Using a Generalized Neural Network to Identify Airway Obstructions in Anesthetized Patients Post-Operatively based on Photoplethysmography

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***Abstract*- Photoplethysmography has been recently studied as a non-invasive indicator of circulatory and respiratory function. In this study, photoplethysmographic (PPG) data were recorded from patients under the influence of anesthesia, but not intubated. Both time and frequency domain features were extracted from the PPG and used as inputs to a neural network classifier. This classifier considers inter-subject variability so that it generalizes well to a large population. This classifier provided 86.1% accuracy to classify segments as being times of 'obstructed' vs. 'normal' airways status.**

INTRODUCTION

The pulse oximeter is a standard tool used in operating rooms around the world to detect blood oxygen saturation. Much more information can be obtained, however, through the study and exploitation of its photoplethysmogram (PPG) output. The PPG is a pulsatile waveform that provides an indirect measurement of blood volume under the sensor [1]. The temporal behavior of this signal is influenced both by the cardiac and respiratory cycles. Respiratory induced variations (RIV) in PPG amplitude have been documented and associated with airway obstruction, hypovolemia, and hypotension [2-4].

Anesthetized patients with undiagnosed obstructive sleep apnea are at risk of sudden respiratory failure after receiving anesthesia because of repressed respiratory and hemodynamic responses [5]. Even those patients without airway disorders may be at some risk. While a patient is being operated on under the influence of anesthetics, many factors can initiate complications in airway management, including neurological and physical. The most prominent neurological cause is the fact that the body is in a drug-induced state. Muscle relaxants in particular can disrupt respiration, and the physician cannot fully predict the extent to which this medication will affect an individual [6, 7]. In addition, mechanical factors, such as body position can interrupt normal function [8]. The body is in a markedly vulnerable state post-operatively due to the trauma involved in surgical operations [1], which can leave a patient particularly susceptible to airway obstructions.

The goal of this study is to use advanced signal processing techniques to develop an algorithm. This process will be used for the analysis of the PPG in order to the extraction of useful information regarding airway status. In particular, these techniques will utilize a forehead reflectance pulse oximeter to identify and distinguish between normal breathing events and obstructed airway events on patients under anesthesia. Such techniques have already proven successful for networks trained specifically for certain individuals [9]. This study aims to take into account inter-subject variability so that one network may be trained with data from a variety of subjects and can successfully classify airway status for any patient.

METHODS

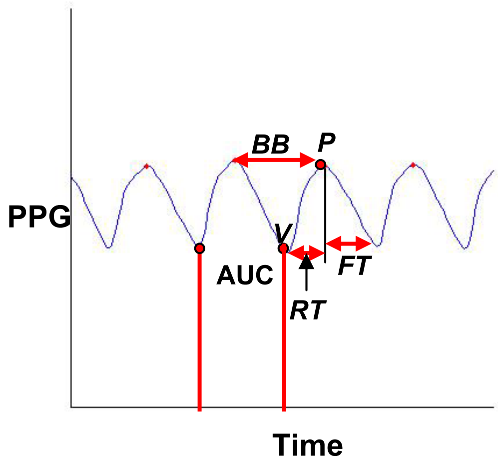
Patients were recruited with IRB approval from the surgical center at Dartmouth Hitchcock Medical Center. Data from a Nonin™ reflectance pulse-oximeter placed on the forehead were gathered in the operating room after extubation, but before transfer to the post anesthesia care unit (PACU). This period covered the time after the body experienced the trauma of surgery, when the patient was under the anesthetics, but was expected to be breathing independent of a mechanical respirator. The gold standard used to identify obstruction events involved a combination of signal from a pair of respiratory straps located on the thorax and abdomen, a CO_2 end tidal volume indicator, and an annotated collection of observations made by a trained anesthesiologist at the time of data recording.

PPG data were segmented with the aid of these supplemental sensors, and segments were grouped as 'normal' or 'obstructed' airway status. Signal analysis was performed on a MATLAB™ platform. Using a peak finding algorithm, local peaks of the PPG were identified and classified as occurring during one of these 'normal' or 'obstructed' periods. Both time and frequency domain features were then extracted for each segment. Time domain features were calculated from each pulse of the raw PPG, including peak and valley amplitudes, beat-to-beat interval time, rise time, fall time, and area under each peak, as illustrated in Figure 1a. Values for features in the time domain were averaged over all of the peaks in one segment. Additional time domain features included the difference between the highest and lowest peak as well as the difference between the highest and lowest valley during a segment. These differences gave an indication of the RIV strength during each segment. In order to extract frequency domain features, the PPG signals were first transformed to the frequency domain using parametric autoregressive (AR) techniques that employed the Burg algorithm. The following features were then extracted:

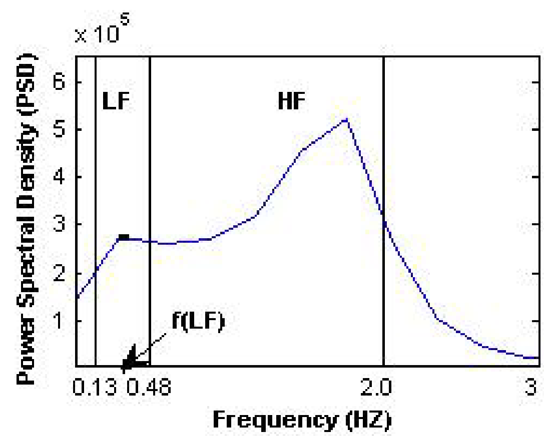
normalized low frequency power (LF/LF+HF) and the frequency of the LF peak (f(LF)), as shown in Figure 1b. For this purpose, low frequency was defined as the interval 0.2 Hz to 1.0 Hz to give and indication of respiration and high frequency was defined as the interval 1.0Hz to 2.0 Hz to give an indication of circulation [10].

The time domain features have been shown to be accurate indicators of respiratory function [11] as well as airway obstructions in patients with chronic pulmonary disease [12]. The two frequency features give an indication of respiratory effort and function as compared to effort and function of the circulatory system. Once these features were calculated, values were averaged over all peaks in a segment to obtain one set of 8 features per segment.

These values provided the inputs to a neural network classifier. Due to the nonlinearity of biological systems, a 4-layer, feed-forward, backpropagation network was built [11, 13], as illustrated in Figure 2. The first layer consisted of the 10 input features, the second layer increased the dimension space to 20 neurons, the third layer contained 10 neurons, and 1 of 2 outputs were given, which identified the class of the segment as 'normal' or 'obstructed'.



a.



b.

Figure 1. Time (a.) and frequency (b.) domain features extracted from each peak of the pulse oximeter waveform. Time domain features labeled include the beat to beat interval (BB) in seconds, the height of the peak (P) and valley (V) of each pulse, the rise time (RT) and fall time (FT) of each pulse in seconds, and the area under the curve for each pulse (AUC). Frequency domain features were defined by the low frequency band (LF) and the high frequency band (HF) where f(LF) denotes the frequency at which power peaked in the LF range.

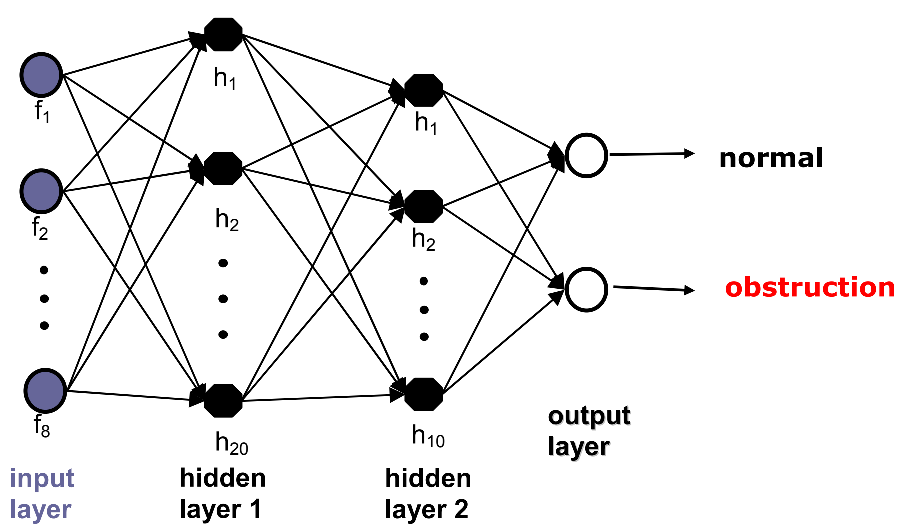


Figure 2. Setup for backpropagation neural network. The input layer consisted of 8 features, two hidden layers had 20 and 10 nodes, respectively, and the output indicated either normal or obstruction.

After the data were normalized on a scale from -1.0 to 1.0, the network was trained and tested on a subject by subject basis in order to reduce the effects of inter-subject variability. Half of the segments from each subject were used to train the network and the remaining half were used to test its performance.

The performance of each network was measured in terms of how well each segment in the 'test' group was classified. Sensitivity, specificity, and accuracy of the networks were calculated for each subject trial and used as performance metrics—sensitivity being the correct identification of an obstruction event, specificity being the correct identification of a normal event, and accuracy being the correct classification in general. Due to the random assignment of weights, one network may perform differently depending on the initial weight assignment at the start of the training process. Therefore, the same network was trained and tested five times to obtain an average performance index.

RESULTS

In total, successful data were gathered from 10 subjects (10 subjects did not experience any obstructions post-operatively). An example of the raw PPG from a subject that was breathing normally then obstructed is shown in Figure 3. A clear distinction is seen during the transition from one event to the next.

The minimum number of 5 second segments for any one subject was 18; therefore, in order to equally represent each subject in training, 18 segments from each were used. In addition, an attempt was made to have equal representation of obstruction events and normal breathing events. Therefore, when possible, these 18 segments included 9 of normal breathing and 9 during obstruction events. In total, 180 segments were used, 118 of normal breathing, 62 of obstruction events.

Using a leave one out method of training, the neural network classified with an average sensitivity of 72.9%, a specificity of 93.0%, a positive predictive value of 84.7%, a negative predictive value of 86.8%, and an overall accuracy of 86.1%.

DISCUSSION

These results indicate that the time and frequency features of the PPG are capable of distinguishing between normal and obstructed airway events. Figure 3 illustrates some clear changes between an 'obstruction' segment and an immediately preceding 'normal' segment. During normal breathing, a clear low frequency respiratory induced variation (RIV) is present, which virtually disappears once the airway is obstructed. In addition the pulse amplitude, the change in amplitude from valley to peak in the time domain shows a clear increase during the obstruction. The physiological implications of these waveform changes have yet to be investigated, but it is clear that features from both the time and the frequency domain are necessary to capture the differences in airway status.

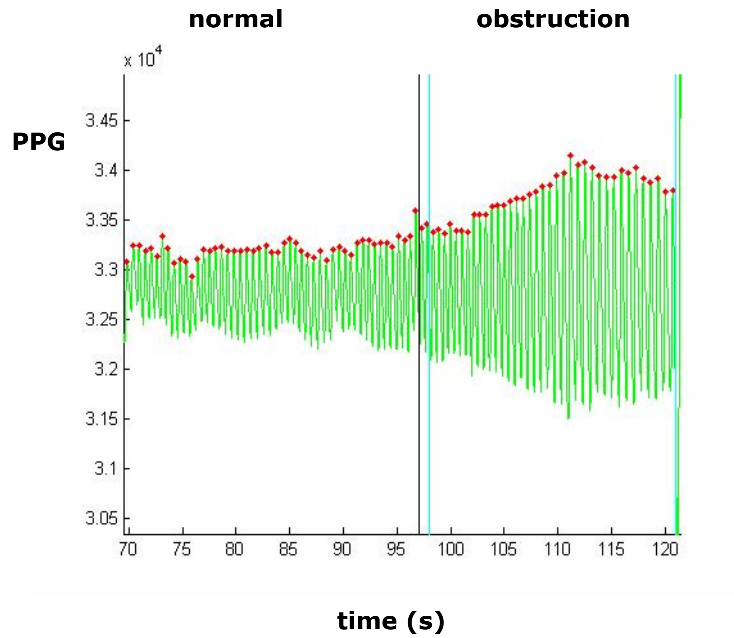


Figure 3. Raw PPG from one subject beginning during normal breathing and transitioning to an obstruction event.

The lower sensitivity performance of the neural network classifier may be attributed to the fact that considerably more of the segments were 'normal' events and fewer were 'obstructed' events. This allowed the network to better train for the 'normal' cases, resulting in a better classification for these segments when compared with segments from 'obstructed' events. Overall, the combination of these features have performed well at classifying normal and obstructed airway functions. The encouraging positive predictive value verifies that when a segment is identified as an obstruction it is done with great confidence. Similarly, the negative predictive value indicates only a 13.2% rate of false alarms as compared to a 28 % false alarm rate of the accepted standard of thoracic impedance bands.

The ability of neural networks to capture nonlinear patterns among a collection of inputs allows them to be appropriate classifiers for such complex physiological systems. The performance values verify that this particular network has potential to identify airway status. Improvements, however, must still be made.

Immediate focus will be placed on increasing the number of training vectors in the 'obstruction' category. This quantity balancing should improve the networks ability to recognize segments in each category, therefore, increasing sensitivity and accuracy. In addition, a more in depth study of each of the features will be conducted. This investigation will provide insight into which features are contributing to most of the variability, or contributing mostly to the classification, and may be completed using a principal components analysis. Further studies will also increase the data set. Instead of just focusing on post-operative patients, we will also consider pre-operative and peri-operative patients who are under anesthesia, but maintaining spontaneous breathing. This increase in data will allow us to determine the influence of surgical trauma on the ability of the PPG to identify airway status.

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