Secure Face Matching Using Fully Homomorphic Encryption

Vishnu Boddeti
Michigan State University

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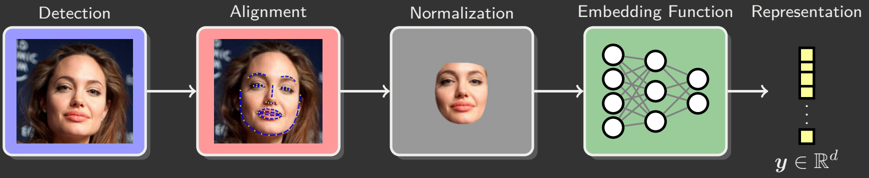
>>> Face Representation and Matching

* Face Representation:



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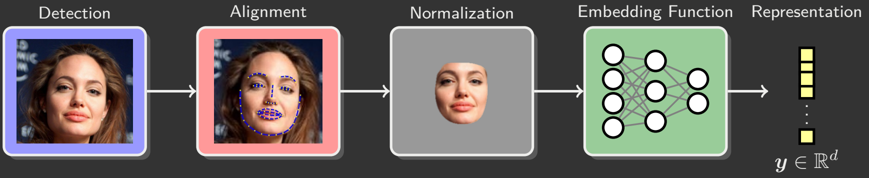
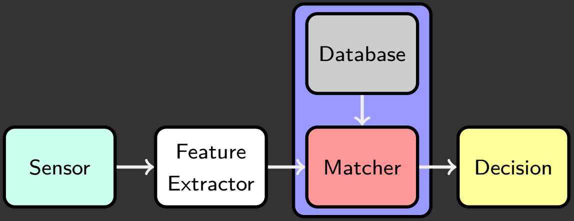


* Face Matching:

>>> Security Vulnerabilities

- Attacks on Biometric Systems:



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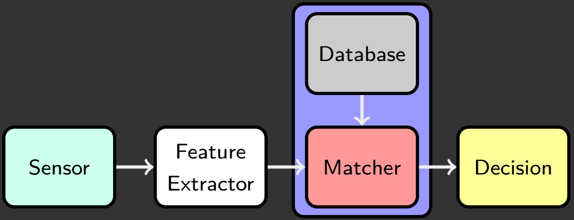

- Attacks on Templates:
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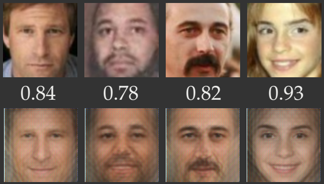

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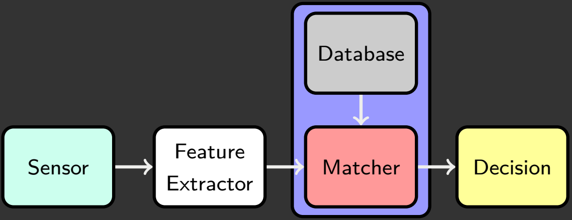
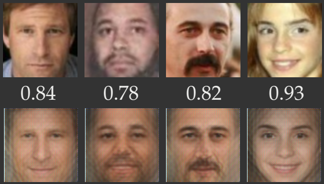
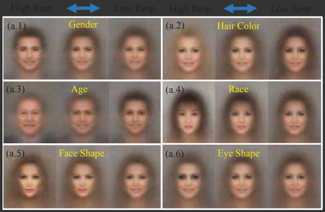


* Attacks on Templates:
  * Face reconstruction from template[1]
  * Privacy leakage through attribute prediction from template





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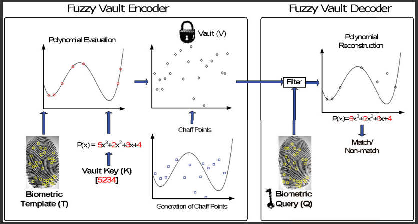

(a) Fuzzy Vault

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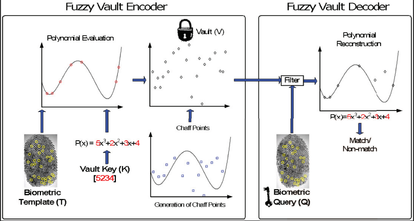

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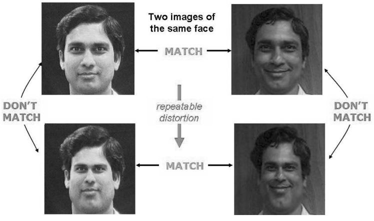

(b) Geometrical Transformations

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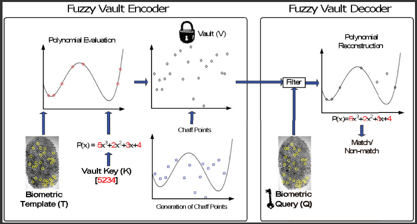

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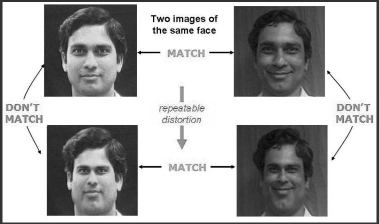

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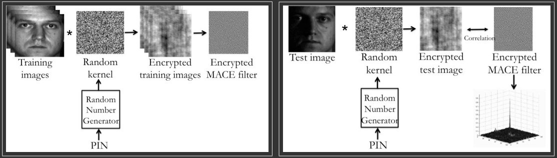

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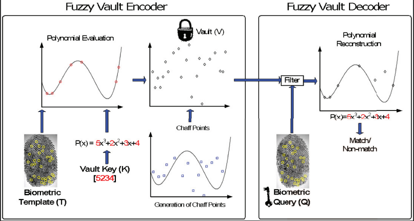

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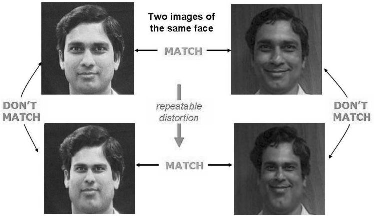

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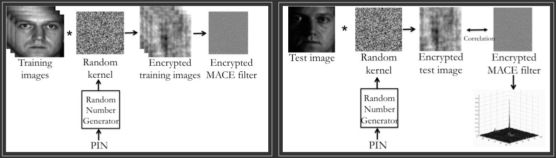

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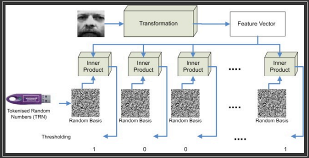

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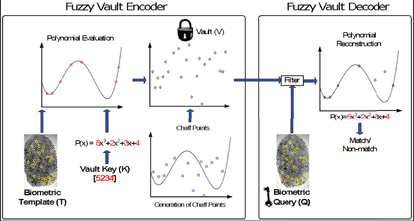

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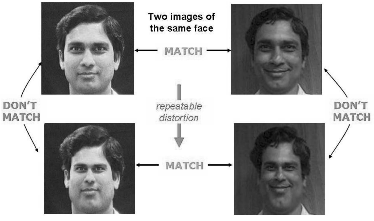

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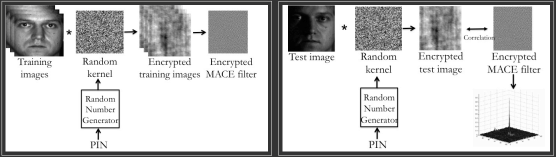

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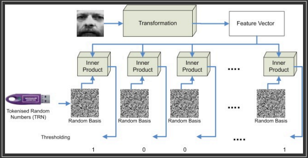

(d) Biohashing

* 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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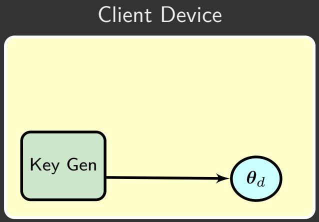

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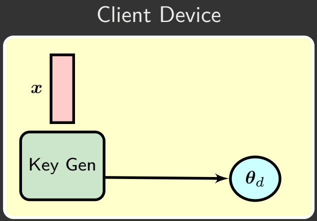

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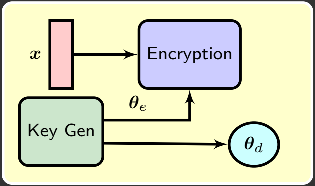

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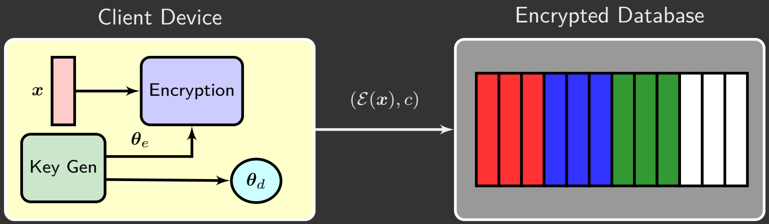

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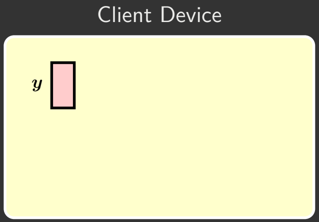

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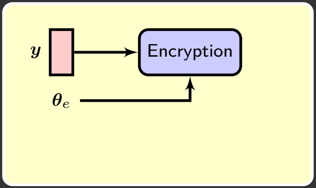

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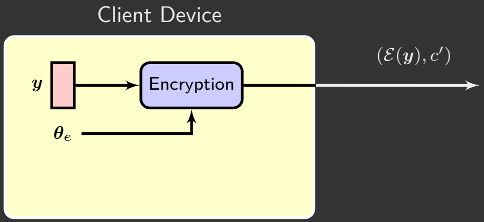

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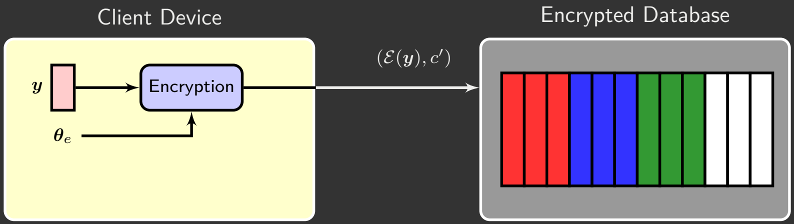

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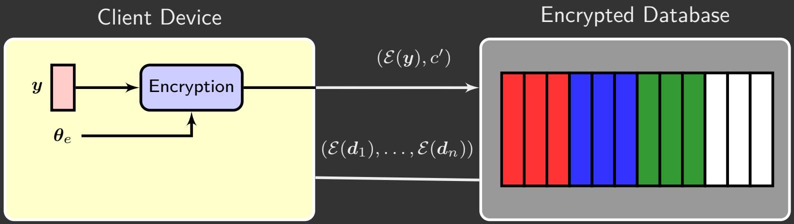

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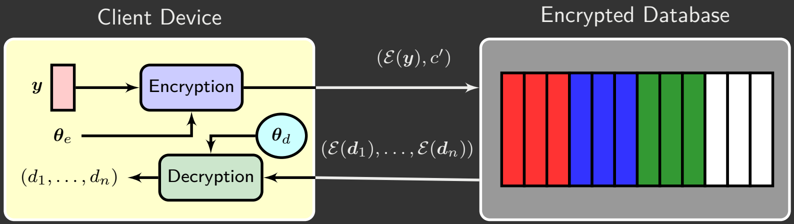

>>> Homomorphic Inner Products

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$$\begin{aligned} \text{Euclidean Distance: } d(\boldsymbol{x}, \boldsymbol{y}) &= \|\boldsymbol{x} - \boldsymbol{y}\|_2^2 = \boldsymbol{x}^T\boldsymbol{x} + \boldsymbol{y}^T\boldsymbol{y} - 2\boldsymbol{x}^T\boldsymbol{y} \\ \text{Cosine Similarity: } s(\boldsymbol{x}, \boldsymbol{y}) &= \frac{\boldsymbol{x}^T\boldsymbol{y}}{\|\boldsymbol{x}\|\|\boldsymbol{y}\|} \end{aligned}$$

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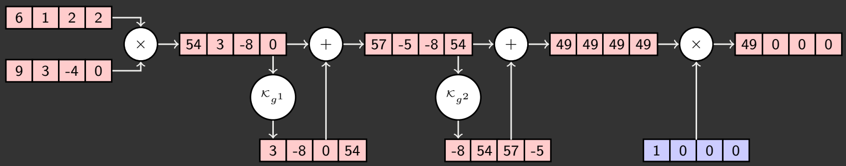
  * Encode entire vector at once + repetitive circular shift and addition



>>> 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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* Template 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	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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128	512	3.48	16.0	280.19	343.81	0.08	624.07	16.5	0.58	1.80	0.07	2.45	16.0
	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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    * 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