

PCG-Based Exercise Fatigue Detection Method Using FRFT-Based Fusion Model

Xinxin Ma, Xinhua Su[✉], Huanmin Ge

Abstract: Accurate detection of exercise fatigue based on physiological signals is vital for reasonable physical activity. As a non-invasive technology, phonocardiogram (PCG) signals possess a robust capability to reflect cardiovascular information, and their data acquisition devices are quite convenient. In this study, a novel hybrid approach of fractional Fourier transform (FRFT) combined with linear and discrete wavelet transform (DWT) features extracted from PCG is proposed for PCG multi-class classification. The proposed system enhances the fatigue detection performance by combining optimized FRFT features with an effective aggregation of linear features and DWT features. The FRFT technique is employed to convert the 1-D PCG signal into 2-D image which is sent to a pre-trained convolutional neural network structure, called VGG-16. The features from the VGG-16 were concatenated with the linear and DWT features to form fused features. The fused features are sent to support vector machine (SVM) to distinguish six distinct fatigue levels. Experimental results demonstrate that the proposed fused features outperform other feature combinations significantly.

Keywords: exercise fatigue; phonocardiogram (PCG); fractional Fourier transform (FRFT); discrete wavelet transform (DWT); feature fusion

1 Introduction

Physical activity, as an essential part of human life, is essential to maintain physical and mental health. Various studies have shown that regular exercise can reduce the incidence of coronary heart disease and restrain the progression of atherosclerotic cardiovascular disease [1–3]. However, improper exercise techniques and unreasonable exercise intensity can lead to sports-related injuries, and in severe cases, result in health issues such as tachycardia and myocardial strain,

sometimes even posing a threat to life [4–7]. Therefore, there is an imperative to find effective approaches to monitor an individual's level of exercise fatigue, ensuring that they can monitor the physical condition and reduce potential risks of injury.

Typically, exercisers tend to assess their level of exercise fatigue, relying on observations of physiological indicators such as respiratory rate, heart rate, and exercise duration. However, this subjective approach is prone to bias. Consequently, an increasing number of researchers have begun to explore other physiological indicators that encompass richer information [8–10]. Electromyography (EMG) can reflect the electrical activity of local muscle, and Sugay et al. proposed the use of EMG to monitor neuromuscular fatigue during sustained exercise [11]. Physical fatigue not only reduces the body's exercise ability but also causes neurological function decline. So, electroencephalograms (EEG) can also detect

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physical fatigue. Lakhan et al. combined EEG and wavelet transform to identify the stress of the humans and obtained good results [12]. Yang et al. extracted features of EEG signals during exercise fatigue is performed, the method can effectively distinguish between exercise fatigue [13]. Electrocardiogram (ECG) as the gold standard for cardiac status, which contain rich exercise-related features and high diagnostic accuracy. Afzaal et al. recorded signals such as ECG during exercise, the system could identify the physical state of athletes with 97% accuracy [14]. Zhu et al. used short-time Fourier transform (STFT) to transform ECG, combined with convolutional neural network (CNN) for deep learning, to achieve effective classification of exercise fatigue [15]. In addition to this, some researchers have used other physiological indicators for fatigue recognition. Cui et al. employed integrated health monitoring technology to diagnose exercise-induced fatigue in rhythmic gymnastics, achieving an accuracy rate of 85% [16]. Pero et al. monitored the urinary composition of the human body after exercise and assessed the fatigue state of athletes based on changes in urine composition before and after exercise [17].

However, due to changes in the amplitude of movement, higher sweating, and the influence of the stratum corneum, some physiological indicators can produce greater noise and reduce the accuracy of the test data. Improper operation of ECG acquisition equipment can even lead to safety issues such as cross-infection. To enhance the real-time and practical aspects of fatigue detection, it is essential to employ easily obtainable physiological signals and simplify the fatigue assessment process. Phonocardiography (PCG), a significant physiological signal, can objectively reflect changes in the autonomic nervous system and plays a crucial role in identifying and assessing one's health status. PCG acquisition devices are designed to be simple and convenient to wear, allowing for the collection of heart sound

signals during physical activity without the need for direct contact with the body surface. Lei et al. utilized support vector machines (SVM) and multi-channel PCG signals to develop a model for measuring athlete heart rate detection [18]. Wang et al. combined PCG and electrocardiogram (ECG) signals and employed a deep learning model for the detection of exercise fatigue [19]. To make exercise fatigue detection more convenient and efficient, this study introduces a fatigue detection method based on PCG, which combines FRFT features with PCG linear and discrete wavelet transform (DWT) features, resulting in improved accuracy. The primary contributions of this study are as follows:

- 1) The fractional Fourier transform (FRFT) is used to convert 1D PCG signals recorded during exercise into 2D spectrograms, which were passed through the VGG-16 network and map each image to a FRFT-based feature vector.

- 2) Linear features reveal global differences, DWT features highlight frequency details, and FRFT-based features optimize signal representation. The integration of these features enables a more comprehensive analysis of the signal.

- 3) The support vector machine (S-VM) is famous for excellent classification performance and is employed to detect exercise fatigue. The results indicate that integrating features based on PCG significantly enhances the detection performance of exercise fatigue.

The following is the outline of the sections in this paper: Section 2 introduces the public dataset and signal preprocessing. Section 3 presents the feature engineering. Section 4 discusses the experimental results. Section 5 provides the discussion and conclusion of this article.

2 Dataset and Preprocessing

To evaluate the effectiveness of our proposed method in detecting exercise fatigue, we utilized a synchronized ECG and PCG database [20]. 24 male subjects between the ages of 23 and 29 took

part in the experiment, and the experiment was conducted indoors. Participants were in good physical condition, and no one shows or has ever experienced autonomic or cardiovascular disease symptoms as determined by structured interviews. Each volunteer performed a specific exercise. Three hours before the test, the subjects' diets are controlled, that is, they can drink water, but eating and, alcohol intake and caffeinated beverages are banned. Then data are acquired.

This database consists of 69 simultaneous ECG and PCG recordings, in which 8 records have a duration of 30 s and 61 records have a duration of 30 min. All sampled at a frequency of 8 kHz. The dataset encompasses six different lev-

els of exercise fatigue, which are as follows: Level 1: Physiological signals at rest in a lying position. Level 2: Subjects remained calm and seated without any activity. Level 3: Subjects engaged in light activity, walking at a steady speed of 3.7 km/h. Level 4: Subjects cycled at a constant speed on a stationary bike. Level 5: Subjects cycled on a stationary bike with gradually increasing resistance until reaching fatigue. Level 6: Subjects ran at an incrementally increasing speed until they reached a state of fatigue. Fig. 1 shows different signal waveforms.

16 noise-free 30 min PCG signals was selected for our study. To improve computational efficiency, each record was divided into segments of 100 000 data points and downsam-

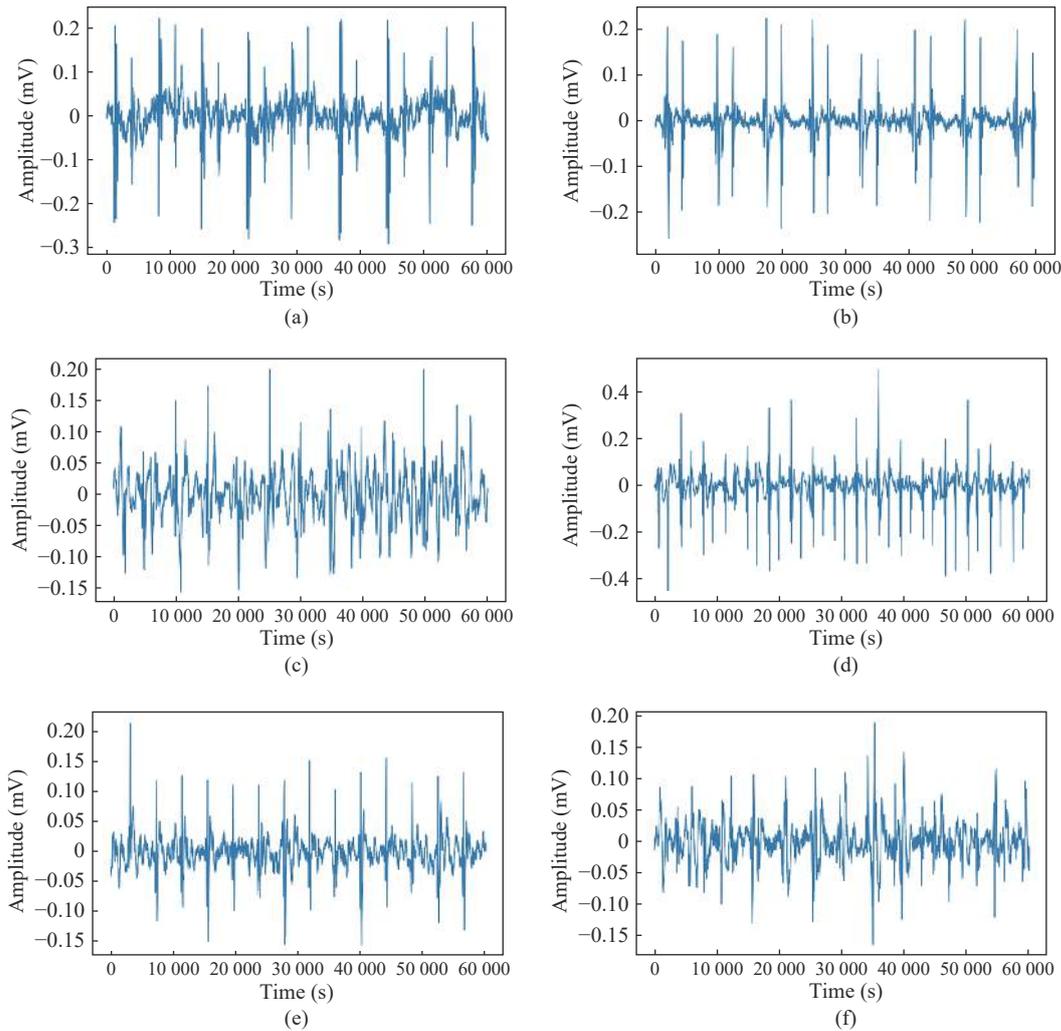


Fig. 1 PCG signals from different exercises: (a) lying in bed; (b) sitting in an armchair; (c) walking at a constant speed; (d) pedaling a stationary bicycle; (e) riding a stationary bicycle; (f) Bruce protocol treadmill stress test

pled. Due to the limited number of data records for fatigue levels 2 and 6, an imbalance in the dataset occurred, affecting the sample sizes across different categories. When the dataset exhibits an imbalance, models are prone to exhibit a bias toward categories with a larger number of samples. This bias can result in suboptimal performance on categories with fewer samples. To address this, the study employed a shifting window with overlap for data enhancement on the records corresponding to fatigue levels 2 and 6. This approach aids in enhancing the model's ability to recognize minority classes, improving the model's generalization capability and reducing the risk of overfitting. Tab. 1 provides detailed information about the dataset.

Tab. 1 Dataset detail

Classes	Number
Fatigue level 1	429
Fatigue level 2	442
Fatigue level 3	429
Fatigue level 4	429
Fatigue level 5	429
Fatigue level 6	442
Total	2600

3 Methodology

The proposed exercise fatigue detection method in this study comprises three main stages. The first stage involves preprocessing, including the selection of synchronized data from publicly

available PCG and ECG datasets, signal segmentation, and performing data augmentation. The second stage is composed of transforming 1-D signals into 2-D images, feature extraction, and feature concatenation. The third stage employs machine learning models to assess exercise fatigue.

The overall structure of this method is illustrated in Fig. 2, and the following subsections will provide detailed explanations of each component of the method.

3.1 Linear Features

The linear features of the PCG signal are primarily employed to describe and analyze fundamental statistical information, thus reflecting the overall characteristics and distribution pattern of the signal. In this work, the mean, variance, and standard deviation of PCG samples are calculated to measure the amount of dispersion in the PCG relative to its mean. Maximum and minimum to evaluate the extreme values of the sample. Also, the higher-order statistics such as kurtosis and skewness are obtained to assess the probability distribution of each sample series. Specific equations can be found in Tab. 2.

3.2 Discrete Wavelet Features

Discrete wavelet transformation (DWT) is a mathematical method used for multiscale analysis of signals, capable of revealing subtle variations in signals at different frequency levels [21–23]. DWT was applied to PCG to extract crucial features. For the signal $X(t)$, the wavelet

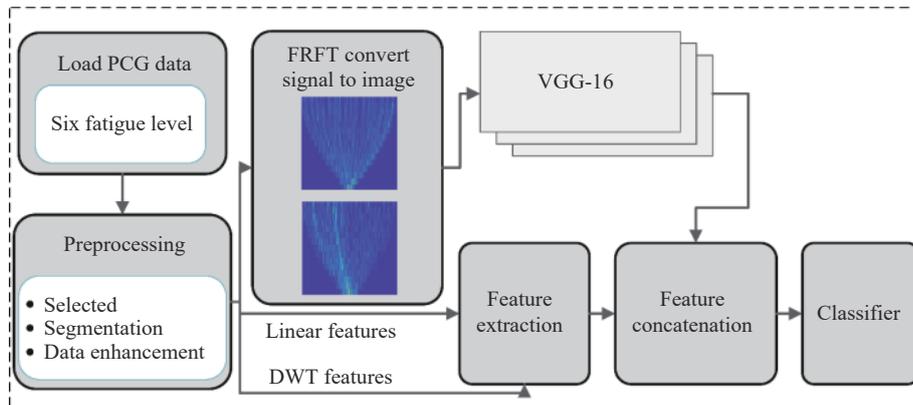


Fig. 2 Architecture of the proposed exercise fatigue detection method

Tab. 2 PCG linear features

Feature	Formula
Mean	$\sum X/t$
Standard deviation	$\sqrt{(\sum (X - \mu)^2)/t}$
Variance	$\sum (X - \mu)^2/t$
Maximum	—
Minimum	—
Skewness	$[\sum (X - \mu)^3/t] / \sigma^3$
Kurtosis	$[\sum (X - \mu)^4/t] / \sigma^4 - 3$

Note: X is the value of a particular feature; t is the number of observations of a feature over time; μ is the mean of the feature over time; σ is the standard deviation of the feature over time.

transform equation is as follows:

$$DWT_{a,b} = \int X(t)\psi_{a,b}(t)dt \quad (1)$$

where a is the scale (height and width dilatation parameter), b is the offset on the time axis and $\psi_{a,b}(t)$ is the mother wavelet. PCG application of the wavelet transform results in an approximation coefficient and a series of detail coefficients. Approximation coefficients represent the low-frequency components of the signal, reflecting the main trend or outline of the signal. Detail coefficients signify the high-frequency components, revealing the rapid changes within the signal. Combine approximation and all detail coefficients into a single long vector, then calculate the mean, variance, standard deviation, maximum, minimum, kurtosis, skewness of the vector. These wavelet features provide local or detailed information of the signal at different resolutions. In the current study, mother wavelet and decomposition layer are set to db4 and 5, respectively, to achieve the best results.

3.3 Fractional Fourier Transform Features

3.3.1 Fractional Fourier Transform

The FRFT is a mathematical transformation method utilized in the fields of signal processing and image processing [24, 25]. It is an extension of the Fourier Transform that enables more flexible frequency domain analysis of signals. Unlike the standard Fourier transform, the FRFT allows the analysis of signals using non-integer fre-

quency domain rotation angles. The FRFT of a 1-D signal $x(t)$, defined from the perspective of integral transform, is given by

$$X_p(u) = F^p[x](u) = \int_{-\infty}^{+\infty} x(t)K_p(t, u)dt \quad (2)$$

The operator F^p represents the FRFT, and the expression for the kernel function $K_p(t, u)$ is as follows:

$$K_p(t, u) = \begin{cases} A_p e^{i(t^2 \cot \varphi - 2ut \csc \varphi + u^2 \cot \varphi)}, p \neq 0 \\ \delta(t - u), p = 0 \\ \delta(t + u), p = \pm 2 \end{cases} \quad (3)$$

where

$$A_p = \exp[-jpsgn(\sin \varphi)/4 + j\varphi/2]/|\sin \varphi|^{0.5}$$

$$\varphi = p\pi/2$$

When $p = 0$ or $p = \pm 2$, the kernel $K_p(t, u)$ respectively becomes $\delta(t - u)$ and $\delta(t + u)$, δ refers to the Dirac delta function [26]. The kernel is known to have the following expansion [27]

$$K_p(t, u) = \sum_{k=0}^{\infty} \psi_k(t)e^{-j\frac{\pi k p}{2}}\psi_k(u) \quad (4)$$

$\psi_k(t)$ is the k -th Hermite-Gaussian function. Here, $\exp(-jpkp/2)$ is the p -th power of the eigenvalue $\lambda_k = \exp(-j\pi k/2)$ of the ordinary Fourier transform. When $p = 1$, the FRFT reduces to the ordinary Fourier transform:

$$F[x](t_1) = \int_{-\infty}^{\infty} e^{-j2\pi t_1 t} x(t)dt \quad (5)$$

where t_1 is the frequency domain variable.

3.3.2 FRFT Features by VGG-16

This study observes the variations in the signal's time-frequency characteristics as the fractional order parameter “ p ” increases in increments of 0.07 within the range from 0 to 1, obtaining the corresponding time-frequency plots. Fig. 3 displays FRFT spectrograms for six levels of exercise fatigue. The vertical axis represents frequency, while the horizontal axis represents time. The frequencies of PCG signals vary with different degrees of fatigue.

Training a CNN from the beginning would require high computational time along with the

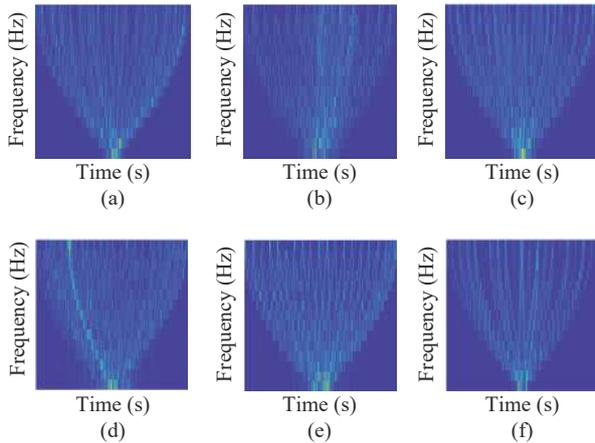


Fig. 3 PCG spectrograms after FRFT processing: (a) lying in bed; (b) sitting in an armchair; (c) walking at a constant speed; (d) pedaling a stationary bicycle; (e) riding a stationary bicycle; (f) Bruce protocol treadmill stress test

problem of overfitting. This study employed a pre-trained VGG-16, which is a deep convolutional neural network model proposed in 2014 [28, 29]. In the current work, after transforming the PCG into image using the FRFT technique, the 2-D image is sent to the VGG-16 network, which is employed to extract automatically the important subtle features from 2-D time-frequency. The fully connected multi-layer perceptron (MLP) is not used for classification due to its high computational cost, instead, add 2-D average pooling layer to choose the optimal features from the VGG-16 output features to be concatenated with linear and DWT features. Then, the concatenated features are sent to a machine learning (ML) classifier.

4 Results

Classify the selected features by applying SVM methods [30]. The parameters of these methods

are given as follows. Radial basis function (RBF) kernel, box constraint level is chosen as five, one-vs-all coding setting is used for SVM classifier. To calculate the results of the model based on fused features, and the following evaluation metrics were employed: Overall accuracy (OA), average precision (AP), F1-score (F1), geometric mean (GM), Cohen’s Kappa(CK) and Matthew correlation coefficient(MCC) [31–33]. To authenticate the diagnosis results and tackle deviation issues, the 10-fold cross-validation technique is utilized. The computed results of the SVM are shown in Tab. 3. Fig. 4 illustrates the accuracy of each fold using SVM.

The classification accuracy obtained from fusion features (the combination of linear features, DWT features, and FRFT features) was found to be 85.30%. It can be observed that combining the optimized selected FRFT features with both linear and DWT features achieve superior performance over other combinations. Specifically, the accuracy of this fusion approach surpasses that of the optimized selected FRFT features alone by 4.23%, linear features alone by 4.97%, and DWT features alone by 5.05%. It is noteworthy that the accuracy of fusion features is 2.78% higher than the accuracy achieved by merely fusing linear and DWT features. This result indicates that the incorporation of optimized FRFT features has enhanced the quality of features and improved classification performance.

5 Discussion and Conclusion

PCG can reflect the human body’s state during physical activity. To effectively detect excessive exercise fatigue, this study proposes a PCG-based

Tab. 3 Classification results obtained from SVM for different features

Features	OA	AP	F1	GM	CK	MCC
Linear features	80.33	80.37	80.08	78.70	76.40	76.75
DWT features	80.25	80.28	80.04	78.80	76.31	76.60
FRFT features	81.07	81.01	80.90	80.03	77.28	77.35
Linear features and DWT features	82.52	82.55	82.22	81.34	79.03	79.36
Fusion features	85.30	85.25	85.28	84.69	82.35	82.40

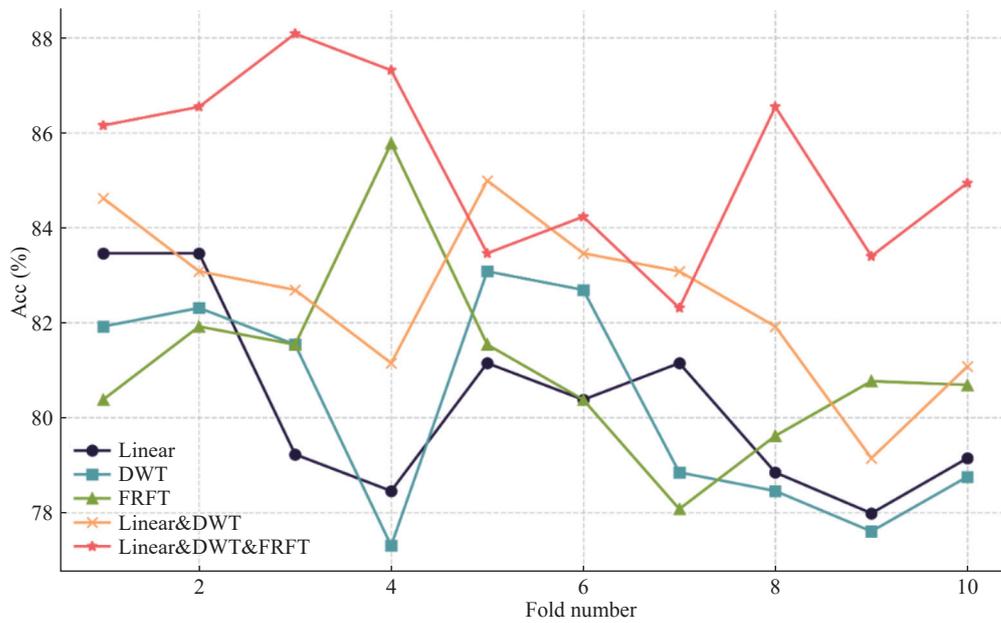


Fig. 4 Average accuracy of the proposed fatigue detection system for each fold using SVM

exercise fatigue detection method using FRFT-based fusion model. In this research, we apply FRFT transformation to the 1-D PCG signals to obtain the 2-D time-frequency plot. These 2-D representations are input into the VGG-16 model to extract 512 essential FRFT features. The optimized FRFT features are then combined with both linear and DWT features representing the fundamental differences between six fatigue classes. The resulted concatenated features are sent to the SVM classifier to differentiate the six classes. The proposed approach is applied to real PCG records, and the performance is evaluated in terms of Acc, Pr, F1, GM, CK, and MCC. The experimental results demonstrate that the proposed method provides accurate multi-class classification results with overall average Acc of 85.30%, Pr of 85.25%, F1 of 85.28%, GM of 84.69%, CK of 82.35%, MCC of 82.40%. This reveals the usefulness of the proposed PCG multi-class classification approach in a real-time exercise setting.

In the future, we plan to use the short-time fractional Fourier transform to process heart sound signals during exercise, aiming to obtain more time-frequency information. Additionally, we intend to expand the size of our exercise

dataset, covering a broader range of exercise scenarios to enhance the model's generalization ability. These measures will contribute to further improving the performance and reliability of our fatigue detection system.

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