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Survey on Electrocardiogram Signals Analysis and Characterization

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Abstract

The analysis and evaluation of Electrocardiogram (ECG) signal quality play a crucial role in significantly enhancing the diagnostic accuracy and reliability of unsupervised ECG analysis systems. In practical scenarios, ECG signals are frequently subject to various types of noise and artifacts. Consequently, numerous assessment methods have been introduced, utilizing features from both the ECG signal and noise, alongside machine learning classifiers or heuristic decision rules. This article presents a survey on current state-of-the-art methods and underscores the practical limitations of existing assessment approaches. Drawing from previous studies and our own research, it is evident that there is a substantial demand for a lightweight ECG noise analysis framework. Such a framework is essential for real-time detection, localization, and classification of single and combined ECG noises, especially within the constraints of wearable ECG monitoring devices that often have limited resources. **Keywords:** Signal Analysis, Electrocardiogram, Machine Learning, Deep Learning

1 Introduction

According to [1], an electrocardiogram (ECG) serves as a measure of the heart's electrical activity evolution over time, reflecting the propagation of action potentials throughout the entire heart during each cardiac cycle. Simply put, the ECG records the collective signals generated by cell populations undergoing changes in their membrane potentials at a specific moment. The ECG captures distinctive waveforms of electrical variations during the depolarization and repolarization of the atria and ventricles.

In the context of an ECG, the human body is conceptualized as a substantial volume conductor comprising tissues and a conductive medium in which the heart is situated. As the heart undergoes the cardiac cycle, coordinated action potentials travel through its chambers, causing one section of the heart tissue to depolarize while another remains at rest or polarized, following the usual pattern [2, 3].

The observed voltages' intensity is influenced by the electrodes' orientation relative to the dipole ends, with signal amplitudes proportional to the mass of tissue contributing to the dipole at any given time. Electrodes are typically placed on the skin's surface to detect the voltages generated by these electrical fields, thereby producing the ECG [1].

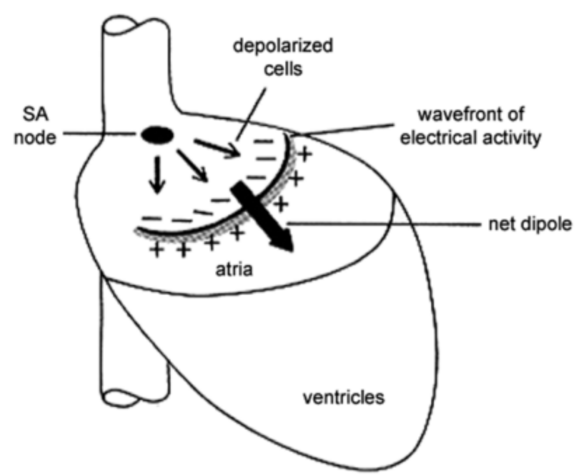

Figure 1: Conduction at the Sinoatrial Node, Cells within the Atria undergo Depolarization

The identification of inherent electrical activity within the heart traces back to the 1840s. In 1842, Italian physicist Carlo Matteucci made the groundbreaking discovery that each heartbeat is accompanied by an electrical current. Shortly thereafter, German scientist Emil DuBois-Reymond published the first action potential associated with muscular contraction [4]. In 1856, Rudolph von Koelliker and Heinrich Miller utilized a galvanometer to record the initial cardiac action potential. Subsequently, Augustus D. Waller achieved the first recording of the human electrocardiogram (ECG) after Gabriel Lippmann invented the capillary electrometer in the early 1870s. The inaugural device is depicted in Figure 2.

A pivotal moment in the field of cardiac electrocardiography occurred with Willem Einthoven's invention of the string galvanometer in 1901. The following year, he released the first electrocardiogram (ECG) utilizing his innovative string galvanometer. Einthoven's creation featured a substantial electromagnet with a delicate silver-

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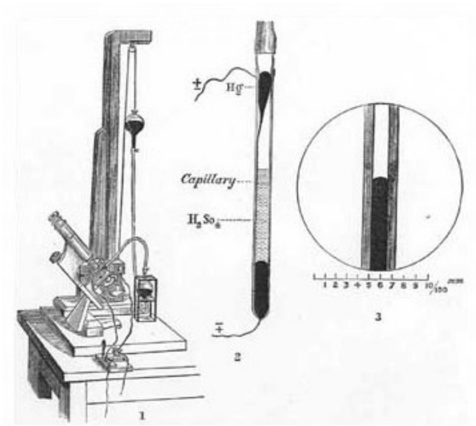

Figure 2: Lippmann electrometer

coated string stretched across it; electrical currents passing through the thread induced lateral movements within the magnetic field of the electromagnet.

Einthoven made another significant contribution to cardiac electrophysiology by establishing a mathematical correlation between the direction and magnitude of deflections recorded by the three limb leads. This proposition became known as Einthoven's triangle. Prior to Frank Wilson's delineation of unipolar leads and the precordial lead configuration, the conventional three-limb leads were employed for three decades. The current 12-lead ECG layout incorporates the traditional Einthoven limb leads, alongside the precordial and unipolar limb leads based on Wilson's advancements.

Originally manufactured in 1905 by the Cambridge Scientific Instrument Company in London, this instrument allowed electrical impulses to be transmitted from a hospital located over a mile away to Einthoven's laboratory via a telephone cable. However, bedside machines did not become available until the 1920s. In 1935, the Sanborn Company produced a smaller version of the unit weighing approximately 25 pounds.

Norman Jeff Holter's invention of the Holter monitor in 1949 marked a significant milestone, enabling the application of electrocardiography (ECG) in nonclinical settings. The initial version of this device, a 75-pound backpack, had the capability to continuously record ECG signals and transmit them via radio. Subsequent iterations of such monitors have undergone substantial size reduction, and the signals are now digitally recorded. Modern, miniaturized versions allow for extended patient monitoring periods, typically lasting 24 hours, facilitating the diagnosis of rhythm abnormalities or ischemic heart diseases. The Holter monitor depicted in Figure 3 represents one of the latest iterations.

Figure 3: Holter-Edan ECG device

2 Related Work

Tobón and Falk [5] introduced a novel approach to enhance the denoising of ECG signals through spectro-temporal filtering. Comparative assessments with a state-of-the-art wavelet-based enhancement algorithm demonstrated the superiority of the proposed method across various performance metrics, particularly in extremely noisy conditions. Specifically, the suggested method exhibited an approximately 11 dB improvement in Signal-to-Noise Ratio (SNR) and achieved a Heart Rate (HR) error percentage of 2%, as opposed to 57% in the presence of the noisy signal and 6% with the wavelet-enhanced ECG. The proposed solution not only elevated SNR and HR estimation but also enhanced heart rate variability measurement, presenting opportunities for accurate ECG data analysis with low-cost devices in field settings. However, further investigation is essential to validate these findings in a controlled clinical environment, involving scenarios like abrupt changes in heart rate, such as arrhythmia, especially in conditions like atrial fibrillation or significant ventricular entropy.

Seeuws *et al.* [6] examined the application of auto-encoders, a subset of unsupervised deep learning models, for assessing the quality of ECG signals. Two quality indicators derived from a trained auto-encoder, namely AE-logMSE and AE-LLH, consistently exhibited strong performance across the evaluated tasks in comparison to established benchmarks. The evaluation tasks extended beyond the conventional anomaly detection scenarios for auto-encoders. In addition to excelling in binary quality scoring, AE-logMSE and AE-LLH demonstrated robust performance in assessing correlation with various noise levels.

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Lee *et al.* [7] utilized a Generative Adversarial Network (GAN) to produce V-leads ECG signals derived from MLII lead ECG signals, specifically a limb lead. This study distinguishes itself from prior research by incorporating R-peak alignment, ordered time-sequence embedding, and the use of a paired dataset. Unlike current portable ECG devices, which often provide limited ECG signals from limb leads, this study addresses the limitations by introducing methods like R-peak detection and S-T segment analysis for ECG applications. The accuracy of ECG pattern reconstruction is deemed crucial for the efficacy of these applications. The R-peak-aligned GAN explored in this study has the potential to enable the retrieval of lead-ECG signals via portable ECG leads, making the recovered data applicable in both mobile environments and clinical settings. Additionally, the one-to-multi lead reconstruction may contribute to the advancement of sophisticated portable ECG hardware, alleviating issues related to the inconvenience of attaching multiple leads and data storage space limitations.

Edla *et al.* [8] formulated statistical techniques to dynamically model and estimate parameters of ECG signals utilizing sequential Bayesian approaches. They implemented a straightforward Bayesian Maximum Likelihood (ML) classifier to differentiate between various cardiac conditions. These models offer the benefit of eliminating the need for user-defined parameters, conducting early-stage processing to acquire a priori information about ECG signals for filter initialization or ECG fiducial point delineation, and adapting to alterations in ECG signal morphology. The derived model parameters furnish features suitable for the automatic classification of cardiac arrhythmias, diminishing the reliance on manual annotation and facilitating prompt diagnoses.

Hinatsu *et al.* [9] explored the estimation of cardiovascular signals, specifically electrocardiogram (ECG) and photoplethysmogram (PPG) waveforms, by utilizing skin vibrations in the form of piezoelectric plethysmogram (PEPG) signals. ECG and PPG measurements hold significance in biomedical and security applications, and PEPG signals offer a means to estimate ECG and PPG waveforms based on physiological activities in the cardiovascular system. The research delved into the estimation procedure for ECG and PPG signal waveforms from PEPG signals employing frequency analysis. An experiment was conducted using a dataset that included ECG, PPG, and PEPG signals to assess estimation performance. The outcomes reveal successful estimation of ECG and PPG waveforms from PEPG signals, with errors of less than 15% and 10%, respectively.

Contamination of electrocardiogram (ECG) signals by motion artifact (MA), often caused by body movement or sensor displacement, leads to the distortion of crucial clinical features. This study introduces a Monte Carlo filter (MCF)-based approach for real-time removal of MA from single-channel ECG signals, particularly applicable in telecardiology systems. The methodology involves R-peak detection, beat extraction, and principal component (PC) analysis on clean ECG beats. The PC with the highest energy is identified as the feature beat, which is then employed to successively denoise MA-corrupted beats using the MCF, resulting in a clean ECG pattern. Banerjee and Singh [10] proposed a novel method for weight calculation and resampling to enhance the MCF's performance. Evaluation on the IEEE Signal Processing Cup Challenge 2015 ECG database and MIT-BIH arrhythmia records demonstrated an improvement in signal-to-noise ratio between 10 and 15 dB after MA removal. Real-time testing on ECG data from ten healthy volunteers, collected using the AD8232 ECG module and Raspberry Pi, revealed a correlation coefficient exceeding 0.99 between the original and denoised signals. The algorithm proved effective in removing MA from any single-channel, MA-corrupted ECG signal, regardless of lead category, using features from clean beats. Comparative analysis against previously published works affirmed the superior performance of the proposed method in MA removal from ECG, along with real-time data collection, processing, and transmission.

3 Proposed Approach

To address the critical role of Electrocardiogram (ECG) signal quality analysis and enhance the diagnostic accuracy of unsupervised ECG analysis systems, a novel approach is proposed. The methodology involves the development of a lightweight ECG noise analysis framework designed for real-time detection, localization, and classification of single and combined ECG noises. The proposed framework aims to overcome the practical limitations observed in current state-of-the-art methods. Leveraging features from both the ECG signal and noise, machine learning classifiers or heuristic decision rules will be employed in the assessment process. Special attention will be given to the resource constraints of wearable ECG monitoring devices, ensuring the framework's adaptability to limited resources.

4 Conclusion and Future Work

This survey seeks to contribute to the advancement of ECG signal quality analysis by introducing a lightweight and efficient noise analysis framework. By addressing the challenges posed by various types of noise and artifacts in practical scenarios, the framework aims to enhance the diagnostic reliability of unsupervised ECG analysis systems. The survey of current state-of-the-art methods, along with insights from previous studies and our own research, underscores the need for such an innovative solution. The successful implementation of the proposed framework is expected to significantly impact the field of wearable ECG

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monitoring devices, providing a valuable tool for real-time noise detection and classification.

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