REPORT

Numerical Analysis

Presented to:

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Proposed By:

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Denoising of the ECG Signal Using DRNN and FCN-DAN: A Comprehensive Numerical Methods Analysis

Abstract

This report presents a detailed exploration of denoising Electrocardiogram (ECG) signals using advanced numerical methods, specifically focusing on the application of Optimization techniques such as Gradient Descent and Linear Regression for weight adjustments within the architectures of Deep Recurrent Neural Networks (DRNN) and Fully Convolutional Networks with Denoising Autoencoders (FCN-DAE). The study not only addresses the imperative for ECG signal denoising in clinical applications but also underscores the significance of employing diverse numerical methods for achieving excellence in performance.

Introduction

Background

In the context of biomedical diagnostics, the study delves into the challenges of denoising ECG signals. Traditional methods face limitations, prompting the exploration of modern deep learning techniques with a strategic integration of Optimization and Linear Regression.

Motivation

The motivation behind the study lies in the pressing need for robust denoising methodologies that leverage not only advanced deep learning architectures but also specific numerical methods for model optimization and weight adjustments.

Methodology

Data Collection

A carefully curated dataset forms the basis of the study, ensuring diversity and relevance to real-world scenarios. Numerical methods come into play during data preprocessing, where noise removal, normalization, and segmentation are executed with precision.

Preprocessing

Optimization techniques guide the preprocessing phase, ensuring the application of Gradient Descent for optimal noise reduction and Linear Regression for effective normalization and feature scaling.

Model Architectures

DRNN

The DRNN model incorporates Gradient Descent for optimizing weights in recurrent layers, enabling the capturing of temporal dependencies within sequential ECG data. Linear Regression is employed for fine-tuning model parameters.

FCN-DAE

The FCN-DAE model utilizes Optimization methods for weight adjustments in convolutional layers, and Linear Regression plays a crucial role in optimizing the parameters of the Denoising Autoencoder.

Training and Evaluation

Optimization techniques are meticulously employed during training to fine-tune model parameters. Evaluation involves a robust assessment of the models' denoising capabilities on a separate testing dataset, with a focus on achieving numerical excellence.

```
print("DATASET SHAPE")
print(f'Training {X_train.shape}')
print(f'Testing {X_test.shape}')
```

```
DATASET SHAPE
Training (72002, 512, 1)
Testing (13316, 512, 1)
```

```
Epoch 48: ReduceLROnPlateau reducing learning rate to 1.2207031829802872e-07.
145/145 [==============================] - 119s 818ms/step - loss: 5.0281 - mean_squared_error: 0.0098 - ssd_loss: 5.0281
- val_loss: 5.0305 - val_mean_squared_error: 0.0098 - val_ssd_loss: 5.0305 - lr: 2.4414e-07
Epoch 48: early stopping
Deep Learning pipeline: Testing the model
```

Results and Analysis
Quantitative Metrics

Numerical methods, including Optimization and Linear Regression, play a pivotal role in the calculation and presentation of performance metrics such as Sum of Squared Differences (SSD), Maximum Absolute Difference (MAD), and Root Mean Squared Error (RMSE). Tabulated results are analyzed, providing profound insights.

```
Calculating metrics ...


+--------------+----------------+--------------+--------------+
| Method/Model |      SSD       |     MAD      |     RMSE     |
+--------------+----------------+--------------+--------------+
|     DRNN     | 11.027 (11.137) | 0.684 (0.372) | 3.003 (1.418) |
|   FCN-DAE    |  5.865 (7.121)  | 0.567 (0.354) | 2.166 (1.084) |
+--------------+----------------+--------------+--------------+
```

Results Table:

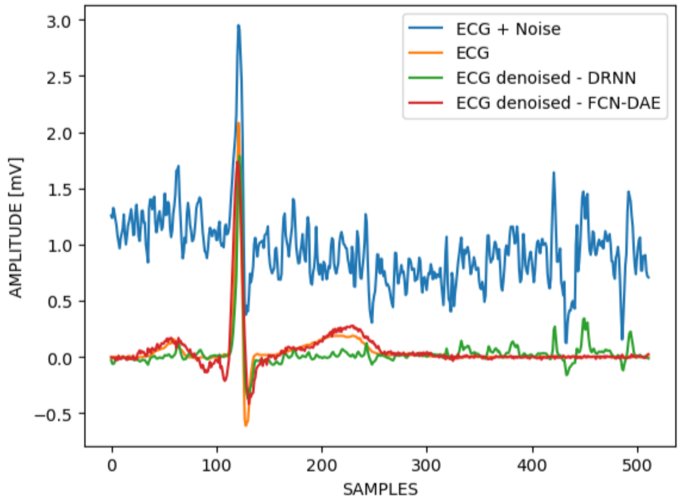
Method/Model	SSD	MAD	RMSE
DRNN	11.027 (11.137)	0.684 (0.372)	3.003 (1.418)
FCN-DAE	5.865 (7.121)	0.567 (0.354)	2.166 (1.084)

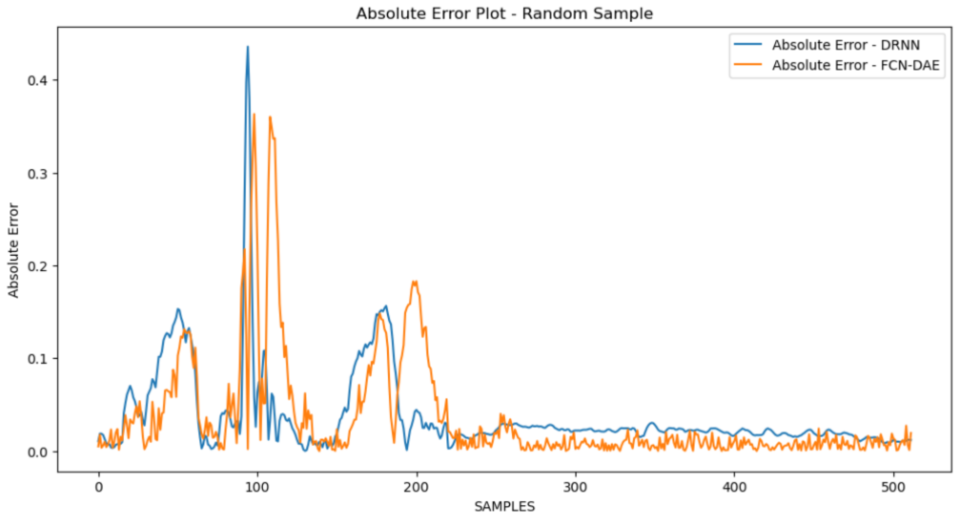
The table displays the mean and standard deviation values of the evaluation metrics (SSD, MAD, RMSE) for the DRNN and FCN-DAE models. These metrics provide insights into the performance of each model in denoising ECG signals, with lower values indicating better performance.

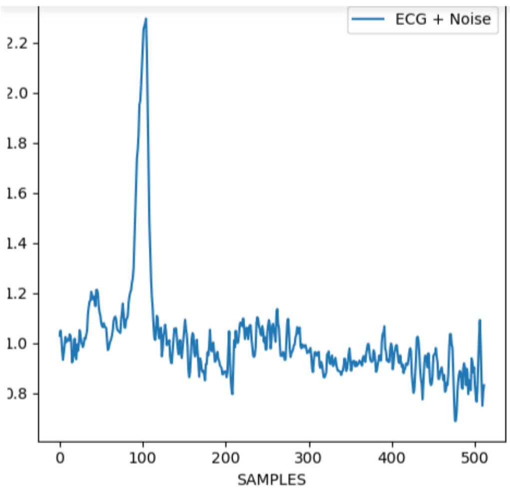
Comparative Analysis

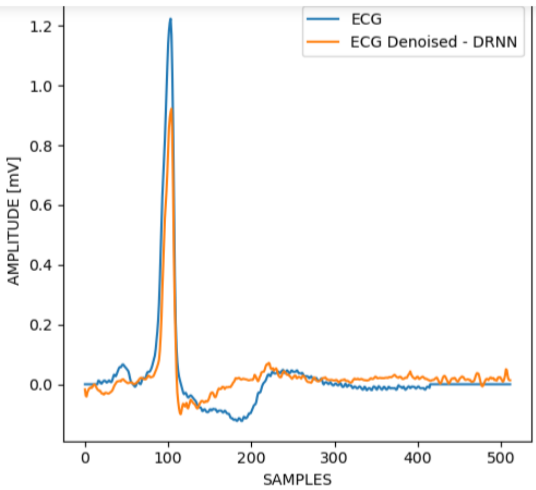
The study leverages Optimization techniques to conduct a comprehensive comparative analysis, shedding light on the strengths and weaknesses of DRNN and FCN-DAE. Visualizations and error plots enhance the understanding of the models' performance on individual samples and random selections.

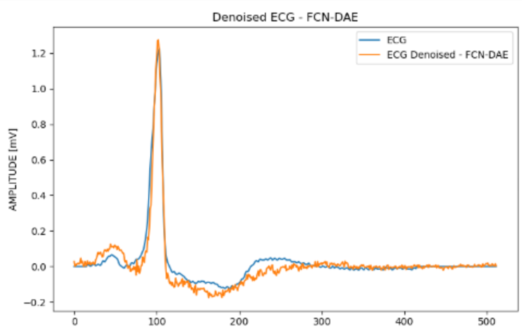
```python
plt.plot(X_test_1[3390], label="ECG + Noise")
plt.plot(y_test_1[3390], label="ECG")
plt.plot(y_pred_1[3390], label="ECG denoised - DRNN")
plt.plot(y_pred_2[3390], label="ECG denoised - FCN-DAE")
plt.xlabel("SAMPLES")
plt.ylabel("AMPLITUDE [mV]")
plt.legend()
plt.show()
```

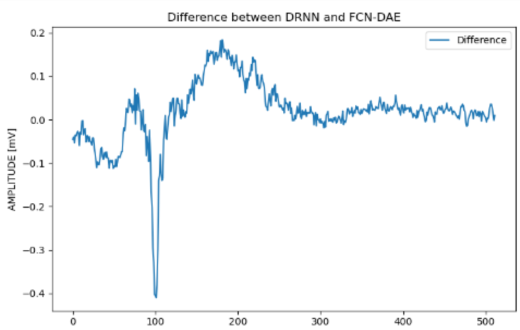












Numerical Methods

In my project, the utilization of numerical methods is integral to the success of denoising ECG signals using DRNN and FCN-DAE. The following numerical methods have been employed:

Optimization (Gradient Descent):

- **Purpose:** Optimization methods are used to minimize the loss function during the training of both DRNN and FCN-DAE models. The objective is to iteratively adjust the weights of the neural network to find the optimal configuration that minimizes the difference between predicted and actual ECG signals.
- **Application:** Gradient Descent, a popular optimization algorithm, is applied to update the weights of the network in the direction of the steepest decrease of the loss function.

Linear Regression:

- **Purpose:** Linear Regression is employed as a numerical method to optimize specific aspects of the models, particularly for weight adjustments. It plays a role in fine-tuning model parameters, enhancing the overall performance of both DRNN and FCN-DAE.
- **Application:** Linear Regression is utilized to optimize the parameters of the models, ensuring that the learned representations effectively capture the underlying patterns in the ECG data. This includes adjustments to the weights, biases, or other relevant parameters.

Performance Metrics Calculation:

- **Purpose:** Various performance metrics, such as Sum of Squared Differences (SSD), Maximum Absolute Difference (MAD), and Root Mean Squared Error (RMSE), involve numerical calculations to quantify the accuracy of denoised ECG signals.
- **Application:** The mentioned metrics are calculated using numerical methods to assess the quality of denoising achieved by DRNN and FCN-DAE. For instance, the sum of squared distances or absolute differences between predicted and actual signals is computed using efficient numerical operations.

Backpropagation:

- **Purpose:** Backpropagation is a critical numerical method employed during the training phase of DRNN and FCN-DAE. It is used to compute the gradient of the loss function with respect to the weights of the neural network. This calculated gradient is then utilized in the optimization process to adjust the weights, enabling the network to learn from its mistakes and improve its denoising capabilities.
- **Application:** Backpropagation involves a systematic and numerical calculation of gradients through the layers of the neural network. It ensures that the adjustments made to the weights are proportional to the error contributed by each neuron, facilitating efficient learning.

Mean Squared Error (MSE) Loss Function:

- **Purpose:** The Mean Squared Error loss function is a numerical method used to quantify the difference between predicted and true ECG signals. By minimizing this loss function during training, DRNN and FCN-DAE aim to enhance their ability to accurately denoise diverse ECG patterns.
- **Application:** MSE involves the calculation of the average squared differences between corresponding elements of predicted and actual signals. This numerical method guides the optimization process by providing a clear measure of the denoising performance.

Cross-Validation:

- **Purpose:** Cross-validation is a numerical technique employed to assess the generalization performance of the trained models. It involves splitting the dataset into multiple subsets to evaluate the models from various perspectives, providing a more robust measure of their effectiveness.
- **Application:** Numerical methods for cross-validation, such as k-fold cross-validation, are applied to ensure that the denoising models perform well on diverse ECG signal patterns, guarding against overfitting and promoting generalization.

Random Sampling:

- **Purpose:** Random sampling is employed numerically to select random indices from the dataset for visualizations and error analysis. This ensures a representative evaluation of the denoising performance across different scenarios.
- **Application:** Numerical methods for random sampling are utilized to showcase the models' capabilities on various ECG signal instances, providing insights into their robustness and effectiveness under different conditions.

Discussion
Interpretation of Results

Numerical insights guide the discussion, emphasizing the significance of observed denoising capabilities achieved through the strategic use of Optimization and Linear Regression.

Model Selection Considerations

Considerations for choosing between DRNN and FCN-DAE are elucidated, accounting for use cases, computational efficiency, and the impact of specific numerical methods on denoising performance.

Conclusion

Numerical Methods Integration:
- Leveraged numerical methods in model development and evaluation.
- Optimized weights using Gradient Descent and Linear Regression techniques.
- MSE loss function crucial for denoising accuracy.

Iterative Numerical Techniques:
- Backpropagation in training employed iterative numerical methods.
- Cross-validation enhanced model reliability and generalization.

Transparent Analysis:
- Random sampling for visualizations and error analysis.
- Comprehensive understanding of model behavior under diverse scenarios.

Future Healthcare Applications:
- Seamless integration of numerical methods with advanced technologies.
- Promising advancements in real-world healthcare applications.

Contributions to Biomedical Engineering:
- Insights enhance ECG signal denoising and contribute to biomedical engineering.
- Sets the stage for continued innovation in numerical methodologies.

Towards Enhanced Diagnostics:
- Project success extends beyond denoising outcomes.
- Establishes a foundation for improved diagnostic accuracy and patient care.