Wave Masking: Effect of Padding Techniques on the Reconstruction of Electrocardiogram

Ekenedirichukwu N. Obianom, Noor Qaqos, Abdulhamed M. Jasim, Shamsu Idris Abdullahi, Fan Feng, G. André Ng, Xin Li

University of Leicester, Leicester, United Kingdom

Abstract

This study evaluates enhancements to the wave masking (WM) preprocessing technique for ECG signal reconstruction. It focused on different padding schemes and the role of temporal dependency (TD) while using a linear regression model. Three padding methods (zero (WMZ), boundary (WMB), and sigmoid (WMS)) were tested, both independently and in combination with TD (WM_TD).

Across five ECG leads (V1, V2, V4, V5, V6), all methods showed similar average performance, with correlation coefficients (r) ranging from 0.887 to 0.895 and RMSE between 0.161 and 0.166. The sigmoid padding method (WMS) consistently produced the most visually coherent ECG morphology. Importantly, the computational cost of WMS is comparable to WMZ (the initial scheme), enabling seamless adoption without altering system architecture. However, the best performance was achieved with the combined WM_TD approach, which yielded an average r of 0.895 and RMSE of 0.161.

WMS is chosen as the go-to WM technique as it has similar results to other techniques but the best morphological output. The study highlights how subtle preprocessing choices (like padding type) can lead to meaningful improvements in morphology, guiding future research in biomedical signal reconstruction.

1. Introduction

Reconstruction of electrocardiogram (ECG) signals involves synthesizing specific leads from a new lead configuration or a subset of existing leads. This need commonly arises due to noise contamination during recording, lead misplacement, or the design of compact embedded systems aimed at reducing the number of electrodes required. While numerous models have been developed for ECG reconstruction with promising results, it is important to acknowledge that further progress may lie not only in creating increasingly complex models, but also in rethinking and optimizing the preprocessing of the available signals. Enhancing preprocessing techniques can significantly improve reconstruction accuracy while maintaining model simplicity and efficiency.

Masking and temporal dependency (TD) are well established modelling techniques for designing prediction models in deep learning (DL) environments [1, 2]. Masking is a technique in image recognition used for highlighting specific regions of an input image, thereby enhancing the model's ability to recognize or predict certain images or features. Similarly, TD addresses the sequential relationship within time-series data, enabling models to capture dependencies across time steps. This is particularly relevant for data that have trend features within them like ECG.

Recent works have shown that these concepts which were usually reserved for DL algorithms could be useful in reconstructing 12-lead ECG while using linear algorithms [3, 4]. These works adapted these techniques to linear regression and showed that these adaptations improved the performance of the models. Their model showed comparable performance to DL models at a reduced computational requirement. However, the adapted method (wave masking – WM) masked the ECG signal with zeros (zero-padding). This masking scheme introduced a sharp transition in the signal where the ECG was masked. [4] considered the possibility that a different padding scheme might improve the performance of the model.

This insight has led to the considerations of using either the baseline of the ECG (baseline-padding), a sigmoid (sigmoid-padding), or a hybrid of these and TD to mitigate the abrupt changes introduced by zero-padding. This study aims to evaluate the performance of LR models in ECG reconstruction using various WM and TD variants and hybrid approaches. The preprocessing techniques analysed include

1. WM with zero-padding (WMZ).
2. WM with sigmoid function padding (WMS).
3. WM with signal baseline padding (WMB).
4. Incorporating temporal dependency (TD).
5. Hybrid of WM and TD (WM_TD).

2. Method

2.1. Dataset

The dataset employed in this study comprises 4,250 records, randomly selected from the CODE-15% dataset [5], based on specific inclusion criteria outlined in the accompanying metadata. The selection ensured each ECG came from a unique patient, was classified as normal, showed no monitored heart conditions, and had no missing leads.

Following selection, the ECG records were standardized to a duration of 10 seconds, resampled to 500 Hz, and subsequently denoised, delineated and their baseline extracted using the ECGdeli MATLAB toolbox [6]. They were denoised using standard filters and thresholds: high pass filter of 0.3Hz, low pass filter of 120Hz and notch filter of 60Hz. It is paramount to note that delineation was done using only leads I, II, and V3 as recommended by Butchy, Jain, Leasure, Covalesky and Mintz [7], and these leads will be the input leads for reconstruction.

For each preprocessing pipeline, 3,500 records were used for training the models, while 750 records were reserved for testing, ensuring consistency and reproducibility across all experiments.

2.2. Pipelines

Every pipeline designed in this work follows the base linear model pipeline. This model states that a dependent variable is equal to the sum of the scaled version of one or more independent variables and a shifting constant. For the work done here, the dependent variable are leads V1, V2, V4, V5, and V6. This can be described mathematically as.

$$V = AX + C \quad \ldots \quad eqn1$$

$$where: A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1q} \\ a_{21} & a_{22} & \cdots & a_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ a_{51} & a_{52} & \cdots & a_{5q} \end{bmatrix}$$

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_q \end{bmatrix}, C = \begin{bmatrix} c_1 \\ c_2 \\ c_4 \\ c_5 \\ c_6 \end{bmatrix}, V = \begin{bmatrix} V_1 \\ V_2 \\ V_4 \\ V_5 \\ V_6 \end{bmatrix}$$

$$in\ words:$$
$$A = 5\ by\ q\ matrix\ of\ coefficents$$
$$X = q\ by\ 1\ column\ matrix\ of\ input\ variables$$
$$C = 5\ by\ 1\ column\ matrix\ of\ constants$$
$$V = 5\ by\ 1\ column\ matrix\ of\ output\ values$$

Eqn1 describes the relationship between the input variables and the ECG leads being simulated. V includes the potentials of the simulated leads at a given point in time. X are the input values needed to calculate the value of V. Depending on the pipeline chosen, X could range from ECG leads to including augmented values. A are the scaling values for X for every value of V. Finally, C are the shifting constants for every value of V. Every pipeline designed here considers the implications of using diverse X values to reduce the error between V and its expected (original) value.

2.2.1. Wave Masking Pipeline

Wave masking (WM), which is adapted from masking in image recognition highlights specific regions of an input signal by obscuring the unneeded regions. In ECG reconstruction this includes masking other parts of the ECG to point out the component waves including P wave, T wave, and QRS [4].

The specific pipeline used here was to extract each component waves from the leads they are expressed prominently between leads I, II, and V3. T wave, P wave, and QRS were extracted from leads I, II, and V3 respectively, by wave masking other parts of the signal. These component waves, in conjunction to the leads they were extracted from were used as the input value to the linear model. This is mathematically presented in eqn2.

$$X = \begin{bmatrix} Lead\ I \\ Lead\ II \\ V_3 \\ T\ wave \\ P\ wave \\ QRS \end{bmatrix} \quad \ldots \quad eqn2$$

The initial design of this method used zero-padding masking scheme. This involved masking the unneeded portions of the signal with zeros. This introduced sharp transitions. Therefore, this paper has explored the possibility of masking with a sigmoid or the baseline of the signal itself.

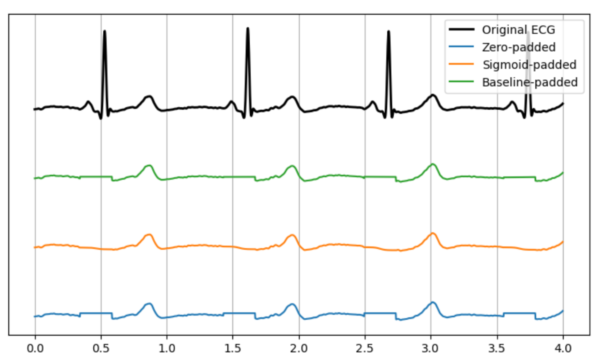

Figure 1. Different padding wave masking approaches performed on masking the QRS and P wave.

2.2.2. Temporal Dependency Pipeline

Temporal dependency involves using the past samples to predict the next sample. This is adapted from recurrent neural networks (RNNs) [3]. Using past samples allows the model to seemingly retain short-term memory. That way, predictions can be made by considering the effect of the past values. This was adapted to the linear regression model to give the same effect. After tuning, it was found that the goldilocks sample length is 100 samples for a 500Hz ECG signal. Since the input leads to the model are leads I, II, and V3; for every value of this lead being used to predict V, there are 99 past samples used in conjunction. This is mathematically shown in eqn3.

$$X = \begin{bmatrix} Lead\ I_n \\ \vdots \\ Lead\ I_{n-99} \\ Lead\ II_n \\ \vdots \\ Lead\ II_{n-99} \\ V3_n \\ \vdots \\ V3_{n-99} \end{bmatrix} \quad \dots \quad eqn3$$

$where\ n\ signifies\ the\ current\ sample\ being\ predicted$

2.2.3. Hybrid Pipeline

This pipeline is the combination of the best performing WMZ technique and TD. It includes the extraction of the component waves from the signal and the inclusion of past samples as variables. This pipeline aims to combine the strengths of the former two pipelines.

$$X = \begin{bmatrix} Lead\ I_n \\ \vdots \\ Lead\ I_{n-99} \\ Lead\ II_n \\ \vdots \\ Lead\ II_{n-99} \\ V3_n \\ \vdots \\ V3_{n-99} \\ T\ wave_n \\ \vdots \\ T\ wave_{n-99} \\ P\ wave_n \\ \vdots \\ P\ wave_{n-99} \\ QRS_n \\ \vdots \\ QRS_{n-99} \end{bmatrix} \quad \dots \quad eqn4$$

$where\ n\ signifies\ the\ current\ sample\ being\ predicted$

3. Results

The wave masking pipelines demonstrated consistent performance across different padding schemes, as shown in Table 1. On average, the three variations (WMZ, WMB, and WMS) produced similar results in terms of correlation and RMSE, suggesting that the choice of padding had minimal impact on quantitative reconstruction accuracy.

However, visual inspection of the reconstructed signals in Figure 2 reveals subtle yet meaningful differences. Among the three, WMS produced the smoothest and most physiologically coherent reconstructions, with fewer sharp transitions or discontinuities in the waveform. In contrast, WMZ and WMB exhibited more abrupt changes in the signal morphology, likely due to the artifacts introduced at the masked regions by their respective padding strategies.

In comparison, the TD model performed worse overall than the WM pipelines, indicating that simply leveraging temporal relationships in the signal was less effective than emphasizing waveform structure through masking. Interestingly, the combined approach (WM_TD) yielded slightly improved average performance metrics compared to the standalone WM or TD models. This suggests that integrating both wave masking and temporal dependencies offers complementary benefits. Nonetheless, visual analysis still favoured WMS, which retained the smoothest and most stable signal morphology.

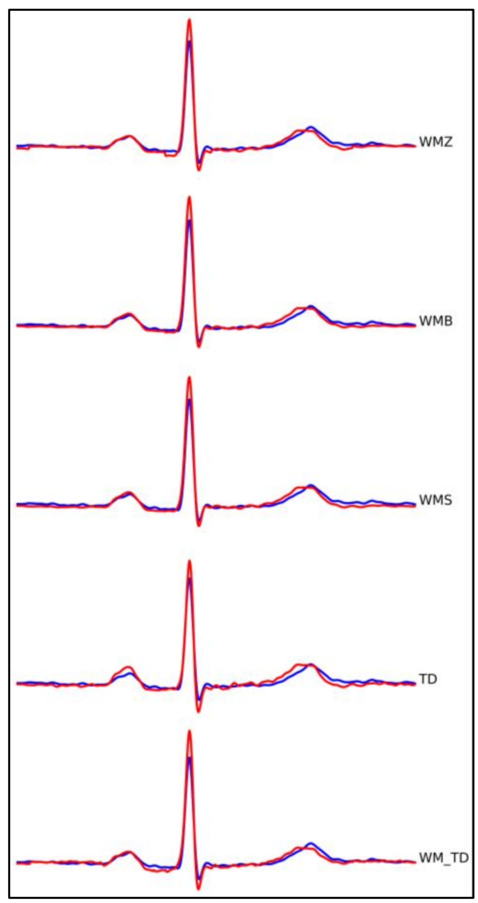

Figure 2. Visual reconstruction of the lead V5 using the

Table 1. Average correlation (r) and RMSE of the reconstructed leads using various pipelines.

Pipeline ➔	WMZ		WMB		**WMS**		TD		WM_TD	
Leads 🡻	r	RMSE	r	RMSE	**r**	**RMSE**	r	RMSE	r	RMSE
V1	0.869	0.129	0.869	0.130	**0.868**	**0.130**	0.871	0.129	0.875	0.125
V2	0.837	0.198	0.839	0.198	**0.840**	**0.197**	0.831	0.199	0.854	0.192
V4	0.900	0.176	0.900	0.175	**0.900**	**0.175**	0.898	0.178	0.901	0.174
V5	0.921	0.173	0.922	0.173	**0.921**	**0.173**	0.916	0.177	0.922	0.171
V6	0.927	0.143	0.928	0.143	**0.928**	**0.143**	0.919	0.149	0.924	0.144
Average	0.891	0.164	0.892	0.164	**0.891**	**0.164**	0.887	0.166	0.895	0.161

different pipelines.

4. Discussion and Conclusion

This paper focused on evaluating new approaches for implementing the wave masking (WM) preprocessing technique and explored the role of temporal dependency (TD) in improving ECG reconstruction using linear regression. The study examined both TD as a standalone method and in combination with wave masking (WM_TD). The results showed comparable performance across all wave masking padding schemes; however, sigmoid padding produced the most visually coherent ECG morphology.

In ECG interpretation, signal morphology is of paramount importance. Accurate reconstruction of waveform shape is essential for clinical reliability, and the findings indicate that sigmoid padding in the WM pipeline best preserves this morphology. Given that the computational requirements of sigmoid padding are like those of zero padding, it can be adopted as a preferred alternative without requiring changes to the underlying system architecture.

It is important to note that this analysis was conducted exclusively on normal ECG data from the CODE-15% dataset. Further evaluation is necessary using more diverse datasets that include varied populations and abnormal heart conditions to validate the generalisability of the findings and the robustness of the wave masking and sigmoid padding approach.

Additionally, while the study applied wave masking within a linear regression framework, future work should explore its use with a variety of machine learning and deep learning models. This would determine whether the technique can consistently enhance model performance without increasing complexity, particularly in systems where low latency, simplicity, and efficiency are important, such as in wearable or embedded health devices.

Finally, this research highlights a broader insight: subtle design choices in preprocessing (such as the type of padding or activation function) can lead to significant perceptual and diagnostic improvements in signal reconstruction. This opens further research opportunities in adapting and optimizing these techniques for ECG reconstruction and other time-series and biomedical signal processing applications.

References

[1] D. Vranay, M. Hliboký, L. Kovács, and P. Sinčák, “Using Segmentation to Boost Classification Performance and Explainability in CapsNets,” *Machine Learning and Knowledge Extraction,* vol. 6, no. 3, pp. 1439-1465, 2024.

[2] T. Lin, B. G. Horne, and C. L. Giles, “How embedded memory in recurrent neural network architectures helps learning long-term temporal dependencies,” *Neural Networks,* vol. 11, no. 5, pp. 861-868, 1998/07/01/, 1998.

[3] E. N. Obianom, A. M. Jasim, N. Qaqos, A. G. Ng, and X. Li, "Simultaneous Denoising and Reconstruction of 12-Lead Electrocardiogram." pp. 298-303.

[4] E. N. Obianom, A. G. Ng, and X. Li, “The Potential of Wave Masking in 12-Lead Electrocardiogram Reconstruction,” 2024.

[5] A. H. Ribeiro, G. Paixao, E. M. Lima, M. H. Ribeiro, M. M. Pinto Filho, P. R. Gomes, D. M. Oliveira, W. Meira Jr, T. B. Schon, and A. L. P. Ribeiro, “CODE-15%: A large scale annotated dataset of 12-lead ECGs,” *Zenodo, Jun,* vol. 9, 2021.

[6] N. Pilia, C. Nagel, G. Lenis, S. Becker, O. Dössel, and A. Loewe, “ECGdeli - An open source ECG delineation toolbox for MATLAB,” *SoftwareX,* vol. 13, pp. 100639, 2021/01/01/, 2021.

[7] A. A. Butchy, U. Jain, M. T. Leasure, V. A. Covalesky, and G. S. Mintz, “Importance of Electrode Selection and Number in Reconstructing Standard Twelve Lead Electrocardiograms,” *Biomedicines,* vol. 11, no. 6, pp. 25, 2023.

Address for correspondence:

Ekenedirichukwu N. Obianom
University of Leicester, University Road, Leicester, United Kingdom. LE1 7RH.
eno3@leicester.ac.uk