A System Identification Approach to Subject-Specific QT-RR Dynamics in ECG-Based Myocardial Infarction Classification

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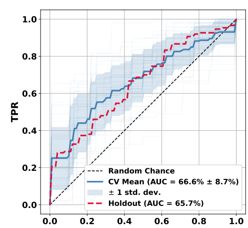
QT-based ECG risk assessment relies on accurate heart-rate adjustment. Conventional formulas like Bazett and Fridericia ignore temporal QT–RR adaptation, limiting their use in high-risk groups with abnormal repolarization. We propose a system-identification framework modeling QT as a nonlinear dynamical system of current and past RR intervals, enabling subject-specific QT adaptation to RR changes for generalizable dynamical ECG biomarkers with the equation: $\mathrm{QT}_n = \mathcal{F}_T(\{\mathrm{RR}_k : t_n - T < t_k \leq t_n\}) + \varepsilon_n$.

RR and QT intervals were extracted from Holter ECGs of 418 post-MI and control participants in the MIMS2 cohort during 699 mental and physical stress test recordings. We trained a recurrent neural network (LSTM) to predict beat-wise QT intervals based on both past and current RR intervals. The global model was initially trained on mental-stress data, then fine-tuned for each subject, and tested on each subject's unseen physical-stress data; the opposite setup was also evaluated. Accuracy was assessed using mean absolute error (MAE) and correlation coefficient (CC) over memory lengths of 5–120 s. QT dynamics exhibit finite memory, with an optimal 60 s history window yielding an MAE of 12.8$\pm$3.4 ms and a CC of 0.80$\pm$0.11; performance plateaus beyond this.

Then, trained models simulated QT responses to controlled RR sequences mimicking a stress test, producing normalized QT–RR hysteresis loops. Exercise- and recovery-phase QT values on a common RR grid (400:50:1200 ms) defined subject-specific features for MI classification, compared to nine classical QT-correction features. XGBoost, SVM, and Logistic-Regression classifiers were trained on 309 participants and tested on 104 unseen participants. Dynamic QT–RR features improved MI classification over classical QTc, increasing training AUROC from 65.0$\pm$10.4% to 66.6$\pm$8.7% and testing AUROC from 63.1% to 65.7% (see figure).



These findings demonstrate that subject-specific finite-memory models capture QT–RR dynamics, providing dynamic biomarkers that outperform traditional MI classification and underscore the significance of repolarization dynamics.