On the Security of Picture Gesture Authentication

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Picture Gesture Authentication (PGA)

• A built-in feature in Microsoft Windows 8

60 million Windows 8 licenses have been sold

400 million computers and tablets will run
 Windows 8 in one year

How PGA Works

Welcome to picture password

Picture password is a new way to help you protect your touchscreen PC. You choose the picture -- and the gestures you use with it -- to create a password that's uniquely yours.

When you've chosen a picture, you "draw" directly on the touchscreen to create a combination of taps, straight lines, or circles. The size, position, and direction of your gestures become part of your picture password.

Choose picture



How PGA Works

Autonomous picture selection by users

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Choose picture



How PGA Works

- Three types of gestures are allowed
 - Тар
 - Circle
 - Line

Set up your gestures

Draw three gestures on your picture. You can use any combination of circles, straight lines, and taps.

Remember, the size, position, and direction of your gestures -- and the order in which you make them -become part of your picture password.

123





Cancel

Research Questions

- I. How to understand user-choice patterns in PGA?
 - Background Pictures
 - Gesture Location
 - Gesture Type
 - Gesture Order
- 2. How to use these patterns to guess PGA password?



Part I: Analysis of more than 10,000 PGA passwords collected from user studies

Part 2: A fully automated attack framework on PGA

Part 3: Attack results on collected passwords

I. Web-based PGA system

- Similarity to Windows PGA
 - Workflow
 - Appearance
- 2. Data collection
- 3. Analysis: survey and results

- Dataset-I
 - ASU undergraduate computer security class (Fall 2012)
 - 56 participants
 - 58 unique pictures
 - 86 passwords
 - 2,536 login attempts



CSE 465: Informa	tion Assura	nce (2	012 Fall)		
Announcements Syllabus Lecture Notes Assianments	E Leo	ture N	Notes		
	Date	Lecture	Topic	Notes	Reading
Group Projects Change Password	Aug 24, 2012	1	Security Objectives and Basic Concepts	Note-1	Chapter 1
inish Survey	Aug 31, 2012	2	Authentication I	Note-2	Chapter 11
	Sep 7, 2012	3	Authentication II and Access Control I	Note-3	Chapter 2.1-2.2, 5 & Supplemental document #1
	Sep 14, 2012	4	Access Control II	Note-4	Chapter 6.1-6.2, 27 & Supplemental document #2
	Sep 21, 2012	5	Cryptography I	Note-5	Chapter 8.1-8.2.3
	Sep 28, 2012	6	Cryptography II	Note-6	Chapter 8.3-8.4, 9.3, 9.5 & Md5collision.zip
	Oct 5, 2012	7	Authentication in Distributed Systems	Note-7	Supplemental document #3
	Oct 12, 2012	8	Network Security I	Note-8	Chapter 23.3.1 - 23.3
	Oct 19, 2012	9	Network Security II	Note-9	Chapters 10.4.2 Supplemental Link
	Oct 26, 2012	10	Intrusion Detection	Note-10	Chapters 22
	Nov 2, 2012	11	Database Security & Risk Management and Information Assurance	<u>Note-11</u> Overview	Chapters 18
	Nov 16, 2012	12	Group Project Presentation I	Note-12	Corresponding proposals
	Nov 30,	12	Group Project Procentation II	Noto 13	Corresponding

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- Dataset-2
 - Scenario: The password is used to protect your bank account
 - Amazon MTurk
 - 15 pictures selected in advance
 - 762 participants

• 10,039 passwords



- Survey questions
 - General information of the subject
 - General feeling towards PGA
 - How she/he selects a background picture
 - How she/he selects a password

Background Picture

People, Civilization, Landscape, Computer-generated, Animal, Others



Why or why not picture of people

- Advocates:
 - i) it is more friendly

'The image was special to me so I enjoy seeing it when I log in'

ii) it is easier for remembering passwords

'Marking points on a person is easier to remember'

iii) it makes password more secure
'The picture is personal so it should be much harder for someone to guess the

þassword'

- Others:
 - i) leak his or her identify or privacy

'revealing myself or my family to anyone who picks up the device'

Background Picture

People, Civilization, Landscape, Computer-generated, Animal, Others



Why computer-generated pictures

- Dataset-I population characteristics:
 - 81.8% Male
 - 63.6% Age 18-24, 24.0% Age 25-34
 - I00% College students
- Survey answers:
 - 'computer game is something I am interested [in] it'
 - 'computer games picture is personalized to my interests and enjoyable to look at'

Why computer-generated pictures

- Dataset-I population characteristics:
 - 81.8% Male

The background picture tells much about the user's identity, personality and interests.

- Survey answers:
 - *computer game is something I am interested [in] it*
 - 'computer games picture is personalized to my interests and enjoyable to look at'

	Dataset-1	Dateset-2
I try to find locations where special objects are.	72.7%	59.6%
I try to find locations where some special shapes are.	24.2%	21.9%
I try to find locations where colors are different from their surroundings.	0%	8.7%
I randomly choose a location to draw without thinking about the background picture.	3.0%	10.1%

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Which of the following best describes what you are considering when you choose locations to perform gestures?

Most users tend to draw passwords on Points-of-Interest (Pols) in the background picture.

I try to find locations where colors are different from their surroundings.		8.7%
I randomly choose a location to draw without thinking about the background picture.	3.0%	10.1%

Gesture Locations (Picture of People)

- Dataset-I
 - 22 subjects uploaded 27 pictures of people
 - 31 passwords (93 gestures)

Attributes	# Gesture	# Password	# S ubject
Eye	36 (38.7%)	20 (64.5%)	19 (86.3%)
Nose	21 (22.5%)	13 (48.1%)	10 (45.4%)
Hand/Finger	6 (6.4%)	5 (18.5%)	4 (18.2%)
Jaw	5 (5.3%)	3 (11.1%)	3 (13.7%)
Face	4 (4.3%)	2 (7.4%)	2 (9.1%)

Part I: User-choice Patterns Gesture Locations (Civilization)

- Dataset-I
 - Two versions of Starry Night uploaded by two participants





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Part I: User-choice Patterns Gesture Locations (Civilization)

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Gesture I: Tap a star Gesture 2: Tap a star Gesture 3: Tap a star Gesture I: Tap a star Gesture 2: Tap a star Gesture 3: Tap a star Part I: User-choice Patterns Gesture Locations (Civilization)

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Windows PGA Advertisements



Asia





Windows PGA Advertisements



Asia

Windows PGA Advertisements



Asia

South America

Windows PGA Advertisements



Windows PGA Advertisements



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Windows PGA Advertisements



Part 2: Attack Framework

- To generate dictionaries that have potential passwords
 - Picture-specific dictionary
 - Rank passwords with likelihood
 - Work on previously unseen pictures
- Our approach
 - Automatically learns user-choices patterns in the training pictures and corresponding passwords
 - Then applies these patterns to the target picture for dictionary generation

Part 2: Attack Framework

Selection Function

- Selection function
 - Models the password creating process that users go through
 - Takes two types of parameters
 - Gesture type, such as tap, circle, line
 - Pol attribute, such as face, eye, ...
 - Generates a group of gestures

Part 2: Attack Framework Selection Function (Examples)

s : {tap,circle,line} x Pol Attributes*

s(circle, face) Circle a face in the picture

s(line, nose, nose) Line a nose to another nose in the picture

s(tap, nose) Tap a nose in the picture Part 2: Attack Framework Extract Selection Functions Password



Points-of-Interest



Part 2: Attack Framework Extract Selection Functions circle Password



face Points-of-Interest




Points-of-Interest



Function I: s(circle , face)



Points-of-Interest





Points-of-Interest



Function 2: s(line, nose, nose)



Points-of-Interest





Points-of-Interest



Function 3: s(tap, nose)



Function I: s(circle, face) Output: 4 gestures



Function I: s(circle, face) Output: 4 gestures

Function 2: s(line, nose, nose) Output: 12 gestures



Function I: s(circle, face) Output: 4 gestures Function 2: s(line, nose, nose) Output: 12 gestures

Function 3: s(tap, nose) Output: 4 gestures



Function 1: s(circle, face) Output: 4 gestures Function 2: s(line, nose, nose) Output: 12 gestures

Function 3: s(tap, nose) Output: 4 gestures

Number of potential passwords: 4×12×4 = 192

Part 2: Attack Framework

Rank Selection Functions

- I. BestCover algorithm
 - Derived from emts (Zhang et al., CCS'10)
 - Optimizes guessing order for passwords in the training dataset
- 2. Unbiased algorithm
 - Reduces the biased Points-of-Interest distributions in the training set

Part 3: Attack Results

Automatically Identify Pols

- OpenCV as the computer vision framework
 - Object detection
 - Face, eye, nose, mouth, ear, body
 - Low-level feature detection
 - Circle
 - Color
 - Objectness measure: Alexe et al. (TPAMI'I 2)
 - Other standout regions

Part 3: Attack Results Points-of-Interest Sets

- Pols of Dataset-I
- P¹_{A-40} Identified by OpenCV
 40 Pols at most

- Pols of Dataset-2
- P_{A-40}^2 Identified by OpenCV
 - 40 Pols at most
- Pols of Dataset-2 P_{L-15}^2 Manually labeled
 - I5 Pols at most

Part 3: Attack Results Methodology

- Guessability on passwords of previously unseen pictures
- Dictionary size: 2^19 = 524,288

Part 3: Attack Results Dateset-I vs. Dateset-2



Part 3: Attack Results BestCover vs. Unbiased



Part 3: Attack Results BestCover vs. Unbiased

60 training passwords Unbiased 23.44%



Part 3: Attack Results Labeled Pol set vs. OpenCV-Identified Pol set



Part 3: Attack Results

Simple Pictures (Unbiased algorithm)



Part 3: Attack Results Portraits (Unbiased algorithm)



Part 3: Attack Results

Complex Picture (Unbiased algorithm)



Part 3: Attack Results Online Attacks on Dataset-2



PGA Password Strength Meter

- <u>https://honeyproject1.fulton.asu.edu/stmidx</u>
- BestCover algorithm
- Generate dictionary and calculate strength in 20

seconds



Summary and Future Work

- We have presented an analysis of user-choice patterns in PGA passwords
- We have proposed an attack framework on PGA
- We have evaluated our approach on collected datasets
- We plan to improve online attack results by integrating shoulder-surfing and smudge attacks into our framework

Thank you! Q&A