Automatic Realtime Detection of Atrial Fibrillation and Congestive Heart Failure Based on Heart Rate Variability Analysis

- Simple, Convenient & Innovative Approach -

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Vital Signs Monitoring using ECG, Plethysmogram and Piezoelectric Pulse Transducer Signals
Electrocardiogram (ECG)

- Interpretation of electrical activity of the heart
- Electrodes attached to surface of the skin
- Amplifies tiny electrical changes on the skin
- Heart Muscle depolarizes during each heartbeat

*source from findmeacure.com
Plethysmography (PPG)

- **Principle of Operation**
  - Deoxygenated blood absorbs more red light
  - Oxygenated blood absorbs more infrared light.

- Red and infrared LEDs on one side
- Photodetector on the opposite side.
- Ratio of Red to Infrared (R/IR) is the signal.
- Empirically converted to \( \text{SpO}_2 \) readings.
- Beating of the heart causes pulse changes in the \( \text{SpO}_2 \) signal.
- This is the Photoplethysmogram (PPG) signal.
Piezoelectric Transducers

- Produce ultrasonic frequencies
- Used as pressure meters
  - Traffic lights to detect traffic
  - Printing, vibration control and noise suppression
  - Industrial and military vehicles
- Can detect heart beat
Health Monitoring (Vital Sign Extraction)

Research on vital sign extraction from ECG, PPG and Piezoelectric transducer

- Heart Rate Variability
- Respiratory Rate
- Atrial Fibrillation
- Atrial Tachycardia
- Atrial Flutter
- Congestive Heart Failure
- Autonomous Nervous system
- Blood Volume Loss
- Early diagnosis of Diabetes
Atrial Fibrillation (AF)

• The most commonly encountered arrhythmia in clinical practice.

• Afflicts more than 2.3 million Americans and 4.5 million in the EU.

• 66% increase in no. of hospitalizations in the past 20 years

• Global cost per patient per annum: $3600! “Total societal burden”: $15.7 billion in the EU per annum

• Associated with stroke (15%), sick sinus syndrome, hypoxia, increased atrial pressure, pericarditis

• Prevalence of Asymptomatic AF
NSR vs AF

* Source from Children’s Heart Specialists PSC
AF Characteristics

AF: 1) P-wave absence
2) Irregular RR intervals
Holter Recordings: Normal Sinus Rhythm
Holter Recordings: Atrial Fibrillation
Extraction of RR intervals from ECG

ECG

R-R_{49}  R-R_{50}  R-R_{51}

62  63  64  65  66

R-R, ms

0  60  120

Time, sec
Impact on the RR-interval Time Series

Typical RR intervals during Atrial Fibrillation

- Blue line: RRI
- Red line: AF Detect

 Axes:
- RR Interval (ms) on the y-axis
- Beat no. on the x-axis
Impact on the RR-interval Time Series (contd.)

![Graph showing impact on RR-interval Time Series](image)

- **RRI**: Blue line
- **AF Detect**: Red line

**RR Interval (ms)** vs **Beat no.**

Values range from 100 to 1000 ms.
Two broad categories of AF

RR intervals for Paroxysmal Atrial Fibrillation
Two broad categories of AF (contd.)

RR Intervals for Persistent Atrial Fibrillation
Objective

- Design an efficient algorithm to accurately detect atrial fibrillation rhythms
  - Applicable for Holter monitoring (e.g., paroxysmal AF)
  - Look for irregular RR intervals instead of P-waves
- Test accuracy using different types of data.
Previous Attempts at automatic detection of AF

- Moody & Mark (1983)
  - Markov models
- Duverney et al (2001)
  - Wavelet Transform of RR Intervals
- Tateno and Glass (2001)
  - Coeff. Of Variation of RR & ΔRR
  - Kolmogorov-Smirnov test to compare test RR & ΔRR histograms with standard density histograms of RR & ΔRR during AF
MIT BIH Atrial Fibrillation database
(http://www.physionet.org/physiobank/database/afdb)
- 25 Data sets containing a total of 299 AF episodes.
- Sampled at 250 Hz for 10 hrs.
- Contains a mixture of AF, atrial flutter, NSR etc.
- Tateno & Glass used AF episodes from this database to build standard density histograms.
Databases Used (contd.)

- MIT BIH Arrhythmia Database
  (http://physionet.org/physiobank/database/mitdb/)
  - Divided into 2 categories
    - 100 Series (23 subjects) : Contains no AF rhythm
    - 200 Series (25 subjects) : Contains mixture of AF and other arrhythmias
  - Sampled at 360 Hz for 30 minutes
  - Tateno & Glass used this database as a test database.

- 76 Holter data (24 hrs) provided by The Scottcare Corporation (Cleveland, Ohio).
Methods

• Hypothesis: AF is random

- RMSSD (root mean squares of successive difference of HRV, AF signal has larger RMSSD)

- Turning point ratio (TPR)

- Shannon Entropy (SE) (AF signal has higher SE)
STEP 1: RMSSD DURING AF

Threshold
STEP 2: TPR DURING AF

Upper threshold

Lower threshold
STEP 3: SHANNON ENTROPY

Threshold

True Annotation
RESULT

Original

RMSSD

Turning Point ratio

Shannon Entropy
RESULT

Original

RMSSD

Turning Point ratio

Shannon Entropy
**Algorithm for AF Detection**

- Consider a segment of 128 RR intervals

- If RMSSD ≥ threshold, proceed to calculate the TPR

- If TPR ≥ threshold, proceed to calculate the Shannon Entropy

- If Shannon Entropy ≥ threshold, segment is AF
MEASUREMENT OF ACCURACY

- Divide detection results into 4 categories

- True Positive (TP): AF is detected as AF
- True Negative (TN): Non-AF is detected as non-AF
- False Positive (FP): Non-AF is detected as AF
- False Negative (FN): AF is detected as non-AF

Give rise to inaccuracy
SENSITIVITY AND SPECIFICITY

- **Sensitivity** = \[ \frac{\text{No. of True Positives}}{(\text{No. of True Positives} + \text{No. of False Negatives})} \]

  = \[ \frac{TP}{(TP+FN)} \]

- **Specificity** = \[ \frac{\text{No. of True Negatives}}{(\text{No. of True Negatives} + \text{No. of False Positives})} \]

  = \[ \frac{TN}{(TN+FP)} \]
**FINAL THRESHOLD**

- Using the ROC curves, the thresholds obtained were:
  - For RMSSD: RMSSD ≥ 0.1 \times \text{mean of RRI series}
  - For TPR: 0.54 ≤ TPR ≤ 0.77
  - For SE: SE ≥ 0.70

- For these thresholds beat-to-beat accuracy:
  - MIT-BIH AFIB database
    - Sensitivity = 94%;
    - Specificity = 95%;
  - MIT-BIH Arrhythmia database
    - Sensitivity = 90 %
    - Specificity = 91 %
  - 76 Holter database (The Scottcare Corporation)
    - Sensitivity = 95 %
    - Specificity = 87 %
AF detection using Time-Varying Coherence Function

Given RRI time series, we define two adjacent RRI segments

\[ S_{i+1:i+seg}(n) = - \sum_{i=1}^{P_1} a(n,i)S_{i+1:i+seg}(n-i) + \sum_{j=0}^{Q_1} b(n,j)S_{i+seg+1:i+2\cdot seg}(n-j) \]

\[ S_{i+seg+1:i+2\cdot seg}(n) = - \sum_{i=1}^{P_1} \alpha(n,i)S_{i+seg+1:i+2\cdot seg}(n-i) + \sum_{j=0}^{Q_1} \beta(n,j)S_{i+1:i+seg}(n-j) \]

**J. Lee et al., “Atrial Fibrillation Detection using Time-Varying Coherence Function,” IEEE Transactions on Biomedical Engineering, 2013.**
AF detection using TVCF

Hypothesis

1) Given **two adjacent NSR RRI**, they can be modeled with **AR and MA model**

2) **AF RRI** has **random characteristics**

3) Given **either or both RRI segments contain AF**, they can be modeled mainly **AR models**

\[
TVCF = \left| \frac{\sum_{l=0}^{Q_1} b(l) e^{-j\omega_l}}{1 + \sum_{i=1}^{P_1} a(i) e^{-j\omega_i}} \right| \left| \frac{\sum_{l=0}^{Q_2} \beta(l) e^{-j\omega_l}}{1 + \sum_{i=1}^{P_2} a(i) e^{-j\omega_i}} \right|^2
\]
Example (1-1)

Calculate TVCF
• MIT-BIH AF database subject 8455
• ARMA by Time-Varying Optimal Parameter Search (TVOPS)
• Initial model (5,5)
• 64 point FFT
• segment length 128 beats
Example (1-2)

Resultant TVCF
Result

- Tested on 23 subjects from MIT-BIH AF database
- Good ability of beat by beat detection

- Given total 479,986 AF beats, $18.7 \pm 16.4$ beats error
- Sensitivity: 98.2%, Specificity: 97.7% Accuracy: 97.9%
## Comparison

<table>
<thead>
<tr>
<th>Methods</th>
<th>MIT-BIH AF database</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sensitivity (%)</td>
</tr>
<tr>
<td>TVCF w/ SE</td>
<td>98.2</td>
</tr>
<tr>
<td>Dash et al [1]</td>
<td>94.4</td>
</tr>
<tr>
<td>Tateno et al [2]</td>
<td>94.4</td>
</tr>
<tr>
<td>Huang et al [3]</td>
<td>96.1</td>
</tr>
<tr>
<td>Logan el al [4]</td>
<td>96.0</td>
</tr>
<tr>
<td>Kikillus et al [5]</td>
<td>94.4</td>
</tr>
</tbody>
</table>

HEART FAILURE

- Results from any structural or functional abnormality that impairs the ability of the ventricle to eject blood (Systolic Heart Failure) or to fill with blood (Diastolic Heart Failure).
CLASSIFICATION OF HEART FAILURE

New York Heart Association (NYHA)

- **Class I** – symptoms of HF only at levels that would limit normal individuals.
- **Class II** – symptoms of HF with ordinary exertion
- **Class III** – symptoms of HF on less than ordinary exertion
- **Class IV** – symptoms of HF at rest
Simultaneous Detection of AF and CHF

- RMSSD -

<table>
<thead>
<tr>
<th>Classification</th>
<th>Mean ± SD</th>
<th>Median</th>
<th>IQR</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSSD / Mean</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AF</td>
<td>0.1907 ± 0.0783</td>
<td>0.1858</td>
<td>0.1090</td>
</tr>
<tr>
<td>NSR</td>
<td>0.0354 ± 0.0274</td>
<td>0.0297</td>
<td>0.0221</td>
</tr>
<tr>
<td>CHF (NYHA I ~ III)</td>
<td>0.0210 ± 0.0509</td>
<td>0.0137</td>
<td>0.0096</td>
</tr>
<tr>
<td>CHF (NYHA III &amp; IV)</td>
<td>0.0135 ± 0.0287</td>
<td>0.0102</td>
<td>0.0056</td>
</tr>
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</table>
Simultaneous Detection of AF and CHF - Sample Entropy -

<table>
<thead>
<tr>
<th>Classification</th>
<th>Mean ± SD</th>
<th>Median</th>
<th>IQR</th>
</tr>
</thead>
<tbody>
<tr>
<td>SampEn</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AF</td>
<td>2.0002 ± 0.6771</td>
<td>1.8971</td>
<td>0.9808</td>
</tr>
<tr>
<td>NSR</td>
<td>0.4705 ± 0.3520</td>
<td>0.4055</td>
<td>0.4305</td>
</tr>
<tr>
<td>CHF (NYHA I ~ III)</td>
<td>0.1467 ± 0.2123</td>
<td>0.0488</td>
<td>0.2144</td>
</tr>
<tr>
<td>CHF (NYHA III &amp; IV)</td>
<td>0.0623 ± 0.1316</td>
<td>0.0000</td>
<td>0.0783</td>
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</table>
Simultaneous Detection of AF and CHF - Shannon Entropy -

<table>
<thead>
<tr>
<th>ShEn</th>
<th>Classification</th>
<th>Mean ± SD</th>
<th>Median</th>
<th>IQR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AF</td>
<td>0.6762 ± 0.0634</td>
<td>0.6808</td>
<td>0.0991</td>
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<tr>
<td></td>
<td>NSR</td>
<td>0.5605 ± 0.1319</td>
<td>0.5818</td>
<td>0.1722</td>
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<tr>
<td></td>
<td>CHF (NYHA I ~ III)</td>
<td>0.3296 ± 0.1654</td>
<td>0.3247</td>
<td>0.2398</td>
</tr>
<tr>
<td></td>
<td>CHF (NYHA III &amp; IV)</td>
<td>0.4188 ± 0.1340</td>
<td>0.4151</td>
<td>0.1824</td>
</tr>
</tbody>
</table>
In the era of Smartphone
Health Monitoring using a Smart Phone

Currently being developed with Android phone and iPhone

Touch finger on a camera
Health Monitoring using a Smart Phone

What does it mean?

Which vital signs can be extracted?

How?

Why is it important?

- Heart Rate Variability
- Respiratory Rate
- Atrial Fibrillation
- Atrial Tachycardia
- Atrial Flutter
- Congestive Heart Failure
- Autonomous Nervous system
- Blood Volume Loss
- Early diagnosis of Diabetes
Vital Signs using Smart Phone (1)

1. Heart Rate Variability

Signal from a smart phone !!!

Blue: HRV from a smart phone

Black: HRV from a commercial ECG machine *


* HEWLETT PACKARD 78354A 46
Vital Signs using Smart Phone (2)

2. Oxygen Saturation

**Thick:** Oxygen saturation from a smart phone

**Thin:** Oxygen saturation from a commercial pulse oximeter*

\[ SpO2 = A - B \frac{AC_{RED}}{DC_{RED}} - \frac{AC_{BLUE}}{DC_{BLUE}} \]

* Philips Agilent M1191A

Vital Signs using Smart Phone (3)

3. Respiratory Rate

Optimal Parameter Search Criterion (AR model)

Combined with PF

Time-varying AR model

Vital Signs using Smart Phone (4-1)

Hypothesis

1) Given **two adjacent NSR RRI**, they can be modeled with **AR and MA model**
2) **AF RRI** has **random characteristics**
3) Given **either or both RRI segments contain AF**, they can be modeled mainly **AR models**

![Resultant TVCF](image)

We tested with several databases *
1. MIT-BIH AF database (n=25)
2. MIT-BIH NSR database (n=23)
3. MIT-BIH Arrythmia database (n=48)
4. Clinical Data from Scottcare Corporation, OH, USA (n=78)
5. Clinical Data from University of Massachusetts, medical school (n=62)

\[ 180 \sim 250 \text{ Hz} \]

Smart phone (iphone, ipad, android phone supports up to 30 Hz)
4. Atrial Fibrillation

Accuracy is higher than any other recently published algorithm.

Need to investigate the algorithm with signals from a smart phone.

*Potential risk*
- Traditional ECG signal sampling rate is higher than 200 Hz
- Smart phone can support up to 25~30 fps.
- This low sampling rate may affect the performance (need to find different threshold values)

iPhone 4S prototype for AF detection. As shown in “Atrial Fibrillation Detection Using an iPhone 4S,” by Lee et al., p. 204.
Clinical Application
Coming Soon!!!

- 실시간 맥박형 보여짐
- 평균 심박수

- 실시간 심박수
- 최종진단 날은 시간
- 심장질환 진단결과

1. 심방세동
2. 응혈성 심부전증
3. 심실기외수축
4. 심방기외수축
5. 정상

- 심박수 위험도
- 전문의의 최종진단 참고를 위한 측정 중 사용자의 증상매모

카메라에 손가락 영상측정
실시간 맥박, 심박수 모니터링

1분후
심장질환 진단결과들 보여줌
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