SIGNAL RECONSTRUCTIONS FOR ECG-TRANSMEMBRANE VOLTAGE POTENTIALS USING TRANSFORMERS

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INTRODUCTION

Transmembrane voltage potential (TMP) signals are crucial for diagnosing heart conditions, but **electrocardiogram (ECG)** recordings often suffer from **noise and time-step limitations**, hindering accurate TMP reconstruction.

We propose two deep learning models to recover TMP signals from corrupted ECG data:

- **LSTM model** – Maps ECG inputs to TMP outputs in a one-to-one manner.
- **Transformer model** – Generates TMP signals using attention mechanisms for improved temporal modeling.

Our results show that both models outperform state-of-the-art 1D CNNs in TMP recovery.

PROBLEM FORMULATION

The inverse problem of electrocardiography reconstructs the heart's electrical activity from body-surface ECG signals. The forward model is:

$$\mathbf{X} = \mathcal{A}(\mathbf{V}) + \mathbf{N}$$

where:

- $\mathbf{X}$: Observed ECG signals (n body-surface locations, t time points).
- $\mathbf{V}$: Transmembrane voltage signals at mmm epicardial locations.
- $\mathcal{A}$: Forward operator modeling cardiac sources.
- $\mathbf{N}$: Measurement noise.

We estimate the TMP $\hat{\mathbf{V}}$ by minimizing:

Mean Squared Error (MSE):

$$\mathcal{L}(\mathbf{V}, \hat{\mathbf{V}}; \Theta) = \frac{1}{|\mathcal{X}|} \sum_{k=1}^{|\mathcal{X}|} \|\hat{\mathbf{V}}_k - \mathbf{V}_k\|_F^2$$

Huber Loss (robust to outliers):

$$\mathcal{L}_\delta(\alpha, \beta) = \begin{cases} \frac{1}{2}|\alpha - \beta|^2, & |\alpha - \beta| \le \delta \\ \delta\left(|\alpha - \beta| - \frac{1}{2}\delta\right), & \text{otherwise} \end{cases}$$

PROPOSED MODELS

Model I: 1D CNN

- Reproduced SqueezeNet-based 1D CNN from [2].
- Trained from scratch with original hyperparameters for direct comparison.
- Serves as a baseline with **392,907 parameters**.

Model II: CNN-LSTM

- Combines CNN layers for spatial features and LSTM layers for temporal dynamics.
- Architecture:
  - CNN layers: 3 layers with 64, 128, and 256 filters.
  - LSTM layer: Hidden size 64.
  - Fully connected output layer.
  - **213,835 parameters.**

Model III: Transformer

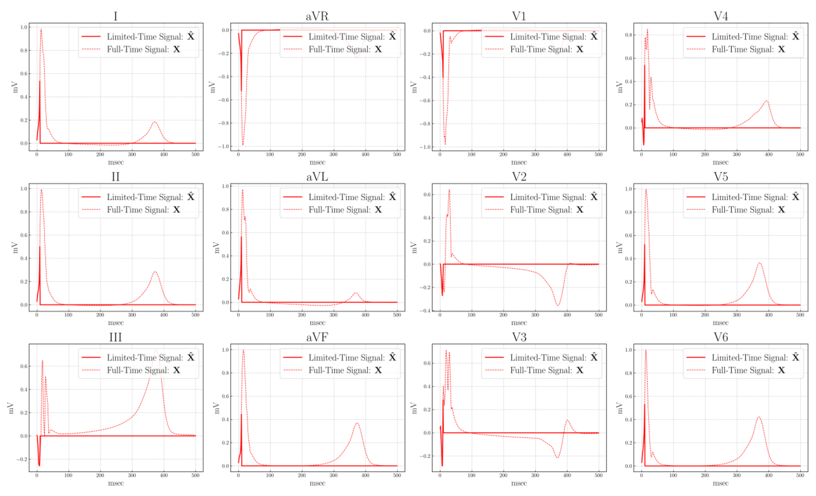
- Encoder-decoder architecture leveraging attention for temporal modeling.
- **Encoder input layer**: Uses stacked Conv1D from 1D CNN model.
- **Training:**
  - Processes ECG in 10 time-step segments.
  - Decoder predicts the next TMP segment, guided by a sine-cosine position encoding strategy [3].
- **Inference:**
  - Uses predicted TMP segments iteratively for full signal reconstruction.
- **824,731 parameters**.

DATASET

We evaluate our approach using the **Simulated Intracardiac Transmembrane Voltage Recordings and ECG Signals** dataset [1], which contains **16,117** paired ECG and TMP signals. Voltages are measured in millivolts (mV) and time in milliseconds (ms).

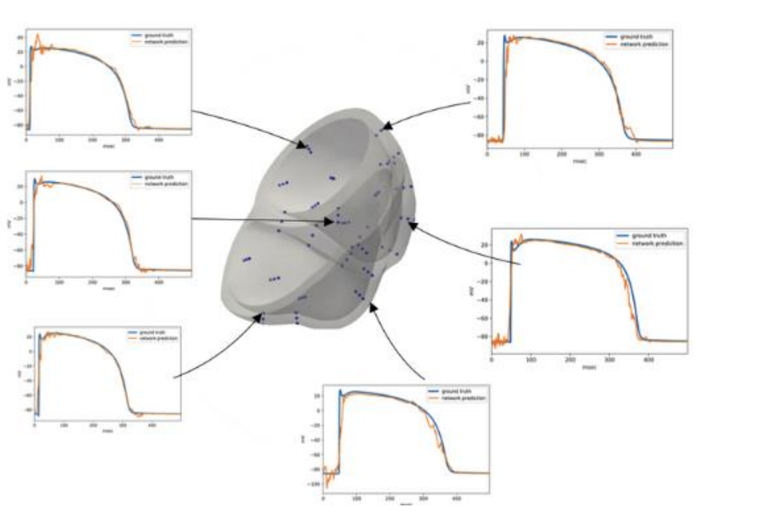
NUMERICAL EXPERIMENTS

ECG signals



$\mathbf{X} \in \mathbb{R}^{12 \times 500}$: **12-lead** ECG recordings measuring voltage over **500ms**.

TMP signals



$\mathbf{V} \in \mathbb{R}^{75 \times 500}$: Voltage measured at **75 intracardiac locations** over **500ms.**

We conduct two types of experiments:

Experiment I: Full-time sequence

- Models trained on the full ECG signal ($\mathbf{X} \in \mathbb{R}^{12 \times 500}$).
- During testing:
  - LSTM and 1D CNN use the full ECG signal.
  - Transformer uses only the first **10-time steps** ($\mathbf{X_0} \in \mathbb{R}^{12 \times 10}$)

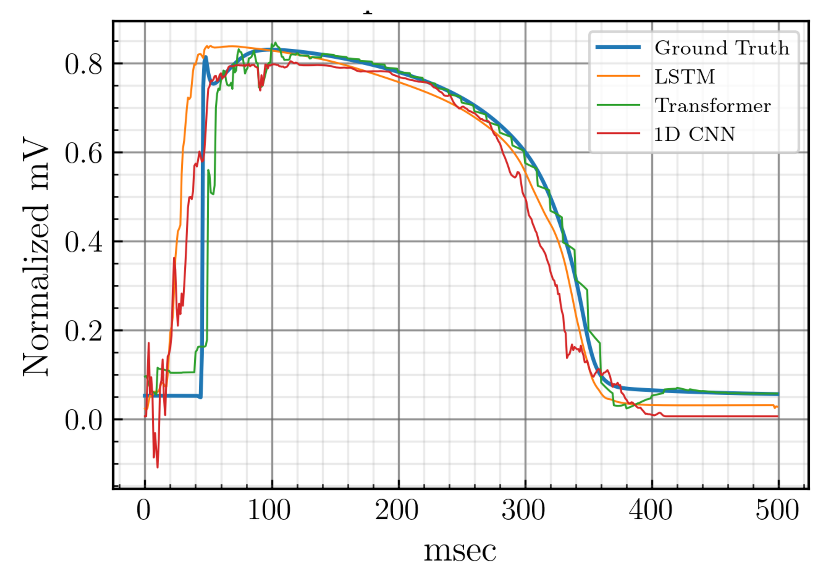
Experiment II: Limited-time sequence

- LSTM and 1D CNN—trained on full data—are tested with limited-time inputs for fair comparison with the transformer.
- Input: $\hat{\mathbf{X}} = [\mathbf{X_0}\ 0]$, where $0 \in \mathbb{R}^{12 \times 490}$ is zero-padding.
- Output: Reconstructs TMP signal ($\mathbf{V} \in \mathbb{R}^{75 \times 500}$).

RESULTS

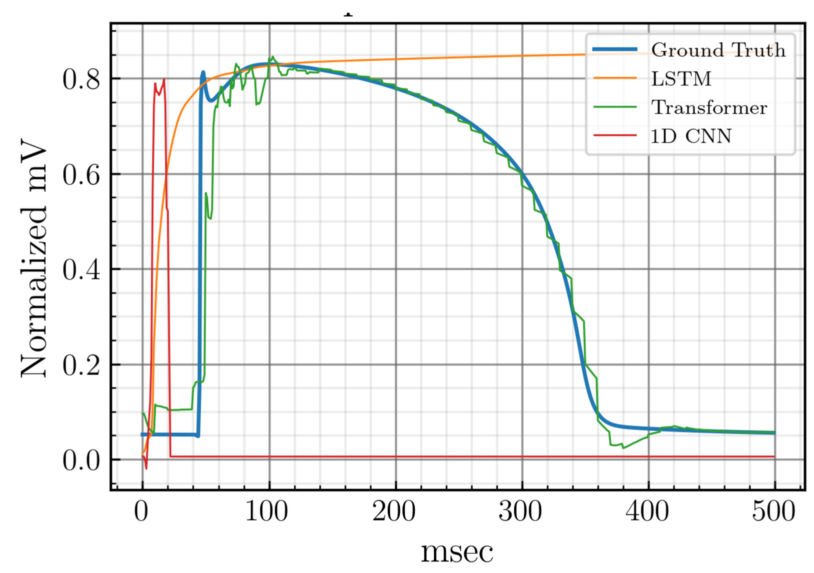
Experiment I: Full-time sequence

Metric \ Model	1D CNN	LSTM	Transformer
MAE (↓)	0.0733	0.0364	**0.0357**
MSE (↓)	0.0194	**0.0063**	0.0069
R^2 (↑)	0.8270	0.9409	**0.9412**
Pearson (↑)	0.9158	0.9703	**0.9704**
Spearman (↑)	0.8496	**0.9359**	0.9030



Experiment II: Limited-time sequence

Metric \ Model	1D CNN	LSTM	Transformer
MAE (↓)	0.4785	0.3148	**0.0357**
MSE (↓)	0.3392	0.1618	0.0069
R^2 (↑)	-2.0007	0.4013	**0.9412**
Pearson (↑)	-0.1101	-0.5209	**0.9704**
Spearman (↑)	-0.0347	0.0679	**0.9030**



CONCLUSIONS

- **Electromagnetic methods** for measuring voltage within the body can be costly and prone to errors.
- We propose an **alternative approach** for reconstructing transmembrane potentials directly from ECG signals.
- The **transformer model** captures temporal relationships in body-surface potential measurements to accurately reconstruct transmembrane potentials with only a **few milliseconds of data**.

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REFERENCES

Lawrence Livermore National Laboratory

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