Lead Selection Protocols for the Reconstruction of 12-Lead Electrocardiogram

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Abstract

Electrocardiogram (ECG) lead reduction and signal reconstruction are critical for enabling compact, wearable cardiac monitoring systems. This study builds on years of foundational research by systematically evaluating various lead selection protocols to determine the most effective subset of leads for reconstructing a full 12-lead ECG.

Unlike previous studies that often conflate lead selection with reconstruction techniques, this work decouples the two by applying a standardized linear transformation method across all protocols. Among the evaluated approaches, the protocol proposed by Finlay et al. demonstrated the highest performance, achieving a correlation coefficient of 0.93 and the lowest RMSE of 0.10mV. Three protocols consistently identified the same optimal lead set (III, aVR, and V3) highlighting its reliability. These three leads offer strong spatial diversity and high correlation with the remaining ECG signals, making them highly effective for signal reconstruction.

The findings have practical implications for the development of efficient and cost-effective wearable ECG devices. By using a standardized, evidence-based lead subset, even simple reconstruction models can achieve high performance, reducing the need for complex algorithms and enabling scalable health technology solutions.

1. Introduction

Electrocardiogram (ECG) reconstruction is the synthesis of ECG leads from a recorded set of leads [1]. In the context of 12-lead ECG systems, this becomes particularly important in cases where some leads are corrupted by noise, omitted, or entirely unavailable. This is also relevant in telemedicine and mobile health applications, where reduced lead sets are often employed to simplify data acquisition and enhance user comfort. By enabling the recovery of missing leads, ECG reconstruction supports more accurate diagnosis, monitoring, and prognosis, even in resource-constrained or remote settings.

Numerous studies have shown promising results in ECG reconstruction; however, they frequently employ different sets of recorded leads as input to their reconstruction models [1]. Although various input lead combinations have demonstrated dependable performance, it is evident that the selection of input leads plays a significant role in determining the effectiveness of the reconstruction model. Subtle design choices, such as which leads are used as input, can have considerable impact on the performance of the model [1, 2].

While several influential studies have attempted to identify optimal lead sets for reconstruction, these methods often differ in both design and evaluation criteria [3-5]. To fairly compare their effectiveness, these approaches must be tested on a common dataset using a consistent reconstruction model. This paper adopts linear regression (due to its simplicity and transparency) to evaluate six lead selection protocols, with the goal of identifying the most effective input lead set for ECG reconstruction.

2. Method

2.1. Dataset

The dataset used in this study consists of 1,000 ECG records, randomly selected from the CODE-15% dataset [6] based on specific inclusion criteria detailed in the accompanying metadata. Selection was restricted to recordings from unique patients, each classified as normal, with no documented cardiac conditions and no missing leads.

After selection, all ECG signals were standardized to a duration of 10 seconds and uniformly resampled to 500 Hz. Preprocessing was performed using the ECGdeli MATLAB toolbox [7], which included denoising, and baseline extraction. Denoising was conducted using standard filtering techniques with the following parameters: a high-pass filter at 0.3 Hz to remove baseline wander, a low-pass filter at 120 Hz to eliminate high-frequency noise, and a notch filter at 60 Hz to suppress power line interference.

2.2. Pipeline

The reconstruction pipeline for testing every protocol is illustrated in Figure 1. Each protocol was applied to the complete dataset to determine a hierarchy of leads based on its selection criteria. The top three leads identified by each lead selection protocol are used as inputs to a linear regression model, which reconstructs the remaining nine leads. The decision to use three input leads is based on the findings of Schreck, Tricarico, Frank, Thielen, Chhibber, Brotea and Leber [8], who demonstrated that three leads can capture approximately 99% of the information contained in a standard 12-lead ECG.

$$Y = XA + C \ \dots eqn1$$

$$where: A = \begin{bmatrix} a_{11} & \cdots & a_{19} \\ \vdots & \ddots & \vdots \\ a_{31} & \cdots & a_{39} \end{bmatrix}$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_9 \end{bmatrix}, x = [x_1 \quad x_2 \quad x_3]$$

$$where: Y = 9\ by\ 1\ column\ matrix\ of\ output\ values$$
$$X = 1\ by\ 3\ column\ matrix\ of\ input\ variables$$
$$A = 3\ by\ 9\ matrix\ of\ coefficents$$
$$C = 1\ by\ 9\ column\ matrix\ of\ constants$$

It is important to note that while the original studies employed various reconstruction techniques, linear transformation (eqn1) is used consistently throughout this study. This uniform approach allows for a controlled evaluation of the impact of different lead selection protocols, ensuring methodological consistency and isolating the influence of lead choice on reconstruction performance.

Moreover, the protocols evaluated in this study were originally developed for identifying reduced lead sets in body surface potential mapping (BSPM). Due to their demonstrated effectiveness in that context, they are adapted here for application in 12-lead ECG reconstruction.

Each protocol will be assessed by comparing the synthesised leads (generated using the top three leads recommended by the protocol) to the original recorded leads. The evaluation was conducted using two key performance metrics: correlation coefficient and root mean square error (RMSE). These metrics provide a comprehensive assessment of both the morphological similarity and amplitude accuracy of the reconstructed signals.

To ensure robust and reproducible evaluation, each lead selection protocol was assessed using ten-fold cross-validation. This consistent validation strategy provided a fair comparison across all experiments and minimized the risk of overfitting.

Figure 1. Pipeline for the testing each selection protocol. The top three selected leads are inputs and the remining nine are outputs.

2.2.1 Protocol 1

This protocol establishes lead hierarchy using a cross-correlation approach. Each lead is correlated with every other lead (excluding self-correlation to prevent artificially inflating the influence of any single lead). The average correlation value for each lead is then computed (eqn2), and the leads are ranked based on these averages, with higher average correlations indicating greater relevance.

$$\bar{\rho}_j = \frac{1}{n-1} \sum_{\substack{i=1 \\ i \neq j}}^{n} \rho_{ij} \ \dots eqn2$$

$$where:$$
$$\bar{\rho}_j = average\ correlation\ of\ lead\ j\ to\ all\ leads$$
$$\rho_{ij} = correlation\ of\ lead\ i\ to\ lead\ j$$
$$j = observed\ lead\ at\ any\ given\ point\ in\ time$$
$$i = other\ leads\ in\ the\ lead\ set$$
$$n = number\ of\ leads\ in\ lead\ set$$

2.2.2 Protocol 2

This protocol is based on the methodology proposed by Lux, Smith, Wyatt and Abildskov [3]. It is designed to quantify the information index of each lead relative to all other leads, as defined in eqn3. Once the information index (I_j) is calculated for each lead, the three leads with the highest I_j values are selected for the reconstruction task. These leads are considered to carry the most comprehensive information about the remaining ECG signals.

$$I_j = \sum_{i=1}^{n} \sigma_i^2 \rho_{ij}^2 \ \dots eqn3$$

$$where: I_j = information\ index\ of\ lead\ j$$
$$\sigma_i = standard\ deviation\ of\ the\ lead\ i$$

2.2.3 Protocol 3, 4, 5

These protocols are based on the methods proposed by Finlay, Nugent, Donnelly, Lux, McCullagh and Black [4]. They operate by iteratively identifying the most informative ECG leads until all leads have been ranked, leaving only one unranked. The process begins by using each lead individually to reconstruct the remaining leads through linear transformation. A performance metric

(correlation, RMSE, or a combined multi-objective criterion (MOC)) is then applied to evaluate and select the most informative lead.

In subsequent iterations, the best-performing lead from the previous step is combined with each of the remaining unranked leads to reconstruct the others. The evaluation metric is reapplied to determine the next most informative lead. This iterative process continues until all leads have been ranked based on their relative informativeness. Protocol 3 uses correlation as the evaluation metric, selecting leads with the highest average correlation as the most informative. Protocol 4 uses RMSE, ranking leads with the lowest average error as most important. Protocol 5 MOC that integrates both correlation and RMSE into a unified score, where a lower MOC value indicates a better-performing lead. The method for calculating MOC is detailed in eqn4.

$$MOC_J = rank_\rho(j) + rank_{RMSE}(j) \dots eqn4$$

$$where:$$

$$rank_\rho(j) = rank\ of\ lead\ j\ based\ on\ correlation\ (1 = highest\ correlation)$$

$$rank_{RMSE}(j) = rank\ of\ lead\ j\ based\ on\ RMSE\ (1 = lowest\ error)$$

2.2.4 Protocol 6

This protocol is based on the methodology proposed by Barr, Spach and Herman-Giddens [5]. It utilizes principal component analysis (PCA) to derive principal components from the ECG signals and ranks the leads according to their contributions to these components. While the original study employed 30 principal components due to its use of a 150-lead body surface potential map (BSPM), this study limits the analysis to the top 3 principal components, aligning with the use of a standard 12-lead ECG dataset.

Once the top 3 principal components are identified, the contribution of each lead to these components is measured and summed, as described in eqn5. The three leads with the highest cumulative contribution scores are then selected as the input leads for reconstruction under this protocol.

$$Importance_j = \sum_{k=1}^{N} |G_{k,j}| \dots eqn5$$

$$where:$$

$$Importance_j = sum\ of\ the\ contributions\ of\ lead\ j$$

$$N = number\ of\ components$$

$$k = the\ component\ in\ being\ examined$$

$$G_{k,j} = the\ importance\ of\ lead\ j\ to\ component\ k$$

3. Results

The results of this study demonstrate that Protocols 3, 4, and 5 yielded the highest performance across metrics, as shown in Table 1. These protocols, which use correlation, RMSE, and MOC, all identified a similar optimal lead set: III, aVR, and V3. This input lead combination proved most effective in reconstructing the remaining ECG leads.

This finding aligns closely with the work of Butchy, Jain, Leasure, Covalesky and Mintz [9], who concluded that two limb leads and lead V3 offer the best coverage for full 12-lead ECG reconstruction. Their results emphasized the value of combining spatially diverse leads with high correlation to the rest of the ECG.

Table 1. Average correlation (r) and RMSE in mV of the synthesized leads against the original. The leads are based on the hierarchy chosen by the protocols investigated. "std" is the standard deviation of the metric to its left.

Protocol	Top 3 Leads	r	std	RMSE	std
1	V4, V5, II	0.74	0.28	0.15	0.14
2	V1, V6, aVL	0.83	0.22	0.16	0.16
3	**aVR, III, V3**	**0.93**	**0.11**	**0.10**	**0.13**
4	**aVR, III, V3**	**0.93**	**0.11**	**0.10**	**0.13**
5	**aVR, III, V3**	**0.93**	**0.11**	**0.10**	**0.13**
6	V3, V2, II	0.76	0.25	0.13	0.14

4. Discussion and Conclusion

The results indicate that the approach proposed by Finlay, Nugent, Donnelly, Lux, McCullagh and Black [4] is the most effective for lead selection, demonstrating the highest correlation and lowest RMSE among the evaluated methods. This performance may be attributed to the protocol's emphasis on correlation and RMSE as the primary evaluation metrics. The findings further reveal that two limb leads, along with precordial lead V3 (Figure 2), serve as the most suitable input leads for signal reconstruction compared to the configurations recommended by alternative protocols.

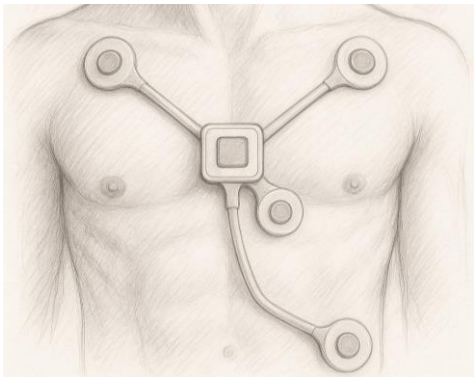

Figure 2. The locations of the electrodes of a wearable ECG device that captures the input lead set recommended from the findings.

This study builds on years of foundational research in ECG lead reduction and signal reconstruction, aiming to advance the field by identifying the most effective leads for reconstructing a full 12-lead ECG. Unlike prior studies that often entangle lead selection with the reconstruction technique itself, this work deliberately decouples the two processes. By standardizing the reconstruction method (using linear transformation across all experiments) it isolates and evaluates the true impact of lead choice. The goal is to provide a clear, evidence-based recommendation for the optimal subset of leads to be used in ECG reconstruction, regardless of the model employed.

This standardisation and selection of lead set has significant implications for the design of wearable ECG devices. In the absence of a highly specialized clinical requirement, adopting a standard lead set (as recommended by the findings of this study and shown in Figure 2) can maximize efficiency and accuracy across applications. Furthermore, with a more informative and effective lead subset, even simple reconstruction models can achieve strong performance, reducing the need for complex, resource-intensive algorithms. This, in turn, simplifies the architecture of embedded systems, leading to reductions in both design complexity and manufacturing cost, which are key considerations in the development of scalable, affordable wearable health technology.

It is also important to acknowledge the limitations of this study. The analysis was conducted using a single dataset, specifically the CODE-15% dataset, which is distinct from the datasets originally used by the designers of the evaluated lead selection protocols. Additionally, the study focused exclusively on ECGs classified as "normal." While this ensures controlled evaluation, it limits the immediate applicability of the results to broader clinical contexts.

To enhance the generalisability and clinical relevance of the recommended lead set, future work should involve testing on multiple datasets that reflect diverse patient populations, including those with various cardiac abnormalities. It would also be valuable to validate the proposed lead set using non-linear reconstruction models, such as deep neural networks or other advanced machine learning techniques. This would help assess whether the lead set maintains its effectiveness across a wider range of reconstruction strategies and real-world conditions, ultimately supporting its adoption in both research and clinical practice.

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