IMPERIAL

Cardiac Electrophysiology
& AI Research Group

Learning to Predict Global Atrial Fibrillation Dynamics from Sparse Measurements

Temporal Graph Reading Group

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27/03/2025

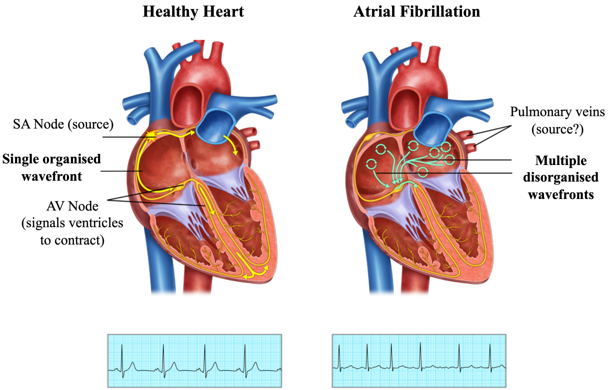
Atrial Fibrillation (AF)

Prevalence

- Most common cardiac arrhythmia with lifetime risk of 1 in 3.
- Affects 37.5 million people worldwide (0.5% of global population).
- Projected 60% rise by 2050.

Burden

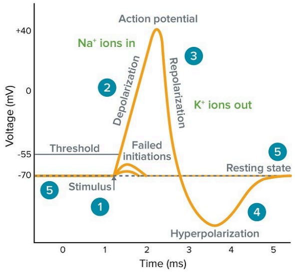
- Major cause of stroke, heart failure, and death.
- Major cost to global healthcare (2.4% of annual UK healthcare budget).



Propagation Dynamics in AF
The Local Level

The Cable Equation:

$$\frac{\partial V}{\partial t} = \nabla \cdot (D\nabla V) - \frac{I_{ion}(V; y)}{C_m}$$
$$\frac{\partial y}{\partial t} = g(V; y)$$



- $V(x, y, z, t)$: Membrane potential
- $\nabla \cdot (D\nabla V)$: Diffusion/coupling term
- I_{ion}: Total ionic current across membrane
- C_m: Membrane capacitance
- y: Vector of various ionic channel currents
- $g(V; y)$: Functions governing channel dynamics

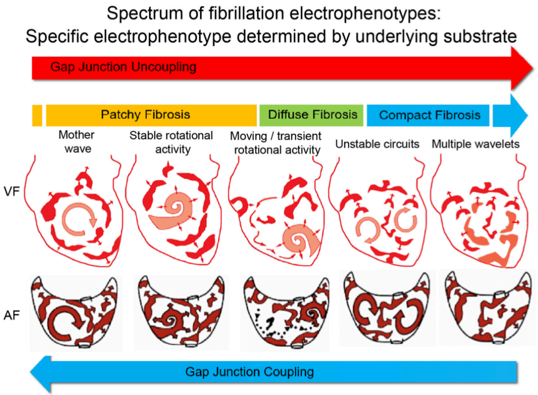
Properties:

- Neighbouring spatial regions are electrically coupled.
- Anisotropic diffusion through the $\nabla \cdot (D\nabla V)$ term.
- Local D and $\frac{I_{ion}}{C_m}$ affect global wave patterns.
- Threshold-dependent activation and recovery dynamics.

Propagation Dynamics in AF
The Global Level

The Mechanisms Sustaining AF

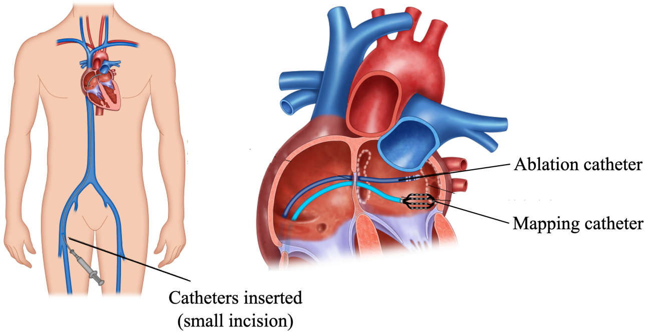
- Heterogeneous disorder with diverse electrophenotypes.
- Spatio-temporal dynamics vary in a spectrum from organised to disorganised chaos.
- Triggers that sustain the AF dynamics may originate from the pulmonary veins.



AF Ablation & The Need for Accurate Mapping

The Challenge of AF Ablation

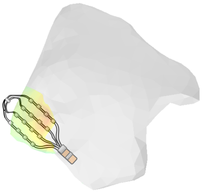
- Electrical isolation of the pulmonary veins from the left atria has success rates at best 50% at 5 years for persistent AF (Scherr et al. 2015).
- One-size-fits-all approach for a heterogeneous disease.
- Personalised treatment requires accurate identification of the fibrillation mechanism.

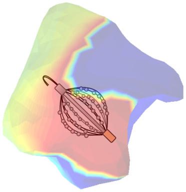


Mapping Limitations

- Current technologies face a trade-off in achieving global coverage and high resolution mapping.

The Trade-off in AF Mapping
Contact vs. Non-Contact Mapping





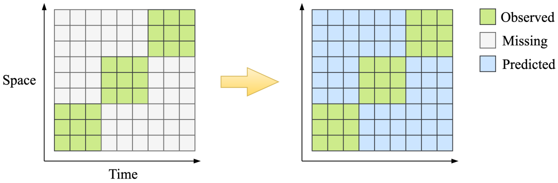
Contact Mapping

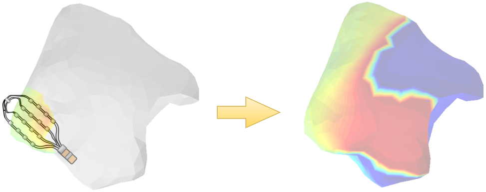
- ✓ Precise measurements at contact locations.
- ✓ Standard clinical approach.
- × Limited coverage (10% of atrium).
- × Sequential collection process.
- × Recordings cannot be sensibly stitched in AF.

Non-Contact Mapping

- ✓ Global coverage of atrial surface.
- ✓ Simultaneous whole-chamber recording.
- × Low spatial resolution.
- × Not routinely used clinically.
- × Increased procedural risk and cost.

Introducing Imputation Mapping





Spatio-Temporal Imputation Framework

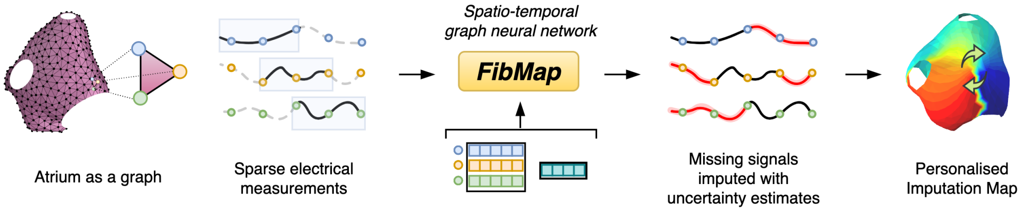
- Contact mapping provides sparse observations (10% of atrium).
- Formulate imputation mapping as a matrix completion problem (space vs. time).
- Learn spatio-temporal patterns from observed values to reconstruct missing regions.
- Leverage atrial surface geometry as an inductive bias in the processing.

Key Challenges for AF Imputation

- Propagating information across highly sparse observations.
- Managing unknown parameters affecting AF dynamics.
- Balancing personalisation vs. generalisation.
- Efficiently training and adapting to new patients.
- Quantifying uncertainty in reconstructions.

Imputation Mapping via FibMap

A Graph Recurrent Neural Network for AF Mapping



1) Personalise
Patient-specific parameters capture unique AF dynamics.

2) Encode
Signal values, mask, and patient-specific parameters transformed to a hidden representation.

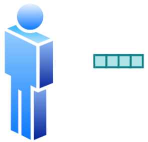
3) Process
Bidirectional graph-RNN propagates information across space and time from observed regions.

4) Decode
Spatio-temporal representations from both directions combined to reconstruct missing signals.

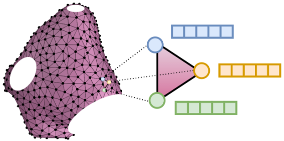
Imputation Mapping via FibMap
Personalise

Balancing Globality and Locality in GRNNs

- GRNNs are inherently global models.
- Global models may struggle to capture node (and patient)-specific dynamics.
- Node embeddings allow for a hybrid global-local approach (Cini et al. 2023).



Patient embeddings
Capture properties of the patient
(e.g. blood pressure, ...)



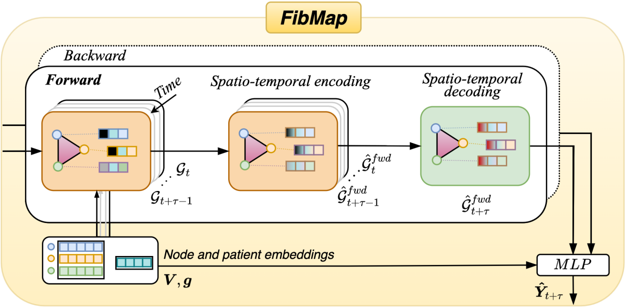
Node embeddings
Capture properties of the tissue
(e.g. conductivity, ...)

Personalising FibMap

- Node embeddings $\mathbf{V}^{(p)} \in \mathbb{R}^{N\times q}$ capture latent spatial tissue properties.
- Patient embeddings $\mathbf{g}^{(p)} \in \mathbb{R}^{r}$ capture global dynamics specific to each patient.
- May provide interpretable insights for electrophenotyping.

Imputation Mapping via FibMap

Encode, Process, Decode



Encode: Transform inputs into initial hidden representation

$$\mathbf{H}_t^0 = \mathrm{MLP}_{\mathrm{enc}}([\mathbf{X}_t^{(p)} \odot \mathbf{M}_t^{(p)} \| \mathbf{M}_t^{(p)} \| \mathbf{g}^{(p)} \| \mathbf{V}^{(p)}]) \tag{1}$$

$\mathbf{X}_t^{(p)}$: observations, $\mathbf{M}_t^{(p)}$: masks,
$\mathbf{g}^{(p)}$: patient embeddings, $\mathbf{V}^{(p)}$: node embeddings.

Process: K gated-graph RNN layers

$$\begin{aligned}
\mathbf{Z}_t^k &= \mathbf{H}_{t-1}^k, \\
\mathbf{R}_t^k &= \sigma(\mathrm{MP}_r^k([\mathbf{Z}_t^k \| \mathbf{H}_{t-1}^k], \mathcal{E})), \\
\mathbf{U}_t^k &= \sigma(\mathrm{MP}_u^k([\mathbf{Z}_t^k \| \mathbf{H}_{t-1}^k], \mathcal{E})), \\
\mathbf{C}_t^k &= \tanh(\mathrm{MP}_c^k([\mathbf{Z}_t^k \| \mathbf{R}_t^k \odot \mathbf{H}_{t-1}^k], \mathcal{E})), \\
\mathbf{H}_t^k &= \mathbf{U}_t^k \odot \mathbf{H}_{t-1}^k + (1 - \mathbf{U}_t^k) \odot \mathbf{C}_t^k
\end{aligned}$$

Decode: Two-stage iterative imputation

- Stage 1: $\mathbf{H}_t^K \rightarrow$ initial predictions.
- Stage 2: Predictions refined on the graph.
- Outputs: $\hat{\mathbf{y}}_{t,i}[c]$ at quantiles τ_c for uncertainty estimation.

Imputation Mapping via FibMap

Why a GRNN? Drawing Analogies with Local Physics

The Cable Equation

$$\frac{\partial V}{\partial t} = \nabla \cdot (D \nabla V) - \frac{I_{ion}(V; y)}{C_m}$$
$$\frac{\partial y}{\partial t} = g(V; y)$$

Physical Properties:

1. Neighbouring spatial regions are coupled.
2. Anisotropic diffusion through the $\nabla \cdot (D \nabla V)$ term.
3. Local D and $\frac{I_{ion}}{C_m}$ affect global wave patterns.
4. Threshold-dependent activation and recovery dynamics.

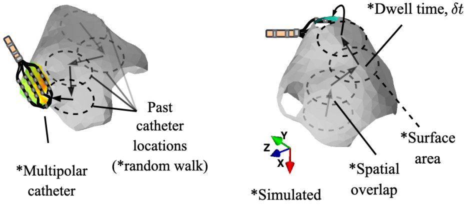
FibMap:

1. Expressed through the graph topology.
2. Anisotropic message passing functions are learnt.
3. Embeddings may capture local parameters.
4. Gated-RNN may capture these non-linear dynamics.

Imputation Mapping via FibMap
Dataset & Training Approach

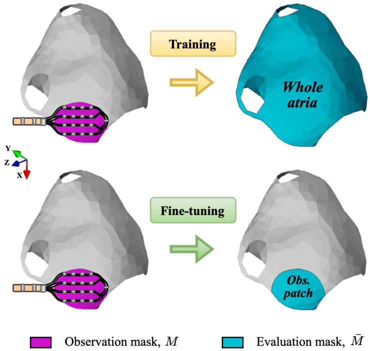
Dataset

- 51 persistent AF patients.
- AcQMap non-contact recordings:
  - Recordings 5-20 seconds per patient;
  - ≈3500 nodes, 3000 Hz;
  - Provides real examples of human AF dynamics;
  - Avoids simplified mathematical models.



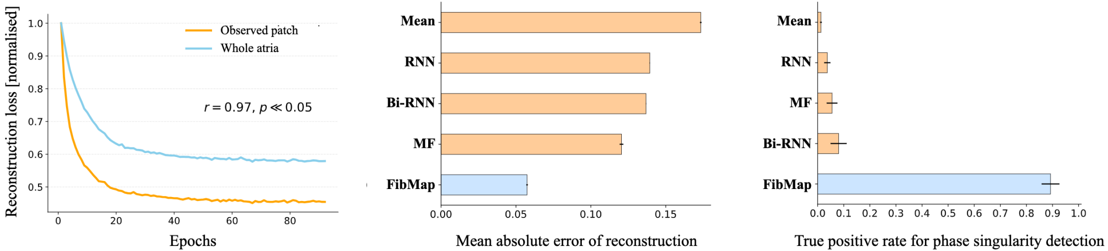
Model Training Strategy

- Self-supervised learning approach: contact mapping is simulated.



Quantitative Results

Reconstruction Performance on Test Patients



Fine-Tuning Validation

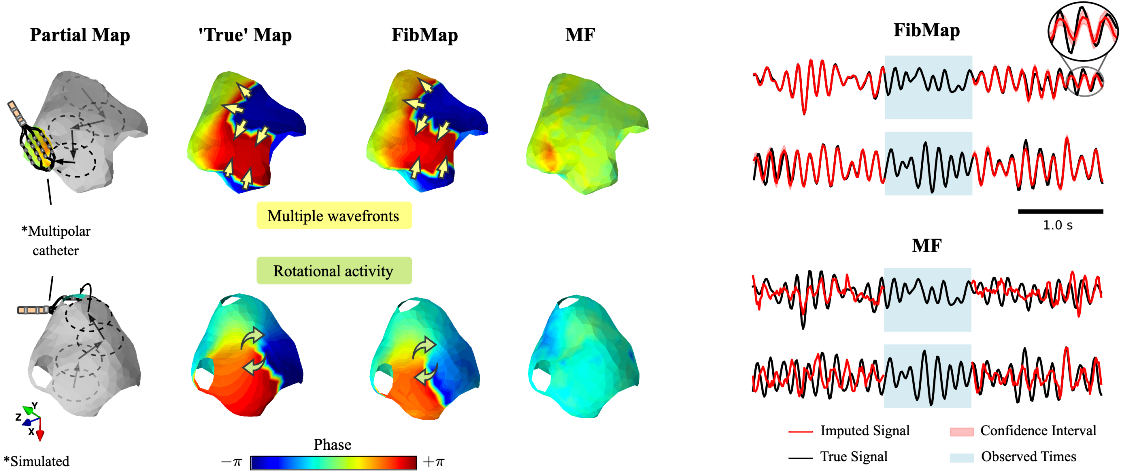
- Strong correlation between observed patch and whole atria losses (r $= 0.97$).
- Enables fast and accurate reconstruction from limited observations (22 mins per patient).

Performance Highlights

- 210% improvement in reconstruction accuracy (MAE) over best baseline.
- 11.1$\times$ better phase singularity detection (TPR of 89% vs 8%).

Qualitative Results

Visualisation of Imputation Maps



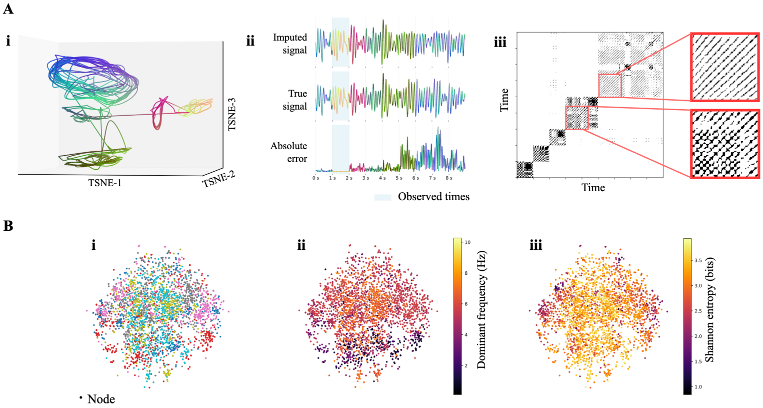
Hidden State and Embedding Analysis
Insights for Electrophenotyping

State-Space Dynamics

- Hidden states reveal the chaotic dynamics of AF.
- Orbital patterns around fixed points.
- Recurrence plot reveals structured dynamics.

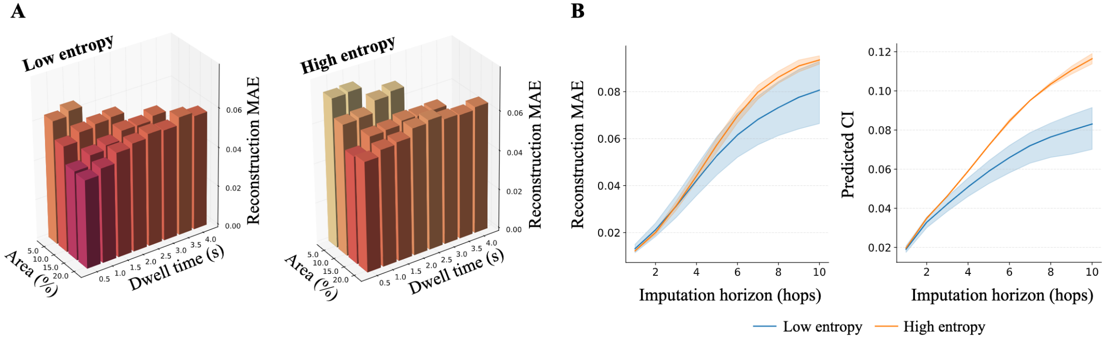
Embedding Analysis

- Node embeddings capture dominant frequency and entropy.
- Potential for AF electrophenotyping.



Sensitivity Analysis

Performance with Variations in Sequential Contact Mapping

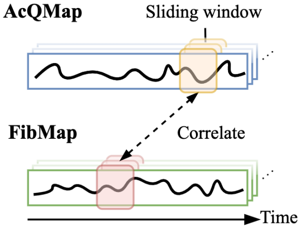


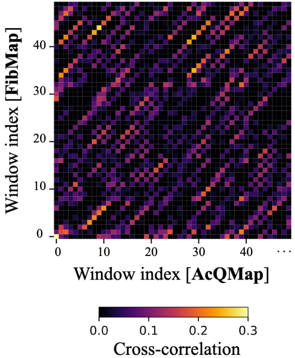
- Prediction accuracy ↑ as dwell time ↓, mapping area ↑, and for more organised AF.
- Prediction error and intervals ↑ as the distance in space and time from valid observations ↑.

Clinical Proof-of-Concept
Methodology

Approach

- EnSite Precision HD Grid (contact) vs. AcQMap (ground truth).
- Non-contemporaneous recordings from 3 test set patients.
- Cross-correlation analysis across different time windows.
- Statistical comparison of patient-specific patterns.



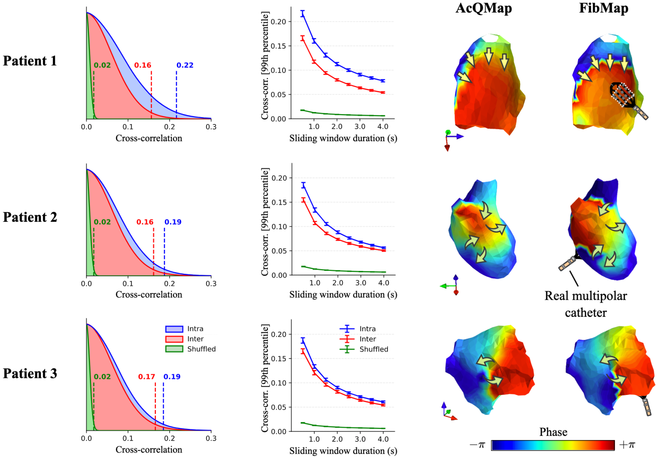


Clinical Proof-of-Concept

Results on Real-World Contact Mapping

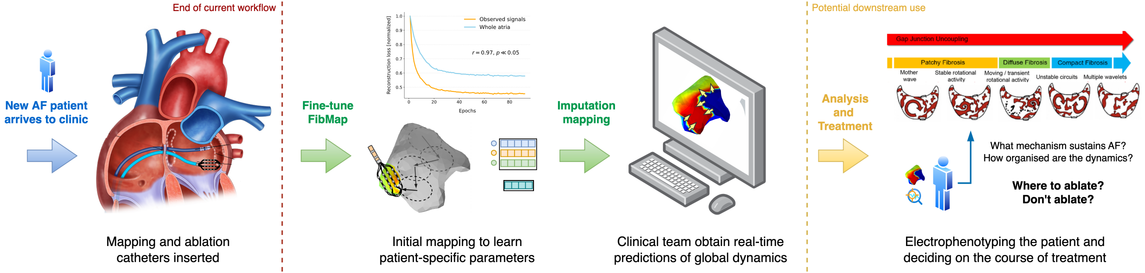
Key Findings

- FibMap captures patient-specific dynamics.
- Significantly higher intra-patient correlations vs. inter-patient.
- Consistent across multiple time scales.
- Reconstructs elements of dynamics not visible in original HD Grid data.
- Demonstrates clinical utility with existing catheters.



Envisioned Clinical Use

Imputation Mapping in Practice



A Path Towards Personalised AF Treatment?

- Imputation mapping predicts global propagation dynamics from sparse measurements.
- Downstream analysis of global maps could enable electrophenotyping of patients and stratification for treatments.
- Moving beyond one-size-fits-all treatment could improve clinical outcomes.

Future Directions

Current Limitations

- Trained on non-contact AcQMap data in the absence of true global ground truth.
- Need to determine optimal spatio-temporal resolution for guiding treatment decisions.

Technical Improvements

- Augment training with high-resolution simulated data to improve resolution if needed.
- Explore hierarchical architectures with virtual nodes for improving long-range imputations.

Clinical Validation

- Validate model's state-space and embedding representations for electrophenotyping.
- Compare with organised arrhythmias (e.g., atrial tachycardia) where sequential mapping can be stitched together.
- Prospective clinical trial: one-size-fits-all vs. imputation-guided personalised ablation strategies.

Summary and Conclusions

FibMap: Key Contributions

- Novel imputation mapping approach for AF.
- 210% improvement over baseline methods.
- 11× better phase singularity detection.
- Fast adaptation to new patients (22 min).
- Uncertainty estimation to guide interpretation.
- Real-world proof-of-concept with clinical data.
- Interpretable patient embeddings and model state-spaces.

Clinical Impact

- Integrates seamlessly with existing clinical catheters and workflows.
- Reveals AF mechanisms not visible with conventional mapping.
- Potential to reduce procedure time, complexity, and risk.
- Pathway to personalised AF treatment beyond one-size-fits-all approaches.

Acknowledgements

Thank you to AI4Health Center, British Heart Foundation, and the Swiss National Science Foundation for their support. Thank you also to our clinical collaborators and the patients who contributed to this research.

Thank you.
Questions?

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