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HealthGuard: Heart Attack and RespiratoryMonitoring System

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***Abstract*—** The method for producing respiration- derived cardiogram (RDC) and electrocardiogram (ECG) derived respiration (EDR) utilising a respiratory stretch sensor from a single lead ECG is presented in this study. The objective of the study is to detect heartbeats and compute the heart rate (HR) using the respiration signal. It also aims to rebuild the respiration waveform and compute the respiration rate using ECG QRS heartbeat complexes data. The accuracy of both approaches will be evaluated by comparing reference points to located QRS complexes and inspiration maxima. The results of this study will eventually aid in the development of new, more precise, and effective techniques for detecting heartbeats in respiratory signals, leading to improved cardiovascular disease diagnosis and management, particularly during sleep, when respiration monitoring is crucial for identifying apnea and other breathing problems , a recognised cause of cardiovascular disorders and ones that are associated to a lower quality of life. Additionally, the results of this study might be used to assess if it is feasible to use low-cost, no-contact wearable sensors to collect cardiac and respiratory data simultaneously.

Keywords

respiration, cardiology, electrocardiogram, plethysmography, signal processing, fantasia, MATLAB

Introduction

ECGs as well as respiratory rate measurements are often done in hospitals across the world to assess patient health. Respiratory rates are often checked as one of a patient's vital signs, whereas ECGs help in the detection and treatment of cardiovascular diseases [1]. With cardiovascular disease being the most prevalent noncommunicable disease around the globe and accounting for 17.9 million deaths in 2019 and chronic respiratory disease being the third-greatest cause of death with 4.1 million deaths in the same year, the demand for these medical measurements is on the rise [2].

Hospitals must closely monitor patients' vital signs in order to diagnose their conditions and intervene quickly before things get worse.Nevertheless, since nursing staff are usually busy, there is frequently insufficient monitoring of individuals throughout wards at hospitals with few observations [3]. The "gold standard" evaluation of respiratory rates beyond intensive care units is based on healthcare professionals measuring chest undulations over a minute.professionals measuring chest undulations over a minute.But because of their excessive workloads,

professionals may simply record for a fraction of this time and extrapolate, which may cause errors [4]. Moreover, ongoing oxygen consumption statistics instead of single-threshold findings need to be accurately documented for the purpose to address medical ambiguity [5].
The constant collection of breathing rates (RR) via an ECG, which is an electrocardiogram, is a promising method for improving accuracy and efficiency in breathing rate estimation [6]. Three primary factors allow lung knowledge to be recorded within an ECG even if it is not readily apparent by the waveform: breathing sinus ventricular fibrillation shifts in an electrode's position relative to the heart's chambers within the respiration phase, and variations of thorax resistance [7]. Baseline wander, spectrum assessment through a heart monitor plus seismocardiogram (SCG), R-R peaking oscillation, with R-R maximum amplitude shift applying only one electrocardiogram leads to assess sinus rhythms are other methods of identifying ECG-derived breathing (EDR) [8].

However, many breathing outputs indicate proof of heart cycles. In trials with a simple, low-cost contactless reactive chest bands to gauge the exertion needed to respire as well as estimate temporal and cardio blood flow, a heartbeat's pulse might be acknowledged in validated volumetric information [9]. Over a paused airflow, records from breathing induction ultrasound reveal cardiovascular rhythms. As suggested by certain ECG evaluations, heart rate pulses within blood oxygen usage information are synchronised [10].

Concurrently, there's also an increasing movement closer to the application of mobile devices for recording client cardiology within medical facilities as well as—more importantly—after the person being treated leaves the premises [11, 12]. This demonstrates why it could be beneficial to integrate cardiovascular as well as breathing tracking onto an item that collects breathing or cardiovascular data and also derives the absent information from the present device. Similar to this, as wearables like ring bracelets [13] and multiple senses wearables [14] gain popularity, further algorithms over the extraction of precise cardiologic as well as breathe data—obtained through an electrocardiogram (ECG) or other type of plethysmography—will be needed for the identification and management of a wide range of medical disorders.

The present investigation aims to satisfy a gap within the scientific community since no other study has made an effort to estimate pulse maxima positions across a longerduration utilising the readily accessible dataset. The initial technique for identifying heartbeats within breathing impulses occurs when the cardiac frequency lies near the noise level. The study presents an analysis of the benefits and drawbacks of the proposed approach along with recommendations regarding enhanced approaches that could boost the percentage of truly successful pulse monitoring.

The accomplishments of this work may result in the establishment of new, more precise, and effective techniques for identifying heartbeats in respiratory signals that are leading to improved cardiovascular disease diagnosis and management, particularly during sleep, where ventilation monitoring is essential to controlling the progression of cardiovascular ailments.
look for breathing problems including a condition known apnea as that is frequently linked with a decreased standard of existence as well as is an established risk of heart disease. Furthermore, this investigation could examine the feasibility of collecting heart and breathing statistics concurrently through one piece of equipment using inexpensive, non- contact wearable devices.

I. Literature Reviiew

The retrieval of breathing data gathered from ECG signals has been discussed in a number of papers in the current literature. Varon et al. [15] discuss 12 research that employ various techniques for extracting respiration from electrocardiogram (EC data and explore 10 options for recovering oxygen from only a single lead ECG. For the detection of several heart disease conditions, including irregular heartbeat, myocardial infarction, ventricular fibrillation and COPD, various techniques for locating QRS impulses in noisy or otherwise degraded datasets are provided [16–18].

However, research on the detection of heartbeats using respiratory data is scant. The two techniques that are most frequently used to identify heartbeats are a method called empirical mode decomposition (EMD) [21,22] and the visual evaluation [9,10,19,20].

1. Heartbeat Recognition

According to latest research, resistance as well as induction techniques for obtaining cardiovascular along with respiration volumetric estimates via chest bands—where the occurrence of a pulse can be observed by examining the bands throughout the breaths—have been investigated [9,10, 19]. With the goal to monitor respiration, stress enrollment, as well as cardiac rhythm within the artificial arms and legs of five lower-leg

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those with disabilities, Hornero et al. [20] handle electrical resistance ultrasound from electromechanical devices.

EMD was used in other studies [21,22] to distinguish between heartbeats produced in various ways. However, it was noted that leveraging the EMD technique automatically and easily is challenging since it requires individual identification and a suitable combination of the IMFs related to cardiac activity, in spite of initiatives by Puizzi et al. [21] to integrate the analysis of the principal components.

Bandpass filtering and Fourier adaptations were applied in the signal processing process by Fontecave-Jallon et al. [23], Piuzzi et al. [21], and Kroshel [24] to accentuate heartbeats in non-ECG data.

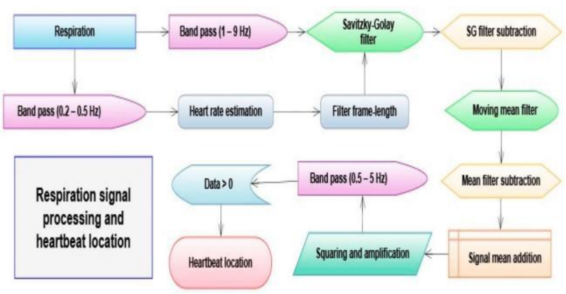
2. Respiration Derived

Both oxygen consumption (RR) and ECG-derived respiration (EDR) have been extensively researched in the literature. Finding comparative studies that combine a variety of investigations to assess the effectiveness of different therapies is therefore not difficult. Another paper assessed 12 studies that used diverse methods of obtaining EDR, while one study examined more than three hundred RR estimate strategies [25]. The Fantasia, database was referenced in four other studies [26,27,28,29] that examined more than three methodologies.

In order to extract the RR from a technique called photoplethysmography (PPG), more than 100 approaches have been devised [25]. Calculating respiration rates may be done in a number of different ways. One approach is to keep an eye on changes in the R- and S-waves' duration or amplitude. Another method is to track bandwidth modulation or the variations in R-S amplitude.

Another approach is to evaluate changes in the gradients and angles of the QRS complexes or to contrast the size of the QRS complexes [15].

More advanced techniques for extracting information from QRS complexes include principal component analysis, individual wavelet transformation, empirical mode disintegration, variational mode extraction, and variable-frequency complex demodulation process [15].



Sharma and Sharma [27] use a novel method based on Hermite foundation functions to derive the RR and contrast their algorithm with seven prior RR derivation techniques. In a different research that employed EDR methods to identify RR, Schmidt et al. [28] used fourth-order central moments, while Dong et al. [26] tested the efficacy of their two-stage EDR by recreating a respiration cycle using seven established methodologies.

Method smoother on the characteristics generated from the initial instant (mean frequency) of the power waveform utilising many interactive algorithms.

Methodology

By creating techniques in the framework of MATLAB and employing the Fantasia database, the goals of this study are achieved [30]. The ECG and respiratory measurements of 40 persons who were viewing the movie Fantasy at the time the information was gathered are stored in the publicly accessible Fantasia database. The respiration data came from the thorax, whereas the recordings came from one particular lead (lead II). In the study, there were 20 younger and 20 older volunteers. Prior to 1996, ten "rigorously screened healthy" study participants aged between 21 and 34 and 10 who were 68 to 81 years old were noted, with an additional 20 people added after 2000. The recordings were made in order to assess how healthy sinus breathing cardiac period dynamics changed with aging [30]. The Physionet databank made the recordings accessible to the public, but no other information on the research participants is available.The subjects in the Varon et al. [15] studies used the sleeping and driving information sets were found to be easier and more challenging to work with, respectively, whereas the Fantasia database was chosen since it has a tolerable difficulty level in reconstructing the electroencephalogram (EDR) because individuals are awake but supine. This makes the Fantasia a database an excellent demonstrating ground for newly created computations.

3.1. Heartrate Recognition

Compared to the method employed in this inquiry, EMD attempts in this work fail to succeed as well. The precision of the EMD process still requires pre- and post-processing. The use of a bandpass filter is important as a first step to prevent signal distortion. Additionally, to properly localize heartbeats, post-EMD signal changes were needed. At that moment, skipping the EMD step increases positive results. As a result, this work's recommended method for identifying your heartbeats from ventilation data does not make use of EMD. In conclusion, our method entails the following steps: signal preparation, signal modification, and observation.

Signal Preparation (3.1.1)

The respiration signal is processed using bandpass effects, filtering subtractions, and array operations to identify heartbeats. The method is depicted in Figure 1 using a flowchart.

Figure 1 shows a signal processing approach for locating heartbeats in a respiratory signal.

The rate of breathing is used to determine the heartbeat's

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approximate location in the beginning. This is achieved by using a bandpass filter that only lets through frequencies from the respondents' respiratory data between 0.2 and 0.5 Hz. The total amount of breaths is determined by an automated algorithm. To get the expected heartbeat-to-beat interval, divide the typical time between your heartbeats by three. Warning: When looking for heartbeat locations when the ratio varies, utilising a fixed ratio with three heartbeats every breath leads to discrepancies.Heart rates per breath within the Fantasia database vary from 4 to 1.8, with a median of

3.06. A future algorithm improvement would involve modifying heart inter-beat durations using heartbeats that have been recognized.

A bandpass filter is used to process the original respiration indication, eliminating any data with a frequency range between 1 Hz and 9 Hz. This effectively lowers baseline drift (0.15 to 0.8 Hz), respiration (0.15 to
0.8 Hz), and powerline noise (50 to 60 Hz).

A third-order Savitzky-Golay filter's frame length is determined by how many data points are derived from the duration of the cardiac inter-beat interval at a sampling rate of 250 Hz. This filter effectively maintains high-frequency signal components while being used to smooth data. Without using extra computing power, a third order setup produces the necessary results. The final result of this filter is seen in Figure 2 after it has been eliminated from the band-passed input. The filtered pulse signal is shown in the lower panel, while the raw breathing signal is shown in the top panel. This technique lengthens the peak of the pulse R wave without adding new peaks to the peak of breathing (a issue the approach faces when a longer frame length is used).

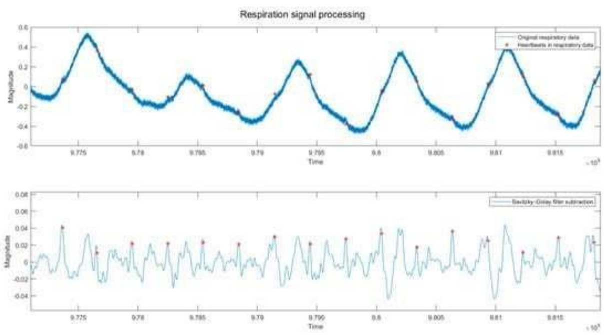


Figure 2 is a diagram. Filtered breathing is a cardiological symptom. The heartbeats can only be seen in the original waveform between the vertical lines in the first panel. The second panel's filtered waveforms are more exact, although they still have noise artefacts.

Signal Manipulation 3.1.2

The filtering signal may still contain a significant amount of noise, and despite the comparably strong R and T peaks in Figure 2, it may not always be possible to distinguish the resultant heartbeats. Breathing harmonics are one type of noise floor interference that cannot be removed without changing how easily the heartbeat can be seen in the resulting signal. It is possible that signal differentiation brought on by the participant's physical structure is the source of the lack of cardiovascular spikes or apparent chaos.

3. Detection of Heartbeats

With a prerequisite peak length of 65% corresponding to the predicted heartbeat-to-beat distance as well as greater than 8% of the average height, peaks are located using the built-in MATLAB (findpeaks) method. These proportions enable the hunt to refocus on the succeeding pulse peaks following an incorrect recognition. A typical physiological latency of 120 ms is applied to the array of pulse locations in MATLAB before being compared to the provided annotations. The results of Hornero et al. [21], who observed a lag of around 150 ms between both signals, are consistent with such physiological delay. The detected heartbeats are shown as small circles in Figure 3c. Additionally, asterisks are used to indicate the observations for the electrocardiogram (ECG) signal in the Fantasia collection.

To measure the sensitivity as well as the precision of calculated heartbeat designations, the arrays containing the time locations for observed heartbeats were contrasted with the source heartbeat labelling sites. The positioning inside the designated annotations was compared for both true and false positives using the detected locations array. Another examination compared the arrays discovered and used the given annotations to identify erroneous negative placements.

True positives are any discrepancies between the specified and detected markings that take place within 140 ms (35 data points at a sampling rate of 250 Hz). As seen in Figure 4, false negatives are identified when a calculated notation comes more than 140 milliseconds after the provided Fantasia annotations. Any other is what is commonly referred to as an untrue positive or false negative.False negatives are additionally identified if there is no peak observed between the markers 140 milliseconds before the peak. One the other hand, the wrong peak is one that is within a minimum of 0.32 s or 80 points of information.

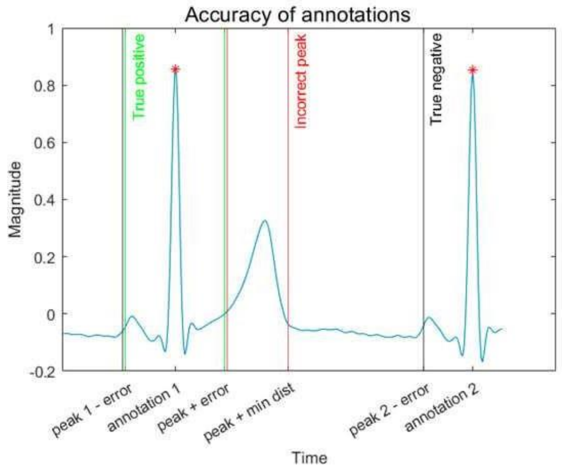


Figure 4. Highlights the situations in which the algorithm produced misleading favourable findings and also incorrect unfavorable predictions associated with your heart rates. The sampling time used with a 250- hertz sampling frequency was approximately 140 ms, totaling 35 observations. Another blue line depicts the electrocardiogram's QRS waveforms that have two R maxima. A red asterisk highlights the comment locations referenced.

Mistakenly identified wave patterns were found at 320 ms following the account of the pulse. The information gathered might be utilized in subsequent versions of the validation procedure to determine an increase in real positives and a decrease in incorrect negatives.

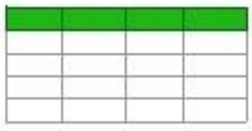
4. Results

4.1.Heart Beat Location

Valid and Invalid Positives

For individuals who have a conventional PQRST (a pulse's regular pattern rhythm defined by PQRST).) waveforms data from an electrocardiogram (ECG), when the cardiac waveform can be acknowledged from the surrounding noise. The P waves reflect depolarization of the atrium, the QRS denotes the period of heart polarisation, and the T component of the waveform complex represents ventricular repolarization. The method outlined in this study performed exceptionally well whenever the estimated HR matched the actual HR. The first table lists the proportions, precision, sensitiveness, true positive, false positive, and other metrics for every individual in the Fantasia collection.

Table 1. Includes the geographical location regarding respiration-derived cardiology (RDC) as well as the coefficient of Pearson's (p), Harmony correlation (c), mean absolute error (MAE), percentage error (PE), and normalized root average square error (NRMSE). Results derived from the per-minute evaluations which remained unchanged appeared superior over those that resulted



from the usage of the 'best fit' approach.

In 12 participants with appropriate ECG heart rate patterns including pulse-to-breath proportions, the technique's results of true positive heartbeat localization was >60%, as can be seen in Table 1, below. Among all participants, true positives were discovered 52.36% of the time, while the false T peak was discovered 8.44% of the time. False positives mean of 40.5% and negative mean of 45.73% for noisy or atypical collection signals.

2. Correlation and Error

The technique's precision and responsiveness as measured against the source annotations are shown by the MAE, PE, and NRMSE figures, which for the entire database are 7.24 bpm, 12%, and 0.15, respectively. A slight connection is shown by Pearson's coefficient of 0.56, which has a p-value of 0.01. These measurements, which haven't been changed for the optimal fit, appropriately reflect their data's responsiveness and precision.

Both true positive heartbeats and false positive heartbeat identifications provide the minimal MAE and PE, as well as a large Pearson's factor, all of which are computed through heart rates. This is because if a false positive heartbeat was detected instead of a true positive heartbeat, the occurrence of the predicted remained the same.

3. Respiration Derivation

Valid and Invalid Positives

With an uncomplicated average variation in phase adjustment conducted for each participant's data as necessary, the programme discovered 80% of the breathing spikes to approximately half a heartbeat of the original inspiration extremes. This result is given in Table 2. The procedure also discovered a mean of 104% breathing peak periods, that is similar to the PE estimate of 4.78% from the study of the most appropriate fits every minute shown in Table 3. In relation to sensitivity, the older respondents' answers were only slightly better than the younger ones', but considerably less accurate.

4. Error and Correlation

The methodology beat previous techniques utilising a single EDR technique with respect to MAE and percentage error, with MAEs of 0.89 and 1.07 and PEs of 4.78% and 6.60% for young and senior patients, respectively. These numbers are in line with the level of accuracy attained by Orphanidou et al. [29], who eliminated all one-minute intervals with an average absolute difference of exceeding two bpm. In both categories, the Pearson correlation coefficient holds significance at >0.6, while the overall database's NRMSE is 0.21.

5. Conclusions

The rapid cardiac contraction (RDC) method fails to perform well with lower benchmark cardiac rates whenever there is enough distortion due to the disruption located wherever an inaccurate heart rate prediction occurs. The weak concordance connection points to a restricted heart rate range and a strong link to anticipated rates. On the contrary hand, the NRMSE value of 0.14 for the entire collection is encouraging and shows excellent agreement with expected cardiac rates.

It could be beneficial to acquire crisper information having a greater signal-to-noise ratio (SNR) for additional studies as well as enhanced methods for estimating expected heart rates using sections of information throughout breathing minima, which could enhance heart rate identifications. However, this work demonstrated the capability of the algorithm that was developed to identify heartbeats in respiratory data and compensate for skipped heartbeats.

An economical wearable gadget could transmit heart rate impulses utilising the produced pattern. The suggested improvements and suggestions for improved gathering of data techniques may lead to superior performance for early diagnosis and management of cardiovascular illnesses. Overall, the foundation has been set for further investigation towards the identification of heartbeats in ventilation impulses.

The techniques covered in the present research are designed to assess captured impulses from the wearable band invented by [9,19], where heartbeats have been visually confirmed in the breathing statistics. Considering few necessary technique adjustments, these techniques are designed to be used to assess SCG data along with various respiratory or cardiovascular signals.

Despite the cost being considerably lower but still significant relationship coefficients, PE and PE.

Considering different single-method respiration waveforms and produced breathing rates, the algorithm behaved identically.

II. Results and Discussion

After 16 periods, the algorithm we used incorrectly identified an aggregate of 90 images from the 313 test examples, for an identification rate of 71.5%. For an algorithm with only 16 epochs, CPU school, and an initial training time of 13 minutes, the outcomes are not too awful. Despite the reality that few of these photos are difficult to recognize, our subject will be ready to classify them properly. In this case, our system can classify the picture below as a "airplane" and recognize it as such.

```
loss: 1.0235 - accuracy: 0.7155
[1.0235388278961182, 0.715499997138977]
```

Even if certain photos are difficult to recognize, our mannequin ought to be capable of categorizing data accurately. As a case study, our system is able to recognize as well as classify the subsequent picture as an "airplane".

It is currently proven that it is possible to get a rate of respiration that is accurate to 4.7% based on the genuine RR among young study subjects. The compiled waveform, which averages 4.24% of the actual total amount of inhalations, accurately detects inhalation rises.

The research study showed that using both techniques, could be achieved to obtain cardiac and respiratory rates from just one input. Eliminating distortion from one's respiration signals throughout recovery which might be done by using resistance chest bands, might be necessary to get accurate heart rate measurements.

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