Context-based adaptive QRS clustering in real-time

Doctoral Meeting initiative (CITIUS)

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Universidade de Santiago de Compostela

Doctoral Meeting - November 15, 2013

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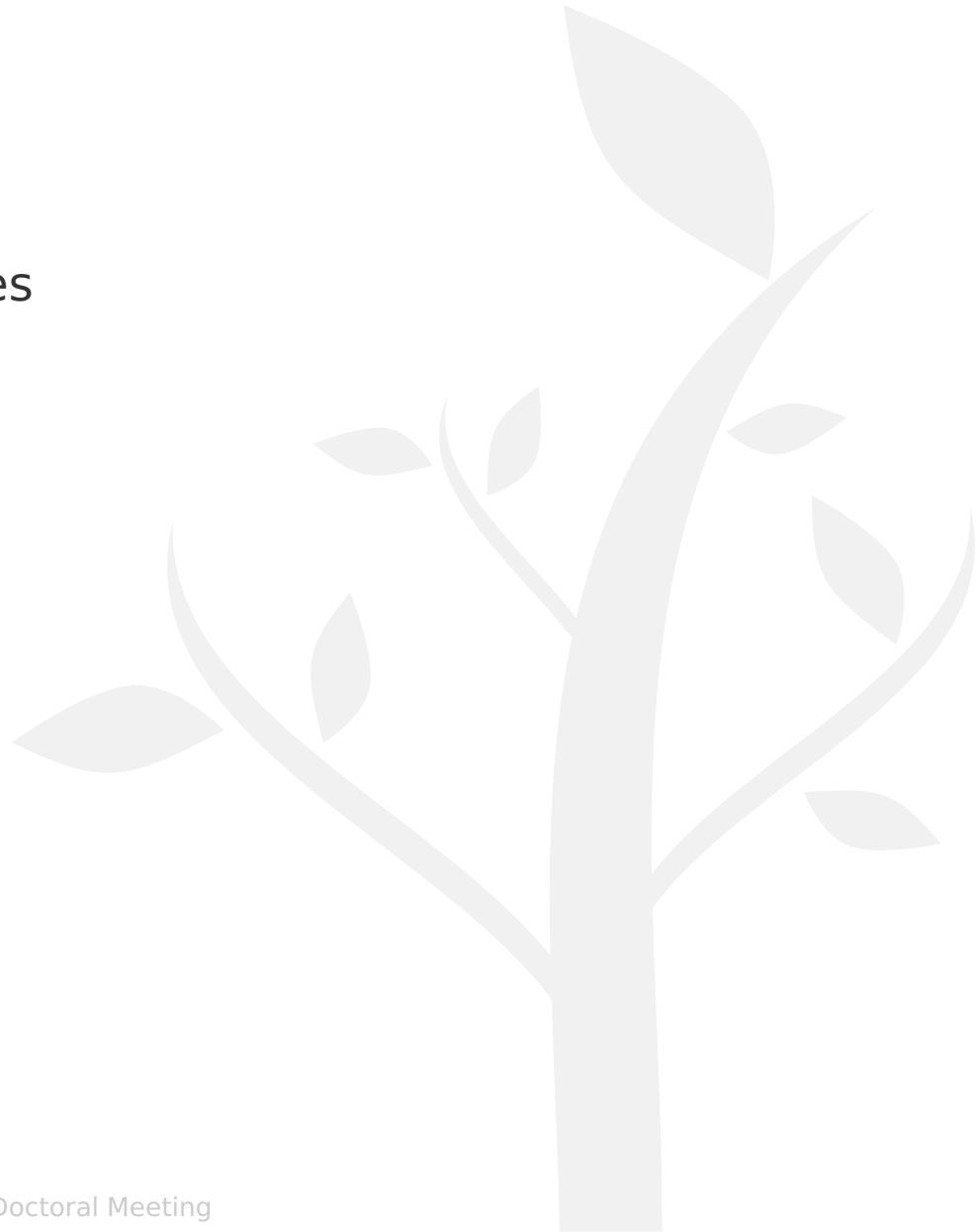
Outline



Outline

Cardiovascular diseases

Key facts (from WHO, March 2013)

- CVDs are the number one cause of death globally: more people die annually from CVDs than from any other cause
- An estimated 17.3 million people died from CVDs in 2008.
- An estimated 80 % of these deaths were due coronary heart disease or due to stroke.

- These kind of diseases affect the normal heart function, so monitoring the heart condition is a key tool for its diagnosis.

Arhythmias

Cardiac arrhythmias are relevant signs present in a almost all CVDs.

Arrhythmia

"Arrhythmia" refers to any change from the normal sequence of activation and conduction of electrical impulse of a heartbeat.

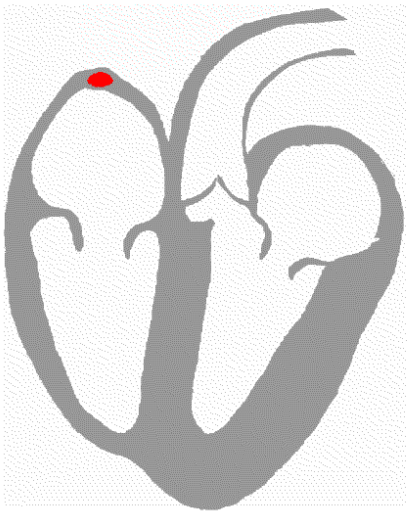
- There are two main sources of arrhythmias:
  - Automatism disorder.
  - Conduction disorder.

Electrocardiogram

- The electrocardiogram (ECG) is invaluable tool for arrhythmia detection.
- ECG is a widespread, inexpensive and non-invasive test that can be performed in an ambulatory context.

Electrocardiogram

- The ECG is the recording of the electrical activity of the heart as detected by electrodes attached to the surface of the skin.



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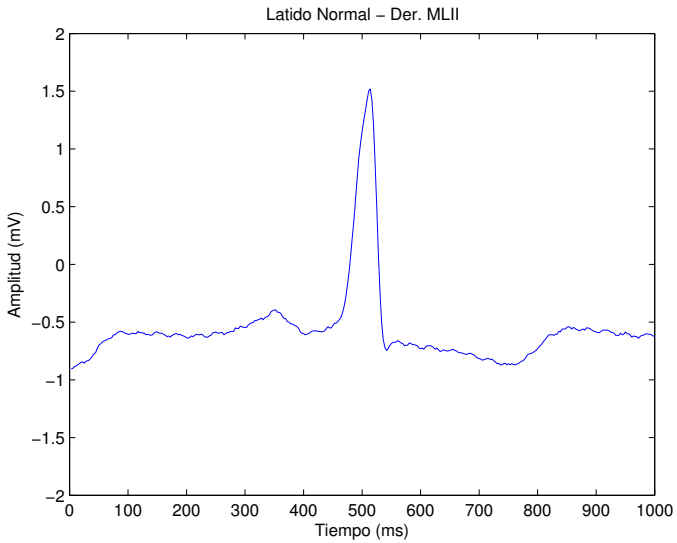
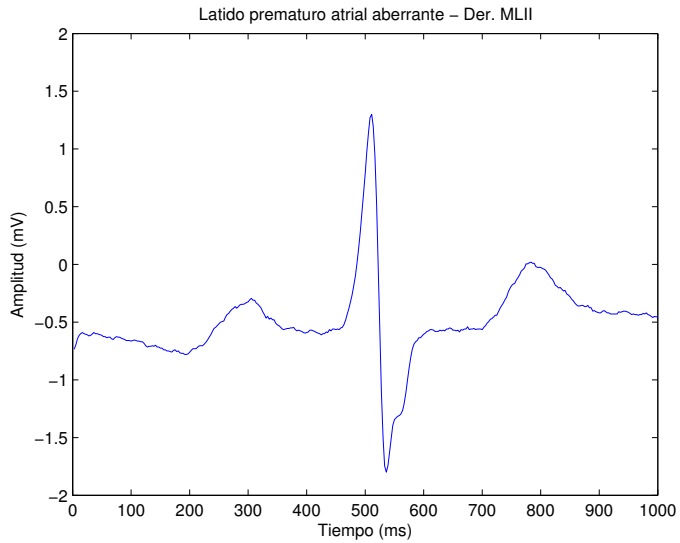
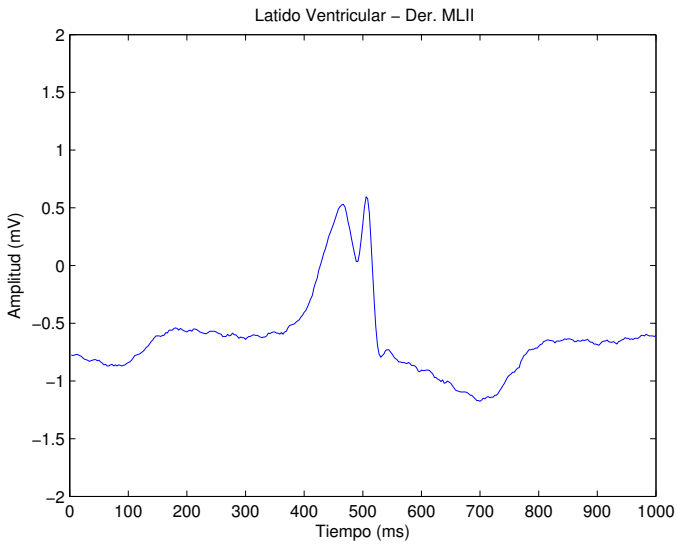
- Each electrode provides a signal lead with different projections of the electric field generated inside the heart.
- The beat morphology in the ECG depends on:
  - Observed lead.
  - Body position.
  - Activation point.
  - Propagation pathway.

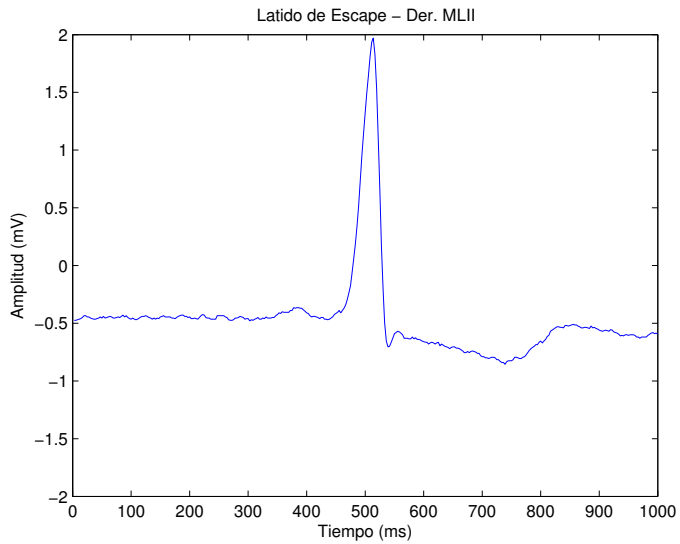
Electrocardiogram

Beat morphologies with different activation points.



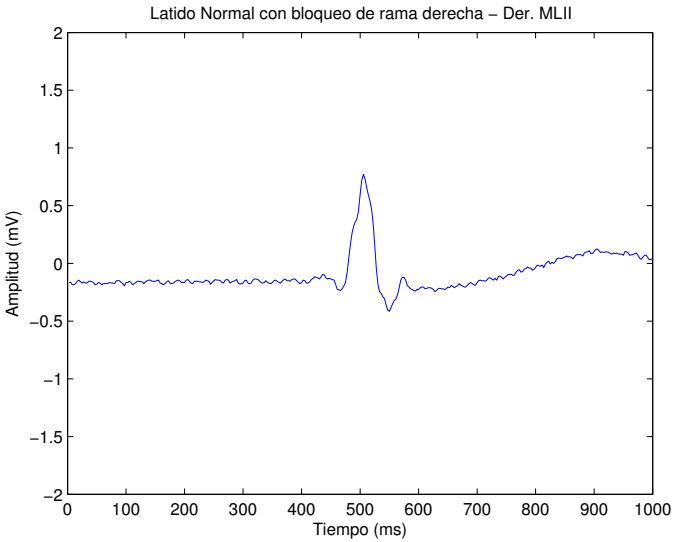


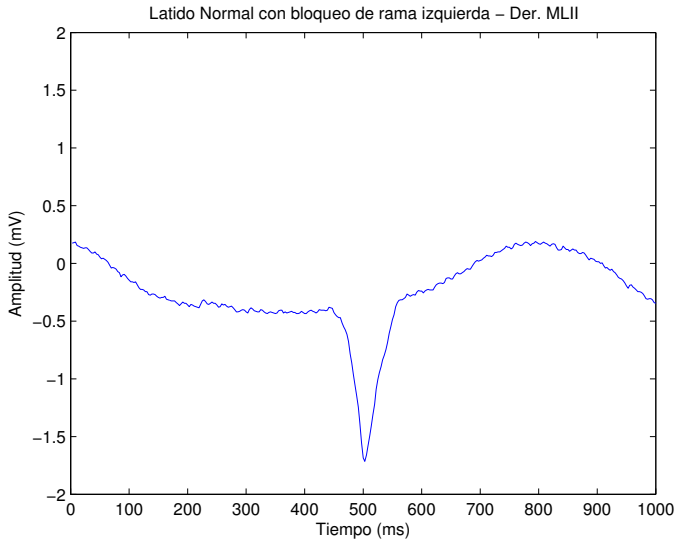


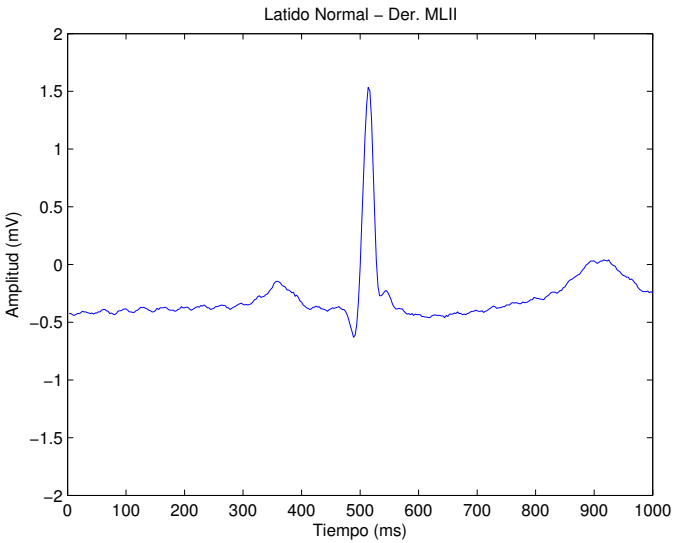


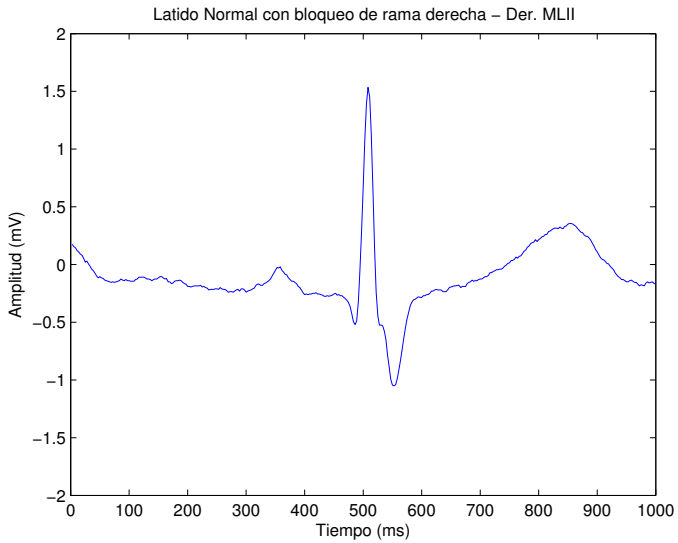
Electrocardiogram

Beat morphologies with atrial activation and conduction disorder.

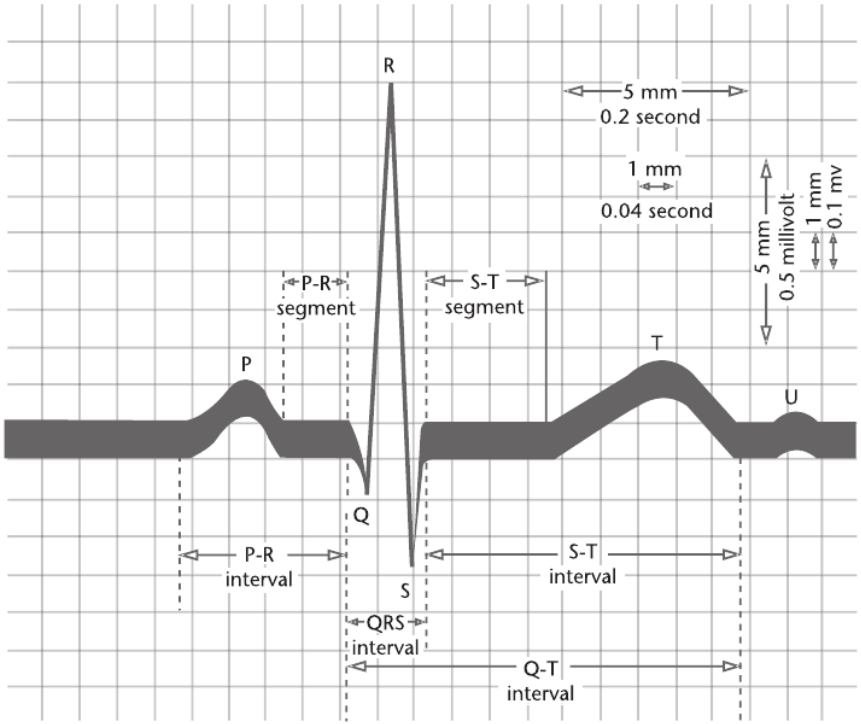








Electrocardiogram



- The normal cardiac cycle comprises a set of stages with a correspondence in the ECG:
  - Atrial depolarization
    - P wave
  - AV node delay
    - PQ segment
  - Atrial repolarization + Ventricular depolarization
    - QRS complex
  - Ventricular repolarization
    - T wave

Definition of the problem

- Arrhythmias have effect on the ECG, affecting the beat morphology and/or beat rhythm.
- ECG review is a time consuming and error prone task.
- Specially in case of long ambulatory ECG recordings.
  - Intermitent arrhythmias.
  - Patients at risk.
- Ambulatory ECG recordings have a high noise level.
- Response time may be critical but offline processing is performed.

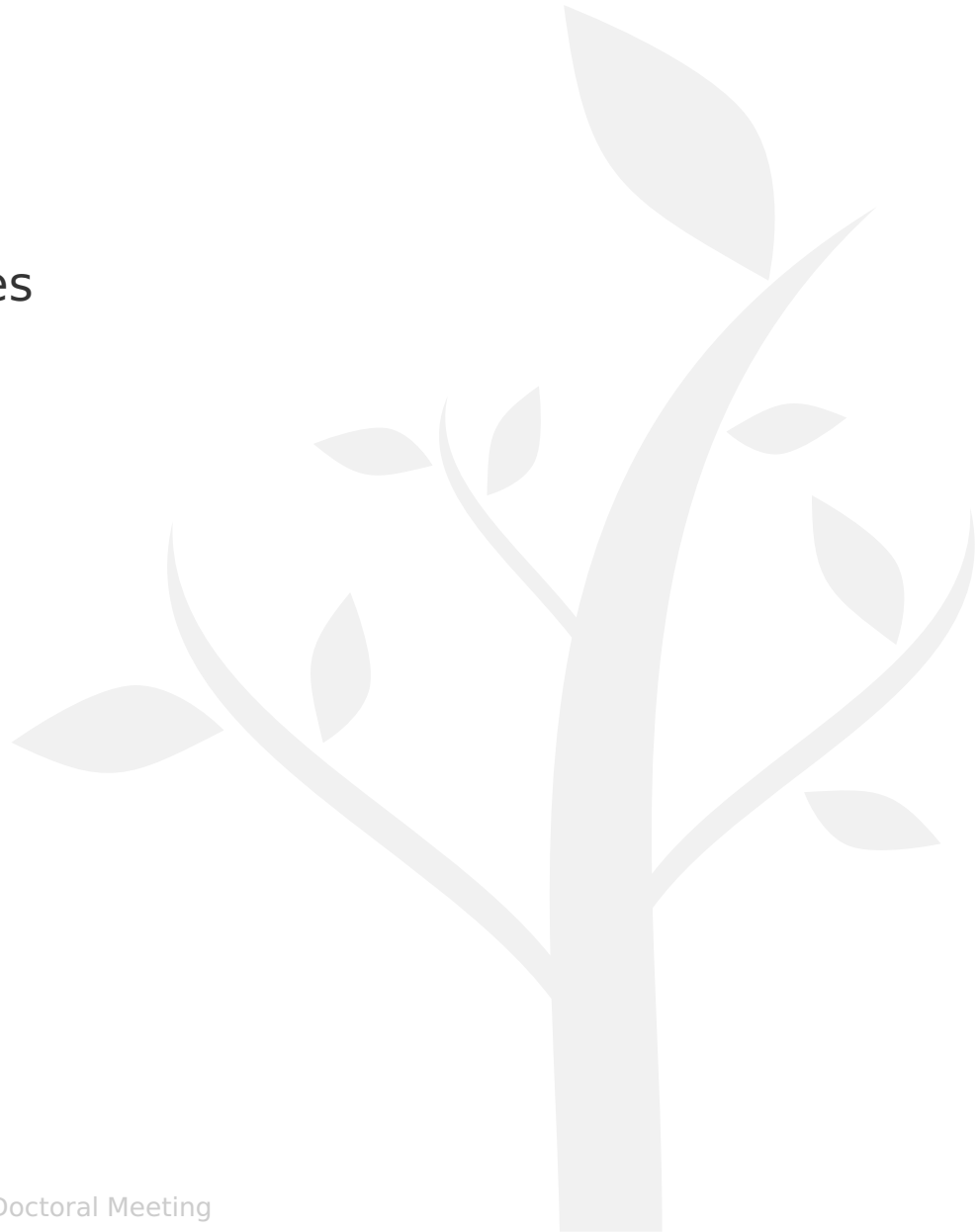
Definition of the problem

How can we help?

We will focus on arrhythmias that alter QRS morphology.

- Providing the beat morphologies present in a recording greatly reduce the revision time and also reduce the time to diagnosis.
- Showing the morphology evolution can also help in diagnosis.
- The real-time availability of beat morphologies can help to a timely detection of relevant events and reduce the response time.
- Promediated beats greatly reduce the noise making the identification of beat types easier for the cardiologist.

Outline



Research Hypotheses

- There is a low number of conduction pathways for the heartbeat.
- Ambulatory ECG has a high level of noise.
  - The parameters measured from individual beats are inaccurate.
  - P wave is often hidden by noise.
- QRS morphologies can evolve over time.
- QRS morphologies suffers from a high variability.
  - Intra-person and inter-person variability.
- The relevance of the differences between QRS morphologies depends not only on its magnitud but also on its location in the QRS waves.

Research Objectives

Objectives

Desing and develop a real-time method to group the QRS morphologies present in a recording up to any given time. This method should:

- obtain the set of different morphologies present in a recording.
- minimize the number of duplicated morphologies.
- allow a dynamic number of different QRS morphologies.
- not limit the number of morphologies to be detected.
- be robust to noise.
- capture the temporal evolution of QRS morphologies.

State-of-the-art

- Nowadays, much effort concentrated on supervised classification.
- All clustering approaches shared the same characteristics.
  - Offline clustering
  - Static clustering
  - Number of clusters is limited apriori.
- Limitations of existent approaches:
  - Do not capture the temporal evolution of morphologies.
  - Do not analyze the morphologies in their temporal context.
  - Rare morphologies can be ignored.

Outline

Methodology

- Our main objective is to develop an algorithm to cluster QRS of **detected** beats. $\Rightarrow$ Premise: Beat detection is already solved.
- Signal conditioning:
  - ECG signal is contaminated by noise from several sources:
    - Baseline wandering.
    - EMG noise.
    - Motion artifacts.
    - Powerline interference.
  - We focused on baseline wandering as the main source of distortion of QRS morphology.

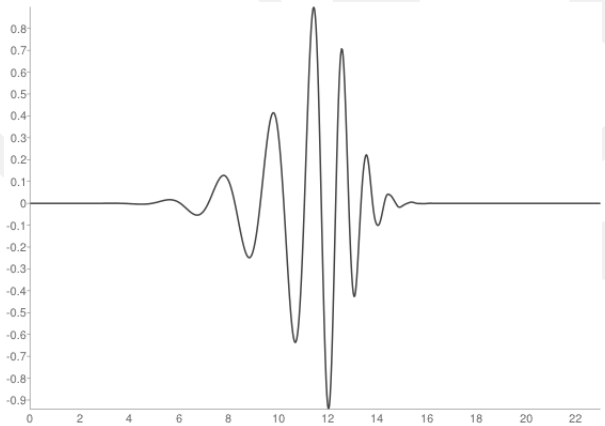
Baseline wandering

- The frecuency spectra of ECG and noise are usually overlaped.
  - Frequency domain filters require very low cutoff frequency
- We use the Discrete Wavelet Transform (DWT)
  - Time-frequency transform
  - Better spatial localization in high frequencies than Fourier transform.
  - Good frequency localization in low frequency components.

- Calculation:
  - Convolution with discrete wavelets.

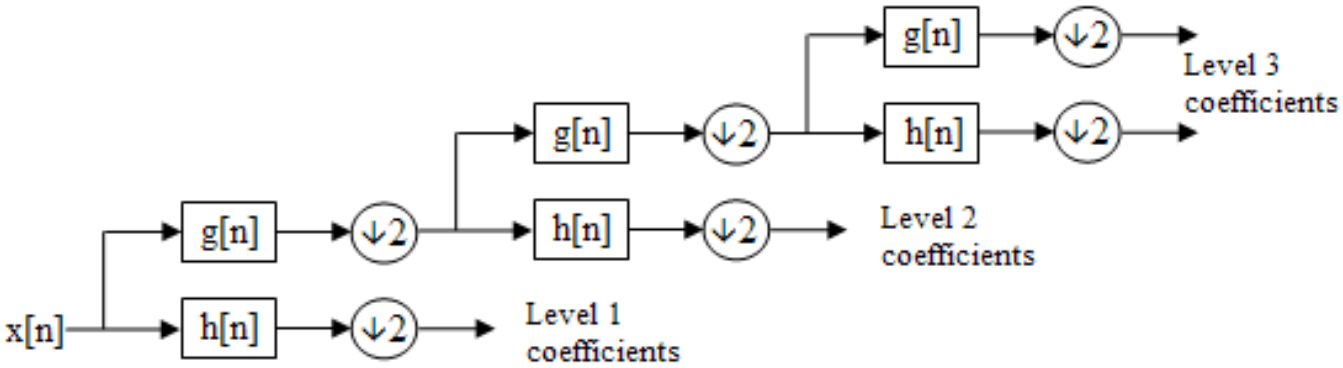
$$approx[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

$$detail[n] = (x * h)[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k]$$

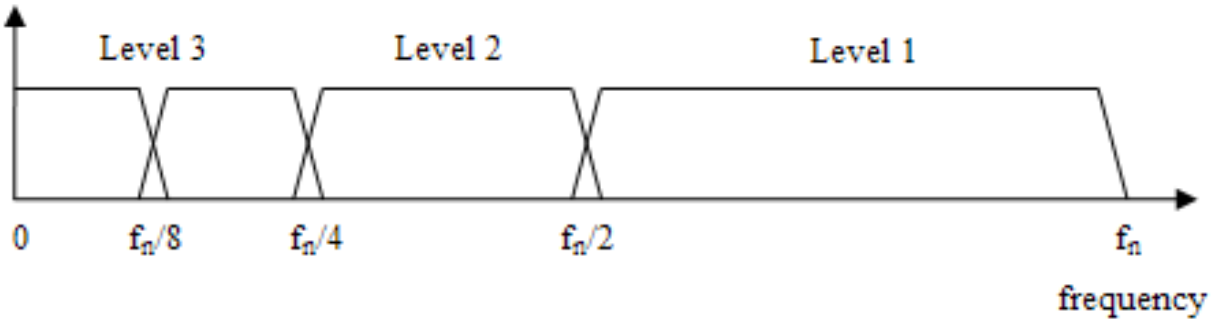


Baseline wandering

- Iterative application of DWT



- Frequency spectrum for each DWT decomposition level.

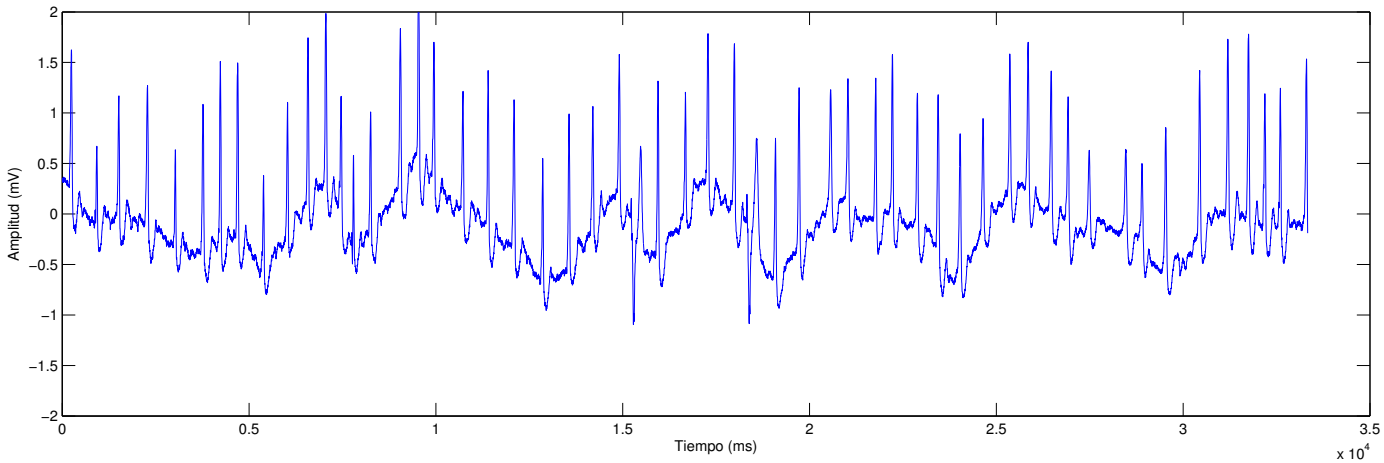


Baseline wandering

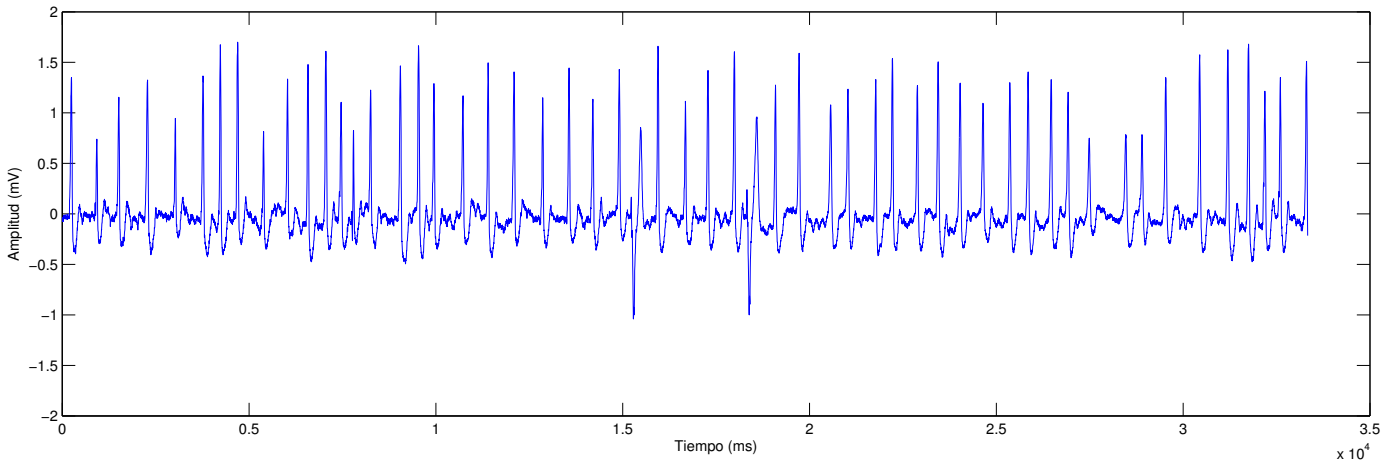
- Remove the first band below 0.70Hz.
- Implementation using Quadrature mirror filters.
  - Non causal symmetric filters.
  - Finite delay (21 samples per level).
  - Allows online execution.

Baseline wandering

- Sample ECG segment with baseline wandering ($Fs = 360Hz$)



- Baseline removed using DWT (8 level decomposition).



QRS clustering

- We propose a dynamic clustering method.
  - Clusters can be created, merged or modified during the recording.
- Let C denote a time series $C = \{C_1, C_2, \ldots, C_n, \ldots\}$
  - $C_n = \{C_n^c \mid 1 \leq c \leq N_n\}$: set of clusters at beat n.
    - Represent those QRS morphologies appeared from the begining of the recording up to beat n.
  - C_n^c is the set of beats assigned to the cluster c at beat n
  - N_n number of clusters at beat n

QRS characterization

- Let $S = \{\boldsymbol{s}_t \mid \boldsymbol{s}_t \in \mathbb{R}^L\}$ denote a time series which represents the multilead ECG signal, where L is the number of leads and $\boldsymbol{s}_t = (s_t^1, \ldots, s_t^L)$ is the vector of samples at time t for all leads.
- The nth beat (with fiducial mark at time t) is represented by a fixed-length subsequence of w samples (w^- before and w^+ after t)
  - $\boldsymbol{q}_n^l = \{q_1^l, \ldots, q_j^l, \ldots, q_w^l\}$
- Let $\mathcal{K}$ denote the **curvature** at $q_j \in \boldsymbol{q}_n$ where $2 \leq j \leq w-1$:
  - $\mathcal{K}(q_j, \boldsymbol{q}_n) = \max_{i \in I_j^-, k \in I_j^+} \cos \widehat{q_i q_j q_k}$
- We define the **support region** of q_j as $support(q_j) = [r^-, r^+]$
  - $r^- = \min\left(\arg\max_{i \in I_j^-} \cos \widehat{q_i q_j q_k}\right)$ for any fixed $k \in I_j^+$
  - $r^+ = \max\left(\arg\max_{k \in I_j^+} \cos \widehat{q_i q_j q_k}\right)$ for any fixed $i \in I_j^-$

QRS characterization

- We define the set of **dominant points** of $\boldsymbol{q}_n$ as:

$$D_n = \{p_j \,|\, p_j = q_j \wedge q_j \in \boldsymbol{q}_n \wedge j = \underset{a \in support(q_j)}{\arg\max}\ \mathcal{K}(q_a, \boldsymbol{q}_n)\}$$

- And the set of **relevant points** as:

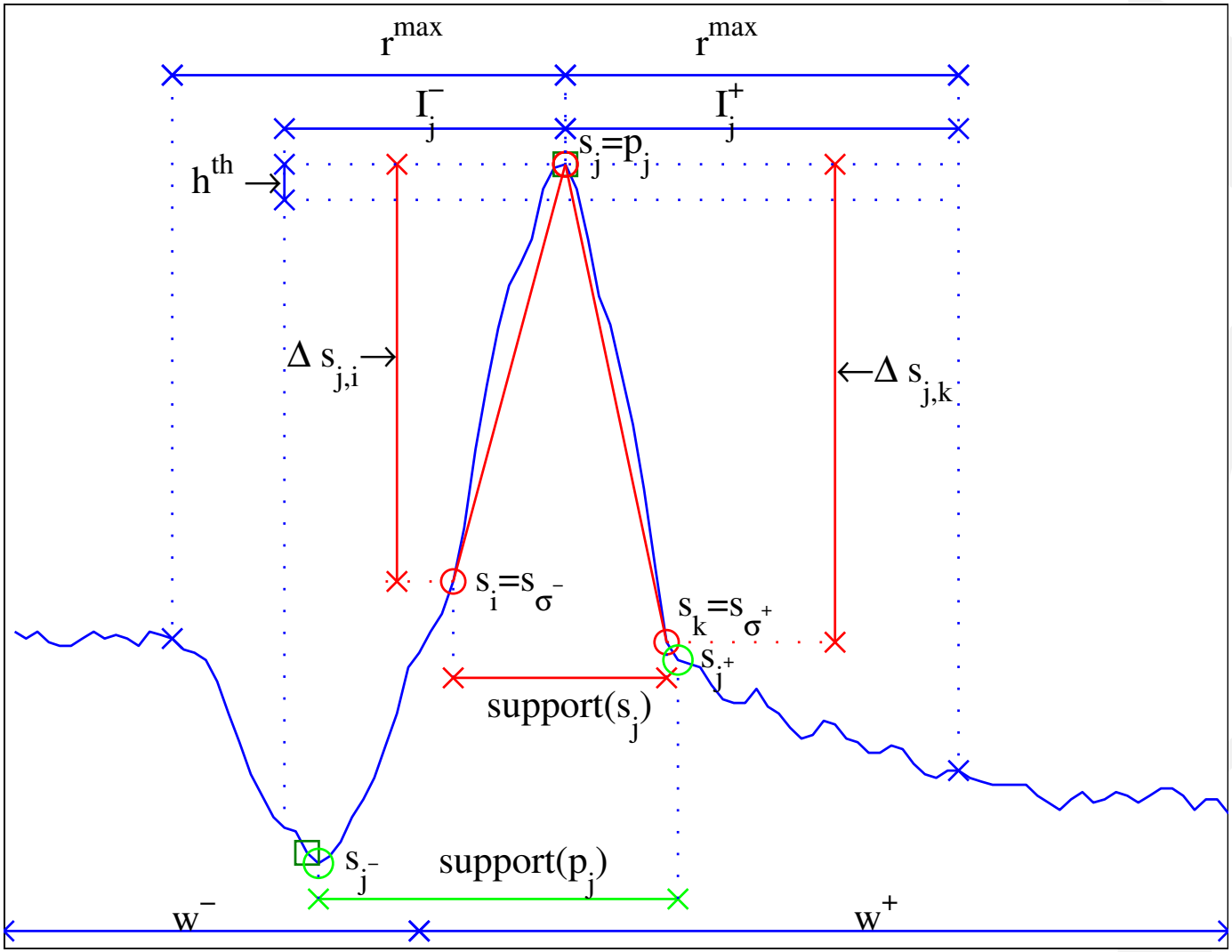
$$R_n = \{p_j \,|\, p_j \in D_n \wedge \Delta q_j > \rho_{QRS}\}$$

where $\Delta q_j = \min(|q_j - q_{r^-}|, |q_j - q_{r^+})$

- The support region for the p_j is redefined as: $support(p_j) = [j^-, j^+]$.
  - $j^- < r^-$ and $j^+ > r^+$ are the sample number nearest to r^- and r^+ where slope sign changes.

QRS characterization

- Relevant points detection.



QRS characterization

- The nth beat is represented by: $B_n = < \boldsymbol{q}_n, P_n >$
  - where $P_n = \{(p_j, support(p_j)) \,|\, p_j \in R_n\}$.
- Each cluster C^c_{n-1} is represented by: $T^c_{n-1} = < \boldsymbol{q}^c_{n-1}, P^c_{n-1} >$
  - $\boldsymbol{q}^c_{n-1} = \{q^c_1, \ldots, q^c_w\}$ is derived from the QRS of its assigned beats.
  - P^c_{n-1} is the set of dominant points and support regions of $\boldsymbol{q}^c_{n-1}$.

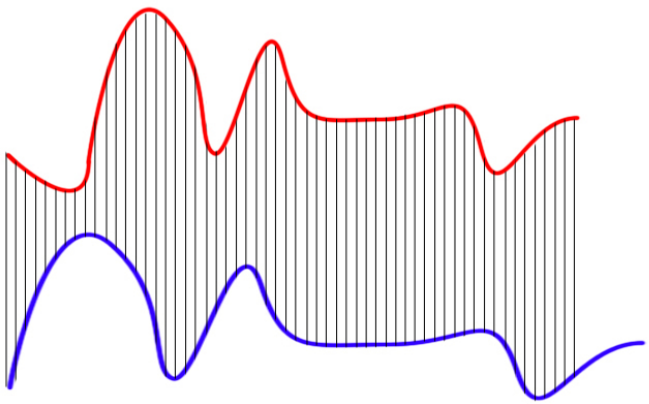
QRS alignment

- Before comparing a beat B_n and a template T^c_{n-1}, they must be temporally aligned.
- We use **derivative Dynamic Time Warping** (dDTW)
  - Nonlinear alignment technique.
  - Corrects misplaced fiducial marks
  - Reduces the differences caused by the height and width variability of the QRS.
- DTW provides a relation $\boldsymbol{m} = (m_1, \ldots, m_K)$ between $\boldsymbol{q}_n$ and $\boldsymbol{q}^c_{n-1}$.
- $\boldsymbol{m}$ is called a **warping path**.
  - $m_k = (x_k, y_k) \in [1,w] \times [1,w], k \in [1,K]$ and $K \geq w$
  - $x_k \in \boldsymbol{q}$ and $y_k \in \boldsymbol{q}^c_{n-1}$

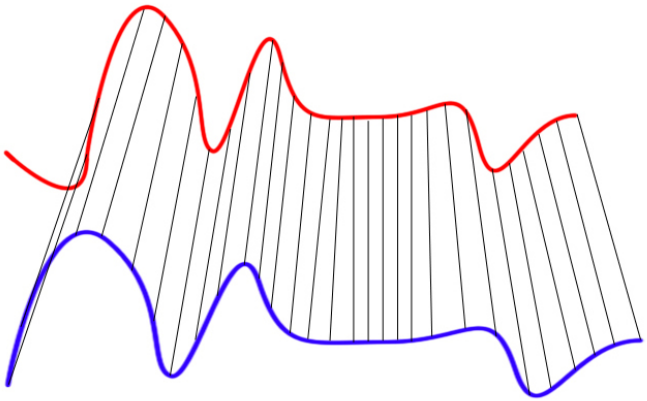
QRS alignment

- The warping path must fulfill three conditions:
  - $m_1 = (1,1)$ and $m_K = (w, w)$
  - $x_i \leq x_k$ and $y_i \leq y_k \ \forall i < k$
  - $m_{k+1} - m_k \in \{(1,1), (1,0), (0,1)\}$
- A cost function is defined: $\mathcal{G}(\boldsymbol{m}) = \sum_{k=1}^{K} \mathcal{G}_l(x_k, y_k)$
  - $\mathcal{G}_l(x, y) = |\dot{q}_x - \dot{q}^c_y|$ is the local cost function associated to each element of $\boldsymbol{m}$
- The derivative is approximated by the first difference.
  - $\dot{\boldsymbol{q}}_n = (\dot{q}_1, ..., \dot{q}_{w-1})$ and $\dot{\boldsymbol{q}}^c_{n-1} = (\dot{q}^c_1, ..., \dot{q}^c_{w-1})$
  - $\dot{q}_x = q_{x+1} - q_x$ and $\dot{q}^c_y = q^c_{y+1} - q^c_y$.
- The optimal warping path is the one that minimizes $\mathcal{G}$.
- We obtain a new aligned signals $\widehat{\boldsymbol{q}}_n$ and $\widehat{\boldsymbol{q}}^c_{n-1}$.

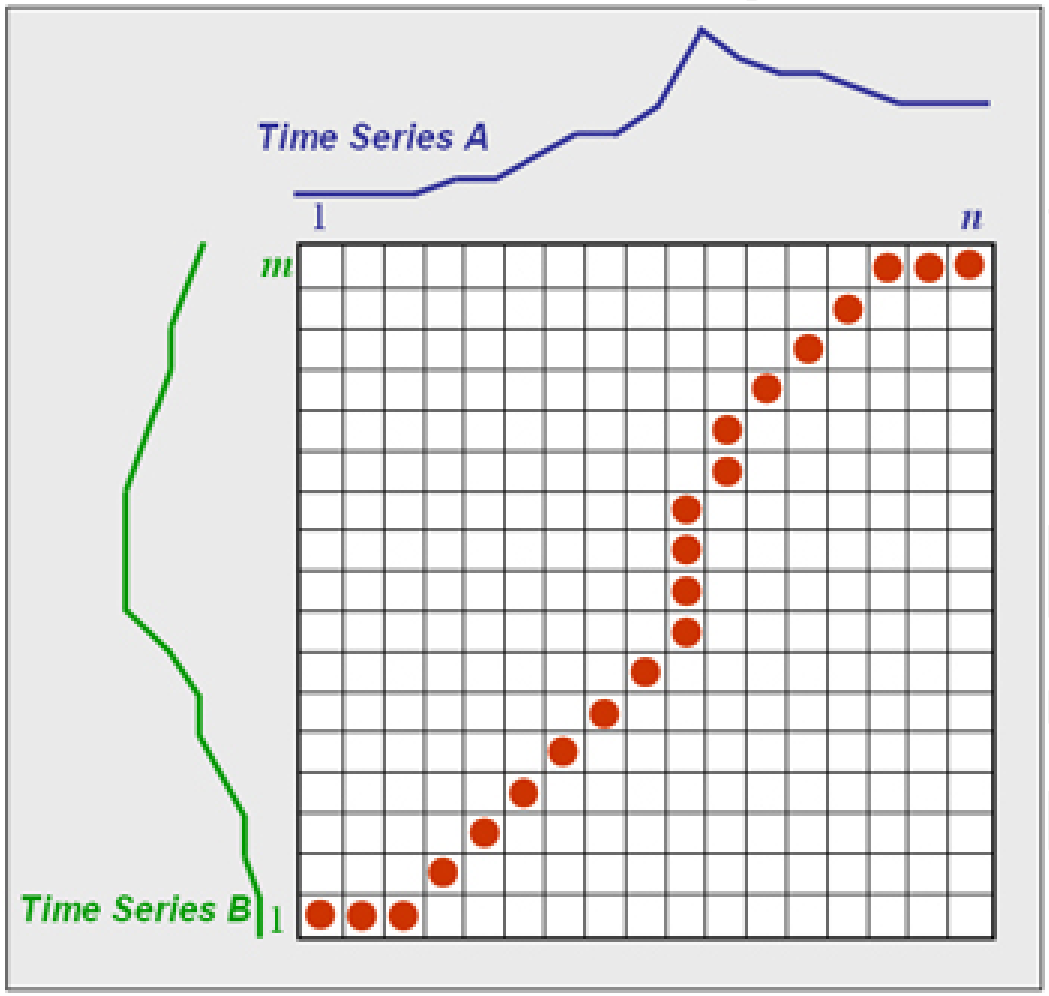
QRS alignment



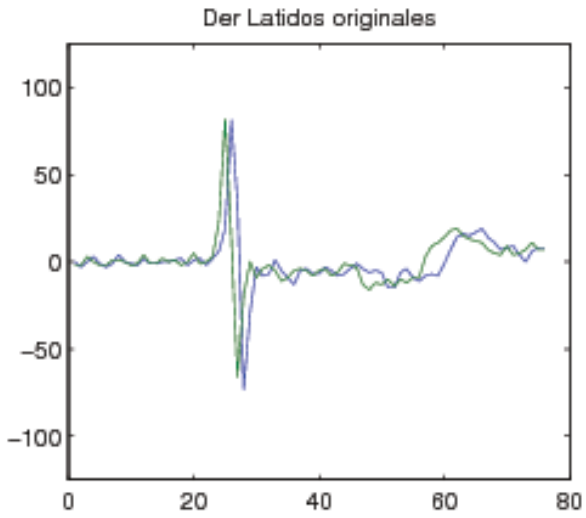
Euclidean Matching

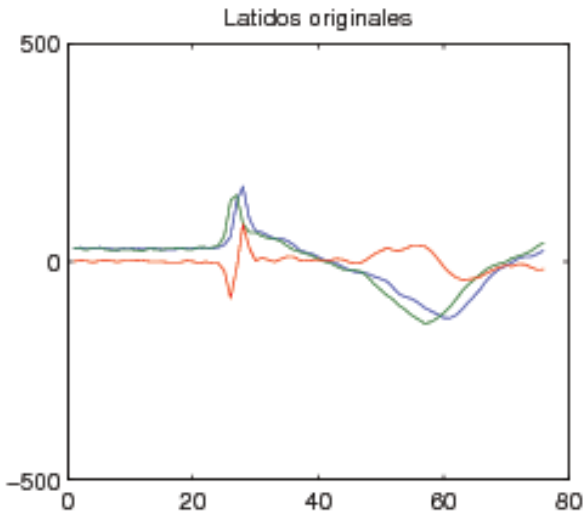


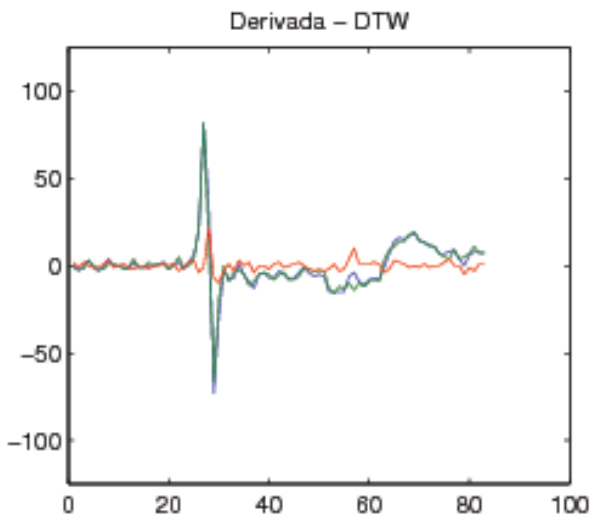
Dynamic Time Warping Matching

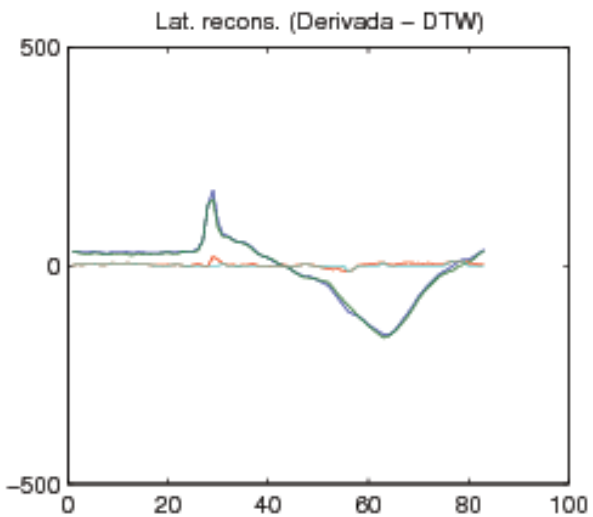


QRS alignment









Similarity

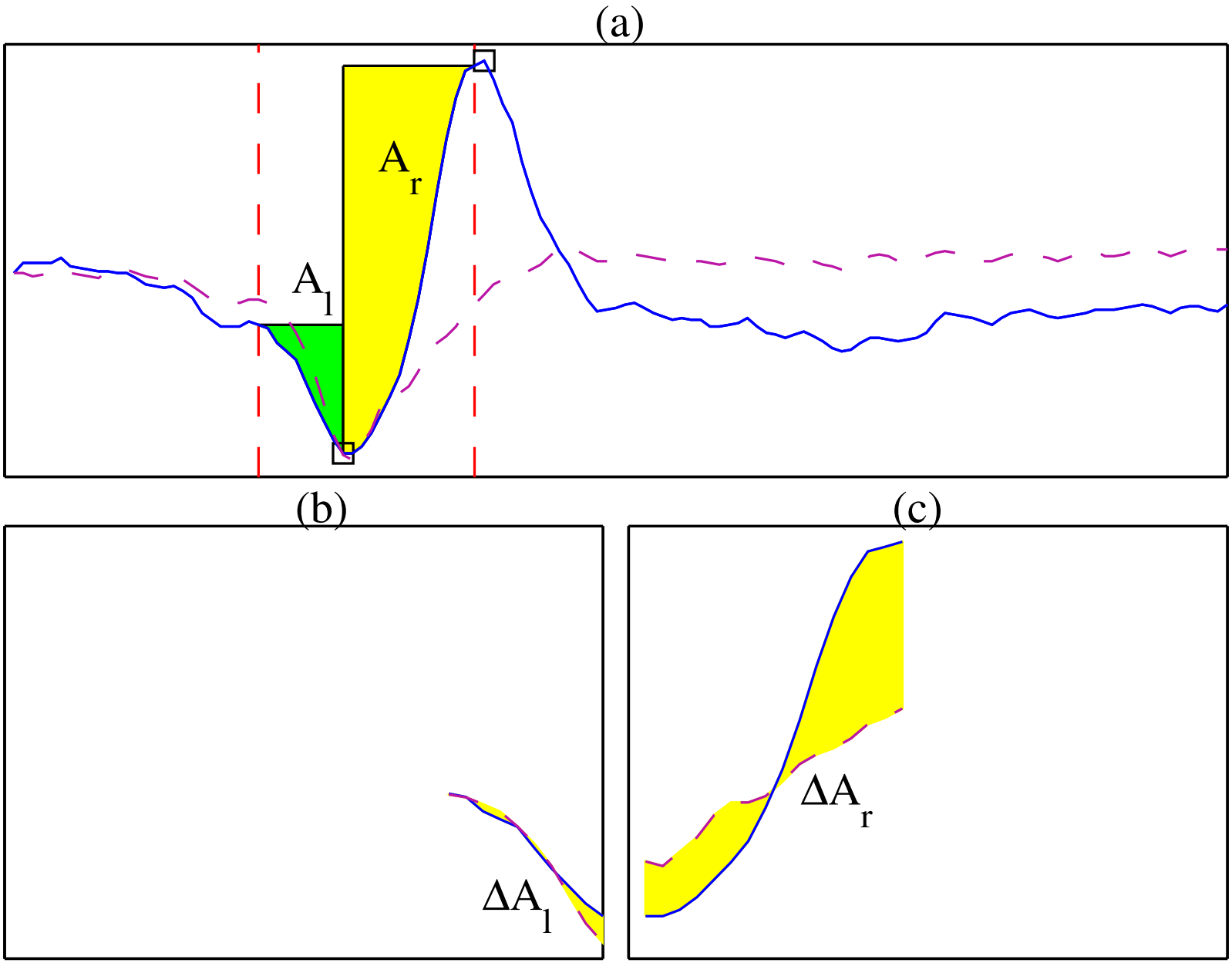
- The comparison between B_n and C_{n-1} is bounded to the support regions of each relevant point.
- The segment $\boldsymbol{q}^c_{n-1}$ is said to **concord with $\boldsymbol{q}_n$ at p_j** $\left(\boldsymbol{q}^c_{n-1} \approx_{p_j} \boldsymbol{q}_n\right)$ if $\boldsymbol{q}^c_{n-1}$ contains a deflection with height $\Delta p^c_{\check{j}} > \rho_{min}$ in $\left[\check{j}^-, \check{j}^+\right]$ likely to be considered a significant waveform.
- We define the **concordance ratio** of $\boldsymbol{q}^c_{n-1}$ with respect to $\boldsymbol{q}_n$ at p_j

$$\mathcal{C}_{p_j}(\boldsymbol{q}^c_{n-1}, \boldsymbol{q}_n) = \frac{\min\left(\Delta p_j, \Delta p^c_{\check{j}}\right)}{\max\left(\Delta p_j, \Delta p^c_{\check{j}}\right)} \quad \text{if } \left(\boldsymbol{q}^c_{n-1} \approx_{p_j} \boldsymbol{q}_n\right)$$

- We define the **local similarity** of $\boldsymbol{q}^c_{n-1}$ with respect to $\boldsymbol{q}_n$ at p_j

$$\mathcal{D}_{p_j}(\boldsymbol{q}^c_{n-1}, \boldsymbol{q}_n) = \left(\frac{(\Delta A^-_j)^2}{A^-_j} + \frac{(\Delta A^+_j)^2}{A^+_j}\right) \times \frac{1}{A^-_j + A^+_j}$$

Similarity



Similarity

- We define the **piecewise similarity** of $\boldsymbol{q}_{n-1}^{c}$ with respect to $\boldsymbol{q}_n$

$$\mathcal{PS}(\boldsymbol{q}_{n-1}^{c}, \boldsymbol{q}_n) = \sum_{p_j \in R_n} \mathcal{C}_{p_j}(\boldsymbol{q}_{n-1}^{c}, \boldsymbol{q}_n) \operatorname{sig}(\mathcal{D}_{p_j}(\boldsymbol{q}_{n-1}^{c}, \boldsymbol{q}_n)) - \max_{p_j | \boldsymbol{q}_{n-1}^{c} \not\approx_{p_j} \boldsymbol{q}_n} \mathcal{D}_{p_j}(\boldsymbol{q}_{n-1}^{c}, \boldsymbol{q}_n)$$

  - $\operatorname{sig}(x) = 1 - \alpha x / \sqrt{1 + (\alpha x)^2}$

- Finally, we define the **similarity** between B_n and T_{n-1}^{c} as:

$$\mathcal{S}(\boldsymbol{q}_n, \boldsymbol{q}_{n-1}^{c}) = \mathcal{PS}(\boldsymbol{q}_{n-1}^{c}, \boldsymbol{q}_n) + \mathcal{PS}(\boldsymbol{q}_n, \boldsymbol{q}_{n-1}^{c})$$

Cluster selection

- For a beat B_n, the best matching cluster C_{n-1}^{win} is searched:
  - The search is first performed within the temporal context of B_n.
    - The most similar template for each lead is obtained: $sim^l = \arg\max_c \mathcal{S}(\boldsymbol{q}_n^l, \boldsymbol{q}_{n-1}^{c,l})$
    - The most similar cluster C_{n-1}^{sim} is obtained as: $sim = \text{mode}\{sim^l \,|\, l \in [1, L]\}$
    - If multiple clusters are selected, the **normalized similarity** is used: $\bar{\mathcal{S}}(\boldsymbol{q}_n^l, \boldsymbol{q}_{n-1}^{c,l}) = \mathcal{S}(\boldsymbol{q}_n^l, \boldsymbol{q}_{n-1}^{c,l}) / (|R_n^l| + |R_{n-1}^{c,l}|)$
  - B_n is assigned to C_{n-1}^{sim} if $\bar{\mathcal{S}}(\boldsymbol{q}_n^l, \boldsymbol{q}_{n-1}^{sim,l}) > \gamma$ must is fulfilled in all leads.
  - Otherwise, a search is first performed whithin the remaining clusters.
    - The most similar cluster C_{n-1}^{sim*} is obtained.
    - if $\bar{\mathcal{S}}(\boldsymbol{q}_n^l, \boldsymbol{q}_{n-1}^{sim*,l}) > \gamma$ is fulfilled in all leads, B_n is assigned to C_{n-1}^{sim*}.
  - If B_n is not assigned neither to C_{n-1}^{sim} nor to C_{n-1}^{sim*}, C_{n-1}^{win} is selected between them and a new cluster is created for B_n.

Cluster set updating

- Updating: If B_n is assigned to C_{n-1}^{win}, this cluster is updated.
  - $C_n^{win} = C_{n-1}^{win} \bigcup B_n$
  - $\boldsymbol{q}_n^{win,l}$ is obtained from $\boldsymbol{q}_n^l$ and $\boldsymbol{q}_{n-1}^{win,l}$
  - $T_n^{win,l} = < \boldsymbol{q}_n^{win,l}, P_n^{win,l} >$
- Creation: If B_n is not assigned, a new cluster C_n^{new} is created.
  - $C_n = C_{n-1} \bigcup \{C_n^{new}\}$
  - $T_n^{new,l} = B_n^l$
- Merging: two clusters C_{n-1}^c and C_{n-1}^{win} can be merged if $\bar{\mathcal{S}}(\boldsymbol{q}_n^{c,l}, \boldsymbol{q}_n^{win,l}) > \gamma'$ and one of the following condition is fulfilled:
  - $\mathcal{S}(\boldsymbol{q}_n^l, \boldsymbol{q}_n^{c,l}) > \gamma$ and $c = \arg\max_{x \neq win} \left(\sum_{l=1}^{L} \mathcal{S}(\boldsymbol{q}_n^l, \boldsymbol{q}_{n-1}^{x,l}) / L \right)$
  - $|C_n^{win}| < \mu$

Cluster set updating

- When C_{n-1}^{c} and C_{n-1}^{win} are merged, the cluster set and the cluster templates are updated acordingly:
  - C_n^c is updated to $C_n^c = C_n^c \bigcup C_n^{win}$.
  - $\boldsymbol{q}_n^{c,l}$ is recalculated from $\boldsymbol{q}_n^{c,l}$ and $\boldsymbol{q}_n^{win,l}$
  - $T_n^{c,l}$ is updated to $T_n^{c,l} = < \boldsymbol{q}_n^{c,l}, P_n^{c,l} >$, where $P_n^{c,l}$ is the set of relevant points and support regions obtained from $\boldsymbol{q}_n^{c,l}$ after the update.

Cluster proliferation

- Adaptive clustering has a main issue:
  - How to discern between noise and rare morphologies avoiding the proliferation of clusters?

Our approach

- Detect noise at two level:
  - At beat level by setting a limit for the number of waves in noise-free QRS complexes.
    - $noise_n^l = true$ if $W_n^l > \eta$ where $W_n = \left|\{p_j \,|\, p_j \in D_n \wedge \Delta s_j > \rho_{min}\}\right|$
  - At segment level by evaluating an interval of N=10 beats each time a new cluster is created.

Cluster proliferation

- Whean a new cluster is created, the clustering analisys forksinto two branches.
  - Noise branch: all beats wich are not assigned to a cluster are considered as noisy.
  - New clusters branch: all beats wich are not assigned to a cluster are considered as new morphologies.
- After an interval of 10 beats, the beats that created a new cluster are evaluated.
  - Those beats that would be assigned to its most similar cluster if the similarity where defined as $\mathcal{S}(\boldsymbol{q}_n, \boldsymbol{q}^c_{n-1}) = \mathcal{PS}(\boldsymbol{q}_n, \boldsymbol{q}^c_{n-1})$ are labeled as noisy.
  - If all the evaluated beats are noisy, the noise branch is selected.
  - Otherwise, the new clusters branch is selected, but the cluster corresponding to noisy beats are removed.

Rhythm analysis

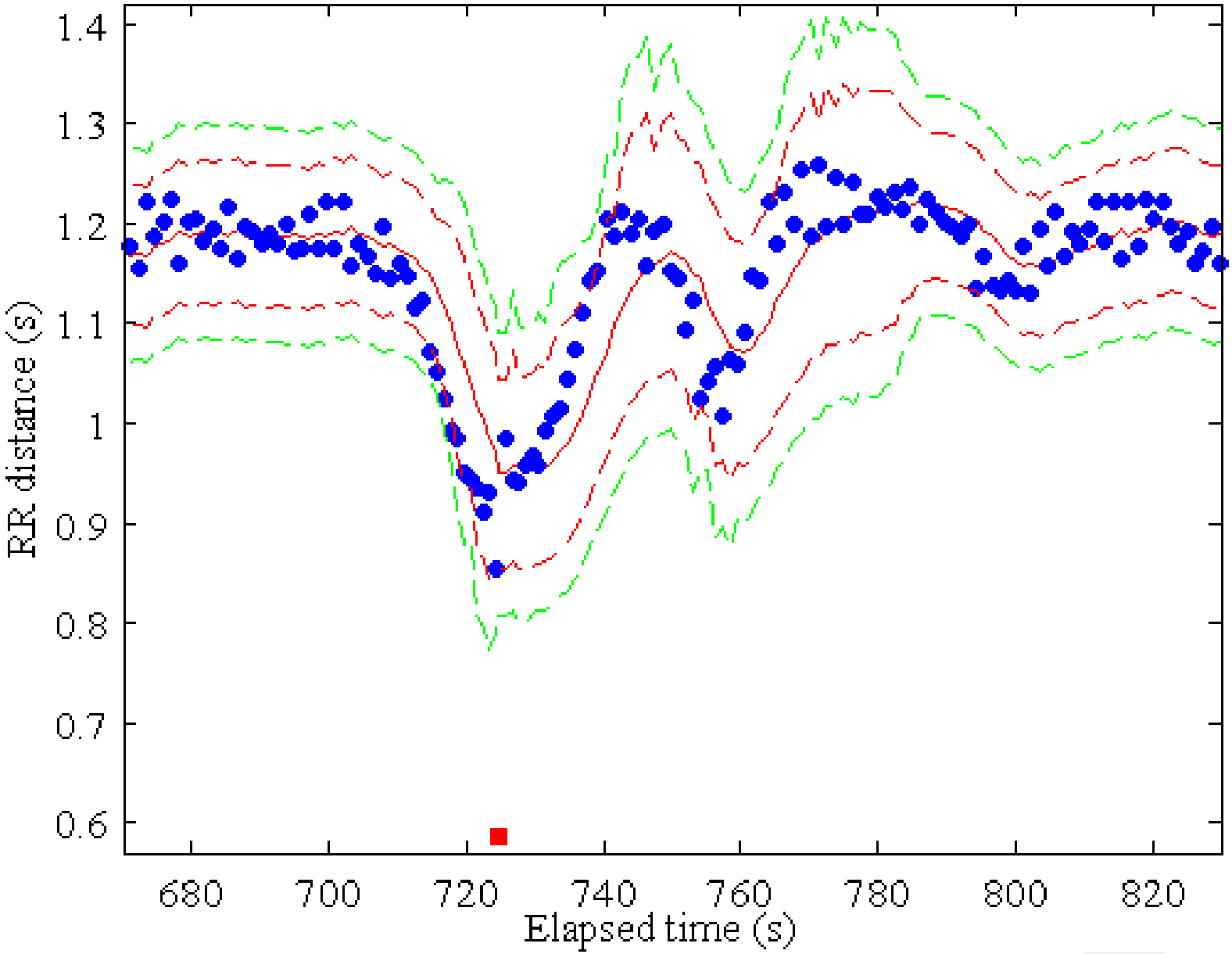
QRS clustering is insufficient to discriminate some kind of beat arrhythmias.

- We need rhythm information.

We model the dinamic component of the cardiac rhythm:

- Stochastic and trend component.
- Only beat with normal rhythm is used in the analysis.
- Trend estimation: exponential smoothing.
- Dispersion of the stochastic component: standard deviation of the detrended series.

Rhythm analysis



Outline

Results

We validated our algorithm with two annotated databases:

- MIT-BIH Arrhythmia database.
  - 48 records of 2-lead ambulatory ECG.
  - 30 minutes long.
  - Manually annotated beat types.
  - Accuracy: 98.71 %
- AHA Database.
  - 155 records of 2-lead ambulatory ECG.
  - 30 minutes long (annotated records).
  - Manually annotated beat types.
  - Accuracy: 99.59 %

Results

- Number of clusters disclosed by record (MIT-BIH Arrhyth. database).

Record	N	N_{RR}	Record	N	N_{RR}	Record	N	N_{RR}
100	5	8	117	3	4	212	4	7
101	3	6	118	3	8	213	18	29
102	12	16	119	5	9	214	21	39
103	11	13	121	5	7	215	14	32
104	18	30	122	1	1	217	27	49
105	10	16	123	3	5	219	13	21
106	27	47	124	12	17	220	2	5
107	9	18	200	20	48	221	11	18
108	18	40	201	13	31	222	4	12
109	11	17	202	6	13	223	26	50
111	7	9	203	28	76	228	11	21
112	3	6	205	14	21	230	3	5
113	3	7	207	58	95	231	6	7
114	7	14	208	22	53	232	2	6
115	5	7	209	5	14	233	22	41
116	7	11	210	26	67	234	5	7

Results

- Global confusion matrix for MIT-BIH Arrhythmia database.

	N	L	R	a	V	F	J	A	S	E	j	/	e	f	Q	!
N	74576	0	7	22	77	90	11	178	2	0	58	0	15	26	11	0
L	3	8059	0	0	1	0	0	0	0	0	0	0	0	0	1	0
R	40	0	7239	0	0	3	29	8	0	0	6	0	0	0	0	0
a	1	0	0	113	5	0	0	4	0	0	0	0	0	0	0	0
V	143	2	0	11	6887	33	0	14	0	0	0	0	0	0	1	5
F	38	4	0	0	138	676	0	0	0	0	0	0	0	0	1	0
J	1	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0
A	58	3	3	4	7	0	1	2339	0	0	0	0	1	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	1	0	0	0	0	0	0	106	0	0	0	0	0	0
j	149	0	0	0	0	0	0	0	0	0	165	0	0	0	0	0
/	7	0	0	0	0	0	0	0	0	0	0	7006	0	138	0	0
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
f	17	0	0	0	0	0	0	0	0	0	0	14	0	818	14	0
Q	1	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0
!	0	1	0	0	12	0	0	0	0	0	0	0	0	0	0	467
Se	99.39	99.88	99.85	75.33	96.63	84.29	50.60	91.98	0	100.00	72.05	99.80	0.00	83.30	15.15	98.94
+P	99.34	99.94	98.83	91.87	97.05	78.88	97.67	96.81	–	99.07	52.55	97.97	–	94.79	83.33	97.29

Results

- Global confusion matrix for AHA database.

	N	V	F	E	/	Q
N	318629	262	158	6	10	74
V	289	32263	202	0	5	61
F	73	170	822	0	4	0
E	0	0	0	6	0	0
/	5	5	83	0	3150	3
Q	55	16	0	0	0	434
Se	99.87	98.63	64.98	50.00	99.40	75.87
+P	99.84	98.30	78.21	100.00	97.01	85.94

Outline

Future work

Some ideas for future work

- Use the clustering results as the base for a beat classification algorithm.
- Develop a detection mechanism for arrhythmias where QRS is not present.
- Improve the QRS alignment procedure for large misalignments.
- Optimize the algorithm for mobile devices.

That’s all

Thanks for your patience.