Smart medical IoT

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MOTIVATION: Heart disease and unsatisfied treatment

- Heart diseases are the number 1 killer in the western world.
- Up to date, there is not satisfactory drug treatments.
- “No change in the number of deaths attributed to heart failure has been observed between 1995 and 2011.”

![Leading Causes of Death](chart.png)

Heart disease continues to kill more Americans than any other cause, followed by stroke at No. 5, according to 2015 federal data.
How are cardiac diseases diagnosed today?

Normal sinus rhythm
Impulses originate at SA node at normal rate
All complexes normal, evenly spaced, Rate 60-100/min

Ventricular tachycardia
Impulses originate at ventricular pacemaker
Wide ventricular complexes. Rate > 120/min

Sinus tachycardia
Impulses originate at S-A node at rapid rate
All complexes normal, evenly spaced. Rate > 100/min

Atrial Fibrillation
Impulses have chaotic, random pathways in atria
Baseline irregular, ventricular response irregular

Future cardiac diseases detection
Medical IoT description in the internet
Making smart IoT
AF increases stroke incidence

9.7M Europeans diagnosed with AF


2.7-3.3% Prevalence of AF in 2030 in EU

Center of Health Protection 2016

€10 billion Annual direct-cost in EU

Incidence of stroke

Without AF
With AF

Increases stroke risk by 480%

200,000 AF induced cases a year in EU
Existing treatments for AF are limited in their outcome

- Catheter ablation
- Cardioversion
- Drug treatments

• 30% are repeated procedure
• 25% of the procedures have less than 15% success
Mindset Change:
Treat AF associated effects when AF event is predicted
Timing is everything:
Eliminating AF events and their side effects

User target: Paroxysmal AF patients (2-3 episodes per day)

Time = 12:00 pm
Normal ECG

Time = 12:05 pm
Normal ECG
Beat to beat variability changes before AF event

Intermediate heart rate variability

1.03s  1s  0.98s

High heart rate variability (AF patients)

2s  1s  1.5s

Reduced heart rate variability (just before AF event)

1s  1s  1s

Submitted patent: Yaniv Y. Early prediction and detection of arrhythmogenic events #1863

Challenge: Designing a patient-tailored wearable device based on real time heart rate variability analysis that can predict AF events with low false-negative and false-positive alerts.
Challenges for IoT solution

**Challenge 1:**
Limited automated detection of R peaks (QRS)

**Challenge 2:** Embedding complex algorithms on mobile devices

**Challenge 3:**
Automated diagnosis

[Graph of electrocardiogram data with time and amplitude axes]

http://techno-adviser.blogspot.co.il

https://www.infineon.com
To develop a robust R-peak detector for low quality ECG of patients with cardiac diseases.
Results 1-The R peak detector algorithm

Input: ECG Record

34th order polynomial fit is applied to each 15 sec interval

The signal is smoothed by convolution with kernel of width of 1/50 sec

Derivate the signal and search for the maximal point above the average

Flip the signal

Find the point where \( \frac{d}{dt}=0 \) & \( \frac{d^2}{dt^2}<0 \)

Search if point > \( \frac{\text{max}(\text{signal})+\text{min}(\text{signal})}{2} \)

Is the interval between the point larger than 1.83s?

Is the RR interval smaller then 250 ms?

Artifact, eliminate the adjoin R peak with lower amplitude

Is the RR interval is different than mean±3SD

Artifact

Output: R indexes
Results 1: Detecting the R interval in the presence of sudden patient movement

Gliner et al. Under Review
Results 1: Decoding the R interval in the presence of breathing oscillations

Gliner et al. *Under Review*
Results 1: Detecting the R peak in the presence of high frequency environmental noise

Gliner et al. Under Review
Results 1: Detecting the R peak in the presence of enlarged P or T waves

Gliner et al. *Under Review*
Results 1: Detecting the R peak in the presence of electrical drift

Gliner et al. Under Review
Results 1: Detecting the R peak in the presence of electrical spikes

Gliner et al. *Under Review*
Results 1: Detecting the R peak with reverse ECG polarity

Gliner et al. *Under Review*
Results 1: Detecting the R peak in the presence of premature ventricular contraction

Gliner et al. Under Review
### Results 1: Peak detector performance

<table>
<thead>
<tr>
<th>Non-AF (%)</th>
<th>gqrs algorithm</th>
<th>Pan et al. algorithm</th>
<th>Behar et al. algorithm</th>
<th>Current algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>False negative</td>
<td>0.15</td>
<td>0.49</td>
<td>0.47</td>
<td><strong>0.14</strong></td>
</tr>
<tr>
<td>False positive</td>
<td>0.39</td>
<td>0.33</td>
<td>1.19</td>
<td><strong>0.28</strong></td>
</tr>
<tr>
<td>Positive prediction</td>
<td><strong>99.6</strong></td>
<td><strong>99.7</strong></td>
<td><strong>98.8</strong></td>
<td><strong>99.7</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>AF (%)</th>
<th>gqrs algorithm</th>
<th>Pan et al. algorithm</th>
<th>Behar et al. algorithm</th>
<th>Current algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>False negative</td>
<td>0.42</td>
<td>0.72</td>
<td>2.09</td>
<td><strong>0.34</strong></td>
</tr>
<tr>
<td>False positive</td>
<td>0.79</td>
<td>0.67</td>
<td>5.45</td>
<td><strong>0.25</strong></td>
</tr>
<tr>
<td>Positive prediction</td>
<td><strong>99.2</strong></td>
<td><strong>99.3</strong></td>
<td><strong>95.7</strong></td>
<td><strong>99.7</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total (%)</th>
<th>gqrs algorithm</th>
<th>Pan et al. algorithm</th>
<th>Behar et al. algorithm</th>
<th>Current algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>False negative</td>
<td>0.30</td>
<td>0.30</td>
<td>1.21</td>
<td><strong>0.24</strong></td>
</tr>
<tr>
<td>False positive</td>
<td>0.62</td>
<td>0.62</td>
<td>3.91</td>
<td><strong>0.27</strong></td>
</tr>
<tr>
<td>Positive prediction</td>
<td><strong>99.4</strong></td>
<td><strong>99.4</strong></td>
<td><strong>97.2</strong></td>
<td><strong>99.7</strong></td>
</tr>
</tbody>
</table>
Embedding complex algorithms on mobile devices.

http://techno-adviser.blogspot.co.il
Results 2: Mobile system

1. Download the Matlab Mobile application and install it on the cell phone or tablet.
2. Connect to your Matlab Cloud account and download the source code.
3. Acquire data using the ECG device and upload to the cloud.
4. Download the ECG data from the cloud using Matlab Mobile.
5. Process the data and annotate R-peaks.
Results 2: Peak detection on mobile phones

Gliner et al. *Under Review*
Aim 3

https://www.infineon.com

Automated diagnosis
Aim 3- Database

- 2 datasets: a training set of 8,528 single lead ECG recordings from 9s to just over 60s and a test set containing 3,658 ECG recordings of similar length.
- All recordings consisted of one bipolar channel recorded by an AliveCor device.
- The data was sampled at 300 Hz and filtered by a band pass filter in the device itself.
- The training set data was annotated by a cardiologist to one of the four types: normal (~59.5% of the recordings), AF (~10% of the recordings), other rhythm (~30% of the recordings), and noisy (~0.5% of the recordings).
- 10 trials on the hidden set were allowed
Results 3: Learning strategy and algorithm

ECG Record (Input) → R Peak Detection → P,Q,S,T Peaks Detection → Average Beat Morphology Calc.

62 features calculation from the following categories:
1. Time-frequency domain features
2. Heart rate and heart rate variability
3. Signal entropy
4. Intra-beat temporal intervals variability
5. QRS morphology
6. Average beat morphology

Neural Network Binary Classifier

Quadratic SVM Classifier

Is classified as “Normal”? Yes → Normal
No → Normal
Normal/Other

Output (Normal, Other, AF, Noise)
Aim 3 Results: CinC 2017 challenge classifier results

Cross-validation matrix on the training set:

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>AF</th>
<th>Other</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>4772</td>
<td>9</td>
<td>244</td>
<td>4</td>
</tr>
<tr>
<td>AF</td>
<td>17</td>
<td>650</td>
<td>70</td>
<td>0</td>
</tr>
<tr>
<td>Other</td>
<td>455</td>
<td>51</td>
<td>1960</td>
<td>10</td>
</tr>
<tr>
<td>Noise</td>
<td>35</td>
<td>5</td>
<td>21</td>
<td>225</td>
</tr>
</tbody>
</table>

Normal rhythm: \( F_1n = \frac{2N_n}{\sum N + \sum n} \)

AF rhythm: \( F_1a = \frac{2A_a}{\sum A + \sum a} \)

Other rhythm: \( F_{1o} = \frac{2O_o}{\sum O + \sum o} \)

Results on the hidden set:

<table>
<thead>
<tr>
<th></th>
<th>( F_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>0.9</td>
</tr>
<tr>
<td>AF</td>
<td>0.81</td>
</tr>
<tr>
<td>Other</td>
<td>0.7</td>
</tr>
<tr>
<td>Total</td>
<td>0.8</td>
</tr>
</tbody>
</table>

\[
F_1 = \frac{F_1n + F_1a + F_{1o}}{3}
\]
Summary

Mobile device → Sensor → Alarm → Classifier on the cloud

- Probability
- Shannon entropy

Cloud Infrastructure

False alarm

True alarm

Alert the medical staff

Treatments

True alarm

False alarm
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Thanks for your attention!

The best way to predict the future is to create it.

Peter Drucker
Questions?