Time-Varying Autoregressive Model-Based Multiple Modes Particle Filtering Algorithm for Respiratory Rate Extraction From Pulse Oximeter

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***Abstract*—We present a particle filtering algorithm, which combines both time-invariant (TIV) and time-varying autoregressive (TVAR) models for accurate extraction of breathing frequencies (BFs) that vary either slowly or suddenly. The algorithm sustains its robustness for up to 90 breaths/min (b/m) as well. The proposed algorithm automatically detects stationary and nonstationary breathing dynamics in order to use the appropriate TIV or TVAR algorithm and then uses a particle filter to extract accurate respiratory rates from as low as 6 b/m to as high as 90 b/m. The results were verified on 18 healthy human subjects (16 for metronome and 2 for spontaneous measurements), and the algorithm remained accurate even when the respiratory rate suddenly changed by 24 b/m (either increased or decreased by this amount). Furthermore, simulation examples show that the proposed algorithm remains accurate for SNR ratios as low as −20 dB. We are not aware of any other algorithms that are able to provide accurate TV BF over a wide range of respiratory rates directly from pulse oximeters.**

***Index Terms*—Autoregressive (AR) model, chronic heart failure (CHF), chronic obstructive pulmonary disease, optimal parameter search (OPS), particle filter, pulse oximeters, remote health monitoring, respiratory rate extraction, sleep apnea, sudden infant death syndrome, vital signs.**

I. Introduction

MEASUREMENTS of respiratory rate or breathing frequency (BF) have been clinically performed by monitoring transthoracic impedance or CO_2 levels through a capnograph, but these approaches are all labor intensive and expensive [1]. Respiratory rate is important for many clinical uses, including detecting sleep apnea [2], sudden infant death syndrome [3], chronic heart failure (CHF) [4], and chronic obstructive pulmonary disease [5], and measurements of BF are needed in many intensive care and operative settings. Recently, the use of pulse oximeter for BF extraction has gained significant interests due to its simplicity and noninvasive measurement capability [6], [7]. Acquiring accurate BF from a pulse oximeter is important, because this information allows to characterize whether a low oxygen saturation reading is due to low breathing rates or is the result of other dangerous physiological conditions. The patient's comfort is also improved greatly by obtaining this additional information from the pulse oximeter without having to wear a separate device for respiratory rate measurement.

In the past, a simple fast Fourier transform was used to extract BF directly from the photoplethysmogram (PPG) waveforms, but it has not attracted much attention due to its inaccuracy. Recently, concomitant with increased interest in extracting BF directly from the PPG waveforms, several accurate nonparametric (e.g., time-frequency spectral methods) [6], [7] and parametric [e.g., autoregressive (AR) model-based approaches] [8] methods have been introduced.

One recent promising parametric method is the combination of AR modeling and a single-mode particle-filtering approach, which is capable of obtaining BF as high as 90 breaths/min (b/m) directly from the PPG waveforms [9]. Certainly, the results obtained are a significant improvement since no other methods are able to extract such high breathing rates from the PPG. However, these results are based on constant breathing rates, which is unrealistic in most normal and abnormal conditions. For example, in Cheyne–Stokes respiration especially prevalent in subjects with CHF, the breathing patterns change abruptly [10]. Our technique, which combines an AR model with a particle filter, is designed mainly for constant breathing without any sudden changes in BF. To overcome this limitation of our previous work, we propose, in this study, a novel approach that uses both time-invariant (TIV) and time-varying optimal parameter search (TVOPS) methods combined with a multiple modes particle filter approach to handle both constant and sudden changes in breathing rates, all directly from PPG signals. Specifically, our algorithm first employs the TVOPS to look for varying BFs with an assumption that within a 1 min data segment there can be no more than two different breathing rates. If we do find two different BF, then we use the multiple modes particle filter approach to further increase the accuracy of the initially estimated two BFs via TVOPS. If we find only one BF, then we use TIVOPS followed by a single-mode particle filter to further increase the accuracy of the initially estimated BF. The novelty of this approach is that we automatically appropriate the proper TIV or TV tool of the method as dictated by the dynamics of the data, which ultimately results in more accurate estimation of BF. Henceforth, we term our proposed method the combined TV and TIVOPS-based multiple modes particle filter (COPS-MPF). We compare the efficacy of COPS-MPF to

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Form an initial set of particles, $R^i(0)$, $i=1,\ldots I$, and give them uniform weights $w^i(0) = 1/I$.

1. Obtain TVOPS based respiratory rates $R^1_{tv}(n\text{-}n_{sam}{:}n)$ and $R^2_{tv}(n\text{-}n_{sam}{:}n)$
2. Predict the new set of particles $R^i(n)$
   (a) if $R^1_{tv}(n\text{-}n_{sam}{:}n) \approx R^2_{tv}(n\text{-}n_{sam}{:}n)$, then Propagate resampled set $R^i(n\text{-}n_{sam})$ as in Eq. (3)
   (b) if $R^1_{tv}(n\text{-}n_{sam}{:}n) \neq R^2_{tv}(n\text{-}n_{sam}{:}n)$, then Generate particles as in Eq. (4)
3. Obtain measurement $\boldsymbol{P}(n)$
4. Evaluate each particle weight $w^i(n)$ according to likelihood functions $p(\boldsymbol{P}(n)|R^i(n))$
5. Compute the respiratory state (rate) $R(n)$ as the weighted sum of particles
6. Resample the particles, $\overline{R}^i(n)$

Fig. 1. Summary of the proposed algorithm, COPS-MPF.

both TIVOPS and TIVOPS-PF approaches using pulse oximeter data that were collected from 18 healthy subjects with both metronome and spontaneous breathing rates ranging from 0.2 to 0.6 Hz. Furthermore, we use simulation examples to compare the performance between TIVOPS-PF and COPS-MPF when BF undergoes gradual and sudden changes. The advantage of our approach is that it is real-time realizable, and the algorithm can be embedded in the microprocessor of most existing pulse oximeter devices to provide BFs along with the HR and SpO_2 (pulse oximeter oxygen saturation) readings in real time.

II. Method

A. Respiratory Rate Extraction With AR Model

Our approach to extract BF from the PPG is to use the COPS-MPF algorithm. A detailed summary of the proposed algorithm is provided in Fig. 1, where a TVAR and a TIVAR model are incorporated with multiple-mode particle-filtering algorithm. In general, the COPS-MPF starts with a TVAR model to estimate BFs. The assumption of the TVAR model is that within an analyzed data segment, there can be no more than two different BFs. If two BFs are found, then we use the multiple modes particle filtering approach. Based on the TVAR, if only one BF is found, then we use the TIVAR model to find an initial estimate of BF, and then we use a single-mode particle filter to further enhance the accuracy of breathing rate estimation.

The first phase of the COPS-MPF algorithm involves formulating BF as a TVAR model:

$$x(n) = -\sum_{k=1}^{K} a_{n,k}\, x(n-k) + e(n) \tag{1}$$

where K is the model order, $a_{n,k}$ are the unknown TVAR coefficients and $e(n)$ is the prediction error. We have previously shown that by expanding the TVAR coefficients onto a set of basis functions, these coefficients can be accurately estimated using the least squares method [11]. While either Legendre polynomials or Walsh basis functions can be used, we used the latter since we are interested in also optimal model order for any signal, thus, can be tuned to each signal detecting sudden and gradual changes in BF [12]. Given an initial model order K, the optimal order K_{ops} can be obtained by using our previously developed OPS criterion, which has been shown to be more accurate than either the Akaike or the minimum description length criteria [13], [14]. The OPS can be designed to automatically select the optimal model order without any human subjectivity [14]. Once the unknown TVAR parameters $a_{n,k}$ are estimated, they are formulated as the TV transfer function $H(n,z)$, as shown in the following:

$$\begin{aligned} H(n,z) &= \frac{1}{\sum_{k=1}^{K_{\mathrm{ops}(n)}} a_{n,k} z^{-k}} \\ &= \frac{Z^{K_{\mathrm{ops}(n)}}}{(z-z_1)(z-z_2)\cdots(z-z_{K_{\mathrm{ops}(n)}})}, \end{aligned} \tag{2}$$

where the TVAR coefficients are factorized into $K_{\mathrm{ops}(n)}$ pole terms between samples $n-n_{\mathrm{sam}}$ and n, where n_{sam} is the segment length considered, and $K_{\mathrm{ops}(n)} \leq K$. The real and complex conjugate poles define the power spectral peaks with the larger magnitude poles corresponding to the greater magnitudes [8]. The resonant frequency of each spectral peak is given by the phase angle of the corresponding pole; the phase angle θ of a pole at frequency f is defined as $2\pi f \Delta t$, where Δt is the sampling interval. Among the poles, we set the region of interest for respiratory rates between f_{low} and f_{high} (e.g., 0.15 and 0.9 Hz). Let us denote the number of the pole angles within the region of interest by K_{roi}. If $K_{\mathrm{roi}} \geq 2$, the pole with the highest magnitude is chosen to be representative of the respiratory rate.

B. COPS-MPF Algorithm

The first step to particle generation is to represent a prior probability density function $p(R(n)|P(1{:}n-n_{\mathrm{sam}}))$ by a set of particles. Given the PPG waveform segment $S_{n-n_{\mathrm{sam}}:n}$ (samples between $n-n_{\mathrm{sam}}$ and n), let us denote the TVOPS-based estimated rates by $R_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n)$, which is an array with two values (transitional change values) expressed as $R_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n) = [R^1_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n)\ R^2_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n)]$. When $R^1_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n) \approx R^2_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n)$, we consider the TIVOPS-PF algorithm only, and thus, new particles are generated as

$$R^i(n) = \overline{R}^i(n-n_{\mathrm{sam}}) + Q^i(n) \tag{3}$$

where $R^i(n)$ are the ith generated particles, $i=\{1,2,\ldots,l\}$ for the number of particles I, $Q^i(n)$ is Gaussian noise with $N\left(0,\sigma^2_{\mathrm{gen}}\right)$, and $\overline{R}^i(n{:}n_{\mathrm{sam}})$ represents resampled particles obtained at time $n-n_{\mathrm{sam}}$. On the other hand, when $R^1_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n) \neq R^2_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n)$, new particles are generated with multiple modes as

$$R^{i,j}(n) = R^j_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n) + Q^i(n) \quad \text{for } j = 0,\ 1,\ \text{and } 2 \tag{4}$$

where $R^{i,j}(n)$ are the ith generated particles with $R^j_{\mathrm{tv}}(n-n_{\mathrm{sam}}{:}n)$, $i=\{1,2,\ldots,l\}$ for the number of particles I. Note $j=1$ and 2 corresponds to the models from TVOPS, and $j=0$ is for resampled particles obtained at time $n-n_{\mathrm{sam}}$.

After the new particles that correspond to the prior probability density function $p(R(n)|P(1{:}n-n_{\mathrm{sam}}))$ are generated, each

particle weight is evaluated based on the measurement vector $P(n)$:

$$P(n) = [p_1^a \; p_2^a \; \cdots \; p_k^a \; \cdots \; p_{K_{\rm roi}}^a \; p_1^m \; p_2^m \cdots p_k^m \cdots p_{K_{\rm roi}}^m]^T \tag{5}$$

where P_k^a and p_k^m represent kth pole angle and magnitude, respectively. The weighted particles represent the posterior probability density function of $p(R(n)|P(1{:}n))$. For the particle weight evaluation, we use weighted nearest neighbor likelihood particle filter (WNN-PF), which was reported as the best likelihood function [9]. After the weight evaluation, we normalize the particle weight and calculate the mean of the particles' posterior probability density for the BF extraction. Once the mean of the particles' posterior probability density has been calculated, we resample the particles for the new particle generation at the next time instant $n + n_{\rm sam}$.

C. Single-Mode Particle Filtering Algorithm

The single-mode particle filter algorithm is similar to the multiple mode particle filter as described earlier, and detailed implementations have been provided in our recent publication [9]. Using this approach, we have found that BF ranging from 12–90 b/m can be accurately extracted from the pulse oximeter recordings [9]. While this approach provides estimation of a wide breathing range, its main disadvantage is that it cannot handle sudden BF transition.

D. PPG Data Collection From Human Subjects

For the PPGwaveform acquisition, we used an MP506 pulse oximeter (Nellcor Oximax, Boulder, CO) with reusable sensor (Durasensor DS-100 A), which incorporates a conditioning circuit and has an analog output of 4.864 kHz. The PPG waveforms were collected on 16 healthy subjects. Each subject was instructed to breathe at four different abrupt changes (ACs): 0.2 to 0.6 Hz for AC of 0.4 Hz; 0.2 to 0.5 Hz and 0.3 to 0.6 Hz for AC of 0.3 Hz; 0.2 to 0.4 Hz, 0.3 to 0.5 Hz, and 0.4 to 0.5 Hz for AC of 0.2 Hz; 0.2 to 0.3 Hz, 0.3 to 0.4 Hz, 0.4 to 0.5 Hz, 0.5 to 0.6 Hz for AC of 0.1 Hz. To aid subjects in maintaining the instructed breathing rates, each subject inhaled and exhaled when a timed beeping sound was heard (i.e., 0.2 Hz for the first 150 s and 0.4 Hz for the last 150 s). Among the 16 healthy subjects, 8 females and 8 males of age 21.0 $\pm$ 1.2 years were involved. None of the subjects had cardiorespiratory or related pathologies.

The PPG data were collected in the supine and upright positions. The pulse oximeter sensor was attached to the subjects' left index or middle finger. We also simultaneously measured respiration signals using the Respitrace system, which uses inductive plethysmography to provide calibrated voltage outputs corresponding to rib cage and abdominal compartment volume changes. From the Respitrace system, true BFs were evaluated by counting the number of peaks in a given minute. For all signals, consisting of PPG and respiration signals, we used the PowerLab/4sp (ADInstrument, Inc.) for data acquisition with a sampling rate of 200 Hz and low-pass filtered to 10 Hz. We performed the respiratory rate estimation on 60 s segments. All data segments were shifted by 10 s for the entire PPG recording. We set the initial model order to 30 for the OPS. The breathing rate of interest was set to $f_{\rm low} = 0.15$ Hz and $f_{\rm high} = 0.9$ Hz. The PF parameters were set to $\sigma_{\rm gen}^2 = 0.01$, $\sigma_{\rm gau}^2 = 0.0001$, and $\sigma_w^2 = 0.0025$ [9].

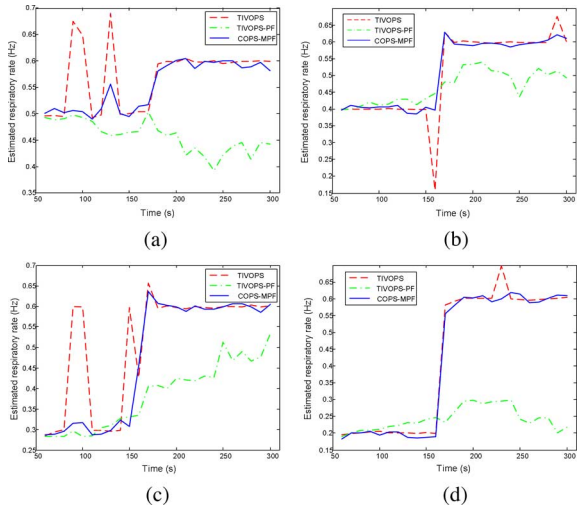

Fig. 2. Estimated BF with ACs in BF from pulse oximeter recording. (a) AC of 0.1 Hz (0.5 to 0.6 Hz); (b) AC of 0.4 Hz (0.4 to 0.6 Hz); (c) AC of 0.3 Hz (0.3 to 0.6 Hz); (d) AC of 0.4 Hz (0.3 to 0.6 Hz).

III. Results

We compare the performance of the COPS-MPF against TIVOPS (without particle filter) and TIVOPS-PF. Fig. 2 shows the results of BF estimation by TIVOPS, TIVOPS-PF, and COPS-MPF at ACs in BF for the following four BF jumps: 0.5 to 0.6 Hz, 0.4 to 0.6 Hz, 0.3 to 0.6 Hz, and 0.2 to 0.6 Hz. For all cases, TIVOPS-PF resulted in accurate estimation for the first 150 s, but it performed poorly when confronted with a sudden change in BF. The TIVOPS, which does not use a particle filter algorithm, also suffers in accuracy. Only the COPS-MPF algorithm shows high accuracy throughout both constant BF and the sudden change in BF.

Fig. 3 shows the root mean square error (RMSE) for each AC of 0.1, 0.2, 0.3, and 0.4 Hz across all 16 subjects. The circles above and below represent the 95th and the 5th percentiles of all estimation results for every subject, respectively. Whiskers above and below represent the 90th and the 10th percentiles, respectively. The bars above, middle, and below represent the 75th, the 50th, and the 25th percentiles, respectively. Asterisk indicates the significant difference between each method. As shown in Fig. 3, the mean values and variances of RMSE were the lowest for COPS-MPF followed by TIVOPS and TIVOPS-PF in all cases. Thus, the COPS-MPF is the most accurate method. These results were statistically significant with $p < 0.01$ among all methods.

To examine the effect of a gradual BF transition, simulations using the test signal as described in (6) were performed with

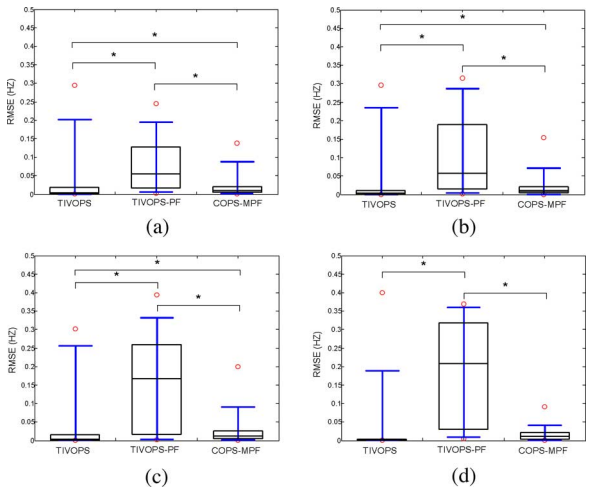

Fig. 3. RMSE distribution according to AC. (a) AC of 0.1 Hz; (b) AC of 0.2 Hz; (c) AC of 0.3 Hz; and (d) AC of 0.4 Hz. Asterisks indicate $p < 0.05$ between each method.

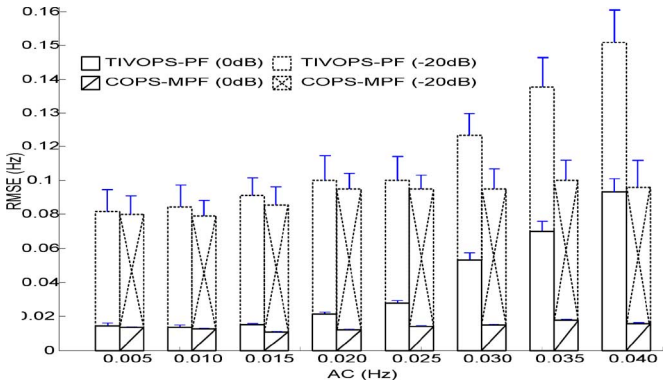

Fig. 4. Comparison with gradual rate change between TIVOPS-PF and COPS-MPF using mean and mean plus standard deviation of RMSEs according to ACs from 0.005 to 0.040 Hz and SNRs of 0 and −20 dB.

additive GWN so that SNR were 0 and −20 dB:

$$y(n) = A_h \cos\left(2\pi f_h(n)\frac{n}{f_s} + \phi_h\right) + A_b \cos\left(2\pi f_b(n)\frac{n}{f_s} + \phi_b\right) + N_a \qquad (6)$$

where $f_h(n)$ and $f_b(n)$ are the heart rate and respiratory rate, respectively. ϕ_h and ϕ_b are phases associated to the heart rate and respiratory rates, respectively, and f_s is the sampling rate. We generated 11 min of data with 66 000 samples with a sampling rate of 100 Hz. The rate $f_b(n)$ was set to 0.2 Hz for the first 1 min, and incremented by 0.005, 0.010, 0.015, 0.020, 0.025, 0.030, 0.035, and 0.040, respectively, every minute. Fig. 4 summarizes the accuracy with mean and standard deviation (SD) of RMSEs based on 100 realizations for TIVOPS-PF and COPS-MPF. For the mean and SD of RMSEs, COPS-MPF was lower than TIVOPS-PF for gradual changes in BF from 0.005 to 0.040, and we observed statistical differences ($p < 0.01$) when the BF changes were equal to or larger than 0.025 Hz for SNR of 0 dB and 0.030 Hz for SNR of −20 dB, respectively.

The performance of TIVOPS-PF and COPS-MPF had no difference when respiratory rates were kept steady via metronome or gradually changed. On the other hand, COPS-MPF was more suitable when BFs were continued with a sudden change. Thus, COPS-MPF is able to handle both gradual and sudden change in BF.

As a pilot demonstration of the robustness of COPS-MPF, we collected PPG data during spontaneous breathing from two male subjects with AC of 0.12 Hz. We performed the respiratory rate estimation on 60 s segments for the entire 5 min data. The data segments were shifted by 10 s for the entire PPG recording, and the true respiratory rates were evaluated by counting the number of peaks measured from the Respitrace system. For the TIVOPS-PF, the mean and variance of RMSEs were 0.0468 and 0.0059, respectively, whereas they were 0.0319 and 0.0022 for COPS-MPF

IV. Conclusion and Discussion

For point-of-care or remote diagnostic health monitoring systems to be effective and widely accepted by end users, their vital sign sensor needs to be multifunctional, inexpensive, and accurate. One sensor that fits these criteria is the pulse oximeter, given its ubiquity and simplicity, and the fact that it is already an accepted device that provides heart rate and oxygen saturation information. Extraction of BF from pulse oximeter data fulfills additional vital sign needs and obviates the need for a separate sensor for measuring breathing rates. Toward this goal, we presented an algorithm, the COPS-MPF, and examined its robustness by comparing it with the methods TIVOPS-PF and TIVOPS. Data were evaluated from 18 healthy subjects whose PPG waveforms were recorded with different abrupt BF change from 0.1 to 0.4 Hz. We found that the COPS-MPF provided better accuracy than did TIVOPS-PF and TIVOPS for all BF changes considered. The robustness of the COPS-MPF was observed whether the respiratory rates changed gradually or abruptly. This suggests that our proposed algorithm is applicable for all BF, whether gated by metronome, or subjected to gradual or sudden changes. In our previous work, TIVOPS-PF was able to provide accurate BFs for a wide range of breathing rates (12–90 b/m). Thus, our COPS-MPF has the same capability to provide this wide range of BF due to the use of the particle filtering approach. The main advantage of the COPS-MPF is that it can handle both slow and sudden breathing transitions because it is designed to automatically appropriate a proper TIV or TV algorithm as dictated by the dynamics of the data.

Sophisticated sensor technology requires a new paradigm that it can be applied to a patient with minimal effort and time, since every precious second saved means a better chance of survival for the patient. Current technology requires attaching multiple sensors for obtaining vital signs as well as ECG electrodes, which can all consume several minutes. Our current work suggests that it is possible to provide reliable respiratory rates, heart rates, and SpO_2 measurements, in real-time (computational time is 50 ms in 2.66 GHz Intel Core2 processor), all from a pulse oximeter device. All that is required for our approach to be commercially viable is to embed the algorithm into the

microprocessor of an existing pulse oximeter device. We believe this is an emerging technology that can have a significant impact, especially in emergency medicine and critical care settings.

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