Reliable Respiratory Rate Extraction using PPG

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***Abstract*—Wearable electronics enable a new look into the health of individuals in a fashion that was never possible before. However, many reliable methods for measuring Respiratory Rate (RR) require wearing gadgets that are impractical in a normal daily life setup. On the other hand, more practical methods, which are less intrusive, are often less reliable. Extracting RR using Photoplethysmogram (PPG) signals is one of the methods in the latter group. A major challenge for this method is the movement artifact, which leads to wrong estimation of RR or failure in its calculation. In this work, we propose a new algorithm, Smart Fusion of Frequency Domain Peak (SFFDP),that outperforms existing algorithm by at least 37% improvement in terms of reliability; i.e., average error, Standard Deviation (STD), and Figure of Merit (FoM). This method does not require any signal other than PPG. Therefore, it can be used in a wide range of wearable devices, such as smart watches, without any hardware additions.**

I. Introduction

Wearable Health-care Systems (WHS) spread their coverage to a wide range of applications [1, 2], being critical physical health domain [3, 4, 5, 6, 7], mental health [1, 8, 9], or well-being and sport activities [1, 2]. However, their development is not free of challenges. In particular, constraints on resources drives the engineers to try to extract as much information possible with as little hardware as possible [10]. Moreover, the uncontrolled environment in which they operate poses challenges on their reliability [5, 10, 7]. Some of these challenges could be addressed by using more complex processing methods. However, those require more computational and energy resources, which are often not sufficiently available on these devices [4, 10]. Therefore, solutions that improve the reliability of the system with minimum overhead on the required resources are extremely valuable. In this paper, we propose such a solution for Respiratory Rate (RR) extraction.

RR is an important physiological measure used in various medical studies [11]. However, common methods for direct measurement of RR, such as mounting a mouth piece, are rather uncomfortable for the subjects. One of the least intrusive methods of measuring RR is inferring it from Photoplethysmogram (PPG) signals. The basic principle of RR extraction using PPG is to use the fact that breathing influences the cardiac system [12]. These influences, depicted in Figure 1, include amplitude and frequency modulation as well as wandering of the baseline. One of the main challenges that many WHS face, which affects the extraction of RR from PPG too, is the movement artifact [10]. In [13], we have provided an in-depth insight into the existing methods for detection and removal of motion artifacts in PPG signals. However, these methods require either extra sensors, or extra computational and energy resources to perform extensive complex calculations. In this work, we present a method that does not need any extra sensor and computationally is very similar to existing algorithms that extract RR from PPG. Nevertheless, the proposed algorithm, Smart Fusion of Frequency Domain Peak (SFFDP), is considerably more robust against movement artifacts.

II. Proposed Method

Figure 2 shows all the steps of the proposed RR extraction algorithm. In the rest of this section, we describe the details of each step.

A. *Prepare Data*

To be able to extract the necessary features of the signal, first the raw data needs to be pre-processed and prepared for the feature extraction step. This preparation includes band-pass filtering to remove the offset and any noise that lays outside the field of interest and extracting the location of local maxima and minima of the Blood Volume Pulse (BVP) signal. Using a finite impulse response filter, namely Butterworth, [14] the peaks can be easily detected since the maxima of the BVP signal cause significantly large spikes. The order of the filter, N, is defined by

$$N = \frac{2 * f_s}{25}, \tag{1}$$

where f_s is the sampling rate. The filter coefficients [14] are

$$b_k = \begin{cases} -1 & for \quad k = 0, ... \frac{N}{2} - 1 \\ 1 & for \quad k = \frac{N}{2}, ..., N - 1 \end{cases} \tag{2}$$

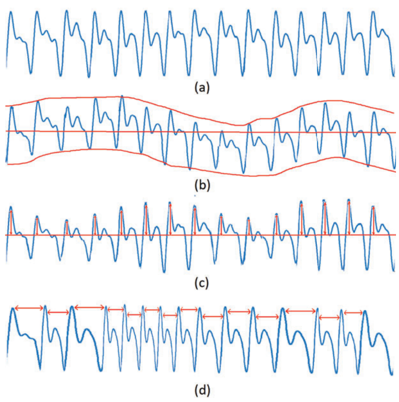

Fig. 1. Respiration caused modulations: (a) none (b) Baseline Wanderer (BW) (c) Amplitude Modulation (AM) (d) Frequency Modulation (FM).

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Fig. 2. Flow chart of the implemented RR extraction algorithm.

TABLE I
DISTRIBUTION OF THE RECORDED DATA

	No movement	Movement
Normal breathing	10	12
Fast breathing	4	4
Slow breathing	4	7

Figure 3 shows the visible improvement on a sample PPG signal before and after application of the filter. Out of the filtered signal, the local extrema are searched with three criteria: (i) Extrema are recognized as such only if they are bigger than the mean value of the signal, (ii) only detect extrema that are $0.4f_s$ apart, (iii) a peak must be surrounded by two troughs and vice-versa (i.e., two peaks or two troughs in a row are dimissed). After that, only the relevant peaks and troughs remain and the extraction of the features can begin.

B. Feature Extraction

First the Amplitude Modulation (AM) feature is extracted by calculating the difference of amplitude between the peaks and troughs, which at the end is normalized to the mean of the signal. The Baseline Wanderer (BW) is calculated by algebraic addition of the amplitude of a peak to its following trough and dividing the value by two, which is then normalized to the mean of the signal. The last feature, Frequency Modulation (FM), is calculated by subtracting the temporal location of each peak and the one after it. At the end it is normalized to the mean of the signal.

C. RR Extraction

For RR extraction, we propose a new estimation method and then use smart fusion which combines the estimation and values extracted from each feature to find a point of agreement between all those values.

1) Proposed Estimation: For estimation of RR, existing methods [15, 16, 17] process the extracted feature and respective properties in the time domain. In our proposed algorithm, Smart Fusion of Frequency Domain Peak (SFFDP), we do not use the features in the time domain like the other ones but work in the frequency domain. Our algorithm searches for the Dominant Frequency (DF) in the extracted signal. First, the signal is detrended and after that, the dominant peak in the range of $0.033 - 2$Hz (which corresponds to a breath rate of 2 to 120 per minute) is searched and found. The breathrate corresponding to the DF is then considered as the estimated RR.

2) Smart Fusion (SFU): The last step is the fusion of the estimated values. To this end, first, the Standard Deviation (STD) of the estimated values from each feature (BW, AM and FM) is calculated for each window. If the STD is below 4, the mean value of these values is calculated and is taken as the RR value of the fusion method. On the other hand, if only two estimations have a STD below 4 and this value is lower than the STD of all three estimations, the mean value of these two estimations is calculated and set as the final RR value of the fusion method. If all STDs exceed 4 then the value of the SFU is set to NaN.

III. EXPERIMENTAL RESULTS

A. Collected Data and Setup

The data set consists of 41 samples from four male healthy volunteers, aged between 26 and 29 years, performing three different kinds of breathing and movements. The first task was normal breathing in the range of 10 to 15 breaths per minute. The second, fast breathing with a breath rate over 15 and the last, slow breathing with a breath rate below 10. During the 60 seconds of measurement, the arm was moved from the table straight into the air and this was repeated three times. Table I shows the distribution of the collected data, and Figure 4 shows an example of a BVP signal with the three movements and their respective artifacts. Subjects' count of their respiration was used as the ground-truth of the respiratory rate.

The proposed algorithm is implemented in Matlab. Sampling frequency of the BVP is 64 Hz and for the filter we have used a 4^{th} order high-pass Infinite Impulse Response (IIR) filter, namely Butterworth, with a 0.05 Hz cut-off frequency and a low-pass one with a 5 Hz cut-off frequency.

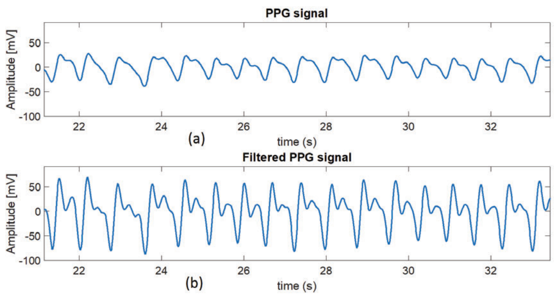

Fig. 3. (a) Original PPG signal and (b) filtered PPG signal.

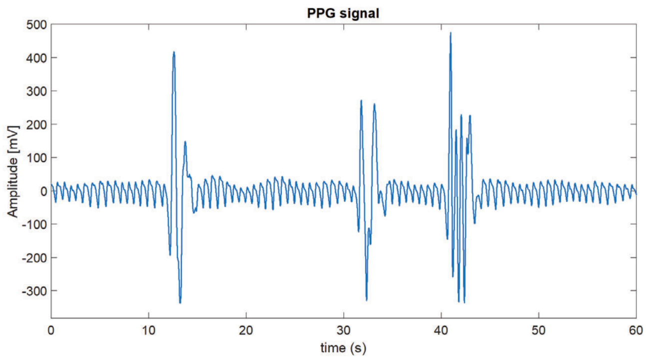

Fig. 4. A BVP with three movement artifacts.

TABLE II
STATISTICAL RESULTS OF THE PROPOSED METHOD, SFFDP.

Window Overlap	Mean|Error| [BPM]	STD	Samples [%]	Window length [s]	FoM
No	3.148	3.214	75.61	28	10.644
Yes	3.351	3.387	75.61	28	11.022

B. Window Size Selection

The performance of the system depends on various parameters such as processing window size. To find the perfect window range, a parameter sweep was performed where the window range was swept from 4 to 30 seconds in a step size of 2. The maximum was set to 30 because the test data are 60 seconds long. If the range exceeds 30 only half of the signal could be analyzed since no second window could be fully formed. Therefore, the range was not increased further. In addition, the same range was tested with 50% overlapping windows. We found out that very small window size, especially below 10s, lead to undersirable performances. For our algorithm, the optimal window size is 28s.

C. Figure of Merit (FoM)

To concretely evaluate the performance and quality of the proposed algorithm as well as other algorithms, we define a FoM, which is calculated by

$$FoM = Mean(|Error|) + STD + 10 \times (1 - CSR^2), \quad (3)$$

where error is measured in Breath per Minute (BPM) and CSR stands for the Computed Samples Ratio, that is the number of samples with successful estimation of RR divided by the overall number of samples. Since CSR is smaller than one and the other two numbers are usually between one and ten, we multiply $(1 - CSR^2)$ with a constant of 10, so that it can be in the order of the other two numbers. Otherwise, the last term would be too small and would have practically no effect on FoM. Thus, the proposed FoM combines the amount of error and reliability (represented by STD) of RR estimation, as well as the number of samples it can successfully estimate. The smaller FoM, the better the algorithm.

D. Results

The proposed algorithm, showed to be able to successfully estimate 75% of the samples in our data set, with a mean error and standard deviation of approximately 3 BPM. This is an acceptable performance for many applications (e.g., Early Warning Score (EWS) [3, 5, 6]), especially given the fact that the data was contaminated with movement artifacts. A summary of the results that we obtained for the proposed algorithm is inserted in Table II. As we see in this table, the performance of the system with and without window overlap is very similar. However, the algorithm without overlapping windows has a slightly better FoM and requires slightly less processing power which makes it overall favorable. Moreover, we observe that a Window Length of 28s was selected for both cases since in our parameter sweep it showed the best performance in both cases.

TABLE III
A SUMMARY OF ALL RR EXTRACTION ALGORITHMS.

	Feature Extraction			RR Estimation			Fusion	
	AM	BW	FM	CO	PD	DF	SFU	TFU
TDPD	✓	✓	✓		✓		✓	
TDCO	✓	✓	✓	✓			✓	
COSTF	✓	✓	✓	✓			✓	✓
SFFDP	✓	✓	✓			✓	✓	

IV. COMPARISONS

A. Existing Algorithms

To be able to have a fair comparison, we implemented three other principle algorithms in literature, namely Time Domain Peak Detection (TDPD), Time Domain - Count Origin (TDCO), and Count Origin - Smart and Time Fusion (COSTF). The first extraction algorithm, TDPD, [15] uses the Peak Detection (PD) for estimation of RR. The second and third algorithms, TDCO and COSTF [16], use Count Origin (CO) method to detect peaks and troughs. In this method, a threshold as 0.2 times the 75th percentile of peak values is defined, and any peaks with an amplitude smaller than this threshold is dismissed. A breath is detected as two consecutive peaks separated by only one trough (with an amplitude less than zero). Moreover, COSTF uses an additional fusion method called Temporal Fusion (TFU) [17]. In Table III, a summary of all the four tested algorithms, including the proposed method (SFFDP), and their features are shown. The key new feature of the proposed algorithm is using DF for its estimation and the new enhanced SFU for the fusion.

It should be noted that compared to the original implementation, in our implementation of other works, we enhanced TDPD, TDCO, and COSTF by changing the PPG peak detection from the detection of the maximum in the raw signal to finding it after applying a filter, as seen in Figure 3, to get a more robust detection. In addition, the fusion algorithm was changed so that it can fuse two estimated values instead of only all three, as it was the case originally. This increases the percentages of calculated samples. A summary of the results we obtained for each algorithm is inserted in Table IV. In Table IV, the STDs for TDPD are 0 because only 2.44% of the samples got calculated. That is only one sample and therefore no STD could be calculated.

B. Comparison

We have summarized the comparison for the best result of each algorithm and their respective FoM improvements in Table V. In this table, the improvements of the proposed algorithm, p, compared to algorithm i are calculated using $Imp. = \frac{FoM_i - FoM_p}{FoM_i}$. We observe that the proposed system has the smallest mean error (3.1 BPM) and STD (only 3.2). We remind the readers that the STD of TDPD is not considered for comparison. Mainly because its value of 0 does not reflect its reliability, but rather its lack of success in estimating more than one sample. With regard to success in estimating RR, the proposed method has a good performance of 75% which is significantly larger than TDPD. This value however, is slightly

TABLE IV
STATISTICAL RESULTS OF OTHER ALGORITHMS IN THE LITERATURE.

Algorithm	Mean|Error| [BPM]	STD	Samples [%]	Window length [s]	Window Overlap	FoM
TDPD	9.226	0	2.44	12		19.220
TDPD	6.877	0	2.44	12	✓	16.871
TDCO	15.418	6.353	97.6	22		22.253
TDCO	15.323	6.156	95.1	22	✓	22.431
COSTF	16.257	6.753	100	28		23.009
COSTF	15.676	6.877	100	30	✓	22.552

TABLE V
COMPARISON OF THE BEST PERFORMANCE OF ALL ALGORITHMS.

Algorithm	Mean|Error| [BPM]	STD	Samples [%]	FoM	Improvement
TDPD	6.877	0	2.44	16.871	37%
TDCO	15.418	6.353	97.6	22.253	52%
COSTF	15.676	6.877	100	22.552	53%
Proposed	3.148	3.214	75.61	10.644	-

lower than TDCO and COSTF, which have a corresponding ratio of 97% and 100%. Nevertheless, this slight degradation in the ratio of successfully estimated samples is compensated by a much larger improvement in the mean error (approximately five times smaller error) and standard deviation (approximately two times smaller). In particular, we note that a mean error of 15, associated with TDCO, and COSTF, is extremely large and being comparable to the actual number of breath per minutes, in most cases, renders it unacceptable. We observe that FoMs reflects these factors as well. In summary, as we can see in Table V, the proposed method (SFFDP), compared to other three existing methods (TDPD, TDCO, and COSTF), has a better performance (smallest FoM) and improves them by 37-53%. This shows the superiority of the proposed method compared to other existing ones.

V. Conclusion

In this paper, we proposed a new RR extraction algorithm, SFFDP, which uses DF and SFU to extract the RR. Our algorithm proved to be significantly more reliable than existing algorithms despite introduction of movement artifacts. The proposed algorithm has an average error of only 3.1 BPM and a STD of 3.2, while successfully calculating 75.6% samples. Compared to others, it shows more than 37% improvement in the FoM, which combines the mean error, STD, and the percentage of successfully estimated samples.

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