**A Novel Multimodal Junctional Ectopic Tachycardia Detection Tool for Children with Congenital Heart Disease**

**Short Title: Junctional Arrhythmia Detection with Machine Learning**

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**Abstract (240 Words)**

**Background:** Junctional ectopic tachycardiac (JET) is a prevalent life-threatening arrhythmia in children with congenital heart disease (CHD), with marked resemblance to normal sinus rhythm (NSR) often leading to delay in diagnosis.

**Objective:** To develop a novel multimodal automated arrhythmia detection tool to identify JET.

**Methods:** A single-center retrospective cohort study of children with CHD was performed. Electrocardiographic (ECG) and central venous pressure data produced by bedside monitors is captured automatically by the SickbayTM platform.

**Results:**

**Conclusion:**

**Keywords:** Congenital Heart Disease, Junctional Ectopic Tachycardia, Machine Learning, Arrhythmia

**BACKGROUND AND SIGNIFICANCE**

Arrhythmias are common during the early postoperative period, following cardiac surgery to repair congenital heart disease (CHD), with junctional ectopic tachycardia (JET) shown to be the most common arrhythmia1,2. JET not only extends intensive care unit (ICU) stay, it also increases patient risk of morbidity and mortality3.

JET is a narrow QRS complex tachyarrhythmia, with electrical activity originating around the atrioventricular (AV) node4. The distinctive electrocardiographic features of JET is the disappearance of P wave or retrograde P waves5. This is similar to sinus tachycardia, which often results in delay in diagnosis and interventions.

An important feature of JET is increase in atrial pressures due to discordant simultaneous contraction of atria and ventricle, resulting in distinctive changes in central venous pressure (CVP) waveforms (PMID: 14716195). Xin et al have previously extracted the distinctive features of CVP to diagnose JET.

We have previously published an end-to-end computational framework that takes raw ECG data as input and predicts the likelihood of junctional ectopic tachycardia (JET) on a per cardiac cycle basis (XXX). However, this algorithm had high false positive rate, which results in false alarms. To improve the performance of previous algorithm, we hypothesized developing a multimodal approach that combines the ECG and CVP features will result in improved performance of algorithm to diagnose JET.

## **METHODS**

### **Patient Cohort**

We performed a retrospective single center cohort study of all postoperative patients with CHD admitted to cardiac intensive care unit at Texas Children’s Hospital. The Institutional Review Board of Baylor College of Medicine approved the study and waived the need for informed consent was waived as this was an observational study performed on aggregate de-identified patient information.

**Data Collection**

Patient cohort selection and data collection are previously described elsewhere (XXX). In brief all patients admitted to the CICU at Texas Children’s Hospital are continuously monitored using standard monitoring equipment. The physiologic data produced by these monitors is captured automatically using the SickbayTM platform (Medical Informatics Corp., Houston, TX). Data captured by Sickbay includes both vital signs and high-resolution waveforms. Vital signs are generally collected once every 2 seconds and include timeseries such as heart rate, respiratory rate, oxygen saturation (SpO2), all blood pressure measurements (mean, systolic, diastolic), all ST segment measurements, and temperatures. Waveform data is generally collected at 60 to 240 Hz, depending on the signal, and includes timeseries such as ECG lead and pressure measurements, chest impedance, and the SpO2 waveform. All data is time-synchronized. All signals and events measured from all devices and patients are passively recorded while they are in the CICU, resulting in a large, rich dataset that can be subdivided based on project.

**ECG Signal Processing**

The proposed method focuses on features based only on ECG data since it is almost always measured. For consistency, only ECG Lead II data is analyzed. Segments of data that include movement artifacts or are non-physiological are discarded. The remaining ECG segments are filtered to remove frequencies outside of the range of 0.5 to 50 Hz.

Two interpretable ECG-only features based on the detection of R and P wave peaks are calculated: P prominence median and PR interval interquartile range (IQR). The detection of R and P wave peaks is implemented as follows.

After applying a 5 Hz 3rd order high-pass Butterworth filter and normalizing by the segment median and interquartile range (IQR), R wave peaks are detected using MATLAB’s *findpeaks* function. Thresholds for the minimum peak prominence, maximum peak width, and minimum peak distance are initialized and then adjusted based on the corresponding identified peak values. These were chosen heuristically as follows: the minimum peak prominence is initialized to 0.3, then set to one third of the 75th percentile identified peak prominence; the maximum peak width is initialized to 0.2 then set to three times the 25th percentile identified peak width; and the minimum peak distance is initialized to 0.2 then set to half the 75th percentile identified peak distance. For the minimum peak distance initialization, one beat every 0.2 seconds corresponds to 300 beats per minute (bpm)8,9. For the maximum peak width initialization, assuming the QRS complex spans approximately 10% of the R-R interval period, an R peak width of 0.2 seconds corresponds to approximately 30 bpm8,9. Inverted R waves are accounted for by finding peaks for both the original and inverted signals and then taking the set of identified peaks that has the higher median peak height.

The largest peak that occurs between 0.2 seconds and 0.07 seconds9 before each of the identified R wave peaks is determined using *findpeaks*. This peak is identified as the P wave unless it appears to be a pacing spike. If the second largest peak occurs after the first largest, has a larger width, and has a height (normalized by the minimum search period value) greater than 30% of that of the largest peak, the second largest peak is taken as the P wave. The first is assumed to be a pacing spike.

All P prominence values are returned by *findpeaks* when the P waves are identified; P prominence is based on the vertical distance between the identified P peaks and the signal’s nearby minima. The median P peak prominence over the past 130 seconds was found to be an important feature for the classification of ECG data as JET or sinus, as is commonly described by physicians experienced with JET patients.

The PR interval is taken to be the time between the identified P and R peaks. The IQR of the PR interval over the past 10 seconds was also found to be useful in the classification of ECG data as JET or sinus. This is because when P waves disappear in JET, the peak detector still chooses the largest peak, but it is an arbitrary peak and thus inconsistent with time.

**Classification Model**

**RESULTS**

**Patient Cohort**

The cohort and label breakdown are shown in Figure 1. The complete cohort for this study consists of 40 patients with CHD and a total of 64.5 expert-labelled hours (of which 509,833 cardiac cycles [R-R intervals] were analyzed): 19.3 hours (147,868 analyzed beats) spanning 35 patients were labelled as JET and 45.2 hours (361,965 analyzed beats) spanning all 40 patients were labelled as sinus. The training cohort consists of 15 patients and a total of 48.3 expert-labelled hours (of which 390,608 R-R intervals were analyzed): 12.9 hours (98,919 analyzed beats) spanning 14 patients were labelled as JET and 35.5 hours (291,689 analyzed beats) spanning all 15 patients were labelled as sinus. The test cohort consists of 25 patients and a total of 16.2 expert-labelled hours (of which 119,225 R-R intervals were analyzed): 6.4 hours (48,949 analyzed beats) spanning 21 patients were labelled as JET and 9.8 hours (70,276 analyzed beats) spanning all 25 patients were labelled as sinus.

Diagram, table

Description automatically generated

Figure 1: Cohort breakdown in terms of expert-labelled hours and the corresponding number of patients they span as well as analyzed beats, for both sinus and JET labels, as well as Training and Test cohorts.

**Feature Extraction**

Figure 4: P prominence median (top) and PR interval IQR (bottom) features shown for expert-labelled sinus (left column) and JET (right column) events for 2 training cohort patients.

## **Performance**

**DISCUSSION**

**Limitations**

**Future Directions**

**CONCLUSION**

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