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RESPIRATORY ANALYSIS WITH ELECTROCARDIOGRAM DATA: EVALUATION OF PAN-TOMPKINS ALGORITHM AND CUBIC CURVE INTERPOLATION METHOD

Mert Süleyman DEMİRSOY[1]*, Ayşe Nur AY GÜL[2]

[1]Sakarya University of Applied Sciences, Faculty of Technology, Department of Mechatronics Engineering, 54050, Sakarya, Türkiye
[2]Sakarya University of Applied Sciences, Biomedical Technologies Application and Research Center, 54050, Sakarya, Türkiye

Abstract: Advancements in bioinstrumentation have facilitated the easier monitoring of biometric signals such as electrocardiogram (ECG) and respiration. This development is particularly crucial for the diagnosis and management of various conditions like stress and sleep disorders. Two commonly used features in heart rate variability (HRV) analysis derived from ECG data are standard deviation and serial correlation coefficients of R-R intervals (the time durations between heartbeats). The former utilizes the fundamental components of QRS complexes, while the latter is designed to extract relationships between respiration and heart rate. In the proposed methodology, R-R wave detection is performed on processed ECG data using the Pan-Tompkins algorithm, and the respiration duration for each R-R interval from respiration data is selected. Additionally, missing respiration data for selected R-R intervals is interpolated based on the interpolation method. The results of this study are compared with the standard interpolation and cubic spline interpolation models to assess the effectiveness of the proposed method and its ability to capture temporal fluctuations. Since standard interpolation fails to accurately detect respiration data from R-R intervals and cannot precisely handle missing R-R intervals in short samples, cubic spline interpolation is recommended as a replacement and its results are presented. The obtained results provide insights into the effectiveness and application of the Pan-Tompkins algorithm, FFT (Fast fourier transform) implementation, and cubic spline interpolation in the selection of respiration and R-wave features. According to the findings of the study, in the analysis conducted on 2-second samples with a 1000 Hz sampling frequency created from each participant's respiratory data set, missing respiratory data were successfully reconstructed from the R-R intervals of the ECG data using standard and cubic curve interpolation methods. Upon examination of RMSE (Root mean square error) values, it was observed that for 30% of the participants, as RMSE values increased, completion counts for standard interpolation increased, while completion counts for cubic curve interpolation decreased. Conversely, when RMSE values decreased, 60% of the participants showed a decrease in completion counts for standard interpolation and an increase in completion counts for cubic curve interpolation. A 10% participant group was identified where there was no apparent relationship between RMSE values and interpolation method. This indicates that in 90% of the participants, there is a linear relationship between the study's interpolation method, RMSE values, and completion counts for missing R-R intervals.

Keywords: Electrocardiogram, Respiration, Pan-Tompkins algorithm, Curve interpolation

***Corresponding author:** Sakarya University of Applied Sciences, Faculty of Technology, Department of Mechatronics Engineering, 54050, Sakarya, Türkiye
E mail: mertdemirsoy@subu.edu.tr (M. S. DEMİRSOY)
Mert Süleyman DEMİRSOY https://orcid.org/0000-0002-7905-2254
Ayşe Nur AY GÜL https://orcid.org/0000-0002-4448-4858

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1. Introduction

Electrocardiogram (ECG) is a graphical representation of electrical waves generated during a process, providing crucial information about the cardiac cycle (Kohler et al., 2002; Luz et al., 2016). Cardiologists utilize ECG to diagnose and monitor heart diseases, including conditions such as arrhythmia detection (Ye et al., 2010; Apandi et al., 2018; Marinho et al., 2019). A normal rhythmic ECG signal includes P-waves, QRS complexes, and T-waves. QRS complexes and R-peaks play a significant role in automated ECG analyses, forming the basis for many algorithms (Harikumar and Shivappriya, 2011; Benosman et al., 2017). By identifying QRS complexes and R-peaks, other waves and features in the ECG can be detected (Kohler et al., 2002). The measurement of biological information such as electrocardiogram (ECG) and respiration has become possible in recent times using devices like wearable sensors and cameras (Rahman et al., 2016; Dias and Paulo Silva Cunha, 2018). Advanced technologies in bioinstrumentation enable the monitoring of physical and psychological conditions in daily life. For instance, it is employed to monitor the elderly based on heart rate (Shin et al., 2012), assess parasympathetic activity using high-frequency components of R-R intervals (the durations between heartbeats) (Hayano and Yuda, 2019), and measure sleep stages using heart rate and respiration (Suzuki et al., 2009). The reliability of vital data obtained from devices is crucial for accurate monitoring. When a portion of vital data is lost due to external factors such as noise, the reliability of indices calculated from vital data will be low.

For example, R-R intervals are commonly used in the calculation of various indices like heart rate. However, movements of the body causing electrode displacement or potential fluctuations caused by artifacts can lead to incorrect measurements of the R-wave. Since missing vital data results in missing R-R intervals, the reliability of indices based on R-R intervals will be low. To fill in missing data or predict values in a specific range of the dataset, linear interpolation and curve interpolation (Choi and Shin, 2018) methods are used. Standard and cubic spline interpolation are two commonly used methods for this purpose. These two methods are employed to predict missing or specific interval data. Cubic spline interpolation generally provides smoother and more accurate results due to the use of a higher-degree polynomial. However, depending on the nature of the data and the characteristics of the dataset, standard interpolation can be sufficient in some cases. However, the longer the missing segment, the greater the deviation between the calculated R-R intervals and the actual R-R intervals. For example, frequencies calculated from interpolated R-R intervals will also be incorrect. Therefore, to interpolate missing R-R intervals accurately, it is necessary to consider heart rate variability (HRV) during the missing period to complete missing R-R intervals. In this study, a dataset was used where 20 healthy and drug-free participants (age ranging from 18 to 28; 9 males and 11 females) were subjected to tasks requiring arithmetic or attention.

This article proposes a method for completing missing RR intervals based on the respiratory duration using the Pan-Tompkins algorithm applied to ECG data in states of mental activity and calmness. Along with this method, cubic spline interpolation also helps complete missing R-R intervals and prevents temporal fluctuations occurring in R-R intervals. As R-R intervals are biometric data, they are influenced by the individual and measurement conditions. Therefore, the proposed method selects respiratory features according to the measured data.

1.1. Studies Related to the Data Set

The dataset known as 'PsPM-CogSF,' created by Bach and Staib (2015), comprises measurements of respiration and electrocardiogram (ECG) during mental arithmetic attention tasks and resting periods. These measurements are used to investigate physiological responses associated with cognitive processes and relaxation states. The matching pursuit algorithm has provided a fast and effective method for extracting tonic sympathetic arousal from spontaneous skin conductance fluctuations. This algorithm has offered a significant alternative for assessing autonomous responses during cognitive tasks and resting periods. Similarly, dynamic causal modeling (DCM) has been employed to predict tonic sympathetic arousal arising from spontaneous skin conductance fluctuations. This methodology, utilizing data obtained from skin conductance fluctuations, has shed light on the physiological relationships between sympathetic arousal and emotional states, contributing to the understanding of cognitive-emotional processes (Bach and Staib, 2015).

The 'PsPM-CogSF' dataset has played a crucial role in developing psychophysiological models for evaluating fear learning and sympathetic activity. These models have provided valuable insights into the relationship between autonomic arousal and cognitive-emotional phenomena, deepening the understanding of fear memory and sympathetic responses. This dataset, utilized by Jelsma and others as well as Cheadle and others to investigate the relationship between sympathetic arousal and experiences of racial discrimination and psychological characteristics, has explored the dynamics of the sympathetic nervous system arousal by examining responses to real-life experiences and psychological features based on physiological measurements in the dataset (Cheadle et al., 2020; Jelsma et al., 2021). Finally, a study titled "Marked Point Process Filtering Approach for Tracking Sympathetic Arousal from Skin Conductance" by Wickramasuriya and Faghih (2020) has been presented.

In summary, the 'PsPM-CogSF' dataset has contributed significantly to research on sympathetic arousal, fear learning, and psychophysiological models. The use of matching pursuit algorithms, dynamic causal modeling, and psychophysiological models has enhanced the understanding of autonomic responses during cognitive tasks, emotional experiences, and real-life stress factors.

2. Materials and Methods

2.1. Completing Missing RRs

The goal was to fill in the missing R-R intervals in the dataset using standard and cubic spline interpolation methods, aiming to complete the missing data and address the gaps. Figure 1 illustrates how R-R intervals can be obtained from the ECG. Initially, a high-amplitude R-wave is extracted from the ECG.

Subsequently, each RR is calculated from the interval between one R wave and the next R wave. However, when there are artifacts in the ECG and R waves are not accurately detected, the R-R intervals will be abnormal. Consequently, data in that region will be lost. The literature suggests various approaches to overcome this problem: improving the accuracy of R-wave detection, identifying abnormal values in R-R intervals, and completing missing R-R intervals. Several methods have been proposed to enhance the accuracy of R-wave detection, such as noise reduction techniques that decrease the impact of noise and enhance the accuracy of R-wave detection (Akshay et al., 2010; Sahoo et al., 2015). Additionally, there is a method using neural networks for R-wave detection (Vijaya et al., 1998). The main method for removing outliers is to decide whether R-R intervals are within the normal range. For example, reliability is determined based on whether R-R intervals are between 250 ms and 1500 ms (Izumi et al., 2015). Linear or second-degree/cubic function-based curve interpolation has been utilized to predict missing R-R intervals (Choi and Shin, 2018). As curve interpolation requires minimal computation, it can be easily applied even in wearable devices. However, as mentioned above, the deviation between real and calculated R-R intervals grows as the duration of data loss increases. To address this issue, methods to complete heart rate using blood pressure and blood flow have been suggested (Li and Clifford, 2008; Borges and Brusamarello, 2016).

Respiration has been identified as one of the key factors in increasing heart rate variability (HRV) (Berntson et al., 1993). Moreover, respiration is known to cause changes in heart rate through respiratory sinus arrhythmia (Berntson et al., 1993). Similarly, heart rate can fluctuate with changes in both deep breathing and respiratory rate (Sroufe, 1971; Chang et al., 2013). For instance, when both respiration and R-R intervals are measured simultaneously, both can be recorded as missing. However, while R-R intervals fluctuate between 250 ms and 1500 ms per beat (Izumi et al., 2015), respiratory changes can range from 3000 ms to 5000 ms per breath (Berntson et al., 1993). Thus, respiration is expected to be useful in completing missing R-R intervals, and changes can be more easily observed than in ECG signals.

It is known that heart rate variability (HRV) varies depending on the depth of respiration (Sroufe, 1971). HRV deepens during deep breathing (Sroufe, 1971). Therefore, in this study, respiration depth is utilized. Additionally, changes in respiratory rate will also create variability in heart rate (Chang et al., 2013). Moreover, HRV is high during slow breathing and low during fast breathing. Therefore, in our approach, respiration duration is used. Figure 2 illustrates the representation of respiration durations in the data set at a sampling frequency of 1000 Hz, showing the data numbers in the periods of mental activity and resting states (data between 0-1400 representing the resting state, and data between 1400-2800 representing the mental activity state).

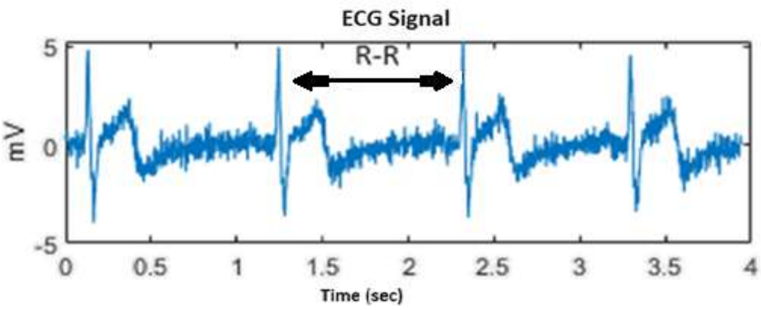


Figure 1. R-R intervals.

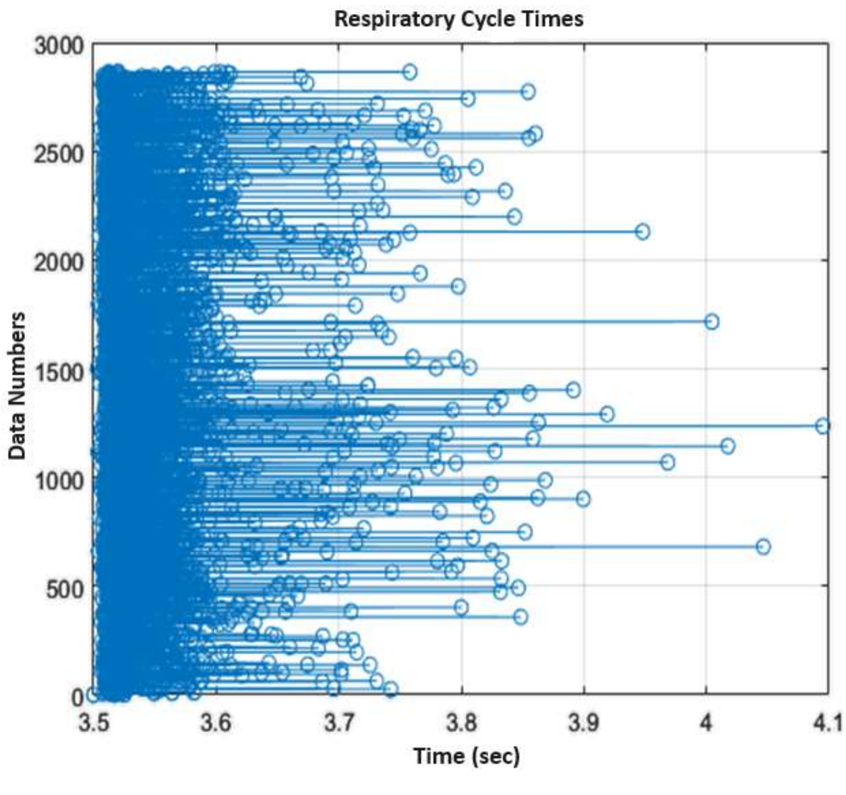


Figure 2. Respiratory time graph during mental activity and rest (x-axis represents time, y-axis represents the number of data).

As shown in Figure 2, signal processing on the FFT model reveals that the average respiration duration during rest is 3.87 seconds at 50 Hz, whereas during mental activity, the average respiration duration is 3.69 seconds. From this, it can be inferred that the heart rate variability (HRV) during rest, indicating the change in heart rate, will be more profound. This implies that RR waves can be more easily detected during rest.

2.2. Preprocessing

Vital signs such as heart rate are known to be significantly influenced by individual characteristics such as gender (Ryan et al., 1994; Chester and Rudolph, 2011). If missing R-R intervals are completed using the same method for everyone, the accuracy of the completed R-R intervals will be debated. This difference also affects the nerves. R-R intervals vary on sympathetic and parasympathetic nerves. When the sympathetic nerves are active, the heart rate variability (HRV) is low. On the other hand, when the parasympathetic nerves are active, the HRV is high. Therefore, reflecting the tendency of the autonomic nervous system during periods of missing R-R intervals is important. The proposed method processes time series data using fast fourier transformation (FFT). Figure 3 illustrates the workflow of the proposed method.

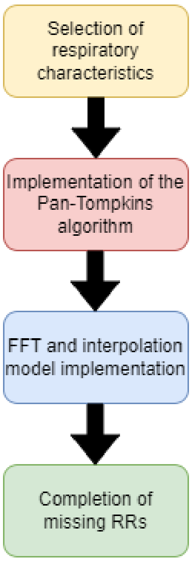


Figure 3. Method flow chart.

Initially, the raw ECG data were processed using a low-pass filter with a cutoff frequency of 100 Hz and a filter order of 3. Subsequently, a high-pass filter with a cutoff frequency of 10 Hz and a filter order of 3 was applied to remove unwanted low-frequency components. Additionally, 50 Hz power line noise was eliminated using a notch filter (Ay et al., 2017). Following these steps, the Pan-Tompkins algorithm was implemented to detect R waves. This algorithm was utilized by testing threshold values separately for each subject's data. Subsequently, the interval wave between Rs and the next R wave was calculated, and RR tachograms were generated. Finally, the graph illustrating the variation of R-R intervals over time was resampled at 30 Hz. To address potential high-frequency electrical noise in the raw respiratory data, a median filter (window size of 0.15 seconds) was applied for smoothing (Ay et al., 2017). Furthermore, the relationship between respiratory features and HRVs was observed by applying FFT after the median filter to calculate respiratory durations. Figure 4 illustrates the preprocessing steps for the ECG data.

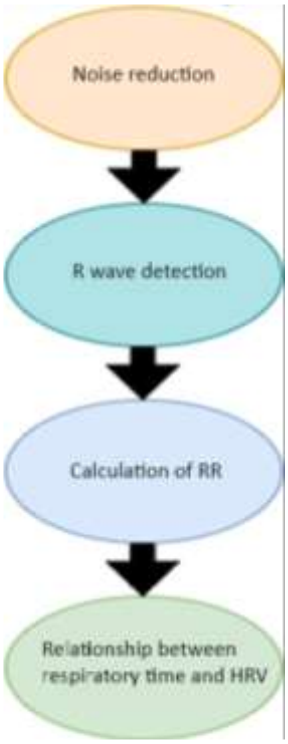


Figure 4. Signal preprocessing steps.

Heart Rate Variability (HRV) analysis is a non-invasive measurement that reflects the autonomic nervous system's regulation of heart rate, extensively utilized in the medical field for evaluating stress, sleep quality, and various cardiovascular conditions. This analysis involves a sequence of signal processing steps for the accurate detection and analysis of R-R intervals, which are the time intervals between consecutive R-waves in an electrocardiogram (ECG) signal. These steps encompass noise reduction, R-wave detection, calculation of R-R intervals, and elucidation of the relationship between respiratory time and HRV. Noise Reduction is the initial step in processing ECG signals for HRV analysis, addressing the contamination of signals with various types of noise (Ay and Yildiz, 2021; Ay and Yildiz, 2023). This phase is crucial for accurate R-wave detection. Techniques such as band-pass filtering and more advanced methods like wavelet transform are employed for effective noise suppression without distorting the ECG signal. R-Wave Detection follows noise reduction and is pivotal for calculating R-R intervals. The Pan-Tompkins algorithm is a popular method in this context, involving filtering, differentiation, squaring, and integration of the ECG signal to emphasize the R-wave feature. Calculation of R-R Intervals is conducted upon accurate R-wave detection. This process measures the time between successive R-wave peaks, typically in milliseconds, and analyzes the variability within these intervals to assess HRV. The relationship between respiratory time and HRV is the final step in the signal processing for HRV analysis. Respiration affects heart rate through respiratory sinus arrhythmia (RSA), significantly impacting HRV measurements. To analyze this relationship, the respiratory signal can be extracted from the ECG signal itself or through other sensors measuring thoracic expansion, with techniques like spectral analysis or time-frequency analysis used to quantify the influence of respiration on HRV. In summary, the signal processing steps involved in HRV analysis, from noise reduction and R-wave detection to the calculation of R-R intervals and understanding the respiratory influence on HRV, are complex but crucial for an accurate and reliable assessment of heart rate variability. These processes enable clinicians and researchers to better comprehend the autonomic regulation of heart rate and its implications for health and disease.

2.3. Development Methods

The accuracy of completing incomplete R-Rs was evaluated using the following methods.

2.3.1. Correlation coefficients

HRV (Heart Rate Variability), is a measure of the variability in heart rate and is typically calculated based on the R-R intervals (time intervals between heartbeats). The changes in the time series of R-R intervals are used to assess HRV. The relationship between HRV and respiration is often examined through the correlation coefficient between respiration and HRV. The correlation coefficient is a statistical measure used to quantify the relationship between two variables. The Pearson Correlation Coefficient is commonly employed to calculate the correlation coefficient on R-R intervals and respiratory data in ECG recordings, and its formula is presented in Equation 1.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (1)$$

Equation 1 represents the number of samples, n. Here, x_i and y_i denote each sample in the R-R intervals and respiratory data, respectively. Additionally, $\bar{x}$, $\bar{y}$ represent the means of R-R intervals and respiratory data. The correlation coefficient takes values between -1 and +1. A positive (+1) correlation indicates a direct linear relationship between the two variables, while a negative (-1) correlation signifies an inverse relationship. A value of 0 indicates no apparent relationship.

The obtained correlation coefficient in this manner represents the connection between R-R intervals and respiratory data. A positive correlation suggests a linear relationship between respiration and HRV, while a negative correlation indicates an inverse relationship. A value close to 0 indicates a lack of a significant relationship between the two datasets. In the utilized dataset (comprising a total of 20 subjects), positive correlations were observed for all but 3 subjects. Subjects 1 and 2 exhibited a negative correlation, while subject 3 showed a correlation coefficient of 0, indicating no discernible relationship between the two variables.

2.3.2. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a measure of the difference between actual and predicted values, commonly employed to assess the performance of a predictive model. It allows evaluating prediction errors on HRV and R-R intervals in ECG and respiratory data. Denoting the predicted values for HRV and R-R intervals as ŷ and the actual values as y_i, the RMSE formula is expressed in Equation 2.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (2)$$

For instance, using this formula for the actual and predicted values of R-R intervals, we can assess the predictive capability of your model. The lower the RMSE value, the higher the predictive power of your model. This evaluation is commonly preferred as a method to measure the prediction performance on R-R intervals or HRV. A lower RMSE value indicates that the model makes predictions closer to the actual data. In our dataset, the RMSE values were measured at a level considered low for 14 subjects and at a level considered high for 6 subjects. This suggests that obtaining more accurate results in completing missing R-R intervals can be achieved by using the data of the 14 subjects, resulting in a lower RMSE.

2.3.3 Pan-Tompkins Algorithm

The Pan-Tompkins algorithm is an algorithm used for QRS detection and is commonly employed to identify R-peaks in ECG signals. This algorithm is designed to define R-peaks in QRS complexes by utilizing the width, slope, and amplitude of an integrated window. The algorithm typically consists of two stages: preprocessing and decision stages. In the preprocessing stage, the raw ECG signal is prepared before entering the QRS detection process. This stage involves reducing noise, organizing the signal, and enhancing the visibility of QRS complexes. It is performed to diminish unwanted noise in the signal and make QRS complexes more easily detectable. In the decision stage, only significant peak points in the signal are considered using a specific threshold, while noise peak points are ignored. This step is taken to identify crucial points in the signal to clearly determine R-peaks.

The Pan-Tompkins algorithm, employing these stages, identifies R-peaks in QRS complexes and is widely used for real-time ECG analysis. Thus, it enables the rapid and reliable detection of prominent points of heartbeats in the ECG signal. In this article, the missing data in respiratory signals will be completed using the curve interpolation method based on the R-peaks detected with the Pan-Tompkins algorithm. As the R-R intervals are identified in the ECG data with the Pan-Tompkins algorithm, the respiratory signals containing missing R-R intervals will be identified through cubic interpolation. Figure 5 illustrates the block diagram of the Pan-Tompkins algorithm.

The detection graph of the R peaks of the filtered ECG signal, where the Pan-Tompkins algorithm was applied and whose threshold value was selected as 60% of the maximum signal amplitude (Hamida El Naser and Naser, 2023), is shown in Figure 6.

2.3.4. Interpolation method

Curve interpolation is a method used to fit a smooth curve or polynomial to a dataset. In the analysis of HRV and R-R intervals in ECG and respiratory data, curve interpolation is employed to complete missing data or represent the dataset more smoothly. Curve interpolation utilizes polynomials to create a smooth curve between data points. This process allows the data to be combined with a smooth curve and aids in the completion of missing or corrupted data. Cubic curves (third-degree polynomials) are commonly used for curve interpolation (Hao et al., 2021). For both data signals (ECG and respiration), cubic curves using these polynomials are applied at each data point to create a smooth curve. The output of the original and cubic curve interpolation applied signals for ECG and respiration data is illustrated in Figure 7.

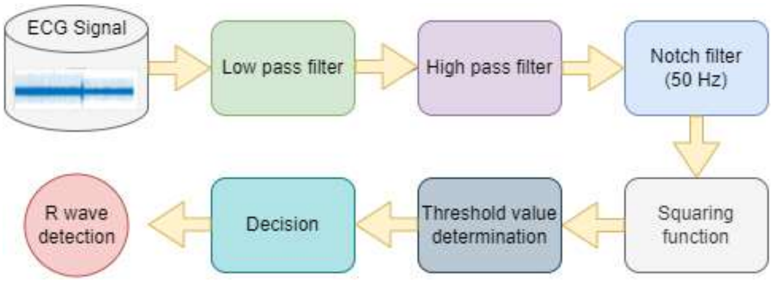


Figure 5. Pan-Tompkins algorithm block diagram.

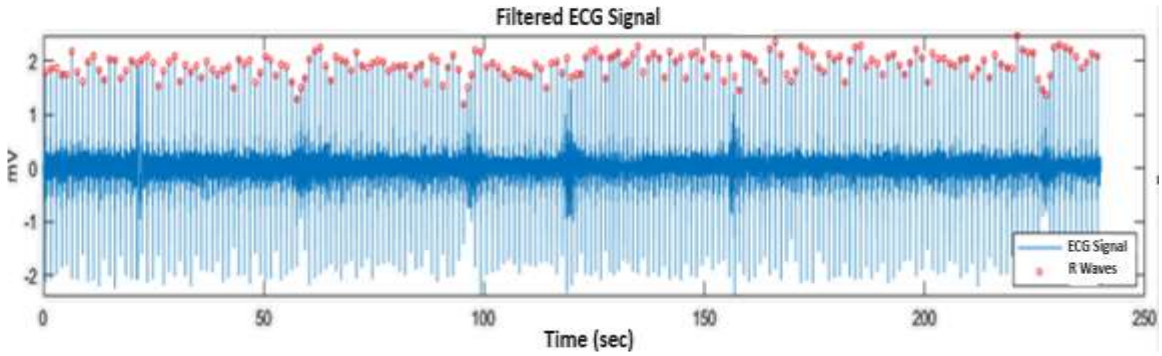


Figure 6. R-peaks with Pan-Tompkins algorithm applied.

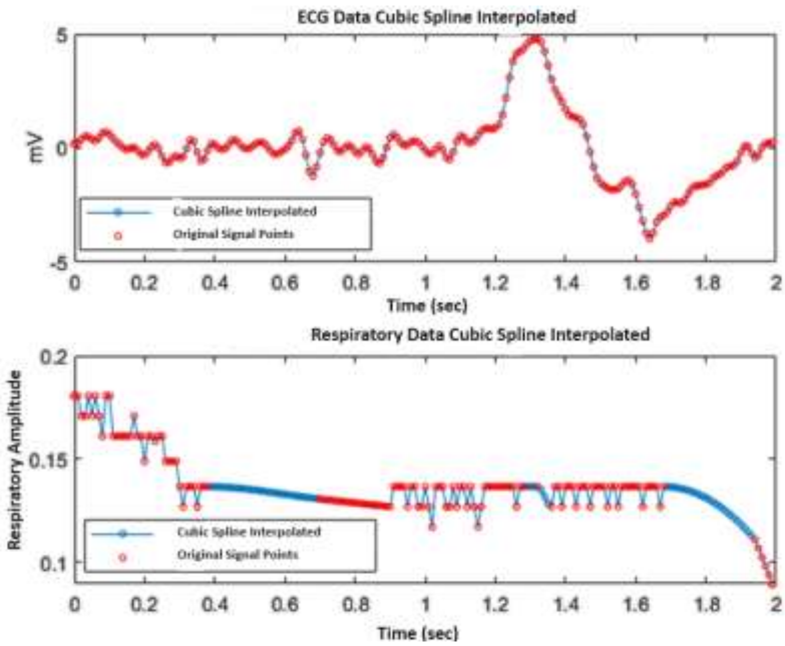


Figure 7. Cubic curve interpolation application in ECG and respiratory data.

In Figure 7, it can be observed that there is no loss in the original ECG data, and when cubic curve interpolation is applied, the values are identical to the original signal. However, in the respiratory data, deviations are present in the original signal, and these discrepancies are detected and mitigated by applying cubic curve interpolation using R-R intervals from the ECG data.

Standard interpolation (first-degree polynomials) applied to both data signals (ECG and Respiration) is illustrated in Figure 8, showing the output of the applied signals.

As depicted in Figure 8, it accurately predicts the ECG data similar to cubic curve interpolation, identifying the real data as it is. However, it is observed that it falls short in detecting the lost respiratory data for the test from the respiratory dataset by relying on R-R intervals in the ECG data. It failed to identify and apply 10 missing respiratory data points between 0.4 and 0.8 seconds in the original data.

3. Results and Discussion

After applying the proposed methods to the ECG and respiratory data in the dataset, the R-peak counts and associated average respiratory durations of the subjects were calculated, and they are presented in Table 1.

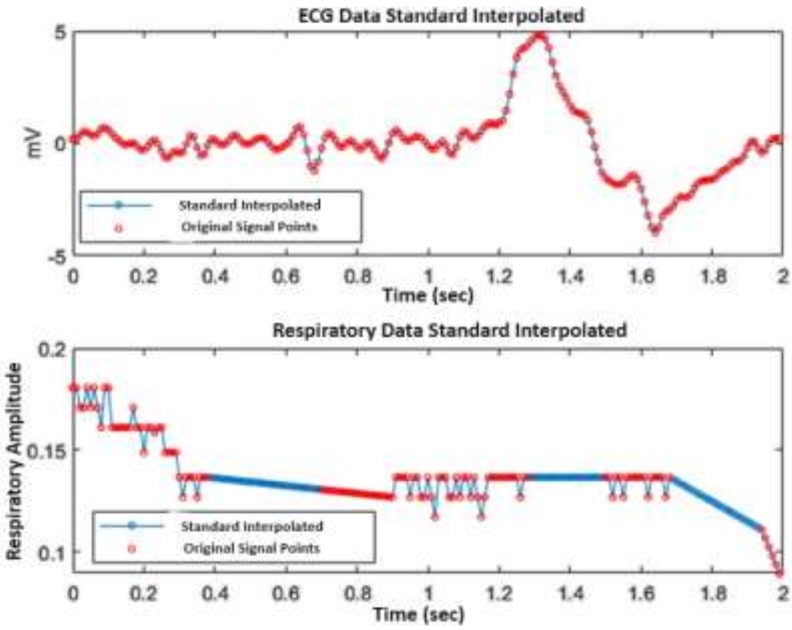


Figure 8. Application of standard interpolation in ECG and respiratory data.

Table 1. R peak numbers and corresponding average breathing times in mental activity and calm states of the subjects in the data set

Subject Order	Number of R peaks between 0-2 min	Number of R peaks between 2-4 min	Average Respiratory Time (sec)
1	135	130	3.32
2	161	165	3.11
3	141	140	3.20
4	231	178	2.05
5	246	201	1.84
6	168	125	2.83
7	251	177	1.92
8	250	145	2.01
9	176	140	2.66
10	235	171	2.03
11	191	165	2.41
12	221	184	1.98
13	165	141	2.71
14	201	179	2.34
15	198	181	2.22
16	155	139	3.04
17	199	146	2.69
18	235	203	1.89
19	181	168	2.45
20	228	184	2.11

In Table 1, it can be observed that the counts of R-peaks during the mental activity state (0-2 minutes) vary compared to the counts during the rest state (2-4 minutes). Generally, R-peak counts tend to be higher during mental activity, while decreasing during the rest state. Most subjects exhibit higher R-peak counts during mental activity, suggesting an increased occurrence of heartbeats. Notably, subjects 4, 5, and 7 demonstrate significantly higher R-peak counts. Overall, a trend of decreased respiratory durations during mental activity compared to the rest state is observed. The increased heart rate is often associated with faster respiratory durations. Additionally, a positive correlation is observed except for subject 3 (subjects 1, 2, and 3). Negative correlation is observed for subjects 1 and 2, while the correlation coefficient for subject 3 is 0, indicating no relationship between respiration and heartbeats for this subject.

In summary, Table 1 highlights the relationship between R-peak counts and respiratory durations during mental activity and rest states. Higher heart rates and shorter respiratory durations are observed during mental activity, whereas lower heart rates and longer respiratory durations are observed during the rest state.

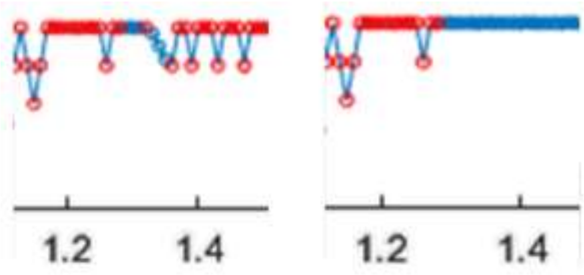
In Table 2, 2-second samples were created from the respiratory data sets for each subject with a sampling frequency of 1000 Hz. An equal number of data points (200 data points for each subject's data set) were randomly removed from the respiratory data sets. Using standard and cubic curve interpolation methods, missing respiratory data were reconstructed from the R-R intervals of the ECG data. The detected data points and RMSE values for the subjects' ECG data, based on the applied methods, are presented in Table 2.

In Table 2, the data completion counts for standard interpolation are lower compared to cubic curve interpolation. This indicates that standard interpolation completes fewer missing data points and fills in fewer data values. Upon examining the RMSE values, it is observed that standard interpolation sometimes has lower and sometimes higher values compared to cubic curve interpolation. This suggests that both methods can exhibit different performances based on the structure of the data set and the distribution of missing data, emphasizing the need to consider these factors to determine which method yields better results. Additionally, when RMSE values approach the mean value of the ECG signal, it is observed that standard interpolation completes more data. However, in this scenario, cubic curve interpolation has completed fewer data points compared to other RMSE values that can be considered low.

If we look at subjects 15, 1, 6, 9, 11, and 10 in order, as RMSE values increase, the completion counts for standard interpolation also increase, while the completion counts for cubic curve interpolation decrease. Conversely, as RMSE values decrease, the completion counts for standard interpolation decrease, and the completion counts for cubic curve interpolation increase. It can be inferred from Table 2 that there is a linear relationship with RMSE values.

Table 2. Relationship between data completion numbers of standard and cubic spline interpolation methods and RMSE values

Subject Order	Standard interpolation number of data completions	Cubic spline interpolation number of data completions	RMSE values (mV)
1	18	161	1.67
2	37	152	2.11
3	25	112	1.94
4	39	95	2.21
5	30	135	1.63
6	26	154	1.74
7	20	196	1.51
8	32	185	1.96
9	27	126	1.84
10	63	76	2.47
11	41	85	2.39
12	18	169	1.71
13	19	152	1.79
14	55	89	2.51
15	15	133	1.46
16	37	185	2.02
17	29	146	1.91
18	18	105	1.79
19	28	151	2.09
20	16	118	1.61



(a) (b)

Figure 9. Cubic curve interpolation method (a) Standard interpolation method (b) (Blue line interpolated signal, red circles original respiratory signal points).

For both methods used to complete missing respiration data from R-R intervals, the respiration data has been reduced to the same number and order for both methods. In Figure 9(a), the cubic curve interpolation method shows that between 1.2 and 1.4 seconds, the original signal is actually in a downward triangular shape. However, in Figure 9(b), standard interpolation draws the period between 1.2 and 1.4 seconds as a straight line. Upon closer examination, cubic curve interpolation appears to provide more accurate and precise results in completing missing data.

The method utilizing 3rd-degree cubic curve interpolation, which leverages respiration features, has yielded significantly more accurate results compared to standard (1st-degree) interpolation when compared with the proposed method. These results indicate an increase in the variability of R-R intervals even in the presence of missing R-R intervals during resting conditions. However, in other situations (e.g., mental activity or arithmetic operations), the autonomic nervous system can fluctuate, potentially leading to decreased accuracy.

On the other hand, short-term repeated results have shown very little difference between the proposed method and 1st-degree standard interpolation for missing R-R intervals (e.g., Figure 8). One possible explanation for this is the short duration of the periods in Figure 8 and Figure 7. However, it is evident that 1st-degree standard interpolation is not suitable for completing missing data. 1st-degree standard interpolation linearly replaces changing R-R intervals over time, ultimately producing R-R intervals with temporal fluctuations. These results suggest that using 3rd-degree cubic curve interpolation without temporal fluctuations will provide more accurate and precise results in completing missing R-R intervals. In the future, it is planned to assess what kind of temporal fluctuations may occur in missing R-R intervals when the proposed methods are used under different conditions.

4. Conclusion

This study aimed to investigate the relationship between heart rate variability (HRV) and respiration and explore appropriate methods for accurately completing missing R-R intervals. The results obtained using Pearson correlation coefficient revealed both positive and negative correlations between respiration and HRV under specific conditions. Consequently, the cubic curve interpolation method facilitated the accurate integration of missing R-R intervals in respiration signals. Analyses conducted indicated that 3rd-degree cubic curve interpolation provided more accurate results compared to standard (1st-degree) interpolation and was more effective in completing missing R-R intervals. This allowed for the more precise completion of changing R-R intervals over time. According to the findings of the study, 85% of the participants exhibited higher R-peak counts during mental activity, particularly noticeable in subjects 4, 5, 7, 8, and 10. This indicates an increase in heartbeats. The tendency of decreased respiratory durations during mental activity compared to the rest state was observed, reflecting the common association of increased heart rate with shorter respiratory durations. These findings suggest that respiration features can be utilized to enhance the accuracy of completing R-R intervals and warrant further evaluation under different conditions in future research.

Author Contributions

The percentage of the author(s) contributions is presented below. All authors reviewed and approved the final version of the manuscript.

	M.S.D.	A.N.A.G.
C	70	30
D	80	20
S	50	50
DCP	90	10
DAI	80	20
L	40	60
W	80	20
CR	50	50
SR	50	50

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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