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Automatic Online Signature Verification based only on FHE Features: an Oxymoron?

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Outline





- 3 FHE features
- Pre-classification Approach
- **(5)** Decision Level Fusion Approach
- 6 Evaluation Protocol





Motivation Why Online Features ?

• Online acquisition devices have become very popular



• Dynamic signing behavior is more difficult to simulate/forge

Motivation Why Features relevant to FHEs?

- Further understanding the signatures and the writer behavior.
- Features thoroughly investigated and accepted by FHEs.



To bridge the gap between the PR and FHEs communities

Motivation Previous work on combination of Global and Time Functions Based features

- **Global Features:** are more simple and intuitive, and easier to compute and compare.
- **Time Functions Based features:** more complex and not so intuitive, but provide dynamic information of the signing process.
- **Different Combinations** of Global and Time Functions based features can be implemented.

Global features and Time Functions Based Features were shown to provide complementary information

Motivation Automatic Signature verification based only on FHEs features?

- Constrain to use only FHE relevant features.
- Try Different Combinations of Global FHE and Time Functions based FHE features.

Global FHE features and Time Functions Based FHE Features could provide complementary information.

Using only FHE relevant features could suffice for the successful implementation of automatic signature verification systems.

Contributions

- Exclusive use of FHE features (both Global and Time Functions based ones).
- **Two Different Combinations** of Global FHE and Time Functions based FHE features.
 - Global FHE Features used for pre-classification followed by Random Forest classification using Time Functions Based FHE features.
 - Oecision Level Fusion of two Random Forest classifiers using respectively Global FHE and Time Functions Based FHE features.
- Evaluation on recent public signature database → Western and Chinese signatures
- Verification results quantified by:
 - EER (Equal Error Rate)
 - Cost of the log-likelihood ratios \hat{C}_{llr}

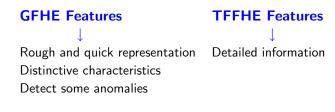
FHE features

- Global FHE features (GFHE): Global features based on pen trajectories (time and space) are relevant to FHE. We choose the following ones:
 - Signature Total Time Duration: T
 - Pen-down Duration: T_{pd}
- **Time Functions FHE features (TFFHE)**: the following time functions relevant to FHE are considered (same as in [1]):
 - velocity magnitude: v_T
 - \bullet velocity direction: θ
 - \bullet curvature: ρ
 - ${\, \bullet \,}$ first order derivative of pen pressure: dp

TFFHE approximation using wavelets \rightarrow keep only the approximation coefficients in a wavelet decomposition.

[1] M. Parodi, J.C. Gómez, M. Liwicki, and L. Alewijnse, "Orthogonal function representation for online signature

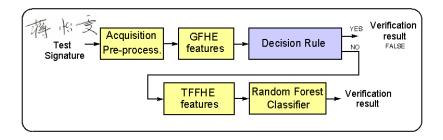
verification: which features should be looked at?", IET Biometrics, vol. 2, no. 4, pp. 137-150, 2013.



Pre-classification

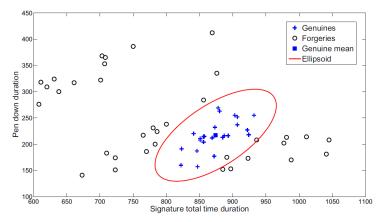
- quickly recognize and classify gross forgeries
- speed up and simplify the verification process

Verification System Scheme



 $\begin{array}{ll} \textbf{Decision rule} \\ \textit{If} & (\mathbf{g}_{test} - \bar{\mathbf{g}}_{train})^T \Sigma_{train}^{-1} (\mathbf{g}_{test} - \bar{\mathbf{g}}_{train}) > \alpha^2 \\ \textit{then} & \textit{signature} = \textit{forgery} \\ \textit{else} & \textit{continue classification} \end{array}$

Decision rule



Hyperellipsoid: $(\mathbf{g}_{test} - \bar{\mathbf{g}}_{train})^T \Sigma_{train}^{-1} (\mathbf{g}_{test} - \bar{\mathbf{g}}_{train}) = \alpha^2$

• Parameter α is computed as:

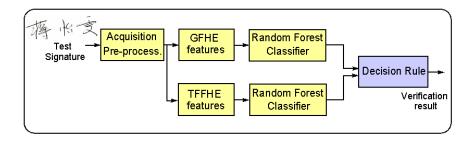
$$\alpha^2 = \max_{A} \max_{A_i} \left\{ (\mathbf{g}_{test} - \bar{\mathbf{g}}_{train})^T \Sigma_{train}^{-1} (\mathbf{g}_{test} - \bar{\mathbf{g}}_{train}) \right\},\,$$

where

- A is the set of all the authors in the Training Set,
- A_i denotes the *i*-th author in the same set.

Decision Level Fusion Approach

Verification System Scheme



Decision rule $P_{fused} = P_{GFHE}^{(1-\beta)} P_{TFFHE}^{\beta}$

(weighted geometrical fusion of likelihood scores of individual classifiers, $0 < \beta < 1$ user defined weighting parameter)

Evaluation Protocol Signature Database

SigComp2011 Dataset[2] presented within ICDAR 2011:

- Publicly available Database
- Signatures acquired using a ballpoint pen on paper

Natural writing process

• Two separate data sets:



Dutch signatures



Chinese signatures

[2] M. Liwicki et al., "Signature verification competition for online and offline skilled forgeries (Sig-Comp2011)," ICDAR 2011.

Evaluation Protocol Signature Database (cont.)

• Forgeries in the Database are skilled forgeries:

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genuine signatures

- Measured data:
 - pen coordinates x and y
 - pen pressure p

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skilled forgeries

Evaluation Protocol Signature Database (cont.)

Datasets in the SigComp2011 Database are divided into two sets: Training Set and Testing Set

Dutch signatures

Training Set							
Authors	Genuines	Forgeries					
10	240	119					
Testing Set							
Authors	Genuines	Forgeries					
54	1296	611					

Chinese signatures

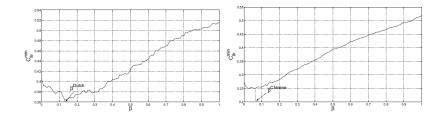
	Training Set							
	Authors	Genuines	Forgeries					
	10	230	429					
1	Testing Set							
	Authors	Genuines	Forgeries					
	10	219	461					

- Training Set \rightarrow optimization of the tuning parameters
- Testing Set → independent testing purposes (5-fold cross-validation)

Evaluation Protocol Optimization of the tuning parameters

Optimization of the tuning parameters is performed over the **Training Set**

- Pre-classification Approach: α
- Decision Level Fusion Approach: $\beta^{Dutch} = 0.13$, $\beta^{Chinese} = 0.06$



Evaluation Protocol Design parameters

• Both Approaches:

- normalized length of the resampled time functions (= 256)
- resolution level of the wavelet approximation (= 3)
- number of trees in the RF classifier (= 500)
- randomly selected splitting variables in the RF classifier (= \sqrt{P} , being P the feature vector dimension)

Verification Results

	Dutch Dataset			Chinese Dataset		
	EER	\hat{C}_{llr}	\hat{C}_{llr}^{min}	EER	\hat{C}_{llr}	\hat{C}_{llr}^{min}
PC	4.42	0.222	0.178	5.98	0.265	0.211
DLF	8.12	0.335	0.298	7.63	0.299	0.251
ASF [1]	6.58	0.243	0.205	7.455	0.296	0.248

 M. Parodi, J.C. Gómez, M. Liwicki, and L. Alewijnse, "Orthogonal function representation for online signature verification: which features should be looked at?", *IET Biometrics*, vol. 2, no. 4, pp. 137-150, 2013.

Conclusions

- Exclusive use of FHE features (both GFHE and TFFHE ones).
- Two Different Combinations of GFHE and TFFHE features.
 - GFHE Features used for pre-classification followed by Random Forest classification using TFFHE features.
 - Oecision Level Fusion of two Random Forest classifiers using respectively GFHE and TFFHE features.
- Evaluation on recent public signature database → Western and Chinese signatures
- Verification results are comparable to the state-of-the-art.

Automatic online signature verification based only on FHE features is not an oxymoron.

Thanks a lot !!! Σε ευχαριστώ πολύ

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Motivation Contributions FHE Features Pre-classification Approach DLF Approach Eval. Protocol Results Conclusions

5-fold Cross Validation (Testing Dataset)

