



NEURAL NETWORK-BASED ALGORITHM FOR ELECTROCARDIOSIGNAL PROCESSING: DEVELOPMENT AND ANALYSIS

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ABSTRACT

This study focuses on the development and analysis of an algorithm utilizing neural network techniques for the processing of electrocardiograms. The proposed approach integrates advanced neural network models to enhance the processing and analysis of intricate electrocardiogram (ECG) data. Through neural network analysis, the algorithm aims to accurately detect and interpret various cardiac patterns and abnormalities within ECG signals, contributing to the efficient diagnosis and monitoring of cardiovascular conditions. The research involves the application of machine learning methodologies, particularly neural networks, to optimize signal processing, enabling robust feature extraction and pattern recognition from ECG data. The study's methodology involves training and validating the neural network algorithm with a diverse dataset of electro cardio signals, ensuring its effectiveness across varying cardiac conditions and patterns. The outcomes of this research aim to offer a sophisticated tool for clinicians and researchers, enhancing the accuracy and speed of ECG analysis, and ultimately contributing to improved clinical decision-making and patient care in cardiology.practitioners for the evolving educational landscape.

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Introduction

Research into artificial neural networks is grounded in the significant disparity between the human brain's information processing and conventional digital computers' methodologies (Haykin, 2006; Pereverzev-Orlov, 1990; Isakov, Lukyanova, & Sushkova, 2008; American College of Cardiology/American Heart Association, 1999; Isakov & Al Khulaidi, 2009). The human brain operates as an incredibly complex, parallel computer that organizes structural components (neurons) to efficiently perform tasks such as sensory signal processing, motor functions, and pattern recognition, operating significantly faster than modern computers (Haykin, 2006).

From birth, the human brain possesses an inherent structure capable of forming its own rules based on accumulated "experience," continually evolving throughout a person's life, particularly in the initial two years (Haykin, 2006; Pereverzev-Orlov, 1990). This process establishes a fundamental structure, but development persists, intertwined with the brain's plasticity—its ability to adapt to the surrounding environment (Isakov et al., 2008).

Similarly, in the realm of artificial neural networks, neurons also develop and function (American College of Cardiology/American Heart Association, 1999; Isakov & Al Khulaidi, 2009). A neural network typically models the information processing method to address a specific task, often using electronic components or programs running on digital computers (Isakov et al., 2008).

Years of research have shown that explicit methods are insufficiently accurate and convenient for widespread practical use in addressing implicit medical issues, such as diagnosis and prognosis (Pereverzev-Orlov, 1990; Isakov & Al Khulaidi, 2009) [2, 5]. Neuro-informational methods demonstrate significant advancements in this field, particularly in electrocardiographic diagnostics (Isakov et al., 2008).

Electrocardio signals necessitate specific preprocessing to train and operate a neural network analyzer, directly influencing the quality of cardiovascular system pathology recognition (Haykin, 2006; Isakov & Al Khulaidi, 2009)].

Therefore, it is crucial to determine the sequence and methods of signal preprocessing for generating electrocardiographic patterns as inputs for the neural network analyzer.

The study of artificial neural networks stems from the profound disparity between the human brain's information processing methods and those employed by conventional digital computers. The brain functions as an intricate, parallel computer, organizing neurons to perform tasks like sensory processing and pattern recognition much faster than modern computers.

From birth, the human brain forms its rules based on accumulated experiences, especially during the initial two years of life. This foundational structure continues to develop throughout life, adapting to the environment through brain plasticity.

In the realm of artificial neural networks, analogous neuronal development occurs to tackle specific tasks using electronic components or computer programs. These networks simulate the information processing approach akin to biological neurons.

Research indicates that explicit methods often lack the accuracy needed for implicit medical issues like diagnosis and prognosis. Neuro-informational techniques, especially in electrocardiographic diagnostics, have displayed significant advancements.

Effective preprocessing of electrocardiographic signals is pivotal for training neural network analyzers, directly influencing the precision of identifying cardiovascular system pathologies.

The distinct approaches of human brain processing and traditional digital computation inspire ongoing studies in artificial neural networks. Mimicking these biological mechanisms can greatly enhance computational systems for medical diagnostics and decision-making.

Methodology

Research Design:

The methodology for analyzing electrocardiograms (ECG) and cardio intervalograms (CIG) involves various critical steps.

Firstly, the ECG analysis necessitates capturing all components of the cardiac cycle within the neural network. This involves interpreting the P-wave (atrial depolarization), QRS complex (ventricular depolarization), and T-wave (ventricular repolarization), each comprising multiple peaks. The distinct R-peak, situated at the cycle's center and possessing high amplitude and frequency, serves as the primary reference point for generating the ECG pattern.

Determining the input vector's length within the neural network is crucial and is contingent upon the temporal window enclosing the cardiac cycle and the signal's sampling frequency. This window encompasses two segments: the pre-R-peak (P, Q, and PQ intervals) and the post-R-peak (R, S, T, and ST intervals). Selection of the appropriate sampling frequency for the input ECG pattern relies on the ECG signal recorder type intended for the neural network analysis. The analysis's relevance spans automated scrutiny of daily ECG recordings and screening studies.

Methodologically, adhering to the ACC/AHA guidelines for ambulatory monitoring entails specific recorder criteria: a minimum 24-hour recording duration, 2-3 ECG channels, a frequency range of no less than 0.5–40 Hz, a sampling frequency of 125 Hz or higher, and a resolution of no less than 5-20 μV . Contemporary ECG recorders typically operate at a 150 Hz sampling frequency, fitting most screening investigations.

Finally, signals with higher sampling frequencies necessitate artificial downsampling to align with the desired frequency. The normalization of signal amplitudes is integral to ensuring compatibility with the network's specified dynamic range for input neurons. The preprocessing of signals with higher sampling frequencies involves artificial downsampling to match the selected frequency. Following this, the final step in constructing the input ECG patterns entails signal normalization, aligning the amplitudes of all input signals within the established dynamic range of the network's input neurons.

In the analysis of cardio intervalograms (CIG), acquired from the temporal difference between consecutive R-peaks on the ECG, the utilization of neural networks proves advantageous in complex scenarios where linear methods offer limited solutions. Such tasks include analyzing correlation rhythmograms. The methodology of correlation rhythmography involves graphically representing sequential pairs of cardiac intervals (preceding and subsequent) on a two-dimensional coordinate plane. The x-axis depicts the R-R magnitude, while the y-axis represents R-R_{n+1}. This graphical representation, termed a correlation rhythmogram or scattergram, is a nonlinear analysis method, particularly valuable when infrequent and abrupt disturbances occur amid a monotonous rhythm.

The scattergram depicts a collection of points, the center of which lies along the bisector. A normal scattergram takes the form of an ellipse elongated along the bisector. This configuration signifies the addition of non-respiratory arrhythmia to respiratory variability. Circular scattergram shapes denote the absence of non-respiratory arrhythmia components. Narrow ovals indicate a prevalence of non-respiratory components in the overall rhythm variability, determined by the "cloud's" length. In cases where statistical and spectral analysis methods prove insufficient or unsuitable for arrhythmia assessment, evaluating the correlation rhythmogram (scattergram) proves prudent.

To generate the input pattern of R-R interferograms for the neural network, utilizing the scattergram instead of the original curve is advisable. Transforming the scattergram into a vector form involves segmenting the scattergram image into a defined number of equal squares. Calculating the number of points within each square produces a matrix, subsequently transformed into a vector by arranging the numbers from left to right and top to bottom into a single column.

Finally, to create CIG patterns, normalizing the resulting vector is essential to mitigate the sample size's influence on the analysis outcome.



Result

In this study, the algorithms employed served a dual purpose: they were not only instrumental in developing the training databases for the neural network-based electrocardiosignal analyzer but were also intended for preparing patterns during routine system operations. Preliminary investigations into these algorithms showcased the system's satisfactory operational efficacy [3, 5], laying the groundwork for further advancements in this domain.

The designed and trained neural network analyzer, validated through real-world scenarios, is anticipated for utilization in tandem with a single-channel ECG recorder within domestic automated cardiovascular system analysis setups. Its applications extend to conducting large-scale express studies for risk group identification and facilitating automated decryption of 24-hour ECG recordings.

The algorithms utilized in this study represent a pivotal component in the development of neural network-based models for electrocardiosignal analysis. Their dual functionality - facilitating database creation for system training and handling patterns during routine operations - underscores their significance in both training and operational phases. This iterative process involves using robust algorithms to compile comprehensive and diverse datasets for neural network training while simultaneously ensuring their practical applicability during real-time operations.

The efficacy of these algorithms was systematically evaluated, laying the foundation for their integration into the operational framework of the neural network-based electrocardiosignal analyzer. Preliminary assessments [3, 5] proved the system's efficiency, acting as a catalyst for its further refinement and implementation.

The designed neural network analyzer, after rigorous training and validation with real-world electrocardiosignal data, emerges as a potent tool for domestic cardiovascular analysis systems. Its intended utilization in conjunction with single-channel ECG recorders demonstrates a commitment to enhancing user accessibility and promoting widespread adoption in everyday clinical settings.

Moreover, the applicability of this neural network analyzer extends beyond singular use cases. Its integration into mass-scale express studies for risk group identification underscores its potential in large-scale epidemiological research, enabling the rapid identification and stratification of risk groups based on cardiac health indicators.

Additionally, its inclusion in automated decryption programs for 24-hour ECG recordings marks a significant leap in streamlining and expediting diagnostic processes. By automating the interpretation of extensive ECG records, this neural network-based system not only enhances diagnostic accuracy but also substantially reduces the time and expertise required for comprehensive analysis.

These outcomes underscore the practical significance of the algorithms employed in this research. Their integration into the neural network-based electrocardiosignal analyzer demonstrates their capacity to not only refine the system's efficiency but also significantly impact the broader landscape of cardiovascular health diagnostics and analysis methodologies.

In summarizing the trajectory of this study, it is evident that the algorithms utilized play a pivotal role in both the preparatory phases - facilitating dataset development for neural network training - and the operational stages - governing pattern analysis within the system. Their efficacy, as demonstrated in preliminary



assessments, forms a solid foundation for their future integration and continued enhancement in real-world cardiovascular analysis applications.

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