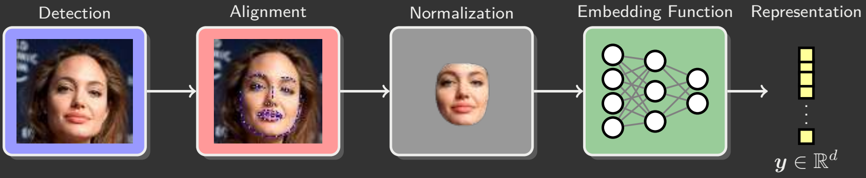
Secure Face Matching Using Fully Homomorphic Encryption

Vishnu Boddeti
Michigan State University

October 23rd, 2018

>>> Face Representation and Matching

* Face Representation:



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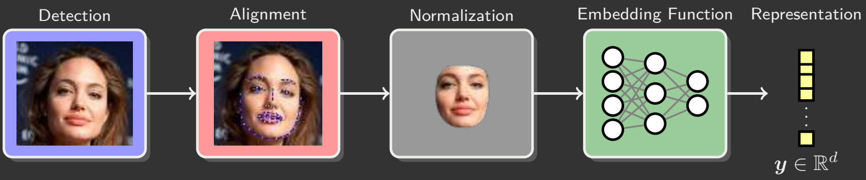
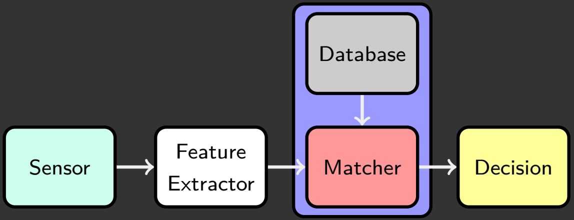


* Face Matching:

>>> Security Vulnerabilities

* Attacks on Biometric Systems:



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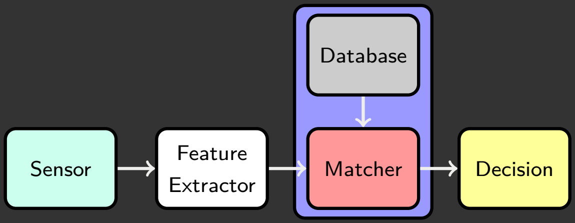

* Attacks on Templates:
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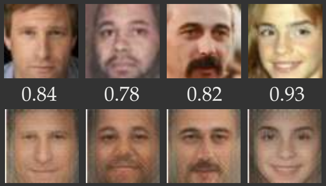

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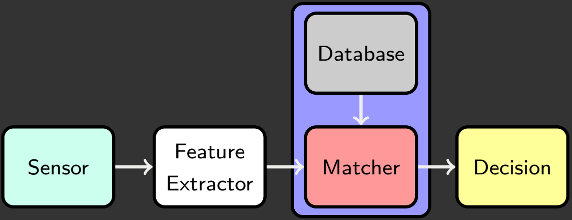
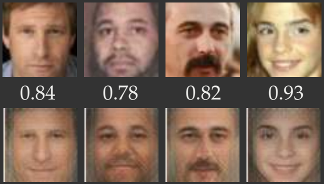
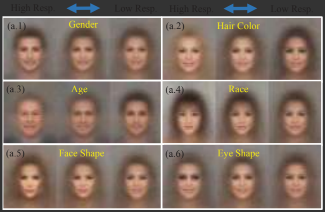


* Attacks on Templates:
  * Face reconstruction from template[1]
  * Privacy leakage through attribute prediction from template





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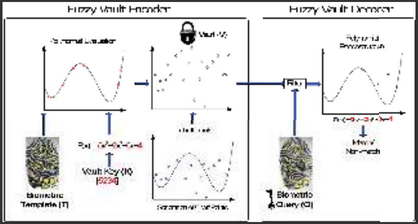

(a) Fuzzy Vault

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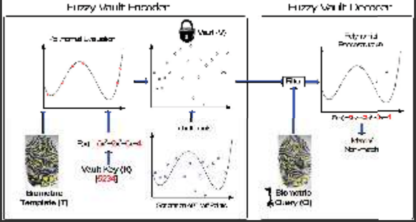

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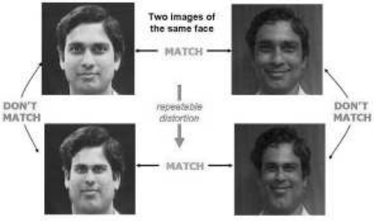

(b) Geometrical Transformations

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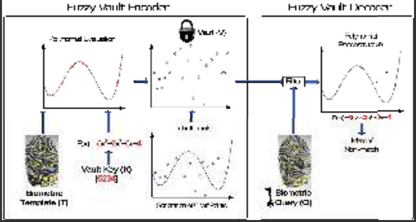

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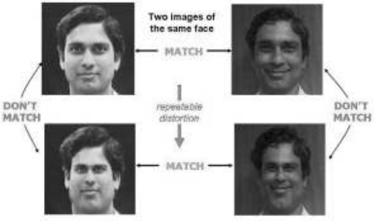

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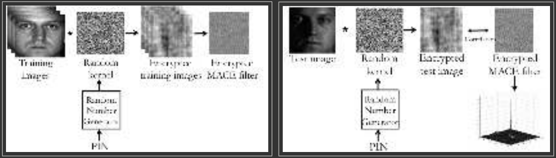

(c) Correlation with Random Masks

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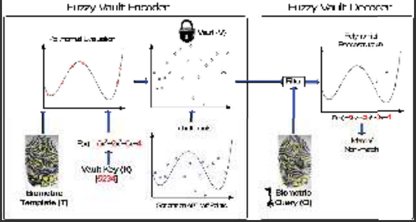

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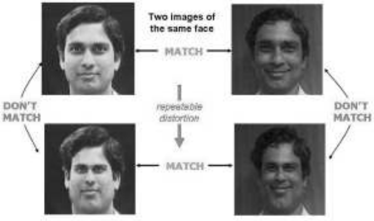

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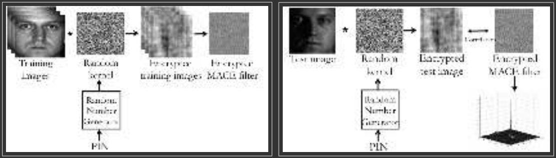

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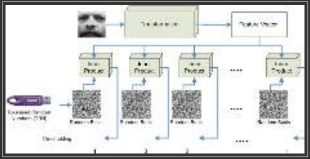

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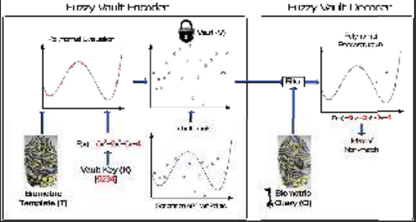

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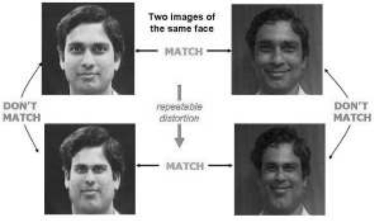

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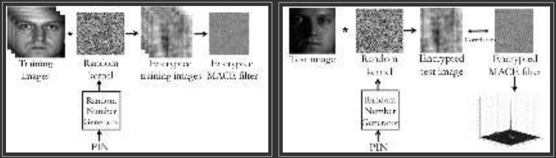

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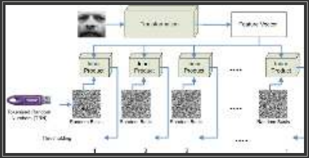

(d) Biohashing

* Drawback: Trade-Off matching performance for template security.

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* Encryption scheme needs to allow computations directly on the encrypted data.

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This Paper Explores:

* feasibility of fully homomorphic encryption for secure face matching.
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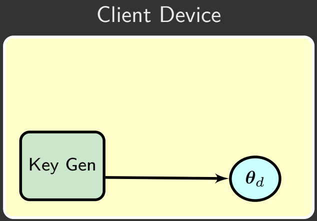

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* Client device:
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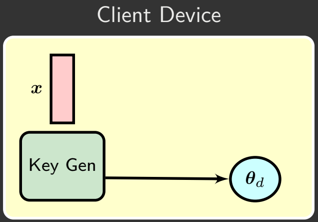
    * captures biometric signature + extracts feature



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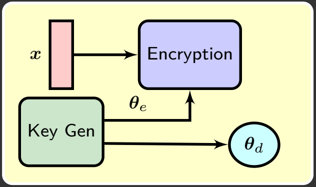

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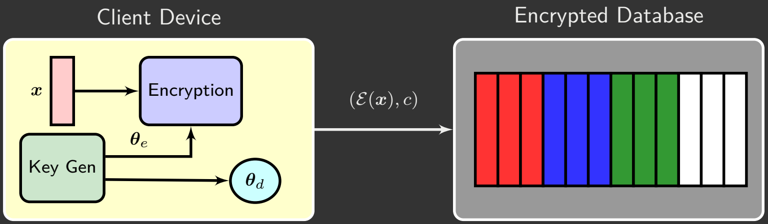

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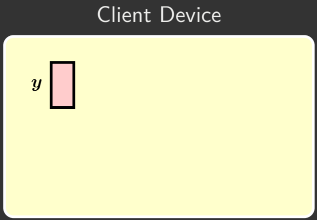

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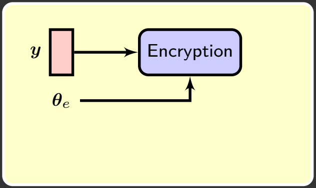

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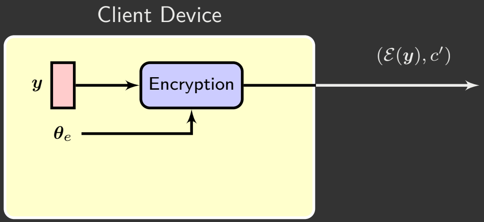

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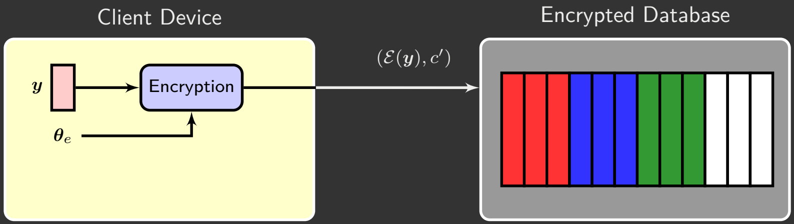

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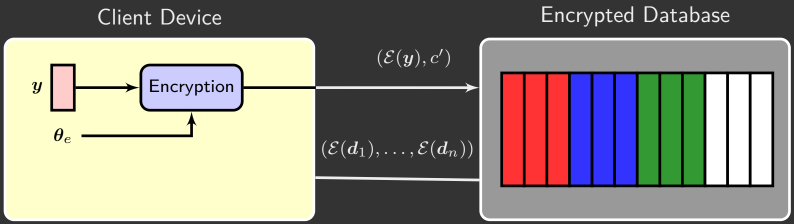

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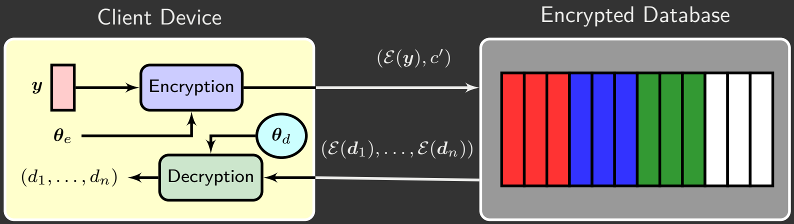
* Client device:
  * decrypts received scores and makes decision



>>> Homomorphic Inner Products

* Feature Matching:

$$
\begin{aligned}
\text{Euclidean Distance: } d(\boldsymbol{x}, \boldsymbol{y}) &= \|\boldsymbol{x} - \boldsymbol{y}\|_2^2 = \boldsymbol{x}^T\boldsymbol{x} + \boldsymbol{y}^T\boldsymbol{y} - 2\boldsymbol{x}^T\boldsymbol{y} \\
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$$s(\boldsymbol{x}, \boldsymbol{y}) = \mathcal{D}\left(\sum_{i=1}^{d} \mathcal{E}(x_i, \boldsymbol{\theta}_e)\mathcal{E}(y_i, \boldsymbol{\theta}_e), \boldsymbol{\theta}_d\right)$$

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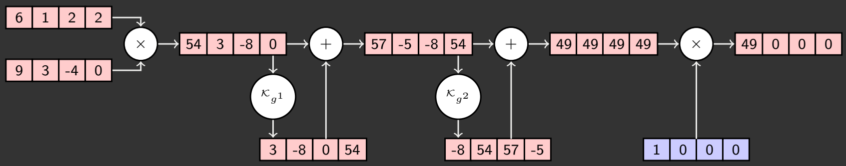
  * Encode entire vector at once + repetitive circular shift and addition



>>> Experimental Setup

* **Datasets:** LFW, IJB-A, IJB-B and CASIA

* **Models:** FaceNet (128-D) and SphereFace (512-D)

* **Evaluation:** True Accept Rate 0.01%, 0.1% and 1% FAR

* **Options:** different quantization, security levels, dimensionality of features

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    * Homomorphic Encryption
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    * Database storage size
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Security in bits (λ)	Dim (d)	No FHE Time (μs)	No FHE Mem (KB)	No Batching Time (ms) Enc	No Batching Time (ms) Score	No Batching Time (ms) Dec	No Batching Time (ms) Total	No Batching Mem (MB)	Batching Time (ms) Enc	Batching Time (ms) Score	Batching Time (ms) Dec	Batching Time (ms) Total	Batching Mem (KB)
	64	0.44	2.0										
	128	0.89	4.0										
	512	3.48	16.0										
	1024	7.49	32.0										

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	128	0.89	4.0	17.57	21.05	0.02	38.64	1.0					
128	512	3.48	16.0	280.19	343.81	0.08	624.07	16.5					
	1024	7.49	32.0	2214.88	2924.75	0.33	5139.97	131.0					

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	1024	7.49	32.0	2214.88	2924.75	0.33	5139.97	131.0	2.27	8.36	0.30	11.42	32.0

>>> Homomorphic Matching Performance

* Face verification: different quantization levels

Table: Face Recognition Accuracy (TAR @ FAR in %)

Dataset	Method	128-D FaceNet			512-D SphereFace		
		0.01%	0.1%	1%	0.01%	0.1%	1%
IJB-B	No FHE	25.77	48.31	74.47	7.86	31.27	69.83
	FHE (2.5×10^{-3})	25.78	48.28	74.46	7.86	31.27	69.82
	FHE (1.0×10^{-2})	25.71	48.31	74.44	7.80	31.29	69.75
	FHE (1.0×10^{-1})	23.75	46.08	72.87	7.49	30.92	67.45

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* Fully homomorphic face matching in encrypted domain is feasible and practical.

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    * Limitation: score thresholding is performed after decryption
    * Consequence: hill climbing attack is still possible from decrypted score
    * Limitation: encryption and decryption key are on client device
    * Consequence: key management on client device is the weakest link