

Key Generation for Body Area Networks

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joint work with Volkan Tuzcu (Medipol Uni.),
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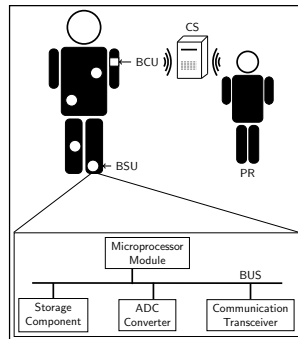
Sabanci University

5 November 2020

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- 2 Deriving Cryptographic Keys from Physiological Signals
- 3 SKA-PS: Secure Key Agreement using Physiological Signals
- 4 SKA-PB: Secure Key Agreement using Pure Biometrics

Introduction

- Telemedicine: use of telecommunications technology to provide medical information and services
- Rapid advances in wearable sensors: lightweight, small-sized, low power and intelligent monitoring
- Body Area Networks: subset of Wireless Sensor Networks
 - Self-organized, self-configured
 - Biosensors: collect data & make decisions
 - *Intra-BAN communication*
- Communication through BCU and CS toward healthcare professional
 - *Beyond-BAN communication*



- Sensing, storage and communication security
 - Monitoring mission critical processes → targeted attacks
 - Attacker → pacemaker: reveal ECG & electrical shock
 - Sensitive personal medical information → privacy loss
 - HIV-positive care worker: suspended and dismissed from work & health status made public knowledge
- Sensing and storage security depends on the device
- Communication security should be strongly fulfilled
 - Perform data fusion & data delivery
 - Communication channel security → multipath
 - Against eavesdropping and integrity attacks for beyond-BAN communication
 - Need for encrypted and authenticated communication for different communication patterns → crypto keys
- Node-to-host association via physiological signals and biometrics

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- Propose 4 *novel* physiological parameter generation techniques and identify 4 appropriate parameters
- *For the first time in literature*, use BP with ECG & PPG
- Demonstrate suitability of generated physiological parameters on being used as cryptographic keys
- Generate temporally variant physiological parameters
- *For the first time in literature*, generate temporally invariant physiological parameters
- Propose a *novel and efficient* key agreement protocol, SKA-PS, providing secure node-to-host association
- Propose a *novel and efficient* biometric key agreement protocol using pure biometrics, SKA-PB.
 - Biometrics with unordered feature set, e.g. fingerprint
 - No helper component
 - Time variant key generation from time invariant biometrics

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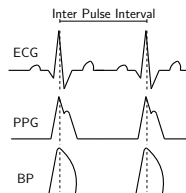
Deriving Cryptographic Keys from Physiological Signals

- Remote health monitoring systems
 - ECG, BP, oxygen saturation (via PPG) and BT
 - Different device specifically designed for recording
 - Specific place on the human body to be attached
- Choice considerations
 - Ability of biosensors on retrieving relevant data
 - Requirements of being used as cryptographic keys
 - Physiological parameter is random
- Appropriate physiological parameters
 - Inter-pulse interval (IPI)
 - Cross-power spectral density (CPSD)
 - Feature-level IPI-CPSD fused

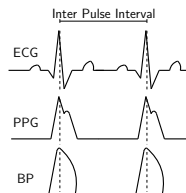
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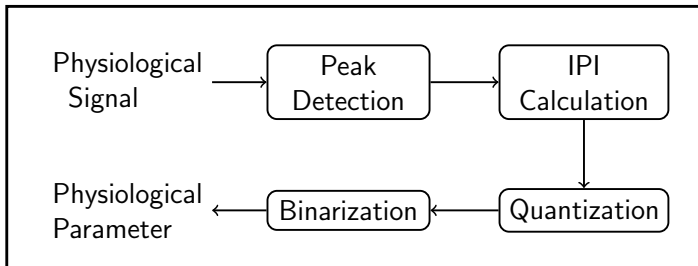
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- Propose 4 physiological parameter generation techniques
 - Time-domain physiological parameter generation
 - Frequency-domain physiological parameter generation
 - Concat-fused physiological parameter generation
 - XOR-fused physiological parameter generation
- Identify 4 appropriate physiological parameters
 - IPI-based physiological parameters
 - CPSD-based physiological parameters
 - IPI-CPSD concat-fused physiological parameters
 - IPI-CPSD xor-fused physiological parameters

-
- D. Karaolan Altop, A. Levi and V. Tuzcu, "Deriving Cryptographic Keys from Physiological Signals", *Pervasive and Mobile Computing*, vol. 39, pp. 65-79, Elsevier, DOI: 10.1016/j.pmcj.2016.08.004, August 2017.
 - D. Karaolan Altop, A. Levi and V. Tuzcu, "Feature-level fusion of physiological parameters to be used as cryptographic keys", *IEEE International Conference on Communications (ICC 2017)*, pp. 1 - 6, Paris, France, May 2017.

Time-Domain Physiological Parameter Generation



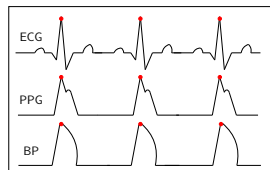
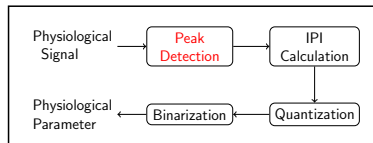
Time-Domain Physiological Parameter Generation

INPUT: *Signal, l, g, min, max, s, n*

OUTPUT: *PhysParam*

```

1: P = FindPeakLocations(Signal)
2: for all i ∈ {1, ..., l} do
3:    $IPI_i^{init} = P_{i+1} - P_i$ 
4: end for
5: IPI = zeros (l/g)
6: k = 1
7: for i = 1 : g : l do
8:   for all j ∈ {1, ..., g} do
9:      $IPI(k) = IPI(k) + IPI^{init}(i + j - 1)$ 
10:  end for
11:  k = k + 1
12: end for
13:  $len_{part} = \text{floor}((max - min)/s)$ 
14: part = zeros (lenpart)
15: code = zeros (lenpart + 1)
16: for all i ∈ {1, ..., lenpart} do
17:   part(i) = min + i * s
18:   code(i) = i mod 2n
19: end for
20: IPIquant = Quantization (IPI, part, code)
21: PhysParam = GrayEncoding (IPIquant)
  
```



Time-Domain Physiological Parameter Generation

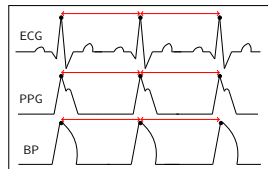
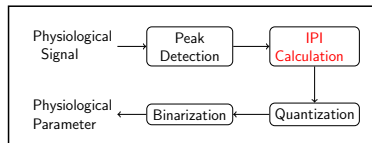
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16: for all  $i \in \{1, \dots, len_{part}\}$  do
17:    $part(i) = min + i * s$ 
18:    $code(i) = i \bmod 2^n$ 
19: end for
20:  $IPI^{quant} = Quantization(IPI, part, code)$ 
21:  $PhysParam = GrayEncoding(IPI^{quant})$ 

```



i.e.: $IPI^{init} = \{6, 8, 6, 3, 8, 9\}$ & $g = 2$

$IPI = \{14, 9, 17\}$

Time-Domain Physiological Parameter Generation

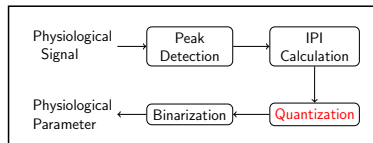
INPUT: *Signal, l, g, min, max, s, n*

OUTPUT: *PhysParam*

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15:  $\text{code} = \text{zeros}(\text{len}_{\text{part}} + 1)$ 
16: for all  $i \in \{1, \dots, \text{len}_{\text{part}}\}$  do
17:    $\text{part}(i) = \text{min} + i * s$ 
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```



i.e.: $IPI = \{14, 9, 17\}$

$\text{min} = 1 \ \& \ \text{max} = 20 \ \& \ s = 5$

Partitions: $\{1 - 5, 6 - 10, 11 - 15, 16 - 20\}$

Codes: $\{0, 1, 2, 3\}$

Quantized IPI sequence: $\{2, 1, 3\}$

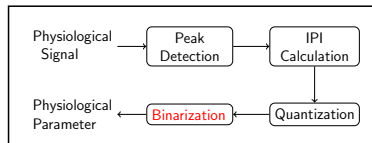
Time-Domain Physiological Parameter Generation

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OUTPUT: *PhysParam*

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16: for all  $i \in \{1, \dots, \text{len}_{\text{part}}\}$  do
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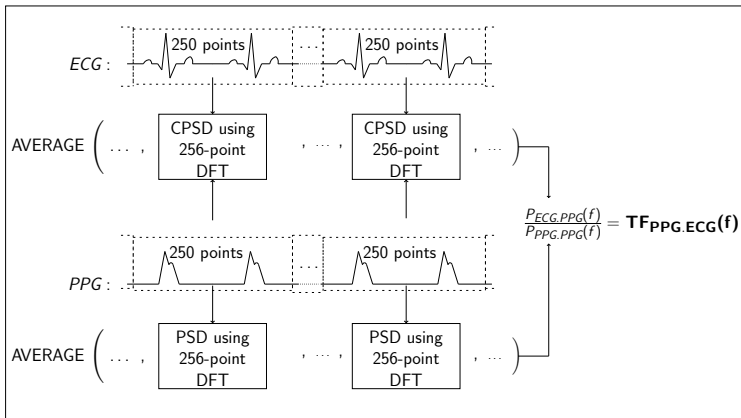


i.e.: Quantized IPI sequence: $\{2, 1, 3\}$

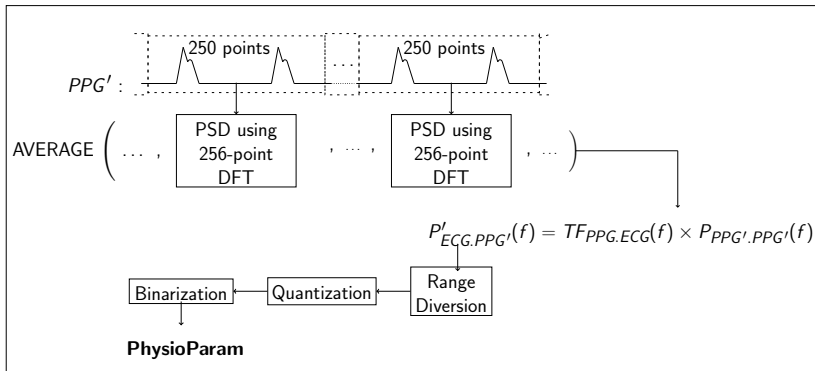
$\{0, 1, 2, 3\} \mapsto \{00, 01, 11, 10\}$

Encoded physiological parameter: $\{11, 01, 10\}$

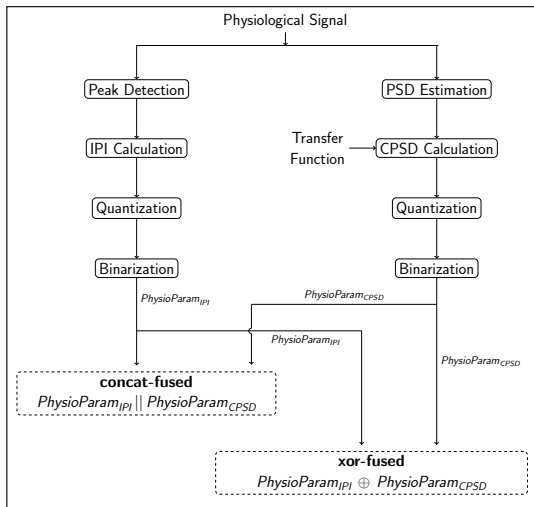
Frequency-Domain Physiological Parameter Generation - Initialization Phase



Frequency-Domain Physiological Parameter Generation - Operational Phase



Fused Physiological Parameter Generation



Experimental Datasets

- PhysioBank-MIMIC-DB

- Simultaneous ECG, PPG and BP signals
- PhysioBank MIMIC II Waveform database
- 50 subjects, 125 Hz

- SU-PhysioDB

- Simultaneous ECG and BP signals
- Collected from volunteers in Sabancı University
- 166 subjects, 4000 Hz
- Now made public: <http://people.sabanciuniv.edu/levi/projects/114E557/>

► Details

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- PhysioBank-MIMIC-DB
 - Simultaneous ECG, PPG and BP signals
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 - Simultaneous ECG and BP signals
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► Details

Performance Metrics

- Randomness
- Distinctiveness
- Error rates
- Temporal variance

Randomness - Shannon Entropy

Closer to 1 $\rightarrow$ Higher Entropy $\rightarrow$ Higher Randomness

s l, g	2	3	4	5	6	7	8	9	10	11	12	13
	PhysioBank-MIMIC-DB											
	IPI				CPSD							
32, 1	0.93	0.84	0.88	0.86								
64, 1	0.90	0.80	0.82	0.76								
128, 1	0.91	0.80	0.73	0.66	0.98	0.97	0.95	0.96				
64, 2	0.94	0.93	0.90	0.87								
128, 2	0.97	0.93	0.92	0.85								
128, 4	0.96	0.93	0.92	0.92	0.99	0.99	0.99	0.99				
	SU-PhysioDB											
	IPI						CPSD					
	32, 1	0.97	0.98	0.97	0.94	0.93	0.90					
64, 1	0.96	0.92	0.87	0.83	0.83	0.84						
128, 1	0.98	0.95	0.91	0.87	0.79	0.75	0.99	0.99	0.99	0.99	0.98	0.97
64, 2	0.97	0.96	0.98	0.98	0.98	0.97						
128, 2	0.99	0.98	0.97	0.94	0.93	0.90						
128, 4	0.99	0.98	0.96	0.96	0.97	0.98	0.99	0.99	0.99	0.98	0.98	0.99

PhysioBank-MIMIC-DB				
$\begin{matrix} s_{IPI} \\ g_{CPSD}, s_{CPSD} \end{matrix}$	3	4	5	
concat-fused	1, 9	0.97	0.97	0.97
	4, 8	0.98	0.98	0.98
	4, 9	0.98	0.98	0.98
xor-fused	1, 9	0.99	0.99	0.99
	4, 8	0.99	0.99	0.99
	4, 9	0.99	0.99	0.99
SU-PhysioDB				
$\begin{matrix} l_{IPI}, g_{IPI}, s_{IPI} \\ s_{CPSD} \end{matrix}$	64, 2, 3	128, 2, 5	128, 4, 4	
concat-fused	9	0.99	0.98	0.99
	11	0.99	0.98	0.99
	12	0.98	0.98	0.98
xor-fused	9	0.99	0.99	0.99
	11	0.99	0.99	0.99
	12	0.99	0.99	0.99

► Example

Randomness - Shannon Entropy

Closer to 1 $\rightarrow$ Higher Entropy $\rightarrow$ Higher Randomness

l, g s	2	3	4	5	6	7	8	9	10	11	12	13	
	PhysioBank-MIMIC-DB												
	IPI				CPSD								
32, 1	0.93	0.84	0.88	0.86									
64, 1	0.90	0.80	0.82	0.76									
128, 1	0.91	0.80	0.73	0.66	0.98	0.97	0.95	0.96					
64, 2	0.94	0.93	0.90	0.87									
128, 2	0.97	0.93	0.92	0.85	0.99	0.99	0.98	0.99					
128, 4	0.96	0.93	0.92	0.92	0.99	0.99	0.99	0.99					
	SU-PhysioDB												
	IPI						CPSD						
32, 1	0.97	0.98	0.97	0.94	0.93	0.90							
64, 1	0.96	0.92	0.87	0.83	0.83	0.84							
128, 1	0.98	0.95	0.91	0.87	0.79	0.75	0.99	0.99	0.99	0.99	0.98	0.97	
64, 2	0.97	0.96	0.98	0.98	0.98	0.97							
128, 2	0.99	0.98	0.97	0.94	0.93	0.90	0.99	0.99	0.99	0.99	0.98	0.98	
128, 4	0.99	0.98	0.96	0.96	0.97	0.98	0.99	0.99	0.99	0.98	0.98	0.99	

PhysioBank-MIMIC-DB				
$\begin{matrix} s_{IPI} \\ g_{CPSD}, s_{CPSD} \end{matrix}$	3	4	5	
concat-fused	1, 9	0.97	0.97	0.97
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	4, 9	0.98	0.98	0.98
xor-fused	1, 9	0.99	0.99	0.99
	4, 8	0.99	0.99	0.99
	4, 9	0.99	0.99	0.99
SU-PhysioDB				
$\begin{matrix} l_{IPI}, g_{IPI}, s_{IPI} \\ s_{CPSD} \end{matrix}$	64, 2, 3	128, 2, 5	128, 4, 4	
concat-fused	9	0.99	0.98	0.99
	11	0.99	0.98	0.99
	12	0.98	0.98	0.98
xor-fused	9	0.99	0.99	0.99
	11	0.99	0.99	0.99
	12	0.99	0.99	0.99

► Example

Randomness - Shannon Entropy

Closer to 1 $\rightarrow$ Higher Entropy $\rightarrow$ Higher Randomness

$\begin{matrix} s \\ l, g \end{matrix}$	2	3	4	5	6	7	8	9	10	11	12	13
	PhysioBank-MIMIC-DB											
	IPI				CPSD							
32, 1	0.93	0.84	0.88	0.86								
64, 1	0.90	0.80	0.82	0.76								
128, 1	0.91	0.80	0.73	0.66	0.98	0.97	0.95	0.96				
64, 2	0.94	0.93	0.90	0.87								
128, 2	0.97	0.93	0.92	0.85	0.99	0.99	0.98	0.99				
128, 4	0.96	0.93	0.92	0.92	0.99	0.99	0.99	0.99				
	SU-PhysioDB											
	IPI						CPSD					
32, 1	0.97	0.98	0.97	0.94	0.93	0.90						
64, 1	0.96	0.92	0.87	0.83	0.83	0.84						
128, 1	0.98	0.95	0.91	0.87	0.79	0.75	0.99	0.99	0.99	0.99	0.98	0.97
64, 2	0.97	0.96	0.98	0.98	0.98	0.97						
128, 2	0.99	0.98	0.97	0.94	0.93	0.90	0.99	0.99	0.99	0.99	0.98	0.98
128, 4	0.99	0.98	0.96	0.96	0.97	0.98	0.99	0.99	0.99	0.98	0.98	0.99

PhysioBank-MIMIC-DB				
$\begin{matrix} s_{IPI} \\ g_{CPSD}, s_{CPSD} \end{matrix}$	3	4	5	
concat-fused	1, 9	0.97	0.97	0.97
	4, 8	0.98	0.98	0.98
	4, 9	0.98	0.98	0.98
xor-fused	1, 9	0.99	0.99	0.99
	4, 8	0.99	0.99	0.99
	4, 9	0.99	0.99	0.99
SU-PhysioDB				
$\begin{matrix} l_{IPI}, g_{IPI}, s_{IPI} \\ s_{CPSD} \end{matrix}$	64, 2, 3	128, 2, 5	128, 4, 4	
concat-fused	9	0.99	0.98	0.99
	11	0.99	0.98	0.99
	12	0.98	0.98	0.98
xor-fused	9	0.99	0.99	0.99
	11	0.99	0.99	0.99
	12	0.99	0.99	0.99

► Example

Randomness - Shannon Entropy

Closer to 1 $\rightarrow$ Higher Entropy $\rightarrow$ Higher Randomness

s l, g	2	3	4	5	6	7	8	9	10	11	12	13
	PhysioBank-MIMIC-DB											
	IPI				CPSD							
32, 1	0.93	0.84	0.88	0.86								
64, 1	0.90	0.80	0.82	0.76								
128, 1	0.91	0.80	0.73	0.66	0.98	0.97	0.95	0.96				
64, 2	0.94	0.93	0.90	0.87								
128, 2	0.97	0.93	0.92	0.85	0.99	0.99	0.98	0.99				
128, 4	0.96	0.93	0.92	0.92	0.99	0.99	0.99	0.99				
	SU-PhysioDB											
	IPI						CPSD					
	32, 1	0.97	0.98	0.97	0.94	0.93	0.90					
64, 1	0.96	0.92	0.87	0.83	0.83	0.84						
128, 1	0.98	0.95	0.91	0.87	0.79	0.75	0.99	0.99	0.99	0.99	0.98	0.97
64, 2	0.97	0.96	0.98	0.98	0.98	0.97						
128, 2	0.99	0.98	0.97	0.94	0.93	0.90						
128, 4	0.99	0.98	0.96	0.96	0.97	0.98	0.99	0.99	0.99	0.98	0.98	0.99

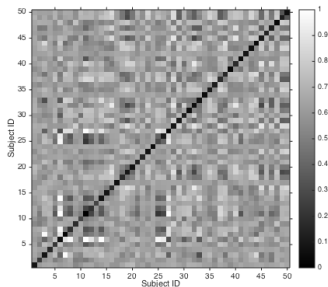
PhysioBank-MIMIC-DB				
$\begin{matrix} s_{IPI} \\ g_{CPSD}, s_{CPSD} \end{matrix}$		3	4	5
concat-fused	1, 9	0.97	0.97	0.97
	4, 8	0.98	0.98	0.98
	4, 9	0.98	0.98	0.98
xor-fused	1, 9	0.99	0.99	0.99
	4, 8	0.99	0.99	0.99
	4, 9	0.99	0.99	0.99
SU-PhysioDB				
$\begin{matrix} l_{IPI}, g_{IPI}, s_{IPI} \\ s_{CPSD} \end{matrix}$		64, 2, 3	128, 2, 5	128, 4, 4
concat-fused	9	0.99	0.98	0.99
	11	0.99	0.98	0.99
	12	0.98	0.98	0.98
xor-fused	9	0.99	0.99	0.99
	11	0.99	0.99	0.99
	12	0.99	0.99	0.99

► Example

Distinctiveness - Hamming Distance

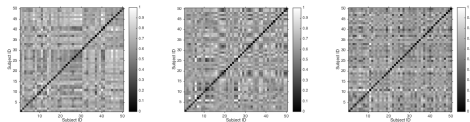
$D_s \Rightarrow$ average Hamming distance among the physiological parameters that are generated from the same host

$D_d \Rightarrow$ average Hamming distance among the physiological parameters that are generated from the different hosts



Distinctiveness - Hamming Distance

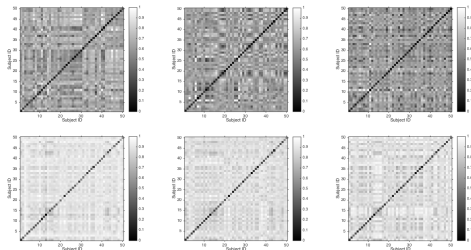
- IPI-based



Distinctiveness - Hamming Distance

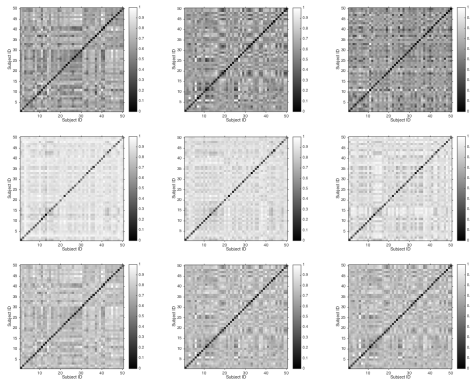
- IPI-based

- CPSPD-based



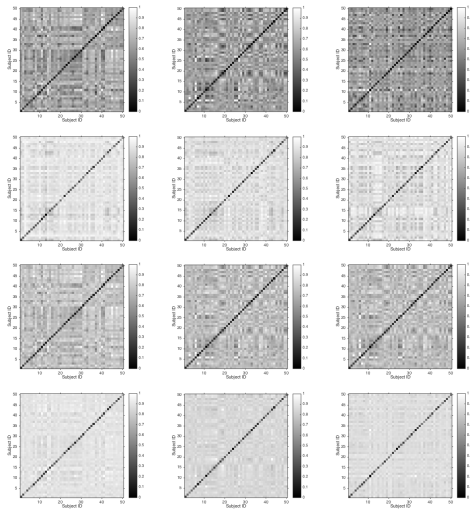
Distinctiveness - Hamming Distance

- IPI-based
- CPSPD-based
- concat-fused



Distinctiveness - Hamming Distance

- IPI-based
- CPSD-based
- concat-fused
- xor-fused



Error Rates - EER (Equal Error Rate)

Dataset	Method	EER(%)
PhysioBank-MIMIC-DB	Time-domain	4.2
	Frequency-domain	15.3
	concat-fused	3.6
	xor-fused	12.0
SU-PhysioDB	Time-domain	4.1
	Frequency-domain	13.4
	concat-fused	2.0
	xor-fused	6.0

Temporal Variance - Temporal Ratio (R)

$R \geq 1$: Temporally Variant

$R < 1$: Temporally Invariant

l, g s	2	3	4	5	6	7	8	9	10	11	12	13
	PhysioBank-MIMIC-DB											
	IPI				CPSD							
32, 1	<u>1.18</u>	0.79	0.57	0.42								
64, 1	<u>2.32</u>	<u>1.33</u>	<u>1.57</u>	0.85								
128, 1	<u>3.76</u>	<u>1.80</u>	<u>1.43</u>	0.99	0.14	0.11	0.09	0.08				
64, 2	<u>2.13</u>	<u>1.78</u>	<u>1.11</u>	0.93								
128, 2	<u>7.68</u>	<u>4.80</u>	<u>2.90</u>	<u>1.63</u>	0.13	0.12	0.10	0.09				
128, 4	<u>4.16</u>	<u>2.41</u>	<u>2.10</u>	<u>1.97</u>	0.11	0.10	0.08	0.08				
	SU-PhysioDB											
	IPI						CPSD					
32, 1	2, 07	1, 69	1, 61	1, 73	1, 39	1, 18						
64, 1	3, 22	2, 46	1, 94	1, 35	1, 24	1, 35						
128, 1	<u>3.14</u>	<u>3.11</u>	<u>2.68</u>	<u>2.40</u>	<u>1.67</u>	<u>1.36</u>	0.24	0.21	0.21	0.18	0.18	0.19
64, 2	2, 45	2, 33	1, 97	1, 64	1, 67	1, 76						
128, 2	3, 21	3, 63	3, 45	2, 66	2, 52	2, 07						
128, 4	3, 16	2, 70	2, 31	2, 32	2, 08	1, 91	0.24	0.24	0.23	0.23	0.22	0.23

PhysioBank-MIMIC-DB				
$\begin{matrix} s_{IPI} \\ g_{CPSD}, s_{CPSD} \end{matrix}$		3	4	5
concat-fused	1, 9	0.58	0.59	0.54
	4, 8	0.69	0.69	0.64
	4, 9	0.64	0.64	0.59
xor-fused	1, 9	<u>1.93</u>	<u>1.76</u>	<u>1.27</u>
	4, 8	<u>1.82</u>	<u>1.39</u>	<u>1.25</u>
	4, 9	<u>1.78</u>	<u>1.43</u>	<u>1.25</u>
SU-PhysioDB				
$\begin{matrix} l_{IPI}, g_{IPI}, s_{IPI} \\ s_{CPSD} \end{matrix}$		64, 2, 3	128, 2, 5	128, 4, 4
concat-fused	9	0.69	0.75	0.69
	11	0.73	0.80	0.73
	12	0.73	0.80	0.74
xor-fused	9	<u>1.05</u>	<u>1.37</u>	<u>1.24</u>
	11	<u>1.25</u>	<u>1.62</u>	<u>1.44</u>
	12	<u>1.38</u>	<u>1.72</u>	<u>1.53</u>

Temporal Variance - Temporal Ratio (R)

$R \geq 1$: Temporally Variant

$R < 1$: Temporally Invariant

$l, g \backslash s$	2	3	4	5	6	7	8	9	10	11	12	13
	PhysioBank-MIMIC-DB											
	IPI				CPSD							
32, 1	<u>1.18</u>	0.79	0.57	0.42								
64, 1	<u>2.32</u>	<u>1.33</u>	<u>1.57</u>	0.85								
128, 1	<u>3.76</u>	<u>1.80</u>	<u>1.43</u>	0.99	0.14	0.11	0.09	0.08				
64, 2	<u>2.13</u>	<u>1.78</u>	<u>1.11</u>	0.93								
128, 2	<u>7.68</u>	<u>4.80</u>	<u>2.90</u>	<u>1.63</u>	0.13	0.12	0.10	0.09				
128, 4	<u>4.16</u>	<u>2.41</u>	<u>2.10</u>	<u>1.97</u>	0.11	0.10	0.08	0.08				
	SU-PhysioDB											
	IPI						CPSD					
32, 1	<u>2, 07</u>	<u>1, 69</u>	<u>1, 61</u>	<u>1, 73</u>	<u>1, 39</u>	<u>1, 18</u>						
64, 1	<u>3, 22</u>	<u>2, 46</u>	<u>1, 94</u>	<u>1, 35</u>	<u>1, 24</u>	<u>1, 35</u>						
128, 1	<u>3.14</u>	<u>3.11</u>	<u>2.68</u>	<u>2.40</u>	<u>1.67</u>	<u>1.36</u>	0.24	0.21	0.21	0.18	0.18	0.19
64, 2	<u>2, 45</u>	<u>2, 33</u>	<u>1, 97</u>	<u>1, 64</u>	<u>1, 67</u>	<u>1, 76</u>						
128, 2	<u>3, 21</u>	<u>3, 63</u>	<u>3, 45</u>	<u>2, 66</u>	<u>2, 52</u>	<u>2, 07</u>						
128, 4	<u>3, 16</u>	<u>2, 70</u>	<u>2, 31</u>	<u>2, 32</u>	<u>2, 08</u>	<u>1, 91</u>	0.24	0.24	0.23	0.23	0.22	0.23

PhysioBank-MIMIC-DB				
$g_{CPSD}, s_{CPSD} \backslash s_{IPI}$		3	4	5
concat-fused	1, 9	0.58	0.59	0.54
	4, 8	0.69	0.69	0.64
	4, 9	0.64	0.64	0.59
xor-fused	1, 9	1.93	1.76	1.27
	4, 8	1.82	1.39	1.25
	4, 9	1.78	1.43	1.25
SU-PhysioDB				
$l_{IPI}, g_{IPI}, s_{IPI} \backslash s_{CPSD}$		64, 2, 3	128, 2, 5	128, 4, 4
concat-fused	9	0.69	0.75	0.69
	11	0.73	0.80	0.73
	12	0.73	0.80	0.74
xor-fused	9	1.05	1.37	1.24
	11	1.25	1.62	1.44
	12	1.38	1.72	1.53

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$R \geq 1$: Temporally Variant

$R < 1$: Temporally Invariant

$l, g \backslash s$	2	3	4	5	6	7	8	9	10	11	12	13
	PhysioBank-MIMIC-DB											
	IPI				CPSD							
32, 1	<u>1.18</u>	0.79	0.57	0.42								
64, 1	<u>2.32</u>	<u>1.33</u>	<u>1.57</u>	0.85								
128, 1	<u>3.76</u>	<u>1.80</u>	<u>1.43</u>	0.99	0.14	0.11	0.09	0.08				
64, 2	<u>2.13</u>	<u>1.78</u>	<u>1.11</u>	0.93								
128, 2	<u>7.68</u>	<u>4.80</u>	<u>2.90</u>	<u>1.63</u>	0.13	0.12	0.10	0.09				
128, 4	<u>4.16</u>	<u>2.41</u>	<u>2.10</u>	<u>1.97</u>	0.11	0.10	0.08	0.08				
	SU-PhysioDB											
	IPI						CPSD					
32, 1	2, 07	<u>1, 69</u>	1, 61	1, 73	1, 39	1, 18						
64, 1	3, 22	2, 46	1, 94	1, 35	1, 24	1, 35						
128, 1	<u>3.14</u>	<u>3.11</u>	<u>2.68</u>	<u>2.40</u>	<u>1.67</u>	<u>1.36</u>	0.24	0.21	0.21	0.18	0.18	0.19
64, 2	2, 45	2, 33	1, 97	1, 64	1, 67	1, 76						
128, 2	3, 21	<u>3, 63</u>	3, 45	2, 66	2, 52	2, 07						
128, 4	3, 16	2, 70	2, 31	2, 32	2, 08	1, 91	0.24	0.24	0.23	0.23	0.22	0.23

PhysioBank-MIMIC-DB				
$g_{CPSD}, s_{CPSD} \backslash s_{IPI}$		3	4	5
concat-fused	1, 9	0.58	0.59	0.54
	4, 8	0.69	0.69	0.64
	4, 9	0.64	0.64	0.59
xor-fused	1, 9	<u>1.93</u>	<u>1.76</u>	<u>1.27</u>
	4, 8	<u>1.82</u>	<u>1.39</u>	<u>1.25</u>
	4, 9	<u>1.78</u>	<u>1.43</u>	<u>1.25</u>
SU-PhysioDB				
$l_{IPI}, g_{IPI}, s_{IPI} \backslash s_{CPSD}$		64, 2, 3	128, 2, 5	128, 4, 4
concat-fused	9	0.69	0.75	0.69
	11	0.73	0.80	0.73
	12	0.73	0.80	0.74
xor-fused	9	<u>1.05</u>	<u>1.37</u>	<u>1.24</u>
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	12	<u>1.38</u>	<u>1.72</u>	<u>1.53</u>

Deriving Cryptographic Keys from Physiological Signals

SKA-PS: Secure Key Agreement using Physiological Signals

SKA-PB: Secure Key Agreement using Pure Biometrics

	Randomness	Distinctiveness	Temporal Variance	EER
singular IPI-based	✓	✓	✓	✓✓
singular CPSD-based	✓✓	✓✓✓	✗	✓
concat-fused	✓✓	✓✓	✗	✓✓
xor-fused	✓✓	✓✓✓	✓	✓

- Each can be used in the key management protocols designed to secure the intra-BAN communications
 - Key binding (fuzzy commitment/vault)
 - Key generation
- Either directly or via some protocol regulations

SKA-PS: Secure Key Agreement using Physiological Signals

- *Secure Key Agreement using Physiological Signals*
 - Generates symmetric cryptographic keys from physiological parameters
 - Secure key agreement $\Rightarrow$ application of *set reconciliation* technique
 - *Set Reconciliation*: finite field based protocol in which parties have two different sets and they learn the set differences without revealing the actual contents of the sets
 - Physiological parameter sequences $\Rightarrow$ appropriate sets
- Employ 2 different biosensors:
 - *Source biosensor*
 - *Conforming biosensor*
- Instantiate our protocol model using the IPI values derived from the ECG and BP signals

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 - Physiological parameter sequences $\Rightarrow$ appropriate sets
- Employ 2 different biosensors:
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- Instantiate our protocol model using the IPI values derived from the ECG and BP signals

SKA-PS with Modifications on Set Reconciliation

- Input: Generated physiological parameters after quantization but before binarization, i.e. some integers
- Aim of biosensors: agree on a symmetric shared key
 - Conforming biosensor $\xrightarrow{\text{reconcile}}$ source biosensor set
 - So what is going to be the set? All elements in a single set?
 - Conforming biosensor must understand where to remove and add difference elements
 - The way of doing this is to sort all elements in both sets; however, sorting reduces the randomness (not good)
 - Without sorting, the only option is brute-force search for the place of the elements $\rightarrow$ enormous computational cost

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SKA-PS with Modifications on Set Reconciliation

- *Our Solution:* Part by part processing
- Divide the input physiological parameters into sets with fixed number of *sorted* elements (in our tests 4 and 8)
- Protocol works in round-manner
 - Biosensors aim to find r matching sets
 - Start with r sets and try to reconcile them (only small amount of missing elements are allowed for each set)
 - If all successfully reconciled, Bingo!!! key is agreed
 - Otherwise add one more set and try all possible combinations with r subsets to reconcile
 - Continue until:
 - They find r successfully reconciled sets and key is agreed, or
 - All sets are tried and no matching protocol terminates

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SKA-PS with Modifications on Set Reconciliation

- *Our Solution:* Part by part processing
- Divide the input physiological parameters into sets with fixed number of *sorted* elements (in our tests 4 and 8)
- Protocol works in round-manner
 - Biosensors aim to find r matching sets
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 - If all successfully reconciled, Bingo!!! key is agreed
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 - Continue until:
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Inputs and Performance Metrics

- Input physiological parameter
 - IPI-based physiological parameter
- Performance metrics
 - True match and false match rates
 - Randomness, distinctiveness and temporal variance
 - Computational, communication and storage complexity

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True Match and False Match Rates

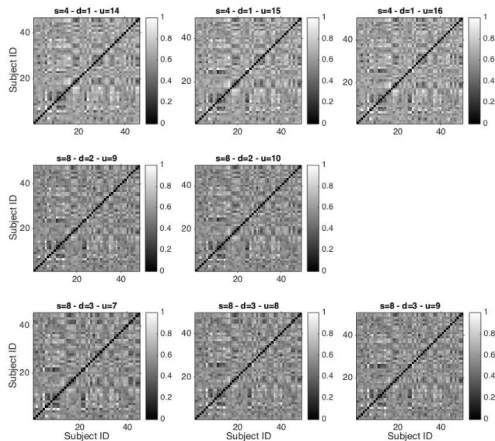
Parameters			True Match Rate (%)	False Match Rate (%)
s	d	n		
4	1	14	95	0
		15	99	0
		16	100	0.06
8	2	9	98	0.04
		10	99	0.04
	3	7	95	0.06
		8	99	0.22
		9	100	0.51

Randomness and Temporal Variance

Parameters			Randomness	Temporal Ratio
s	d	n		
4	1	14	0.9114	3.16
		15	0.9101	3.19
		16	0.9105	3.29
8	2	9	0.9092	2.48
		10	0.9099	2.50
	3	7	0.9091	2.37
		8	0.9100	2.64
		9	0.9109	2.69

► Example

Distinctiveness



Complexity: Average Number of Protocol Rounds

Parameters			Average Number of Protocol Rounds	
s	d	n	Source Biosensor	Conforming Biosensor
4	1	14	17.33	12.26
		15	71.78	50.13
		16	114.74	72.91
8	2	9	4.64	3.41
		10	5.81	4.09
	3	7	1	1
		8	1.28	1.14
		9	1.63	1.37

Complexity: Average Number of Protocol Rounds

Parameters			Average Number of Protocol Rounds	
s	d	n	Source Biosensor	Listening Biosensor
4	1	14	1.55	12.26
		15	71.78	50.13
		16	114.74	72.91
	2	9	4.64	3.41
		10	5.81	4.09
8	3	7	1	1
		8	1.28	1.14
		9	1.63	1.37

ON THE AVERAGE

Total key agreement latency: 6 sec

Communication complexity: 58 Byte

Storage complexity: 197 Byte

Conclusions for SKA-PS

- SKA-PS enables biosensors to agree on symmetric keys
 - Directly generated from the sensed data
 - Remarkably high true match rates
 - Exceedingly low false match rates
 - Low computational, communication and storage costs
- SKA-PS meets the requirements of BANs stemming from the limitations of the biosensors
 - Can fill the "lightweight security protocol"-gap in the literature

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Conclusions and Future Directions for Intra-BAN part

- Intra-BAN communication architecture
 - Secure node-to-host association
 - Use of physiological signals
 - Highly random and distinctive physiological parameters
 - Low error rate possessing physiological parameters
 - Dynamic key agreement with low costs

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 - Secure node-to-host association
 - Use of physiological signals
 - Highly random and distinctive physiological parameters
 - Low error rate possessing physiological parameters
 - Dynamic key agreement with low costs
- Future work
 - Hardware implementation
 - Other physiological signals

SKA-PB: Secure Key Agreement using Pure Biometrics

- Our key agreement protocol for beyond-BAN communication
 - Round-manner
 - At each round, try to find a common set of minutiae
 - At the end
 - Either, low similarity score so no key agreed
 - Or, agreement on a secure symmetric key
- *Secure key: User-defined, time-varying, random*

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Enrollment Phase

- Three fingerprint images of same finger; FP_1 , FP_2 , FP_3
- Minutiae extraction: $(x, y, type)$
 - x : x-coordinate of the minutia
 - y : y-coordinate of the minutia
 - $type$: type of the minutia, *end* or *bifurcation*



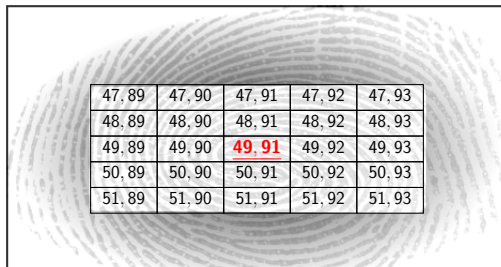
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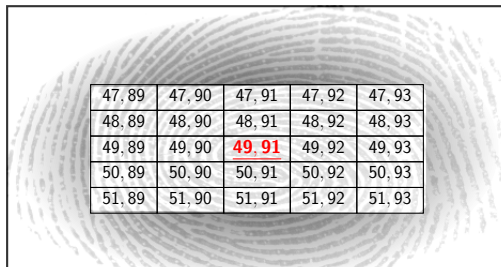
Enrollment Phase

- *Neighborhood relation*
 - T_{dist} : Pre-defined distance threshold
 - In the T_{dist} -neighborhood of (x_j, y_j)
 - x -coordinate in $[x_j - T_{dist}, x_j + T_{dist}]$
 - y -coordinate in $[y_j - T_{dist}, y_j + T_{dist}]$
- Quantize all minutiae at most T_{dist} -away to one representative minutia with smallest y -coordinate

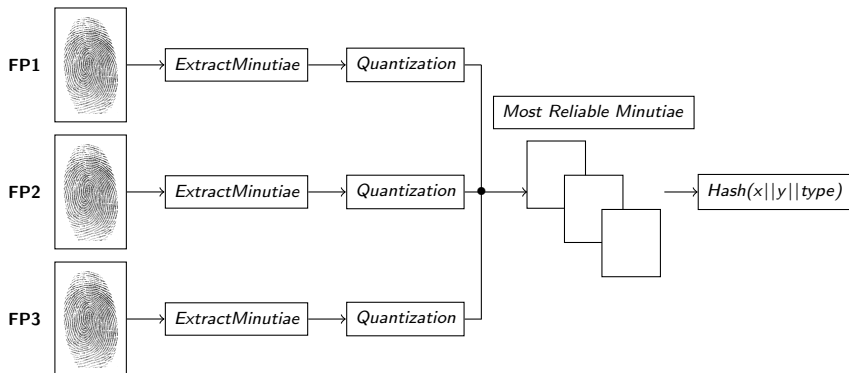


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Enrollment Phase



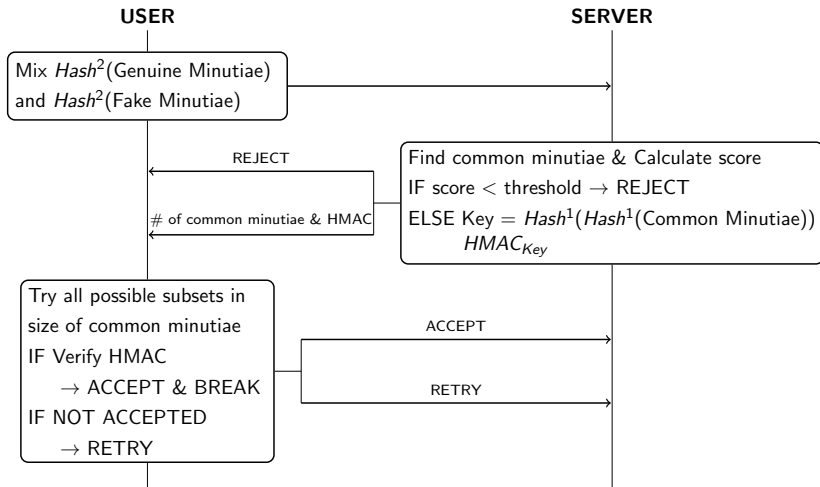
Verification Phase

- As in the enrollment phase, user side
 - Three fingerprint images of the same finger
 - Quantization according to the T_{dist} -neighborhood
 - Most reliable minutiae
 - Hash
- Fake minutiae points generation
 - 10 times the number of genuine minutiae points
 - Indistinguishable from a genuine minutia point
 - We preserve T_{dist} -neighborhood relation

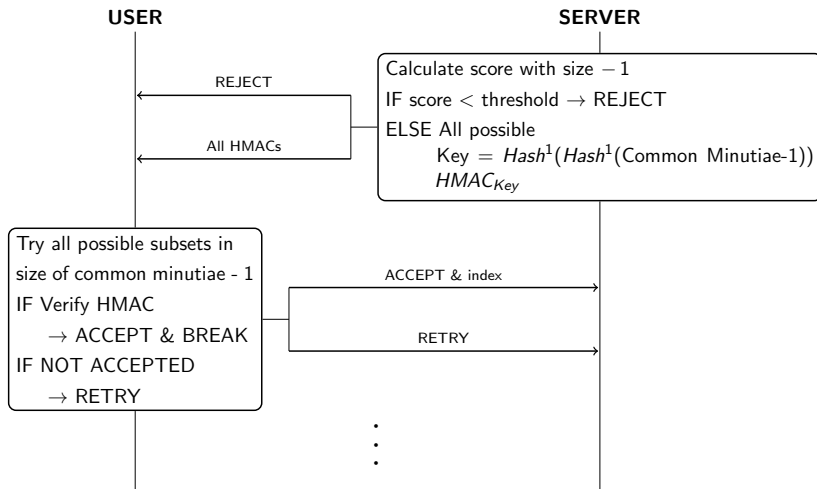
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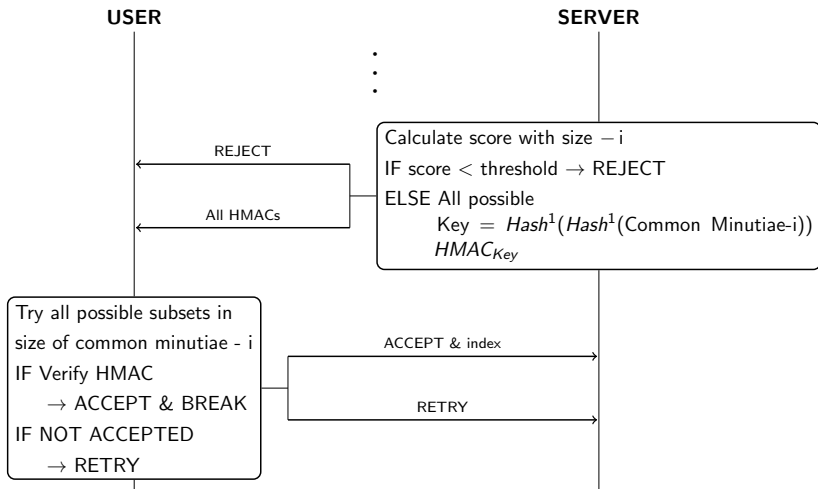
The Protocol



The Protocol



The Protocol

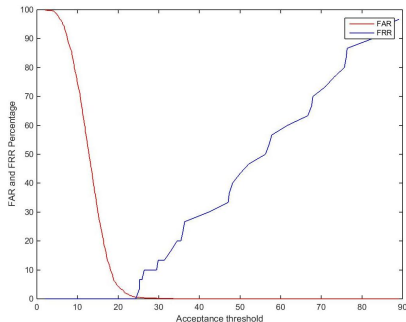


Settings

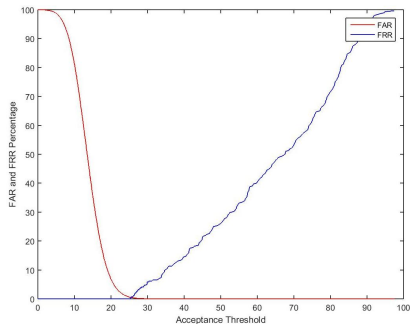
- 1st Dataset: 30 fingerprints from Verifinger Sample Database*
 - 8 impressions: 3 for server, 5 for user
- 2nd Dataset: 292 fingerprints from volunteers in Sabanci University
 - 10 impressions: 3 for server, 7 for user
- Alignment in MATLAB using intensity values
- Minutiae extraction using Neurotechnology Biometric SDK 5.0 Verifinger, <http://www.neurotechnology.com/>
- Both genuine and impostor tests
- 256-bit keys

Verification Performance

- 0.57 % EER with 1st dataset



- 0.48 % EER with 2nd dataset



Brute-force Attack Analysis

- Trying all possible keys $\Rightarrow 2^{256} \Rightarrow$ infeasible
- Intelligent brute-force attack
 - Generate all possible minutiae locations and types, and hashes
 - Does not search all possible minutiae combination $\Rightarrow$ Naive brute-force
 - Decrease search space to genuine and fake minutiae set of which hashes are transmitted during the protocol
 - Try all possible subsets and verify any HMAC
 - 1st dataset
 - $\Rightarrow 2^{256}$ hashes and HMAC verifications
 - 2nd dataset
 - $\Rightarrow 2^{256}$ hashes and HMAC verifications

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 - $\Rightarrow 2^{118}$ hash and HMAC verifications

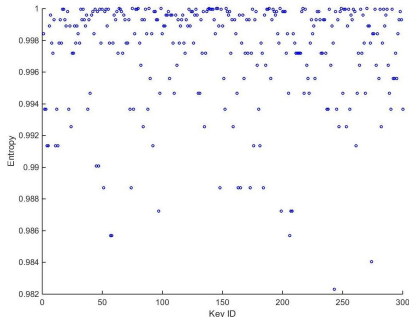
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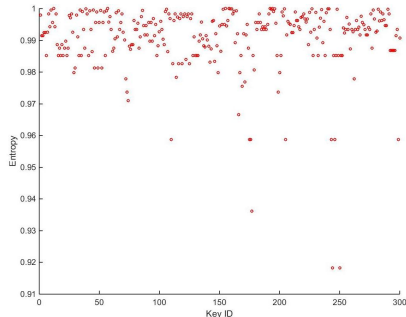
Randomness-Shannon's Entropy

1st dataset

- All keys' entropy
 $\text{Hash}(x||y||\text{type})$



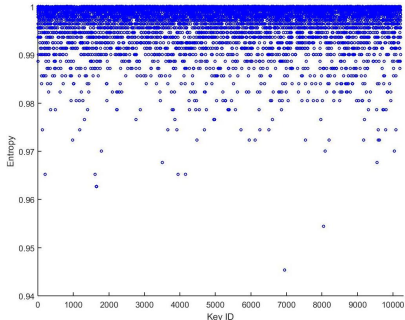
- Minutiae' entropy
 $(x||y||\text{type})$



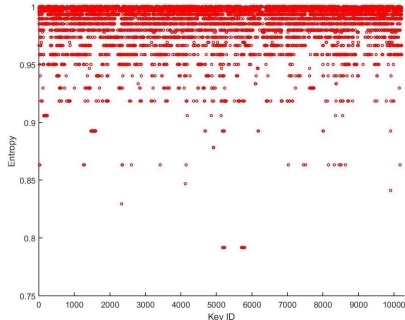
Randomness-Shannon's Entropy

2nd dataset

- All keys' entropy
 $Hash(x||y||type)$



- Minutiae' entropy
 $(x||y||type)$



Distinctiveness-Hamming Distance

- Same user must have different key after each protocol run
- Different users must have different keys
- Hamming Distance
 - Measuring the distinctiveness of the generated keys
 - Number of bits which are different at the same positions of two equal length strings
 - Closer to midpoint (128 for our case) → the more different keys

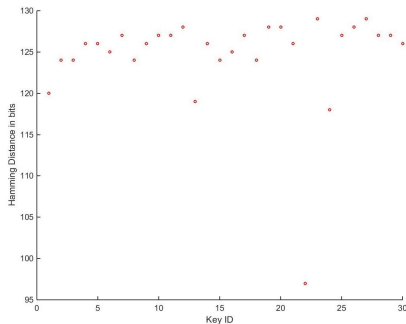
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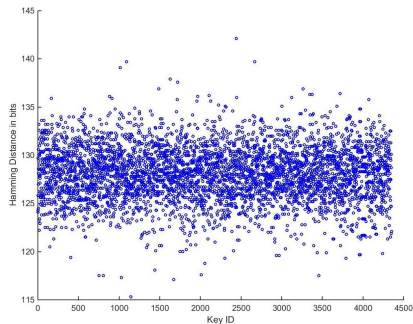
Distinctiveness-Hamming Distance

1st dataset

● Same user's keys



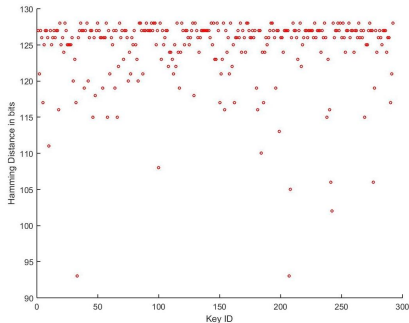
● Different users' keys



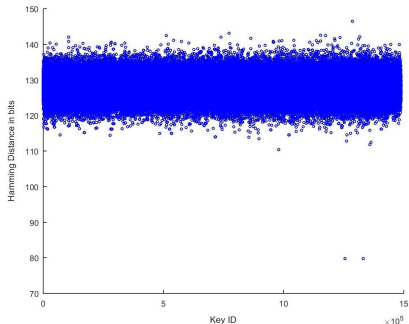
Distinctiveness-Hamming Distance

2nd dataset

● Same user's keys



● Different users' keys



Computational Complexity

$$\sum_{i=n_{com}}^{n_{com}^{key}} \binom{n_{com}}{i}$$

n_{com} : Number of common found minutiae by the server

n_{com}^{key} : Number of minutiae with which the key is generated

- Average server complexity
 - 2^{17} with 1st dataset
 - 2^9 with 2nd dataset

$$\sum_{i=n_{com}}^{n_{com}^{key}} \binom{n_u}{i}$$

n_u : Number of genuine minutiae on the user side

- Average user complexity
 - 2^{39} with 1st dataset
 - 2^{41} with 2nd dataset

Communication Complexity

- Total size of the messages sent by the server
 - 1st Dataset $\cong$ 22.4 MB
 - 2nd Dataset $\cong$ 332.8 KB
- Total size of the messages sent by the user
 - 1st Dataset $\cong$ 13.75 KB
 - 2nd Dataset $\cong$ 17.2 KB

Memory Requirements

1st Dataset

- Server side
 - Average storage is 578.8 KB per subject
- User side
 - Average storage is 15 KB for each user

2nd Dataset

- Server side
 - Average storage is 702.8 KB per subject
- User side
 - Average storage is 18.75 KB for each user

Conclusions

- Design and analysis of a new bio-cryptographic key agreement protocol
- Secure key agreement without any helper or random data
- Resistance against known attacks
- Random and distinctive keys
- Computational complexity is relatively higher for user, but feasible for server
- Acceptable communication and memory overhead

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Future Work (Completed)

- Template renewal process $\Rightarrow$ Non-invertible cancelable template
- Adaptation to ordered set of biometric features

Acknowledgments

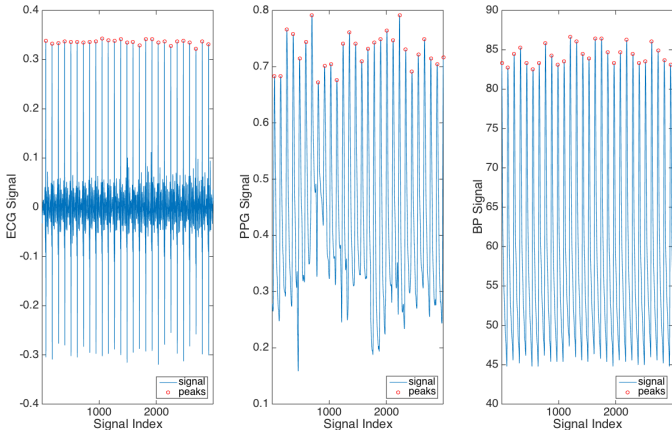
- This work was supported by TÜBİTAK (Scientific and Technological Research Council of Turkey) under grant 114E557
- Duygu Karaoğlu Altop was supported by TÜBİTAK BİDEB 2211-C and Turkcell Academy Technology Leaders Graduate Scholarship Program
- Dilara Akdoğan was supported by TÜBİTAK BİDEB 2228

THANK YOU!



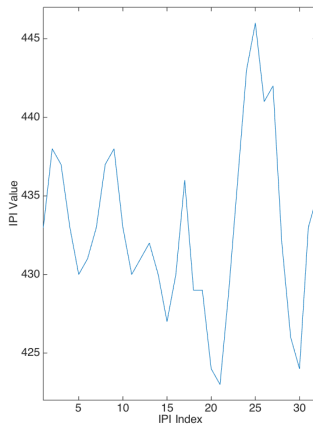
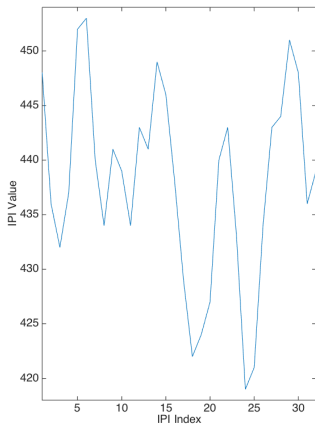
Example: IPI Peak Points

- FFT filtering and Matlab's *findpeaks* function
- Manual accuracy check → working correctly 100%



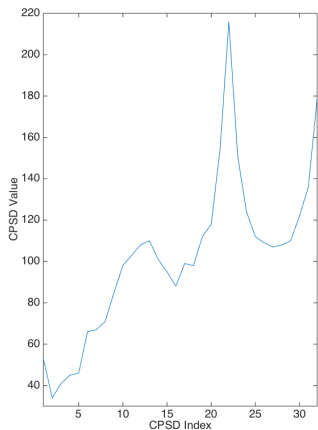
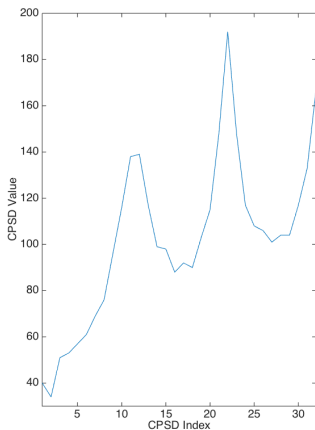
Example: IPI Sequence

- Generated IPI sequences - just before quantization
 - $l = 128, g = 4 \Rightarrow$ IPI sequence length: 32
 - From 2 different users' BP signals



Example: CPSD Sequence

- Generated CPSD sequences - just before quantization
 - $l = 128, g = 4 \Rightarrow$ CPSD sequence length: 32
 - From 2 different users' BP signals



SU-PhysioDB Dataset Details



SU-PhysioDB Dataset Details

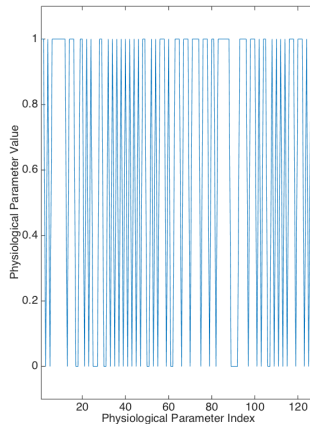
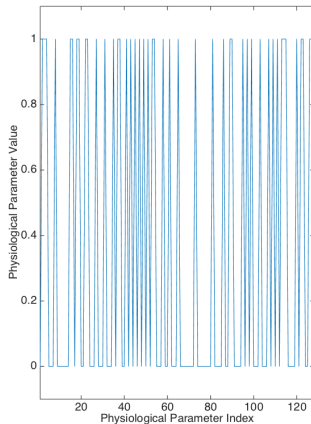


SU-PhysioDB Dataset Details



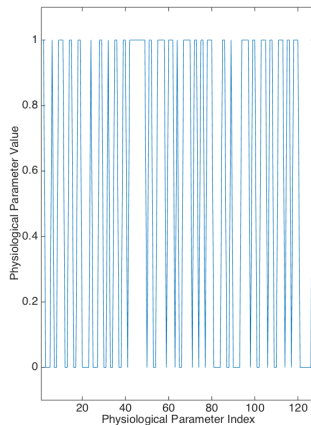
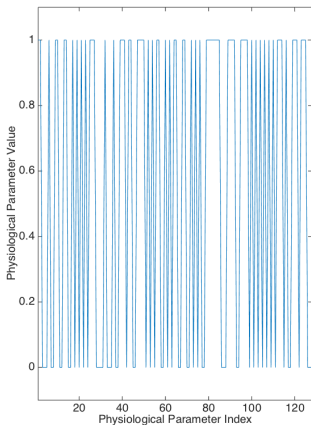
Example: IPI-based Physiological Parameter

- Generated IPI-based physiological parameters
 - $l = 128$, $g = 4$, $s = 4$
 - From 2 different users' BP signals



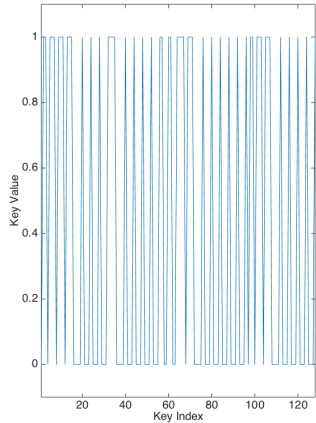
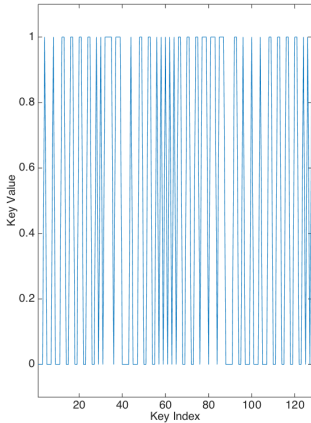
Example: CPSD-based Physiological Parameter

- Generated CPSD-based physiological parameters
 - $l = 128$, $g = 4$, $s = 9$
 - From 2 different users' BP signals



Example: Agreed Symmetric Key

- Agreed symmetric cryptographic keys
 - From 2 different users' BP signals



Protocol Parameters

- s should not be too large
 - Output: $(4 * s * b)$ -bit cryptographic keys
 - Key strength: 2^{4*s*b}
 - Set strength: 2^{4s}
 - Sorting decreases the number of possible combinations
 - Set: $\{0, 1\}$
 - Combinations: $\{\{0, 0\}, \{0, 1\}, \{1, 0\}, \{1, 1\}\}$
 - Sorted combinations: $\{\{0, 0\}, \{0, 1\}, \{1, 1\}\}$
- d can be at most $(s/2 - 1)$
 - Characteristic polynomial of degree s can be solved with $s + 1$ linear equations
 - s also determines whether there is information leakage
- r should be determined based on key strength

r	s	d	Effective Key Length (bits)
11	4	1	≈ 131
7	8	2	≈ 132
		3	

Security Analysis - Threat Model

- Attacker's aim: learn the key or impersonate
- Secure channel is not assumed $\Rightarrow$ attacker can
 - Obtain protocol messages
 - Attacker can learn the number of required sets
 - Learn the combination index
- Attacker can apply
 - Brute-force attack
 - Replay attack
 - Classical impersonation attack

Security Analysis - Resistance Against Attacks

- Brute-force attack
 - Classical brute-force
 - $(4 * s * b)$ -bit cryptographic keys with an effective strength of 131 bits $\rightarrow$ complexity is 2^{131}
 - Roots of the characteristic polynomial
 - Insufficient exchanged information $\rightarrow$ complexity is 2^{4s*r}

r	s	Resistance Against Brute-Force
11	4	2^{176}
7	8	2^{224}

- Replay attack
 - Resists against proven by temporal variance evaluations
- Classical impersonation attack
 - Resists against proven by ultra low false match rates and distinctiveness evaluations

Related Work - Physiological Parameter Generation

- Poon et al.¹ $\Rightarrow$ IPI of PPG/ECG signals
 - Divide IPI into segments $\rightarrow$ map into binary words
- Bao et al.² $\Rightarrow$ IPI of PPG/ECG signals
 - Divide IPI into segments $\rightarrow$ accumulate $\rightarrow$ randomize $\rightarrow$ map into binary words

Method	Key Length (bit)	HTER
Poon et al.	128	4.26
Poon et al.	64	6.98
Bao et al.	64	2.83
Our Methods (max. CPSD-based)	128	0.135

¹C. Poon, Y.-T. Zhang, and S.-D. Bao, "A novel biometrics method to secure wireless body area sensor networks for telemedicine and m-health", *IEEE Communications Magazine*, 2006.

²S.-D. Bao, C. Poon, Y.-T. Zhang, and L.-F. Shen, "Using the timing information of heartbeats as an entity identifier to secure body sensor network", *IEEE Trans. on Information Technology in Biomedicine*, 2008.

Related Work - Key Agreement Protocol

- Fuzzy Vault^{3,4,5} $\Rightarrow$ Frequency feat. of PPG/ECG signals
 - $S_S \cap S'_C < v < S_S \cap S_C$
 - Computational complexity: $\binom{|S_C|}{v+1}$
 - Vault security: $\binom{|R|}{v+1}$
- Set Reconciliation⁶ $\Rightarrow$ IPI of ECG signals
 - $t \leq S_S \cap S_C$ & $2(m - t) < m$
 - Computational complexity: $\binom{m}{t}$
 - Attack complexity: $\binom{m+s}{t+s}$

³ K. K. Venkatasubramanian, A. Banerjee, and S. Gupta, "PSKA: Usable and secure key agreement scheme for body area networks", in *IEEE Trans. on Information Technology in Biomedicine*, 2010.

⁴ K. K. Venkatasubramanian, A. Banerjee, and S. Gupta, "Plethysmogram-based secure inter-sensor communication in body area network", in *Proceedings of MILCOM*, 2008.

⁵ F. Miao, L. Jiang, Y. Li, and Y.-T. Zhang, "Biometrics based novel key distribution solution for body sensor networks", in *Proceedings of IEEE EMBS*, 2009.

⁶ J. Shi, K.-Y. Lam, M. Gu, M. Li, and S.-L. Chung, "Towards energy-efficient secure communications using biometric key distribution in wireless biomedical healthcare networks", in *Proceedings of BMEI*, 2009.

Related Work - Key Agreement Protocol

- Fuzzy Vault $\Rightarrow$ Frequency feat. of PPG/ECG signals
 - $S_S \cap S'_C < v < S_S \cap S_C \Rightarrow 13 < v < 31$
 - Attack complexity: $\binom{|R|}{v+1}$
- Set Reconciliation $\Rightarrow$ IPI of ECG signals
 - $t \leq S_S \cap S_C$ & $2(m - t) < m \Rightarrow 16 < t \leq 17$
 - Attack complexity: $\binom{m+s}{t+s}$

Method	Key Length (bit)	HTER (%)	Attack Complexity
Fuzzy Vault	124	9.65	2^{147}
Set Reconciliation	128	28.33	2^{47}
SKA-PS	131	2.53	2^{176}