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Technical Advances in Respiratory Rate using Fusion Methods: A Review

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Abstract: Respiratory rate (BR) is a basic biological variable that is employed in a range of therapeutic applications. Yet, clinicians manually measure breaths while diagnostically ignoring RR's value. An irregular breathing rate is typically the first indication of a debilitating condition.

In healthcare settings, a reliable estimate of respiratory rate is crucial. Traditional methods estimate RR using either ECG or PPG. However, there is a lack of consensus among existing algorithms in order to improve RR detection performance. One easy method is to fuse the best performing algorithms, which may easily improve the RR estimation. In this review, we will look at how modulation may be used to identify breathing rates using ECG or PPG.

Keywords: Respiratory Rate, Fusion Modulation, electrocardiogram (ECG), photoplethysmogram (PPG), respiratory rate.

I. INTRODUCTION

A. Need for Respiratory Rate

Respiratory Rate (RR) is Respiratory Rate (RR) is a vital predictive and therapeutic marker of wellbeing (sometimes called breathing rate). It could be a profoundly sensitive indicator for an early impairment in a patient [1]. Increasing BR, for case, could be a marker for in-hospital mortality [3], a suggestion of respiratory dysfunction [4], and cardiac arrest [2]. As a result, in critically unwell hospitalized patients, RR is monitored every 4–6 hours [5].

It is also used for emergency medical screening [6] and utilized in primary care to detect pneumonia [7], [8], and sepsis [9], [10], which may also indicate hypercarbia [11] and pulmonary embolism [12], [13]. On the other hand, RR is often determined by physically measuring the motions of the chest wall and cannot be used since this procedure is time-consuming, incorrect [14], and poorly executed [11], [15].

Moreover, RR monitoring isn't extensively used in wearable sensors like activity trackers [16]. As a result, a noninvasive, electronic approach for assessing RR, such as an estimate of RR from the Electroencephalogram (ECG) or Photoplethysmogram, could play a significant role (PPG).

B. PPG and ECG

The PPG and ECG will provide an excellent platform to measure RR sans physical contact in both consumer fitness devices and healthcare. The action potentials eventually result in an electrical current that is captured in each heartbeat, i.e. ECG. Whereas, the RR is a measure of voltage contrast between any two points on the body surface due to current over time [17]. With the help of cheaper electrodes, one can measure ECG [18].

The single-lead ECG can be utilized for screening heart disease and observing ICU patients. Many wearable sensors for patients admitted, as well as personal exercise equipment, will employ ECG monitoring to measure changes in the heart's rhythm and its beating [19].

The time-dependent PPG is a measure of blood volume changes of a tissue bed [20], and it may be measured by attaching a sensor to the skin or photographing a patch of skin with a camera [21]. By illuminating a tissue bed with auxiliary light (such as an LED) [22] or ambient [23]. PPG may be measured at the body's extremities (such as the finger or ear) using a less expensive pulse oximeter probe [9]. Non-contact measurements can be obtained by observing the light reflected from exposed skin regions such as the face or hand [21], [25]. With contact or noncontact methods, we can acquire PPG signals using Smartphones and tablets [26], [27]. The PPG is frequently assessed in a variety of clinical contexts to get values of pulse rate and oxygen saturation i.e SpO2.

RR is continually measured in chronic patients and measured with wearable sensors in ambulatory patients [28]. Furthermore, the PPG is employed in fitness equipment for continuous HR monitoring [29]. Other applications for the PPG include monitoring blood perfusion and monitoring pulse transit time. These make use of PPG signals acquired in many points simultaneously utilizing PPG with single non-contact imaging [21].

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C. ECG and PPG Modulation in Respiratory

The ECG and PPG both exhibit three respiratory modulations, as illustrated in Fig. 1: baseline wander (BW), amplitude modulation (AM), and frequency modulation (FM) [7], [11], [16], [30]. RR algorithms estimate RR by studying one or more of these modulations [7], [29].

Fig. 1. Depicts the three steps of a respiratory rate (RR) algorithm that predicts RR from ECG or PPG data [43].

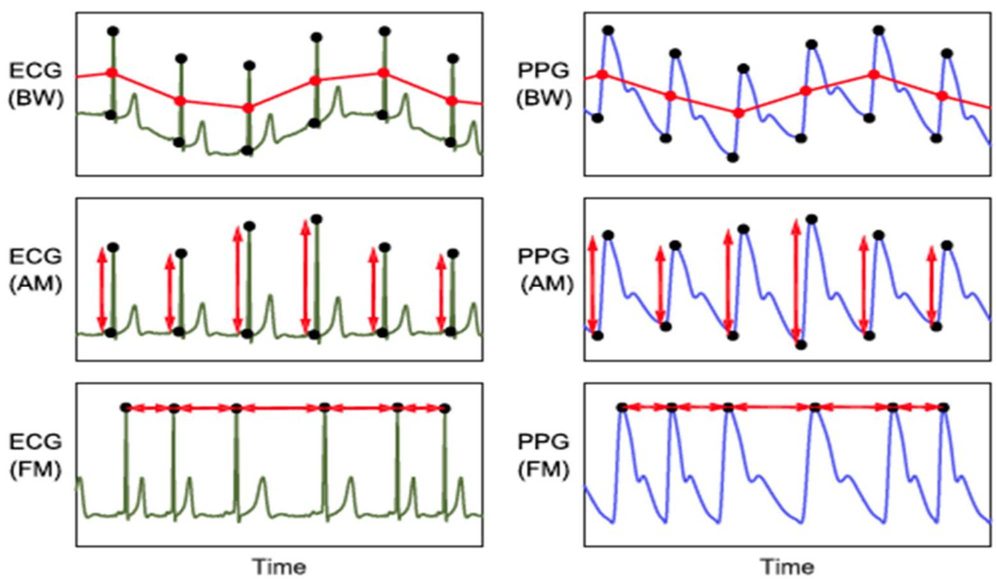

Fig. 2. depicts an example of a feature-based methodology for extracting respiratory signals from ECG (left) and PPG (right) signals: baseline wander (BW), amplitude modulation (AM), and frequency modulation (FM) measurements have been recovered from fiducial points for each pulse (shown as dots) [31].

The physiological processes that induce respiratory modulations are listed here [32]. BW and AM in the ECG are caused by variations in the orientation of the heart's electrical axis relative to the electrodes, as well as variations in thorax impedance [33]. The baseline wander in PPG is triggered by fluctuations in intrathoracic pressure mediated by the arterial tree, as well as vasoconstriction of arteries during inhalation, which moves blood to the veins [34]. Whereas, Amplitude modulation of PPG is caused by a decrease in cardiac output during inhaling as a result of changes in intrathoracic pressure, which results in a fall in pulse amplitude [35]. A feature of respiratory sinus arrhythmia (RSA) is frequency modulation, which is defined by a rise in HR during inhalation and a reduction during expiration. [36]. RSA [32] occurs due to intracardiac pressure changes occurs while inhaling that stretches the sinoatrial node and eventually resulting in an increasing HR. Also, there will be a decrease in heartbeats while exhalation because of the increased vagal outflow decreased [37].

Each modulation's intensity may change between participants and patient groups [11]. Large intersubject differences have been seen [32], [38]. Furthermore, certain modulations, such as FM in aged people, may be reduced in some groups [32]. As a result, several RR algorithms examine several modulations, improving performance [6], [16].

Using various modulation methods, many researchers developed various algorithms to estimate RR from ECG and PPG. There are a plethora of works in this regarding but still there is a dearth in the field of fusion techniques for RR estimation. The main goal of this work is to give a complete overview of the literature, specifically on RR fusion strategies for the ECG and PPG utilizing various modulation approaches. To the best of our knowledge, this review is the first of its kind in the fusion technique to determine RR from PPG and ECG. So far, there aren't many reviews done on the fusion of methods to detect RR from ECG and PPG.

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D. Search Strategy

A literature search was conducted to locate papers reporting fused RR modulations for usage with the ECG or PPG. Manual searches and internet database searches were used to find publications. The search keywords were respiratory estimation, fusion methods, PPG, ECG, and modulation of RR. Our inclusion criteria were mainly given to the fusion of RR estimation from ECG and PPG.

II. DISCUSSION

A. Fusion of RRs

Recently, many studies have started to follow a method of fusion to enhance the procedure of final estimation of breathing rate. To fuse simultaneous RR estimations obtained from distinct respiratory signals, many techniques have been explored. RRs can be detected by fusing basic methods such as averaging mean, median, or mode [6], [40], [53], alternately excluding outlier [40], [43]. There are several ways to estimate the RR from PPG and ECG. First, the quality of the final estimation will be assessed by making use of the standard deviation of the multiple estimations [6]. Second, by weighting the variances of the RRs, they may be integrated [11], [54]. Third, making use of a Kalman filter to fuse RRs that have been weighted based on confidence metrics [49], [50]. Furthermore, potential RRs produced by the fused Autoregression modeling approach employing the pole amplitude or pole ranking criteria [51], [52]. Finally, BRs derived from a single respiratory signal at several time intervals can be blended using temporal smoothing [44] or particle filtering [48]. In 2016, a study by Pimentel et. al. proposed a method to fuse the three respiratory-induced variations (such as RIAV, RIFV, and RIIV) with help of autoregressive models with respect to the corresponding computed spectra. Similarly, Fiedler et al 2020 presented a unique approach for remote respiration rate detection using PPG signals obtained from facial video images in different wavelengths. The influence of alternate implementation stages of the presented approach is investigated in order to optimize the method and gain new insights in this proposed study.

1) Table 1. Fusion of Modulation for Breathing Rate Estimation

a) FM1 Smart Fusion [7]: They assessed the accuracy of RRs calculated from FM, BW, AM, and respiratory signals are analyzed. RR is calculated as the mean only if the standard deviation is less than 4 beats per minute.

b) FM2 Spectral peak-conditioned averaging [41]. The Welch periodogram is used to generate frequency spectra from FM, AM, and BW respiratory signals, which have to be combined to generate average spectra. The only spectrum with a specific percentage of spectral power included within a range of frequencies that are centered on the frequency with the highest spectral response. RR is calculated using the frequency corresponding to the maximum power in the mean spectrum

c) FM3 Criteria for pole magnitude [51]: From the auto-regressive spectral analysis of AM, FM, and BW respiration signals, the respiratory pole is chosen as the largest magnitude pole

d) FM4 the criterion for pole ranking [52]: The highest pole ranking criterion (PRC) is used to choose the pair of poles with maximum magnitude is created by auto-regressive spectral analysis of various respiratory signal modulations. RR is calculated from the selected pair of mean frequency.

e) FM5 [42] by integrating seven independent respiratory-induced modulation results, excellent predictions are allowed for the respiratory rate on both non-moving and motion data. The detection rates were significantly higher when compared with the best existing algorithms.

f) FM6 [47] the method utilizes a number of autoregressive models of various orders to estimate the predominant respiratory frequency in the three respiratory-induced variables derived from the PPG.

2) Temporal, FT1

FT1 Temporal smoothing [44]: estimated RRs, RRest, are smoothed to give the final RR, RRi, using $RR_i = 0.2RR_{est} + 0.8RR_{i-1}$

B. Fusion of RR Estimates

Recently, the fusing step is slowly receiving significant attention due to the observed improvements in computational efficiency when it is utilized [7]. Four modulating fusion methods, FM1,...,4 in table 1, were potentially used to fuse concurrent RR predictions pertaining to each modulation. For smoothing sequential RR estimations obtained from the same individual, temporal fusion (FT1) was selectively used. It could also be used either with or without a previous modulation fusion. This research points to interesting future algorithm development directions.

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In this work, the clever fusion methodology (FM1) increased algorithm performance. This method equally weights RR estimations generated from each respiratory modulation. However, the degree of modulations may be influenced by age and comorbidities. For example, both RSA which causes FM, and thoracic extension which causes BW, and AM will decline with age [45], [46]. The scaling of fusion depends on the intensity of each modulation's manifestation in a specific subject's data that may enhance efficiency. The use of a novel methodology premised on the idea of "model fusion," in which model complexity is determined automatically and unsupervised, resulting in more robust estimates of RR based on a "consensus" of models with varied intricacies. Previously, BR methods that fuse estimates from multiple respiratory signals were extensively used to boost accuracy [7] [51]. The inclusion of a quality evaluation and fusion phase to breathe detection algorithms improved accuracy [16]. More study is needed to evaluate whether the effectiveness of these fusion algorithms in older patients may be enhanced by substituting an alternate respiratory signal for the FM-based input.

III. CONCLUSIONS

Much consideration has been devoted in the literature to the extraction of respiratory signals and the estimate of RR, but less attention has been paid to quality evaluation and fusion. More study on the use of time-domain methods to distinguish individual breathing cycles is needed. It is worth noting that in the research [16], the time-domain methodology beat the frequency-domain approach, despite the fact that time-domain approaches are seldom more advanced than peak detection in the literature. The time-domain algorithms outperformed the frequency-domain methods in-breath detection. This implies that more study into time-domain approaches, which are significantly less reliant on the RR being quasi-stationary, is necessary. If a technique is proved to be effective, it might be used to detect RR during routine physiological exams, providing early warning of clinical worsening. Recently, researchers hypothesized that the RRs generated by several respiratory rate approaches may be blended to boost performance [40], resulting in decreased errors and an increase in the percent of windows in which a RR estimation is provided [54].

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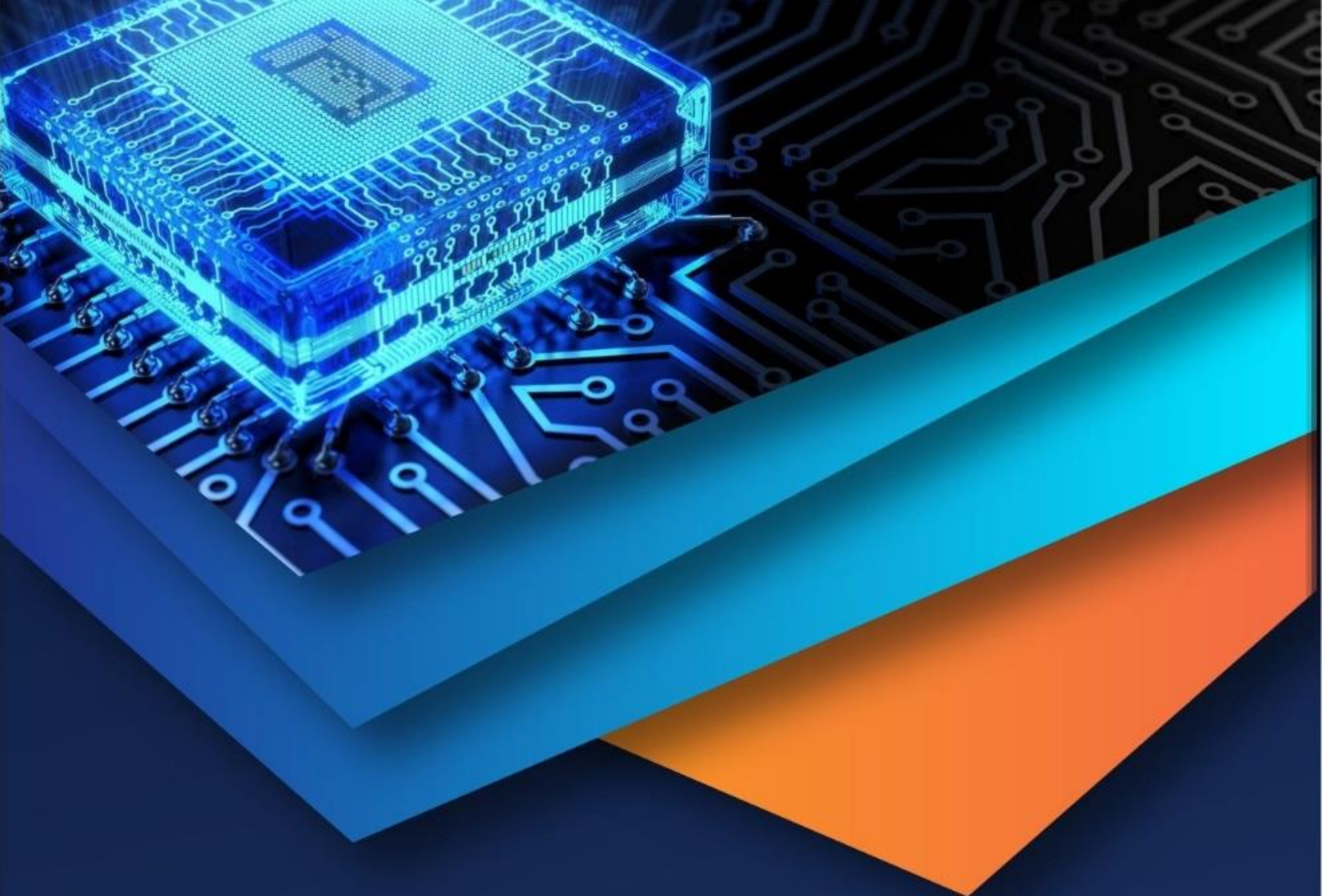

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