Auto-regression-driven, reallocative particle filtering approaches in PPG-based respiration rate estimation

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Abstract—**Interest towards respiratory state assessment with non-obtrusive instrumentation has led to the design of novel algorithmic solutions. Notably, respiratory behavior has been observed to cause modulative changes in two discreetly measurable physiological signals, PPG and ECG. The potential to integrate respiratory rate measurements in widely used instrumentation with no additional cost has made the research of suitable signal processing methods attractive. We have studied and compared auto-regressive (AR) model order optimization and coefficient extraction methods combined with a reallocative particle filtering approach for respiration rate estimation from finger PPG signal. The evaluated coefficient extraction methods were Yule-Walker, Burg, and Least-square. Considered model order optimization methods were Akaike's information criteria (AIC) and Minimum description length. Methods were evaluated with a publicly available dataset comprised of approximately 10-minute measurements from 39 healthy subjects at rest. From the evaluated AR model parameter extraction methods, Burg's method combined AIC performed the best. We obtained the mean absolute error of 2.7 and bias of -0.4 respirations per minute with this combination.**

Keywords— **respiration rate, photoplethysmography, autoregression, particle filtering**

I. Introduction

Respiratory rate (RR) is one of the basic vital parameters and the one to react first to declines in the health status of a patient. While many contemporary instrumentations provide good approximations of respiratory state, they can be obtrusive and increase patient discomfort. Photoplethysmography (PPG) can be used as an alternative source of respiration information because respiratory behavior has been shown to modulate the signal in a way that can be assessed by algorithms. Currently, the primary use of PPG in patient monitoring is for blood oxygen saturation estimation. PPG signal may be recorded discreetly and, more importantly, RR monitoring may be integrated to existing devices for use in instances where respiratory state is currently not constantly monitored.

Charlton et al. recently published a comparison of algorithms for respiration rate estimation from PPG signal [1]. As they proposed, an algorithm or a method can often be divided into three phases: pre-processing of the signal acquired from the instrumentation, extraction of the respiratory signal component, and the determination of respiratory rate. Additionally, the fusion of results from multiple sources can be included to enhance the accuracy of results. The decision on which algorithmic components are used is situational and depends on which modulation components of the signal are present, and whether the approach is based on morphological or filterable features. Thus, a considerable number of combinations can be constructed. The comparison by Charlton et al. included altogether 253 different algorithm combinations, each with varying degrees of efficiency.

While a vast number of algorithms have been recently introduced, we have studied a type of filtering-based method, which has potential to overcome some of the challenges limiting the use of many other approaches, namely not using prior information obtained about the respiration rate and offering potential for real-time implementation. Our study concentrates on the last mandatory algorithm step; determination of respiration rate. We propose using a non-fixed auto-regressive model for describing the frequency content of the signal, followed by particle filtering for finding the particular frequency component induced by the respiration behavior. We compare Akaike's Information Criterion (AIC) and Minimum Description Length (MDL) as the means for auto-regressive model order optimization and Burg, Yule-Walker, and least squares methods for AR model parameter extraction.

A number of auto-regressive models with fixed model orders or novel parameter search criteria has been studied in detail in [2]. However, in our study the primary focus has been shifted to the study of non-fixed auto-regressive model response in the changing, realistic conditions of respiratory behavior and signal artefacts, as well as the constraints particle filtering impose to measurements by recall values.

While other methods for AR model parameter extraction exist and other approaches with autoregression-driven, reallocative particle filtering have been proposed as well, e.g. an optimal parameter search method in [3], we chose to limit our comparison to the aforementioned methods and their combinations.

II. Methods

A. Pre-processing and respiration signal extraction

Respiration modulates the PPG signal in a couple of ways that are partially different from the mechanisms affecting the ECG, which is another widely studied signal for indirect respiration estimation. Respiratory sinus arrhythmia (RSA) directly affects the beat-to-beat intervals in both signals, but while the R-peak amplitude in ECG is modulated by the change of heart's orientation and the lead field of the thorax caused by the respiration, the respiration related amplitude modulation seen in the PPG is different. The amplitude is influenced also by the RSA in addition to venous return, which is modulated through the changes in intra thoracic pressure caused by the respiration. This respiration induced amplitude modulation is the feature of interest in the generation of the respiration signal in our work. [4]

The initial pre-processing step on the signal data acquired from respective instrumentation entails the filtering and downsampling of the raw signal. Downsampling greatly increased the angular resolution for the later data processing. We selected the bandwidth corresponding approximately to 7 to 40 breaths per minute (bpm) as the region of interest (ROI). To preserve the modulative components in this range, a Butterworth filter (3. order, -3dB cut-off at 1 Hz) was applied to signal using forward-backward filtering. Filtered data was then subjected to resampling at 2 Hz frequency.

In the present study, we chose to estimate the average respiration rate in 60-second data segments. Thus, 60 seconds of data was taken at a time and analyzed by the algorithm. The analysis window was then shifted 10 seconds resulting in significant overlap of data. New segment was taken and analyzed resulting in 6 respiration rate estimates per minute.

B. Respiration rate extraction algorithm

AR-model

Pre-processed 60-second signal segment was used to estimate an auto-regressive model by using a Z-transform. The poles of the AR model represent significant frequency components in the modeled signal and the assumption is that the respiration frequency would be among these. The number of poles, i.e. the model order defines the complexity of the model. The model order for each signal segment was chosen such that it minimized the AIC and MDL criterions. The criteria for the model order seeks to ensure that the model contains enough information while not being overly complex. Previously, also the use of fixed model orders has been proposed [2]. However, we studied the use of non-fixed model orders to avoid the inclusion of erroneous terms or modeling the signal with too few terms and possibly even excluding the respiratory component from further analysis. The optimal order of the AR model has been observed to change considerably between assessments. Inclusion of multiple frequencies, in which case the respiration information can be divided in multiple poles, is not problematic as such as the particle filter combines the effect of nearby poles and is therefore able to distinguish the correct respiration rate also in this case. Minimization of the model order criteria also reduces the need for any *a priori* information on the AR model structure.

Optimizing the order of the auto-regressive model is a process interconnected with acquiring the pool of AR coefficients because the optimal model order is specific to the method used for extracting the model parameters. Commonly used AR coefficient extracting methods include Yule-Walker, Burg, and the method of least squares. We studied the performance of each of these methods in combination with AIC and MDL model order optimization methods. In order to apply information criteria to an AR model, we created a set of models in which the model order varied from 1 to 30 and compared the AIC and MDL value for each respective model order and coefficient extraction method in the simulation. For each combination, the data of all the subjects was processed frame by frame. For each frame the results with least criterion error were recorded and handed over to the particle filter.

By analyzing the zero-pole model, we may observe the apparent frequency components related to each signal frame. By limiting the filter -3dB cut-off to low values and imposing a region of interest, plausible components can be observed from the model. In several prior studies, an assumption has been made that the frequency component with the greatest magnitude represents the respiration rate [1, 2]. However, as the ROI may contain a number of poles with nearly the same magnitude, the distinction may not be obvious. By simply choosing the greatest magnitude value to represent respiratory rate, there is a risk of choosing arbitrarily any closely valued pole in the ROI, resulting in significant errors. One possible, although relatively rare cause of erroneous poles in the ROI is the heart rate. We considered this by decreasing the upper edge of the ROI to 0.95 times the heart rate in case the resting rate of the subject is close to the ROI, i.e. 40 bpm.

The problem of selecting the right frequency component is then further assessed by the introduction of particle filtering.

Re-allocation particle filter

The particle filter used here is as described in [5]. An initially fixed number of particles, in our case 100, is used with equal initial weights. Additional Gaussian noise is added to each particle estimate at each cycle to allow for rejuvenation of the distribution estimate. The weighted mean of the particle estimate is taken as the respiratory rate.

The AR model of the signal segment being analyzed contains a vector with magnitudes and angles of each transfer function pole. The particles, effectively the representation of probability density function of the RR of previous frame, are assessed by likelihood functions re-calculating the weights for the particles.

We have followed the observations presented in [5] to use the weighted nearest neighbor method which has been shown to provide attractive accuracy among the related likelihood functions. Effectively, each pole increases the weight of itself and all other poles in the ROI with the effect on other poles diminishing exponentially. Each particle is associated with new weight reflecting the fact that particles should concentrate on areas with high magnitude poles. While some particles increase in weight, some do lose their importance in the particle set. The particle weights are normalized after which the respiratory rate, estimated as the weighted mean of the particle distribution, may be computed.

Resampling is an essential process in the particle filter design that preserves filtering from impoverishment effect [6]. Resampling is a process where particles with negligible, in our case less than the initial, weights are removed while particles larger than the initial weight are preserved. Reallocation resampling entails a type of resampling where major weight particles are split into uniform sized particles that preserve the corresponding angle of evenly aligned set of split particles. According to the weight calculated by the likelihood function, each particle with any multiplier value of original weight was split to corresponding floor function number of particles [5]. As the set of particles were observed to diminish at every cycle, new particles were introduced at the mean frequency band of preserved particles, followed by addition of Gaussian noise. As such, the next signal interval fed to the algorithm faces previous distribution values of converged particles but possibly changing respiration rate may still be accounted for. Should any major transients in respiratory rate occur, the particle filter follows the change to a certain degree.

The particle filter may be characterized by its nature for assuming slight changes in respiratory rate. This is advantageous in instances where major transients may momentarily occur due to introduction of artifacts in the signal or due to the deletion of pole outside the ROI.

C. *Algorithm assessment*

A dataset, comprised of PPG and ECG measurements, from 39 young individuals at rest was recently made publicly available under the name 'VORTAL dataset' in conjunction with publication of an algorithm comparison paper by Charlton et al. [1]. The performance of presented algorithm was evaluated by comparing the PPG derived RR estimate with the reference provided in VORTAL dataset produced by a clinical monitor based on trans-thoracic impedance pneumography measurement. The reference RR values are provided in one-second intervals and the average of these from the same 60-second interval than the PPG signal was used in comparison.

Signal quality of the analyzed data was not evaluated in our study as it was done in [1], in which the PPG segments of poor signal quality were removed. Direct comparison of the results between the studies is therefore not possible nor appropriate.

Given that the Gaussian noise introduced to particle filter results in well-defined single probability distribution along ROI, the respiration rate is defined as the mean of distribution. The initial realizations of particle filter have been observed ill-fated to scatter widely along ROI. Fortunately, often after few realizations, the distribution of the particles is seen to accumulate close to the respiration frequency. First five RR results from the beginning were thus left out from the results. Fig. 1 shows an example comparison of RR estimated from the PPG together with the impedance pneumography based reference RR.

III. RESULTS

The considered methods are evaluated by comparing the mean error (ME), mean absolute error (MAE), and root-mean-square error (RMSE) of the respiration rate estimates. The error values are calculated by comparing each RR value, the mean of particle distribution of the filter, to the corresponding averaged reference value on each shifting 60-second time windows and summing up the data of all participants.

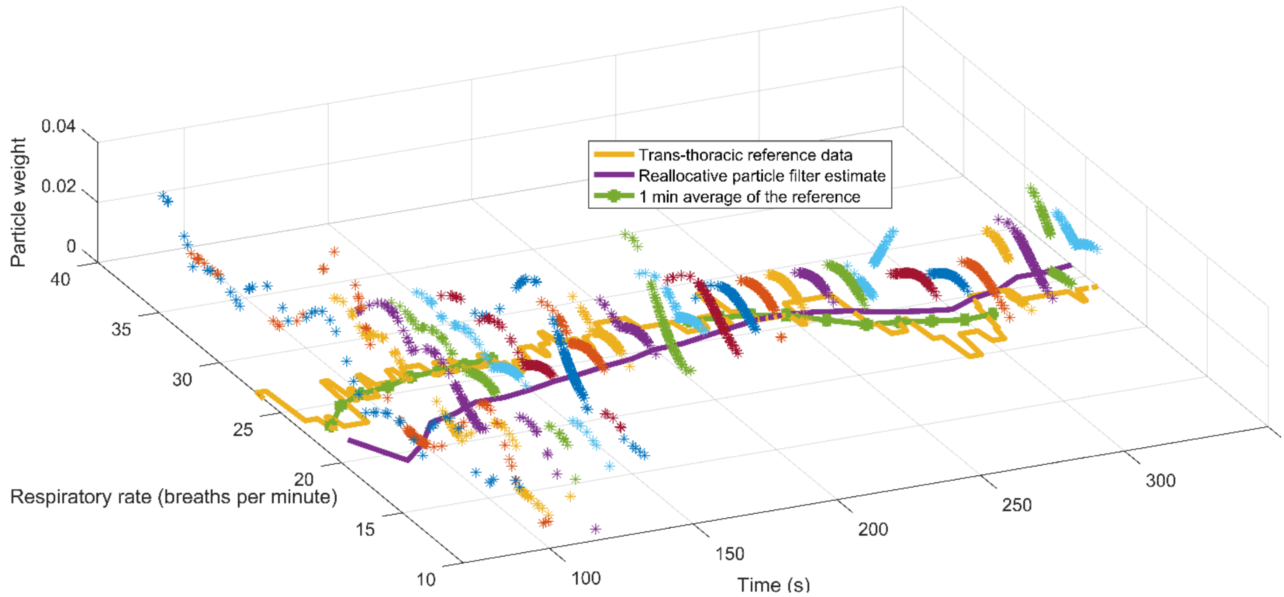

Fig. 1 An example of RR estimation with the particle filter showing distributions of the particles for each filter realization. Raw and smoothed reference RR and the estimated RR are shown in yellow, green, and purple, respectively.

Certain measurements with large transients in the true respiratory rate were difficult for the algorithm to follow. The effect of noise in the signal and the presence of modulative artifacts were not assessed. If none of the poles of the AR model for a certain data segment is located within the ROI, the algorithm is not able to give an RR estimate for that point of time. Values therefore not recalled by autoregression will decrease the RR estimation coverage.

From the results shown in Table 1, we observe that Burg's method provides the most appealing AR parameter extraction method for non-fixed AIC model order selection. This was especially true in instances where pronounced absolute error was to be expected. In regards to the median error values, the methods performed more closely. As seen in Table 2, for a non-fixed AR model, the coverage value, indicating the probability that a pole value could be found within ROI, varied slightly with each method. Least squares method had better recall values for MDL, while for AIC no clear differences were observed. We conclude that particle filtering by non-fixed AR models enhance the accuracy of the results, and the use of Burg's method is the most appealing choice in combination with AIC.

We also tested how removing the particle filter affect the results. As seen in Table 1, RR estimation errors with Yule-Walker parameter search method are significantly larger without the addition of reallocative particle filter. An interesting point worth noticing is the increase of ME in AIC without particle filter, projecting well into median error and MAE.

Table 1 RR estimation error as respirations per minute obtained with evaluated AR model construction methods. ME stands for mean error, i.e. bias, MAE stands for mean absolute error in respirations per minute.

	Median error	ME	MAE
	Yule-Walker		
AIC	1.576	-0.668	3.128
MDL	2.369	-1.158	4.697
	Least-square sense		
AIC	1.853	0.181	3.577
MDL	2.346	-1.871	4.234
	Burg		
AIC	1.494	-0.448	2.699
MDL	2.081	-0.943	4.468
	Yule-Walker, no particle filter		
AIC	3.552	2.135	6.9
MDL	3.146	0.4803	6.044

Table 2 RR estimate coverage (%) with different methods

	YW	LS	Burg
AIC	0.994	0.997	0.997
MDL	0.925	0.942	0.936

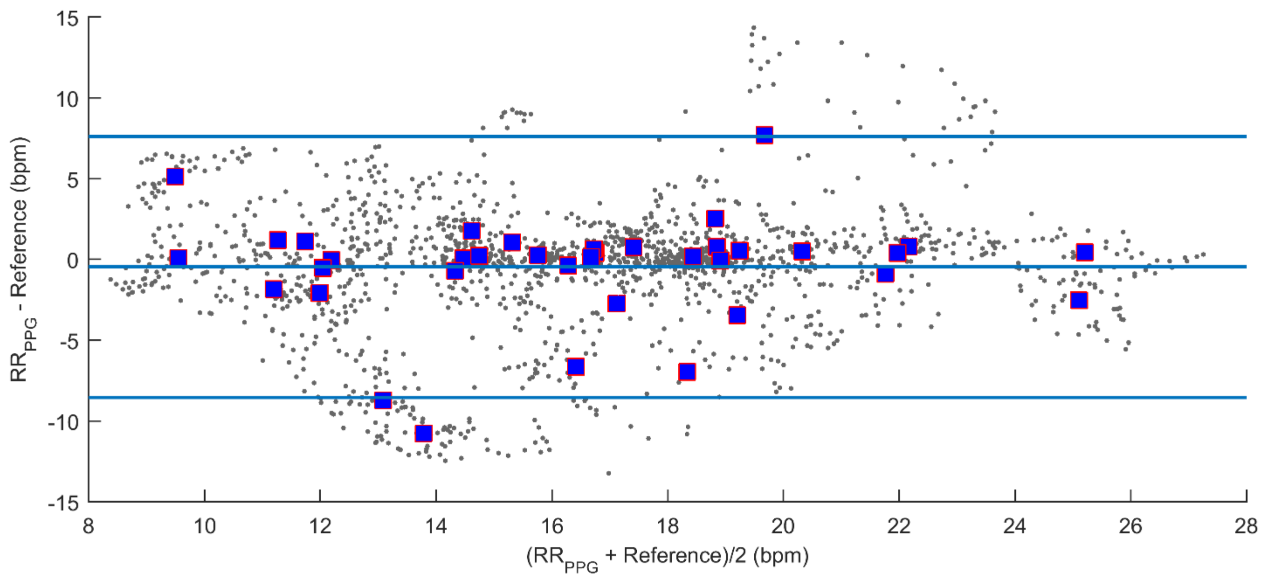

Fig. 2 Bland-Altman plot of the respiration rate results obtained with the proposed algorithm using AIC and Burg AR modeling method and the reference. Grey dots represent individual results and the squares subject averages. Bias as well as the 2σ limits are shown as blue horizontal lines.

When AR model orders were compared, the average model order for all cycles was 23 and 11 for AIC and MDL, respectively, and standard deviation for these model orders were 7.48 and 6.85 showing large variation in optimal model order between signal frames. This supports the suggestion that fixed model order should not be used for this kind of analysis due to highly varying statistical properties of the PPG signal. The recall values support the observation that poles from lower model orders are less likely to be located in the ROI. This is likely to cause some of the error in the measurements due to lack of converging indications for the next available realization. Considerably low model orders also increased the risk of neglecting proper indications of respiration behavior in ROI. This is likely the reason for the fine MAE performance of least-squares method combined with MDL.

Fig. 2 illustrates the Bland-Altman difference plot of a measurement set compared with the reference data. The mean error of the particle filtering combined with AIC and Burg's method show that while most of the subject averages show only slight deviation of the mean error level, a considerable part of the overall error is formed on measurements of certain subjects. These subjects performed worse likely due to emergence of pole clusters near ROI bounds. In addition, the quality of the original PPG measurements may contribute to the error.

IV. CONCLUSION

We have evaluated the performance of an AR-model and particle filter based approach for estimation respiration rate from the photoplethysmographic signal recorded from the finger. The amplitude of the low-pass filtered PPG was used as the feature respiration was assumed to modulate in RR estimation. Despite the promising results, there are many things still left to evaluate and improve in the algorithm, starting from evaluating the possible features in PPG that could be used. Other essential issues for the future work include comparing other alternative methods for AR model optimization and different schemes for particle filter reallocation.

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CONFLICT OF INTEREST

The authors declare having no conflicts of interest.

REFERENCES

1. Charlton, Peter H., et al. "An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram." Physiological measurement 37.4 (2016): 610.
2. Fleming, Susannah, et al. "Non-invasive measurement of respiratory rate in children using the photoplethysmogram." Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE. IEEE, 2008.
3. Lee, Jinseok., and Ki. H. Chon. "Respiratory rate extraction via an autoregressive model using the optimal parameter search criterion." Annals of biomedical engineering 38.10 (2010): 3218-3225.
4. Mason, Laura. "Signal processing methods for non-invasive respiration monitoring." Doctoral Dissertation, University of Oxford, (2002), 175 pages.
5. Lee, Jinseok, and Ki H. Chon. "An autoregressive model-based particle filtering algorithms for extraction of respiratory rates as high as 90 breaths per minute from pulse oximeter." IEEE Transactions on Biomedical Engineering 57.9 (2010): 2158-2167.
6. Arulampalam, M. Sanjeev, et al. "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking." IEEE Transactions on signal processing 50.2 (2002): 174-188.

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