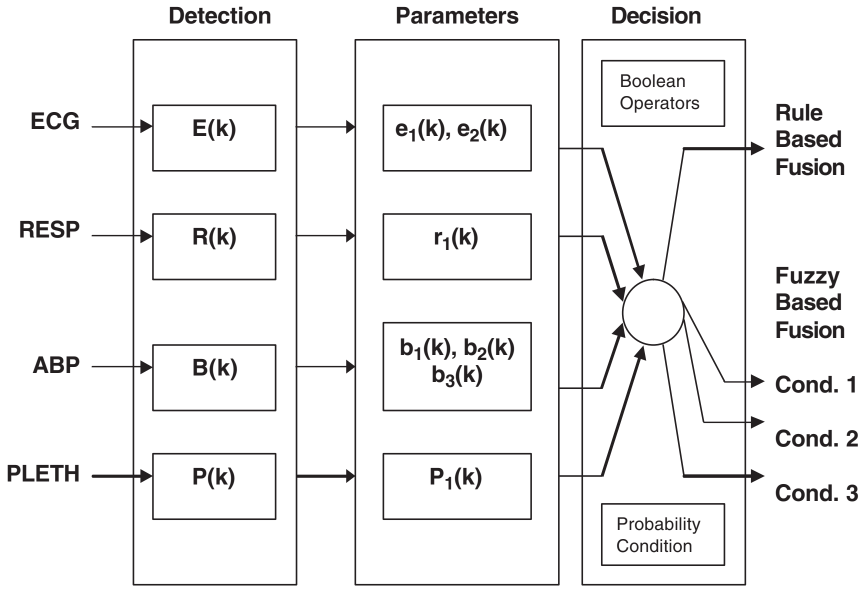

Fig. 6.4. Fuzzy-Logic Decision Function Structure

6.4.1 Fuzzy-Logic Decision Function Created by Fuzzifying Boolean Rules

This method performs a transformation of the Boolean rules to smoothen their boundaries, creating a probabilistic region. The algorithm consists of the following steps. (i) Quantize the patient parameters. For example, heart rate is broken down into 18 steps of 10 BPM/step, blood pressure is broken down into 10 steps of 10 mm/hg /step, oxygen saturation is broken down into 10 steps of 5% per step and respiratory rate is broken down into 10 steps of 10/step. (ii) A 4-dimensional matrix is created with one quantized patient parameter on each dimension. Each element in matrix is assigned a probability $\mathrm{P_r}$ of either 100% or 0% based on the Boolean rules. (iii)A new 4-dimensional matrix is created with the same axis as the first. Each element of matrix $\mathrm{P_r}$ is fuzzified over window of size ‘w’ and assigned a probability P_f using the Eq. 6.10

$$P_f[i][j][k][l] = \sum_{p=-w}^{w} \sum_{q=-w}^{w} \sum_{r=-w}^{w} \sum_{s=-w}^{w} P_r[p][q][r][s]/d \tag{6.10}$$

where d is given by Eq. 6.11, and p, q, r, s indicate the four patient parameters and i, j, k, l indicate the dimension of first, second, third and fourth parameters respectively.

$$d = [1 + \sqrt{(p^2 + q^2 + r^2 + s^2)}] \tag{6.11}$$

$P_f(\max)$ is the maximum value in Eq. (6.12)

$$P_{f'}[i][j][k][l] = (P_f[i][j][k][l]/P_f(\max))x100\% \tag{6.12}$$

Eq. 6.12 is used to normalize the probabilities P_f so that the highest probability is 100%.
P_f (max) is obtained after calculating all of the probabilities, P_f.

Currently, the algorithm is implemented in 4-space with four patient parameters and the fuzzification is based on the distances between parameters over a four dimensional window of size 'w'. It can be extended to more dimensions by considering 'n' parameters and fuzzification can be done over a 'n' dimensional window. In implementation, the fuzzification of probabilities is not done over entire matrix but only over elements in the neighborhood of window 'w'. This is done to reduce computational time. Also, by reducing the size of the neighborhood, the fuzzified boundaries become sharper.

6.4.2 Fuzzy-Logic Patient Deterioration Index

Life threatening events like Left Ventricular Failure, Pulmonary edema, and Right Ventricular Failure are assigned with weights based on the risk factor. Patient Deterioration Index is modeled as shown in the Fig. 6.5. Weights assigned to risk factors are given in Table 6.4. Patient deterioration index is formulated to assess the criticality of the condition of the patient. It is based on the fuzzy logic probabilities of three different critical conditions of the heart. Patient Deterioration Index (μ_{di}) is given by the Eq. 6.13.

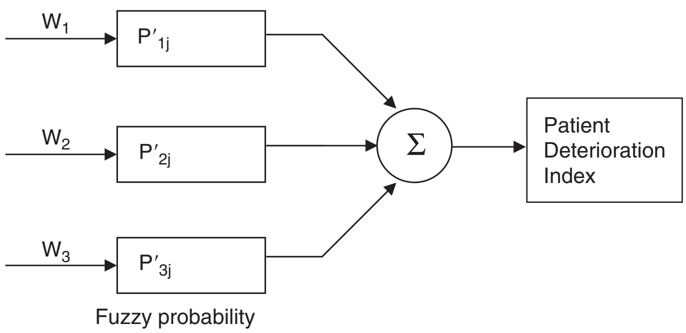

Fig. 6.5. Patient Deterioration Index Function Structure

Table 6.4. Weights assigned to Cardiovascular Problems

Condition	**Risk Factor($\mathbf{W_k}$)**
Left Ventricular Failure	0.40
Right Ventricular Failure	0.10
Pulmonary edema	0.50

$$\mu_{di}(j) = \sum_k W_k P'_{kj} \tag{6.13}$$

Where k refers to the different life threatening problems (left ventricular failure, right ventricular failure and pulmonary edema) and P'_{kj} is the corresponding fuzzy logic probability. Patient deterioration index ranges between 0 and 1 where 0 indicates that patient has no deterioration and 1 indicates maximum deterioration.

The weights ($\mathrm{W_k}$) are assigned depending on the seriousness of the disease. Among the four cardiac abnormalities, Pulmonary edema is considered to be most critical and hence assigned a higher weight. Patient Deterioration Index (μ_{di}) value depends on the weights assigned in Table 6.4. Normal subjects do not have any risk factors, so the weight assigned is 0. Fuzzy probability (P'_{kj}) will yield the percentage of the disorders in the subject considered. The weighted sum of these probabilities will yield a single index, which indicates the cardiac health state.

6.5 Patient States Diagnosis System Implementing Data Fusion

Overview of the patient state diagnosis system using data fusion is shown in Fig. 6.6. Data from specific coronary (CCU) events is required. Acquired data undergoes signal processing and parameters are extracted. These parameters are fused and patient's condition is diagnosed. Patient data is acquired from the Physiobank's MIMIC database. Figure 6.7 shows the multi-modal data from MIMIC Database.

The acquired data undergoes preliminary signal processing to extract patient parameters. Tompkins algorithm is used to detect ECG QRS complexes. The signal is digitally bandpass filtered using cascaded integer high-pass and low-pass filters. Differentiation is done to detect the slope of the ECG and to exaggerate the QRS-complex. Then differentiated signal is squared to make all data points positive and non-linear amplification of the output of the derivative to emphasize the higher frequencies. QRS complexes are detected using an upward and downward threshold called adaptive threshold. These are calculated using running estimates of signal peak and noise peak. Thus the thresholds are dynamically adjusted to improve detection.

Function used to calculate respiratory rate detects global peak, global trough, local peak and local trough. The global peak and trough are defined as the largest and smallest values over the range of the entire data. The local peak and trough are the values of the largest and smallest pieces of data until the respective local maximum or minimum is left. The respiratory rate is extracted based on the number of respirations divided by time period between local peaks in which the breaths occur. The respiratory volume is calculated based on the assumption that the patient's vital capacity (VC), that is, the

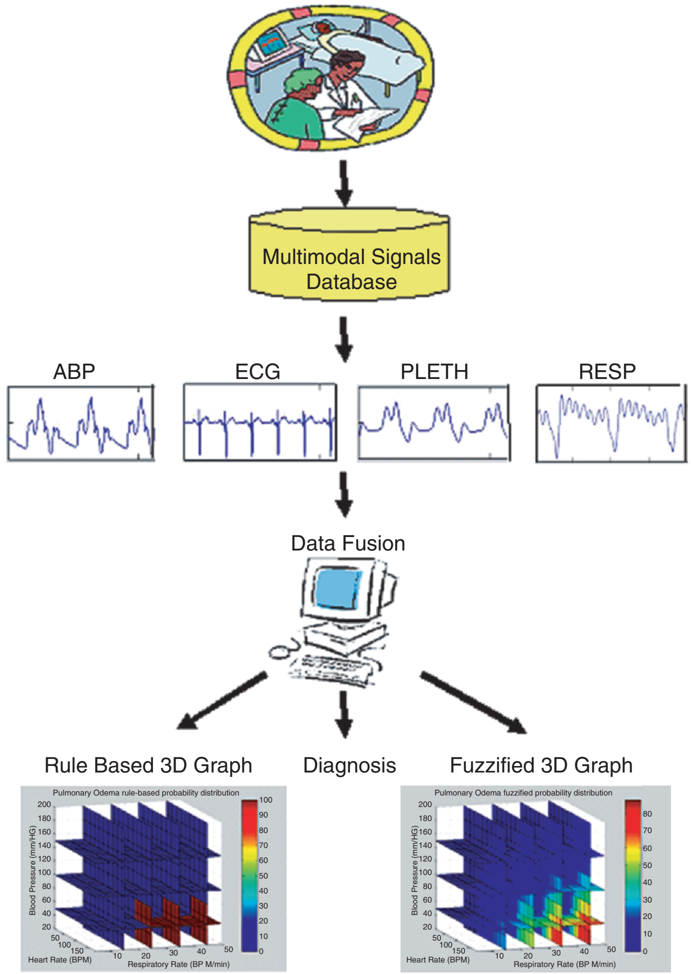

Fig. 6.6. Overview of the Patient state diagnosis system using data fusion

difference between their total lung capacity and residual volume, is 5 litres. It is further assumed that the difference between the global peak and trough corresponds to the vital capacity.

ABP Peaks and troughs are detected based on the local maxima and local minima. Lowest value is stored in the local trough and it is compared with the next data. Minimum value of the data before a peak arrives gives the diastolic and maximum value of the data before a trough arrives gives systolic pressures. Systolic and diastolic pressures are calculated based on the calibrations given in the header file of the data file. Plethysmograph signal is not calibrated and cannot be used in isolation to determine O_2 saturation. The text file found in the same data directory contains the SpO_2 measurements provided by the pleth module.

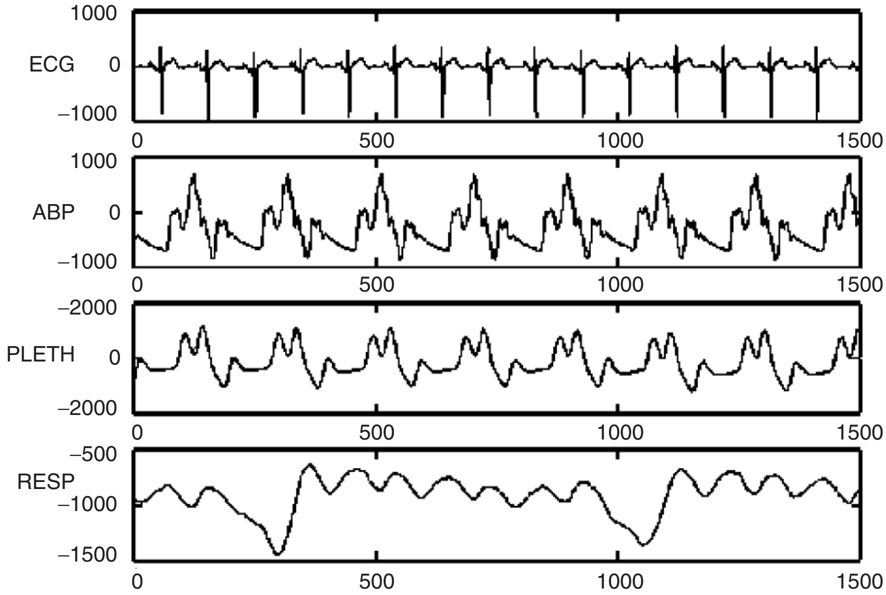

Fig. 6.7. Multi-Modal Data from MIMIC Database

6.6 Results and Discussion

The parameters extracted from the multi-modal signals are used for decision-making using data fusion techniques. The signal information is fused to yield more accurate estimates of the actual patient status information such as the detection of sensor failures, if it has occurred. Status information is based on the fact that "if heart rate indicates the patient's heart has stopped beating but blood pressure signal shows the pressure signal, it is unlikely that the patient's heart has stopped, and more likely that the heart rate sensor (ECG) has failed." This can aid in the elimination of false-positive cases. Status information can be found in lowest part of the Figs. 6.8 and 6.9. Figure. 6.8 indicates the sensor abnormalities as respiratory data is not available and Fig. 6.9 shows that there are no sensor abnormalities detected.

Fuzzy-logic decision function created by fuzzifying Boolean rules is applied to ECG, ABP, PLETH and respiratory signals derived from MIT-MIMIC database. Parameters extracted from the signals are, heart rate, respiratory rate, systolic blood pressure, diastolic blood pressure, mean blood pressure and oxygen saturation. Four-dimensional matrix is formed based on the rule based decision function using the parameters extracted from the signals for each of the three abnormalities discussed below. Elements of the matrix are fuzzified based on the fuzzy-logic decision function.

A program was written in Matlab to graph the rule-based and fuzzy-logic distribution files. It reads the three-dimensional probabilities and graphs

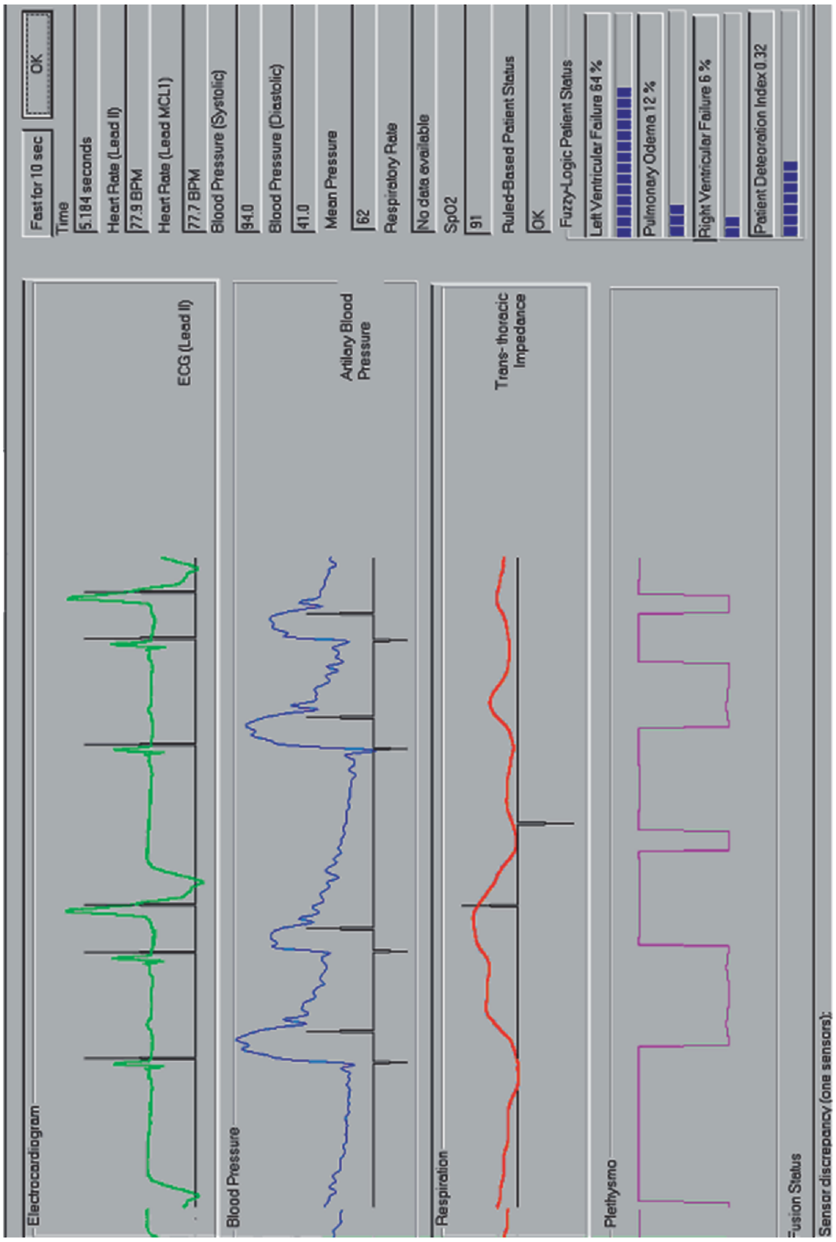

Fig. 6.8. Snapshot of the system showing the sensor discrepancy

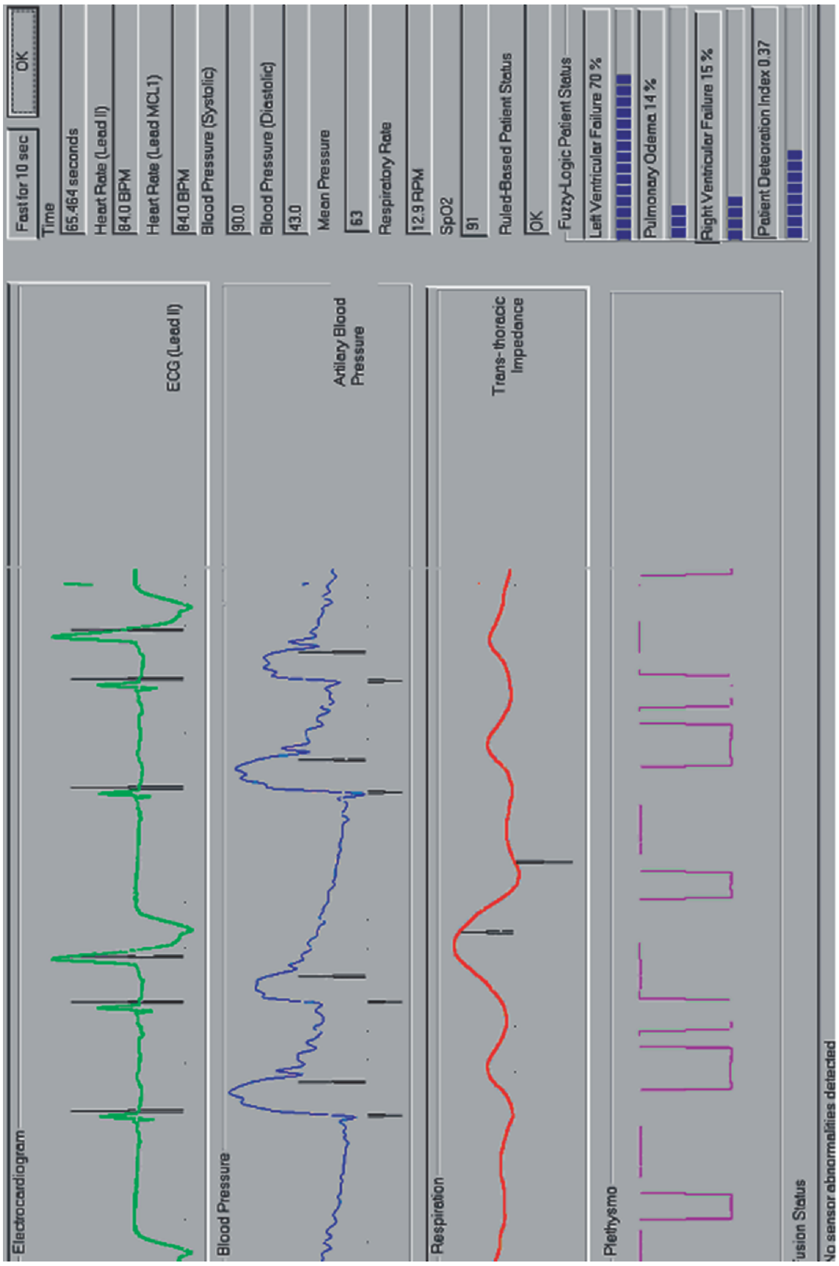

Fig. 6.9. Snapshot of the system showing the patient's deteriorated state

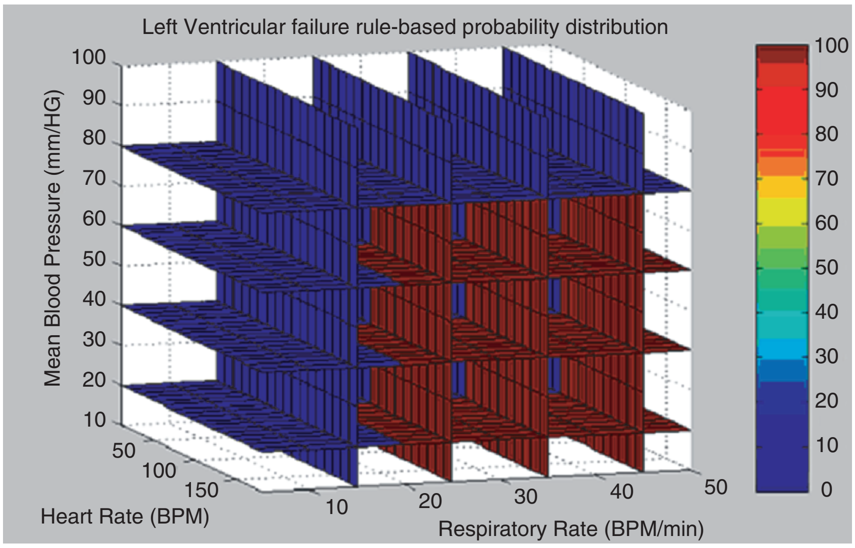

Fig. 6.10. Rule based probablility distribution for Left Ventricular Failure# (color image)

them in slices of a three-dimensional Cartesian graph. It is customized for Left Ventricular Failure, Pulmonary edema and Right Ventricular Failure. Based on the parameter values given in Table 6.1, three dimensional graphs for rule-based and fuzzyfied distributions are shown in Fig. 6.10 and Fig. 6.11 respectively.

Figure 6.10 shows three dimensional graph for left ventricular failure. Three main parameters mean pressure, respiratory rate and heart rate are used to form a three dimensional matrix. Three dimensional graph is formed based on the values of the rule-based matrix. Respiratory axis is divided into 10 slices of 5 respirations per minute each, heart rate axis is divided into 18 slices of 10 beats per minute and mean blood pressure axis is divided into 10 slices of 10 mm/hg. Red colored region indicates that patient has deteriorated based on the rules given in Table 6.1. Patient having heart rate higher than 90 beats per minute and respiratory rate higher than 20 respirations per minute and mean blood pressure lower than 80 mm/hg is diagnosed with left ventricular failure. Figure 6.10 clearly shows the above three conditions and patient's state.

In a rule-based system, a Boolean response is assigned to a condition. Thus a patient either has or does not have a certain condition. In contrast, a fuzzy-logic system attempts to assign a probability that a patient has a certain condition. Diagnosis made by physicians is not based only on crisp rules. Patient having heart rate 89 beats per minute and respiratory rate higher than 19 respirations per minute and mean blood pressure 85 mm/hg is not considered as healthy condition by physician.

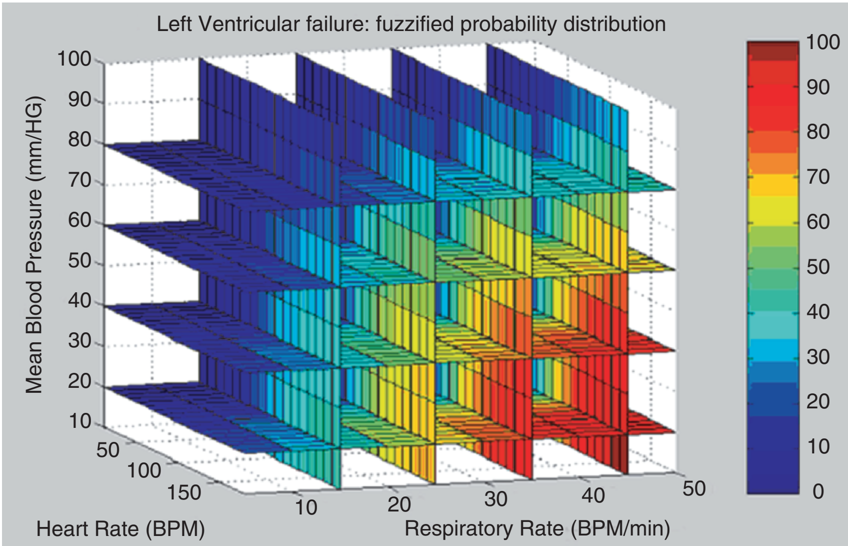

Fig. 6.11. Fuzzy based probability distribution for Left Ventricular Failure# (color image)
[Reprinted with permission from Kannathal N, Rajendra Acharya U, Ng, E. Y. K, Lim Choo Min, Swamy Laxminarayan, "Cardiac health diagnosis using data fusion of Cardiovascular and haemodynamic signals", Computer methods and Programs in Biomedicine, Sweden, 82(2), 2006, 87–96]

The proposed system performance in recognition and classification is evaluated by means of three performance indices viz. classification accuracy, sensitivity, and specificity. The results are given in Table 6.5 and Table 6.6. From the Table 6.6, it can be seen that the proposed system produces promising results with more than 93% diagnostic accuracy. The system is evaluated to have a sensitivity of more than 90% and specificity of more than 91%. The proposed system is intended to aid physicians in ICU environment, where multimodal signals are monitored for long hours. It is not possible for the physician to be attending the patient when the patients are subjected to long term continuous monitoring. The proposed system can give preliminary diagnostics in monitoring the patient.

It has been shown that by combining data sources, better results can be obtained with reduction in the number of false-positive cases. More important, the introduction of fuzzy logic based decision-making improves the likelihood of catching false negative cases that are close to the boundaries of the rule based reasoning. An index called patient deterioration index has been calculated. Testing with limited data has been done and the system is found to perform satisfactorily.

Table 6.5. Results of correct classifications for different clinical classes

Record No	Clinical Class	Correct Classifications		
		Total	TP	TN
211	Respiratory Failure	1705	539	1166
212	CHF / Pulmonary edema	3065	831	2234
213	CHF / Pulmonary edema	4541	2048	2493
214	CHF / Pulmonary edema	2415	1351	1064
215	CHF / Pulmonary edema	2382	1466	916
216	Respiratory Failure	3017	1495	1522
218	Respiratory Failure	1723	782	941
219	Respiratory Failure	1942	797	1145

Table 6.6. Results of accuracy, sensitivity and specificity for different clinical classes

Record No	Accuracy	Sensitivity	Specificity
211	94.41	93.74	94.72
212	93.33	94.22	93.01
213	95.22	90.74	99.24
214	93.42	91.35	96.20
215	94.11	92.26	97.24
216	93.38	93.50	93.26
218	93.19	91.14	94.95
219	95.57	91.71	98.45

6.7 Conclusion

This chapter presents a novel fusion system involving heterogeneous electrophysiological and haemodynamic data for detection of patient states in CCU. Accurate diagnosis of cardiac health using ECG alone is difficult. Hence we have shown that by combining data sources, better results can be obtained with reduction in the number of false-positive cases. And also, to evaluate the severity of the cardiac abnormality, a parameter called patient deterioration index has been proposed. Testing with limited data has been done and the system is found to perform satisfactorily with a diagnostic accuracy of more than 93%.

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