The Potential of Wave Masking in 12-Lead Electrocardiogram Reconstruction

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Abstract

Following the understanding that ECG leads can be reconstructed using non-linear methods, the use of artificial neural networks (ANN) have become a popular norm. However, the intensive computing of ANNs can be daunting. This can be reduced if simpler methodologies could be used to achieve the same results. For this reason, this paper proposes Wave Masked Linear Regression (WMLR) method and compares it to two ANNs, Long-Short Term Memory (LSTM) and Feed Forward Network (FFN).

These methodologies were compared on 80 patients from PTB database. The dataset included 30s ECG resampled to 500hz. The inputs for the methods were leads I, II and V3, while the outputs were V1, V2, V4, V5 and V6. Each method was used to build a generic reconstruction model on the dataset. Pearson correlation (r) was used to compare the reconstruction of each model to the original signal.

WMLR performed as good as the ANNs. Paired t-tests on all leads produced p-values greater than 0.05 between the methods. Mean r of WMLR, LSTM, and FFN methods were 0.924 ± 0.112, 0.906 ± 0.132, and 0.922 ± 0.111 respectively. This showed that linear models can perform as good as ANNs when wave masking is used to alter the pipeline.

1. Introduction

Electrocardiogram (ECG) is a quick way to measure the potential of the heart [1] and the standard 12-lead system (S12) is commonly used in this regard. Despite the preference to this cardiac recording system, it is not immune to faults and there is room for improvements. Noise is often captured simultaneously during recording and can come from various sources including proximal electrical appliances, movement of the patient being recorded, and improper placement of electrodes. As the S12 is made up of 10 electrodes, there is no doubt that reducing the number of electrodes will reduce the amount of noise captured. Therefore, a system with fewer electrodes that can reconstruct the original 12 leads to a high level of accuracy will be favoured.

ECG reconstruction focuses on synthesizing a replica of the original S12 from a subset of leads. This can help in denoising poorly recorded leads and simulating non-recorded leads in systems that employ fewer electrodes for recording. Investigations in this area have sort to use both linear and non-linear techniques [2, 3] and in recent years, non-linear techniques (artificial neural networks) have been favoured. This is justifiable as they can capture relevant information in signals even in the presence of distortions that can occur during recording. However, artificial neural networks (ANNs) have high computing requirements and require large dataset and time to build.

By rethinking linear technique pipelines, simpler yet effective methods can be designed to reconstruct with high levels of accuracy and lesser computing requirements. Therefore, this paper aims to:

1. Expand on the concept of wave-masked linear regression (WMLR) which was introduced in [4].
2. Compare the performance of WMLR to two ANNs: Long-Short Term Memory (LSTM) and Feed Forward Network (FFN); in ECG reconstruction.

2. Method

2.1. Dataset

The dataset used is made up of 30 seconds 12-lead ECGs extracted from 40 healthy and 40 myocardial infarction (MI) patients in the PTB Diagnostic ECG Database [5, 6]. Each ECG was pre-processed with the ECGdeli MATLAB toolbox [7]. The were also passed through a high pass filter at 0.5Hz, a notch filter at 50Hz, and resampled to 500Hz.

2.2. Pipeline Design

Figure 1: Overview of the pipeline design adopted for each of the models used in this analysis

Previously, most authors used leads I, II, and V2 for reconstruction of other leads. Following the work done by

 ISSN: 2325-887X DOI: 10.22489/CinC.2024.188

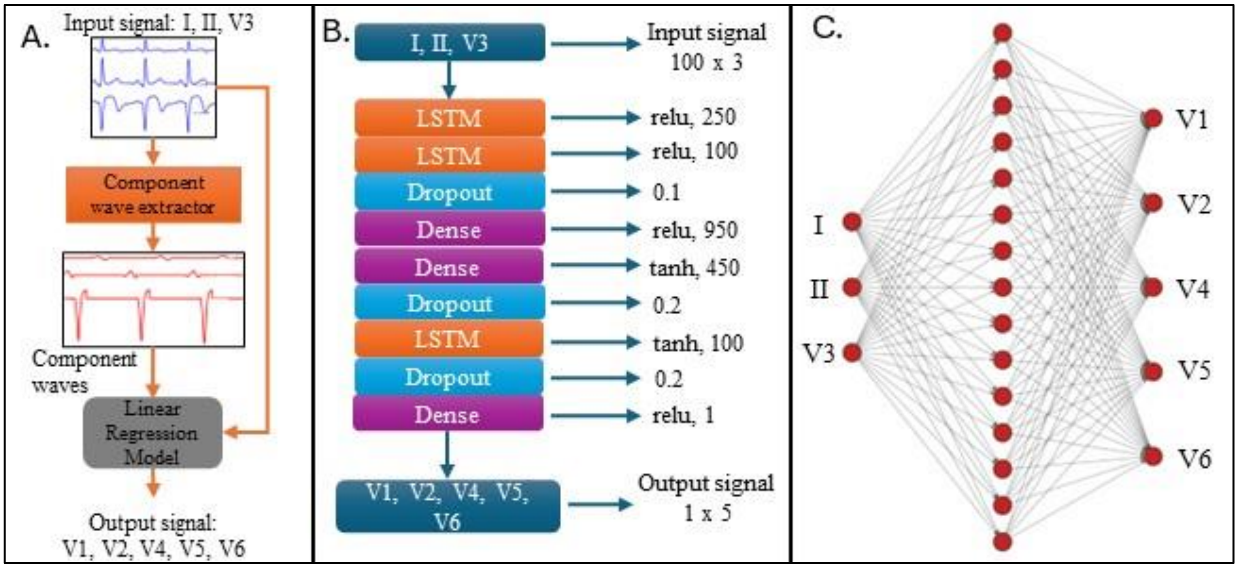

Figure 2: The architecture of each of the models used in this analysis. A: Architecture for the WMLR model. B: Architecture of the LSTM model. C: Architecture of each of the FFN in the ensemble model.

Butchy, Jain, Leasure, Covalesky and Mintz [8] it was found that lead V3 was more correlated to other leads than V2. This recommendation guided the study done in this paper. Every model built in this analysis used leads I, II, and V3 as inputs to reconstruct leads V1, V2, V4, V5 and V6 (Figure 1).

2.2.1. WMLR Architecture

Wave masking is a technique derived from masking in image recognition. It involves highlighting specific or relevant regions of the input to help improve the performance of a model in predicting the output [9]. This method is implemented in this paper by finding the component waves (P wave, T wave, QRS) and masking every other portion of the signal. The component waves were extracted from the available input leads in which they were most prominent (P wave from lead II, T wave from lead I, QRS from lead V3). After extraction, other portions of the signal were masked by zero padding.

That is, three component waves were extracted from three input leads. The input leads and the extracted waves (6 signals) are then used to train a linear regression (LR) model to predict the output leads (Figure 2A). The linear regression model was trained using the least square method. This WMLR was shown to outperform LR models using only recorded leads as input [4].

2.2.2. LSTM Architecture

The architecture built here was a modification of that proposed by Dhahri, Majdoub, Ladhari, Sakly and Msahli [10]. Their architecture was modified and new hyperparameters were proposed using a distributed hyperparameter search based on 80% of the dataset (Figure 2B). The input data was 100 samples (the present sample and 99 past samples) of the three input leads. The output data was the present sample of the five output leads. The model was trained using backpropagation method with a learning rate of 0.0001.

2.2.3. FFN Architecture

The FFN architecture adopted for this analysis was that of Atoui, Fayn and Rubel [3]. This architecture was an ensemble of 50 FFNs. Each FFN had the same architecture which was 3 input nodes, 5 output nodes, and 1 hidden layer with 15 nodes (Figure 2C). The activation function for the input node was relu and the activation function of the hidden layer was selu. Each FFN was also trained using backpropagation. The result of each of the 50 FFN was averaged.

2.3. Performance Analysis

A patient-wise five-fold cross-validation was done on each model. This was done on equal amounts of the healthy and MI patients for each validation. The metrics used in this analysis were correlation (r), and root mean squared error (RMSE). The formulas are:

$$r = \frac{\sum(x_j - \hat{x})(y_j - \hat{y})}{\sqrt{\sum(x_j - \hat{x})^2 \sum(y_j - \hat{y})^2}}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_j - x_j)^2}$$

$where$:
$N = \ total\ number\ of\ observations$
$r = correlation\ coefficient$
$j = observation\ number\ at\ any\ given\ point\ in\ time$
$x_j = original\ sample\ at\ any\ given\ point\ in\ time$
$\hat{x} = mean\ of\ all\ original\ values$
$y_j = predicted\ sample\ at\ any\ given\ point\ in\ time$
$\hat{y} = mean\ of\ all\ predicted\ values$

3. Results

The analysis showed a very similar outcome between the metrics of the three pipelines (Table 1). The average correlation between the reconstructed leads and the baseline was over 0.9 for the three pipelines. The RMSE was below 0.109mV for all the leads for all the models. A paired t-test was also used to compare the RMSE performance of the models. It showed no significant difference between their performance (p-value > 0.05 for all leads).

Figure 3 shows a snapshot of the reconstruction of the three models for one of the healthy patients. It can be seen that in accordance with the statistical results, the figure shows that the three models tend to perform similarly visually. Although, the WMLR and the LSTM models reconstruct the peaks and troughs more closely than the FFN model does.

4. Discussion

With no significant difference between each model, this analysis has shown that linear regression models can perform as good as non-linear models given that the relevant preprocessing steps are taken. It also reinforces the knowledge that various ECG leads have linear relationships. However, noise, interference, diverse heart conditions and bodily differences of humans makes it tough to create a single model that can perfectly reconstruct every patient's ECG from a subset. This is why non-linear methods have gained a lot of favour in the aspect of ECG reconstruction. Nevertheless, linear methods are low-cost and less computationally intensive.

An algorithm, like WMLR, that can take advantage of the simplicity of linear regression and the morphology-highlighting technique of non-linear models is required. This model takes far less time to train, compared to neural networks. The model also needs less space for storage as it is made up of only coefficients needed for reconstruction. Inadvertently, the prediction time is less. This is particularly important in telemedicine.

In wearable devices, emergency care and remote healthcare, less computationally intensive technology is required. It reduces the cost of the devices, increases accessibility to these devices, and improves response time of both the devices and medical professionals.

In further designs, this model can be trained on a lot of

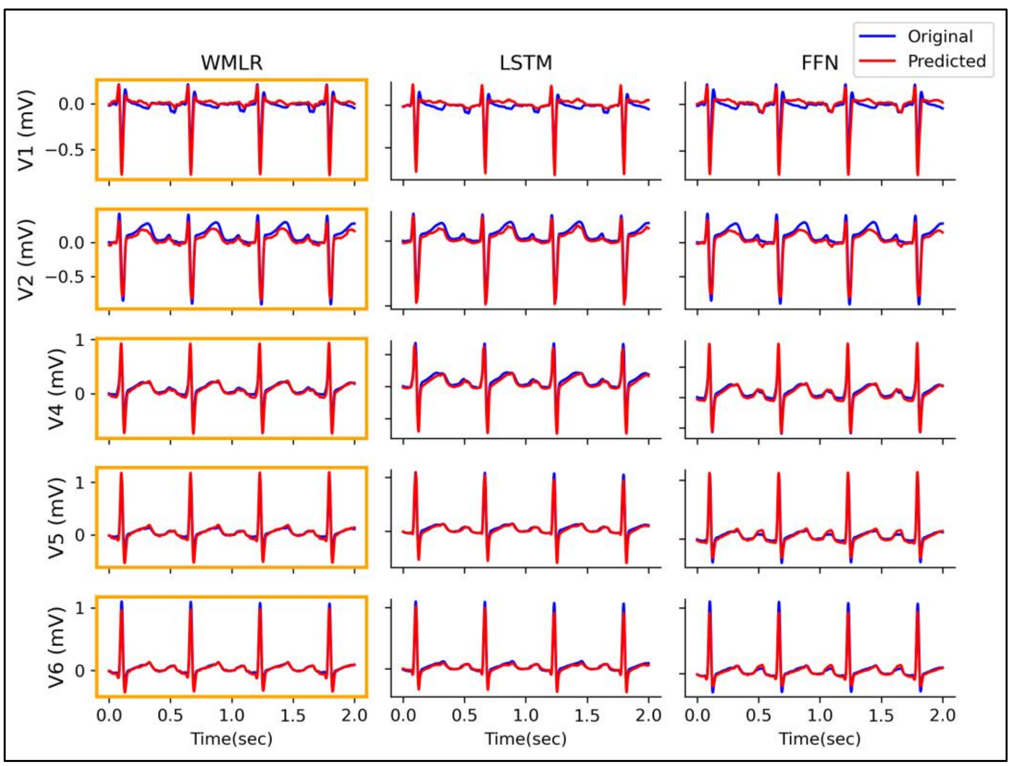

Figure 3: Comparative view of the reconstruction using the 3 pipelines (WMLR, LSTM, FFN) on the same patient. Blue represents the original signal while red represents the reconstructed signal.

Table 1:Correlation and RMSE (measured in mV) of the various models for each lead. The patient-wise mean of each lead and its standard deviation (SD) is shown. The average is shown at the bottom of the table.

Metric ➔	Correlation						RMSE (mV)					
Model ➔	WMLR		LSTM		FFN		WMLR		LSTM		FFN	
Leads 🡻	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
V1	**0.908**	**0.144**	0.873	0.192	0.906	0.141	**0.072**	**0.037**	0.078	0.042	0.073	0.040
V2	**0.961**	**0.055**	0.940	0.089	0.959	0.054	**0.094**	**0.056**	0.109	0.056	0.094	0.055
V4	**0.937**	**0.093**	0.944	0.069	0.938	0.079	**0.076**	**0.037**	0.077	0.033	0.080	0.040
V5	**0.908**	**0.107**	0.889	0.126	0.899	0.117	**0.087**	**0.052**	0.090	0.052	0.090	0.056
V6	**0.908**	**0.158**	0.886	0.182	0.908	0.167	**0.066**	**0.050**	0.076	0.051	0.066	0.052
Average	**0.924**	**0.112**	0.906	0.132	0.922	0.111	**0.079**	**0.047**	0.086	0.047	0.081	0.048

data to improve its performance and the different kinds of heart conditions it can be used to reconstruct. Moreso, the method of wave masking can still be improved. In this paper, the waves were extracted, and the rest were zero padded. It is also possible that other methods could be developed to pad the masked areas. This might help improve the performance of the model.

5. Conclusion

This paper expanded on wave masking in linear regression (WMLR) for ECG reconstruction. It analysed its performance in comparison to neural networks. It showed that given the right preprocessing step, linear regression models may be a better fit for the reconstruction of ECG as compared to neural networks. The results showed no statistical difference between the performance of WMLR, LSTM, and FFN.

This new method brings back the relevance of linear regression in ECG reconstruction while adopting the masking technique in newer algorithms. WMLR can help reduce processing time of medical devices and improve the response time of both the devices and the healthcare practitioners.

Moreso, this method is not limited to linear regression models. It is a preprocessing step that can be extended to other signal analysis algorithms. It may prove worthwhile when training other neural networks like LSTM and recurrent neural networks. The usefulness of this preprocessing step for these models will be dependent on the case study.

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