Simultaneous Atrial Mapping: End of an Era or Promising Future? Insights from Non-contact Mapping Integrated with Frequency, Phase, and Machine Learning Approaches to Identify Drivers from Clinical Data

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Abstract

Non-contact mapping (NCM) offers unique real-time, global atrial activation sensing but is limited by reduced accuracy >4 mm from the catheter. Alternatives, such as basket catheters, face challenges of poor wall contact and resolution. Rotor/re-entry mapping has driven interest in sequential approaches (e.g., PentaRay, HD-Grid), though these assume stable signals, which is problematic in atrial fibrillation (AF). Our studies show dominant frequency (DF) requires ≥84 s for stability, whereas phase singularity (PS) density stabilises within 18 s. Using DF-guided ablation with a near-real-time interface, AF terminated in 4/10 cases before pulmonary vein isolation, with recurrence linked more to stability than absolute DF. Machine learning using recurrence quantification and wavelet clustering achieved up to 70% accuracy in predicting ablation response. Despite discontinuation of EnSite arrays, simultaneous recordings with PentaRay highlight the potential of integrating contact and non-contact mapping with machine learning to enhance AF driver identification.

1. Introduction

Atrial fibrillation (AF)—rapid, irregular atrial activation—quintuples stroke risk and doubles heart-failure risk. In the UK, >1 million people are affected; annual NHS costs are ~£1.435 bn, projected to ~£2.351 bn by 2030. Much of this burden reflects repeat admissions after catheter ablation (CA): with current technology, only ~50% of persistent AF (persAF) patients are arrhythmia-free 12 months after first CA. AF requires a trigger and a sustaining substrate; pulmonary-vein isolation (PVI) treats paroxysmal AF, but poor persAF outcomes imply extra-PV drivers [1, 2]. Atrial regions with complex fractionated atrial electrograms (CFAEs) were reported to represent relevant AF substrate and target sites for AF ablation [3], but the STAR-AF 2 trial showed that additional ablation of a sequential marker failed to improve the outcome, compared to PVI alone [4]. Ablation targeting focal impulse and rotor modulation (FIRM) initially showed high termination rate, but other groups failed to reproduce these results. These techniques were implemented in commercial systems considering single markers, but this has proven insufficient [4, 5] with resultant disappointing clinical outcome in terms of AF recurrence (CONFIRM). Multiple mechanisms may co-exist during persAF [6, 7]. Single processing technique is unlikely to capture all drivers. Precise target identification therefore demands detailed tissue characterisation and patient-specific strategies, with modern data-driven methods increasingly outperforming rule-based approaches.

2. USURP-AF Database and Outcomes - DF ablation in persAF

Ten persAF patients undergoing first time LA catheter ablation were enrolled. Bi-atrial noncontact multi-electrode arrays (EnSite, St. Jude Medical, St. Paul, MN, USA) were inserted in LA. ECG and Virtual Electrogram (VEGM) data were collected simultaneously for 5 minutes before ablation. High DF regions in the LA were identified as described before[8, 9] and 30s (from 5 min recording) of unipolar LA VEGMs (2048-channels[nodes]) were exported to our Matlab platform[10, 11] to guide ablation targeting. Cycle lengths before and after ablating each atrial DF site were recorded. We consider AF cycle length (AFCL) increase>10ms and AF termination as positive ablation result. There were no adverse events in all ten patients. A total of 51 atrial locations [3,206nodes] were ablated: 16 with AFCL increase [1,182nodes], 4 terminated AF [308nodes], 7 AFCL decrease [381nodes] and 24 no AFCL change [1,335nodes]. Three patients had ablation

terminations to atrial flutter or tachycardia before PVI, one ablation to LA silence and subsequent spontaneous SR pre-PVI and one conversion to SR with flecainide alone post-PVI.

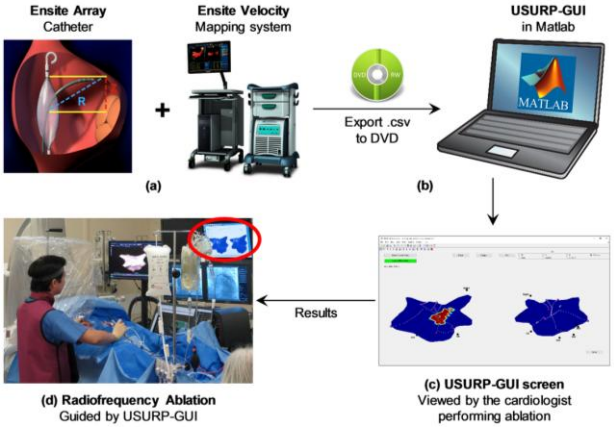

Figure 1. The workflow of using the USURP-GUI platform to guide catheter ablation

3. Feature based approaches

3.1. What we learnt from DF guided ablation

Bar plots show mean ± standard deviation (SD) for each feature by class; pairwise p-values are reported in Table 1. Mean DF (Hz) for the four classes were 4.94 ± 0.23, 5.38 ± 0.67, 5.48 ± 0.71, and 5.33 ± 0.69 (overall p<0.0001p < 0.0001p<0.0001). Temporal DF SDs were 0.39 ± 0.11, 0.69 ± 0.28, 0.64 ± 0.23, and 0.75 ± 0.29 (overall p<0.0001p < 0.0001p<0.0001). Mean OIs were 0.39 ± 0.30, 0.35 ± 0.06, 0.35 ± 0.05, and 0.32 ± 0.05 (overall p<0.0001p < 0.0001p<0.0001). Temporal OI SDs were 0.11 ± 0.01, 0.10 ± 0.02, 0.10 ± 0.02, and 0.09 ± 0.01 (overall p<0.0001p < 0.0001p<0.0001). Notably, most features in the AF-termination class differed significantly from the other classes, indicating phenotypic distinctiveness of termination sites; increasing the number of termination cases may further improve classifier performance on future data.

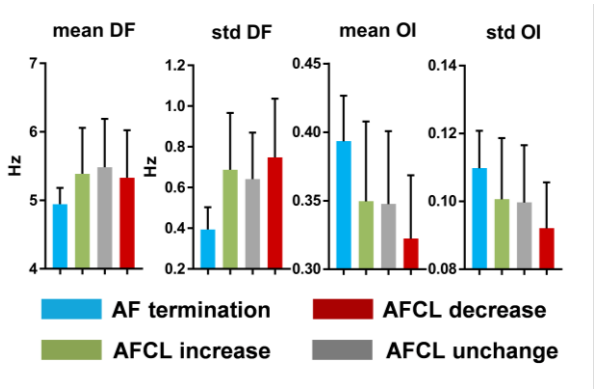

Figure 2. The bar graphs of the 4 features for each class.

Across ablation outcomes, AF termination and AFCL prolongation were not associated with the highest dominant frequency (DF) per se, but consistently required relatively high organization index (OI). Subsequent temporal analyses showed that periods with temporally stable DF tended to co-occur with high OI. Taken together, sites exhibiting moderately elevated DF together with high OI appear enriched for termination mechanisms.

3.2. DF and Recurrent DF

We subsequently observed that recurrent DF (rDF)—i.e., the repeated re-emergence of similar DF values over time—is associated with higher organisation index (OI) and moderately elevated (rather than maximal) DF. This composite phenotype (rDF + high OI + moderate DF) appears more closely linked to atrial regions relevant for

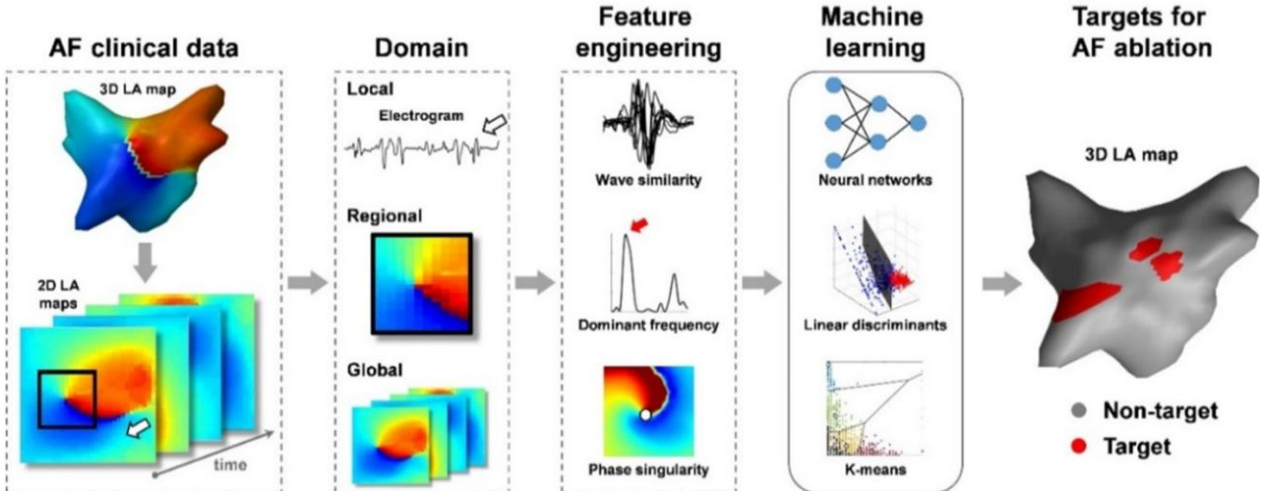

Figure 3. End-to-end pipeline for data-driven AF target identification.

AF modification than instantaneous DF alone.

Using global mapping during persAF, we showed that DF lacks spatiotemporal stability[12], suggesting limitations in previous studies using sequential DF mapping[13]. Cyclical behaviours of high DF (HDF) reappearance in the LA[8], and recurrent behaviour of DF in longer EGM duration (5 mins)[14] have been demonstrated by our group, which suggest that electrical activity of AF is not entirely random. Preliminary data suggest that recurrent HDF pattern regions were observed to have higher organization [14], which was also supported in recent work investigating temporally stable DF[15]. There is, therefore, a need to investigate whether these recurrent, more organised atrial regions are more correlated with the underlying AF drivers as potential targets for ablation.

However, machine-learning models built on DF and OI (including area-averaged OI, aOI) alone did not generalize well to our unpublished hold-out cohort, suggesting additional features are required for robust prediction.

3.3. Rotor and Rotor duration

Rotors (spiral waves) have been observed during atrial arrhythmia and are implicated as localized drivers of fibrillation. Phase mapping is widely used to identify rotor/phase-singularity (PS) sites, yet results can conflict (e.g., FIRM) and remain sensitive to algorithmic choices (search radius, phase-gradient thresholds) and pre-processing filters. In head-to-head testing of three automated rotor-tracking pipelines, we found PS detection to be method-dependent [16], and established that robust PS-density (PSD) estimation requires ≥18 s of data. Notably, DF and PS sites frequently co-localize [9]. Going forward, we will incorporate rotor-derived features (e.g., PSD, rotor dwell/recurrence) alongside organization metrics to improve targeting of AF-modifying regions.

4. Machine learning and Data driven approaches

After domain-driven features (e.g., DF, aOI) failed to generalize for AF substrate targeting, we pivoted to a data-driven strategy with minimal prior assumptions. Rather than prespecifying electrophysiological markers, we let the recordings themselves determine salient spatiotemporal patterns, including recurrent/stable behaviours, and assess their association with AF modification and termination. Our aim, consistent with AI-for-Science, is to extract reproducible, mechanistically plausible signals from the data.

4.1. Time Series features

We extracted 390 features per electrogram (EGM) across three domains—spectral, temporal, and statistical—using the TSFEL Python library. Records were labeled as (i) positive if ablation resulted in AF termination or AF-cycle-length (AFCL) prolongation ≥10 ms, and (ii) negative/neutral if AFCL change was <10 ms or absent. Among all features, the FFT mean coefficient at 10 Hz was most discriminative; a univariate model using this feature achieved 71.74% accuracy (10-fold cross-validation). We identified spectral power at ~10 Hz (near the upper end of the atrial DF band) as a strong univariate marker for AF termination and AFCL prolongation[17].

4.2. Recurrence quantification analysis features

We evaluated supervised learning using non-linear RQA descriptors from short electrogram segments (~3 s) to predict acute ablation outcome. Under an inter-patient split (leave-one-patient-out cross-validation), the RQA feature set achieved 74% accuracy. Feature-importance analysis consistently highlighted measures as most informative—determinism (DET) and length of the longest diagonal line.

4.3. Wavelet scattering coefficient features

Wavelet-scattering features, reduced via principal component analysis and fed to a supervised classifier, predicted ablation outcome from 18-s segments with 79% accuracy. This compact pipeline is a promising direction for outcome prediction.

4.4. Deep learning approaches

We evaluated image-based deep learning using ResNet-50 (spectrograms and recurrence plots), an autoencoder, and transfer learning from ImageNet. Under inter-patient splits (leave-one-patient-out, 10-fold CV), transfer learning with ResNet-50 on spectrograms achieved 62% accuracy; an autoencoder followed by a decision-tree classifier achieved 63%. All results use patient-wise partitions to avoid leakage and provide reproducible baselines.

5. Conclusion

Simultaneous/global mapping remains valuable for AF driver identification, despite known distance-related limitations, because it uniquely captures chamber-wide dynamics in real time. Across analyses, DF alone was insufficient: termination/AFCL prolongation clustered at sites showing moderate DF with high organisation and recurrence. Feature-based pipelines outperformed deep nets: TSFEL features identified a 10 Hz spectral marker

(71.74%), RQA features from ~3 s segments reached 74%. With a small dataset, feature-based pipelines outperform deep learning—e.g., wavelet-scattering+PCA achieved 79% vs ResNet-50 transfer/autoencoder 62–63% (patient-wise CV). These results support a data-driven, hypothesis-light strategy that integrates recurrence/stability, organisation, and rotor-derived features, with rigorous leakage controls. Future work will expand cohorts, perform multi-centre external validation, and translate the pipeline to contact-mapping platforms using our paired non-contact/contact recordings to bridge modalities and enable prospective testing.

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