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Signal processing for abnormalities estimation analysis

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ABSTRACT

Pneumonia, asthma, sudden infant death syndrome (SIDS), and the most recent epidemic, COVID-19, are the most common lung diseases associated with respiratory difficulties. However, existing health monitoring systems use large and in-contact devices, which causes an uncomfortable experience. The difficulty in acquiring breathing signals for non-stationary individuals limits the use of ultra-wideband radar for breathing monitoring. This is due to ineffective signal clutter removal and body movement removal algorithms for collecting accurate breathing signals. This paper proposes a breathing signal analysis for non-contact physiological monitoring to improve quality of life. The radar-based sensors are used for collecting the breathing signal for each subject. The processed signal has been analyzed using continuous wavelet transform (CWT) and wavelet coherence with the Monte Carlo method. The finding shows that there is a significant difference between the three types of breathing patterns; normal, high, and slow. The findings may provide a comprehensive framework for processing and interpreting breathing signals, resulting in breakthroughs in respiratory healthcare, illness management, and overall well-being.

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1. INTRODUCTION

Breathing signal analysis refers to the technique of obtaining useful information from respiratory signals. Breathing is an autonomic process that involves the movement of air into (inhalation) and out of the lungs (exhalation). It consists of tidal volume and respiratory rate which is the important parameter associated with breathing conditions. The normal average breathing pattern is 12 breaths per minute nearly 25,000 times a day and an average of 500 mL per breath of amount air exchanged during breathing. Abnormalities of breathing patterns may occur in rate, rhythm, and in the effort of breathing whereas a resting breathing rate over 25 or under 12 is considered abnormal. However, the measurement using the breathing rate parameter is subject to inaccuracy because it might change during the measurement period [1].

The normal respiratory waveform is depicted in Figure 1. The examination of the respiration waveform detects abnormal respiratory problems. A higher-than-normal breathing rate indicates tachypnea. Bradypnea is characterized by a slower-than-normal respiratory rate. An absence of a waveform indicates apnea. The radar sensor is one of the latest technologies that has been adopted for breathing signal acquisition. The correlation between the chest wall displacement and the tidal movement may produce a microwave signal that produces information about the breathing pattern. This data can be used to distinguish between different types of breathing conditions, such as shallow breathing, deep breathing, slow breathing, quick breathing, and other breathing patterns.

The study of non-contact methods is motivated by the drawbacks of touch-based respiratory signal measurement, including discomfort, disruption of spontaneous breathing, and vulnerability to motion artifacts. By eliminating the need for unpleasant sensors, remote cameras, and radar systems enable discreet monitoring that improves comfort, accuracy, and convenience. They are safer in hospital environments and appropriate for telehealth applications since they enable remote monitoring and are less impacted by motion artifacts. Thus, radar is a non-contact technology that does not require adequate lighting to recognize objects. The three forms of radar include continuous wave (CW) radar [2], [3]. Ultra-wideband (UWB) radar [4], and frequency-modulated continuous wave (FMCW) radar [5]–[7] that may detect human vital signs [8], [9]. UWB radar is a type of radar system that uses signals with exceptionally wide bandwidths, frequently exceeding 500 MHz and reaching several gigahertz. UWB signals feature high data rates and little transmitting power. Because of the exceptionally low power spectral density (PSD) of UWB broadcasts, narrowband technology and UWB systems can coexist without creating undue interference [10].

Also Ullah *et al.* [11] provides a framework for developing a low-cost, hybrid respiratory monitoring system based on a radar impulse-radio ultra-wideband (IR-UWB) radar and an optical depth-sensing camera system as shown in Figure 2. The camera is employed to detect subjects and deliver location information. The components of respiration are then derived from the radar output data. UWB has lower path loss and is less vulnerable to multipath propagation. UWB radar may achieve great sensitivity and accurate range resolution, making it suitable for a wide range of applications such as target detection, imaging, and tracking. Several studies on wireless sensing devices based on UWB to recognize vital signs for healthcare applications [12]. These wireless systems are advertised as having low system complexity, low cost, low energy consumption, and fast data throughput [13]. UWB technology exceptionally has low transmission power which effectively reduces the PSD to a level comparable to background noise, ensuring that UWB signals pose minimal exposure risks to users [14].

Radars are capable of non-contact monitoring. A breathing signal is a recorded representation of the physiological changes that occur while breathing. Sensors that detect chest movement, as well as airflow, can be used to measure these changes. Typically, breathing signals are analyzed in the time domain, frequency domain, or wavelet domain. Before signal processing, many approaches have been used such as the fast Fourier transform (FFT), Hilbert Huang transform, and auto-regressive time-frequency analysis (ARTFA). Hämäläinen *et al.* [15] extracted features from breathing data using FMCW, extreme gradient boosting (XGBoost) classification model, and mel-frequency cepstral coefficient (MFCC) feature extraction techniques. They discovered that this strategy is extremely beneficial before the breathing categorization process. In Purnomo *et al.* [16], the author elaborated on the numerous decomposition approaches that were used in conjunction with principal component analysis (PCA) to analyze the respiration signal and estimate the respiration rate from the photoplethysmography (PPG) signal. The study discovered that combining variational mode decomposition with PCA resulted in excellent accuracy in extracting breathing signals.

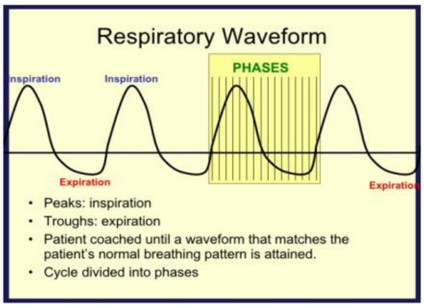


Figure 1. Normal respiratory waveform characteristics [17]

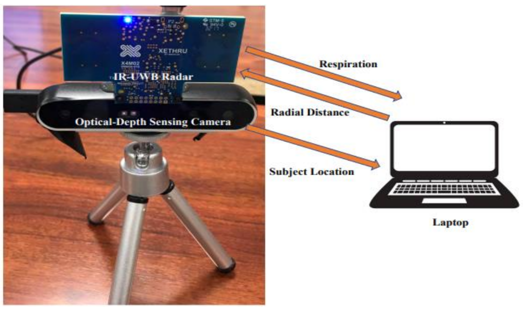


Figure 2. The structure of the hybrid radar-camera system [11]

In researchers [18], [19], continuous wavelet transforms (CWT) as an analysis technique for respiratory sinus arrhythmia (RSA). It is essential for the analysis of RSA that the CWT can track quick fluctuations of the signals in terms of both their amplitude and their phase. Following an evaluation using simulated data, it was determined that the proposed method is superior to the conventional short-time Fourier transform (STFT) analysis in terms of both accuracy and robustness. The CWT is a strong instrument that can be used to break down signals into their constituent frequency components at various time scales. This can be accomplished by analyzing the signals using the CWT. As a result, CWT is ideally suited for the examination which can vary greatly in terms of both the frequency content and the duration of their occurrences. The authors of the research were able to successfully identify and extract wheezes from lung sound recordings from a group of asthma patients, and their method was able to achieve a high degree of accuracy. Wavelet transforms are used by Addison *et al.* to derive a breathing waveform from the PPG [20]–[24]. A CWT employing the complex Morlet wavelet decomposes the PPG signal to generate a scalogram with two bands; the frequency corresponding to the breathing rate and the frequency corresponding to the pulse rate. The peak of the ridge associated with the pulse band is tracked and projected as an amplitude-time or frequency-time signal. Thus, this study proposed to use suitable techniques for data analysis that can be implemented in real time. For signal processing, CWT is utilized to catch up with the changes in the breathing cycle. The CWT breaks down a signal into its frequency components over a range of time scales. This makes it possible to recognize signal features that are present at particular time scales and frequencies.

2. RESEARCH METHOD

2.1. Overview procedure

Figure 3 shows the proposed block diagram of the breathing signal processing. The data collected are swept and converted to a visual scalogram using the CWT approach. Then, wavelet coherence is analyzed by using the Monte Carlo method. By giving a precise time-frequency representation, the CWT approach is a strong tool for analyzing respiratory signals [25]. CWT decomposes the signal into its basic frequency components over time in breathing signal analysis, providing a dynamic perspective of respiratory patterns. Because respiratory patterns can alter in both frequency and amplitude, this is especially valuable for recording the complex fluctuations in breathing signals. Table 1 presents the different tasks given to the subject for the data collection.

Figure 3. Block diagram of signal processing

Table 1. The task for the breathing condition stimulation

Breathing condition	Activities	Duration
Normal breathing	Just sit and breathe normally.	15 minutes of data collection
Low breathing	Sit while taking a deep breath constantly.	15 minutes of data collection
High breathing	The subject needs to do some exercise (e.g., Star jumping or running). Then take a rest while sitting.	Minimum 5 minutes for activities and 15 minutes for data collection

2.2. Experimental setup

2.2.1. Subject

This research has been registered with the National Medical Research Register (NMRR) to ensure it follows ethical and scientific standards. A minimum of 40 people will be taking part in the data collection, and they will be exposed to various stimuli to induce diverse breathing conditions: rest, mild activity, and severe exercise. The radar equipment will be set for the subjects to collect all the data according to the given task as shown in Table 1. In addition, the subject's health is emphasized before the experiment.

2.2.2. Data acquisition

The Novelda X4M200 radar module used for non-contact physiological assessments in this investigation, detects breathing signals through chest movement. The radar is multifunctional, with applications ranging from object detection to monitoring. It works on radio wave principles, emitting electromagnetic waves at a predetermined frequency and measuring reflections from surrounding objects. Its revolutionary technology delivers extensive information about detected items, such as their presence, location, speed, and direction, as well as minor physiological activities such as breathing. This adaptability makes it useful for precise non-contact sensing in applications such as occupancy detection, vital sign monitoring, and security systems. The study included 40 participants, 16 female and 24 males, with a mean age of 21.25 as shown in Figure 4. 5% of participants suffered from respiratory conditions such as bronchitis and asthma. The link between breathing signals and chest movement collected by radar is shown in Figure 5.

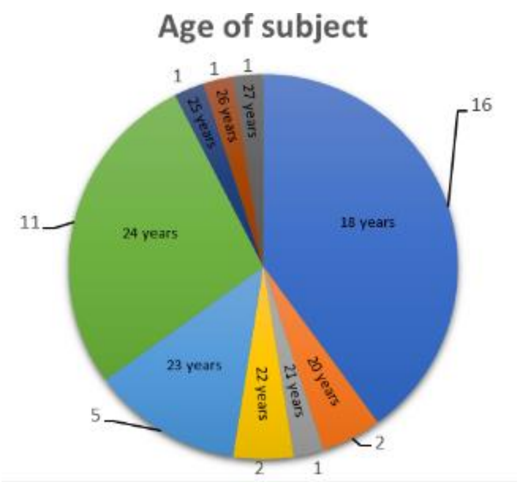


Figure 4. Number of subjects according to the age

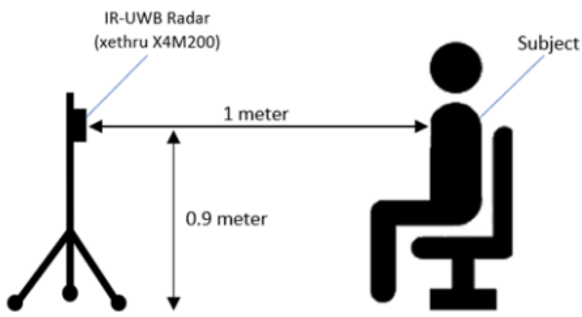


Figure 5. Breathing signals from the chest movement are captured by the radar

2.2.3. Experimental paradigm

This research extracts the breathing rate estimation through the human chest movement. Data collection has been conducted and the illustration of the experiment setup and result are shown in Figures 6-8. Figure 6 demonstrates the position of the subject and the radar setup. The distance range from the subject to the radar is 1 meter and has to be perpendicular to the subject's chest. Figure 7 shows the front view during data collection. While Figure 8 shows the task taken before the experiment.

Figure 6. Experiment set up with the subject

Figure 7. Front view while collecting the data

Figure 8. The activity for high-breathing data collection

2.3. Signal processing

CWT is used to analyze respiratory signals through chest movement that occurs during breathing. Wavelet coherence in the time-frequency domain is used to study the relationship between two signals or time series data. The breathing signal will be analyzed using wavelet transform analysis to obtain energy waveform corresponding to the breathing patterns. This scalogram signal will be used in the classification of breathing conditions. The combination of the CWT with Monte Carlo simulations provides a strong method for analyzing respiratory data that has several specific advantages. CWT enables exact time-frequency analysis, detecting both fast and slow oscillations in the signal, making it especially ideal for respiratory signal analysis, where frequency components can fluctuate greatly. Statistical estimates and uncertainty quantification are made achievable by applying Monte Carlo simulations to CWT results, offering a robust framework for measuring signal variability and dependability. This combination enables quantitative analysis of breathing patterns and diagnosis of abnormalities or anomalies.

3. RESULT AND DISCUSSION

3.1. Pre-processing

The breathing data was imported into MATLAB software to generate the unprocessed breathing signal data collected over 15 minutes. Figure 9 visually represents the raw data reflecting normal breathing patterns in a randomly selected subject. Initially, during the commencement of data collection, the signal exhibits some instability. This initial instability is attributed to the radar system requiring a few minutes to stabilize and function optimally. It's worth noting that the radar sensor's performance is greatly affected by its alignment; it must be precisely perpendicular to the chest for accurate detection of breathing signals. Any deviation from this alignment can result in erratic or inaccurate breathing signal readings.

The signal processing procedure involves a sweeping phase designed to eliminate undesired signal components. Following the acquisition of raw data, this process entails sweeping the signal into validated frames consisting of 3,000 data samples, as demonstrated in Figure 10. Subsequently, the signal is transformed into a visual scalogram, serving as a means to assess the subject's breathing state. A scalogram, derived from the CWT, presents an evolving depiction of the signal's frequency characteristics. In the context of distinguishing between normal, low, and high breathing conditions, the scalogram proves invaluable. Employing CWT to analyze breathing signals and generate scalograms can reveal distinct patterns or features unique to each breathing condition. These patterns may manifest as specific frequency bands or structures within the scalogram.

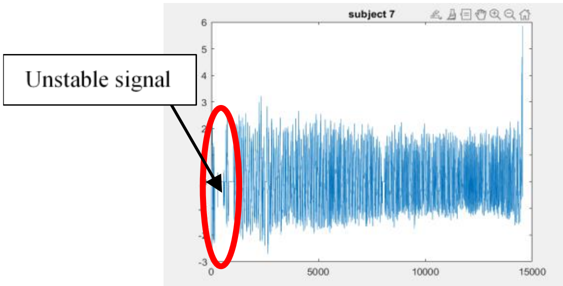


Figure 9. The raw data of normal breathing signals for the subject

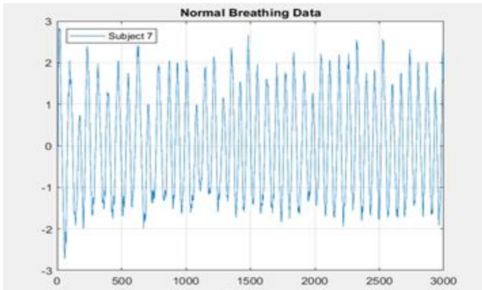


Figure 10. The data samples as a sweeping signal for normal breathing

3.2. Signal processing

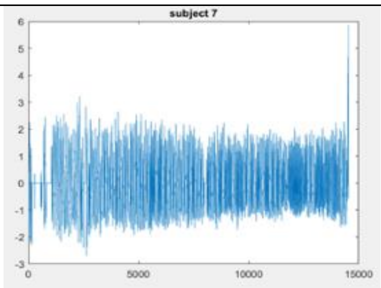
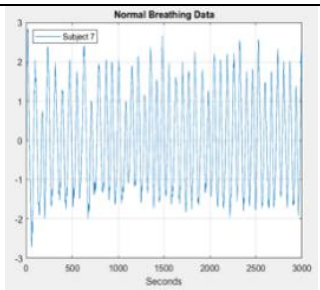
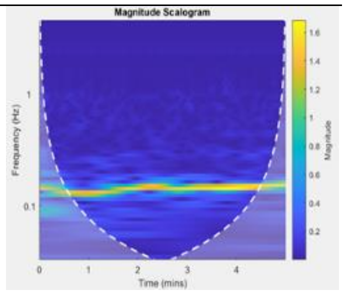
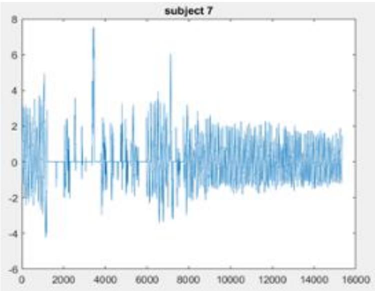
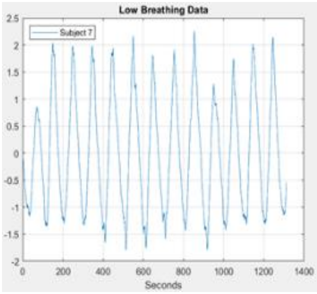
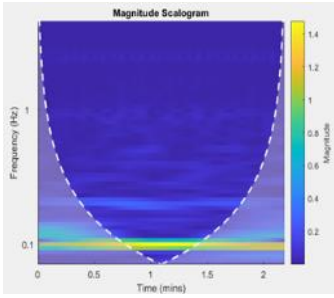
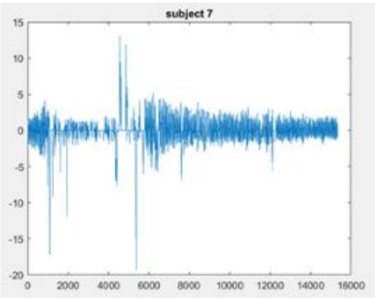
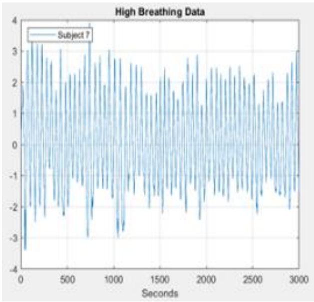
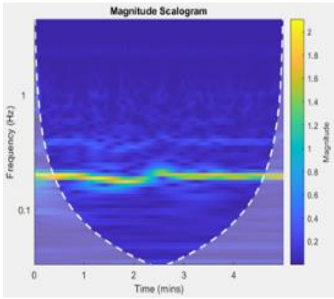
Table 2 shows three different breathing circumstances that the individuals experienced. These conditions are distinguished by particular traits and patterns in the respiratory signal that a sensor records. Examined characteristics include waveform shape, rhythm, amplitude, and respiration rate. The respiratory signal is shown as a strong yellow line on the visual magnitude scalogram, which indicates regular, steady breathing that is indicative of healthy respiration. Blue background tones denote lower signal magnitudes, and red accents denote larger breathing signal magnitudes. Changes in the frequency or intensity components can signify high or low breathing circumstances, respectively. Using wavelet coherence approaches for breathing classification, the suggested coherence analysis seeks to investigate the correlations between respiratory signals.

3.3. Data analysis

Monte Carlo and ANOVA serve as valuable tools for analyzing this dataset. Monte Carlo is employed to assess the significance between two distinct sets of data based on their correlated regions. In contrast, ANOVA is a statistical methodology utilized to examine the variance both within and between groups, aiming to ascertain whether there exist statistically meaningful disparities in the means of these groups. Table 3 presents the analysis of normal breathing data for two different subjects using Monte Carlo, alongside the statistical analysis employing ANOVA. Furthermore, Table 4 illustrates the analysis comparing normal breathing to low breathing within the same subject, aimed at elucidating the statistical significance within these different data groups.

The ANOVA analysis of Table 3 data indicates statistical significance ($p>0.005$), supporting the hypothesis of variations between datasets. The results of Table 4 show non-significant results ($p<0.005$), consistent with the null hypothesis of ANOVA. This emphasizes the value of statistical analysis in identifying relevant trends in respiratory data. Monte Carlo methods were used to estimate coherence importance, which improved accuracy in the presence of signal randomness and noise. These methods also allowed for more efficient coherence estimates.

Table 2. Type of breathing conditions

Breathing condition	Raw data	Sweep data	Visual scalogram
Normal breathing			
Low breathing			
High breathing			

3.4. Discussion

This study looked into the effects of abnormalities in breathing signal processing. Although breathing abnormalities have been studied in the past, their effects on the coherence and time-frequency characteristics of the breathing signal have not been specifically addressed. This is what our proposed methodology seeks to investigate using wavelet coherence analysis using the Monte Carlo method and CWT. We discovered that deviations in the coherence and time-frequency characteristics of the respiratory signal are correlated with abnormalities in its processing. Comparing the suggested approach in this study to traditional approaches, it tended to have an abnormally greater proportion of correctly detecting and characterizing anomalies, improving diagnostic precision and reliability. In this finding, the analysis of breathing signals and the recognition of distinct patterns associated with various respiratory conditions lay an important foundation for future advances in classification purposes. It paves the way for the creation of automated systems capable of effectively classifying individuals into various categories of respiratory disorders. This is possible by employing machine learning or deep learning algorithms, pattern recognition techniques, and data-driven methodologies. These applications have great promise in the healthcare sector since they can help with early diagnosis, personalized therapy planning, and ongoing monitoring of those suffering from respiratory illnesses. Moreover, these classification algorithms may be integrated into wearable devices or telemedicine systems, enabling remote health monitoring and timely intervention. It has the potential to enhance the overall quality of care and improve patient outcomes. This study also looked at the coherence characteristics of breathing signal processing abnormalities. To validate its application in various clinical situations and demographics, further comprehensive research may be necessary. According to our study, the suggested approach that makes use of wavelet coherence analysis is more robust than traditional approaches that only use signal processing techniques. Subsequent studies could focus on refining wavelet coherence analysis settings and creating workable techniques for generating respiratory abnormality diagnoses in real time. According to recent observations, people with abnormal breathing patterns show considerable inconsistencies in the coherence and time-frequency properties of their respiratory signals. Our results provide conclusive evidence that this phenomenon is associated with changes in the breathing signal's coherence and time-frequency domains, as opposed to higher levels of noise or artifacts. The investigation has demonstrated that the use of CWT and coherence analysis with the Monte Carlo method is appropriate for this type of analysis. This approach permits a thorough examination of the intricacies present in the breathing signal and offers significant insights into abnormal respiratory patterns.

Table 3. Data analysis of normal breathing between two different subjects

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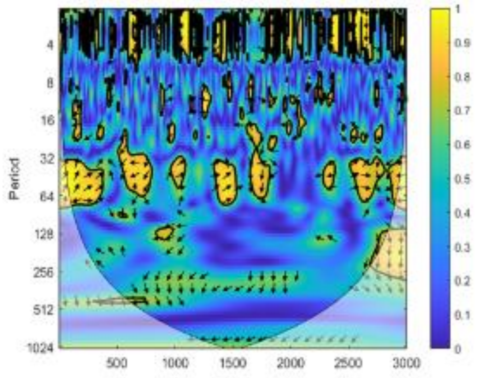
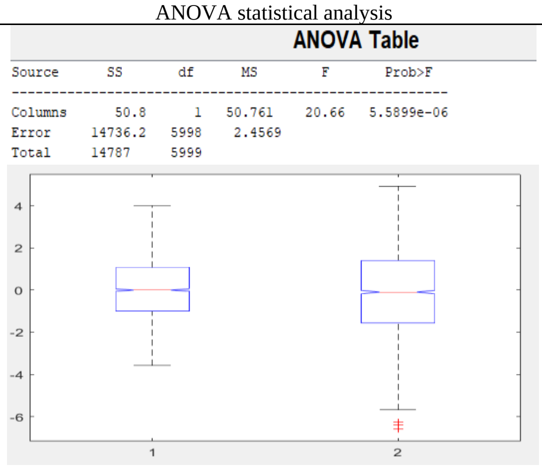
S1&S2</td><td>
</td><td>
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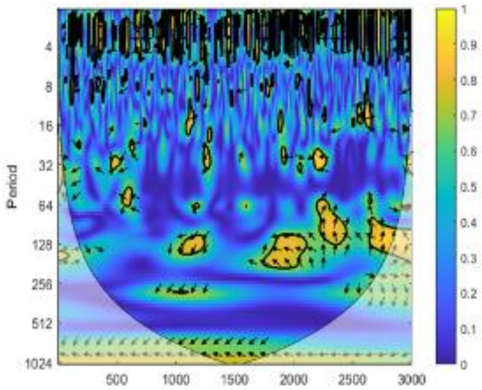
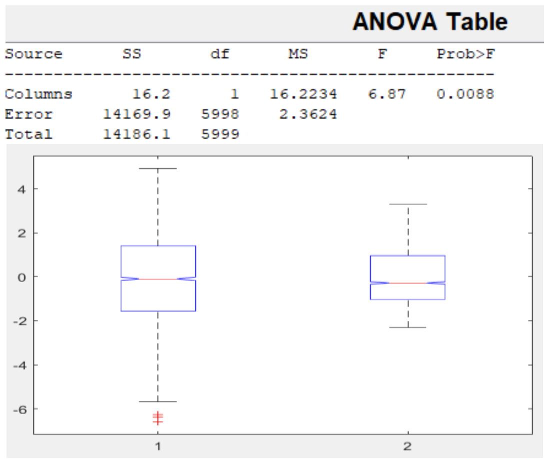
S2&S3</td><td>
</td><td>
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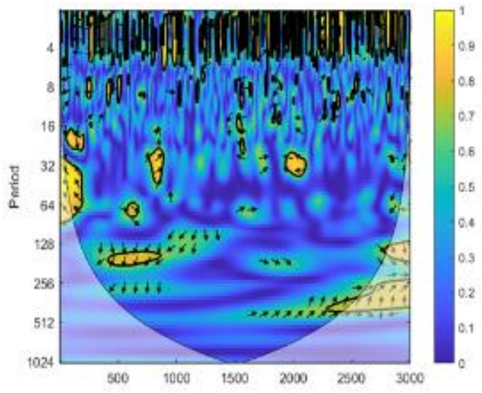
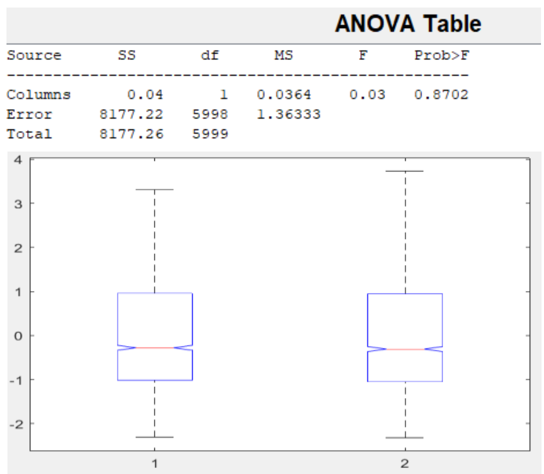
S3&S4</td><td>
</td><td>
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Table 4. Data analysis between normal breathing and low breathing for the subject

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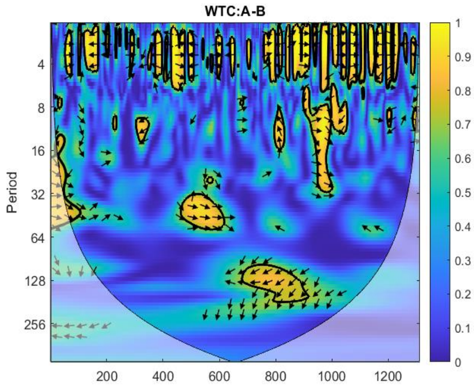
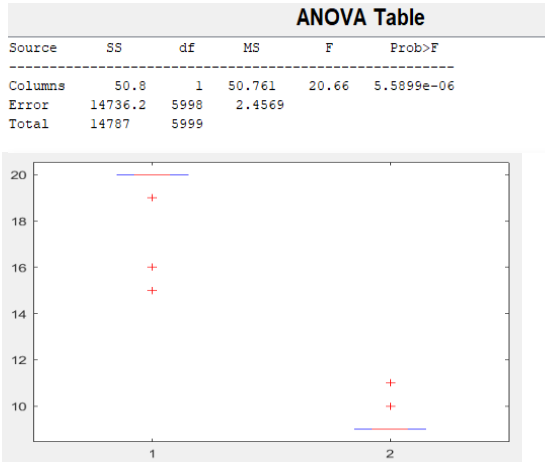
S1&S1</td><td>
</td><td>
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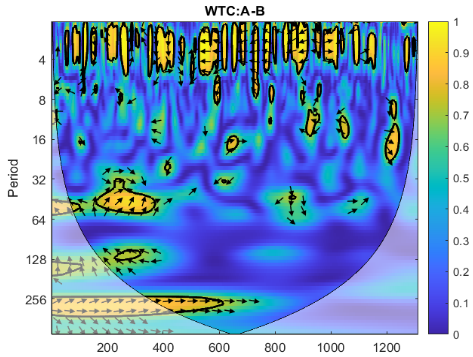
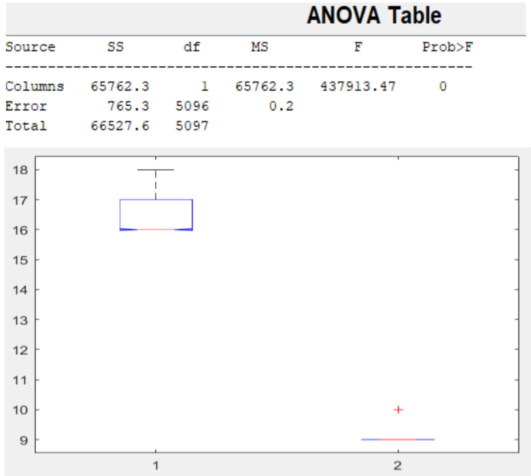
S2&S2</td><td>
</td><td>
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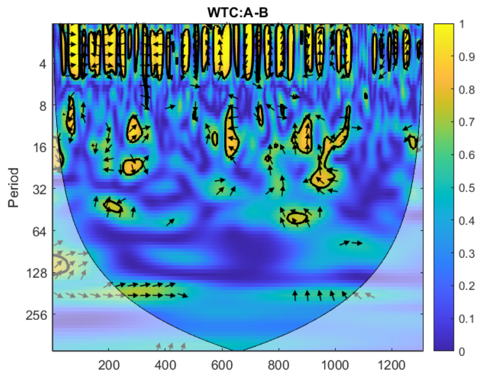
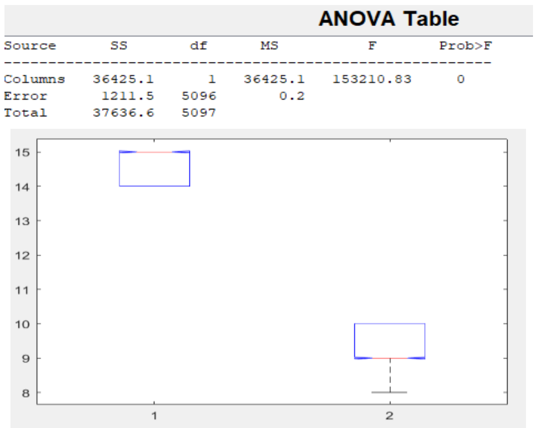
S3&S3</td><td>
</td><td>
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4. CONCLUSION

In summary, the CWT provides rich time-frequency information, supports the time-varying nature of breathing data, and offers valuable insights into respiratory dynamics, making it a powerful tool for breathing signal processing. Its resilience and statistical insights are improved when combined with the Monte Carlo approach, making it possible to identify intricate patterns and anomalies in respiratory signals. With better understanding, monitoring, and diagnosing respiratory-related disorders, this integrated approach offers revolutionary advances in respiratory healthcare. Anticipate future developments in probabilistic and signal processing methods to improve precision, effectiveness, and clinical respiratory health applications even further. Automated classification programs that use technology provide exact diagnoses and personalized treatment plans, potentially revolutionizing respiratory healthcare by allowing for earlier detection and more accessible patient-centric care via wearable devices and telemedicine platforms. We are on the verge of a transformative age in respiratory medicine, with promises of proactive therapies and higher quality of life for patients suffering from respiratory illnesses.

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