Arrhythmia classification from single-lead ECG signals using the inter-patient paradigm

Felipe Meneguitti Dias, Henrique L. M. Monteiro,
Thales Wulfert Cabral, Rayen Naji, Michael Kuehni,
Eduardo José da S. Luz

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MOTIVATION

Motivation

- The electrocardiogram (ECG) is a technology that is capable of recording the electrical activity of the heart.
- If the ECG exhibits adverse behavior, there is a sign of a cardiac problem.
- One of the most common heart diseases is the cardiac arrhythmia, which is characterized by the occurrence of irregular heartbeat.
- A considerable amount of data is produced, and solutions to automate this classification process are so important.

Introduction

- Automatic ECG classification systems has two main paradigms: *intra-patient* and *inter-patient*.
  - *Intra-patient* a subject's heartbeat is used both for building the classification system and for testing.
  - *Inter-patient* used a separate set of subjects for building the classification system, and another for testing.

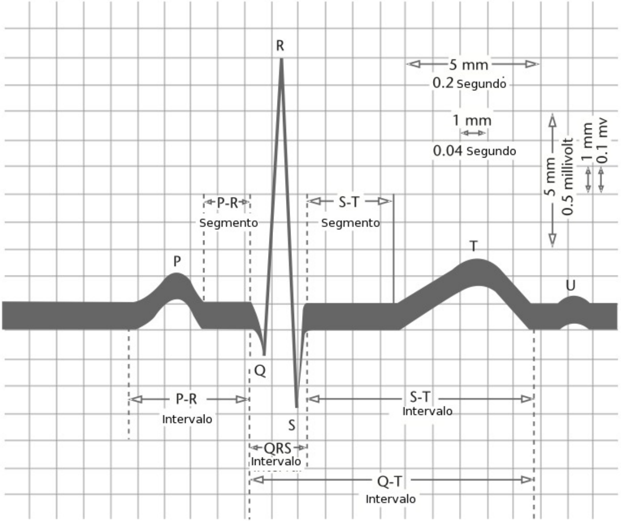
Introduction

- Proposed work (DIAS et al., 2021):
  - Single-lead ECG signals.
  - MIT-BIH Arrhythmia database.
  - Inter-patient paradigm.
  - Group of features: RR intervals, morphological values, and high order statistics.
  - Segmentation errors with jitter.
  - Linear Discriminant classifier (LD).

METHODOLOGY

Methodology

Figura 1: Normal signal ECG (CLIFFORD et al., 2006)



Methodology

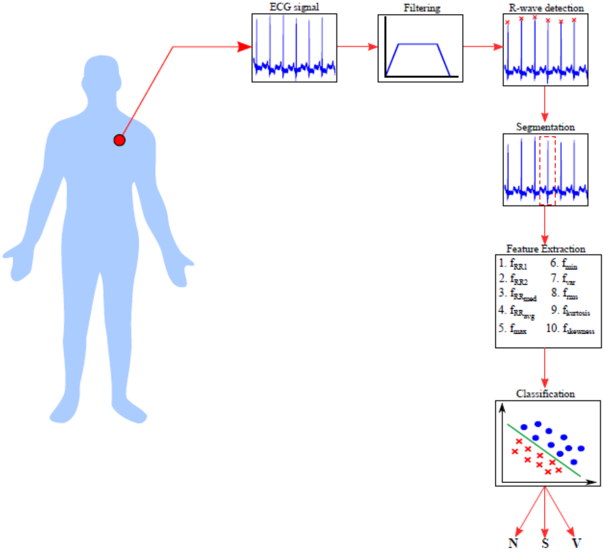


Figura 2: Arrhythmia classification system

Tabela 1: Mapping between MIT-BIH and AAMI labels

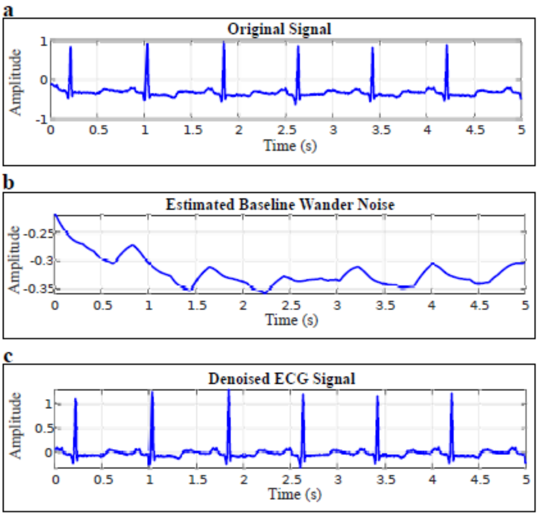
MIT-BIH class	AAMI class	Number of events
Normal beat (N or .) Left bundle branch block beat (L) Right bundle branch block beat (R) Atrial escape beat (e) Nodal (junctional) escape beat (j)	Normal (N)	90125
Atrial premature beat (A) Aberrated atrial premature beat (a) Nodal (junctional) premature beat (J) Supraventricular premature beat (S)	Supraventricular ectopic beat (S)	2781
Premature ventricular contraction (V) Ventricular escape beat (E)	Ventricular ectopic beat (V)	7009
Fusion of ventricular and normal beat (F)	Fusion beat (F)*	803
Paced beat (P or /) Fusion of paced and normal beat (f) Unclassified beat (U)	Unknown beat (Q)*	15

*Classes F ad Q were excluded from the work because of the small sample number.

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

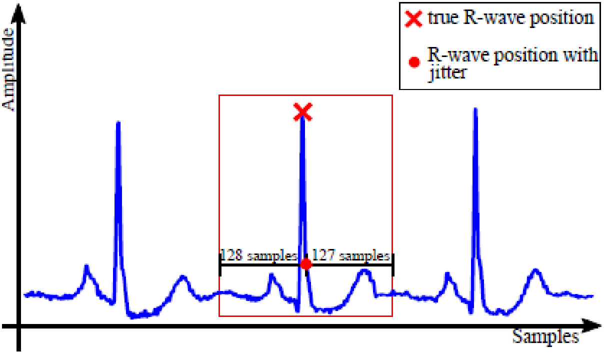
Tabela 2: Distribution of the MIT-BIH recordings between training and testing (CHAZAL; O'DWYER; REILLY, 2004)

Figura 3: Proposed filtering process using two moving average filters (200ms e 600ms)



- Add jitter to the R-wave position given by the database;
- Jitter interval $(\delta) = 0, 1, 2, ..., 18$ samples;
- $\delta = 18$ samples, i.e., 100 ms for sampling rate of 360Hz;
- After the added jitter, it took 128 samples preceding and 127 succeeding the new R-wave position, i.e., 256 samples in total (including the R-wave sample).

Figura 4: Segmentation process when the R-wave position is corrupted with jitter (δ).



- RR Intervals: $f_{RR1}, f_{RR2}, f_{RR_{med}}$ e $f_{RR_{avg}}$
- Morphological: $f_{max}, f_{min}, f_{var}$ e f_{rms} ($L = 256$ samples)
- High order statistics: $f_{kurtosis}$ e $f_{skewness}$

Linear Discriminant (LD):

$$g_k(\mathbf{x}) = \mu_k^T \sum^{-1} \mathbf{x} - \frac{1}{2}\mu_k^T \sum^{-1} \mu_k + \log(P(\omega_k))$$

where:

$k \in \{N, S, V\}$
$\mathbf{x}$: feature vector
μ_k: mean vector*
$\sum$: covariance vector*
$P(\omega_k)$: prior probability**

*Extracted from training data.
**Considered the same for all classes.

RESULTS

All of the metrics were based on measures of true positive (TP^k), false negative (FN), true negative (TN^k), false positive (FP^k), and $k \in \{N, S, V\}$.

$$Se^k = \frac{TP^k}{TP^k + FN^k} \times 100 \qquad \text{(Sensitivity)}$$

$$+P^k = \frac{TP^k}{TP^k + FP^k} \times 100 \qquad \text{(Positive predictive)}$$

$$F_s^k = 2\frac{Se^k(+P^k)}{Se^k + (+P^k)} \qquad \text{(F-score)}$$

Figura 5: Classification performance with diferent values for the added jitter (δ)

δ	Class (N)			Class (S)			Class (V)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V
0	94.5	99.4	96.9	92.5	39.9	55.8	88.6	94.6	91.5
1	94.4	99.4	96.9	92.6	39.9	55.7	88.6	94.6	91.5
2	94.4	99.4	96.9	92.6	39.8	55.7	88.6	94.6	91.5
3	94.4	99.4	96.9	92.5	39.8	55.6	88.6	94.5	91.5
4	94.4	99.4	96.9	92.5	39.7	55.6	88.6	94.5	91.5
5	94.4	99.4	96.9	92.4	39.7	55.5	88.6	94.5	91.5
6	94.3	99.4	96.8	92.2	39.4	55.2	88.6	94.5	91.5
7	94.4	99.4	96.8	92.3	39.5	55.3	88.6	94.5	91.5
8	94.3	99.4	96.8	91.9	39.1	54.9	88.5	94.5	91.4
9	94.3	99.4	96.8	92.0	39.2	55.0	88.6	94.5	91.4
10	94.3	99.4	96.8	92.0	39.2	54.9	88.6	94.5	91.4
11	94.3	99.4	96.8	91.7	38.9	54.6	88.6	94.5	91.4
12	94.2	99.4	96.7	91.5	38.6	54.3	88.5	94.5	91.4
13	94.2	99.4	96.7	91.7	38.7	54.5	88.6	94.5	91.4
14	94.0	99.3	96.6	91.0	38.2	53.8	88.6	93.5	90.9
15	94.1	99.3	96.6	91.1	38.1	53.7	88.5	94.5	91.4
16	94.1	99.3	96.6	91.0	38.0	53.7	88.5	94.5	91.4
17	94.0	99.3	96.6	90.8	37.9	53.4	88.5	94.4	91.4
18	93.7	99.2	96.4	89.7	36.8	52.2	87.9	93.9	90.8

Class S is the one that is more threatened by segmentation errors, varing 7.8% in $+P^S$. The others classes varied 0.8%.

		Predicted			
		N	S	V	Total
Truth	N	41071	2265	145	43481
	S	125	1673	10	1808
	V	108	254	2818	3180
	Total	41304	4192	2973	

Figura 6: Confusion matrix for the proposed classification system for $\delta = 0$.

		Predicted			
		N	S	V	Total
Truth	N	40873	2463	145	43481
	S	178	1619	11	1808
	V	121	265	2794	3180
	Total	41172	4347	2950	

Figura 7: Confusion matrix for the proposed classification system for $\delta = 18$.

Figura 8: Classification performance for RR features with diferent values for the added jitter (δ)

δ	Class (N)			Class (S)			Class (V)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V
0	93.3	99.0	96.1	68.6	37.1	48.1	81.7	63.0	71.1
1	93.3	99.0	96.1	68.7	37.0	48.1	81.6	63.0	71.1
2	93.3	99.0	96.1	68.7	36.9	48.0	81.6	63.0	71.1
3	93.3	99.0	96.1	68.7	36.9	48.0	81.6	63.0	71.1
4	93.3	99.0	96.1	68.7	36.9	48.0	81.5	62.8	71.0
5	93.3	99.0	96.0	69.2	37.0	48.2	81.3	62.9	70.9
6	93.2	99.0	96.0	68.9	36.8	48.0	81.4	62.7	70.8
7	93.2	99.0	96.0	68.7	36.7	47.8	81.3	62.4	70.6
8	93.2	99.0	96.0	68.9	36.7	47.9	81.2	62.3	70.5
9	93.1	99.0	95.9	68.9	36.5	47.7	81.1	61.9	70.2
10	92.9	98.9	95.8	69.3	36.3	47.7	80.9	61.3	69.7
11	92.8	98.9	95.8	69.2	36.3	47.6	80.8	60.7	69.3
12	92.7	98.9	95.7	69.0	36.1	47.4	80.7	60.0	68.8
13	92.5	98.9	95.6	69.1	36.0	47.3	80.5	59.3	68.3
14	92.3	98.9	95.5	69.5	36.0	47.4	80.3	58.2	67.5
15	92.0	98.9	95.3	68.6	35.4	46.7	80.5	56.7	66.5
16	91.7	98.8	95.1	69.9	35.5	47.1	80.0	55.4	65.4
17	91.6	98.9	95.1	69.2	35.4	46.8	80.0	54.5	64.8
18	90.9	98.8	94.7	69.5	34.8	46.4	80.1	52.4	63.3

Class V decreased performance ($Se^V, +P^V$) by 2.0% and 16.8%, respectively.

Figura 9: Classification performance for morphological features with diferent values for the added jitter (δ)

δ	Class (N)			Class (S)			Class (V)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V
0	79.9	98.3	88.2	79.1	14.0	23.7	83.1	92.4	87.5
1	80.0	98.3	88.2	79.1	14.0	23.8	83.2	92.4	87.5
2	80.1	98.3	88.3	79.1	14.1	23.9	83.2	92.4	87.5
3	80.3	98.3	88.4	79.0	14.2	24.0	83.2	92.4	87.5
4	80.6	98.3	88.6	78.8	14.2	24.1	83.1	92.4	87.5
5	80.9	98.3	88.7	78.4	14.4	24.3	83.1	92.4	87.5
6	81.1	98.3	88.9	78.1	14.5	24.4	83.1	92.4	87.5
7	81.5	98.3	89.1	77.7	14.7	24.7	83.0	92.4	87.5
8	81.7	98.3	89.3	77.5	14.8	24.8	82.9	92.5	87.4
9	82.2	98.3	89.5	77.0	15.0	25.1	82.9	92.5	87.4
10	82.5	98.3	89.7	76.6	15.1	25.3	82.8	92.4	87.4
11	82.8	98.3	89.9	76.1	15.3	25.5	82.7	92.4	87.3
12	83.2	98.3	90.1	75.5	15.5	25.7	82.6	92.4	87.2
13	83.5	98.3	90.3	74.9	15.6	25.8	82.5	92.3	87.2
14	84.0	98.2	90.6	73.4	15.7	25.8	82.4	92.3	87.1
15	84.1	98.2	90.6	72.6	15.7	25.7	82.4	92.2	87.0
16	84.4	98.2	90.8	71.1	15.6	25.6	82.4	92.1	87.0
17	84.6	98.1	90.9	69.6	15.5	25.3	82.2	92.0	86.8
18	84.9	98.1	91.0	68.0	15.4	25.1	82.1	91.9	86.7

Class N increase 6.3% in (Se^N), it means the false negatives decreased. Class S decreased 14% (Se^S), and increase 10% ($+P^S$). Class V decreased (Se^V and $+P^V$).

Figura 10: Classification performance for HOS features with diferent values for the added jitter (δ)

δ	Class (N)			Class (S)			Class (V)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V
0	73.0	98.5	83.9	2.2	1.5	1.7	71.1	16.7	27.0
1	73.0	98.5	83.9	2.4	1.6	1.9	71.1	16.7	27.0
2	73.0	98.5	83.9	2.6	1.8	2.1	71.1	16.7	27.0
3	73.0	98.5	83.8	2.9	2.0	2.3	71.1	16.7	27.0
4	72.9	98.5	83.8	3.4	2.3	2.7	71.1	16.7	27.0
5	72.8	98.6	83.8	4.0	2.6	3.2	71.0	16.6	27.0
6	72.7	98.6	83.7	4.9	3.2	3.8	71.1	16.6	26.9
7	72.6	98.6	83.7	6.0	3.8	4.6	71.1	16.6	26.9
8	72.5	98.6	83.6	7.1	4.4	5.4	71.0	16.6	27.0
9	72.4	98.7	83.5	8.3	4.9	6.2	71.1	16.7	27.0
10	72.2	98.7	83.4	9.1	5.3	6.7	71.1	16.7	27.0
11	72.0	98.7	83.2	10.4	5.8	7.4	71.2	16.7	27.1
12	71.8	98.7	83.1	11.4	6.1	7.9	71.1	16.8	27.1
13	71.5	98.7	83.0	12.2	6.2	8.3	71.1	16.8	27.2
14	71.3	98.8	82.8	13.3	6.5	8.8	71.2	16.9	27.3
15	71.1	98.8	82.7	14.1	6.7	9.1	71.2	17.0	27.4
16	70.8	98.8	82.5	15.2	6.9	9.4	71.3	17.0	27.5
17	70.4	98.8	82.2	16.3	6.9	9.7	71.4	17.1	27.6
18	69.8	98.8	81.8	17.0	6.7	9.6	71.4	17.3	27.8

Class N decrease 4.4% in (Se^N). Class S increased both (Se^S and $+P^S$), by 672.7% and 346.7%, respectively. Class V also increased both (Se^V and $+P^V$), by 0.4% and 3.6%, respectively.

Figura 11: Comparison between the proposed methodology and diferent state-of-the-art methods

Work	Class (N)			Class (S)			Class (V)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V
Proposed ($\delta = 0$)	94.5	**99.4**	**96.9**	**92.5**	39.9	55.8	**88.6**	**94.6**	**91.5**
Proposed ($\delta = 18$)	93.7	99.2	96.4	89.7	36.8	52.2	87.9	93.9	90.8
Lin and Yang (2014) [12]	91.6	99.3	95.3	81.4	31.6	45.5	86.2	73.7	79.5
Garcia et. al (2016) [31]	**95.0**	96.5	95.7	29.6	26.4	27.9	85.1	66.3	74.5
Garcia et. al (2017) [32]	94.0	98.0	96.0	62.0	**53.0**	**57.1**	87.3	59.4	70.7

* Values in bold indicate the best result.

Results

Employing DS2 as the training set

Figura 12: Classification perfomance using DS2 for training and DS1 for testing (Opposite to De Chazal's division).

δ	Class (N)			Class (S)			Class (V)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V
0	90.9	97.2	93.9	41.4	13.2	20	72.7	58	64.5
18	90.5	97.1	93.7	42.1	12.8	19.7	72.5	57.7	64.3

There is a considerable decrease regarding the metrics, especially for class S.

Results

Employing DS2 as the training set

		Predicted N	Predicted S	Predicted V	Total
Truth	N	40983	2236	1882	45101
	S	446	379	90	915
	V	756	264	2720	3740
	Total	42185	2879	4692	

Figura 13: Confusion matrix using DS2 for training and DS1 for testing for $\delta = 0$.

		Predicted N	Predicted S	Predicted V	Total
Truth	N	40846	2360	1895	45101
	S	450	376	89	915
	V	791	242	2707	3740
	Total	42087	2978	4691	

Figura 14: Confusion matrix using DS2 for training and DS1 for testing for $\delta = 18$.

Figura 15: Classification performance using Leave-one-out cross-validation (LOPOCV) approach

δ	Class (N)			Class (S)			Class (V)		
	$\mathbf{Se^N}$	$\mathbf{+P^N}$	$\mathbf{F_s^N}$	$\mathbf{Se^S}$	$\mathbf{+P^S}$	$\mathbf{F_s^S}$	$\mathbf{Se^V}$	$\mathbf{+P^V}$	$\mathbf{F_s^V}$
0	91.7	98.2	94.8	73.5	25.5	37.8	78.5	71.6	75.4
18	91.0	98.0	94.4	72.1	23.6	35.6	78.7	70.8	74.5

There are some metrics decreased, but is not significant as reported in the former alternative evaluation approach (DS2 for training and DS1 for testing). The highest variation was 7.4% for the class S ($+P^V$).

Results

Leave-one-out cross-validation (LOPOCV) approach

		Predicted			
		N	S	V	Total
Truth	N	81203	5295	2084	88582
	S	627	2001	95	2723
	V	859	559	5502	6920
	Total	82689	7855	7681	

Figura 16: Confusion matrix using Leave-one-out cross-validation (LOPOCV) approach for $\delta = 0$.

		Predicted			
		N	S	V	Total
Truth	N	80611	5826	2145	88582
	S	662	1964	97	2723
	V	945	532	5443	6920
	Total	82218	8322	7685	

Figura 17: Confusion matrix using Leave-one-out cross-validation (LOPOCV) approach for $\delta = 18$.

Figura 18: Comparison between the proposed methodology and diferent state-of-the-art methods that uses four classes: N, S, V, and F.

Work	Class (N)			Class (S)			Class (V)			Class (F)		
	Se^N	$+P^N$	F_s^N	Se^S	$+P^S$	F_s^S	Se^V	$+P^V$	F_s^V	Se^F	$+P^F$	F_s^F
Proposed ($\delta = 0$)	79.2	**99.6**	88.2	**92.2**	39.7	55.0	87.2	**92.8**	89.9	81.4	4.6	8.6
Proposed ($\delta = 18$)	77.9	99.4	87.3	90.6	36.9	52.5	87.2	92.6	89.8	81.4	4.4	8.3
De Chazal et al. (2004) [8]	86.9	99.2	92.6	75.9	38.5	51.1	77.7	81.6	79.6	89.4	8.6	15.7
Zhang et al. (2014) [11]	88.9	99.0	93.7	79.1	36.0	49.5	85.5	92.7	89.0	**93.8**	13.7	23.9
Shi et al. (2019) [9]	**92.1**	99.5	**95.7**	91.7	**46.2**	**61.4**	**95.1**	88.1	**91.5**	61.6	**15.2**	**24.4**

* Values in bold indicate the best result.

Results

Including the Fusion beat class (F)

		Predicted				
		N	S	V	F	Total
Truth	N	34629	2217	140	6495	43481
	S	98	1651	8	51	1808
	V	58	224	2775	123	3180
	F	16	1	56	314	387
	Total	34801	4093	2979	6983	

Figura 19: Confusion matrix including the Fusion beat class (F) for $\delta = 0$.

		Predicted				
		N	S	V	F	Total
Truth	N	34216	2432	142	6691	43481
	S	141	1616	9	42	1808
	V	81	255	2752	92	3180
	F	15	1	59	312	387
	Total	34453	4304	2962	7137	

Figura 20: Confusion matrix including the Fusion beat class (F) for $\delta = 18$.

CONCLUSION

Conclusion

1. Authors:
   - The proposed method achieves competitive results when comparing with other state-of-the-art techniques.
   - The approach is feasible to be applied in real scenarios where noise, errors in the detection of the R-wave, and the inter-patient paradigm are present.
2. Critics:
   - Results were shown in details;
   - The proposed method is reproducible;
   - The best results were obtained using $\delta = 0$.
   - The proposed method has not been evaluated with all minority classes (F, Q).

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