Event-Centered Feature Modeling of Arrhythmic ECG Episodes

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Abstract

Electrocardiogram (ECG) arrhythmia detection is traditionally formulated as a beat-level classification problem, where individual heartbeats are classified independently based on local signal characteristics. Although this approach has achieved strong results on widely used datasets, it largely ignores the temporal structure of arrhythmic episodes, which are events that unfold over time with distinct onset, persistence, and evolution, and are not fully defined by isolated beats. Beat-level representations can be limited in capturing long-term temporal dependencies in ECG signals, leading to episode-level modeling of multi-beat or complete arrhythmic events. However, their ability to generalize across patients under strict, leakage-free evaluation—where no data from the same ECG record or overlapping segments appears in both training and testing—remains unclear[1]. In this study, we investigate the limits and potential of event-centered ECG modeling under strict record-wise evaluation, focusing on distinguishing episode-level temporal coherence from patterns driven by individual beats. Experiments use the MIT-BIH Arrhyth-

Table 1. Waveform-level post-onset forecasting performance under
5-fold record-wise cross-validation (MAE; lower is better)

Method	MAE (mean $\pm$ std)
Zero predictor (baseline)	0.91 ± 0.17
Class-mean waveform template	0.97 ± 0.16
AR(10) autoregressive model	0.93 ± 0.16
PCA-based regression	1.78 ± 0.45
1D CNN regressor	0.96 ± 0.14

mia Database [2, 3], which contains annotated ECG recordings sampled at 360 Hz and covering normal, atrial, and ventricular rhythms. Event-centered ECG modeling represents signals by aligning ECG segments relative to arrhythmic episode onsets, rather than to individual beats or arbitrary sliding windows. Episode onsets correspond to annotated rhythm transition markers indicating the beginning of abnormal cardiac rhythm activity. Let $x(t)$ denote a continuous ECG signal and let t_0 represent an annotated arrhythmic episode onset. An event-centered window is defined as

$$w(t_0) = \{x(t) \mid t \in [t_0 - T_{\text{pre}},\ t_0 + T_{\text{post}}]\}, \tag{1}$$

where T_{pre} denotes the pre-onset context duration and T_{post} denotes the post-onset episode duration. Fixed-length event-centered windows are signal segments of identical duration extracted around each episode onset, designed to preserve a consistent pre-to-post transition across episodes and patients. In this work, fixed-length event-centered windows of total duration 8 seconds are used, with $T_{\text{pre}} = 2$ seconds and $T_{\text{post}} = 6$ seconds. Episode-level temporal coherence is defined here as the extent to which post-onset ECG behavior can be inferred from pre-onset signal characteristics within the same arrhythmic episode, beyond what is explained by isolated beat characteristics. All experiments are evaluated using 5-fold record-wise cross-validation, where all windows originating from the same ECG record are assigned to the same fold, ensuring strict patient independence and preventing information leakage. We first evaluate whether the pre-onset waveform segment can predict the post-onset waveform segment under record-wise evaluation. We use three simple baselines: a zero predictor; an autoregressive model of order 10 (AR(10)) fit on the pre-onset segment and rolled forward to predict the post-onset signal; and a class-mean template that predicts the average post-onset waveform computed from training windows of the same arrhythmia class (normal, atrial, or ventricular). We then evaluate two more expressive waveform-level modeling strategies: a one-dimensional convolutional neural network (1D CNN) regressor mapping pre-onset to post-onset waveforms, and PCA-based regression using linear prediction in a reduced post-onset space.

Table 1 shows that waveform-level forecasting models do not outperform simple baselines under record-wise evaluation. These results suggest that predicting full ECG waveforms across patients is challenging, mainly because heart signal patterns vary across patients and over time, a concern previously emphasized in the eval-

Table 2. Event-centered dataset composition and feature predictability

Item	NORMAL	ATRIAL	VENTRICULAR
Number of event-centered windows	222	164	34

Post-onset feature	Rel. improvement	Interpretation
Band power (15–40 Hz)	+45.2%	high-frequency persistence
Line length	+16.0%	temporal roughness persistence
Spectral centroid	+12.1%	spectral shift predictability
Zero-crossing rate	+3.5%	oscillatory roughness

uation of arrhythmia detection systems [4]. Motivated by these findings, we shift focus to feature-level event-centered modeling which focuses on physiological descriptors that may persist across onset even when waveform morphology does not. From both pre- and post-onset segments, we extract signal-derived physiological features capturing signal energy, dispersion, short-term temporal variability and frequency content [5], [6]. Ridge regression models [7] are trained to predict post-onset feature values from pre-onset features and compared against mean-feature baselines as illustrated in Table 2. Ridge regression improves prediction for a subset of post-onset features (particularly high-frequency band power, line length, spectral centroid, and zero-crossing rate) while amplitude and low-frequency features remain unpredictable. Thus, event-centered alignment supports feature-level but not waveform-level prediction under patient-independent evaluation.

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