Estimation of Respiratory Rate From ECG, Photoplethysmogram, and Piezoelectric Pulse Transducer Signals: A Comparative Study of Time–Frequency Methods

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***Abstract*—We compare the performance of two different time–frequency-based breathing rate (BR) detection algorithms when used on three different physiological signals: the ECG, the photoplethysmogram (PPG), and the piezoelectric pulse transducer (PZO) signal. Studies carried out over the past have shown the existence of amplitude and/or FMs due to respiration in physiological signals, such as those mentioned. In a recent study, we analyzed the PPG signal and detected the FM and amplitude modulation effect that controlled breathing had on it, and inferred the rate of respiration using the time–frequency spectrum (TFS) (via a wavelet (WT) or complex demodulation (CDM) approach). We showed that such TFS BR detection methods were very accurate and consistently outperformed the exclusively time-domain autoregressive modeling (AR) method, especially in the real-time (data length of 1 min) case. We now explore the possibility of using these methods on the ECG and the finger PZO signal, of which only the former has been previously used with some success to derive BR. Testing performed on 15 healthy human subjects for a range of BR and two body positions showed that though the PPG signal gave the most consistently high performance, the ECG and PZO also proved to be reasonably accurate over longer time segments. Furthermore, the CDM approach was on average either better than or comparable to the WT method in terms of both accuracy and repeatability of the detection.**

***Index Terms*—Complex demodulation (CDM), ECG, piezoelectric sensors, pulse oximeter, respiratory rate, wavelets (WTs).**

I. Introduction

NONINVASIVE respiratory monitoring is an extensive field of research, which has seen widespread interest for several years. The necessity for early detection and diagnosis of potentially dangerous conditions, such as sleep apnea [1], sudden infant death syndrome [2], or chronic obstructive pulmonary disease [3] has fostered the development of several novel methods for measuring respiratory activity [4], especially in ambulatory settings. Indeed, devices such as the capnograph, pulse oximeter, and the inductance plethysmograph are routinely used in hospital and critical care centers to monitor patients' cardiorespiratory status.

The term "respiratory activity" is generally understood to encompass parameters, such as the patients' rate and depth of breathing, and degree of gas exchange [4], all of which are highly quantifiable measures. However, it is important to understand that measuring only one of these parameters is of considerably less use than monitoring all of them, or at least as many as possible. For instance, an inductance plethysmograph (a belt-like device that quantifies the physical expansion of the chest and/or abdominal wall) is a very good estimator of the breathing rate (BR), but provides no information regarding the percentage of oxygen saturation, thus lessening the cost-benefit advantage considerably. To this end, several devices aim to estimate many respiratory activity measures from as few nonobtrusive devices as possible.

In a previous study [5], we attempted to derive estimates of the BR from the signal acquired by the pulse oximeter—a device based on photoplethysmography (PPG) that is used clinically to measure the rate of arterial oxygen saturation (SaO_2) and cardiac rhythms—using a method based on time–frequency spectral (TFS) estimation via complex demodulation (CDM) [6]. The objective is by no means a new one, and several notable methods have been devised to measure respiratory rate from the pulse oximeter signal [7]–[14], although a time–frequency approach (as opposed to operating only in the time domain) is a fairly recent development. We compared the known BR of 15 healthy young subjects with BR estimation from a time-domain autoregressive (AR) method [9] and a wavelet (WT) based TFS method [7], [8], [15]. Our findings confirmed that the inherent nonstationarities and subtle FM, and amplitude modulation in the PPG signal can be best detected using a TFS approach. Furthermore, we also found that the CDM-TFS method performed consistently at par with or better than the WT-based method in terms of accuracy and repeatability, while being considerably faster in terms of computation time.

The aim of the study is to determine whether a similar BR estimation method would work with other signals associated with cardiorespiratory status, namely the ECG and the piezoelectric pulse sensor (PZO). Specifically, we are interested in determining, which BR estimation method is optimal for ECG, PPG, and PZO signals.

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The ECG has been used in many different ways to quantify effects of breathing. The most well-known respiration-related effect is its influence on the variability of heart rate (respiratory sinus arrhythmia). However, for the purposes of this study, we are interested only in the rate of respiration. In this regard, there has been a profusion of research on so-called ECG-derived respiratory activity (EDR) measures, with a multitude of signal processing algorithms available to derive respiratory induced modulations from both multilead and single-lead ECG signals. The simplest single-lead ECG algorithms utilize the amplitude modulations in or variations in area under the QRS complex or T-wave [16]. Usually, some signal processing method for canceling baseline wander is used to enhance the detection in the presence of noise or artifacts [17]. Alternatively, one can also use the heart-rate time series (RR interval series) derived from accurate QRS complex detection algorithms applied to the ECG [16]. However, it is generally understood that the presence of pacemakers and/or abnormal heart rhythms renders the heart-rate method much less useful. As a result, we concentrate on simply the raw ECG signal in this study and do not attempt to derive any heart-rate series from it.

The piezoelectric sensor has been used in many studies to measure the arterial pulse signal. It relies on the property of the piezoelectric material to produce electrical potentials in response to applied mechanical stress (the reverse is also true, i.e., application of an electric field across the material will produce stress/strain variations in the material). Although piezoelectric finger-pulse sensors have been around for some time, there is a surprising dearth of literature on its applications and potential uses, especially in the field of respiratory monitoring. Nonperipheral piezoelectric sensors have been used to detect breathing effects, utilizing the pyroelectric property [18], which directly measures the electric potential changes produced when the piezoelectric ceramic is impacted by respiratory airflow, or by placing a piezoelectric transducer under the body [19], therefore it can directly measure the mechanical effects of heartbeat and breathing, although Sato *et al.* [19] have only used this on anesthetized mice. To the best of our knowledge, extraction of breathing signals from the piezoelectric finger pulse has only been done in one study, that of Chen *et al.* [20], which attempted to extract the breathing signal from a polyvinylidene fluoride (PVDF) sensor using simple time-domain filtering techniques.

Given the outlined scenarios, we aim to compare the WT TFS and the CDM methods' accuracy (median% detection error) and repeatability (interquartile range (IQR) of % detection error) when applied to the three physiological signals discussed earlier. The objective is to determine, which of these three widely used signals gives the best estimates of BR when used in real-time settings. Moreover, we aim to find any differences in performances arising because of differences in TFS-estimation methods (CDM or WT decomposition).

II. Methods

A. Data Acquisition

Data were collected on 15 healthy subjects (seven female and eight male, mean age 21 $\pm$ 1.2 years) using four different sensors. An MP506 pulse oximeter (Nellcor Oximax, Boulder, CO) reusable sensor (Durasensor DS-100 A) incorporating a conditioning circuit with analog output of 4.864 kHz was attached to each subject's left index finger. On the right index finger, the piezoelectric sensor (Jameco Electronics, Belmont CA) was attached using a simple Velcro belt strap. A single-lead ECG signal was obtained using a standard three electrode system, with two electrodes on the chest and one close to the waist. Breathing signal was also acquired via the Respitrace system, which uses inductive plethysmography to provide calibrated voltage outputs corresponding to rib cage and abdominal compartment volume changes. No subject had cardiorespiratory related pathologies. Data were collected in the upright and supine positions. The subjects were instructed to breathe at a constant rate according to a timed beeping sound, i.e., to start an inspiration whenever they heard a beep sound programmed at a chosen frequency. The data were collected for breathing frequencies ranging from 0.2 to 0.6 Hz at an increment of 0.1 Hz. We did not perform analysis higher than 0.6 Hz, since both the WT and CDM approaches did not provide accurate BR estimation results. Further, we did not include 0.1 Hz because the Mayer wave has a characteristic at the same frequency and may confound BR detection. The subjects were given a minute to practice breathing at the beeping rate. Three minutes of data were then collected for each frequency for each subject, for both upright and supine positions, with appropriate rest periods given to all subjects while the metronome beeping frequency was being changed. Since in this study, we are merely interested in the rate of respiration and not the depth (amplitude), a simple fast Fourier transform and/or manual counting of the number of peaks can be done on the Respitrace signal to obtain the true BR. Data acquisition was done using the ADInstruments PowerLab/4Sp data acquisition system and routed into the PC via a USB port. Chart v4.2.2 software (ADInstruments, Colorado Springs, CO) was used to sample the analog signal at 200 Hz.

The BR estimation algorithms (implemented on MATLAB) were applied to 1-min segments of the signal with an overlap of 50 s. Thus, BR was updated every 10 s. The 1-min signal segment sampled at 200 Hz was first downsampled to 20 Hz (after low-pass filtering to prevent aliasing), and then, demeaned and normalized. After this, one of the two BR estimation methods described later is applied to the signal.

B. BR Detection Algorithms

1) Variable Frequency CDM Method for TFS Estimation: We have described the CDM method in previous studies in detail [5], [6] and present only a brief overview next.

Consider a sinusoidal signal $x(t)$ to be a narrow band oscillation with a center frequency f_0, instantaneous amplitude $A(t)$, phase $\phi(t)$, and the direct current component dc(t)

$$x(t) = \mathrm{dc}(t) + A(t)\cos(2\pi f_0 t + \phi(t)). \tag{1}$$

For a given center frequency, we can extract the instantaneous amplitude information $A(t)$ and phase information $\phi(t)$

by multiplying (1) by $e^{-j2\pi f_0 t}$, which results in the following:

$$z(t) = x(t)e^{-j2\pi f_0 t} = \mathrm{dc}(t)e^{-j2\pi f_0 t} + \left(\frac{A(t)}{2}\right)e^{j\phi(t)} + \left(\frac{A(t)}{2}\right)e^{-j(4\pi f_0 t + \phi(t))}. \quad (2)$$

A leftward shift by $e^{-j2\pi f_0 t}$ results in moving the center frequency f_0 to zero frequency in the spectrum of $z(t)$. If $z(t)$ in (2) is subjected to an ideal low-pass filter (LPF) with a cutoff frequency $f_c < f_0$, then the filtered signal $z_{lp}(t)$ will contain only the component of interest and we obtain the following:

$$z_{lp}(t) = \frac{A(t)}{2}e^{j\phi(t)} \quad (3)$$

$$A(t) = 2\,|z_{lp}(t)| \quad (4)$$

$$\phi(t) = \tan^{-1}\frac{\mathrm{imag}(z_{lp}(t))}{\mathrm{real}(z_{lp}(t))}. \quad (5)$$

The method can easily be extended to the variable frequency case as explained in [6], where the modulating frequency is expressed as $\int_0^t 2\pi f(\tau)d\tau$ and the negative exponential term used for the demodulation is $e^{-j\int_0^t 2\pi f(\tau)d\tau}$. The instantaneous frequency can be obtained using the familiar differentiation of phase information [21] as follows:

$$f(t) = f_0 + \frac{1}{2\pi}\frac{d\phi(t)}{d(t)}. \quad (6)$$

The variable frequency CDM (VFCDM) method, thus involves a two-step procedure. The first step is to use the CDM or what we termed the fixed frequency CDM (FFCDM) to obtain an estimate of the TFS, and the second step is to select only the dominant frequencies of interest for further refinement of the time–frequency resolution using the VFCDM approach. In the first step of the VFCDM method, a bank of LPFs is used to decompose the signal into a suite of band-limited signals. The analytic signals that are obtained from these, through use of the Hilbert transform, then provide estimates of instantaneous amplitude, frequency, and phase within each frequency band.

2) WT Decomposition Method for TFS Estimation: Leonard *et al.* [11], [15], [22] utilize the WT decomposition method to get an estimate of the TFS of the PPG signal. This is an established method, which has been used in a wide range of applications to get TFS estimates. In accordance with recommendations by Leonard *et al.*, we used a Morlet WT with a half-length of five samples at the coarsest scale to get a scalogram of the signal. For further technical details the reader may refer to [11], [15], [22].

3) Extraction of the FM Sequence: Note that filtering or peak detection procedures on the measured ECG, PPG, and PZO data are not required prior to computation of TFS via the VFCDM. This is certainly one of the notable advantages of our approach. After the TFS of the unaltered signal (ECG, PPG, or PZO) is obtained either through the VFCDM or the WT methods, the variation of the peaks at the pulse frequency are extracted. One can do this relatively simply, since the peak at the heart-rate frequency (approximately 1 Hz for healthy hearts) is easily the highest of all other peaks for any of the three signals considered. We thus define a "ridge band" around the heart-rate frequency. For each time point, we detect the frequency within this "ridge band" at which the spectrum has maximum amplitude. We can thus obtain a time series of frequency values, which we call the "FM sequence". In keeping with our assumption that breathing has a FM effect on the signal, we then find the power spectrum of this FM sequence using a Welch method. The frequency at which the highest peak occurs (within a specified feasible breathing frequency range of 0.15–0.7 Hz) is the detected BR. Other technical details of the algorithm can be found in [5].

Fig. 1 shows an example implementation of the algorithm for the PPG signal of a subject breathing at 0.2 Hz (12 breaths per minute) using the VFCDM and WT approaches. Note that the y-axes' ranges in Fig. 1(c) and (d) are slightly different. This is because, in the WT methodology, frequency is an approximate conversion from "scale", whereas the VFCDM approach uses the standard definition of frequency as periodicity of sinusoids.

III. Results

A complete comparison of both methods for the three signals considered requires statistical comparisons of detection accuracy, and consistency for a variety of breathing conditions and true BRs. Similar to the analysis methods in our previous study [5], we divided the BRs into two different categories. BRs of 0.2 and 0.3 Hz were grouped into low-frequency (LF) group, while BR's of 0.4, 0.5, and 0.6 Hz were categorized as members of the high-frequency (HF) group. We also studied the effect of body position (supine or upright) on the detection performance. Hence, we have four broad categories of test conditions, namely supine LF, supine HF, upright LF, and upright HF. As mentioned earlier, 3 min of data were collected for each subject for each BR for two different body positions. For each such 3-minute dataset, detection was carried out for 1-min data segments with an overlap of 50 s. Hence for each subject, there were 13 different observations for each BR (in supine and upright condition).

In order to measure performance of the detector, we quantified the accuracy as well as the repeatability of each method. For this, we first calculate the percentage detection error for every 1-min data segment for each method as follows:

$$\%\mathrm{Error} = \frac{\text{Detected BR} - \text{True BR}}{\text{True BR}} \times 100. \quad (7)$$

We next quantified the "accuracy" as the median detection error% over the 13 observations for each 3-min dataset. The "repeatability" is measured as the IQR (difference between the 75th and 25th percentile) of the detection error% over the 13 observations. In general, we observed that the methods studied had nonnormal distributions of the detection error% over the 3-min dataset. Therefore, we use the median and IQR instead of the mean and standard deviation of the observed errors. Accordingly, the statistical tests used are also nonparametric. The two performance measures "accuracy" and "repeatability" defined earlier are inverse metrics, i.e., the closer the value of median error% (or IQR of error%) is to zero the better the "accuracy" (or "repeatability").

In order to perform a compact statistical hypothesis testing for differences in the two performance metrics between different

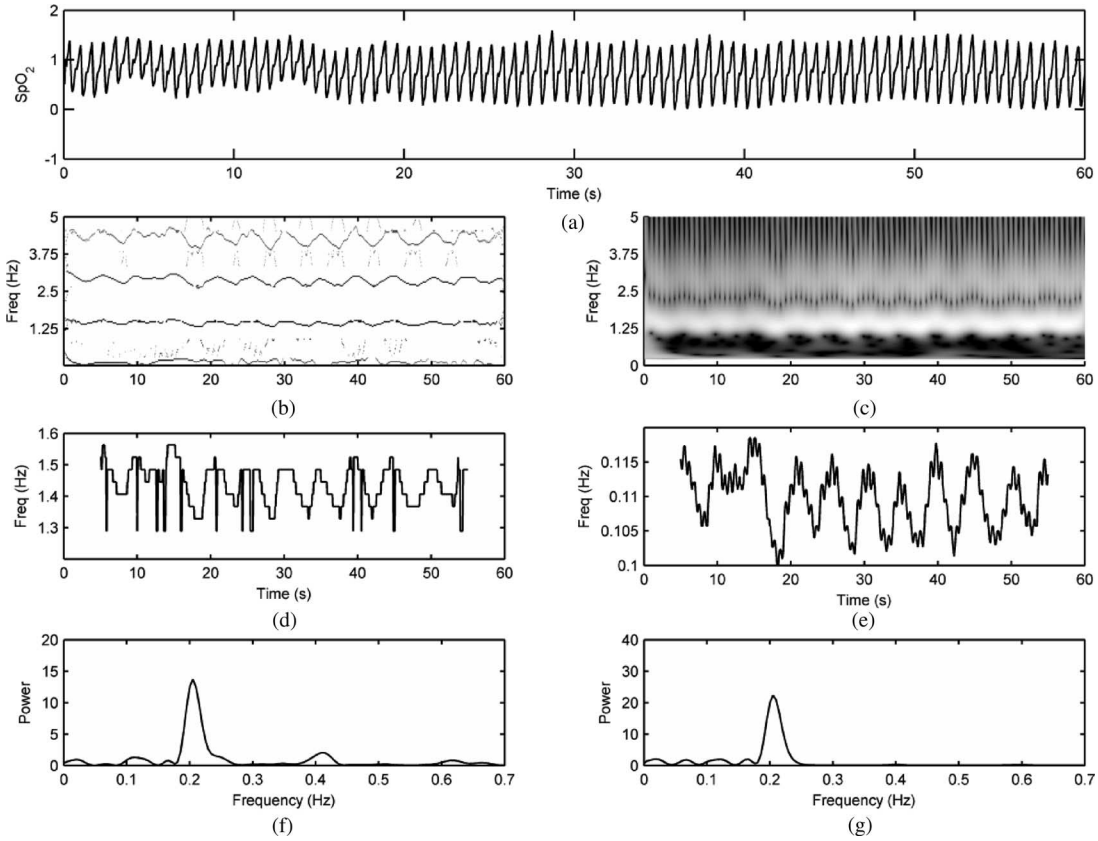


Fig. 1. Example BR estimation from the PPG signal using the VFCDM and WT methods. (a) Raw PPG signal acquired at 200 Hz. After low-pass filtering and downsampling to 20 Hz, the TFS is estimated using (b) the VFCDM algorithm or (c) the WT algorithm. (d) and (e) FM sequence (variation of the pulse frequency (around 1.4 Hz) component) extracted using a peak detection algorithm from the two methods. (f) and (g) Welch periodograms of the FM sequences extracted from the two TF spectra. A clear peak is visible at 0.2 Hz, which is the true BR (12 beats per minute).

methods, we define six different categories of results for each of the four breathing conditions (supine LF, supine HF, upright LF, and upright HF), namely WT-ECG (WTFM-ECG), WT-PPG (WTFM-PPG), WT-PZO (WTFM-PZO), VFCDMFM-ECG, VFCDMFM-PPG, and VFCDMFM-PZO. To test for differences in median "accuracy" and "repeatability", we used the Kruskal–Wallis test, which is the nonparametric equivalent of the one-way analysis of variance test. If significant differences ($p < 0.05$) were found, we used a multiple comparison procedure on ranks to find pairs of methods that had different median values.

A. Differences in "Accuracy" (Median% Error Across 3-min Detection)

Fig. 2 shows the distributions of median percentage detection errors across the population of the 15 subjects for each method for each of the four test conditions, the PPG signal provided the best results with regard to accuracy (lowest median% error). Table Ishows the numerical statistics (median range and IQR) for the "accuracy" across the population of test subjects. The median and IQR would be equivalent to the population means and standard deviations of accuracies had the distributions been normal. However, the differences in accuracy were not always significant. In the supine-LF and upright-LF cases, the WTFM-PPG and the VFCDMFM-PPG methods were significantly more accurate than all other methods; there was no significant difference between the two PPG methods. For the supine-HF case, the WTFM-PPG method was found to be significantly more likely to underestimate the BR than the VFCDMFM-PZO method, while no other significant differences were found. For the upright HF case, no significant accuracy differences were found between any pair of methods. Overall, it would be fair to say that although the PPG methods were much better with regard to accuracy, nearly all six methods gave fairly good average BR estimates over 3 min of data. The exception was the WT-FM method in the supine-HF test condition, which was found to consistently underestimate the true BR. These results are summarized in Table II.

B. Differences in "Repeatability" (IQR of % Detection Error)

Fig. 3 shows the distribution of the repeatability values for all 15 subjects for the four test conditions studied. Table III shows the numerical statistics (median range and IQR) for the "repeatability" across the population of test subjects. The median and IQR would be equivalent to the population means and standard deviations of repeatabilities, had the distributions been normal. Once again, the PPG signal generally gave much better results than the ECG or the PZO signal, i.e., the rate tracking ability of the BR detection method is much better when the pulse oximeter is used. However, it is instructive to note that the CDM

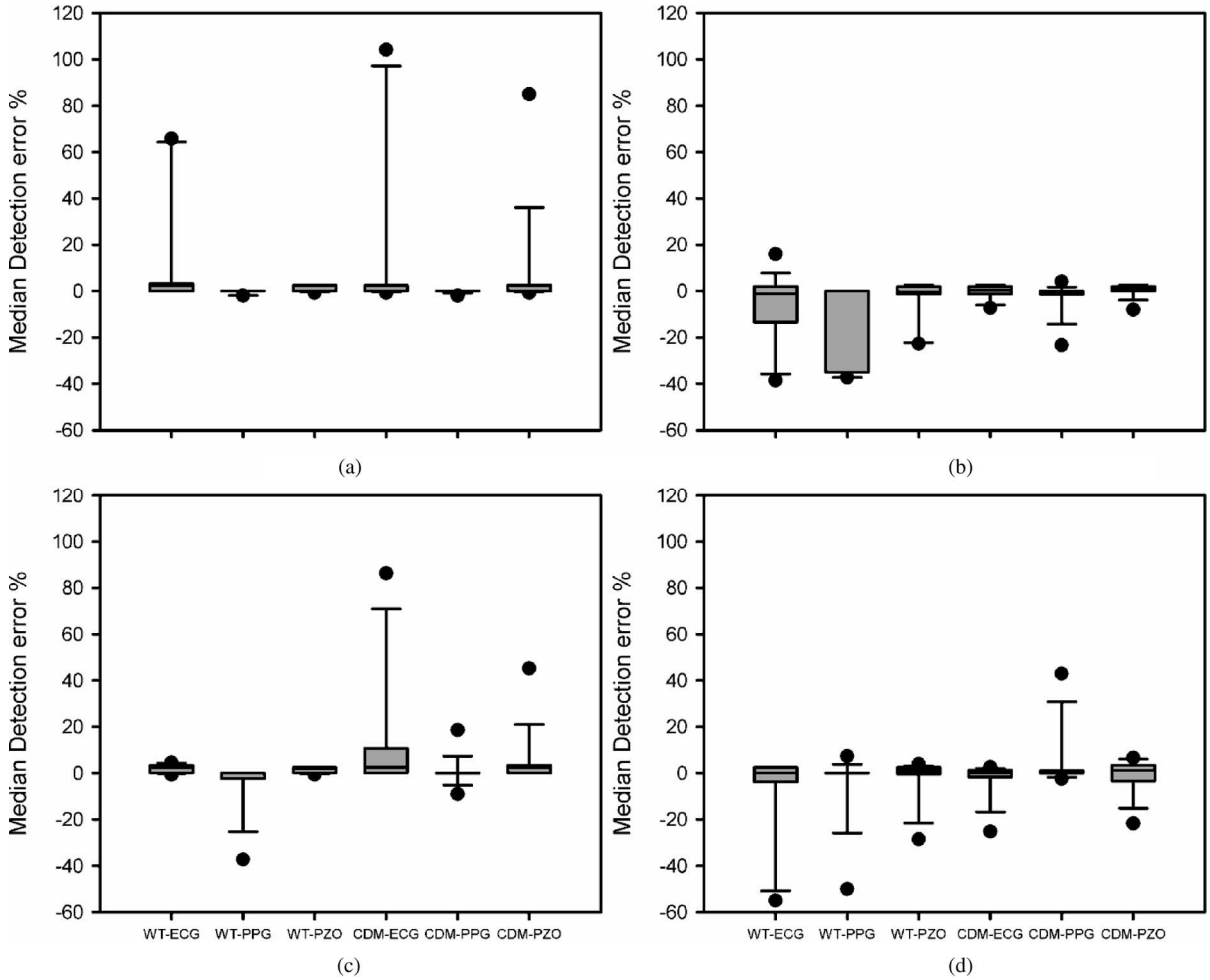


Fig. 2. Distributions of "accuracy" median% detection errors across the 15 subjects breathing in (a) supine position and low BRs (0.2–0.3 Hz), (b) supine position and at high BRs (0.4, 0.5, and 0.6 Hz), (c) upright position at low BRs, and (d) upright position and high BRs. The closer the median detection error set to zero, the better the accuracy of the method. The lower boundary of the box closest to zero indicates the 25th percentile, a line within the box marks the median, and the upper boundary of the box farthest from zero indicates the 75th percentile. Hence, the grey area of the box is an indication of the spread, i.e., the variation in median error (or IQR), across the population. Whiskers (error bars) above and below the box indicate the 90th and 10th percentiles. Solid circles represent the 5th and 95th percentiles.

TABLE I
POPULATION STATISTICS FOR MEDIAN% DETECTION ERRORS ("ACCURACIES") FOR EACH METHOD STUDIED FOR DIFFERENT TEST CONDITIONS

Test State	WTFM ECG		WTFM PPG		WTFM PZO		VFCDMFM ECG		VFCDMFM PPG		VFCDMFM PZO	
	Median of Median % Error	IQR of Median % Error	Median of Median % Error	IQR of Median % Error	Median of Median % Error	IQR of Median % Error	Median of Median % Error	IQR of Median % Error	Median of Median % Error	IQR of Median % Error	Median of Median % Error	IQR of Median % Error
Sup. LF	2.50	2.64	0.00	0.00	2.50	2.40	2.50	2.40	0.00	0.00	2.50	2.40
Sup. HF	-1.00	12.31	0.00	26.51	-0.39	3.02	0.34	3.09	0.00	1.18	1.00	1.90
Upr. LF	2.50	3.03	0.00	1.83	2.08	2.40	2.50	9.90	0.00	0.00	2.50	2.43
Upr. HF	0.10	5.25	0.00	0.00	0.92	2.75	0.10	2.75	0.00	1.07	1.25	5.97

method (applied to the PPG) showed remarkably lower value of IQR of % errors than all the other methods studied here. For each of the four different test conditions, the VFCDMFM-PPG method had significantly lower ($p < 0.05$) IQR% errors than any other method, as summarized in Table IV. Additionally, in the supine-LF case, we found that the WTFM-ECG method showed significantly lower repeatability (higher IQR of % error) than the WTFM-PPG method. No other significant pairwise differences were found for the methods studied, for any of the four different test conditions.

TABLE II
HYPOTHESIS TESTING RESULTS FOR MEDIAN% DETECTION ERRORS ("ACCURACIES") FOR DIFFERENT PAIRS OF METHODS UNDER DIFFERENT TEST CONDITIONS

Test Condition	Method-Pairs having Significant Differences in "Median % Detection Error"
Supine LF	**WTFM-PPG** < all other methods except VFCDMFM-PPG **VFCDMFM-PPG** < all other methods except WTFM-PPG No other significant differences
Supine HF	WTFM-PPG < **VFCDMFM-PZO** No other significant differences
Upright LF	**WTFM-PPG** < all other methods except VFCDMFM-PPG **VFCDMFM-PPG** < all other methods except WTFM-PPG No other significant differences
Upright HF	No significant differences

Higher accuracy is implied by median errors more tightly bound around zero. In this case, the more accurate method is denoted in boldface.

IV. DISCUSSION

Respiratory rate detection in a real-time noninvasive setting is an important requirement in many clinical settings, ambulatory, or otherwise. In several situations, it is necessary to have continuous monitoring of respiratory activity, which involves not only the measurement of actual saturation levels but also of BR. For example, a patient can maintain relatively good O_2 saturation levels with high BRs and *vice versa*. Thus, having information on BRs can lead to better diagnostic care when used in combination with O_2 saturation data.

While technology for capnography or inductive plethysmography methods has been becoming increasingly less cumbersome, they are still quite clumsy to use and may contribute to patient discomfort, especially for very young or very old subjects. Alternatively, using a manual counting method for BR estimation is not only highly labor intensive, but also quite subjective, especially in those cases where the mechanical effects of breathing are subtle [23]. Human observers usually view the movement of the abdomen and/or rib cage to detect expiration or inhalation. However, there is a tendency to overestimate this effect in the presence of low-tidal volume that may frequently lead to inaccuracies in breathing detection [23]. Sometimes variations of skin color are used to estimate the degree of respiratory gas exchange, a method that is quite obviously prone to errors. Even if these problems can be somehow overcome (maybe through adequate training) the cost-benefit ratio of employing dedicated human observers for continuous monitoring of respiration is too low for it to remain a viable option.

In recent years, the development of (generally) error-free, easy-to-use, noninvasive devices in order to measure physiological signals has given rise to several attempts to measure the effects of respiration from different signals. For instance, the effect of respiration on the ECG has long been known; and this fact has been utilized in numerous hardware and software approaches to measure respiratory frequency (the so-called EDR). Leonard *et al.* [11], [15], [22], Nilsson *et al.* [13], [24], [25], Shelley *et al.* [14], and several others have shown the power of the pulse plethysmograph in estimating the effects of breathing. In a previous study [5], we have shown the use of a novel TFS estimation method in estimating the FM effect that breathing has on the PPG signal and deriving the respiratory rate from this. In this study, we extended the method for use on other physiological signals of interest, namely the ECG and the peripheral piezoelectric pulse sensor signal. We concentrated on the two methods that we found were best suited (based on results obtained in [5]) for a real-time estimation of the BR: the WT decomposition VFCDM methods.

First of all, the results of the current study suggest strongly that there is a FM effect of breathing on all three physiological signals studied. While the effects of breathing on the ECG and PPG have been well documented, the effect on the piezoelectric pulse signal is less widely reported. Moreover, most EDR methods concentrate solely on amplitude modulation effects on the ECG signal (which generally show up as morphological changes that may be difficult to detect in the presence of line noise) or in the form of the well-known respiratory sinus arrhythmia effect on the RR interval time-series. Hence, our study helps to show that there is a fairly significant modulating effect of respiration on the pulse rate frequency components of these three signals.

The results obtained for the performance metrics for these methods ("accuracy" and "repeatability") showed that for most conditions, the PPG-based estimates of the BR were much more accurate than both ECG-derived and PZO-derived BR estimates. This result is somewhat expected, since it is intuitive that the level of oxygen saturation (SpO_2) would certainly be much more influenced directly by the amount of air, a person breathes in, than the ECG signal, which is known to be influenced significantly by mechanical as well as direct breathing effects.

Having said this, one should note that nearly all six methods studied showed remarkably good median% error values for all the four conditions studied (supine LF, supine HF, upright LF, and upright HF). This suggests that the data length available for each method plays a major part in accurate and precise estimation of the BR, i.e., if the clinical situation allows for 3-min data to be used (as opposed to 1-min segments), any of these three signals may be used with reasonable accuracy to find an estimate of the BR. In fact, the statistical hypothesis testing results confirmed this. In terms of accuracy, while the PPG-based methods (either WT or CDM) were more accurate than the others, there was no significant difference in accuracy between any other method-pair, while the overall percentage detection errors remained in the $\pm 5\%$ range for all conditions. The only exceptions to this were the WT-PPG and the WT-ECG methods' accuracies in the supine-HF condition, which showed significant underestimation of the BR (high negative% detection error).

The "repeatability" results are more varied. Once again we found that the VFCDMFM-PPG method showed much lower spread in detection errors (less IQR of the % detection error) than all other methods. This means that the VFCDMFM-PPG method was consistently able to estimate the true BR with high accuracy over a 3-min period, whereas the other five methods were more susceptible to noise and/or rate dependent errors. This is clear from Fig. 3(b)–(d), which shows the high value of the IQR of detection errors for all methods studied. However, for the supine-LF case, this effect was not present (except

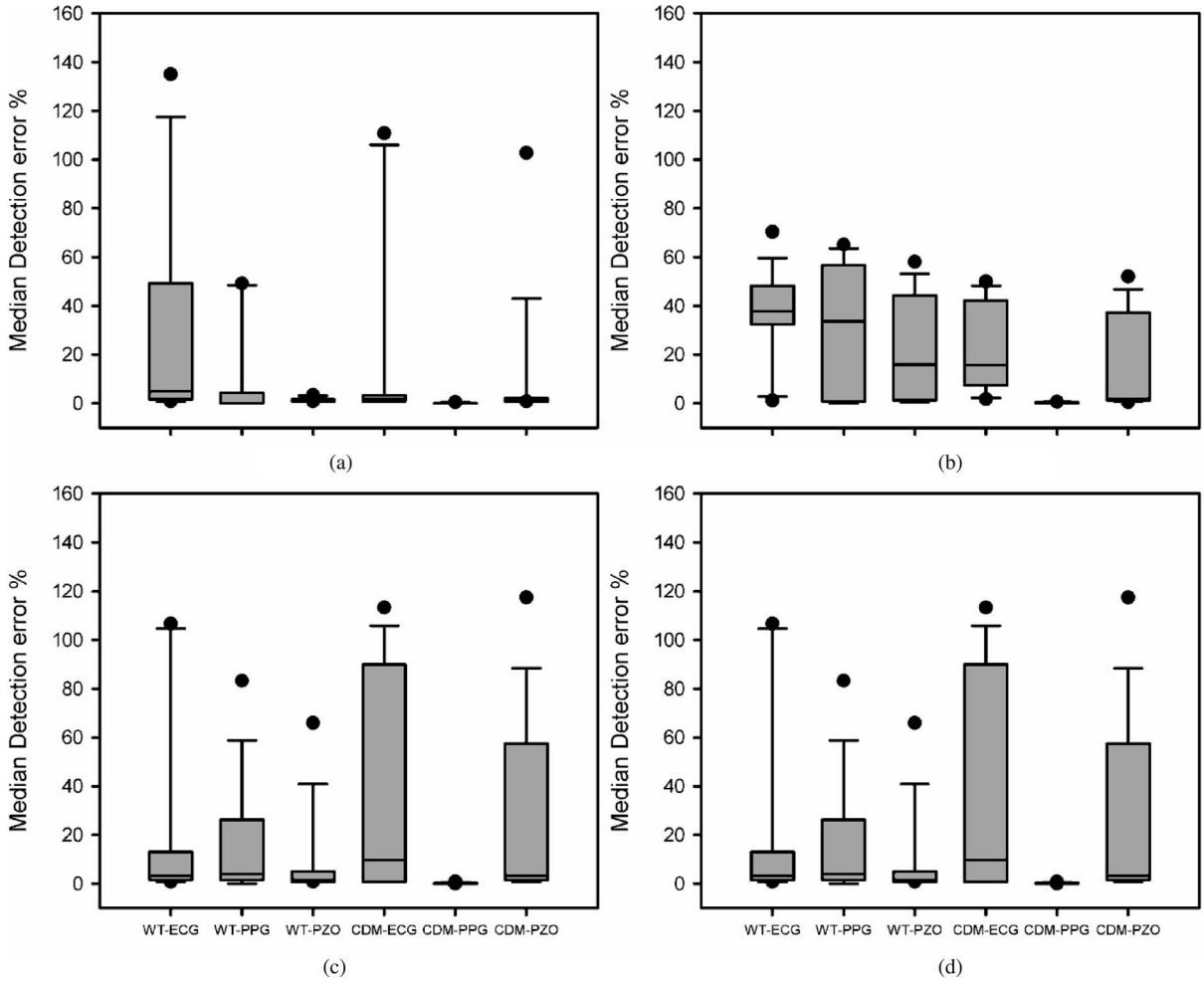


Fig. 3. Distributions of "repeatability" IQR% detection errors across the 15 subjects breathing in (a) supine position and low BRs (0.2–0.3 Hz), (b) supine position and at high BRs (0.4,0.5, and 0.6 Hz), (c) upright position at low BRs, and (d) upright position and high BRs. The closer the IQR is to 0%, the better the repeatability (ability to consistently track the BR). The lower boundary of the box closest to zero indicates the 25th percentile, a line within the box marks the median, and the upper boundary of the box farthest from zero indicates the 75th percentile. Hence, the grey area of the box is an indication of the spread, i.e., the variation in median error (or IQR), across the population. Whiskers (error bars) above and below the box indicate the 90th and 10th percentiles. Solid circles represent the 5th and 95th percentiles.

TABLE III
POPULATION STATISTICS FOR IQR% DETECTION ERRORS ("REPEATABILITIES") FOR EACH METHOD STUDIED FOR DIFFERENT TEST CONDITIONS

Test State	WTFM ECG		WTFM PPG		WTFM PZO		VFCDMFM ECG		VFCDMFM PPG		VFCDMFM PZO	
	Median of IQR % Error	IQR of IQR % Error	Median of IQR % Error	IQR of IQR % Error	Median of IQR % Error	IQR of IQR % Error	Median of IQR % Error	IQR of IQR % Error	Median of IQR % Error	IQR of IQR % Error	Median of IQR % Error	IQR of IQR % Error
Sup. LF	5.00	46.73	0.00	4.23	1.63	0.83	1.63	2.02	0.00	0.04	1.67	1.11
Sup. HF	37.69	14.20	33.61	54.81	15.88	42.86	15.83	30.82	0.07	0.45	1.95	28.27
Upr. LF	3.33	10.63	4.05	23.27	1.67	4.17	9.77	87.08	0.07	0.23	3.33	42.75
Upr. HF	12.25	28.06	35.62	70.58	13.23	37.61	30.25	39.30	0.23	0.50	25.06	22.39

in the case of the WTFM-ECG method), which suggests that any of these methods may be used in a continuous monitoring situation (such as when monitoring for apneic events) during sleep or light relaxation. Presumably, such a condition leads to decreased movement artifacts and allows relatively constant BRs on average. On the other hand, it is somewhat unclear why these algorithms (apart from the PPG methods) show such inconsistent estimation results (high IQR of % error). Certainly, the effect of standing upright on the pulse-pressure and heart-rate signal is well documented, and it may be that such an effect masks the FM effect of inspiration and expiration.

The presence of rate-dependent error was not found by Leonard *et al.* [15], although our previous study [5] revealed that when shorter time segments (1-min length as opposed to

TABLE IV
HYPOTHESIS TESTING RESULTS FOR IQR OF % DETECTION ERRORS ("REPEATABILITIES") FOR DIFFERENT PAIRS OF METHODS UNDER DIFFERENT TEST CONDITIONS

Test Condition	Method-Pairs having Significant Differences in "IQR % Detection Error"
Supine LF	**VFCDMFM-PPG** < all other methods **WTFM-PPG** < WTFM-ECG No other significant differences
Supine HF	**VFCDMFM-PPG** < all other methods No other significant differences
Upright LF	**VFCDMFM-PPG** < all other methods No other significant differences
Upright HF	**VFCDMFM-PPG** < all other methods No significant differences

Higher repeatability is implied by IQR's closer to zero. The more repeatable method is denoted in boldface.

3-min segments used by Leonard *et al.* [15]) were used, the % detection error increased with an increase in true BR of the subject. This is made clear in Fig. 3, which shows the effect of higher BR in the greater spread of % errors for the HF conditions in both supine as well as upright cases. We have previously speculated that a probable reason for such an effect is the fact that with higher respiratory rates, the persistent oscillations required for confirmation of either amplitude or FM may not always be present. So although the FM effect may be seen for some of the 1-min segments, it may not be consistently present throughout the breathing period. Further studies may look into the possible development of an adaptive technique that can be utilized to output a BR estimate only when the presence of FM is confirmed, but stick with the past value if it is not.

We did not collect data on spontaneous breathing because we believe our choice of using the metronome breathing allows us to better estimate near real-time performance of the algorithm since our results are based on 1-min data segments that are shifted every 10 s. In our opinion, spontaneous breathing masks the true performance of the algorithms since the results in the literature are often reported based on the averaged respiratory rates over the duration of 3 min [9], [11]. Thus, rather than comparing the results based on the averaged respiratory rate over the entire duration of the data segment, we believe our choice of reporting the results based on each 10 s shift provides better assessment of the algorithms as well as their near real-time performances. In addition, we can better gauge the true performance of the algorithms since the subjects are breathing at or very closely to the instructed respiratory rate.

In our opinion, the current study shows a different perspective on the effect of respiration on signals, such as the ECG and the PZO. Certainly, the nonstationarity inherent in most physiological signals makes the use of time–frequency methods highly desirable as opposed to exclusively time-domain methods such as autoregressive modeling [9]. The limitations usually associated with TFS estimation methods are the lack of sufficient concomitant time and frequency resolution, a problem that was solved to a significant extent with the advent of the WT decomposition method and has been considerably enhanced by the VFCDM [6]. Of course, one can also explore other successful methods for TFS estimation such as the Pseudo-Wigner Ville method or even the short-time Fourier Transform (STFT) [14] methods. However, we concentrated on the WT method when comparing the CDM approach, since it was the only well-established TFS estimation method that had been used previously for BR estimation from the PPG signal.

While the studies by Leonard *et al.* [11] are commendable, we note that they require the measurement of both amplitude and FM sequences (as opposed to only the FM sequence) from the PPG signal. A separate polling algorithm is then required to find the best BR estimate from either AM or FM sequences. Instead, our previous study found that actually the FM sequence gave very good results by itself in almost all cases studied [5], which is why we have not included the results for AM methods lest the statistical analysis became even more complicated.

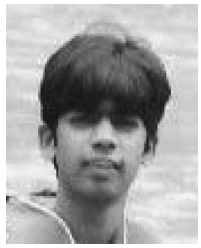
Another advantage of using the VFCDM method is the considerable increase in speed afforded by the two-step approach (extracting the so-called "backbone" frequency components before going for even higher resolution extraction of spectral components). By our estimation the VFCDM method as implemented on the MATLAB platform could perform the BR extraction in about 0.3 s compared to nearly 2 s for the WT method, clearly a significant increase in speed.

In summary, we have shown that TFS-estimation-based methods may be used with success to detect the presence of FM or amplitude modulation as a direct result of respiration on three different physiological signals (the ECG, PPG, and the PZO signal). Especially in the case of continuous real-time setting, it is desirable to minimize patient inconvenience, so extracting as many physiologically important parameters as possible from as few wearable sensors as possible is important. The VFCDM-FM algorithm presents itself as a fast and accurate alternative to traditional time domain only algorithms that have been traditionally used to extract respiratory frequency from the ECG or pulse signals. We stress that in situations, where the PPG signal is available, it should be used to get the best BR estimate. Another point worth mentioning is that we have found in our earlier study [5] that by appropriately tuning the inner parameters of the methods (for instance the F_w parameter for the VFCDM method), one could obtain varying values for the accuracy. It is possible that such tuning may improve (or degrade) the performance of the algorithms on different physiological signals. Hence, future work will attempt to study more closely the effect of varying such tuning parameters on the accuracy of the method, particularly the VFCDM-FM method. Additionally, we will also concentrate on testing the algorithm on spontaneously breathing subjects as well as on subjects whose BR is rapidly changing from low to high (or randomly), in order to check whether the algorithm is able to reliably sense the change in respiration rate. Decreasing the required data segment length as well as increasing the speed of execution even more, will also be explored.

REFERENCES

[1] M. Younes, "Role of respiratory control mechanisms in the pathogenesis of obstructive sleep disorders," *J. Appl. Physiol.*, vol. 105, pp. 1389–405, Nov. 2008.

[2] T. Rantonen, J. Jalonen, J. Gronlund, K. Antila, D. Southall, and I. Valimaki, "Increased amplitude modulation of continuous respiration precedes sudden infant death syndrome detection by spectral estimation of respirogram," *Early Hum. Dev.*, vol. 53, pp. 53–63, Nov. 1998.
[3] M. Hasselgren, M. Arne, A. Lindahl, S. Janson, and B. Lundback, "Estimated prevalences of respiratory symptoms, asthma and chronic obstructive pulmonary disease related to detection rate in primary health care," *Scand. J. Prim. Health Care*, vol. 19, pp. 54–57, Mar. 2001.
[4] M. Folke, L. Cernerud, M. Ekstrom, and B. Hok, "Critical review of noninvasive respiratory monitoring in medical care," *Med. Biol. Eng. Comput.*, vol. 41, pp. 377–83, Jul. 2003.
[5] K. H. Chon, S. Dash, and K. H. Ju, "Estimation of respiratory rate from photoplethysmogram data using time-frequency spectral estimation," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 8, pp. 2054–2063, Aug. 2009.
[6] H. Wang, K. Siu, K. Ju, and K. H. Chon, "A high resolution approach to estimating time-frequency spectra and their amplitudes," *Ann. Biomed. Eng.*, vol. 34, pp. 326–338, Feb. 2006.
[7] P. S. Addison and J. N. Watson, "Secondary wavelet feature decoupling (SWFD) and its use in detecting patient respiration from the photoplethysmogram," in *Proc. Eng. Med. Biol. Soc., 2003. Proc. 25th Annu. Int. Conf. IEEE*, vol. 3, pp. 2602–2605.
[8] D. Clifton, J. Douglas, P. Addison, and J. Watson, "Measurement of respiratory rate from the photoplethysmogram in chest clinic patients," *J. Clin. Monit. Comput.*, vol. 21, pp. 55–61, 2007.
[9] S. G. Fleming and L. Tarassenko, "A comparison of signal processing techniques for the extraction of breathing rate from the photoplethysmogram," *Int. J. Biomed. Sci.*, vol. 2, pp. 232–236, 2007.
[10] A. Johansson, P. A. Oberg, and G. Sedin, "Monitoring of heart and respiratory rates in newborn infants using a new photoplethysmographic technique," *J. Clin. Monit. Comput.*, vol. 15, pp. 461–457, Dec. 1999.
[11] P. Leonard, T. F. Beattie, P. S. Addison, and J. N. Watson, "Standard pulse oximeters can be used to monitor respiratory rate," *Emerg. Med. J.*, vol. 20, pp. 524–525, Nov. 2003.
[12] K. Nakajima, T. Tamura, and H. Miike, "Monitoring of heart and respiratory rates by photoplethysmography using a digital filtering technique," *Med. Eng. Phys.*, vol. 18, pp. 365–372, 1996.
[13] L. Nilsson, A. Johansson, and S. Kalman, "Respiration can be monitored by photoplethysmography with high sensitivity and specificity regardless of anaesthesia and ventilatory mode," *Acta Anaesthesiol. Scand.*, vol. 49, pp. 1157–1162, 2005.
[14] K. H. Shelley, A. A. Awad, R. G. Stout, and D. G. Silverman, "The use of joint time frequency analysis to quantify the effect of ventilation on the pulse oximeter waveform," *J. Clin. Monit. Comput.*, vol. 20, pp. 81–87, Apr. 2006.
[15] P. A. Leonard, D. Clifton, P. S. Addison, J. N. Watson, and T. Beattie, "An automated algorithm for determining respiratory rate by photoplethysmogram in children," *Acta Paediatr.*, vol. 95, pp. 1124–1128, 2006.
[16] R. Bailon, L. Sornmo, and P. Laguna, "A robust method for ECG-based estimation of the respiratory frequency during stress testing," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 7, pp. 1273–1285, Jul. 2006.
[17] P. Langley, E. Bowers, and A. Murray, "Principal component analysis as a tool for analysing beat-to-beat changes in electrocardiogram features: Application to electrocardiogram derived respiration," *IEEE Trans. Biomed. Eng.*, vol. 7, p. 7, Apr. 2010.
[18] Y. P. Huang, M. S. Young, and C. C. Tai, "Noninvasive respiratory monitoring system based on the piezoceramic transducer's pyroelectric effect," *Rev. Sci. Instrum.*, vol. 79, pp. 035103-1–035103-9, Mar. 2008.
[19] S. Sato, K. Yamada, and N. Inagaki, "System for simultaneously monitoring heart and breathing rate in mice using a piezoelectric transducer," *Med. Biol. Eng. Comput.*, vol. 44, pp. 353–362, May 2006.
[20] Y. Chen, L. Wang, and W. H. Ko, "A piezopolymer finger pulse and breathing wave sensor," *Sens. Actuators A: Phys.*, vol. 23, pp. 879–882, 1990.
[21] A. Monti, C. Medigue, and L. Mangin, "Instantaneous parameter estimation in cardiovascular time series by harmonic and time-frequency analysis," *IEEE Trans. Biomed. Eng.*, vol. 49, no. 12, pp. 1547–1556, Dec. 2002.
[22] P. Leonard, N. R. Grubb, P. S. Addison, D. Clifton, and J. N. Watson, "An algorithm for the detection of individual breaths from the pulse oximeter waveform," *J. Clin. Monit. Comput.*, vol. 18, pp. 309–312, Dec. 2004.
[23] B. J. Semmes, M. J. Tobin, J. V. Snyder, and A. Grenvik, "Subjective and objective measurement of tidal volume in critically ill patients," *Chest*, vol. 87, pp. 577–579, May 1985.
[24] L. Nilsson, T. Goscinski, S. Kalman, L. G. Lindberg, and A. Johansson, "Combined photoplethysmographic monitoring of respiration rate and pulse: A comparison between different measurement sites in spontaneously breathing subjects," *Acta Anaesthesiol. Scand.*, vol. 51, pp. 1250–1257, 2007.
[25] L. Nilsson, A. Johansson, and S. Kalman, "Monitoring of respiratory rate in postoperative care using a new photoplethysmographic technique," *J. Clin. Monit. Comput.*, vol. 16, pp. 309–315, 2000.



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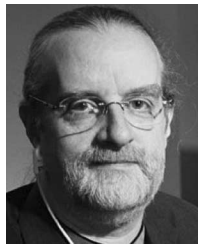

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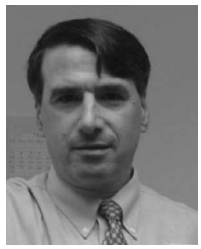

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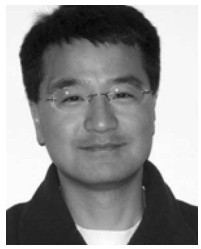

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