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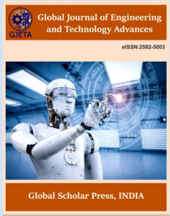

(REVIEW ARTICLE)

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# Review of various feature extraction approaches for ERG signal analysis: Advantages and drawbacks

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## Abstract

This article presents a comprehensive examination of various techniques used to extract features from Electroretinogram (ERG) signals for analysis purposes. ERG signals are crucial in the diagnosis and study of retinal diseases. The accurate extraction of informative features from ERG signals is vital for understanding retinal function and identifying abnormalities. This review specifically focuses on different methods employed for feature extraction in ERG signal analysis, highlighting their respective advantages and disadvantages. The article explores a range of established methods, namely time-domain, frequency-domain, time-frequency domain analysis, and machine learning delves into the difficulties and constraints linked to these strategies, such as signal noise, artifacts, and computational complexity. Its objective is to offer a thorough evaluation of the merits and drawbacks of diverse feature extraction techniques, with the aim of aiding researchers and clinicians in their selection of suitable methods for the analysis of ERG signals.

**Keywords:** Electroretinogram; Time-domain analysis; Frequency-domain analysis; Time-frequency analysis; Machine learning.

## 1. Introduction

Electroretinogram (ERG) signals are indispensable for diagnosing, monitoring, and studying retinal diseases. These signals, generated by the retina in response to light stimuli, offer valuable insights into retinal function and health. Analyzing ERG signals involves extracting informative features that capture the underlying physiological characteristics, enabling accurate interpretation and detection of abnormalities. The extraction of these features is crucial for understanding retinal function, identifying diseases, and abnormalities [1-4]. Numerous feature extraction approaches have been developed over the years to analyze ERG signals and extract relevant information. These approaches encompass various techniques that capture different aspects of the ERG waveform, including amplitude, latency, frequency components, and temporal patterns. Quantifying these features provides valuable insights into retinal health, facilitating early diagnosis, treatment monitoring, and prognosis evaluation. This paper aims to comprehensively review feature extraction approaches for ERG signal analysis, focusing on their advantages and drawbacks [5-8]. The review aims to assist researchers and clinicians in selecting appropriate methods for their specific needs. Feature extraction approaches play a critical role in unraveling the complex information within ERG signals, providing insights into retinal function, disease diagnosis, and treatment monitoring. The complexity of ERG signals underscores the importance of feature extraction approaches. ERG waveforms consist of multiple components representing different retinal processes. Extracting relevant features allows researchers to focus on specific aspects,

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unraveling underlying physiological mechanisms. Quantifying features such as amplitude, latency, and frequency characteristics helps identify abnormalities, monitor disease progression, and evaluate treatment outcomes [9, 10]. Feature extraction approaches also enable comparison and analysis of ERG signals across subjects and conditions, establishing objective criteria for evaluating retinal function and disease severity. Standardization allows consistent interpretation, facilitating reliable comparisons. Moreover, feature extraction approaches enable the development of automated diagnostic tools and computer-aided systems [11-14]. Machine learning algorithms trained on informative features can classify ERG signals, differentiate normal from abnormal responses, and detect specific retinal diseases. Automation enhances efficiency and accuracy, supporting clinicians in decision-making. Feature extraction approaches provide insights into underlying mechanisms of retinal diseases by identifying patterns and markers associated with different conditions. This understanding advances knowledge, identifies biomarkers, and guides targeted interventions. Furthermore, feature extraction enables monitoring of disease progression and treatment efficacy over time. Longitudinal quantification of relevant features assesses changes, tracks progression, and optimizes patient outcomes. In summary, feature extraction approaches are crucial in ERG signal analysis. They interpret complex waveforms, support diagnosis and monitoring, facilitate comparisons, develop automated tools, and provide insights into retinal conditions. Extracting informative features advances understanding of retinal function and improves patient care.

## 2. Time-Domain Feature Extraction Approaches

In the analysis of Electroretinogram (ERG) signals, time-domain feature extraction approaches play a significant role in capturing the temporal characteristics of the ERG waveform. These approaches focus on extracting features related to the morphology, peak time, and amplitude of the signal. By quantifying these features, researchers and clinicians can gain valuable insights into the underlying physiological processes and detect abnormalities [15-18].

One commonly used time-domain feature extraction method is the analysis of waveform morphology. This involves visually examining the shape of the ERG waveform and identifying characteristic features such as peaks and troughs. The presence, absence, or changes in the morphology of the waveform can provide indications of retinal dysfunction or disease progression [19, 20].

An essential component of time-domain feature extraction involves quantifying the timing and magnitude of specific peaks or troughs within the waveform following the stimulus onset. Peak time measurement enables the evaluation of retinal response timing, offering valuable insights into the performance of retinal cells. Conversely, amplitude represents the magnitude of the ERG response. Variations in amplitude can indicate changes in retinal sensitivity or the presence of abnormalities [21-25].

Time-domain feature extraction approaches offer several advantages in ERG signal analysis. Firstly, ERG signals offer a direct evaluation of the temporal attributes of the waveform, enabling correlation with specific retinal processes. Secondly, these methods do not necessitate complex signal processing techniques, rendering them uncomplicated and computationally efficient. Moreover, time-domain analysis facilitates the detection of subtle alterations in waveform morphology that may be challenging to identify using alternative methodologies.

However, time-domain feature extraction approaches also have their limitations. One drawback is their sensitivity to noise and artifacts present in the ERG signals. These disturbances can introduce inaccuracies in the extracted features, affecting the reliability of the analysis. Additionally, time-domain analysis may not fully capture complex temporal patterns or frequency-related information present in the signals [26, 27].

Despite these limitations, time-domain feature extraction approaches remain valuable tools in ERG signal analysis. ERG signals offer valuable information regarding the temporal aspects of the waveform, enabling the identification of abnormalities and providing relevant data for clinical decision-making. When researchers and clinicians choose feature extraction methods for their specific research or clinical purposes, it is crucial to thoroughly evaluate the benefits and constraints associated with time-domain analysis.

## 3. Frequency-Domain Feature Extraction Approaches

Examining the frequency-domain characteristics of the ERG signal offers valuable insights into the underlying physiological processes and aids in the detection of abnormalities. This section explores various approaches for extracting frequency-domain features when analyzing the ERG signal [28 - 33].

- Fourier Transform: The Fourier Transform is a widely employed method for frequency-domain analysis of signals, including the ERG. It decomposes the signal into its constituent frequency components, revealing the power spectrum and frequency distribution. By analyzing the amplitudes and phases of specific frequency components, researchers can obtain significant information about retinal function.
- Power Spectrum Analysis: Power spectrum analysis involves calculating the power spectral density (PSD) of the ERG signal. This approach provides a quantitative measure of the signal's energy distribution across different frequencies. By examining the PSD, researchers can identify frequency bands that are particularly relevant to retinal function and abnormalities.
- Spectral Entropy: Spectral entropy quantifies the complexity of the signal in the frequency domain by measuring the distribution of energy across different frequency components. Higher spectral entropy values indicate a more diverse and complex frequency distribution, while lower values suggest a more focused and concentrated distribution. Analyzing spectral entropy can provide insights into the complexity of retinal responses and help differentiate between normal and abnormal ERG signals.
- Coherence Analysis: Coherence analysis measures the degree of linear relationship between two signals in the frequency domain. By examining the coherence between different components of the ERG signal, researchers can assess the functional connectivity and synchronization of retinal responses. Coherence analysis provides valuable insights into the temporal relationship between different frequency components and their contribution to retinal function.
- Higher-Order Spectral Analysis: Higher-order spectral analysis techniques, such as bispectrum and bicoherence analysis, surpass traditional power spectrum analysis by capturing nonlinear interactions between different frequency components. These techniques unveil hidden relationships and nonlinear dynamics in the ERG signal, offering a deeper understanding of retinal function and abnormalities.

## 4. Time-Frequency Domain Feature Extraction Approaches

Time-frequency domain feature extraction methods offer a combined representation of the time and frequency characteristics of Electroretinogram (ERG) signals. These methods aim to capture the dynamic changes in the spectral content of the signals over time, enabling a thorough analysis of both temporal and frequency components. By extracting features from the time-frequency domain, valuable insights into the temporal dynamics and frequency variations of ERG signals can be obtained by researchers and clinicians. One commonly utilized technique for time-frequency domain feature extraction is the Wavelet Transform, which allows for a multi-resolution analysis, enabling the examination of the signal's frequency content at different scales [34-36]. By decomposing the ERG signal into time-frequency components, the Wavelet Transform can effectively capture transient events and frequency variations that may not be easily detectable using other methods. Scalogram and spectrogram analysis, two popular techniques based on the Wavelet Transform, provide visual representations of the time-frequency characteristics of the signal. Time-frequency domain feature extraction approaches offer several advantages in ERG signal analysis Firstly; these methods provide a direct evaluation of the temporal attributes of the waveform, allowing for correlation with specific retinal processes. Secondly, these approaches are relatively simple and computationally efficient, as they do not necessitate complex signal processing techniques. Moreover, time-domain analysis facilitates the detection of subtle alterations in waveform morphology that may be challenging to identify using alternative methods. Nevertheless, it is crucial to recognize the constraints associated with time-domain feature extraction techniques [37, 38]. One limitation is their vulnerability to noise and artifacts present in the ERG signals, which can introduce inaccuracies in the extracted features and affect the analysis's dependability. The decomposition of the signal into time-frequency components requires additional computational resources and careful selection of analysis parameters. Additionally, the interpretation of time-frequency representations can be challenging, as it necessitates expertise in understanding the trade-offs between time and frequency resolution. Despite these limitations, time-frequency domain feature extraction approaches remain valuable tools in ERG signal analysis. They offer a unique perspective on the temporal and frequency characteristics of the waveform, facilitating a more comprehensive understanding of retinal function and the detection of abnormalities. Researchers and clinicians should consider the advantages and limitations of time-frequency analysis when selecting appropriate feature extraction methods for their specific research or clinical applications [39, 40].

## 5. Artificial Neural Network Feature Extraction Approaches

Artificial Neural Networks (ANNs) have garnered considerable attention in recent years due to their capacity to extract features from complex datasets, including Electroretinogram (ERG) signals. ANNs are computational models inspired by the structure and functioning of the human brain, comprising interconnected layers of artificial neurons [41-43]. These networks possess the ability to learn and extract meaningful features from raw data, making them well-suited for feature extraction in ERG signal analysis. One commonly employed approach for feature extraction using ANNs is the utilization of deep learning architectures, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs). CNNs excel in extracting spatial features from multidimensional data, making them particularly suitable for analyzing ERG signals. By training the network on a large dataset of ERG signals, CNNs can automatically learn discriminative features that are relevant for specific tasks, such as disease classification or abnormality detection. On the other hand, RNNs are designed to capture temporal dependencies in sequential data, which can be advantageous in analyzing time-varying aspects of ERG signals. ANN-based feature extraction approaches offer several advantages in ERG signal analysis. Firstly, they possess the capability to extract high-level abstract features from raw data, which may not be easily discernible using traditional feature extraction methods. This enables a more comprehensive analysis of ERG signals, potentially leading to improved accuracy in disease diagnosis and monitoring. Secondly, ANNs can adapt and learn from large datasets, facilitating automated and data-driven feature extraction without the need for manual feature engineering. This reduces reliance on domain expertise and potentially paves the way for objective and automated analysis of ERG signals [44-46]. However, it is important to acknowledge the limitations of ANN-based feature extraction approaches. One significant drawback is the requirement for large amounts of annotated training data. ANNs typically necessitate a substantial dataset to effectively learn representative features. Acquiring such datasets with well-labeled ERG signals can be challenging, particularly for rare or specialized retinal diseases. Additionally, ANNs are often perceived as "black-box" models, as the learned features may not be directly interpretable, limiting the insights gained from the feature extraction process. Another limitation is the computational complexity and resource requirements associated with training and deploying ANNs. Training deep learning models can be computationally intensive and often demands specialized hardware. Moreover, deploying these models in real-time or resource-constrained environments may pose challenges due to the computational demands [47, 48]. Despite these limitations, ANN-based feature extraction approaches hold promise in ERG signal analysis. Their ability to automatically learn discriminative features from raw data can contribute to improved accuracy and efficiency in disease diagnosis and monitoring. Researchers and clinicians should carefully consider the advantages and limitations of ANN-based approaches when selecting appropriate feature extraction methods for their specific research or clinical applications.

## 6. Conclusions and Future Works

This comprehensive review examines and compares various approaches for feature extraction in the analysis of Electroretinogram (ERG) signals. The approaches discussed include time-domain analysis, frequency-domain analysis, time-frequency domain analysis, and artificial neural network (ANN) analysis. Each approach has its own advantages and drawbacks, providing valuable insights into ERG signals and influencing their suitability for specific research or clinical applications. Time-domain analysis focuses on the morphology and temporal parameters of the ERG waveform, allowing for the identification of key features such as peak time and amplitude. It excels in detecting subtle changes in waveform morphology and is computationally efficient. However, it may be sensitive to noise and artifacts, which can affect the accuracy of feature extraction. Frequency-domain analysis explores the frequency components and power distribution of ERG signals, providing insights into their spectral characteristics and identifying abnormalities associated with specific frequency ranges. It offers quantitative measures of power distribution and facilitates objective comparisons. However, careful consideration of spectral analysis methods and signal-to-noise ratio is necessary. Time-frequency domain analysis combines time and frequency information, capturing dynamic changes in ERG signals. It provides a comprehensive representation of the signals, enabling the detection of transient events and frequency variations. This approach offers insights into the temporal dynamics of retinal responses and underlying physiological processes. However, it introduces complexities in parameter selection and computational requirements. ANN-based feature extraction approaches, such as deep learning architectures like CNNs and RNNs, have emerged as powerful tools in ERG signal analysis. They automatically learn discriminative features from raw data, eliminating the need for manual feature engineering. ANN-based approaches capture complex patterns and relationships in the data. However, challenges such as the requirement for large labeled datasets, interpretability of learned features, and computational demands should be considered. In conclusion, the choice of feature extraction approach depends on specific research or clinical objectives. Time-domain analysis captures waveform morphology, frequency-domain analysis identifies abnormalities in specific frequency ranges, time-frequency domain analysis provides comprehensive insights, and ANN-based analysis automates feature extraction from raw data. Understanding the advantages and limitations of each approach is crucial in selecting appropriate methods for specific applications. Future research in feature extraction for ERG signal analysis can focus on integrating different approaches to leverage their strengths and mitigate limitations. Combining time-domain, frequency-domain, and time-frequency domain features could provide a more comprehensive understanding of ERG signals. Additionally, incorporating ANN-based feature extraction with traditional approaches may improve accuracy and efficiency. Addressing challenges associated with ANN-based approaches, such as interpretability and visualization of learned features, and mitigating the requirement for large labeled datasets are important areas of exploration. Further research is also warranted in the development of automated and objective feature extraction methods, including integration with advanced signal processing techniques and exploration of novel feature extraction approaches.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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