Recent Advances in Signature Biometrics

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Recent Advances in Signature Biometris

– Universal Background Models
– User-dependent HMMs
– Device-dependent Feature Selection

Recent advances in online signature: UBMs (I)

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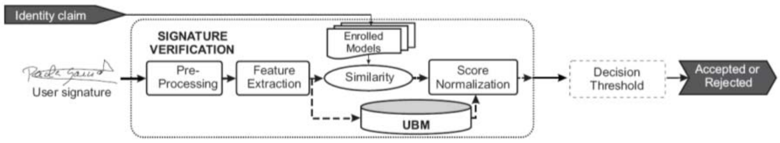
- **Universal Background Models (UBMs)**:
  - Statistical Models of an “average” user
  - During enrollment, the user model is adapted from the UBM using the training data (robust against small training set sizes)
  - In the matching process, the user signature is compared to his claimed template an the resulting score is normalized by its similarity to the UBM
- UBMs have been applied with great success in Speaker Verification Systems



- Results (tablet): approx. half EER_random while maintaining EER_skilled

[Martinez-Diaz, Fierrez, et al., IEEE BTAS 2007]

Recent advances in online signature: UBMs (II)

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- Adaptation is based on the Maximum a Posteriori (MAP) algorithm.
- For each user, a specific set of GMM parameters is derived:

Probabilistic alignment and sufficient statistics between the user vector $\mathbf{x}_t$ and de UBM are computed

1

$$P(i\,|\,\mathbf{x}_t) = \frac{\omega_i p_i(\mathbf{x}_t)}{\sum_{j=1}^{N} \omega_j p_j(\mathbf{x}_t)}$$

$$n_i = \sum_{t=1}^{T} \omega_i P(i\,|\,\mathbf{x}_t)$$

$$E_i(\mathbf{x}) = \frac{1}{n_i} \sum_{t=1}^{T} P(i\,|\,\mathbf{x}_t)\mathbf{x}_t$$

$$E_i(\mathbf{x}^2) = \frac{1}{n_i} \sum_{t=1}^{T} P(i\,|\,\mathbf{x}_t)\mathbf{x}_t^2$$

The adaptation coefficient α controls the contribution of old an new parameters

2

$$\alpha = \frac{n_i}{n_i + r}$$

Relevance factor (must be specified)

Parameters are updated

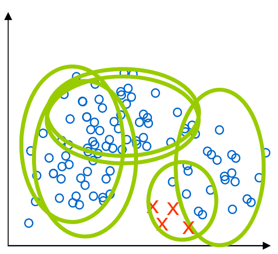
3

$$\hat{\omega}_i = \left[\alpha n_i / T + (1-\alpha)\omega_i\right]\gamma$$

$$\hat{\mu}_i = \alpha E_i(\mathbf{x}) + (1-\alpha)\mu_i$$

$$\hat{\sigma}_i^2 = \alpha E_i(\mathbf{x}^2) + (1-\alpha)(\sigma_i^2 - \mu_i^2) - \hat{\mu}_i^2$$

Example



[Martinez-Diaz, Fierrez, et al., IEEE BTAS 2007]

Recent advances in online signature: UBMs (III)

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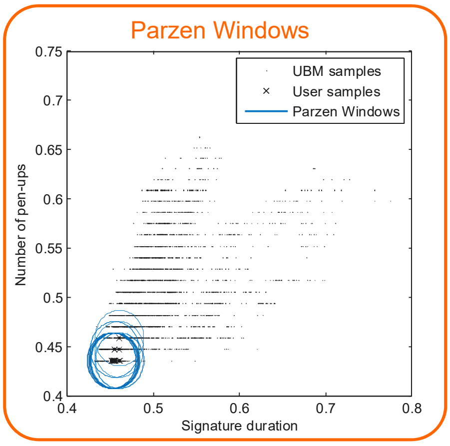
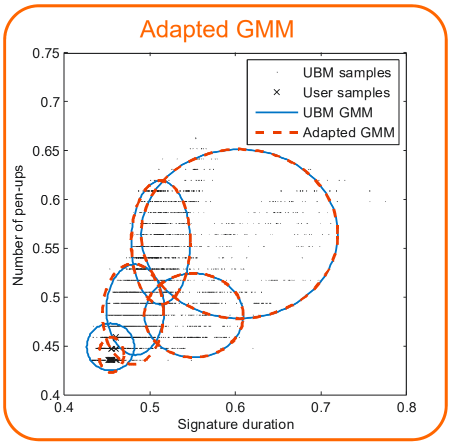
- Example of 2-dimensional Parzen Windows and Adapted GMM:





[Martinez-Diaz, Fierrez, et al., IEEE BTAS 2007]

Recent advances in online signature: UD HMMs

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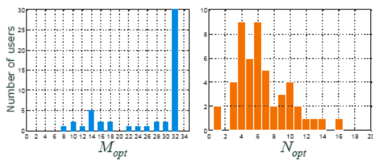
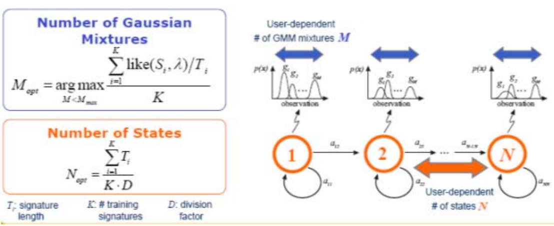
Histograms of N_{opt} and M_{opt} for D=42 and M_{max}=32

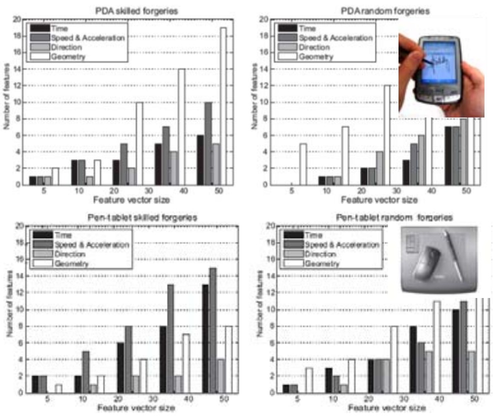


Scenario	EER random forgeries	EER skilled forgeries
Baseline (N=4; M=16)	7.3%	20.5%
User-dependent (D=42; M_{max}=32)	5.2%	15.8%



[Martinez-Diaz, Fierrez, et al., ICFHR 2007]

Recent advances in online signature: Feat. Select.



- The best set of features is very different between Tablet and PDA, specially for skilled forgeries:

  → Features based on Time, Speed, and Acceleration are best for Tablet

  → Geometry features are best for PDA

⇩

Table 1. PDA scenario EER comparison for random (rd) and skilled (sk) forgeries.

System	EER_{rd}	EER_{sk}
Proposed system (HMM+features)	4.0%	11.9%
BMEC best for skilled forgeries [11]	8.07%	13.43%
BMEC best for random forgeries [8]	4.03%	13.58%

- Future work: Biosecure Signature Evaluation Campaign (ICB-09)

[Martinez-Diaz, Fierrez, et al., ICPR 2007]

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