Estimation of Respiratory Information from the Built-In Pressure Sensors of a Dialysis Machine

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Abstract

The purpose of the present study is to determine the feasibility of estimating respiratory information from the built-in pressure sensors of a dialysis machine. The study database consists of simultaneous recordings of pressure signals and capnographic signals from 6 patients during 7 hemodialysis treatment sessions. Respiration rates were estimated using respiratory induced variations in the beat-to-beat interval series of the cardiac component of the pressure signal and respiratory induced baseline variations in the pressure signal, respectively. The estimated respiration rates were compared to a reference respiration rate determined from the capnograhpic signal. The root-mean-square error of the estimated respiration rate from the baseline variations of the pressure signal was 2.10 breaths/min; the corresponding error of the estimated respiration rate from the beat-to-beat interval series of the cardiac component was 4.95 breaths/min. The results suggest that it is possible to estimate respiratory information from the pressure sensors.

1. Introduction

Nocturnal home dialysis is getting increasingly popular, and during conventional in center dialysis treatment it is also common that patients sleep. The prevalence of sleep apnea in the chronic kidney disease population has been estimated to 30% or more, which can be compared to 2-4% in the general population [1]. Automated detection of sleep apnea is of particular interest during unsupervised home dialysis but can also be used for detection of silent sleep apnea, i.e., when the patient is not snoring, during conventional dialysis treatment. Although sleep apnea is common in patients with chronic renal failure, monitoring of respiratory information is not part of the clinical routine during hemodialysis. Introducing additional sensors to estimate respiratory information would cause patient discomfort and increased workload for the nursing staff. To avoid additional costs for monitoring, it would be highly desirable to take advantage of the built-in pressure sensors of the hemodialysis machine to extract respiratory information.

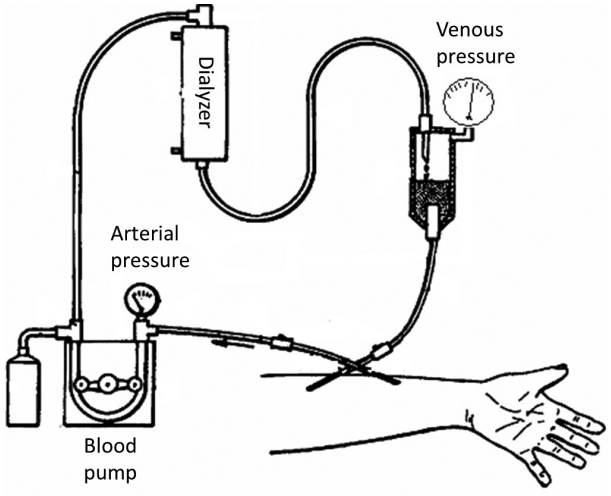

Figure 1. The extracorporeal blood circuit of a hemodialysis machine with venous and arterial pressure sensors and a peristaltic blood pump.

The main part of the pressure variations in the extracorporeal blood circuit (Fig 1) are caused by the peristaltic pump, but variations caused by heart beats and respiration are also present. These biological pressure variations are of much smaller magnitude than the pressure variations caused by the peristaltic pump, making extraction of cardiac and respiratory information from the pressure signal challenging.

Respiratory induced variations in peripheral blood volume measured using photoplethysmograpyh (PPG) has been extensively studied [2]. Several methods have been proposed for estimation of respiratory rate from PPG signals e.g., using respiratory induced frequency variations, respiratory induced intensity variations, respiratory in-

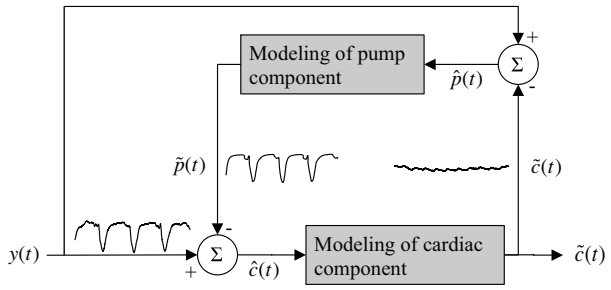

Figure 2. Overview of the method for extracting cardiac information from the pressure signal.

duced amplitude variations [3] and frequency modulation of the PPG waveform [4]. The pressure signal obtained from the extracorporeal blod circuit of the dialysis machine can be expected to contain respiratory induced variations similar to those found in PPG signals. However, these respiratory induced variations are concealed by the pressure variations caused by the blood pump of the dialysis machine.

Recently, we presented a method for extracting cardiac information from the extracorporeal sensors of a dialysis machine [5]. The method was evaluated on simulated and real data, showing that heart pulse occurrence times can be estimated fairly accurate from the pressure signal when the magnitude of cardiac component is sufficiently large. The purpose of the present study is to determine the feasibility of extracting respiratory information from the extracorporeal pressure sensors of the dialysis machine using (1) the heart pulse occurrence times of the cardiac component in the pressure signal and (2) respiratory induced baseline pressure signal variations.

2. Methods

The cardiac component was extracted from the pressure signal using an alternating iterative technique, where successively better estimate of the pump-induced pressure variations are subtracted from the pressure signal [5]. Briefly, the cardiac component $\hat{c}(t)$ is estimated by subtracting a modelled pump signal $\tilde{p}(t)$ from the observed pressure signal $y(t)$, and the pump-induced pressure variation component $\hat{p}(t)$ is estimated by subtracting a modeled cardiac signal $\tilde{c}(t)$ from $y(t)$, see Fig. 2. For each iteration, the modelled signals $\tilde{p}(t)$ and $\tilde{c}(t)$ are refined, which gradually decreases the amount of pump/cardiac signal remainders in the estimates.

The pump profile and the cardiac profile are two central concepts of the signal modeling; the pump profile characterizes the changes in pressure that occur during one revolution of the blood pump, whereas the cardiac profile characterizes the changes in pressure that occur during one cardiac cycle. Both profiles are obtained by ensemble averaging of signal cycle segments which first have been normalized with respect to their duration. For each iteration, the cardiac profile and the pump profile are recalculated. An initial estimate of the cardiac component $\hat{c}(t)$ is obtained by subtracting a periodic extension of the pump profile from the pressure signal $y(t)$. The model cardiac signal $\tilde{c}(t)$ is created by concatenation of cardiac profiles which have first been scaled with respect to the duration of the each cardiac cycle, so that it best fits the cardiac signal $\hat{c}(t)$ in the least square error sense. When modeling the pump signal $\tilde{p}(t)$, each pump revolution has its own individual period length, thereby accounting for the fact that pump speed can vary slightly from revolution to revolution. Similarly to the cardiac signal modeling, a least square error criterion is employed to estimate the duration of each pump cycle.

When the difference between successive estimates of pump period times is sufficiently small, the iteration process terminates and the heart pulse occurrence times are estimated from a lowpass filtered cardiac signal $\hat{c}(t)$ using the mid-amplitude point of each heartbeat [6]. A uniformly sampled and smoothed instantaneous heart rate signal was obtained from the estimated occurrence times interval series using Berger algorithm [7]; the sampling frequency of the heart rate signal was set to 4 Hz to match the sampling frequency of the reference capnographic signal. The short-time Fourier transform (256 point, 16s overlap) was used for time-frequency analysis of the heart rate signal; the respiratory rate was estimated by the position of the maximum peak of the power spectrum in the 0.15 to 0.4 Hz range. Similar methodology was used to estimate the respiration rate from the baseline variations of the pressure signal, following DC-offset removal and resampling at 4 Hz, and from the reference capnographic signal, respectively.

3. Dataset

The study database consists of simultaneously recorded pressure signals and capnographic signals from 6 patients during 7 hemodialysis treatment. The data was acquired at Skåne Universital Hospital, Lund, Sweden, in a study approved by the local ethics review board. Patient characteristics is summarized in Table 1. From each recording, one manually selected 20-min segment with sufficient signal quality was used for evaluation.

4. Results

The spectra of 1-min segments of the baseline variations of the pressure signal, the heart rate signal derived from the cardiac component of the pressure signal, and the reference capnographic signal, respectively, are displayed in

Table 1. Patient characteristics.

Male (Female)	5 (1)
Age (years)	61.3 ± 13.2
Weight (kg)	84.9 ± 18.1
Time on dialysis (months)	52.8 ± 26.1

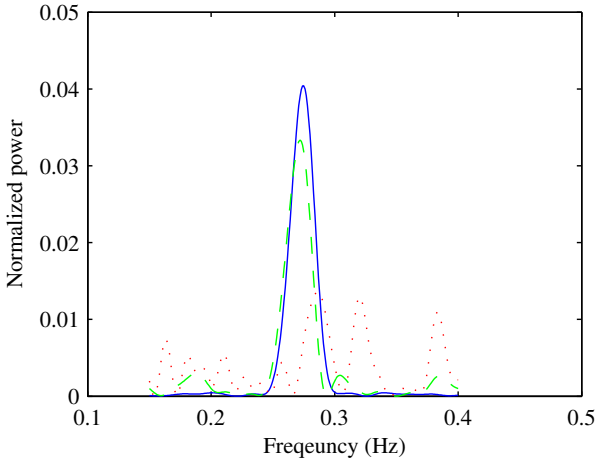

Figure 3. Normalized spectra from corresponding one-minute segments of heart rate derived from the cardiac component of the pressure signal (dotted red), baseline variations of the pressure signal (dashed green), and reference capnographic signal (solid blue).

Fig. 3. Whereas the spectrum of the baseline variations of the pressure signal exhibits a clear peak almost overlapping with the spectral peak of the reference capnographic signal at 0.27 Hz corresponding to 16.2 breaths/min, the spectrum of the heart rate signal is multimodal and its maximum peak is located at 0.29 Hz corresponding to 17.4 breaths/min.

The differences between respiration rate estimated using heart rate derived from extracted cardiac component and respiration rate estimated from the reference capnographic signal for all analyzed 1-min segments are plotted versus respiration rate estimated from the reference capnographic signal in Fig. 4. The corresponding differences between estimated respiration rate using baseline variations of the pressure signal and reference capnographic signal are plotted in Fig. 5. The average difference was -0.015 ± 5.38 breaths/min for respiration rates extracted from the cardiac component, and 0.073 ± 2.55 breaths/min for respiration rates estimated from the baseline variations of the pressure signal.

The trends of the estimated respiration rates for one patient during 20 min, obtained from the pressure signal, the heart rate signal derived from the cardiac component of the pressure signal, and the capnographic signal, respectively,

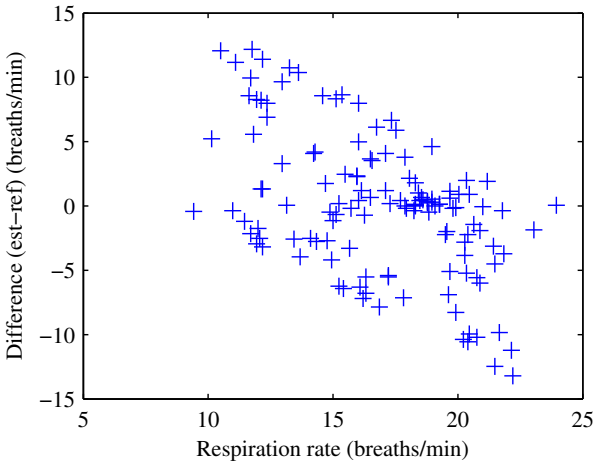

Figure 4. Differences between respiration rate estimates from the reference capnographic signal and from the extracted cardiac component versus respiration rate estimates from the reference capnographic signal.

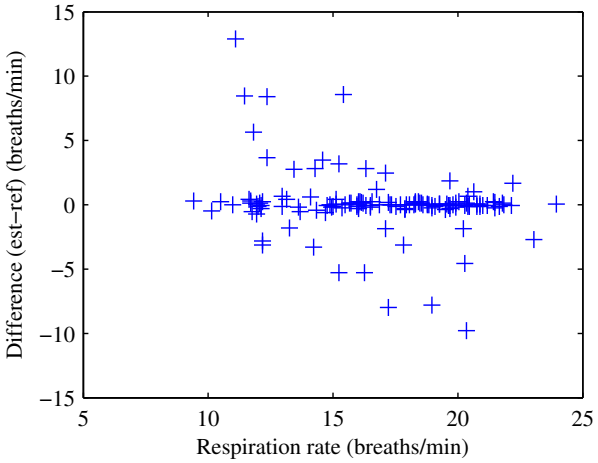

Figure 5. Differences between respiration rate estimates from the reference capnographic signal and from the baseline pressure variations versus respiration rate estimates from the reference capnographic signal.

are displayed in Fig. 6. For this particular patient, the root-mean-square (rms) error of the estimated respiration rate obtained using the baseline variations of the pressure signal as compared to the reference capnographic signal was 0.79 breaths/min whereas the corresponding error of respiration rate obtained using the beat-to-beat series of the extracted cardiac component was 3.14 breaths/min.

The distributions of rms error in estimated respiration rate obtained from the cardiac component of the pressure signal and the baseline variations, respectively, among the patients in the study population are displayed in Fig. 7. The average rms error for respiration rate obtained using the ex-

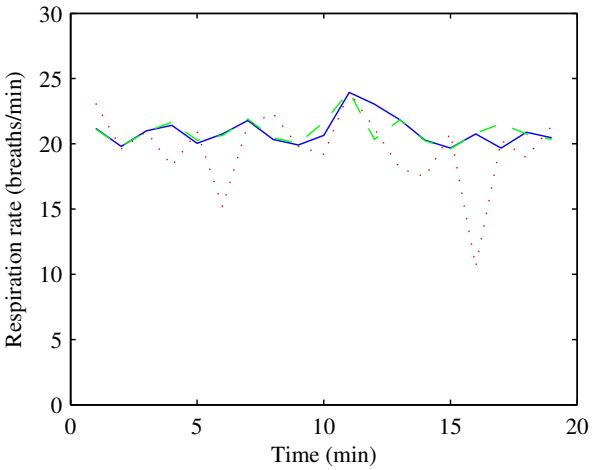

Figure 6. Respiration rate trends of one patient estimated using (dotted red) heart rate derived from the cardiac component of the pressure signal, (dashed green) the pressure signal, and (solid blue) reference capnograhic signal.

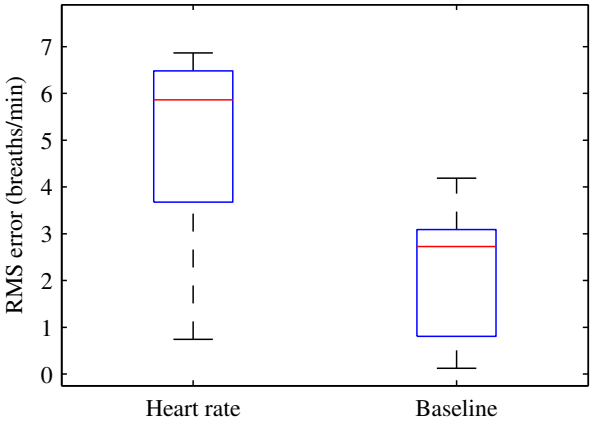

Figure 7. Distribution of rms error of estimated respiration rate obtained from extracted heart rate and from baseline variations in the pressure signal, respectively.

tracted cardiac component was 4.95 breaths/min, whereas the corresponding value for respiration rate extracted from the baseline pressure variations was 2.10 breaths/min. According to the Wilcoxon signed rank test, the rms error was significantly larger for respiration rate estimates obtained from the cardiac component of the pressure signal than for respiration rate estimates obtained from the baseline variations of the pressure signal ($p < 0.05$).

5. Discussion and Conclusions

The feasibility of extracting respiratory information from the extracorporeal pressure sensors of the dialysis machine using heart pulse occurrence times of the extracted cardiac component and respiration induced baseline variations, respectively, was tested. Estimation of respiration rate from the respiratory induced baseline variations proved to be significantly more accurate than estimation of respiratory rate from the extracted cardiac component of the pressure signal. One reason for this results may be that autonomic response is often impaired in dialysis patiens [8]. Another reason may be insufficient accuracy of the estimated heart pulse occurrent times. The results suggest that it is possible to estimate respiratory information from the pressure sensors of a dialysis machine.

References

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