Incorporating Touch Biometrics to Mobile One-Time Passwords: Exploration of Digits

Ruben Tolosana, Ruben Vera-Rodriguez, Julian Fierrez and Javier Ortega-Garcia

BiDA Lab- Biometrics and Data Pattern Analytics Lab Universidad Autonoma de Madrid, Spain









- 1. Introduction
- 2. e-BioDigit Database
- 3. Handwritten Touch Biometric System
- 4. Experimental Work
- 5. Conclusions and future Work





1. Introduction

- 2. e-BioDigit Database
- 3. Handwritten Touch Biometric System
- 4. Experimental Work
- 5. Conclusions and Future Work







• Mobile devices have become an indispensable tool for most people nowadays





Social Networks



On-Line Payments



- Public and Private Sectors are aware of the importance of mobile devices in our society
- Deployment of their services through security and user-friendly mobile applications







- Public and Private Sectors are aware of the importance of mobile devices in our society
- Deployment of their services through security and user-friendly mobile applications





• However, difficult to accomplish using only traditional approaches



Personal Identification Number (PIN)



One-Time Password (OTP)



()



• Biometric recognition schemes can cope with these problems as they combine:





• Behavioural biometric systems very attractive on mobile scenarios











Touch Biometrics Handwritten Signature

4 / 17

Graphical Passwords



Proposed Approach

• Incorporate touch biometrics to mobile one-time passwords (OTP):







Proposed Approach

• Incorporate touch biometrics to mobile one-time passwords (OTP):





Advantages:

- Users do not memorize passwords
- User-friendly interface (mobile scenarios)
- Security level easily configurable
 - # enrolment samples
 - Length password



e-BioDigit Database

- 1. Introduction
- 2. e-BioDigit Database
- 3. Handwritten Touch Biometric System
- 4. Experimental Work
- 5. Conclusions and Future Work







e-BioDigit Database*



• Acquisition: one handwritten digit at a time. Only X and Y time information



7/17

*Available at: https://atvs.ii.uam.es/atvs/e-BioDigit.html

3

Handwritten Touch Biometric System

- 1. Introduction
- 2. e-BioDigit Database
- 3. Handwritten Touch Biometric System
- 4. Experimental Work
- 5. Conclusions and Future Work







Touch Biometric System

• Feature Extraction and Selection:

#	Feature
1	X-coordinate: x_n
2	Y-coordinate: y_n
3	Path-tangent angle: θ_n
4	Path velocity magnitude: v_n
5	Log curvature radius: ρ_n
6	Total acceleration magnitude: a_n
7-12	First-order derivative of features 1-7:
	$\dot{x_n}, \dot{y_n}, \dot{\theta_n}, \dot{v_n}, \dot{\rho_n}, \dot{a_n}$
13-14	Second-order derivative of features 1-2:
	$\ddot{x_n}, \ddot{y_n}$
15	Ratio of the minimum over the maximum
	speed over a 5-samples window: v_n^r
16-17	Angle of consecutive samples and first-
	order derivative: α_n , $\dot{\alpha_n}$
18	Sine: s_n
19	Cosine: c_n
20	Stroke length to width ratio over a 5-
	samples window: r_n^5
21	Stroke length to width ratio over a 7-
	7
	samples window: r_n^2

- 21 time functions for each handwritten digit
- Selection of best time functions for each digit
 - Sequential Forward Feature Selection Algorithm (SFFS)



Touch Biometric System

• Feature Extraction and Selection:

	· ·
#	Feature
1	X-coordinate: x_n
2	Y-coordinate: y_n
3	Path-tangent angle: θ_n
4	Path velocity magnitude: v_n
5	Log curvature radius: ρ_n
6	Total acceleration magnitude: a_n
7-12	First-order derivative of features 1-7:
	$\dot{x_n}, \dot{y_n}, \dot{\theta_n}, \dot{v_n}, \dot{\rho_n}, \dot{a_n}$
13-14	Second-order derivative of features 1-2:
	$\ddot{x_n}, \ddot{y_n}$
15	Ratio of the minimum over the maximum
	speed over a 5-samples window: v_n^r
16-17	Angle of consecutive samples and first-
	order derivative: α_n , $\dot{\alpha_n}$
18	Sine: s_n
19	Cosine: c_n
20	Stroke length to width ratio over a 5-
	samples window: r_n^5
21	Stroke length to width ratio over a 7-
	samples window: r_n^7

- 21 time functions for each handwritten digit
- Selection of best time functions for each digit
 - Sequential Forward Feature Selection Algorithm (SFFS)

Matcher:

Dynamic Time Warping (DTW)









Experimental Work

- 1. Introduction
- 2. e-BioDigit Database
- 3. Handwritten Touch Biometric System
- 4. Experimental Work
- 5. Conclusions and Future Work







Experimental Protocol

- Development: 50 users of e-BioDigit database
- Evaluation: remaining 43 users of e-BioDigit database
- Genuine Scores 3 weeks User i Session 1 Session 2 **TRAINING TESTING** Impostor Scores 3 weeks User i Session 1 TRAINING **TESTING** 9/17

Experiment 1: One-Digit Results

• Analysis of the potential of each numerical digit





Experiment 1: One-Digit Results

• System performance results in terms of EER (%) on the evaluation dataset

	Handwritten Numerical Digit										
	0	1	2	3	4	5	6	7	8	9	
EER (%)	33.0	34.0	30.9	32.3	22.0	21.7	33.6	21.8	21.8	27.0	

enrolment samples per digit: 1

- High different system performance between numerical digits
- Digit 5 and 7 provide the best system performance results





User A: sample 1 User A: sample 2









- Analysis of the system performance regarding:
 - Length of handwritten password



- # enrolment samples per digit





12 / 17

• System performance results in terms of EER (%) on the evaluation dataset

		# Digits that comprise the password									
S		1	2	3	4	5	6	7	8		
mple	1	21.7	14.0	11.6	11.6	9.3	8.5	8.5	8.5		
nt sa digit	2										
lmer per c	3										
enro	4										

Improvement of system performance when adding more digits to the password

- e.g. absolute improvement of 7.7% EER between 1- and 2-digit passwords



• System performance results in terms of EER (%) on the evaluation dataset

	# Digits that comprise the password										
	1	2	3	4	5	6	7	8			
1	21.7										
2	18.6										
3	16.3										
4	16.9										
	1 2 3 4	1 1 <td< td=""><td>1 2 1 21.7 2 18.6 3 16.3 4 16.9</td><td># Digits th 1 2 3 1 21.7 </td><td># Digits that comprise 1 2 3 4 1 21.7 </td><td># Digits that comprise the part of the</td><td># Digits that comprise the password123456121.7218.6316.3<td< td=""><td># Digits that comprise the password1234567121.7218.6316.3<td< td=""></td<></td></td<></td></td<>	1 2 1 21.7 2 18.6 3 16.3 4 16.9	# Digits th 1 2 3 1 21.7	# Digits that comprise 1 2 3 4 1 21.7	# Digits that comprise the part of the	# Digits that comprise the password123456121.7218.6316.3 <td< td=""><td># Digits that comprise the password1234567121.7218.6316.3<td< td=""></td<></td></td<>	# Digits that comprise the password1234567121.7218.6316.3 <td< td=""></td<>			

Improvement of System performance when adding more enrolment samples

- e.g. absolute improvement of 4.8% EER between 1 and 4 enrolment samples



• System performance results in terms of EER (%) on the evaluation dataset

	# Digits that comprise the password									
4	5	6	7	8						
5 11.6	9.3	8.5	8.5	8.5						
7.4	7.3	4.6	4.6	4.6						
5.9	4.7	4.6	3.8	4.6						
6.1	4.7	4.6	4.3	4.8						
	4 5 11.6 7.4 5.9 6.1	45511.69.367.47.35.94.76.14.7	456511.69.38.567.47.34.655.94.74.666.14.74.6	4567511.69.38.58.567.47.34.64.645.94.74.63.856.14.74.64.3						

• However, there is a limit in the system performance improvement with:

- Length of the password (6/7 digits)
- # enrolment samples per digit (3)



Comparison to State-of-the-Art Systems

Method	Verification Pe	formance (EER)	Participants
	Random Forgeries	Skilled Forgeries	-
Lock Pattern Dynamics	-	10.39% avg.	32
Touchscreen Gestures	1.58%	-	34
Touchscreen Gestures	15.0%	-	190
Touchscreen Gestures	3.0%	-	75
Touchscreen Gestures	~3.0%	-	71
Graphical Passwords	3.4%	22.1%	100
Handwritten Signatures	5.04%	-	180
Handwritten Signatures	0.5%	17.9%	65
Handwritten Characters	_	FAR = 10.42%	32
Tranuwittuell Characters	_	FRR = unknown	52
Handwritten Digits	-	3.8%	93
	Method Lock Pattern Dynamics Touchscreen Gestures Touchscreen Gestures Touchscreen Gestures Touchscreen Gestures Graphical Passwords Handwritten Signatures Handwritten Signatures Handwritten Digits	MethodVerification Pe Random ForgeriesLock Pattern Dynamics-Touchscreen Gestures1.58%Touchscreen Gestures15.0%Touchscreen Gestures3.0%Touchscreen Gestures3.0%Graphical Passwords3.4%Handwritten Signatures0.5%Handwritten Characters-Handwritten Digits-	MethodVerification Pe Random Forgeriesformance (EER) Random ForgeriesLock Pattern Dynamics- 10.39% avg.Touchscreen Gestures 1.58% -Touchscreen Gestures 15.0% -Touchscreen Gestures 3.0% -Handwritten Signatures 5.04% -Handwritten Signatures 0.5% 17.9% Handwritten Characters-FAR = 10.42% FRR = unknownHandwritten Digits- 3.8%

• Proposed approach outperforms other touch biometric approaches for skilled forgeries

- User-friendly interface 🙄
- Small number of enrolment samples 🙄

5

Conclusions and Future Work

- 1. Introduction
- 2. e-BioDigit Database
- 3. Handwritten Touch Biometrics
- 4. Experimental Work
- 5. Conclusions and Future Work







Conclusions

• We incorporate touch biometrics to password-based mobile authentication systems







- Perform a complete analysis regarding:
 - Which are the most discriminative handwritten digits
 - How performance improves with # enrolment samples per digit and length of the password
- e-BioDigit database is publicly available to the research community



17 / 17



Available at: https://atvs.ii.uam.es/atvs/e-BioDigit.html

Future Work

• We will extend this approach to:



• We will improve the core matcher through Deep Learning techniques

* R. Tolosana, R. Vera-Rodriguez, Julian Fierrez and Javier Ortega-Garcia, "Exploring Recurrent Neural Networks for On-Line Handwritten Signature Biometrics", IEEE Access, pp. 1 - 11, 2018



Incorporating Touch Biometrics to Mobile One-Time Passwords: Exploration of Digits

Ruben Tolosana, Ruben Vera-Rodriguez, Julian Fierrez and Javier Ortega-Garcia

BiDA Lab- Biometrics and Data Pattern Analytics Lab Universidad Autonoma de Madrid, Spain





