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Detection of Respiration in Central Venous Pressure Using State Machine

Douglas E. Dow and Alejandra P. Garcia, *Members, IEEE*

Abstract— **Reliable information from patient monitors enhances treatment for critically ill patients. Redundant sources for information would aid identification of faulty sensors and leads, and improve presentation of physiological data. Respiratory information can be obtained from several sources, including airway pressure and central venous pressure (CVP). CVP signals have been analyzed using frequency information to isolate the respiration related part of the signal or to obtain statistics about respiration. This study uses a state machine algorithm to detect the timing of each cycle of respiration. A state machine has advantages of enforcing a predictable cycle of expiration and inspiration. The detection of respiratory cycles can be done in real-time, allowing identification of irregular periods between inspirations and prolonged periods with no inspiration, for which an alert may be issued. The algorithm was tested on data obtain from the PhysioNet database of recordings from intensive care patients. The airway pressure signal was used to determine the "true values" of the timing of each respiratory cycle for checking the accuracy of the algorithm analyzing the CVP signal. Parameters of the algorithm were found that would result in a true positive value of above 98% for detection of each cycle of respiration from analysis of the CVP signal, compared to analysis of the RESP signal.**

I. Introduction

Care of patients in emergency room and intensive care requires knowledge of cardiovascular and respiratory function. Vital functions in critically ill patients may undergo slow changes over hours or rapid changes under a minute, which should be addressed by changes in treatment. For treatment to be modified appropriately, reliable measurements that reflect the function, and especially changes, within the cardiovascular and respiratory systems needs to be determined and communicated to the medical staff. The accuracy of information from patient monitors may be affected by artifacts such as changes in each sensor or lead wires, changes in body position and other factors unrelated to the actual physiological function that the measurement is meant to reflect. When presented with measurement signals that would indicate a less stable and viable physiological state, medical staff may need to consider whether the cause of the poorer signals is a problem with the sensors and patient monitoring system, or changes within the physiological state of the patient. This consideration may delay or misdirect appropriate treatment.

All authors are with Wentworth Institute of Technology, College of Engineering and Technology, 550 Huntington Ave., Boston, MA 02115, USA. D. E. Dow is with the departments of Biomedical Engineering, and of Electrical Engineering and Technology (phone: 617-989-4134; fax: 617-989-4591; e-mail: d.dow@ieee.org). A. P. Garcia is in the Electromechanical Engineering program, with a concentration in Biomedical Systems Engineering (e-mail: garciaa2@wit.edu).

One way to improve reliability of the measurements is to have redundant sources to determine each measurand. For example, if one source for a measurand showed no viable signal, but another source for the same measurand showed a viable physiological signal, then a software algorithm could use that information toward determination of a probable interpretation of the conflicting measurements, and communicate to the medical staff that the sensors and leads related the first source should be checked, but the physiological function is reflected by the measurements from the second source.

Information about the timing of respiration can be determined by analyzing signals from multiple sources, including airway pressure (RESP), Photoplethysmography [1, 2], and central venous pressure (CVP) [3-6]. The amplitude of the pressure signal of CVP contains modulation that reflects intrathoracic pressure fluctuations that occur with respiration, as well as cardiac contractions.

Respiratory information has been obtained from CVP signals using several methods based on filtering or analysis of frequency components. Such methods to isolate the respiratory signal include band pass filter [3, 6], frequency power spectra using transfer function analysis [4], independent component analysis [6], squared coherence analysis [2], and Kalman filter [7]. These methods have been used to obtain statistical information about the respiratory signal, such as rate of respiration [2, 4]. However, detection of the times of individual cycles of inspiration and expiration was not shown within these reports. Detection of individual cycles of respiration could be used to detect irregular intervals between cycles of respiration and possibly make an alert after detecting a prolonged period without a respiration event, so that an intervention could be taken toward restoration of respiratory activity. A software algorithm that would compare redundant respiratory information from multiple sources could use the timing of recently detected inspiratory cycles to determine whether the sensors from one source were not functioning, but viable respiratory cycles were still occurring.

We have previously developed an algorithm based on a state machine that analyzes sequential samples of electromyogram signals from diaphragm muscles in rats during cycles of spontaneous respirations [8-9]. Respiration has a restricted cycle of desirable states, progressing from periods of expiration to periods of inspiration. A state-machine is a method to track the progression through the cycle of respiration, in that it encodes history by classifying the current state, which then restricts possible choices from that state. Advantages of the state machine approach are the enforcement of the inspiration and expiration phases of the respiratory cycle, low computation cost, and real-time detection of the inspirations.

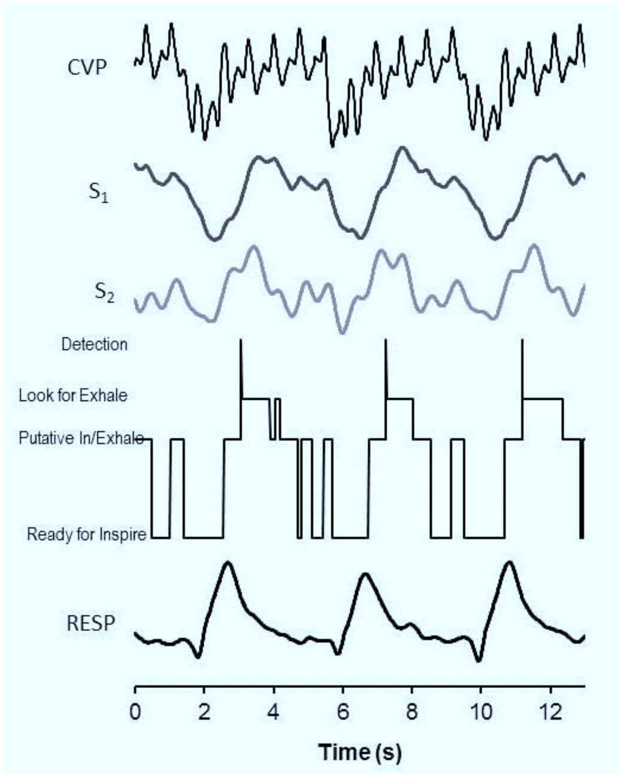

Fig. 1: Example traces of the measured traces, derived values and state. CVP and RESP are the signals from the PhysioNet that were analyzed by the algorithm. S_1 and S_2 are the slope values of the linear fit of the moving time windows of n_1 and n_2. The values of the State Machine are plotted for the states of Detection, Look for Exhale, Putative Inhale or Putative Exhale, and Ready for Inspire.

In the present study, we have modified the state machine algorithm for applications of CVP signals from human patients. The purpose of the study was to adjust the parameters of the algorithm to maximize the number of true positives (TP) for having one detection of a respiratory cycle from the CVP signal per respiratory cycle detected from the airway pressure (RESP) signal. The state-machine classified the second derivative of a moving window of the CVP signal values. The algorithm was tested on CVP signals derived from patients in intensive care units (ICU) that were recorded and made available on the PhysioNet (www.physionet.org) database [10].

II. MATERIALS AND METHODS

A. *Determination of Respiration Timing from Airway Pressure Signal*

RESP and CVP signals that were simultaneously recorded for a patient were used to determine the timing of each cycle of respiration in the 10-minute recorded signal. The RESP signal was used to determine the "true value" of the timing for each cycle of respiration. These values were later used to determine the accuracy of the algorithm that was analyzing the CVP signal to determine the timing of each cycle of respiration.

Maximum and minimum values between rising and falling edges of the RESP signal were determined. The timing of the rising and falling edges was when the values crossed the mean value. For the rising trace between the adjacent minimum and maximum values, the 5 percentile value was considered the start of the inspiration, and the 95 percentile value was considered the end of the inspiration. The RESP signal with the determined start and end timings of each inspiration were visually inspected as a quality control. These values that defined the timing of each respiratory cycle were used as the "true values" for comparing the values that were determined by the new algorithm that analyzed the CVP signal. An example of the CVP and RESP signal that was analyzed is shown in Fig. 1.

B. *Signal Representation of the CVP Signal*

In the recorded CVP signal, X_i denoted the discrete time-series value of the most recent CVP sample, and X_{i-1} was the value sampled just prior to X_i.

The points X_i in the CVP were sequentially analyzed, such that only the current X_i point and prior points were used for the analysis. For each X_i, a subset of the most recent n_1 points of X was selected. The first derivative of this set of points was determined by doing a linear fit using the least square method. For this linear fit, the CVP value was along the y-axis and the time value was along the x-axis. The slope of this linear fit was denoted S_j, and stored in an array of S_1 values, one S_j value for each X_i point. Then for each new S_j value, a subset of the most recent n_2 points of S_1 was selected. Finding the slope of these points determined the second derivative for the corresponding X_i point. The second derivative was denoted S_i and stored in an array S_2, one S_i value for each X_i value of the CVP signal. An example of the derived S_1 and S_2 traces is shown in Fig. 1.

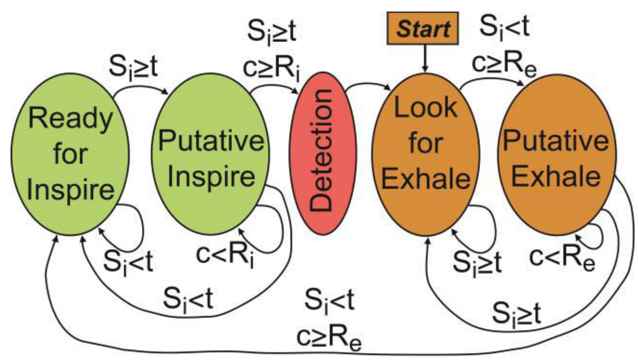

Fig. 2: State machine used to characterize the state of the respiratory cycle based on the second derivative (S_i) of the most recent set of points sampled of the CVP signal. To pass from the Look for Exhale state to the Putative Exhale, the S_i value needed to be below the Threshold value (t). Then to pass to the Ready for Inspire state, the S_i value had to remain below t for R_e samples. Similarly, to pass from the Putative Inspire state to the Detection state, the S_i needed to remain equal or above t for R_i samples. The Detection state would indicate that an inspiration had been detected. The time at this detection would be recorded as the time of an inspiration. If the algorithm works properly, there should be one and only one Detection event for each full cycle of respiration.

The array of second derivatives (S_i) of the two windows (most recent n_1 points for the first derivative, and most recent

n_2 points for the second derivative) was used as the signal representation and given as input to the state machine.

C. Characterization by State Machine

A state-machine (Fig. 2) was utilized to characterize each new second derivative S_i and determine the current state. The design of the state-machine was intended to enforce a cyclic pattern of a period of exhalation, followed by a period of inspiration. The algorithm began in the Look for Exhale state, one of five states that the algorithm cycled through.

In the Look for Exhale state, if S_i was below threshold, the algorithm switched to the Putative Exhale state, and a counter variable, c, was reset to 0 (Fig. 2). For the algorithm to pass from the Putative Exhale state to the Ready for Inspire state, the value for S_i had to remain below the threshold for a certain number of times, R_e. The duration of time corresponding to a particular R_e value depended on the frequency of sampling, which was 125 Hz in this study.

Once in the Ready for Inspire state, the algorithm began to look for activity that might indicate inspiration. If a S_i value was at or above threshold, the algorithm advanced to the next state, Putative Inspire, and the counter c was reset to 0 (Fig. 2). For the algorithm to pass from the Putative Inspire state to the Detection state, the value for S_i had to remain at or above the threshold for R_i number of times.

Once in the Detection state, the time was recorded, indicating that an inspiratory event had been detected. If working properly, the algorithm should detect one and only one Detection event for each full cycle of respiration. Following Detection, the Look for Exhale state was entered (Fig. 2), and the algorithm repeats the cycle. An example of the resulting states from the input signals is shown in Fig. 1.

D. Testing Methods

The timing of each inspiration from the CVP algorithm was compared with the timings that were determined from the RESP signal. The CVP derived timings were considered the experimental ones, and the timings from the RESP signals were considered the "true values". A True Positive event was assigned if one and only one inspiration was detected from the CVP signal for each cycle of respiration. The timings of the cycle of respiration were defined as beginning at one detection of inspiration and ending at the next detection of inspiration from the RESP signal. A True Positive was not accredited if either 0 or more than 1 inspiration were detected from the CVP signal during the time duration of a cycle of inspiration from the RESP signal

E. Source of Data

The data recordings to test the algorithm on were obtained from the PhysioNet (www.physionet.org) database [10]. The records selected were obtained from database "Challenge 2009 Test Set A" and "Challenge 2009 Test Set B". Data were recorded from patients in ICU. The data was sampled at 125 Hz. A 10 minute period for each of 14 records were selected based on having both a RESP and CVP signal during periods of respiratory activity. The selected recording periods were downloaded, stored as a file and utilized for analysis of the algorithm.

F. Computing Platform

The algorithm was implemented in the LabView (National Instruments, Austin, TX, USA) programming language and was run on a Windows based personal computer.

Table 1: Parameter definitions and values tested by algorithm to search for values yielding highest TP %.

Parm	Description / values tested
n_1	Number of most recent X_i points to find 1st Derivative
	16, 32, 64, 128, 256, 512
n_2	Number of most recent S_j points to find the 2nd Derivative
	16, 32, 64, 128, 256, 512
R_i	Number of S_i points that had to remain at or above Thr to enter the Detection state
	2, 4, 8, 16, 32, 64, 128, 256
R_e	Number of S_i points that had to remain below Thr to enter the Ready for Inspire state
	4, 8, 16, 32, 64, 128, 256, 512
Thr	Threshold
	-0.4, -0.3, -0.2, 0, 0.2

III. Results

The algorithm was applied to the CVP signals (Fig. 1). A search of the parameters was conducted to find parameter values that resulted in high TP % values. Table 1 shows the parameter values tested.

Fig. 3 shows the results of this analysis. Eleven sets of parameter values resulted in the highest values found for TP %, which were just above 98%. The values of the algorithm parameters that resulted in high values for TP% were as follows: n_1 is 256, n_2 is 64, R_i is 64, R_e is 64 and Thr is -0.3.

IV. Conclusion

A state machine algorithm has been developed and tested to detect the timing of each respiratory cycle based on the CVP signal. The algorithm shows promise as being a method to obtain the breath by breath timing of inspirations, based on the CVP signal. This could be used as a redundant source of respiratory information that could be coordinated by the software controlling patient monitors. Having redundant sources for critical information, such as respiration, would allow intelligent software to present more reliable, useful and timely information to the medical staff. For example, consider a case where a viable respiratory pattern ceased in the signal derived in one source, but a viable respiratory pattern was still maintained in the signal from another source. After analysis, intelligent software might communicate to the medical staff to check the sensor and leads for the potentially faulty source, but communicate that the patient still appears to be maintaining a viable respiratory signal. Such an envisioned system may enhance care of patients by providing more reliable information and allowing more timely adjustments to the treatment as appropriate.

Further testing will be necessary to determine how accurate and reliable this algorithm is, and how suitable for further development toward possible clinical application.

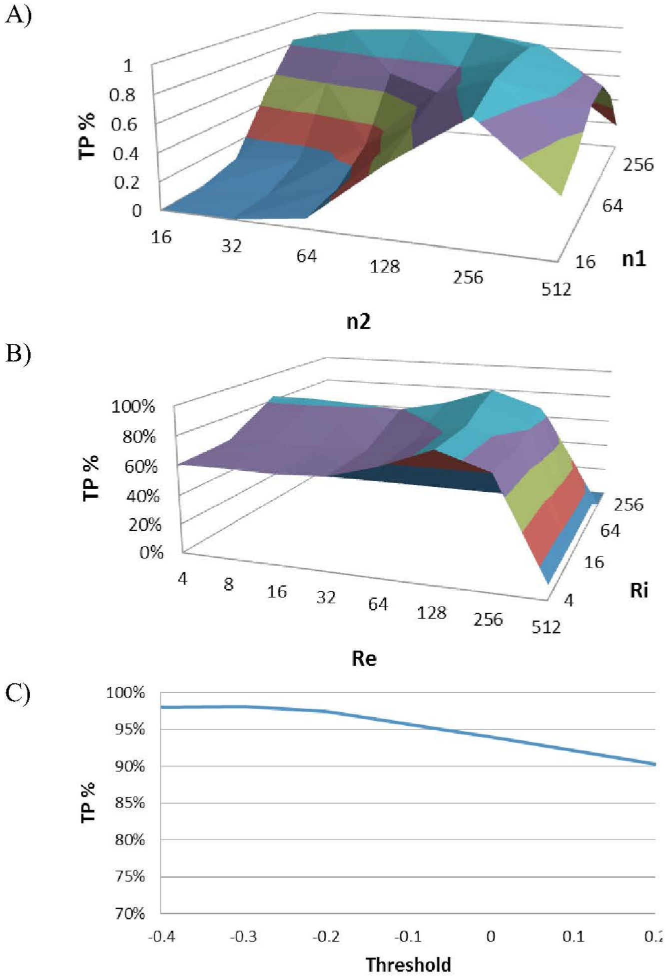

Fig. 3: Results of the search of parameter values for the algorithm that resulted in high TP %. Parameters of the n_1 and n_2 are varied in (A), parameters R_e and R_i are varied in (B), and parameter Threshold is varied in (C). Except for the parameters being varied in each plot, the other values are as follows: n_1 is 256, n_2 is 64, R_i is 64, R_e is 64 and Thr is -0.3. These parameter values were among those that resulted in the highest values of TP %, just above 98%.

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