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Time-variant traits analysis in respiratory doppler radar's signal

Suraya Zainuddin, Masrullizam Mat Ibrahim, Haslinah Mohd Nasir, Nur Fatin Shazwani Nor Razman, and Mohd Zhafran Zainal Abidin

***Abstract*—Doppler radar-based respiratory monitoring offers a non-contact, physiologic assessment of breathing patterns. However, the inherent time-variant nature of respiratory signals presents challenges in accurate characterisation and classification. This study investigates the analysis of time-variant traits in respiratory Doppler radar signals using a feature extraction framework that integrates statistical features, Hilbert transform, discrete wavelet transforms (DWT), and fractal dimension analysis. The methodology begins with signal pre-processing to remove noise and enhance the signal for clarity. Statistical features, including mean, skewness, and kurtosis, are extracted to quantify signal variability. The Hilbert transform is employed to analyse instantaneous amplitude and phase variations, while DWT is used for multi-resolution decomposition to capture respiratory signal dynamics across different frequency scales over time. Additionally, fractal dimension analysis provides insights into the complexity and irregularity of breathing patterns in the time series. Machine learning-based classification models are applied to distinguish between normal and abnormal respiratory conditions. Results demonstrate the effectiveness of the proposed approach in enhancing respiratory signal characterisation and classification by utilising the Hilbert Transform over a Subspace Discriminant model with an accuracy rate of 92.3%. The findings suggest that integrating these feature extraction techniques can significantly improve non-invasive respiratory monitoring.**

***Keywords*—Respiratory Doppler Signal; Time-variant Traits; Machine Learning; Statistical Feature; Hilbert transform; Discrete Wavelet Transform; Fractal Dimension**

I. INTRODUCTION

RESPIRATORY monitoring is a critical component in medical diagnostics, sleep studies, and remote health monitoring, playing a key role in detecting respiratory disorders [1] such as sleep apnea, chronic obstructive pulmonary disease (COPD) [2], and abnormal breathing patterns associated with neurological conditions. In clinical and occupational environments, contact-based methods for monitoring respiratory rate are based on measuring sound, airflow, temperature, and chest wall motion [3]. Traditional respiratory monitoring methods, including spirometry and plethysmography [4], as well as wearable chest sensors, often require physical contact with the patient, which can be uncomfortable for long-term monitoring and may introduce compliance issues [5]. Additionally, contact-based sensors are prone to displacement and motion artefacts, reducing the reliability of measurements [6],[7]. Contact-based respiratory monitoring often results in motion artefacts and user discomfort. Despite this, such sensors are commonly used to evaluate breathing patterns related to respiratory issues. Detecting irregular breathing rhythms is vital for diagnosing diseases and monitoring health [8]. Abnormal respiratory patterns can be caused by conditions such as heart failure, stroke [9], damage to the respiratory center, opioid use, and weakened respiratory muscles. Various medical conditions, including trauma and metabolic disorders, may also lead to erratic breathing.

To overcome these limitations, Doppler radar-based respiratory monitoring has emerged as a promising non-contact alternative that enables continuous tracking of respiratory activity without needing physical attachment to the body [10][11]. By analysing frequency and phase shifts in reflected radar signals caused by chest or abdominal movements, Doppler radar provides a real-time and unobtrusive solution for respiratory assessment [12],[13].

Despite its advantages, the analysis of Doppler radar signals for respiratory monitoring presents significant challenges due to the time-variant nature of respiratory signals. Multiple factors influence breathing patterns, including physiological variations, subject motion, environmental disturbances [14], and noise [15] in radar measurements. Unlike static signals, respiratory signals exhibit temporal fluctuations in frequency, amplitude, and phase, making it challenging to extract consistent and meaningful features. Traditional signal processing methods, such as Fourier transform-based frequency analysis, are often insufficient in capturing these dynamic variations. This limitation necessitates advanced feature extraction techniques that can better characterise respiratory signals' non-stationary and non-linear properties, improving classification accuracy and predictive modelling for abnormal breathing patterns.

To address these challenges, this study introduces an advanced feature extraction framework that integrates statistical features, Hilbert transforms, discrete wavelet transforms (DWT), and fractal dimension analysis to enhance time-variant

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Suraya Zainuddin, Masrullizam Mat Ibrahim, Haslinah Mohd Nasir and Nur Fatin Shazwani Nor Razman are with Faculty of Electronics and Computer Technology and Engineering, Universiti Teknikal Malaysia Melaka (UTeM), Malaysia (e-mail: suraya@utem.edu.my, masrullizam@utem.edu.my, haslinah@utem.edu.my, m022210030@student.utem.edu.my).

Mohd Zhafran Zainal Abidin is with Faculty of Medicine, University Teknologi MARA (UiTM), Malaysia (e-mail: zhafran@uitm.edu.my).

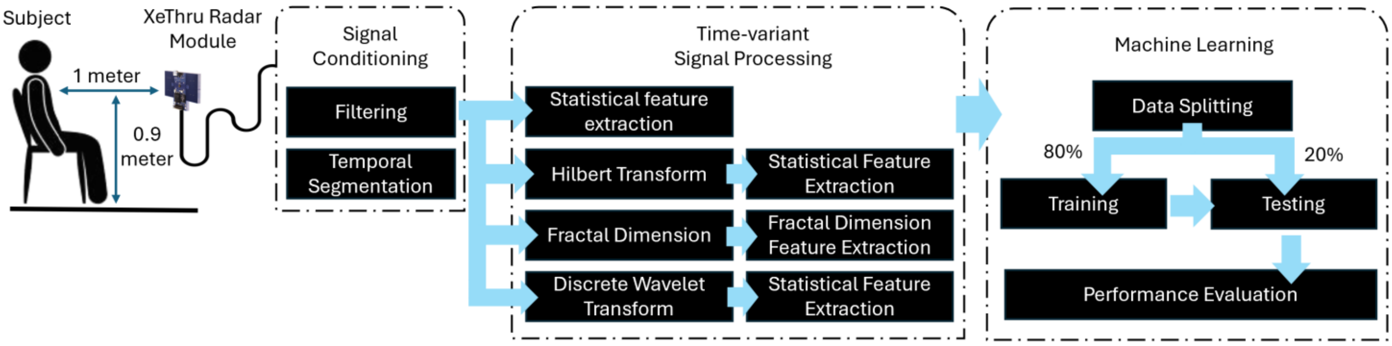

Fig. 1. Block diagram of the proposed respiratory Doppler signal analysis

trait analysis in respiratory Doppler radar signals. Statistical features, including mean, skewness, and kurtosis, provide insights into the overall distribution and variability of the signal. While the Hilbert transform is applied to extract instantaneous amplitude and phase variations, offering a detailed representation of respiratory dynamics over time [16]. The discrete wavelet transform (DWT) is also utilised to enable multi-resolution decomposition, allowing time-frequency analysis at different scales, which is crucial for detecting subtle respiratory fluctuations over time [17]. Additionally, fractal dimension analysis is applied to Additionally, fractal dimension analysis is applied to quantify the complexity and irregularity of breathing patterns, providing a way for distinguishing between normal and abnormal respiration [18], [19].

Consequently, there is growing interest in leveraging technology to identify respiratory irregularities. Artificial intelligence (AI), which requires minimal human input, shows significant potential in this area. AI encompasses four main types: reinforcement learning, supervised learning, semi-supervised learning, and unsupervised learning. Among them, supervised learning, which includes classification, regression, and forecasting, uses labelled data to help machines learn and apply functions in machine and deep learning applications.

Hence, this paper presents the application of feature extraction techniques in conjunction with a machine learning-based classification model to distinguish between various respiratory conditions. By exploiting time-variant traits, the proposed framework enhances the robustness and accuracy of respiratory monitoring. The experimental results demonstrate the effectiveness of this approach, highlighting its potential for improving non-contact respiratory monitoring and early detection of respiratory anomalies.

The remainder of this paper is organised as follows: The next section provides an overview of related work in Doppler radar-based respiratory monitoring and existing signal processing techniques. The methodology section details the proposed framework, including signal pre-processing, feature extraction, and classification models. The experimental results and performance evaluation are then presented, followed by a discussion of findings, and future research directions. Finally, the conclusion summarises key contributions and highlights future improvements for enhancing non-contact respiratory monitoring using Doppler radar technology.

II. Methodology

This study presents an advanced feature extraction and classification framework for analysing time-variant traits in respiratory Doppler radar signals. Figure 1 illustrates the overall methodology used to classify human-related radar signals combining time-variant trait extraction and machine learning.

The experimental configuration for acquiring breathing signals utilising a XeThru X4M200 radar module [20]. This radar module is an ultra-wideband (UWB) single-chip transceiver that operates between 6.0 and 8.5 GHz with a low power consumption of less than 120 mW [21]. The integration of the XeThru X4M200 module with the XeThru Explorer acquisition software is achieved via a USB cable.

The process begins with data acquisition, where a subject is placed at a fixed distance from a XeThru X4M200 radar module. The radar is positioned approximately one meter in front of the person and 0.9 meters above the ground, ensuring that it is aligned to capture the desired physiological signals, such as subtle chest movements or breathing patterns.

Once the radar signal is collected, it undergoes signal conditioning. This stage involves filtering to remove noise and unwanted signals, followed by temporal segmentation, where the continuous signal is divided into significant time segments of 3,000 sample points each, thereby preventing bias in the analysis due to longer signals. These conditioned signals are then forwarded to the time-variant signal processing stage, where various feature extraction techniques are applied.

In the time-variant signal processing phase, several approaches are used to capture different characteristics of the time-domain signal. The first method is statistical feature extraction, which captures basic signal properties of mean, standard deviation, root mean square (RMS), peak value, skewness, kurtosis, crest factor and energy value.

The second method involves applying the Hilbert Transform (HT), which produces instantaneous amplitude, instantaneous phase and instantaneous frequency. The third technique utilises the Discrete Wavelet Transform (DWT) to decompose the signal into different frequency components, allowing for the analysis of localised frequency changes over time. Both HT and DWT outputs are applied to statistical feature extraction.

Incorporating statistical feature extraction after applying the HT or DWT helps to simplify and enhance the transformed

TABLE I
TASK ASSIGNED FOR RESPIRATORY STIMULATION

Respiratory Condition	Activities	Duration
Normal	The subject is instructed to remain seated and engage in spontaneous/ normal, unforced breathing.	Data is collected continuously for a period of 15 minutes.
High	The subject engages in light physical activities such as jumping or running, followed by a seated resting phase.	A minimum of 5 minutes is allocated for the exercise activities, followed by an additional 15 minutes dedicated to data collection during the resting phase.
Low	The subject remains seated and performs deep breathing consistently throughout the duration.	Data is collected continuously for a period of 15 minutes.

signals for better classification. While HT and DWT capture rich time-frequency details, their raw outputs are often too complex or high-dimensional for direct use. Statistical features summarise this information into compact, interpretable values. This makes the data more manageable, reduces overfitting, and improves the performance and robustness of machine learning models. It also allows for easier comparison and combination with other feature types.

Lastly, the final method calculates the Fractal Dimension (FD) of the signal to measure its complexity and irregular patterns. Three types of FD are used, which are Petrosian, Higuchi, and Box-Counting. Petrosian FD provides a fast estimate based on signal sign changes, Higuchi FD captures fine structural details over time, and Box-Counting FD reflects spatial complexity using geometric coverage. Together, these features provide a detailed view of the signal's irregularity, helping to improve classification by capturing subtle differences in respiratory patterns.

The final stage of the methodology involves the application of machine learning. The extracted features are split into two datasets, with 80% used for training and 20% used for testing. The training data is used to teach the models to recognise patterns in the signals, while the testing data evaluates how well the trained models perform on new, unseen data. This leads to the final step of performance evaluation, where the classification accuracy of each model and feature extraction technique is measured.

A. Data Acquisition and Preprocessing

The study has been registered with the National Medical Research Register (NMRR) for the record, and subjects provided consent to participate in the experiment. A total of 75 participants, comprising 40 males and 35 females aged 18 to 27 years, were involved as subjects. Various activities and tasks were conducted by participants to provide three groups of respiratory patterns, which are normal, high and low. Activities for stimulating respiratory conditions are summarised in Table I. The number of 225 datasets were collected consists of 33.85% normal breathing, 32.82% high breathing, and 33.33% low breathing.

Doppler radar operates by transmitting electromagnetic waves toward a target and analysing the reflected signals, where frequency shifts correspond to respiratory motion [22],[23]. The experimental setup involved a continuous-wave (CW) Doppler radar system positioned to face the subject's chest or abdomen at a fixed distance. The received signals were recorded over a predefined duration under controlled conditions, capturing variations in breathing patterns.

The raw radar signals underwent several pre-processing steps to ensure reliability. First, DC removal was applied to eliminate baseline drift and static clutter caused by body posture and environmental interference. Next, digital bandpass filters were implemented to allow frequencies within the radar's operational bandwidth while attenuating out-of-band noise and interference. These signal conditioning processes were conducted on the radar chip. Normalisation was followed to standardise the signal amplitude, reducing variations due to subject positioning. The signals were segmented into fixed-length windows for further feature extraction, ensuring a consistent analysis framework across different subjects and conditions. The normalisation process utilised MATLAB software.

B. Feature Extraction

This study employed a feature extraction approach that integrated statistical features, Hilbert Transform, Discrete Wavelet Transform (DWT), and fractal dimension analysis to capture the time-variant traits in Doppler radar respiratory signals. Each technique contributes to a more comprehensive understanding of the frequency, amplitude, and complexity of a time-domain signal.

Statistical features provide key insights into the distribution and variability of the respiratory signal. The extracted measures include mean, which represents the average respiratory amplitude; Standard deviation, which measures the dispersion of the signal around its mean; Root-means-square, which represents the effective power or energy of the signal; Peak value, represents the maximum absolute value of the signal; skewness, which quantifies the asymmetry in the signal distribution; and kurtosis, which evaluates the peakedness of the signal. These statistical indicators help distinguish between normal and abnormal breathing patterns.

The second approach was the Hilbert transform. It was applied to analyse instantaneous respiratory dynamics. It extracted features such as the instantaneous amplitude envelope, which reflects breathing intensity over time; the instantaneous phase shift, which captures phase variations associated with different respiratory states; and the instantaneous frequency, which provides a finer resolution of breathing rate changes. These features enhance the temporal resolution of respiratory monitoring.

Next, the discrete wavelet transform (DWT) decomposed the respiratory signal into multiple frequency components, enabling a detailed time-frequency analysis. This transformation is performed using the Daubechies wavelet (db4), which is well-suited for biomedical signal processing. The wavelet decomposition extracts features such as approximation coefficients, which represent overall respiratory trends, and detail coefficients, which capture finer respiratory fluctuations. Energy distribution across wavelet levels is also computed to quantify spectral variations in respiratory activity.

To further analyse the respiratory signal's complexity and irregularity, fractal dimension analysis is conducted using the Higuchi fractal dimension (HFD) method. This technique calculates the signal's self-similarity, with higher values indicating increased complexity due to irregular breathing patterns. By incorporating fractal analysis, the proposed framework improves its ability to differentiate between normal and disordered breathing conditions.

C. Classification Model

Various machine learning-based classification models were applied to distinguish between normal and abnormal respiratory patterns based on the extracted features. Various classification algorithms are evaluated, including Decision Trees (DT), Support Vector Machine (SVM), Random Forest (RF), Naïve Bayes (NB) and K-Nearest Neighbour (KNN).

SVM is known for its effectiveness in handling high-dimensional feature spaces, especially when employing a radial basis function (RBF) kernel, which enables non-linear classification by mapping input data into a higher-dimensional space. This makes SVM particularly powerful in complex pattern recognition problems [24]. While RF classifier is commonly employed as an ensemble learning approach to enhance classification robustness by aggregating multiple decision trees [25], [26]. The DT classifier is known for its interpretability and low computational cost, providing a clear and intuitive way to understand classification logic through a hierarchical structure of decisions [27]. It is well-suited for exploring data analysis and real-time decision-making scenarios [28]. Additionally, NB is considered due to its simplicity, efficiency, and strong performance with relatively small training data sets [29]. It works on the principle of conditional probability and assumes feature independence, making it highly scalable and effective in many text classification and medical diagnosis tasks. Finally, KNN algorithms were explored due to their widely recognised intuitive simplicity, flexibility in adapting to different types of data, and minimal assumptions about the underlying data distribution, making them suitable for a broad range of classification and regression tasks [30], [31]. By leveraging the strengths of these diverse models, the study aims to comprehensively assess and compare their effectiveness in detecting irregular respiratory patterns, ultimately contributing to more reliable and accurate respiratory monitoring systems.

The dataset was divided into training (80%) and testing (20%) subsets to ensure model generalisation and 10-fold cross-validation was used for performance optimisation. This approach reduces the risk of overfitting and ensures that the model can effectively adapt to new respiratory patterns.

III. RESULTS

The classification results presented in Table II reflects the performance of various machine learning models using different time-variant signal feature extraction techniques, namely Statistical Features, Hilbert Transform, Fractal Dimension, and Discrete Wavelet Transform. These approaches were evaluated to determine their ability to effectively represent radar-derived breathing signals and enable accurate classification of respiratory patterns.

Among all the tested feature extraction methods, the Hilbert Transform consistently delivered the highest performance across multiple classifiers. Notably, the Subspace Discriminant model achieved the highest test accuracy of 92.3%, followed closely by the Coarse Tree, Bagged Trees, and Linear Discriminant, each reaching 84.6%. This finding suggests that the Hilbert Transform is highly effective in preserving critical time-frequency features, such as instantaneous amplitude and phase, which are valuable for distinguishing between different breathing states. Similarly, the Linear SVM also showed strong performance under the Hilbert Transform, achieving an accuracy of 82.1%. However, it is important to note that the Quadratic Discriminant model failed under this feature set, indicating a limitation in compatibility or numerical stability with the Hilbert-transformed data.

The Fractal Dimension feature set demonstrated reliable and moderately high performance across most models, highlighting its robustness in capturing the complexity and irregularity of breathing signals. Models such as Quadratic SVM and Linear Discriminant achieved accuracies of 79.5%, while many others, including Subspace Discriminant, Cubic SVM, and various neural networks, maintained accuracies in the range of 71.8% to 74.4%. These results confirmed that fractal features are capable of generalising well across different classifier architectures, offering a good balance between performance and consistency.

The Discrete Wavelet Transform presented moderate classification performance, with Coarse Gaussian SVM yielding the highest accuracy of 56.4% in this category. Several other models, such as Linear SVM, Cubic SVM, and Neural Networks, performed in the 48% to 51% range. This outcome suggests that while wavelet decomposition captures multiscale frequency information, it may not provide sufficiently distinctive features on its own or may require further post-processing to enhance classification accuracy.

In contrast, the Statistical Feature consistently showed the lowest classification performance. Most models produced accuracies below 45%, with only a few exceptions, such as Linear SVM (43.6%), Coarse Tree (38.5%), and Subspace Discriminant (38.5%). These results suggest that simple statistical descriptors, although easy to compute, may lack the depth and sensitivity required to capture meaningful variations in radar-based respiratory signals.

Overall, the analysis highlights the crucial role of feature extraction in determining classification accuracy. The Hilbert Transform stands out as the most powerful method for enhancing model performance, particularly when used with discriminant analysis and ensemble models. The Fractal Dimension offers a robust alternative with broad model compatibility, while Discrete Wavelet Transform and Statistical Features may require further enhancement or hybridisation to reach comparable levels of accuracy. These insights can guide future work in optimising radar-based respiration monitoring systems, especially in selecting the most suitable signal processing techniques for real-time or clinical applications.

The result was further analysed in terms of the confusion matrix. Figure 2 illustrates the classification performance of the Subspace Discriminant model using features extracted through the Hilbert Transform, which previously achieved the highest overall accuracy. The model was evaluated on three respiratory classes, which are high, low, and normal breathing. The diagonal elements of the matrix indicate correctly classified instances, with 30.77% of high breathing cases, 35.90% of low breathing cases, and 25.64% of normal breathing cases accurately identified by the model. These results demonstrate that the classifier is most effective at recognising the low breathing pattern, which achieved the highest true positive rate among the three classes.

Misclassifications are reflected in the off-diagonal values. For example, 5.13% of normal breathing instances were incorrectly predicted as high, while 2.56% are misclassified as low. This strong class separation highlights the discriminative strength of the Hilbert Transform features when used with a Subspace Discriminant classifier. Overall, the confusion matrix confirms that this combination provides reliable classification performance, particularly in distinguishing subtle variations in respiratory patterns captured through Doppler radar signals.

TABLE II
THE CLASSIFICATION PERFORMANCE OF TIME-VARIANT ANALYSIS

Model	Statistical Feature	Hilbert Transform	Fractal Dimension	Discrete Wavelet Transform
Fine Tree	28.2	79.5	64.1	46.2
Medium Tree	30.8	79.5	64.1	46.2
Coarse Tree	38.5	**84.6**	66.7	51.3
Linear Discriminant	41.0	**84.6**	79.5	48.7
Quadratic Discriminant	41.0	Failed	74.4	41.0
Gaussian Naïve Bayes	33.3	51.3	69.2	53.8
Kernel Naïve Bayes	33.3	59.0	71.8	48.7
Linear SVM	43.6	**82.1**	74.4	48.7
Quadratic SVM	41.0	76.9	79.5	46.2
Cubic SVM	33.3	66.7	71.8	51.3
Fine Gaussian SVM	41.0	41.0	74.4	41.0
Medium Gaussian SVM	41.0	76.9	74.4	53.8
Coarse Gaussian SVM	33.3	61.5	74.4	56.4
Fine KNN	33.3	53.8	71.8	38.5
Medium KNN	35.9	56.4	69.2	51.3
Coarse KNN	41.0	41.0	74.4	43.6
Cosine KNN	33.3	56.4	66.7	59.0
Cubic KNN	41.0	51.3	69.2	48.7
Weighted KNN	35.9	56.4	69.2	46.2
Boosted Trees	28.2	74.4	66.7	30.8
Bagged Trees	35.9	**84.6**	66.7	43.6
Subspace Discriminant	38.5	**92.3***	79.5	53.8
Subspace KNN	30.8	33.3	64.1	46.2
RUS Boosted Trees	30.8	74.4	64.1	30.8
Narrow Neural Network	41.0	64.1	74.4	48.7
Medium Neural Network	41.0	74.4	74.4	46.2
Wide Neural Network	43.6	71.8	66.7	51.3
Bilayered Neural Network	33.3	71.8	74.4	48.7
Trilayered Neural Network	38.5	79.5	74.4	48.7
SVM Kernel	46.2	38.5	71.8	43.6
Logistic Regression Kernel	38.5	43.6	69.2	41.0

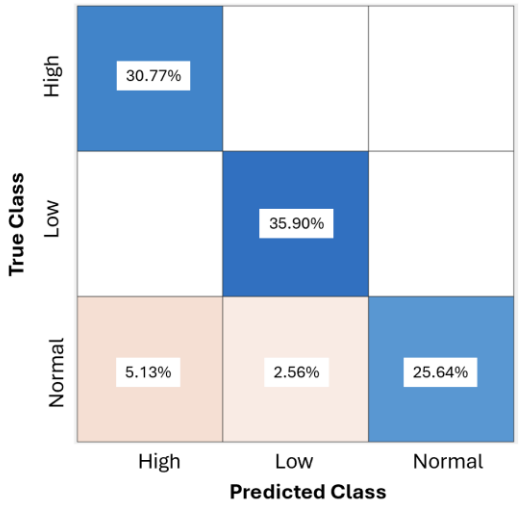

Fig. 2. Confusion Matrix of Subspace Discriminant

Conclusion

In conclusion, this study demonstrates that time-variant feature representation is critical for accurate Doppler radar–based respiratory classification. Among all evaluated methods, Hilbert Transform features achieved the highest discriminative power, with the Subspace Discriminant classifier reaching an accuracy of 92.3%, supported by strong class separability in the confusion matrix. Fractal dimension features showed consistent, moderate performance across classifiers, while Discrete Wavelet Transform and statistical features were less effective. These findings confirm the superiority of instantaneous signal descriptors for non-contact respiratory monitoring applications.

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