Automated detection of electrocardiographic diagnostic features through an interplay between Spatial Aggregation and Computational Geometry

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B. Taccardi, Univ. of Utah
Outline

- Functional Imaging & Image Based Diagnosis
- Electrocardiographic maps: a valuable support to the assessment of the cardiac electric function
- Automated Feature Extraction through Spatial Aggregation and Computational Geometry: approach and methods
- Diagnostic features for reentry arrhythmias due to conduction block

Results

- Sensitivity to noise and tuning parameters

Conclusions & Future work
Functional Imaging & Image Based Diagnosis

Spatially referenced measures of a relevant variable

Visual representation of the variable’s course within an anatomical framework
Functional Imaging & Image Based Diagnosis

Spatially referenced measures of a relevant variable

Feature extraction methods

Visual representation of the variable’s course within an anatomical framework

Identification of visual expressions of salient events (features)
Functional Imaging & Image Based Diagnosis

Spatially referenced measures of a relevant variable

Feature extraction methods

Visual representation of the variable’s course within an anatomical framework

Identification of visual expressions of salient events (features)

Image Based Diagnosis:

Imagistic Reasoning process, performed through salient features identification. It aims at

- Describing the physical phenomena in terms of key events
- Searching for specific patterns that are known to characterize classes of pathologies
Core task of any form of IR is **Feature Extraction:**

**multiple level abstraction of spatial objects that encapsulate key properties of the physical system**

Key computational issues:
- Encoding of specific domain knowledge and relations (spatial contiguity, topological adjacencies, function-based similarities …)
- Representation/manipulation of abstract spatial objects

**Goal:**

Computational framework for **automated map interpretation**; emulation of IR through Spatial Aggregation and Computational Geometry methods
Imaging of the cardiac electric activity

ECGs: well established interpretative rationale. Poor spatial resolution.

Maps (BS, epicardium, endocardium...): high spatial resolution.

Map interpretation (visual features ↔ underlying phenomena) requires specialized skills. Automated tools would greatly impact on clinical practice.

Epicardial maps: can be obtained noninvasively. Precise localization of events. → High diagnostic potential.

Epicardial activation maps
Activation time at $x$: minimum of the time derivative of the electric potential $u(x,t)$
→ An activation map embeds an important qualitative state of the potential. It conveys synthetical info about spatio-temporal events (wavefront kinematics).
An example: activation isochrones during VT

Measured map from isolated dog heart experiments described in:
Burnes, J. E. et al. Circulation
2000;102:2152-2158
Excitation starts here
(breakthrough site)
Spatially dense isochrones

↓

very-slow conduction
Conduction block (v<v*)
Conduction block
Reentry propagation pattern
Feature extraction problem

INPUT

- 3D geometry and activation time field:

\[ \Omega_h = \{x_i\}, \quad \tau_i = \tau(x_i), \quad i=1..N \]

Current data: model geometry, simplified scenarios, little added noise.

OUTPUT

- Wavefront kinematics: spatio-temporal sequence of isochrones

\[ I_k = \{ x \mid \tau(x) = k \cdot \Delta \tau \} \]

- Wavefront breakthrough and extinction sites

\[ R_b = \{ x \mid \tau(x) = \min \tau \}, \quad R_e = \{ x \mid \tau(x) = \max \tau \} \]

- Propagation velocity patterns (in particular \( \text{vmax} \))

- VerySlow conduction region

\[ L = \{ x \mid v(x) < v^* = 0.1 \text{ m/sec} \} \]

- \( L \neq \emptyset \): Conduction block / reentry circuit
Inference mechanisms ground on the integration of

- **Spatial Aggregation (SA):** QSR methodology for multiple level abstraction, from a numeric field, of spatial objects fulfilling specified relations. SA predicates exploit specific domain knowledge and qualitative mappings of physical variables.

- **Computational Geometry:** to define and manage suitable symbolic representations of the abstracted spatial objects.

**Approach & Methods**

Numeric field → multi-layered symbolic description of the structure and behavior of the physical vars associated with it.
Spatial Aggregation (Bailey-Kellog, Yip, Zhao, 1996--; Ironi, Tentoni, 2003-)

Aggregate: spatial contiguity of objects is explicated through a neighbourhood graph

Classify: contiguous objects sharing a property are gathered into homogeneous classes

Redescribe: each class is instantiated as a new object

Hierarchical strategy in aggregating spatial objects to abstract a field at different levels
Overview of the abstraction processes

Field data (mesh + act. times)
\[ \Omega_h = \{x_i, \mathcal{N}_\Omega\}, \quad \mathcal{T}_h = \{\tau_i\} \]

Isopoints \( \mathcal{P} \)

Contiguity \( \mathcal{N}_\mathcal{P} \)

Breakthrough & extinction regions \( \mathcal{R}_b, \mathcal{R}_e \)

wf propagation velocity \( \mathbf{v} \)

Isochrones \( \mathcal{I} \)

Contiguity \( \mathcal{N}_\mathcal{I} \)

Contiguity \( \mathcal{N}_{\mathcal{P} | \mathcal{I}} \)

Contiguity \( \mathcal{N}_{\mathcal{W}} \)

W-fragments \( \mathcal{W} \)

Contiguity mapping

Qualitative mapping

SA abstraction

New object

SimilarlyActivated

q: \([0, T] \rightarrow Q_z\)

v direction

v magnitude

\( \mu_1: \mathbf{v}(I) \rightarrow Q_v \)

W-fragments propagation direction

Qualitative propagation velocity bands

.... and more

Double reentry circuit identification

1. VerySlow conduction region $\mathcal{L} = \{ x \mid v(x) < v^* \} \neq \emptyset$,
2. **Line of block** $\mathcal{L}^*$ (redescription of $\mathcal{L}$),
3. Reentry pattern; critical close-and-counterposed $e/b$ couple.

- $\partial \mathcal{L}$ is abstracted as $v^*$-contour;
- $\mathcal{L}$ is redescribed by its **gross skeleton** $\mathcal{L}^*$, which captures its structure at a **low complexity** scale, retaining the topology;
- Propagation lines exiting the blocked area get classified. Ending site $e$ proximal and counterposed to $b$ is identified;
Algorithm (Gross skeleton):
Given $\partial \mathcal{L} = \text{closed polyline } \{v^*-\text{contour}\}$, vertices $P_1..P_n$,

1 - Compute the Voronoi approximation $\mathcal{M}$ of its medial axis:
   1.a Build Voronoi diagram related to $\{P_1..P_n\}$
   1.b Keep only edges internal to $\mathcal{L}$;
Algorithm (Gross skeleton):

Given $\partial \mathcal{L} = \text{closed polyline } \{v^*-\text{contour }\}$, vertices $P_1..P_n$.

1 - Compute the Voronoi approximation $\mathcal{M}$ of its medial axis:
   1.a Build Voronoi diagram related to $\{P_1..P_n\}$
   1.b Keep only edges internal to $\mathcal{L}$;

Remarks:

- $\mathcal{M}$ is a topological skeleton, whose #branches corresponds to contour’s complexity (#curvature extrema)
- $\mathcal{M}$ is sensitive to noise $\rightarrow$ inadequate as a shape global descriptor
- Many applications (obj recognition, reasoning tasks..), don’t need fine scale details

Pruning is crucial to get rid of spurious / irrelevant details.

Unneeded info about finer contour details can be dropped to obtain a simplified skeleton that represents the global structure of the region.
Algorithm (Gross skeleton):

Given $\partial \mathcal{L} = \text{closed polyline} \{v^*-\text{contour} \}$, vertices $P_1..P_n$,

1 - Compute the Voronoi approximation $\mathcal{M}$ of its medial axis:
   1.a Build Voronoi diagram related to $\{P_1..P_n\}$
   1.b Keep only edges internal to $\mathcal{L}$;

2 - Define “index of relevance” (*) of an edge $E$ of $\mathcal{M}$
   $$\beta (E) = \frac{2l}{|\partial \mathcal{L}|}$$
   where $l$ is the shortest path connecting vertices $P_i$ with $P_k$ along $\partial \mathcal{L}$, $P_i, P_k$ are the generators of Voronoi edge $E$.

3 - For each edge $E$ of $\mathcal{M}$, prune edge if $\beta (E) < \beta^*$ (relevance criterion).

The resulting graph $\mathcal{L}^*$ represents the gross structure of $\mathcal{L}$, retaining its topology at a lower complexity scale.

Algorithm (Gross skeleton):

Given $\partial L = \text{closed polyline } \{\nu^*-\text{contour}\}$, vertices $P_1..P_n$,

1 - Compute the Voronoi approximation $\mathcal{M}$ of its medial axis:
   1.a Build Voronoi diagram related to $\{P_1..P_n\}$
   1.b Keep only edges internal to $L$;

2 - Define “index of relevance” (*) of an edge $E$ of $\mathcal{M}$
   \[ \beta(E) = \frac{2l}{|\partial L|} \]
   where $l$ is the shortest path connecting vertices $P_i$ with $P_k$ along $\partial L$, $P_i, P_k$ are the generators of Voronoi edge $E$.

3 - For each edge $E$ of $\mathcal{M}$, prune edge if $\beta(E) < \beta^*$ (relevance criterion).
Choice of $\beta^*$

$k(.) = \#\text{branches (complexity)}$

$\Phi(.) = \text{diameter of minimal bounding circle (extension)}$

$V: \text{region's boundary}$

$P: \text{gross skeleton (=pruned } \mathcal{M})$

\[\beta^* = \arg \left[ \left( \max \frac{\Phi(P)}{\Phi(V)} \right)^{\frac{d k(P)}{d \beta}} \approx 0 \right] \]
\( \beta^* = 0.25 \)

\( n = 30 \) perturbations

\( \text{SNR} = 148.3 \)

\( V \): region’s boundary

\( M \): medial axis

\( P \): gross skeleton (pruned m.a.)

Initial configuration \( (V_0, P_0, M_0) \)

Worst perturbation \( (k(M)=10) \)
\[ \beta^* = 0.25 \]

\[ \delta(P,P') = \text{displacement of } P \text{ w.r. to } P' \]

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<thead>
<tr>
<th></th>
<th>mean (^(^\wedge^))</th>
<th>st.dev.</th>
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<tbody>
<tr>
<td>(\Phi(P'))</td>
<td>1.8</td>
<td>7.0 e-2</td>
</tr>
<tr>
<td>(\Phi(V))</td>
<td>2.4</td>
<td>1.6 e-2</td>
</tr>
<tr>
<td>(\delta(P,P_0))</td>
<td>3.8 e-2</td>
<td>8.2 e-3</td>
</tr>
<tr>
<td>(\delta(V,V_0))</td>
<td>4.7 e-2</td>
<td>1.5 e-2</td>
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\( \beta^* = 0.25 \)

\[
\hat{k}(M) = 8.17 \quad \text{range} = 3 \div 10
\]

\[
\hat{k}(P) = 0 \quad \text{range} = 0 \div 0
\]

\[
\hat{\delta}(P, P_0)/\hat{\Phi}(P) = 2.1\%
\]

\[
\hat{\delta}(V, V_0)/\hat{\Phi}(V) = 2.0\%
\]

\[
\hat{\Phi}(P)/\hat{\Phi}(V) = 74.6\%
\]

\[
\Phi(P_0)/\Phi(V_0) = 74.0\%
\]

\[
\text{err}(\Phi(P)) = \left| \Phi(P) - \Phi(P_0) \right|/\Phi(P_0) = 5.2 \times 10^{-3}
\]

\[
\delta(P, P') = \text{displacement of } P \text{ w.r. to } P'
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Some results

Input data

Isopoints’ ngraph

Isochrones, breakthrough and exit sites
Check for conduction blocks

Very-slow conduction region

Medial axis and gross skeleton

Line of conduction block
Classification of propagation lines

Global outcome
Conclusions & future work

Both numerical and qualitative pieces of information and methods are exploited within a **SA conceptual framework** for IR, focused on the **extraction of spatial objects**, corresponding to **salient spatio-temporal features, at multiple scales**.

**Map interpretation task is currently tailored to Electrocardiography**

**Further steps**: definition of a vocabulary of features, and rules for their comparison; automated explanation of results

- More propagation features (e.g. primary area) according to advancements of the interpretation rationale
- More simulated data related to pathological conditions
- Deeper treatment of noise
Fig. 4A