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Signal Quality and Cross-Session Robustness in ECG Biometric Authentication: A Review of Methods and Challenges

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Abstract– Electrocardiogram (ECG)-based biometric authentication uses physiological signals to verify a claimed identity. Its practical performance depends not only on the classifier but also on acquisition conditions, preprocessing, segmentation, feature representation, and the protocol used to evaluate genuine and impostor attempts. This paper presents a proposed study of ECG signal processing for biometric verification, with particular attention to signal quality and cross-session variability. A staged pipeline is outlined, beginning with a conventional feature-based baseline and progressing to quality-aware processing and, where data permit, learned representations. The proposed evaluation separates enrollment and verification data and emphasizes false acceptance rate, false rejection rate, equal error rate, and receiver operating characteristic analysis. Public ECG databases, including ECG-ID, are considered as candidate resources, subject to their suitability for the final protocol. No experimental results are claimed in this draft; the contribution is a reproducible study design to be refined after a focused review and implementation .

Key Words: ECG biometrics, biometric verification, signal preprocessing, feature extraction, signal quality, cross-session evaluation.

1.INTRODUCTION

Biometric systems infer or verify identity from measurable human characteristics. ECG biometrics use the electrical activity associated with cardiac cycles as a physiological signal. In contrast with external traits, an ECG is acquired through electrodes and is affected by sensor placement, contact quality, movement, physiological state, and recording duration. These factors make signal processing an integral part of the recognition pipeline rather than a purely preliminary operation.

Two tasks must be distinguished. Identification searches a gallery to determine which enrolled subject most closely matches a sample (1:N), whereas verification tests whether a sample supports a claimed identity (1:1). Identification accuracy alone therefore does not fully characterize an authentication system. Verification requires genuine and impostor comparisons and operating measures such as false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER).

Recent reviews organize ECG biometric methods across acquisition protocols, databases, feature extraction, and classification [1]–[3]. Comparative work has also considered different devices, leads, and single- versus multi-session settings [4]. These studies motivate careful evaluation beyond random beat-level splits, which can inadvertently place highly correlated segments from one recording in both training and test sets.

This paper defines a proposed investigation of the relationship between signal quality, preprocessing, and cross-session ECG verification. The aim is not to claim a new biometric principle, but to establish a transparent experimental workflow in which candidate processing changes can be evaluated under a consistent protocol.

2. BACKGROUND AND RELATED WORK

A. ECG Signal Characteristics

A conventional ECG cycle is commonly described by the P wave, QRS complex, and T wave. The QRS complex reflects ventricular depolarization and is often used to locate cardiac cycles. ECG morphology and timing can provide subject-discriminative information, but their measured values also depend on lead configuration, electrode placement, noise, and physiological variation. A feature useful for clinical interpretation is not automatically suitable for identity verification; biometric usefulness must be demonstrated using an appropriate subject-level protocol.

B. Acquisition and Dataset Considerations

ECG biometric studies use both databases collected specifically for recognition and clinical databases originally intended for other purposes. The ECG-ID database is a public resource with recordings from 90 volunteers and is frequently used in biometric research [5]. Its recording characteristics and subject count make it useful for prototyping, but the dataset should not be treated as a substitute for large-scale or deployment-specific validation. Database suitability depends on the number of subjects, recording sessions, acquisition conditions, and availability of identity labels.

Acquisition choices can affect recognition outcomes. A systematic review of ECG data acquisition methods discusses factors such as lead configuration and recording protocol [2]. For a reproducible experiment, the selected dataset version,

subject inclusion criteria, sampling frequency, recording lengths, and session definitions should be reported explicitly.

C. Processing and Feature Representation

A typical ECG processing chain may include baseline correction, filtering, R-peak detection, beat segmentation, normalization, and feature extraction. Filtering must be selected with care: aggressive filtering can distort waveform morphology and thereby alter downstream features. R-peak errors can shift beat windows or cause invalid segments, so detector performance and segmentation quality should be inspected before model training.

Handcrafted representations may describe temporal intervals, amplitudes, morphology, or statistical properties of beats. Conventional classifiers such as support vector machines (SVMs) and random forests can provide interpretable baselines. Deep models, including one dimensional convolutional neural networks (1D CNNs), can learn representations from waveform segments, but their performance depends on sufficient independent training data and leakage-resistant validation. A 2023 benchmark study explicitly examined verification and identification and feature selection, will be fitted only on training data. across multiple recording scenarios, illustrating the importance of evaluation protocol [4].

D. Evaluation Challenges

A system may appear highly accurate when train and test samples share recording-specific characteristics. A subject- and session-aware split is more informative when the research question concerns persistence across time. In verification, the number and construction of genuine and impostor trials influence reported metrics. Thresholds should be selected on validation data, not optimized on the final test set. When class balance is artificial, accuracy alone can be misleading; FAR, FRR, EER, and ROC curves should be reported with their trial definitions.

3. PROBLEM STATEMENT AND OBJECTIVES

The central problem considered in this study is the sensitivity of ECG-based verification to signal quality and recording-session variation. A processing pipeline that performs well on clean or closely related recordings may produce more false rejections or false acceptances when applied to recordings acquired under different conditions. The study will examine whether explicit signal-quality handling and carefully selected preprocessing improve verification performance without concealing the cost of rejecting unusable samples.

A. Dataset and Protocol

ECG-ID is a candidate dataset because it contains subject-labelled ECG recordings and has been used in biometric studies [5]. Before implementation, its current documentation and files should be inspected to confirm the available sessions, signal format, subject distribution, and suitability for verification. If its recording structure does not support a meaningful cross-session test for the chosen subjects, the study must report that limitation or select an additional dataset.

Partitioning will be performed at the recording or session level, not by randomly splitting beats from the same recording. Enrollment recordings will form subject reference templates; validation recordings will be used to select model settings and thresholds; and test recordings will be held out until final evaluation. The precise split will be fixed before model comparison. All transformations whose parameters are learned from data, including scaling

B. Preprocessing and Segmentation

The raw signal will first be inspected for missing values, clipping, baseline drift, and obvious artifacts. A suitable band-pass or baseline-correction method will be selected based on the signal sampling rate and the morphology that must be preserved. Filter parameters will be documented and applied consistently. R-peaks will then be detected using a validated detector, with visual inspection of representative records and checks for missed or duplicate detections.

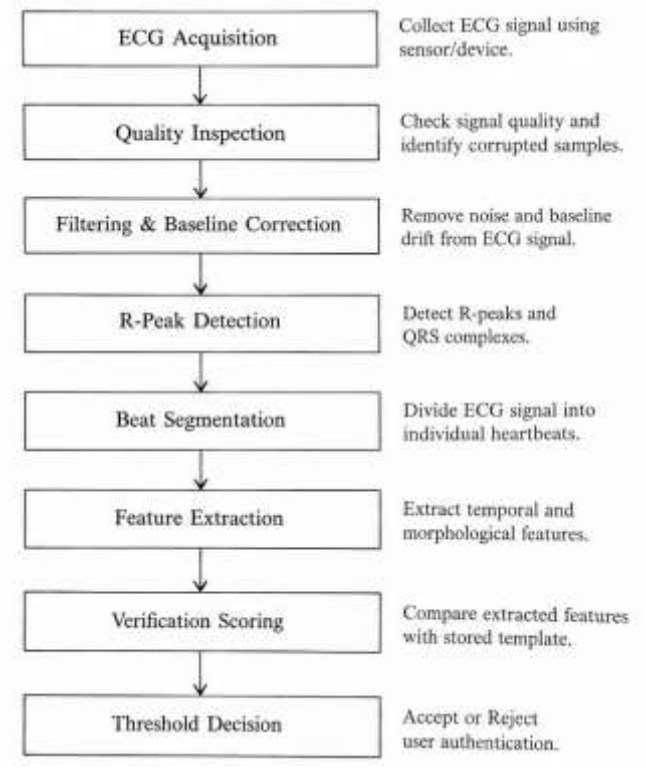
For each accepted R-peak, a fixed window around the peak will be extracted, provided that the window remains within the recording. The window duration and alignment will be selected using the literature and dataset characteristics. Segments failing predefined quality criteria may be flagged or excluded. The rejection rate must be reported because a quality gate can improve conditional accuracy while reducing the number of samples that the system can process.

C. Feature Extraction and Verification

The baseline will use a compact set of handcrafted temporal and morphological features, selected after examining prior work and the available sampling rate. Features will be standardized using training-set statistics. An SVM will serve as a conventional baseline; a random forest may be included as a secondary comparison if the sample size supports it. A learned 1D CNN representation is an optional advanced experiment rather than a required component.

For verification, a model or similarity function will compare a probe recording with the claimed user's enrollment representation. The output score will be compared with a threshold selected on validation data. Scores above or below the threshold will be mapped to accept or reject according to the score convention. The direction of the score and the threshold-selection rule will be explicitly documented.

D. Proposed Architecture



The architecture is deliberately modular. The baseline omits explicit quality rejection; the second configuration adds quality assessment; and an optional third configuration replaces handcrafted features with learned representations. Each modification will be evaluated separately to attribute observed differences to specific design choices.

F. Processing Algorithm

The following high-level procedure summarizes the proposed experimental workflow. It is intentionally independent of a specific library so that implementation details can be reported separately.

Algorithm 1: ECG verification pipeline

Input: ECG recordings, subject labels, recording/session identifiers; Output: verification scores and evaluation metrics.

1) Inspect the recordings and confirm sampling rate, labels, and session metadata. 2) Create recording-level enrollment, validation, and test partitions according to the prespecified protocol. 3) Fit any data-dependent preprocessing or scaling parameters using training data only. 4) Filter each recording and detect R-peaks using the selected detector. 5) Segment beats and calculate the predefined quality indicators. 6) Retain or flag segments according to the fixed quality rule. 7) Extract the selected features or learned representation. 8) Build enrollment references and compute genuine and impostor verification scores. 9) Select the operating threshold on validation scores. 10) Apply the frozen threshold to test scores and calculate FAR, FRR, EER, and ROC-AUC as appropriate.

The baseline and quality-aware variants will share the same data partitions and score construction wherever possible. This reduces confounding and allows the incremental effect of the quality gate to be examined. If the optional CNN is implemented, its training procedure, architecture, loss function, stopping rule, and random seed will be documented. Model complexity and training time may also be recorded as supplementary measures.

G. Reporting Plan

The results section will include a dataset summary, a diagram of the final implemented pipeline, a table of preprocessing configurations, and a table of verification metrics. Each table will identify the evaluation scenario and test population. A confusion matrix may be included for a clearly defined classification experiment, but it will not replace biometric verification metrics. Any difference between methods will be discussed in light of the number of subjects, sessions, genuine trials, impostor trials, and rejected segments.

4. EXPECTED ANALYSIS AND LIMITATIONS

The experiments are designed to determine whether signal-quality assessment and cross-session-aware evaluation materially change the interpretation of ECG verification performance. A quality-aware method may reduce errors on accepted segments but may also reject genuine samples. A learned representation may capture complex morphology, but it may also overfit when the number of independent subjects or sessions is limited. These possibilities will be assessed from measured results rather than assumed in advance.

Likely limitations include the size and acquisition conditions of public ECG datasets, differences between clinical and biometric collection protocols, possible changes in physiology over time, and the limited generalizability of results from a single database. ECG is sensitive physiological information; any future deployment would require informed consent, secure storage, access control, and a clear retention policy. A public benchmark result alone cannot establish security against spoofing or presentation attacks.

5. FUTURE SCOPE

The present study mainly focuses on improving the quality and usability of ECG signals for biometric applications. Although the preprocessing stage plays an important role in obtaining reliable ECG information, several aspects of ECG-based authentication still require further investigation. Future studies can explore more effective approaches for extracting meaningful information from processed ECG signals and examine how different computational techniques can be used to improve authentication performance.

Further research can also consider practical conditions in which ECG signals may vary because of noise, recording devices, different sessions, and changes in physiological conditions. The reliability of authentication under such conditions remains an important area of study. In addition, the protection of ECG data and biometric information needs careful consideration before such systems can be adopted in practical applications.

These directions can help in developing ECG biometric systems that are more reliable and suitable for real-world use while addressing the challenges associated with signal quality, authentication, and protection of biometric information.

Future research can investigate advanced deep learning architectures such as CNN, LSTM, can evaluate ECG authentication across different recording sessions, wearable devices, electrode configurations, and acquisition environments to improve real-world reliability.

6.CONCLUSION

ECG-based biometric authentication depends on effective signal preprocessing, reliable quality assessment, and appropriate verification protocols. The reviewed literature highlights the importance of distinguishing identification from verification and evaluating systems using metrics such as FAR, FRR, and EER. Signal quality and cross-session variations remain important challenges that can affect authentication reliability. Quality-based rejection may improve the reliability of accepted signals but can also reduce system coverage. Fair evaluation requires proper data partitioning, clear reporting of experimental settings, and prevention of data leakage. Furthermore, differences in datasets and acquisition conditions limit the generalizability of existing findings. Future research should explore advanced computational approaches for ECG feature learning and authentication, while addressing security, privacy, and robustness under varying recording conditions, to support the development of reliable and practical ECG-based biometric systems.These considerations can support the development of more reliable and practical ECG-based biometric authentication systems.

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