On Purely Automated Attacks and Click-Based Graphical Passwords *

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Abstract

We present and evaluate various methods for purely automated attacks against click-based graphical passwords. Our purely automated methods combine click-order heuristics with focus-of-attention scan-paths generated from a computational model of visual attention. Our method results in a significantly better automated attack than previous work, guessing 8-15% of passwords for two representative images using dictionaries of less than $2^{24.6}$ entries, and about 16% of passwords on each of these images using dictionaries of less than $2^{31.4}$ entries (where the full password space is 2^{43}). Relaxing our click-order pattern substantially increased the efficacy of our attack albeit with larger dictionaries of $2^{34.7}$ entries, allowing attacks that guessed 48-54% of passwords (compared to previous results of 0.9% and 9.1% on the same two images with 2^{35} guesses). These latter automated attacks are independent of focus-of-attention models, and are based on image-independent guessing patterns. Our results show that automated attacks, which are easier to arrange than human-seeded attacks and are more scalable to systems that use multiple images, pose a significant threat.

1 Introduction

Graphical passwords are an alternative to traditional text passwords, whereby a user must remember an image (or parts of an image) in place of a word. They are motivated in part by the well-known fact that people are better at remembering images than words [19]. There are many different types of graphical passwords; among the more popular approaches is *click-based graphical passwords* [31, 16, 2, 13, 6], which require users to click on a sequence of points on one or more background images. The most effective attack strategy to date on these schemes appears to be human-seeded attacks [27], although such attacks are more difficult to arrange than attacks based on purely automated means and do not scale well for systems that use multiple images. In this paper, we pursue purely automated approaches for guessing attacks.

We pursue heuristic-based strategies for purely automated dictionary generation (e.g., based on click-order patterns), and strategies to prioritize these dictionaries using image processing methods to identify points that users are more likely to choose. We hypothesize that users will choose click-points according to a click-order pattern, to help remember the password as fewer "chunks" [8]. We further examine use of the DIAG click-order pattern [27], which captures arcs that are consistent in both horizontal and vertical directions, and a subset of this pattern that we call LINE that captures only horizontal and vertical lines. We relax the rules on these definitions, showing that a "lazy" approach to these click-order patterns is substantially more effective.

We further hypothesize that users will choose click-points based on their preference for certain points in the image, and that their preference for certain points will be influenced by how much they are naturally attracted to those points. *Attention* is the cognitive process of selectively focusing on one aspect of the environment while ignoring others, a mechanism that helps us prioritize sensory information. There are two different categories of visual attention models: bottom-up and top-down. *Bottom-up* visual attention captures how attention is drawn to the parts of a scene or image that are salient or conspicuous. It is what naturally draws us to look at the unexpected or different parts of a scene, prioritizing them from the other consistent parts. For example, if an image contains a large number of objects that are blue, and only one is yellow, human attention will instinctively focus on the yellow object. *Top-down* visual attention is task-dependent, based on cognitive, volitional control. With a priori knowledge about what object(s) to look for, our attention is brought to the parts of the scene containing those object(s). For example, if a user decides that people with dark hair are of interest for some reason, the user's attention would shift between objects with features that might indicate a dark-haired person.

*Version: Sept.15, 2008. The third author acknowledges NSERC funding under a Discovery Grant and as Canada Research Chair in Network and Software Security.

Our contributions include the best purely automated attacks to date against click-based graphical passwords, an evaluation of how the model of Itti et al. [15] relates to user-selected click-based graphical passwords, and a new spatial clustering algorithm. Two different hypotheses were tested regarding how users might choose their click-points relative to Itti's model. Our methods were tested using the same field study database used by Thorpe et al. [27], allowing us to compare performance. We found that a "lazy" approach to click-order patterns produced a substantially better automated attack than previous methods with comparable dictionary sizes and images [27, 10], guessing 48-54% of passwords (compared to 0.9-9.1% previously) on two different images used in a long-term field study with a dictionary of about 2^{35} entries. Furthermore, we were able to optimize this dictionary using Itti's model, producing dictionaries whose efficacy is comparable to human-seeded attacks [27]: one dictionary of $2^{30.3}$ entries guessed 15.8% of passwords on one image, and on a second image a dictionary of $2^{31.4}$ entries guessed 16.5% of passwords.

The remainder of this paper proceeds as follows. Section 2 discusses background and related work, including computational models of visual attention. We describe our purely automated attack generation methods in Section 3, results in Section 4, future work in Section 5, and conclusions in Section 6.

2 Background and Related Work

We discuss computational models of visual attention in Section 2.1, and terminology in Section 2.2. Many different types of graphical passwords have been proposed to date (see surveys [26, 20]). Here we give a brief overview focused on click-based graphical password schemes and other work on modeling user choice in graphical passwords.

Click-based graphical password schemes require a user to click on a set of points on one or more presented background images. In Blonder's proposal [2] users must click on a set of predefined tap regions. In *V-go*, by PassLogix [24], users must click on predefined objects in the picture in a specific sequence. In the Jansen et al. [16] variation for PDAs, users click an ordered sequence of visible grid squares imposed on a background image; the squares are intended to help the user repeat their click-points in subsequent logins.

PassPoints [32, 31, 30] allows users to click a sequence of five points anywhere on an image while allowing a degree of error tolerance using robust discretization [1]. Various studies have shown that PassPoints has acceptable usability [30, 32, 31, 5]. *visKey*, a commercial system for the Pocket PC, appears similar but allows the user to choose the number of click-points and set the error tolerance. In the Persuasive Cued Click-Points (PCCP) [4, 6] variation, a user clicks on a single point on each of five images, guided partially by a randomly placed viewport; each image displayed (after the first) is dependent on the previous click-point.

Two previous studies have examined the security of PassPoints-style graphical passwords. Dirik et al. [10] examine the efficacy of an automated tool for guessing PassPoints passwords. Their method, which does not draw on a standard computational model of visual attention, uses centroids of segments as guesses (but no corners). It was tested against a database of single-session user choices for two images. For the image with a reasonable level of detail, their method guessed 8% of passwords with a dictionary of 2^{32} entries compared to full space of 2^{40} entries. As previously discussed, Thorpe et al. [27] examine both an automated method (based on stage 1 of Itti et al.'s [15] model of visual attention; see Section 2.1), and a human-seeded method (which uses click-point data from a set of users' password choices).

User choice has been successfully modeled for other graphical password schemes. Davis et al. [9] modeled user choice for Faces and Story recognition-based graphical passwords by training a dictionary using a large password database. Van Oorschot et al. [28] model user choice in "Draw-A-Secret" pure-recall graphical passwords [17] motivated by cognitive studies.

2.1 Models of Visual Attention

We conjecture that a significant percentage of users will choose points that draw their attention as components of their click-based passwords, and thus that computational models of visual attention may help pick out more probable click-points. Computational models of bottom-up visual attention are normally defined by features of a digital image, such as intensity, color, and orientation [15, 14].

Computational models of top-down visual attention can be defined by training [22]. The difficulty of these models is that the top-down task must be pre-defined (e.g., find all people in the image), and then a corpus of images that are tagged with the areas containing the subject to find (e.g., people) must be used for training. Navalpakkam et al. [21] discuss an alternate method to create a top-down model, based on Guided Search [33], which weighs visual feature maps according to the top-down task. For example, with a task of locating a red object, a red-sensitive feature map would gain more weight, giving it a higher value in the resulting saliency map. In both cases, assumptions regarding what sort of objects people are looking for are required to create such a model.

In this work, we focus on bottom-up visual attention, using Itti et al.'s [15] computational model of visual attention. We use this particular model as it is quite well-known, and there is empirical evidence that it captures people's bottom-

up visual attention [23]. The general idea behind this model is that areas of an image will be *salient* (or visually "stand out") when they differ from their surroundings.

We now explain Itti's model in further detail. Given an input image, it outputs a focus-of-attention scan-path to model the locations and the order in which a human might automatically and unconsciously attend them. It is composed of two stages: (stage 1) construction of a saliency map based on visual features, and (stage 2) the use of a winner-take-all neural network with inhibition of return to define a specific focus-of-attention scan-path, whose goal is to replicate the order in which a user would scan the image. Thorpe et al. [27] developed an automated attack for click-based graphical passwords that focused only on a variation of stage 1, ordering an attack dictionary based on the raw values of the resulting saliency map. The present paper uses the entire model including stage 2.

In stage 1, the saliency map is created by decomposing the original image into a set of 50 multi-level "feature maps", which extract spatial discontinuities based on color opponency (either red-green or blue-yellow), intensity, or orientation. Each level defines a different size of the center and its surround, in order to account for conspicuous locations of various sizes. All feature maps are then combined into a single saliency map.

In stage 2, a winner-take-all neural network detects the point of highest salience (as indicated by the intensity value of the saliency map), and draws the focus of attention towards this location. Once an area has been attended to, inhibition of return will prevent an area from being the focus again for a period of time. Together, the winner-take-all neural network with inhibition of return produces output in the form of spatio-temporal attentional scan-paths, which follow the order of decreasing saliency as defined by stage 1. Two different normalization types can be used with the model: *LocalMax* and *Iterative* (cf. Figure 1). In Iterative normalization, the neural network will find the next most salient area that has not been inhibited. In LocalMax normalization, the neural network will have a bias towards those areas that are closer to the previously attended location. Each normalization type produces a different scan-path; we study and compare the results of each as relates to our work.

2.2 Terminology

We hypothesize that users are more likely to choose *distinguishable points* as click-points. We define a *distinguishable point* as a point on a digital image that can be easily distinguished and relocated by a user. General ways this could be accomplished include: (1) by using *referencable* points on the image (e.g., a corner), and (2) by using *calculable* points that are based on other referencable parts of the image (e.g., object centers). In related work, Thorpe et al. [27] used corner detection to find referencable points, and Dirik et al. [10] used centroids to find calculable points. Here, we use both approaches to define a *distinguishable points map* δ. We describe the details of each method below.

We use the following additional terminology. Suppose that a user chooses a click-point c as part of her password. The *tolerable error* or *tolerance* t is the error allowed (in both vertical and horizontal directions) for a click-point entered on a subsequent login to be accepted as c. This defines a *tolerance region (T-region)* centered on c, which for an implementation using $t = 9$ pixels, is a 19×19 pixel square. A 19×19 T-region was used in the implementation for collecting the database [27] used herein for evaluating our results.

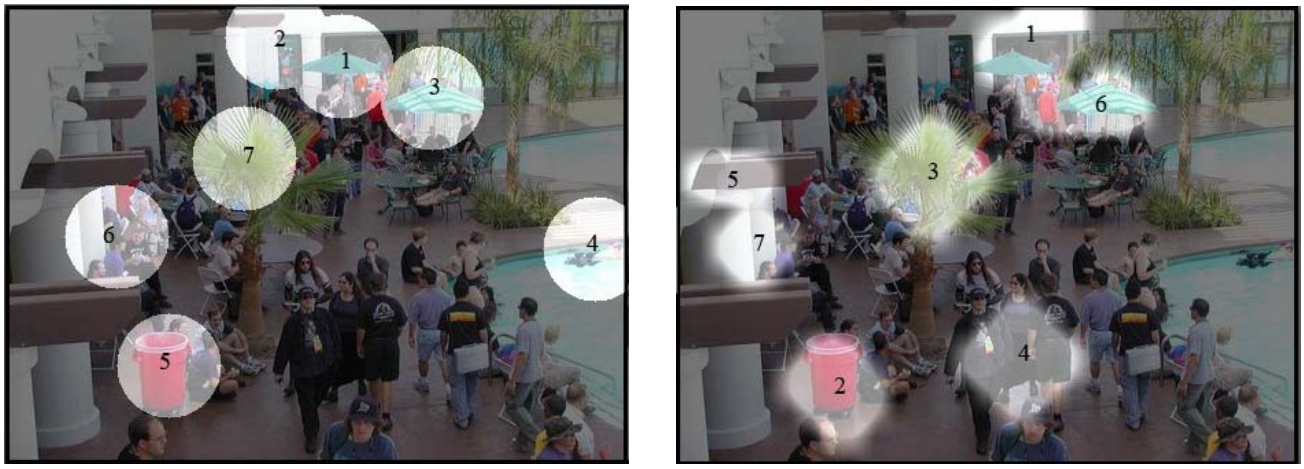
A *window cluster* is a square region of size $n \times n$ for some positive integer n. A *cluster* is a set of one or more points that lie within a window cluster. The center of a window cluster is representative of all the points within the window cluster. An *alphabet* is a set of distinct window centers.

Corner Detection. A *corner* can be defined as the intersection of two edges, where an *edge* is defined by the points in a digital image where there are sharp changes in intensity [11]. A corner can also be defined as a point in whose local neighborhood there are two dominant and different edge directions [11].

We use the harris algorithm [12] as implemented by Kovesi [18] for detecting corners. Harris corner detection first identifies the edges and then those edges are blurred to reduce the effect of any noise. Then an *energy map* is generated, based on the edges that contain local maxima and minima. A local maximum indicates the presence of a corner. We run harris corner detection with the parameters: $\sigma = 1$, $\theta = 1000$ and $r = 3$, where σ is the standard deviation of a smoothing Gaussian filter, θ is a threshold for the maximum number of corners, and r is an inhibition radius, measured in pixels around a detected corner.

Figure 2 shows the *pool* image where each detected corner is illustrated by a '+'. We also create a *binary corners map*, which is a specialized type of *binary map* (i.e., a one-to-one mapping from its pixels of value 0 or 1 to the pixels of the original image). In a binary corners map, when a pixel is a corner in the original image, its corresponding value is 1; otherwise it is 0.

Centroid Detection. To find the centers of objects, we first partition the digital image into segments using *image segmentation*, the goal of which is to change the representation of an image into something more meaningful and easier to analyze [25]. We use the mean-shift segmentation algorithm [7], which takes a feature (range) bandwidth, spatial bandwidth, and a minimum region area (in pixels) as input. We set these parameters to 7, 9, and 50 respectively, which we found empirically to provide an acceptable segmentation



(a) LocalMax normalization

(b) Iterative normalization

Figure 1. pool image with the first 7 items in the scan-path.

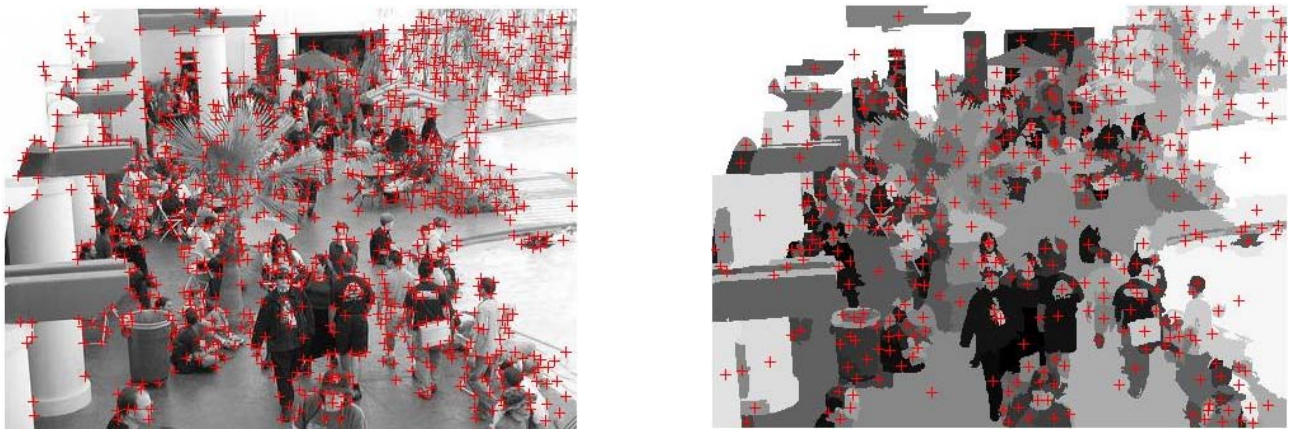


Figure 2. Corner detection (left) and center detection (right) output for pool.

with the smallest resulting number of segments.

After segmentation, we calculate the center of each segment (centroid) by calculating the arithmetic mean of each coordinate of the segment's points. In other words, the center (X_S, Y_S) of segment S is calculated by $X_S = \frac{1}{n(S)} \sum_{i \in S} x_i$ and $Y_S = \frac{1}{n(S)} \sum_{i \in S} y_i$, where x_i and y_i are pixel coordinates, and $n(S)$ denotes the *total number* of pixels in segment S. The x coordinates of all points in S are involved in calculating X_S, not only those along the maximum width.

Figure 2(b) illustrates the resulting segments of the *pool* image with different shading. The center of each segment is denoted by a '+'. We also create a *centers map*, which is a binary map of the same size of the corresponding image where each pixel has the value 0 or 1. If a pixel is a center of a segment in the corresponding image, its value is 1; otherwise its value is 0. The *distinguishable points map* δ is a binary map that is the logical (inclusive) "or" of the binary centers map and binary corners map.

3 Experimental Methodology

We pursue attacks that use click-order patterns and image processing methods for creating more efficient, ordered attack sub-dictionaries. We describe the specific click-order patterns we examine and their specification in Section 3.2. The image processing methods which we used for further optimization are described in Section 3.1, along with the *window clustering* algorithm we use to optimize the dictionary.

3.1 Image Processing Method

We used the Saliency Toolbox [29] implemented in Matlab. The weights of all feature maps used by the toolbox

are set to one, to indicate that orientation, intensity and colors have the same level of importance. All the other settings of this toolbox are set to *default* except normalization type, which can be either *Iterative* or *LocalMax*. Since each of these two normalization types cause different spatio-temporal attentional scan-paths, we tested both in our experiments. For each, we examine two different styles of generating a dictionary for use in a guessing attack described below.

For each dictionary guessing style, we generate a map of candidate click-points using our distinguishable points map δ as a bitmask to the resulting attracted regions of the image (i.e., using a logical "and"). We then refine this binary map of candidate points as follows.

Window Clustering Algorithm. We assume that an attacker's goal is to guess the largest number of passwords with the fewest guesses. After creating a set of points for a guessing dictionary (which might be used in passwords in any ordering of five clicks), many of them may be within the same tolerance region, and thus could be redundant (effectively guessing the same point). We devised a "clustering" method to normalize a set of points to a single value. The intuition is that given the system error tolerance, one point would be accepted as a correct entry for all others within its tolerance region. A previous clustering algorithm [27] centers each cluster on one of the original input points.

We introduce an alternative, *Window Clustering*, based on setting a window of fixed size (not necessarily the same size as the tolerance region) over the largest number of points it can cover. We then replace those candidate points inside the window with the geometric *center* of the window. Thus, the center of the cluster is not necessarily one of the original input points. Figure 3 shows an example set of

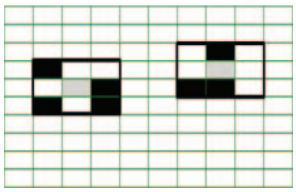


Figure 3. Window Clustering

candidate points with black squares, where each square represents a pixel. These 7 candidate points are covered with two 3×3 windows and will be represented by the centers of the two windows illustrated with grey squares.

Window Clustering is a greedy algorithm with a fixed window size. Starting with all candidate points, it finds the next position for the window that covers the maximum number of remaining points (ties are broken arbitrarily). It then stores the center of the window to represent the points in the window, and erases the corresponding points. It continues this process until no candidate points remain. In our experiments, the candidate points we use are the points with value 1 in S_b of Section 3.1.1 and B_i of Section 3.1.2. The window size is set to 19×19 in our experiments.

3.1.1 Guessing Style: Ordered by Scan-Path

The hypothesis here is that users may choose their password points from separate attracted regions, following the order of the focus-of-attention scan-path. The ordered dictionary described in this subsection is designed to test this hypothesis.

Using the visual attention tool, we generate *S*, a set of binary maps, where each binary map is generated in a single step of the scan-path. $S = \{A_1, A_2, ..., A_n\}$ where A_i denotes the generated binary map in step i and n is the total number of steps. Pixels of a binary map A_i have value 1 if they belong to the attracted region of step i, otherwise 0. $S_b = \{A_1 \wedge \delta, A_2 \wedge \delta, ..., A_n \wedge \delta\}$, and then the window clustering algorithm is run separately on each element in S_b to create S_c. S_c contains n sets of candidate points, each set containing the cluster centers produced from running the clustering algorithm on the corresponding element of S_b . To create each entry of the dictionary, we choose all sets of five elements of S_c and then order these elements by increasing index. Finally, we choose one point from each of these five elements, while retaining the element ordering, to put in the dictionary. Thus each dictionary entry is a five-point graphical password, where each point belongs to an element of S_c, and the five points (each belonging to a distinct scan-path element) are ordered by the order of the 5 elements in the scan-path.

3.1.2 Guessing Style: Unordered Incremental

Here the hypothesis is that users may choose their click-points based on points that fall along the focus-of-attention scan-path, but not necessarily in the order of the scan-path. The unordered incremental (UI) dictionary is designed to test this hypothesis. We call the UI dictionary with *LocalMax* normalization VA_1, and with *Iterative* normalization VA_2.

Using the visual attention tool, we generate a set of binary maps S', where the i^{th} binary map is generated from all of the steps until step i in a scan-path: $S' = \{B_1, B_2, ..., B_n\}$ where $B_i = A_1 \vee A_2 \vee ... \vee A_i$. In other words, $B_i = B_{i-1} \vee A_i$ and $B_1 = A_1$. Next, we calculate $\{C_1, C_2, ..., C_n\}$ where $C_i = B_i \wedge \delta$, the intersection (logical "and") of each element B_i with δ, and run the window clustering algorithm on each C_i to produce D_i, the resulting set of cluster centers (which are pixel locations on the image). A sub-dictionary P_i is all 5-permutations of the elements of D_i, and so the final dictionary $P = \{P_1, P_2, \ldots, P_n\}$ is ordered by the number

of steps in the scan-path that are considered, e.g., all passwords from P_2 are only guessed after those in P_1 are exhausted.

3.2 Click-order Patterns and Relaxation

We examine two click-order patterns alone (DIAG and LINE), and with what we call $lazy$ and $super\text{-}lazy$ variations that relax the definition of the patterns alone. The two click-order patterns are (1) DIAG and (2) LINE, a subset of DIAG that we introduce herein. DIAG includes any sequence of 5 click-points that follow *both* a consistent vertical and horizontal direction (e.g., straight lines in any direction, most arcs, and step-patterns). LINE includes any sequence of 5 click-points that follow either a vertical or horizontal line. More specifically, DIAG = $LR\_TB \cup LR\_BT \cup RL\_TB \cup RL\_BT$. Thus DIAG is the union of four sets of passwords. In the descriptive name of each set, the first two letters show the horizontal direction and the last two are related to vertical direction. LR and RL denote left-to-right and right-to-left respectively; TB and BT denote top-to-bottom and bottom-to-top respectively. Each of the four sets in DIAG consists of all 5-point passwords whose successive pairs of points $(x_i, y_i), (x_{i+1}, y_{i+1})$ satisfy the specified constraints. By convention, the positive y axis extends downward from the top-left pixel of the image.

LR_BT: $(x_i \leq x_{i+1} + \tau) \ \wedge \ (y_i \geq y_{i+1} - \tau)$
RL_BT: $(x_i \geq x_{i+1} - \tau) \ \wedge \ (y_i \geq y_{i+1} - \tau)$
LR_TB: $(x_i \leq x_{i+1} + \tau) \ \wedge \ (y_i \leq y_{i+1} + \tau)$
RL_TB: $(x_i \geq x_{i+1} - \tau) \ \wedge \ (y_i \leq y_{i+1} + \tau)$

Similarly, LINE = $LR \cup RL \cup BT \cup TB$, where the four sets in LINE consist of all passwords whose successive pairs of points satisfy analogous constraints as follows.

LR: $(x_i \leq x_{i+1} + \tau) \wedge (|y_i - y_{i+1}| \leq \tau)$
RL: $(x_i \geq x_{i+1} - \tau) \wedge (|y_i - y_{i+1}| \leq \tau)$
BT: $(y_i \geq y_{i+1} + \tau) \wedge (|x_i - x_{i+1}| \leq \tau)$
TB: $(y_i \leq y_{i+1} + \tau) \wedge (|x_i - x_{i+1}| \leq \tau)$

For both LINE and DIAG, the allowance τ serves the purpose of relaxing the pattern, since although the user might be inclined to select points along a line, the elements of that line may be influenced by which click-points the user otherwise prefers. If the image has many straight-line structures, it would seem reasonable to expect that users would choose straighter lines, but in the absence of linear structures in the image, the lines may be more of an approximation. To this end, we introduce two variations on both DIAG and LINE, that relax τ in their above definitions to allow "lazier" lines: "lazy", which uses $\tau = 19$ and "super-lazy", which uses $\tau = 28$. In the normal relaxation case, we use $\tau = 9$ (i.e., equal to the system error tolerance).

We denote a dictionary using a lazy or super-lazy τ with superscripts $+$ and $++$ respectively.

4 Experimental Results

To allow meaningful comparison, we tested our methods by trying to guess users' graphical passwords, using a previous PassPoints user study password database which we summarize below. Sections 4.1 and 4.2 report on the guessing styles of Section 3.1.

Review of User Study. The field study used to allow comparison [27, 5] was 7-weeks or longer (depending on the user), involving 223 user accounts on a web-based implementation of PassPoints to gain access to course notes, assignment solutions, and tutorials. We focus on the field study rather than the related lab study for increased confidence that the passwords we are studying have some degree of long-term memorability. Participants were from three undergraduate classes: two first year courses for computer science students, and a first year course for non-computer science students enrolled in a science degree. Participants used one of two background images, *pool* or *cars* (see Figure 4), carefully preselected to be representative of highly detailed usable images at 451×331 pixels.

Figure 4. cars (originally from [3]). See Figure 1 for pool (unmodified version from [32, 31]).

Passwords had 5 click-points, no two within $t = 9$ pixels of another (vertically and horizontally). Consistent with the previous study, we used only the final passwords exercised by each user (and recalled at least once). These 223 user accounts mapped to 189 distinct users (34 users were in two classes; all but one of them were assigned a different image for each account). Overall, 114 user accounts used *pool* and 109 used *cars* as a background image.

4.1 Ordered Scan-Path Results

We tested the hypothesis that users choose click-points in the order of their focus-of-attention scan-path, using the method of Section 3.1.1. We found that this method did not guess any passwords correctly. This indicates that users do *not* choose click-points along a partial ordering of the scan-path elements the model produces (under the default settings we used).

We see two possible reasons for this result: (1) users do not choose their click-points entirely based on bottom-up visual attention; or (2) the model of visual attention as used does not accurately capture bottom-up visual attention. Our results in Section 4.2 suggest that bottom-up visual attention, according to this computational model, might be a partial factor in user choice.

4.2 Incremental LocalMax and Patterns

We tested our hypothesis that users choose click points based on bottom-up visual attention using VA_1, the incremental attack of Section 3.1.2 with *LocalMax* normalization.[1] The VA_1 attack strategy uses the scan-path to prioritize the dictionary entries; all 5-permutations of points using only the first scan-path element are considered before all 5-permutations using both the first and second elements, etc. This method is applied in combination with the various click-order patterns of Section 3.2, combining VA_1 with each of DIAG and LINE click-order patterns at all laziness modes. The cumulative distribution function (CDF) of our results (until each dictionary is exhausted) are provided in Figure 5.

Dictionary	Entries	% guessed	
		pool	*cars*
$\alpha DIAG$	$2^{33.0}$	21.1%	27.5%
$\alpha DIAG^{+}$, $\alpha DIAG^{++}$	$2^{34.7}$	48.2%	54.1%
$\alpha LINE$	$2^{20.1}$	3.5%	22.0%
$\alpha LINE^{+}$, $\alpha LINE^{++}$	$2^{27.7}$	23.7%	52.3%

Table 1. Results for click-order heuristics.

To examine the efficacy of using click-order pattern heuristics alone (i.e., without additional image processing methods as in Figure 5), we also used the following alphabet α with click-order patterns DIAG and LINE to generate dictionaries αDIAG and αLINE. α is a set of points defined to partition an entire image into T-regions (recall Section 2.2) by placing a grid of 19×19 windows (i.e, the same size as the T-region) over the image. The centers of each window compose the alphabet. Note that the T-region used in creating α is only dependent upon the system error tolerance, and is independent of the τ used in our different relaxation modes. Table 1 presents our results. Note that the values in Table 1 for the dictionaries marked '+' and '++' are the same because the T-regions are non-overlapping, and the difference between $\tau = 19$ and 28 is not sufficient to increase the number of included T-regions.

Many interesting points emerge from the graphs in Figure 5 and values in Table 1. The most notable in terms of success rate is the $\alpha DIAG^{+}$ dictionary of Table 1, which guesses 48% of passwords for *pool* and 54% of passwords for *cars* with dictionaries of less than 2^{35} entries. Previous purely automated attacks [27] against these same images on the same password database, with a dictionary of 2^{35} entries, guessed 9.1% of passwords on *cars* and 0.9% of passwords on *pool*. Similarly, $\alpha LINE^{+}$ of Table 1 guesses 23.7% of passwords for *pool*, and 52.3% of passwords for *cars* using a dictionary of about $2^{27.7}$ entries. It is interesting that when using $\alpha LINE^{+}$ the percentage of passwords guessed for *cars* only drops by about 2%, while the accuracy for *pool* only drops by about 24% (about half as many passwords are guessed), despite a dictionary size reduction of $\frac{1}{2^7}$ times. This implies that $\alpha LINE^{+}$ is the most efficient (in terms of accuracy and dictionary size) click-order pattern studied to date. It is not surprising that the LINE variations work better on the *cars*, given the number of straight line structures in the image and the orientation of the cars in the parking lot. It seems more surprising to see LINE variations working as well as they do for *pool*.

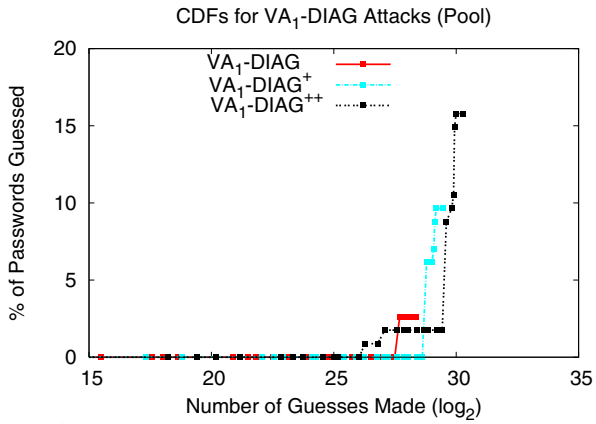
The VA_1 optimization of Figure 5 does appear to create a more efficient dictionary: for the $DIAG^{++}$ variation, we are able to guess 15.8-16.5% in dictionaries of less than $2^{31.3}$ entries, and for the $LINE^{++}$ variation, 7.9-14.7% of passwords using a dictionary of less than $2^{24.6}$ entries. The relative "efficiency" of the dictionaries, however, cannot be extended in their present form to guess a larger percentage of passwords, because the full dictionaries are exhausted.

5 Discussion and Future Work

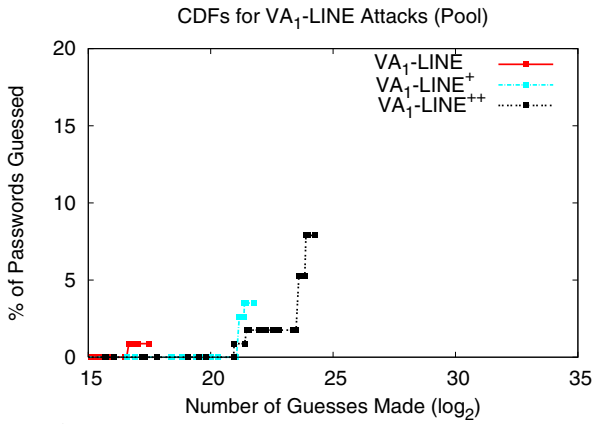
Our overall results indicate that although essentially no users choose their click-points in the strict scan-path order of Itti's model of visual attention, when all permutations of points in the scan-path are considered, it models a meaningful percentage (from an attacker viewpoint) of user passwords. This raises interesting questions regarding how visual attention relates to user choice in graphical passwords. Our results would be consistent with the hypothesis that bottom-up visual attention is a factor in user choice for some users (and/or for some images), but not necessarily for all users.

It would be interesting to further explore whether there

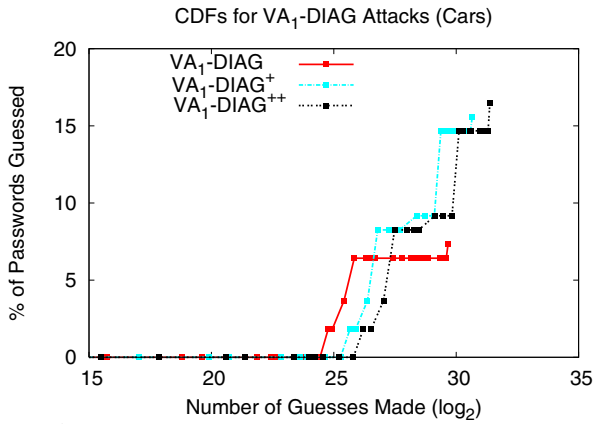
[1] We also tried our attack using VA_2; it did not perform very well, indicating that the apparently small strategy change (global bias for VA_2 vs. local bias for VA_1 in the neural network algorithm) can have a large effect



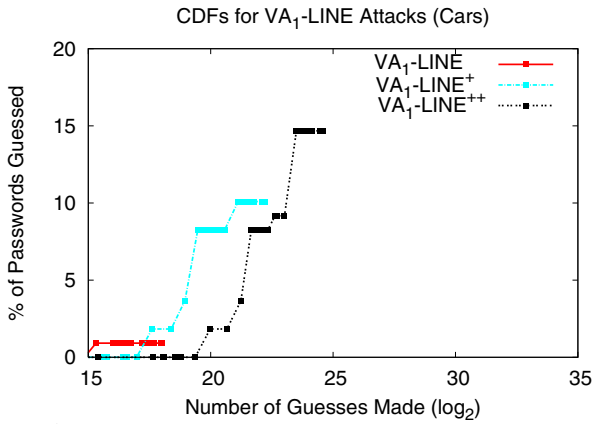
(a) VA_1-DIAG CDFs for *pool*.



(b) VA_1-LINE CDFs for *pool*.



(c) VA_1-DIAG CDFs for *cars*.



(d)VA_1-LINE CDFs for *cars*.

Figure 5. CDFs for different attacks with LocalMax normalization (i.e., VA_1).

are top-down models under various plausible assumptions, that may more accurately model user choice. For example, might the first point be chosen according to bottom-up visual attention, and then the rest chosen in a top-down manner such that they are somehow similar to the first? Alternately, might the entire process be top-down, based on whether the user can find five objects that are similar in some way? Such a top-down theory would be substantially more difficult to model an attack on, but if possible to implement, its results would offer interesting insight.

The distinguishable points map δ could be enhanced in several ways, to refine the attacks presented herein. We expect the dictionaries could be further improved by incorporating other types of *calculable* points, such as north, south, east, and west on circles and squares. Also, changing the parameters to the algorithms we use to identify distinguishable points might provide better results, or changing the parameters for the visual attention model. It would also be interesting to explore whether settings can be optimized for a wide range of images, or if optimal settings are highly-image specific. Regarding our image-independent attacks which rely only on generic patterns and window clustering, exploration of other patterns may prove fruitful.

6 Concluding Remarks

We provide what appears to be the best automated attack against PassPoints-style graphical passwords to date. Click-order patterns, DIAG and LINE, combined with our laziest relaxation rule, yielded highly effective dictionaries. We were able to further reduce the dictionary size while retaining some accuracy using Itti et al.'s [15] computational model of bottom-up visual attention. Our results are a significant improvement on previous work for purely automated guessing PassPoints-style graphical passwords. Using a dictionary of 2^{35} entries, $\alpha DIAG^{++}$, we were able to guess over 48% of user passwords for each of two images, whereas previous work was able to guess 0.9-9.1% [27] for

the same images and user study password database and 8% [10] for a single (comparable) image.

Although these lazy click-order dictionary sizes are not as small as previous dictionaries used for human-seeded attacks, when we combine them with a model of visual attention [15], our results are comparable to the human-seeded results for *cars*. Using a dictionary of $2^{30.3}$ entries, the VA_1-$DIAG^{++}$ dictionary guessed 15.8% of passwords on *pool*, and using a dictionary of about $2^{31.4}$ entries it guessed 16.5% of passwords on *cars*. For *cars*, the basic human-seeded attack [27] guessed 20% of passwords with a dictionary of 2^{33} entries. This suggests that automated attacks provide an effective alternative to a human-seeded attack against PassPoints-style graphical passwords. Furthermore, they allow continuation of an attack through using click-order patterns without prioritization by some other means, guessing more passwords overall than human-seeded methods. Finally, they are arguably much easier for an attacker to launch (removing the requirement of humans to index the images), especially if large image datasets are used. We emphasize that the attack dictionaries used for Table 1 including the dictionary in the previous paragraph, do not rely on visual attention techniques or any image-specific precomputation, implying that the actual dictionaries are the same for all images, though the attack results (i.e., their effectiveness) are image-dependent and of course depend also on the actual passwords chosen by any users in question.

We evaluated different guessing styles using Itti's model and found that using the first 30 steps of the model's scan-path output, none of the user passwords in the database followed along the scan-path order (i.e., 5 ordered points within the 30-element scan-path ordering), but a number of passwords were composed of points within other orderings of the scan-path elements. If we assume that Itti's model using the default settings is an accurate representation of bottom-up visual attention, these results are consistent with bottom-up visual attention being one part of a broader criteria for selecting click-points. Alternately, these click-points might be chosen according to some other phenomenon that happens to have a non-null intersection with this model of bottom-up visual attention.

Using *Iterative* normalization, our attack based on the visual attention model did not perform very well, indicating that the bias of proximity (local saliency vs. global saliency) can have a dramatic effect. Our success using *LocalMax* normalization suggests that users are more likely to choose successive points that are closer to one another than on the other side of the image. The difference in results suggests that the success of the *LocalMax* attack is not a chance effect, but rather it actually locates the parts of the image that users are more inclined to choose as click-points. Even better results may be possible through other (unknown) neural network strategies.

It remains unclear how universal the inducement of users to fall into click-order patterns is across a broad universe of images, or whether image processing measures might effectively filter out images that are more prone to structure-based click-order patterns like those exploited in our attacks.

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