EasiECG: A Novel Inter-Patient Arrhythmia Classification Method using ECG Waves

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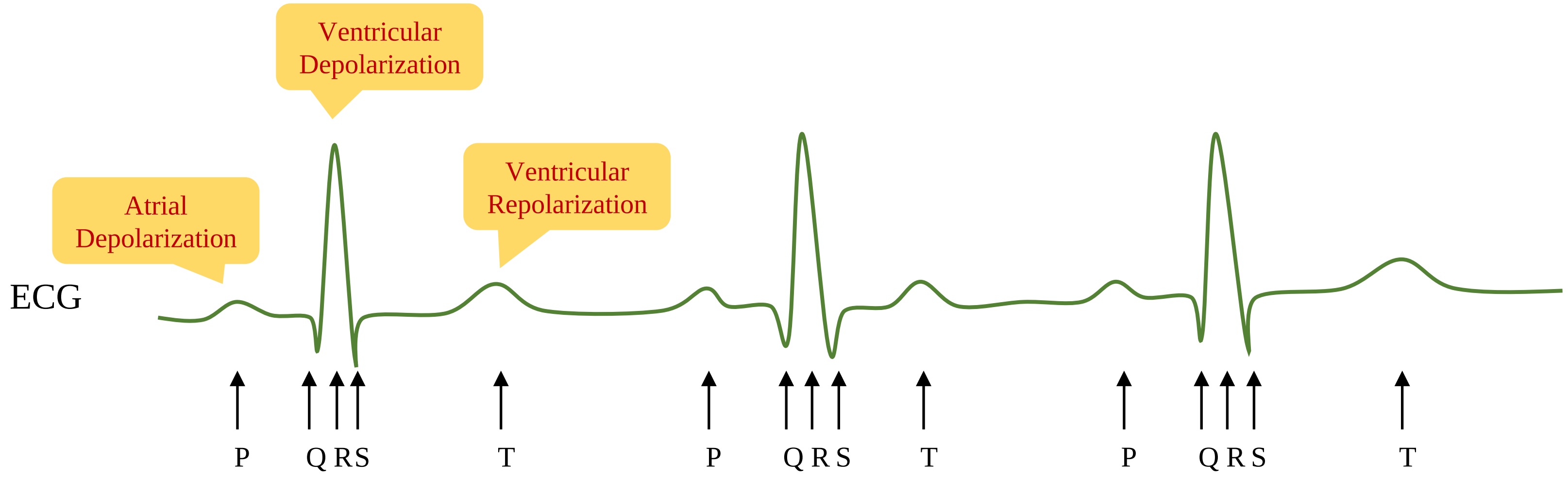
Introduction

- Cardiovascular diseases (CVDs) have become the leading causes of death in most areas of the world.
- Early diagnosis and timely treatment of CVDs are effective means to reduce its harm.
- The electrocardiogram, known as ECG, is used to measure and record the electrical activities of the heart. It has been widely used as the standard tool in the detection of cardiac abnormalities.

Introduction

- In ECG records, a normal heartbeat waveform usually contains a P wave, a QRS complex, and a T wave. These waves are of important medical significance.



Introduction

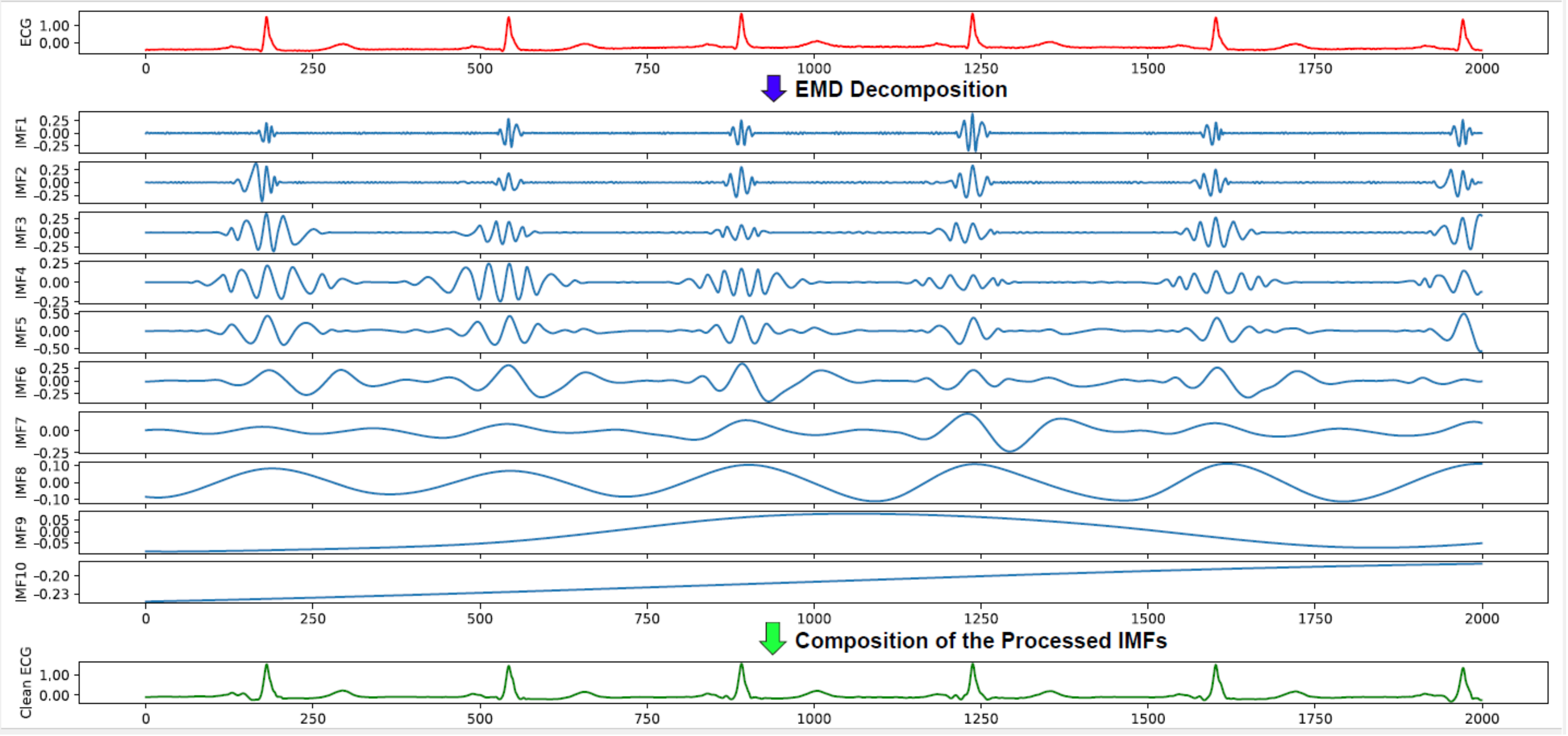
- Since classifications of arrhythmic heartbeats can be very challenging and time-consuming for human-beings, methods based on AI are introduced.

- These methods are further divided into two groups:
  - End-to-end
  - Multi-stage

- In this paper, we propose a medical experience-oriented arrhythmia classification method named EasiECG that requires simple engineering and achieves high accuracy.

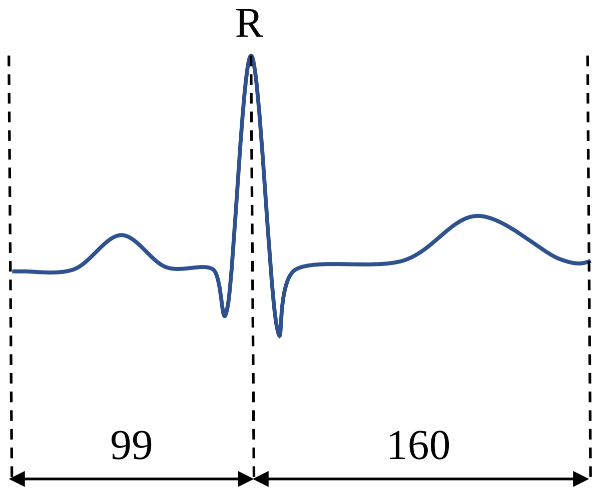
Methodology

- ECG Signal Preprocessing
  - In this paper, ECG signals are obtained from the MIT-BIH arrhythmia database. These raw signals suffer from environmental noise as well as baseline wander…
  - To effectively denoise these ECG signals, we adopt a method based on Empirical Mode Decomposition (EMD).



Methodology

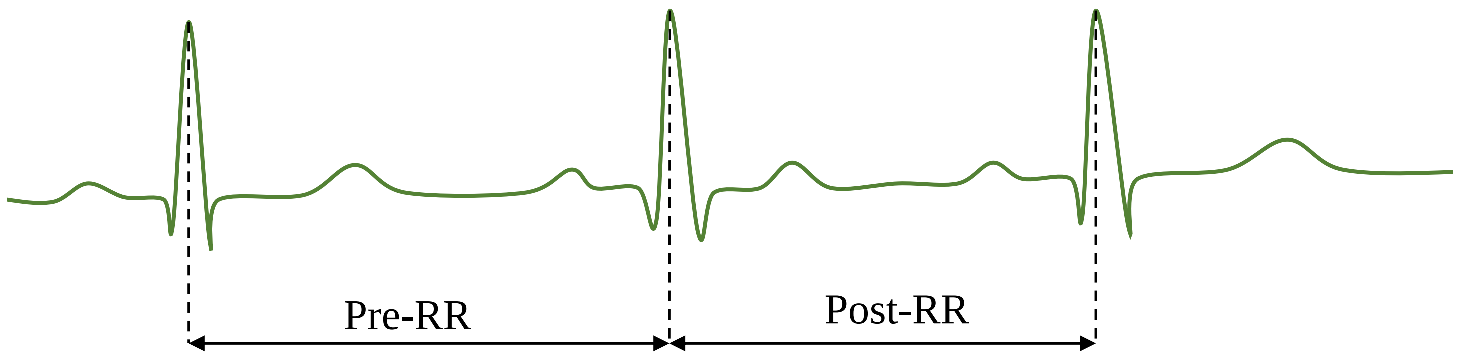
- Heartbeat Detection and Segmentation
  - we then split each ECG record into several segments consisting of 260 samples (99 samples before the R peak and 160 samples following the R peak).
  - In this way, each segment corresponds to only one beat type.



Methodology

- Feature Extraction
  - A total of 12 features are extracted from each ECG segment:
    - PQRST wave locations & amplitudes
    - 2 normalized RR

$$\begin{cases} Ratio_{pre/post} = \dfrac{Pre-RR}{Post-RR} \\[2ex] Ratio_{pre/avg} = \dfrac{Pre-RR}{\sum_{i=1}^{N} Pre-RR_i \Big/ N} \end{cases}$$



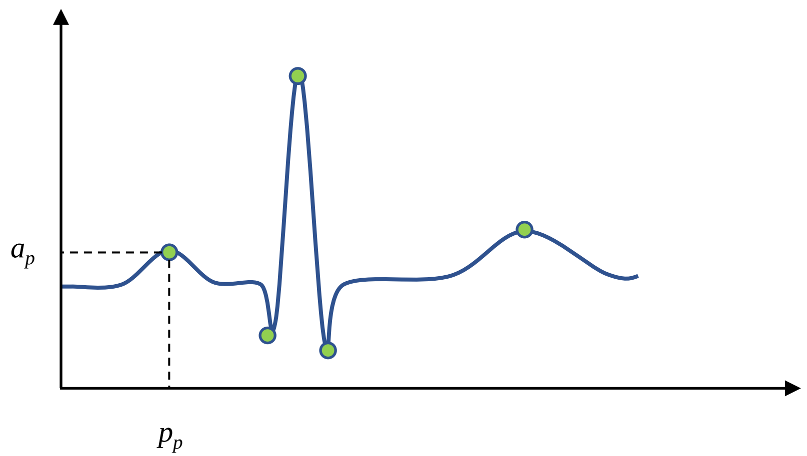
Methodology

- Embedding of features
  - Positions of PQRST waves
  - Amplitudes of PQRST waves

$$p_i, i \in [P,Q,R,S,T]$$
$$a_i, i \in [P,Q,R,S,T]$$

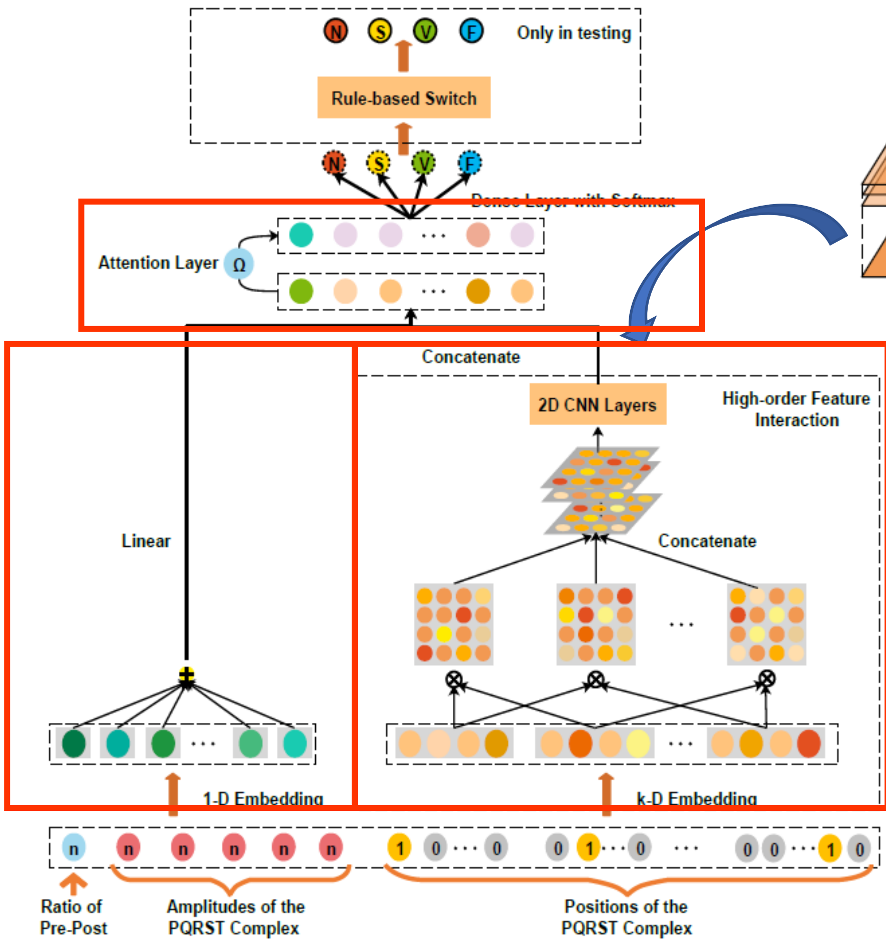
$$\xrightarrow[\text{Embedding}]{W_p^{\,k} \bullet p_i}$$

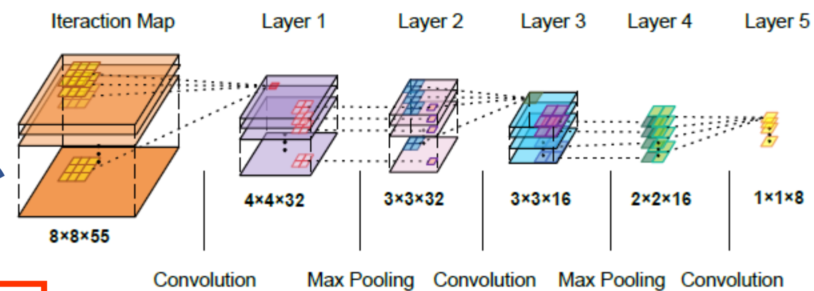
$$P_i^k, A_i^k \in \mathrm{R}^k$$



Methodology

- Model Structure: ACFM





Experiment and Results

- Inter-patient paradigm

TABLE I
MAPPING RELATIONSHIPS BETWEEN AAMI HEARTBEAT CLASSES AND MIT-BIH HEARTBEAT LABELS

AAMI heartbeat class	MIT-BIH heartbeat label
Non-ectopic beats (N)	Normal beats (N) Left bundle branch block beats (L) Right bundle branch block beats (R) Nodal(junctional) escape beats (j) Atrial escape beats (e)
Supra ventricular ectopic beats (S)	Aberrated atrial premature beats (a) Supraventricular premature beats (S) Atrial premature Contraction (A) Nodal(junctional) premature beats (J)
Ventricular ectopic beats (V)	Ventricular flutter wave Ventricular escape beats (E) Premature ventricular contraction (V)
Fusion beats (F)	Fusion of ventricular and normal beat (F)
Unknown beats (Q)	Paced beats (/) Unclassified beats (Q) Fusion of paced and normal beats (f)

DS1 = {101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230}
DS2 = {100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234}

TABLE II
NUMBERS OF BEATS OF FIVE AAMI CLASSES IN DATASETS

AAMI heartbeat class	DS1	DS2	Training Set	Testing Set
N	43765	41935	10000	41935
S	878	1646	878	1646
V	3357	2772	3357	2772
F	378	384	378	384
Q	3	1	-	-
Total	48381	46738	14613	46737

Experiment and Results

- Inter-patient paradigm

TABLE III
COMPARISION OF CLASSIFICATION ACCURACY IN % AGAINST THE STATE-OF-THE-ART ALGORITHMS

Num of classes	Method	N			S			V			F		
		Se	$+P$	$Spec$	Se	$+P$	$Spec$	Se	$+P$	$Spec$	Se	$+P$	$Spec$
3 classes	Llamedo et al.[13]	95	98	-	77	39	-	81	87	-	-	-	-
	Lin and Yang [14]	91.0	99.0	-	81.0	31.0	-	86.0	73.0	-	-	-	-
	Garcia et al.[32]	94.0	98.0	82.6	62.0	53.0	97.9	87.3	59.4	95.9	-	-	-
	Zheng et al.[7]*	90.5	99.6	96.2	90.3	45.2	96.0	91.5	51.3	94.5	-	-	-
	Anwar et al.[18]*	94.8	99.7	97.4	85.9	45.5	96.2	**95.1**	78.5	98.3	-	-	-
	Proposed Method	**95.4**	99.5	95.2	**91.6**	52.1	96.9	92.9	78.8	98.4	-	-	-
4 classes	Chazal et al.[12]	86.9	99.2	-	75.9	38.5	-	77.7	81.9	-	89.3	8.6	-
	Proposed Method	**91.8**	98.8	90.1	**90.4**	57.7	97.6	**93.3**	73.1	97.8	21.4	5.0	96.6

* This result is obtained using our own settings, since the original paper adopts intra-patient paradigm.

TABLE V
NUMBERS OF CORRECTLY CLASSIFIED BEATS IN ABLATION EXPERIMENTS

Methods	N	S	V	F
Proposed Method	38497	1488	2587	82
Ablation Expt 1[1]	36352 (-5.1%)[5]	401 (-66.0%)	2594 (+0.3%)	90 (+2.1%)
Ablation Expt 2[2]	37693 (-1.9%)	1495 (+0.4%)	2342 (-8.8%)	72 (-2.6%)
Ablation Expt 3[3]	38444 (-0.1%)	1411 (-4.7%)	2573 (-0.5%)	0 (-21.4%)
Ablation Expt 4[4]	38815 (+0.8%)	1434 (-3.3%)	2422 (-6.0%)	0 (-21.4%)

[1] Proposed model without Rule-based Switch
[2] Proposed model without attention mechanism
[3] Proposed model using cross-entropy as loss fuction when training
[4] Model based on classical FMs
[5] Numbers in brackets indicate the percentage of increasement(+) / decreasement(-) in sensitivities

TABLE VI
CLASSIFICATION RESULTS OF SAMPLES WITH A MISSING P WAVE IN THE NEW DS2

Class	Correct	False	Total
N	3896 (89.4%[1])	460	4356
S	307 (91.1%[1])	30	337
V	1488 (89.2%[1])	181	1669
F	52 (27.1%[1])	140	192
Total	5743 (87.6%[2])	811	6554

[1] Sensitivity of each class
[2] Overall accuracy := $\sum_{i=N,S,V,F} TP_i / \sum_{i=N,S,V,F} Num_i$, TP_i and Num_i denote True Positive and total samples of class i, respectively.

Thank you!