



# Low-complexity detection of atrial fibrillation in continuous long-term monitoring

Biomedical Signal Processing | 2024 - 2025

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# Introduction

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- For long-term monitoring, non-invasive techniques are required;
- non-invasive methods → small devices must be used, but they have some limitations:
  - limited battery life;
  - limited computational power.
- The proposed algorithm aims to overcome these constraints.



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## 2 The algorithm

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# Introduction

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- uses a few mathematical operators;
- ignores:
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- employs a short window for detection
  - no need to use a large buffer.



# Pipeline of the algorithm

## 2 The algorithm

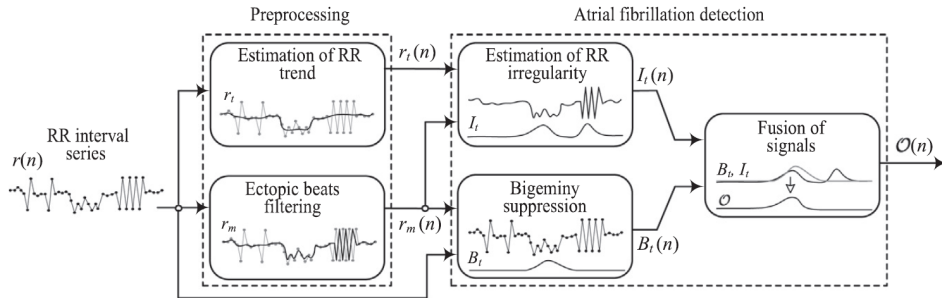


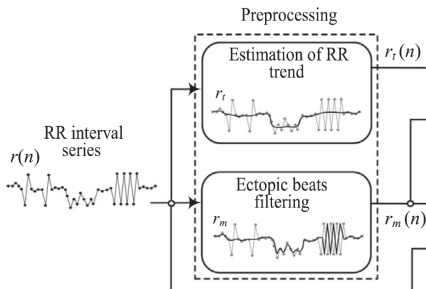
Figure: Block diagram of the algorithm [1]



# Preprocessing - Filters

## 2 The algorithm

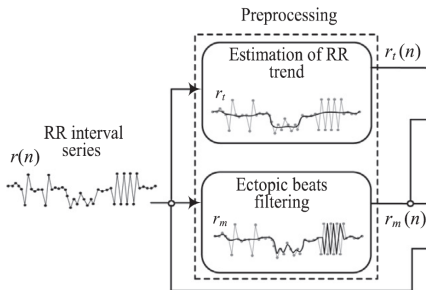
The series is filtered with:





# Preprocessing - Filters

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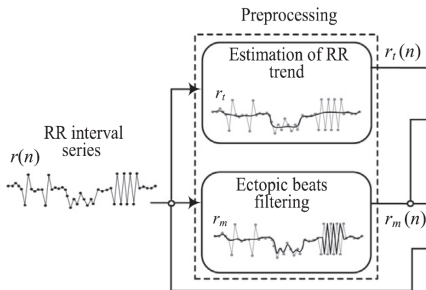
- 3-point Median Filter  $\rightarrow$  reduce the influence of ectopic beats and outlier intervals

$$r_m(n) = \text{median}\{r(n-1), r(n), r(n+1)\};$$



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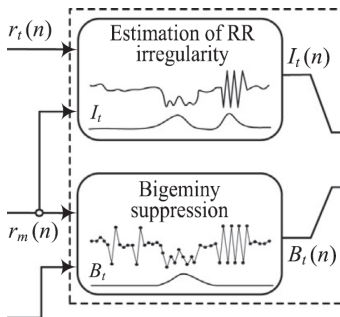
- Exponential Average  $\rightarrow$  estimate the RR trend

$$r_t(n) = r_t(n-1) + \alpha(r(n) - r_t(n-1)).$$



# Atrial Fibrillation detection - Estimation of RR irregularity and Bigeminy suppression

## 2 The algorithm



- Estimation of RR irregularity:

$$M(n) = \frac{2}{N(N-1)} \sum_{j=0}^{N-1} \sum_{k=j+1}^N H(|r(n-j) - r(n-k)| - \gamma)$$

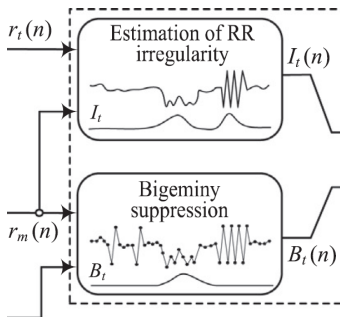
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- Suppression of bigeminy events

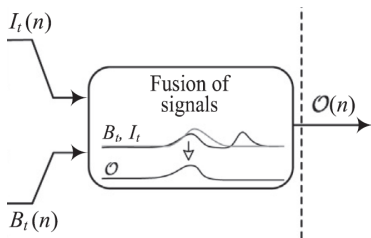
$$B(n) = \left( \frac{\sum_{j=0}^{N-1} r_m(n-j)}{\sum_{j=0}^{N-1} r(n-j)} - 1 \right)^2$$

then filtered with exponential average.



# Atrial Fibrillation detection - Merge and detection

## 2 The algorithm



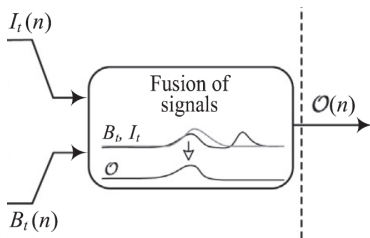
- Final series is obtained by merging:
  - the irregularity detection series;
  - the bigeminy-suppressed series;

$$O(n) = \begin{cases} I_t(n), & B_t(n) \geq \delta \\ B_t(n), & B_t(n) < \delta. \end{cases}$$



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- Atrial Fibrillation is detected where signal exceeds a threshold  $\eta$ .



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## Dataset used

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Performance evaluation using the LTAF Database from PhysioNet, composed by 84 signals.



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Each signal:

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Performance evaluation using the LTAF Database from PhysioNet, composed by 84 signals. Each signal:

- is a recording typically from 20-24 hours;
- contains atrial fibrillation events of varying durations;
- includes rhythm classifications → AFIB label indicates atrial fibrillation.

Record	N	SVTA	VT	AFIB	B	T	IVR	AB	SBR
00	5 (18:31:31)	-	40 (0:42)	44 (2:14:54)	-	-	-	-	-
01	457 (3:38:53)	25 (0:58)	-	53 (16:13:06)	16 (1:46)	6 (0:53)	-	293 (27:36)	83 (10:02)
03	1648 (14:56:49)	11 (0:32)	2 (0:03)	22 (1:20:03)	2 (0:13)	1 (0:14)	-	34 (4:53)	1587 (7:52:53)
05	14 (24:17:02)	2 (0:05)	-	3 (0:40)	-	-	-	8 (0:29)	-
06	48 (24:22:27)	16 (0:29)	-	19 (45:04)	-	-	-	11 (0:44)	1 (0:01)
07	499 (21:25:26)	28 (1:21)	-	8 (3:24:47)	416 (33:44)	1 (0:07)	-	51 (4:27)	-
08	20 (25:42:48)	13 (0:17)	-	4 (1:38)	1 (0:04)	-	-	1 (0:04)	-
10	148 (8:23:01)	68 (3:35)	-	80 (17:07:44)	-	-	-	1 (0:05)	-

Figure: Table of rhythms [2]



# Measurements

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- Algorithm executed with values suggested by the reference paper ( $\alpha = 0.02, \gamma = 0.03, N = 8, \delta = 2e^{-4}, \eta = 0.725$ );



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  3. computation of performance metrics.



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- after the execution of the algorithm:
  1. generation of an array for AF predictions;
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for each signal.





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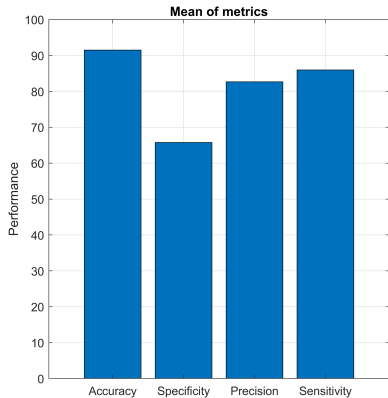
## 4 Results

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# Overall results

4 Results

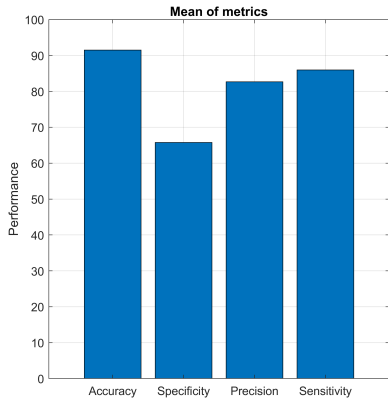


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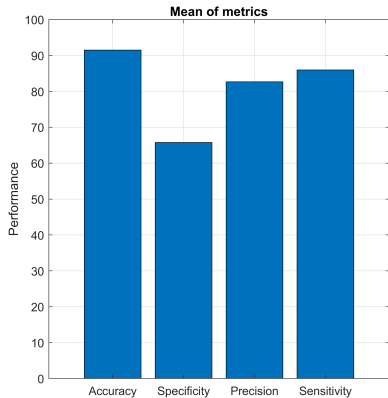
Overall:

- Mean of accuracy  $\approx 92\%$



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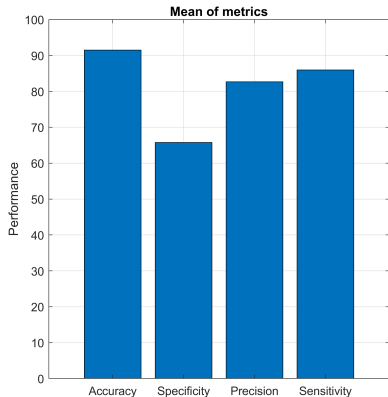
Overall:

- Mean of accuracy  $\approx 92\%$ 
  - 56 signals result with accuracy  $> 96\%$ ;



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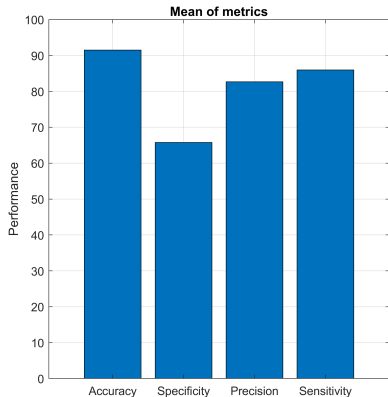
Overall:

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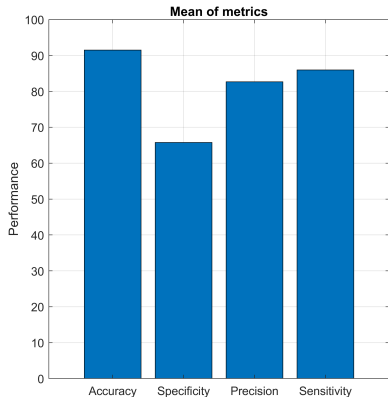
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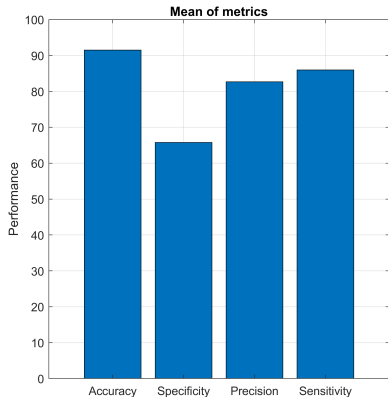
Overall:

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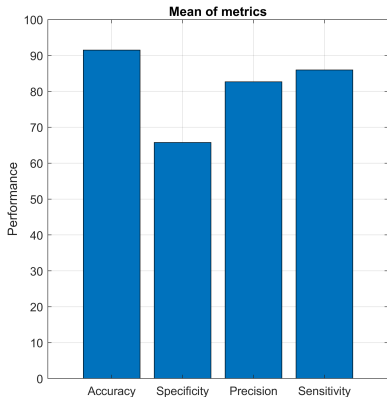
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  - 56 signals result with accuracy  $> 96\%$ ;
- Mean of precision  $\approx 83\%$ 
  - influenced by misclassifications;
- Mean of sensibility  $\approx 86\%$
- Mean of specificity  $\approx 66\%$ 
  - strongly lowered by false positives in long AF events.



# Lacks of precision and sensibility

4 Results

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# Lacks of precision and sensibility

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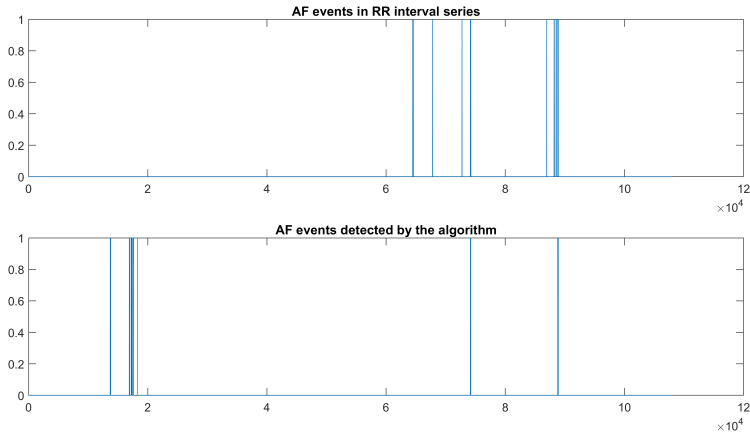
Lacks of precision and sensibility are caused by:

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- changes in the heart's rhythm:
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    - (algorithm removes only ectopic beats and bigeminy events);
  - they could be wrongly classified as AF.



$\alpha = 0.02$  of signal 19

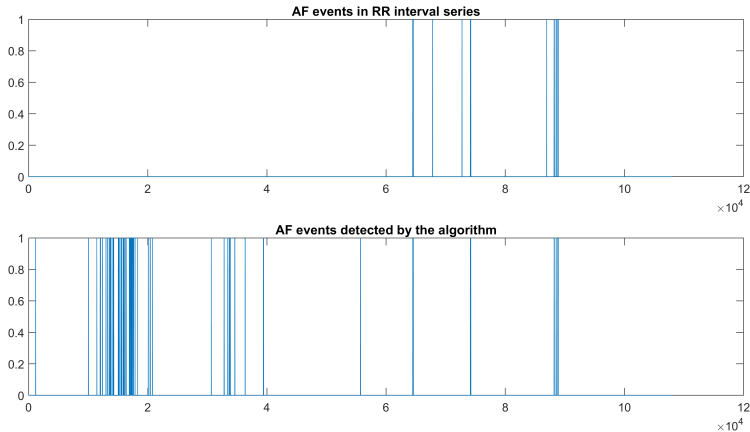
4 Results





# $\alpha = 0.06$ on signal 19

4 Results





# Low mean of specificity

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- Low values detected most in long AF events
  - specificity values were close to zero;
  - algorithm does not detect short pauses of no-AF;
- other metrics remain with high values;
- without them, specificity  $\approx 86\%$ .





# Low mean of specificity

## 4 Results

Signal	Accuracy	Precision	Sensibility	Specificity	Percentual_of_AF_in_the_signal
11	99,92	100	99,93	0	99,31
20	99,84	100	99,84	0	99,94
25	98,5	98,5	100	0	98,35
33	98,78	98,91	99,87	0	98,96
34	99,89	99,98	99,91	0	99,92
43	99,94	99,99	99,95	0	99,97
44	99,95	99,99	99,95	0	99,96
48	99,97	99,97	100	0	99,96
60	99,96	100	99,96	0	98,95
62	99,87	99,87	100	0	99,83
65	93,85	100	93,86	0	99,59
68	99,92	99,99	99,94	0	99,69
103	59,66	59,68	99,96	0	51,87
203	98,23	99,97	98,26	0	99,91
204	98,58	98,63	99,94	0	98,33
206	99,98	99,98	100	0	99,15
207	99,86	99,91	99,95	0	99,26

Figure: Signals where specificity = 0

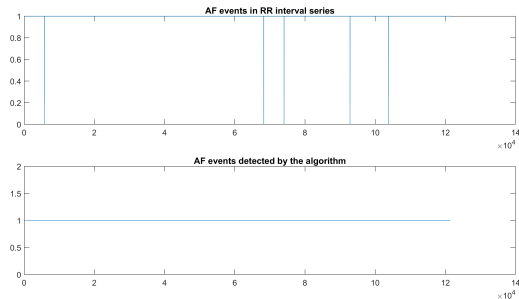


Figure: Ground truth and prediction of signal 206



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# Conclusions

## 5 Conclusions

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- ✗ has worse performance in the presence of short AF events;



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- ✗ misclassifications occur on changes of rhythm;



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The proposed algorithm:

- ✗ has worse performance in the presence of short AF events;
- ✗ misclassifications occur on changes of rhythm;
- ✓ efficiently detects long AF events with good results.



## References

### 6 Conclusions

- [1] Andrius Petrėnas, Vaidotas Marozas, and Leif Sörnmo. “Low-complexity detection of atrial fibrillation in continuous long-term monitoring”. In: *Computers in Biology and Medicine*, 65 (2015), pp. 184–191.
- [2] PhysioNet. *Tables of beats and rhythms*. URL: <https://physionet.org/files/ltafdb/1.0.0/tables.shtml>.