A Three-Way Investigation of a Game-CAPTCHA: Automated Attacks, Relay Attacks and Usability

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ABSTRACT

Existing captcha solutions on the Internet are a major source of user frustration. Game captchas are an interesting and, to date, little-studied approach claiming to make captcha solving a fun activity for the users. One broad form of such captchas – called *Dynamic Cognitive Game (DCG) captchas* – challenge the user to perform a game-like cognitive task interacting with a series of dynamic images. We pursue a comprehensive analysis of a representative category of DCG captchas. We formalize, design and implement such captchas, and dissect them across: (1) fully automated attacks, (2) human-solver relay attacks, and (3) usability. Our results suggest that the studied DCG captchas exhibit high usability and, unlike other known captchas, offer some resistance to relay attacks, but they are also vulnerable to our novel dictionary-based automated attack.

1. INTRODUCTION

The abuse of the resources of online services using automated means, such as denial-of-service or password dictionary attacks, is a common security problem. To prevent such abuse, a primary defense mechanism is CAPTCHA [2] (denoted "captcha"), a tool aimed to distinguish a human user from a computer based on a task that is easier for the former but much harder for the latter.

The most commonly encountered captchas today take the form of a garbled string of words or characters, but many other variants have also been proposed (we refer the reader to [30], [7], [17] which provide excellent review of different captcha categories). Unfortunately, existing captchas suffer from several problems. *First*, successful automated attacks have been developed against many existing schemes. For example, algorithms have been designed that can achieve character segmentation with a 90% success rate [18]. Real world attacks have also been launched against captchas employed by Internet giants [15, 19, 27].

Second, low-cost attacks have been conceived whereby challenges are relayed to, and solved by, users on different web sites or paid human-solvers in the crowd [10, 13, 16]. In fact, it has been shown that [23] such relay attacks are much more viable in practice than automated attacks due to their simplicity and low economical costs.

Third, the same distortions that are used to hide the underlying content of a captcha puzzle from computers can also severely degrade human usability [9,31]. More alarmingly, such usability degradation can be so severe on many occasions that users get frustrated and give up using the services that deploy captchas. Consequently, companies lose customers and suffer economic losses [25].

Given these problems, there is an urgent need to consider alternatives that place the *human user at the center of the captcha design*. *Game captchas* offer a promising approach by attempting to make captcha solving a fun activity for the users. These are challenges that are built using games that might be enjoyable and easy to play for humans, but hard for computers.

In this paper, we focus on a broad form of game captchas, called *Dynamic Cognitive Game (DCG)* captchas. This captcha challenges a user to perform a *game*-like *cognitive* task interacting with a series of *dynamic* images. Specifically, we consider a representative DCG captcha category which involves objects floating around within the images, and the user's task is to match the objects with their respective target(s) and drag/drop them to the target location(s). A startup called "are you a human" [4, 26] has recently been offering such DCG captchas.

Besides promising to significantly improve user experience, DCG captchas are an appealing platform for touch screen enabled mobile devices (such as smartphones). Traditional captchas are known to be quite difficult on such devices due to their small displays and key/touch pads, while touch screen games are much easier and already popular. Motivated by these unique and compelling advantages of DCG captchas, we set out to investigate their security and usability. Specifically, we pursue a comprehensive study of DCG captchas, analyzing them from three broad yet intersecting dimensions: (1) *usability*, (2) *fully automated attacks*, and (3) *human-solver relay attacks*. Our main contributions are as follows:

1. We formalize, design and implement four instances of a representative category of DCG captchas. (*Sections 2 and 3*)
2. We conduct a usability study of these instances, evaluating them in terms of time-to-completion, error rates and perceived usability. Our results indicate the overall usability to be very good. (*Section 4*)
3. We develop a novel, fully automated framework to attack these DCG captcha instances based on image processing techniques and principles of unsupervised learning. The attack is compu-

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tationally efficient and highly accurate, but requires building a dictionary to be effective. (*Section 5*)

4. We explore different variants of human-solver relay attacks against DCG captchas. Specifically, we show that the most simplistic form of relay attack (in line with traditional captcha relay attack) reduces to a *reaction time task* for the solver, and conduct a user study to evaluate the performance of this attack. In general, our results indicate that DCG captchas with mobile answer objects offer some level of resistance to relay attacks, differentiating them from other captchas. Our user study may also be of independent interest in other human-centered computing domains. (*Section 6*)

2. BACKGROUND

We use the term Dynamic Cognitive Game (DCG) captcha to define the broad captcha schemes that form the focus of our work. We characterize a DCG captcha as having the following features: (1) *dynamic* because it involves objects moving around in image frames; (2) either *cognitive* because it is a form of a puzzle that relates to the semantics of the images or *image recognition* because it involves visual recognition; and (3) a *game* because it aims to make captcha solving task a fun activity for the user. In this section, we discuss the security model and design choices for DCG captcha, and present the DCG captcha category and associated instances studied in this paper.

2.1 Security Model and Design Choices

The DCG captcha design objective is the same as that of captcha: a bot (automated computer program) must only be able to solve captcha challenges with no better than a negligible probability (but a human should be able to solve with a sufficiently high probability).[1]

A pre-requisite for the security of a DCG captcha implementation (or any captcha for that matter) is that the responses to the challenge must not be provided to the client machine in clear text. For example, in a character recognition captcha, the characters embedded within the images should not be leaked out to the client. To avoid such leakage in the context of DCG captchas, it is important to provide a suitable underlying game platform for run-time support of the implemented captcha. Web-based games are commonly developed using Flash and HTML5 in conjunction with JavaScript. However, both these platforms operate by downloading the game code to the client machine and executing it locally. Thus, if these game platforms were directly used to implement DCG captchas, the client machine will know the correct objects and the positions of their corresponding target region(s), which can be used by the bot to construct the responses to the server challenges relatively easily. This will undermine the security of DCG captchas.

The above problem can be addressed by employing encryption and obfuscation of the game code which will make it difficult for the attacker (bot) on the client machine to extract the game code and thus the correct responses. Commercial tools, such as SWF Encrypt [3], exist which can be used to achieve this functionality. This approach works under a security model in which it is assumed that the bot does not have the capability to learn the keys used to decrypt the code and to deobfuscate the code. A similar model where the attacker has only partial control over the client machine has also been employed in prior work [28].

In our model, we assume that the implementation provides continuous feedback to the user as to whether the objects dragged and dropped to specific target region(s) correspond to correct answers or not. The server also indicates when the game successfully finishes, or times out. This feedback mechanism is essential from the usability perspective otherwise the users may get confused during the solving process. The attacker is free to utilize all of this feedback in attempting to solve the challenges, but within the time-out. We also assume that it is possible for the server to preclude brute force attacks, such as when the attacker tries to drag and drop the regions within the image exhaustively/repeatedly so as to complete the game successfully. Such a detection is possible by simply capping the number of drag/drop attempts per moving object.[2]

In addition to automated attacks, the security model for DCG captchas (and any other captcha) must also consider human-solver relay attacks [10, 23]. In fact, it has been shown that such relay attacks are much more appealing to the attackers than automated attacks currently due to their simplicity and low cost [23]. In a relay attack, the bot forwards the captcha challenges to a human user elsewhere on the Internet (either a payed solver or an unsuspecting user accessing a web-site [14]); the user solves the challenges and sends the responses back to the bot; and the bot simply relays these responses to the server. Unfortunately, most, if not all, existing captcha solutions are insecure under such a relay attack model. For example, character recognition captchas are routinely broken via such relay attacks [23]. For DCG captchas to offer better security than existing captchas, they should provide some resistance to such human-solver relay attacks (this is indeed the case as we demonstrate in Section 6).

2.2 Game Instances and Parameters

Many forms of DCG captchas are possible. For example, they may be based on visual matching or semantic matching of objects, may consist of multiple target objects or none at all, and may involve static or moving targets. In this paper, we focus on one representative category, and four associated instances, of DCG captcha with static target(s) (see Figure 1). Specifically, our studied DCG captcha instances involve:

1. *single target object*, such as place the ship in the sea (the Ships game).
2. *two target objects*, such as match the shapes (the Shapes game).
3. *three target objects*, such as feed the animals (the Animals game).
4. *no target objects*, such as park the boat (the Parking game), where the target area does not consist of any objects.

The Shapes game is based on visual matching whereas the other games involve semantic matching.

For each of these 4 instances, different parameterizations affect security and usability. These include: (1) the number of foreground moving objects, including answer objects and other "noisy" objects; and (2) the speed with which the objects move. The larger the number of objects and higher the speed, the more difficult and time consuming it might be for the human user to identify the objects and drag/drop them, which may degrade usability. However, increasing the number and speed of objects may also make it harder for a computer program to play the games successfully, which may improve security. Thus, for our analysis of the DCG captcha, we will evaluate the effect of these parameters for captcha usability and captcha security (against automated as well as relay attacks).

[1] For example, target thresholds might limit bot success rates below 0.6% [32], and human user success rates above 90% [11].

[2] The "are you a human" DCG captcha implementation claims to adopt a sophisticated (proprietary) mechanism, based on mouse events, to differentiate human game playing activity from an automated activity. We did not implement such a human-vs-bot behavioral analysis component because our paper's goal is to examine the underlying captcha scheme only. A behavioral component can be added to other captchas also and represents a topic orthogonal to our work. Besides, it is not clear if behavioral analysis would add security; it may instead degrade usability by increasing false negatives.

(a) Ships Game

(b) Shapes Game

(c) Parking Game

(d) Animals Game

Figure 1: Static snapshots of 4 game instances of a representative DCG captcha analyzed in this paper (targets are static; objects are mobile)

3. DESIGN AND IMPLEMENTATION

Due to legal considerations, we did not resort to directly evaluate an existing DCG captcha implementation (e.g., "are you a human" DCG captchas). In particular, developing automated attacks against these captchas directly violates the company's asserted terms and conditions [5]. Instead, we designed and implemented our own equivalent and generalized versions of DCG captchas from scratch, and analyzed these versions. Developing our own versions also allowed us to freely vary the game parameters, such as the number and speed of objects, and investigate the DCG captcha security and usability with respect to these parameters.[3]

We created four instances of games as specified in Section 2.2 using Adobe Flash.

The game image/frame size is 360 x 130 pixels, which can easily fit onto a web page such as in a web form. Each game starts by placing the objects in certain pre-specified locations on the image. Then, each object picks a random direction in which it will move. A total of 8 directions were used, namely, N, S, E, W, NE, NW, SE and SW. If the chosen direction is one of E, W, S, or N, the object will move (across X or Y axis) by 1 pixel per frame in that direction. Otherwise, the object will move $\sqrt{2} = 1.414$ pixels per frame along the hypotenuse, corresponding to 1 pixel across both X and Y axes. This means that on an average the object moves 1.207 $[= (1 * 4 + 1.414 * 4)/8]$ pixels per frame. The object continues in the current direction until colliding with another object or the game border, whereupon it moves in a new random direction.

The game starts when the user presses a "Start" button on the screen center. Each game briefly explains to users their task, e.g., "Place the ships on the sea." The game ends when the user clicks/drags all the correct objects onto their corresponding target(s), in which case a "Game Complete" message is provided. To successfully match an object with its target, the user clicks inside the bounding box across the shape of the object, drags the object and drops it by releasing it inside the bounding box across the respective target. The game must be successfully completed within a fixed time (we allow 60s); the user gets feedback on the correctness of every drag-drop, by a star on success and a cross on failure (Figure 6, Appendix A).

For each of the 4 games, we set 5 parameterizations, choosing object speed (low, medium, high) as (10, 20, 40) frames per second (FPS), and number of moving objects as (4, 5, 6). (These frame rates translate into average object speeds of 12.07, 24.14 and 48.28 pixels/second, resp., given the objects move 1.207 pixels/frame.) For each game, we used 5 combinations of speed and number of objects: (10 FPS, 4 objects); (20 FPS, 4 objects); (20 FPS, 5 objects); (20 FPS, 6 objects); and (40 FPS, 4 objects). This resulted in a total of 20 games in our corpus.

[3]Although our implementation and analyses does not directly involve the "are you a human" captchas, it is generalized enough for our results to be applicable to these captchas also (i.e., the ones that fall under the categories evaluated in our work).

4. USABILITY

In this section, we report on a usability study of our representative DCG captcha category.

4.1 Study Design, Goals, and Process

Our study involved **40 participants** who were primarily students from various backgrounds. (For demographics, see Appendix A, Table 9). The study was *web-based* and comprised of three phases. The *pre-study phase* involved registering and briefly explaining the participants about the protocols of the study. In particular, the participants were shown "consent information," which they had to agree before proceeding with the study. This was followed by collecting participant demographics and then the participants playing the different DCG captcha games. This *actual study phase* attempted to mimic a realistic captcha scenario which typically involves filling out a form followed by solving captcha. To avoid explicit priming, however, we did not mention that the study is about captcha or security, but rather indicated that it is about assessing the usability of a web interface. In the *post-study phase*, participants answered questions about their experience with the tested DCG captchas. This comprised the standard SUS (Simple Usability Scale) questions [8], a standard 10-item 5-point Likert scale ('1' represents "Strong disagreement" and '5' represents "Strong agreement"). SUS polls satisfaction with respect to computer systems [6], in order to assess their usability. Additionally, we asked several other questions related to the games' usability.

In the actual study phase, each participant played 20 instances as discussed in Section 3, aimed at understanding how different parameterizations impact users' solving capabilities. The order of games presented to different participants involved a standard 20x20 Latin Square design to counter-balance learning effects. Via our study, our goal was to assess the following aspects of the DCG captchas:

1. *Efficiency*: time taken to complete each game.
2. *Robustness*: likelihood of not completing the game, and of incorrect drag and drop attempts.
3. *Effect of Game Parameters*: the effect of the object speed and number on completion time and error rates.
4. *User Experience*: participants' SUS ratings and qualitative feedback about their experience with the games.

For each tested game, completion times, and errors were automatically logged by our web-interface software.

4.2 Study Results

We now provide the results from our usability study, including time to completion and error rates, as well as perceived qualitative aspects of the methods based on user ratings.

Completion Time: Table 1 shows the completion time per game type. Clearly, all games turned out to be quite fast, lasting for less than 10s on an average. Users took longest to solve the Animals game with an average time of 9.10s, whereas the other games took almost half of this time. This might have been due to increased semantic load on the users in the Animals game to identify three target objects and then match them with the corresponding answer objects. Moreover, we noticed a decrease in the solving time (equal to 3.84s) when the target objects were decreased to 2 (i.e., in the Shapes game), and this time was comparable to games which had 1 target object in the challenge (Ships and Parking). A one-way repeated-measures ANOVA test showed significant difference (at 95% confidence) in the mean timings of all 4 types of games ($p < 0.0001$, $F = 79.98$). Aalyzing further using pairwise paired t-tests with Bonferroni correction, we found significant difference between the mean times of following pairs: Animals and Parking ($p < 0.001$), Ships and Shapes ($p < 0.0005$), Animals and Ships ($p < 0.001$), Animals and Shapes ($p < 0.001$), and Parking and Shapes ($p = 0.0024$).

Table 1: Error rates per click and completion time per game type

Game Type	Completion Time (s) *mean (std dev)*	Error Rate Per Click *mean*
Ships	4.51 (1.00)	0.04
Animals	9.10 (0.96)	0.05
Parking	4.37 (0.90)	0.09
Shapes	5.26 (0.59)	0.03

Error Rates: An important result is that all the tested games yielded 100% accuracy (*overall error rate of 0%*). In other words, none of the participant failed to complete any of the games within the time out. This suggests our DCG captchas instances are quite robust to human errors.

Next, we calculated the likelihood of incorrect drag and drop attempts (*error rate per click*). For example, in the Animals game, an incorrect attempt would be to feed the monkey with a flower instead of a banana. We define the error rate per click as the number of incorrect objects (from the pool of all foreground objects) dragged to the target area *divided by* the total number of objects dragged and dropped. The results are depicted in Table 1. We observe that the Shape game yields the smallest average per click error rate of 3%. This suggests that the visual matching task (as in the Shapes game) is less error prone compared to the semantic matching task (as in the other games). The game challenge which seemed most difficult for participants was the Parking game (average per click error rate 9%). Since objects in this game are relatively small, participants may have had some difficulty to identify them.

Effect of Object Speed and Number: Table 2 shows the performance of the game captchas in terms of per click error rates and completion time as per different object speeds. We can see that the maximum number of per click errors were committed at 10 FPS speed. Looking at the average timings, we find that it took longest to complete the games when the objects move at the fastest speed of 40 FPS, while 20 FPS yielded fastest completion time followed by 10 FPS. ANOVA test revealed statistical difference among the mean completion time corresponding to three speeds ($p = 0.0045$, $F = 5.65$). Further analyzing using the t-test with Bonferroni correction, we found statistical difference between the mean timing corresponding to the following pair of speeds only: 10 FPS and 20 FPS ($p = 0.0001$).

Table 2: Error rates per click and completion time per object speeds

Object Speed	Completion Time (s) *mean (std dev)*	Error Rate Per Click *mean*
10 FPS	5.74 (2.11)	0.06
20 FPS	4.90 (2.22)	0.05
40 FPS	6.53 (2.87)	0.04

Another aspect of the usability analysis included testing the effect of increase in the number of objects (including noisy answer objects) on the overall game performance. Table 3 summarizes the per click error rates and completion time against different number of objects. Here, we can see a clear pattern of increase, albeit very minor, in average completion time and average rate with increase in the number of objects. This is intuitive because increasing the number of objects increases the cognitive load on the users which may slow down the game play and introduce chances of errors. ANOVA test did not indicate this difference to be significant, however.

User Experience: Now, we analyze the data collected from the participants during the post-study phase. The average SUS score came out to be 73.88 (standard deviation = 6.94). Considering that the average SUS scores for user-friendly industrial software tends to hover in the 60–70 range [21], the usability of our DCG game captcha instances can be rated as high.

Table 3: Error rates per click & completion time per # of objects

# of Objects	Completion Time (s) *mean (std dev)*	Error Rate Per Click *mean*
6	6.58 (1.69)	0.06
5	5.30 (2.28)	0.05
4	4.90 (2.22)	0.04

In addition to SUS, we asked the participants a few 5-point Likert scale questions about the usability of the games ('1' means "Strong Disagreement"). Specifically, we asked if the games were "visually attractive" and "pleasurable," and whether they would like to use them in "practice." Table 4, shows the corresponding average Likert scores. We found that 47% percent participants felt that the games were visually attractive and 45% said that it was pleasurable to play the games. These numbers indicate the promising usability exhibited by the games. We further inquired users if they noticed change in speed or number of objects in the games. 27.5% noticed no change (increase and/or decrease) in speed of objects, whereas only 22.5% noticed no change in number of objects (see Table 5). Thus, the change in the number of objects and speed (within the limits we tested) was noticeable by a large fraction of participants.

Table 4: User feedback on game attributes

Attribute	Likert Score *mean (std dev)*
Visually Attractive	3.18 (0.94)
Pleasurable	3.33 (0.96)

Table 5: % of users noticing change in speed and number of objects

Object Speed	(%)
Moved faster	30
Moved slower	5
No change	27.5
Both slower and faster	37.5
Number of objects	(%)
Increased	47.5
Decreased	2.5
No change	22.5
Both increase and decrease	27.5

Summary of Usability Analysis: Our results suggest that the DCG captcha representatives tested in this work offer very good usability, resulting in short completion times (less than 10s), very low error rates (0% per game completion, and less than 10% per drag and drop attempt),[4] and good user ratings. We found that increasing the object speed and number is likely to degrade the game performance, but up to 6 objects and up to 40 FPS speed yield a good level of usability. Although our study was conducted with a relatively young participant pool, given the simplcity of the games (involving easy matching and clicking tasks), the game performance would generally be in line with these results, as shown by our parallel study with Mechanical Turk participants [22].

5. AUTOMATED ATTACKS

Having validated, via our usability study, that it is quite easy for the human users to play our DCG captcha instances, we next proceeded to determine how difficult these games might be for the computer programs. In this section, we present and evaluate the performance of a fully automated framework that can solve DCG captcha

[4]When contrasted with many traditional captchas [9], these timings are comparable but the accuracies are better.

challenges based on image processing techniques and principles of unsupervised learning. We start by considering random guessing attacks and then demonstrate that our framework performs orders of magnitude better than the former.

5.1 Random Guessing Attack

An attacker given a DCG captcha challenge can always attempt to perform a random guessing attack. Let us assume that the attacker knows which game he is being challenged with as well as the location of the target area (e.g., the blue region containing the target circle and pentagon in the Shapes game) and the moving object area (e.g., the white region in the Shapes game within which the objects move). Although determining the latter in a fully automated fashion is a non-trivial problem (see our attack framework below), an attacker can obtain this knowledge with the help of a human solver.

However, the attacker (bot) still requires knowledge of: (1) the foreground objects (i.e., all the objects in the moving object area) and (2) the target objects (i.e., the objects contained within the target area). A randomized strategy that the attacker could adopt is to pick a random location on the moving object area and drag/drop it to a random location on the target area. More precisely, the attacker can divide the moving object area and the target area into grids of reasonable sizes so as to cover the sizes of foreground moving objects and target objects. For example, the moving object area can be divided into a 10 pixel x 10 pixel grid and target region can be divided into a 3 pixel x 3 pixel grid (given that the target area size is roughly 3 times the object area size). If there are a total of r target objects, the total number of possibilities in which the cells (possibly containing the answer objects) on the object area can be dragged and dropped to the cells on the target area are given by $t = C(100, r) * P(9, r)$. This is equivalent to choosing r cells in the object area out of a total of 100 cells, and then rearranging them on to 9 cells in the target area. Thus, the probability of attacker success in solving the challenge in a single attempt is $1/t$. For the DCG captcha instances targeted in this paper, r is 3, 2 and 1, resulting in the respective success probabilities of 0.00000123%, 0.000281% and 0.1%. Each attempt corresponds to r drag-and-drop events. Even if the attacker is allowed a limited (3-4) number of attempts to solve the captcha, these probabilities are still much lower than the target probabilities for a real-world captcha system security (e.g., 0.6% as suggested by Zhu et al. [32]).

While this analysis suggests that such DCG captchas are not vulnerable to naive guessing attacks, the next step is to subject them to more sophisticated, fully automated attacks, as we pursue below.

5.2 Our Automated Attack and Results

Our attack framework involves the following phases:

1. Learning the background image of the challenge and identifying the foreground moving objects. A background is the canvas on which the foreground objects are rendered. The foreground objects, for example, in the Ships game, as shown in Figure 1(a), are bird, ship, monkey, and squirrel.
2. Identifying the target area and the target area center(s). For example, the sea in the Ships game, and the animals in the Animals game.
3. Identifying and learning the correct answer objects. For example, the ships in the Ships game.
4. Building a dictionary of answer objects and corresponding targets, the background image, the target area and their visual features, and later using this knowledge base to attack the new challenges of the same game.
5. Continuously learning from new challenges containing previously unseen objects.

Next, we elaborate upon our design and matlab-based implementation per each attack phase as well as our experimental results. We note that, on a web forum [1], the author claims to have developed an attack against the "are you a human" captcha. However, *unlike our generalized framework*, this method is perfected for *only one simple game* that has one single target area and a fixed set of answer objects. It is not known whether or how easily this method can be adapted to handle different games, games with multiple instances that carry different sets of answer objects, and those with multiple target objects. Since only one game is cracked, one needs to keep refreshing the game page, if allowed, until that specific game appears. Since no technical details are provided in [1], we can only doubt if any background learning or object extraction is implemented by observing the short time it takes to finish the attack.

(1) Background & Foreground Object Extraction: To extract the static background of a DCG challenge, the intuitive way is to superimpose some sampling frames that cross a valid period (e.g., 40 frames captured at a fixed time interval (0.2s)), then select the most frequent color value (dominant color) from each pixel as the background color for that pixel. This is based on the assumption that the background image is static and the foreground objects are constantly moving, such that the true background color almost always appears as the most frequent (or consistent) color observed for a pixel. By subtracting the background image from a video frame, the foreground moving objects become readily extractable. To further reduce the computational cost, a 6-bit color code[5], rather than a 24-bit or 3-byte representation of a color value, is used to code the video frame, the learned background image, and the learned foreground objects.

However, one drawback of this preliminary method is that if the moving speed of the foreground objects is too slow, especially when some foreground objects hover over a small area, the dominant color values of most pixels in that area will be contributed by the foreground objects instead of by the background. A shadow of foreground objects may appear as pseudo patches in the background image as shown in Figure 2(b) for the Shapes game of Figure 2(a), indicated by the dashed rectangle. Using more sampling frames for initial background learning could alleviate this problem, but resulting in a time-consuming learning procedure. Our preliminary experiment indicates that an average 30.9s, generated by running the above learning method 15 times per game challenge, is needed for learning a game background completely.

In our new method, we overcome the conflict between the number of sampling frames and the pseudo patch effect by actively changing the location of one moving object per sampling frame. In the first step, a few frames N_1 (e.g., 10 frames captured in 0.3s interval) are collected to generate the initial background that is used to extract the foreground object (through background subtraction) in the next step. Because the number of sampling frames is very limited, pseudo patches may exist. The second step, called active learning, is to actively drag-and-drop each moving object to a specified destination, which aims to speed up the object movement in order to reduce the pseudo patch effect. Then, N_2 ($N_2 > N_1$) sampling frames are re-collected whenever a moving object is actively dragged to a new location. Because of the high efficiency of the moving object detection and the latter mouse operations, enough sampling frames (e.g., N_2 = (30, 50)) without/with minor hovering effect could be collected within a short period. The new background is detected again based on the dominant color of the collected frames. Figure 2(c) and 2(d) show the detected background with non-trivial pseudo patches and with a minor patch, resp., by applying the 1st and 2nd steps of the new active learning method on the Shapes game of Figure 2(a). Minor patches could affect the detection of a complete object, but since the affected area is minor, partial matching could still be used in the latter identification of the answer object.

[5] http://en.wikipedia.org/wiki/Color_code

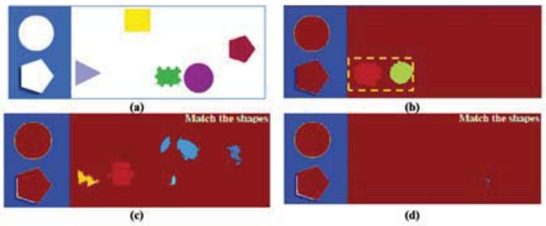

Figure 2: Detected backgrounds. (a) original frame image; (b) detected background with pseudo patches by using preliminary method; (c) detected background with pseudo patches after performing the 1st step of the proposed method; (d) detected background with a minor patch after performing the 2nd step of the proposed method.

Each learned background image is saved in the database. After removing the extracted background from 5-8 equally distant frames from the collected frames, the objects in each of the selected frame are extracted. The objects below a certain size threshold were discarded as noise. The frame with the maximum number of objects was then selected to extract various objects. Using multiple frames for object extraction also helped us discard the frames in which the objects overlapped each other and were hence detected as a single object instead of distinct individual objects.

According to our experimental results, the likelihood of observing such pseudo patches is sufficiently low ($< 7\%$). However, pseudo patches may not pose a big issue. Even though the existence of pseudo patches may result in over-segmented foreground objects when they overlap each other, a partially detected object can still be used to extract visual features and later to locate an object that matches the visual features at the time of attacking.

As the final step as part of this phase, the visual features, coded as color code histograms (a visual feature commonly used to describe the color distribution in an image), of the foreground objects and the background image, are stored in the database, together with some other meta-data such as the object size and dimensions.

(2) Target Area Detection: Identifying the target area requires analysis of the background extracted in the previous phase. For this purpose, we implemented two alternative approaches, namely the *Minimum Bounding Rectangle (MBR)* [12] method and the *Edge-based method*, and compared and contrasted them with regard to detection accuracy and time efficiency.

The MBR-based method is based on the observation that the activity/moving area of foreground objects has no or very little overlap with the target area. Therefore, by detecting and removing the foreground moving area from the background image, a reasonable estimate of the target area can be obtained. As the first step of this approach, the selected 5-8 frames and their foreground object masks from the previous phase are used to identify the foreground moving area mask. More specifically, the foreground mask is generated by identifying those pixels that have a different color code value than that of the corresponding pixels in the background image. Then, a Minimum Bounding Rectangle (MBR) is generated that bounds the area where the foreground objects are detected in the current frame (Figure 3). The final estimate of the foreground moving area, denoted as MBR_{final}, is the superimposition of all the MBRs extracted from the sample frames, also represented as a minimum bounding rectangle (see Figure 3(c)).

After the removal of the entire area bounded by MBR_{final} from the background image, the remaining background is divided into eight sub-areas as shown in Figure 4. The sub-area with the largest area (e.g., sub-area #2 in Figure 4) is identified as the target area, and its centroid is the target center. It is worth noting that the computational cost of this method is very low ($O(MN)$, where N is the number of pixels in a game scene, M is the number of sample frames, and $M \ll N$) since the foreground object masks are readily available as part of the output from the previous phase. In other words, the most time consuming part, which is the extraction of foreground objects ($O(MN^2)$) from sample frames, has been covered in the previous phase.[6]

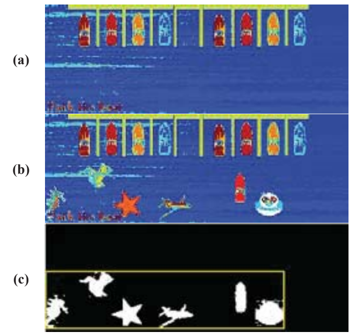

Figure 3: Target Detection. (a) The detected background for the Parking challenge; (b) One sample frame represented in color code; (c) Detected foreground objects from (b) and their MBR.

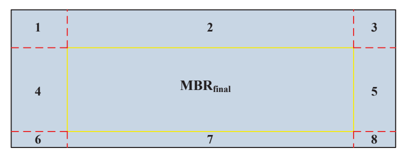

Figure 4: Eight sub-areas generated according to moving area of foreground objects

The Edge-based method employs a different design principle than MBR-based method. It is based on the hypothesis that there are strong edges in the target area because of the likely presence of objects in the target area, such as the dog and the squirrel in the Animals game. The steps involved in the edge-based method are listed below:

1. Collect a sequence of frames and learn the background image as in the MBR-based method.
2. Detect edge pixels on the background image. Group connected edge pixels into edge segments.
3. Remove trivial edge segments that have too few pixels by a user-input threshold.
4. The mean of all the centroids of remaining segments is used as the target area center.

The comparison results of the MBR-based and Edge-based methods are shown in Figure 5. The solid square dot in each game scene in Figure 5(a) is the MBR-detected target area center for that challenge. Also displayed in Figure 5(a) are the detected foreground object moving areas, namely MBR_{final}, displayed as a black rectangle in each game scene. According to our experimental results, MBR-based method was able to detect the correct target area center in all the challenges. In contrast, for the edge-based method, it is difficult to find a global threshold that works for all the challenges. Rather, we need to adjust the threshold for a specific game in order to achieve "reasonably good" results, and this method is also sensitive to the existence of texts in the background. Figure 5(b) shows the "optimal" edge detection result for each challenge with a manually tuned threshold which is different for each challenge. As shown

[6] We also implemented an alternative design, called the *exclusion method* (see Appendix B), which detects the target area by simply removing foreground object pixels accumulated from all the sample frames. However, while this method is slightly faster than the MBR-based method, it is less robust.

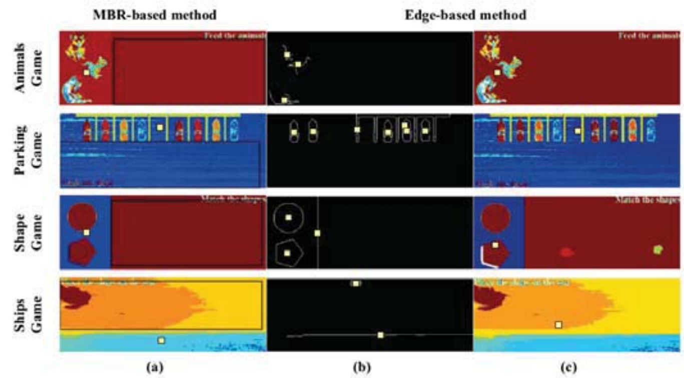

Figure 5: Comparison of the target area center detection results between the MBR-based and the edge-based methods. (a) Results from MBR-based method (solid square dot represents the target area center and black rectangle represents the object moving area); (b) centroids of non-trivial edges from the edge-based method; and (c) final target area centers from the edge-based method.

in Figure 5(c), some target area centers are incorrectly detected because some edge segments belong to the texts that are part of the background but not of the target area. This means that the accuracy of the edge-based method could be significantly undermined by the presence of strong edges in the background that are not part of the target area (e.g., presence of texts) and the absence of objects in the target area (e.g., the absence of objects in the target area of the Ships Game). As for efficiency, the MBR-based method has a time complexity of $O(MN)$ where M is a constant in the range of 5-8, while the time complexity of the edge-based method is $O(NL+N^2)$ where L is a constant in the range of 3-8 estimated based on the typical time complexity of a non-combining edge detection method [29]. Overall, this shows that the MBR method outperforms the Edge method on several aspects.

(3) Answer Object & Target Location Detection: Once the target area is identified, the next step is to identify the correct answer objects and their respective matching sub-target areas. Since a game can not have too many sub-target areas (otherwise, usability will be compromised), we divide the entire probable target area into 9 equal-sized blocks, each represented by its area centroid, drag each foreground object to each of the 9 centroids, and stop and record the knowledge learned whenever there is a "match." A match occurs when an answer object is dragged to its corresponding sub-target area (e.g., a "bone" dragged onto a "dog"). This is detected by monitoring the change of the area summation of all the foreground objects, since an answer object, once dragged to its correct target location, will stay in the target area and therefore result in a reduction of the foreground area. In our experiments, this method has proven 100% effective when applied to all four games. As for efficiency, while the worst case upper bound is $O(N)$, where N is the total number of foreground objects, in practice, much less number of drags are required. Our experimental results show that, with 5 foreground objects for each game (the maximum setting) and 15 training runs for each game, the average number of drags needed for a game is 9, i.e., less than 2 drags per each object on average. In case the server imposes a strict limit on drag/drop attempts, this process can be repeated over mutiple runs.

(4) Knowledge Database Building and Attacking: The background, target area, and learned answer objects as well as their corresponding sub-target areas together constitute the knowledge database for a game. After learning about sufficient number of games, whenever a new game challenge is presented, the knowledge base is checked for the challenge. The target area of the currently presented challenge is matched with the target areas present in the database to identify the challenge. If a match is found, the extraction of objects from the foreground follows. The visual features such as the color code histogram of the currently extracted objects are matched with that of the answer objects in the database for that challenge. The extracted objects identified as correct answer objects are then dragged to their corresponding sub-target areas. To measure the performance of our approach, we ran this attacking module 100 times for each game instance, and the average successful attacking time is 6.9s with the number of foreground objects ranging from 4 to 6. The maximum successful attacking time is 9.3s, observed for an instance of the Animal game with 6 foreground objects. These timings are in line with those exhibited by honest users in our usability study, which will make it impossible for the captcha server to time-out our attack.

(5) Continuous Learning: During attacking, if a challenge matches a game in our database but contains previously unseen answer object(s) (e.g., a new ship object in a Ships game instance), the attack will not terminate successfully. Whenever such a situation arises, an answer object learning module that is similar to the aforementioned module is activated, but differs from the latter in that it only needs to drag a potential answer object to each of the previously learned sub-target areas that have matching answer objects in the database. The newly learned answer objects and their corresponding sub-target area centroids are then added to the knowledge base for that game.

5.3 Discussion and Summary

There are two benefits in the background learning. First, the learned background can be used to quickly extract foreground moving objects. Second, the learned background can be used to locate the target area where foreground answer objects need to be dragged to. The proposed active learning is tested on all 36 game challenges (i.e., 3 (speeds), 3 (# of objects), 4 (game prototypes)). N_1 is set to be 10. The shape objects in the Shape Game have larger size than objects in other games, which easily result in pseudo patch effect when 6 moving objects exist in the game window with limited size. Therefore, N_2 is set to be 50 for the Shape Game challenges with 6 objects while 30 frames is used for all the other game challenges. In total, a complete background can be extracted in average 9.04s that is about three times faster than the preliminary method mentioned earlier (i.e., 30.9s).

The adoption of a large image database for each answer object could pose a challenge to our approach since it allows for the creation of many different foreground answer object configurations for the same game. In the worst case, a challenge may contain none of the previously learned answer objects for that particular game. Continuous learning will be activated in such cases and can also be used as a way for auto attacking in the run time. Such cases fall into the category of "known foreground answer objects and known target objects," and the success rate can be estimated using the number of foreground objects (o), number of answer objects (t), and number of drag and drop attempts allowed for each object (a). For example, if $o = 5$, $t = 3$ and $a = 2$, the success rate is approximately $\frac{2^3}{C(5,3)3!} = 13\%$. Though as low as it seems, the rate itself is not affected by the image database size.

During attacking, there is a time lapse between selecting a foreground object and verifying whether it is an answer object. Both feature extraction and database lookup (through feature matching) take time. In our implementation, we chose to click and hold a selected object until a match with an answer object in the database is registered. In doing so, we guarantee that an answer object, once verified, can be readily dragged and dropped, thus to avoid dealing with the issue of constantly moving objects. However, this approach may fail if a constraint is added by the captcha implementation that limits the amount of time one can hold an object from moving. A less invasive attacking method would be to utilize parallel processing, in which one thread is created to perform feature extraction and comparison, and another parallel thread is used to track and predict the movement of the object currently under verification.

Summary of Automated Attack Analysis: Our attack represents a novel approach to breaking a representative DCG captcha category. Attacking captcha challenges, for which the knowledge already exists in the dictionary, is 100% accurate and has solving times in line with that of human users. However, building the dictionary itself is a relatively slow process. Although this process can be sped-up as we discussed, it may still pose a challenge as the automated attack may need to repeatedly scan the different captcha challenges from the server to continuously build an up-to-date dictionary. The defense strategies for the DCG captcha designers may thus include: (1) incorporating a large game database as well as large object image databases for each game; and (2) setting a lower game time-out (such as 20-30s) within which human users can finish the games but background learning does not fully complete. Since our attack relies on the assumption that the background is static, another viable defense would be to incorporate a dynamically changing background (although this may significantly hurt usability). It is also important to note that, as per the findings reported in [23], the use of fully automated solving services represent economical hurdles for captcha attackers. This applies to traditional captchas as well as DCG captchas. Eventually, this may make automated attacks themselves less viable in practice [23], and further motivates the attacker, similar to other captchas, to switch to human-solver attacks against DCG captchas.

6. RELAY ATTACKS

Human-solver relay attacks are a significant problem facing the captcha community, and most, if not all, existing captchas are completely vulnerable to these attacks routinely executed in the wild [23]. In this section, we assess DCG captchas w.r.t. such attacks.

6.1 Difficulty of Relaying DCG captchas

The attacker's sole motivation behind a captcha relay attack is to completely avoid the computational overhead and complexity involved in breaking the captcha via automated attacks. A pure form of a relay attack, as the name suggests, only requires the attacker to relay the captcha challenge and its response back and forth between the server and a human-solver. For example, relaying a textual captcha simply requires the bot to (asynchronously) send the image containing the captcha challenge to a human-solver and forward the corresponding response from the solver back to the server.

Similarly, even video-based character recognition captchas [24, 30] can be broken via a relay attack by taking enough snapshots of the video to cover the captcha challenge (i.e., the distorted text within the video) which can be solved by remotely located humans. They can also be broken by simply taking a video of the incoming frames and relaying this video to the human-solver.

In contrast, DCG captchas offer some level of resistance to relay attacks, as we argue in the rest of this section. In making this argument, we re-emphasize that the primary motivating factors for a human-solver relay attacker are simplicity, low economical cost and practicality. As such, a relay attack that requires sophistication (e.g., special software, complexity and overhead), is likely not viable in practice [23].

There appears to be a few mechanisms using which DCG captchas could potentially be subject to a relay attack. First, if the server sends the game code to the client (bot), the bot may simply ship the code off to the human-solver, who can complete the game as an honest user would. However, in the DCG captcha security model (Section 2.1), the game code is obfuscated and can be enforced to be executable only in a specific domain/host (e.g., only the client machine challenged with the captcha) authorized by the server using existing tools[7], which will make this attack difficult, if not impossible.

The second possibility, called *Stream Relay*, is for the bot to employ a streaming approach, in which the bot can synchronously relay the incoming game stream from the server over to the solver, and then relay back the corresponding clicks made by the solver to the server. Although the *Stream Relay* attack might work and its possibility can not be completely ruled out, it presents one main obstacle for the attacker. Streaming a large number of game frames over a (usually) slow connection between the bot (e.g., based in the US) and the solver's machine (e.g., based in China) may degrade the game performance (similar to video streaming over slow connections), reducing solving accuracy and increasing response time. Such differences from an average honest user game play session may further be used to detect the attack with high accuracies, as shown in our recent work [22].

These challenges associated with the above relay attack approaches motivate us to consider another much simpler and more economical relay attack approach called *Static Relay*. Here, the bot asynchronously relays a *static snapshot* of the game to a human-solver and uses the responses (locations of answer objects and that of the target objects) from the solver to break the captcha (i.e., drag and drop the object locations provided by the solver to the target object locations provided by the solver).

The Static Relay attack approach is very simple and in line with a traditional captcha attack (and thus represents a viable and economical relay attack). However, it is expected to have poor success rates. The intuitive reason behind this is a natural *loss of synchronization* between the bot and the solver, due to the dynamic nature of DCG captchas (moving objects). In other words, by the time the solver provides the locations of target object and the answer objects within a challenge image (let us call this the n^{th} frame), the objects themselves would have moved in the subsequent, k^{th}, frame ($k > n$), making the prior responses from the solver of no use for the bot corresponding to the k^{th} frame. Recall that the objects move in random directions and often collide with other objects and game border, and therefore it would not be possible for the bot to predict the location of an object in the k^{th} frame given the locations of that object in the n^{th} frame ($n < k$). Such a loss of synchronization will occur due to: (1) communication delay between the bot and human solver's machine, and (2) the manual delay introduced by the solver him/herself in responding to the received challenge.

A determined Static Relay attacker (bot) against the DCG captcha can, however, attempt to maximize the level of synchronization with the solver. Although it may not possible for the attacker to minimize (ideally, eliminate) the communication delays (especially for bots potentially thousand of miles away from human solvers), it may be possible to minimize the manual delay via the introduction of carefully crafted tasks for the human-solver. In the rest of this section, we report on an experiment and the results of an underlying user study in order to evaluate the feasibility of Static Relay attack against our DCG captcha instances. This novel experiment takes the form of a *reaction time* or *reflex action* task for the human-solver. A reaction time task involves performing some operation as soon as a stimulus is provided. A common example is an athlete starting a race as quickly as a pistol is shot. The subject of reaction time has been extensively studied by psychologists (see Kosinski's survey [20]).

6.2 Reaction Time Static Relay Experiment

Our hypothesis is that DCG captchas will be resistant to the *Static Relay* attack, and so we give the attacker a strong power in the following sense: our tests eliminate the communication delay between the bot and the human solver, by putting them on the same machine.

[7] http://www.kindi.com/swf-encryption.php

The focus of the experiment then shifts towards motivating human-solvers to perform at their best by employing meaningful interfaces and by framing the underlying task in a way that is amenable to these solvers. In particular, since attacker's goal is to minimize the delay incurred by the human solver in responding to the challenges, we model human-solver attack as a reaction time [20] task described below. Our Section 6.3 study further facilitates the attacker with human solvers having low response times and quick reflex actions, such as youths in their 20s [20].

Experimental Steps: The reaction time Static Relay attack experiment consists of the following steps:

1. A snapshot of the game challenge is extracted by the bot (B), and the human solver (H) is asked to identify/mark a target object for that game challenge (e.g., the dog in the Shapes game).
2. For each target object identified above, H is asked to identify one answer object in the snapshot specific to the game challenge (e.g., bone for the dog in the Shapes game). However, since B wants to minimize the delay between the time the challenge snapshot is given and the response is received from H, a stimulus will be associated with the snapshot. We make use of a combination of (1) a visual stimulus (the border across the game window flashes in Red) and (2) an audio stimulus (a beeping sound). The task for H is to identify an answer object in the image *as soon as* the stimuli are provided.
3. B will emulate the dragging and dropping of the objects based on the response of H (simply use the pixel values provided by H as the coordinates of the objects and respective targets).
4. Steps 2-3 are repeated until all answer objects for a given target object are identified by H and dragged/dropped by B.
5. Step 1 is repeated until all target objects have been covered.

The experiment succeeds if the captcha game completes successfully, i.e., if all answer objects are dragged to their respective targets by B per input from H.

Experimental Implementation: Our implementation of the above experiment consists of a user interface (UI) developed in Java that interacts with the human solver and a bot. The core of this implementation is designed using an algorithm following which the screen captures are updated and displayed on the screen as well as an algorithm used to make the mouse drag and drop of the objects.

The game starts by the bot capturing an image of the game challenge from the browser (i.e., the captcha challenge that the bot received from the server) and displays that image in the UI. The solver is then asked to click on a target object within that image. After selecting the target, the solver is instructed to click a "Next" button, wait for a flashing and a beep (our stimuli), followed by clicking the object that matches with that target. Once the solver has clicked on the object, the bot takes control of the mouse by clicking and dragging the object to the target in the flash game. The solver must be able to identify and choose the correct object before the object has moved too far in the flash game displayed in the browser. Whether the click is successful or not, a new screen capture is retrieved from the game on the browser. If the solver has chosen the object in time on the UI, then he/she can pick a new target if one exists by clicking on the "New Target" button. If the solver has missed clicking on the object fast enough (i.e., if the click was not successful), the solver will automatically get another attempt to choose the correct object followed by the flashing and the beep. Figure 7, Appendix A depicts the UI of our implementation.

6.3 Static Relay Attack User Study

We now report on a user study of the aforementioned reaction time relay attack experiment presented in Section 6.2.

6.3.1 Study Design, Goals and Process

In the relay attack study, users were given the task to play our 4 game instances through the UI (described above). The study comprised of **20 participants**, primarily Computer Science university students. This sample represents a near ideal scenario for an attacker, given that young people typically have fast reaction times [20], presumably optimizing the likelihood of the success of the relay attack. The demographics of the participants are shown in Appendix A, Table 10. The study design was similar to the one used in our usability study (Section 4). It comprised of three phases. The *pre-study phase* involved registering and briefly explaining the participants about the protocols of the study. This was followed by collecting participant demographics and then the participants playing the games via our interface. The participants were told to perform at their best in playing the games. The *post-study phase* required the participants to respond to a set of questions related to their experience with the games they played as part of the interface, including the SUS questions [8].

Each participant was asked to play the relay versions corresponding to each of the 20 variations of the 4 DCG captcha games as in Section 3; we used ordering based on Latin squares, as in the usability study. The specific goal of our study was to evaluate the reaction time experiment UI in terms of the following aspects:

1. *Efficiency*: time taken to complete the games (and succeeding at the relay attack).
2. *Robustness*: likelihood of not completing the game (relay attack failure), and incorrect drags/drops.
3. *User Experience*: quantitative SUS ratings and qualitative feedback from the participants.
4. *Reaction time*: Time delay between the presentation of the stimuli and the response from the participant. This is a fundamental metric for the feasibility of the attack. If reaction time is large, the likelihood of attack success will be low.

Another important goal of our user study was to compare its performance with that of the usability study. If the two differ significantly, the relay attack can be detected based on this difference.

For each tested game, completion times and errors were automatically logged by the our web-interface software. In addition, we maintained "local logs" of the clicks made by the participants on our game interface to measure the reaction timings.

6.3.2 Study Results

We present various mechanical data, i.e., time to completion and error rates as part of the relay attack study. We further analyze the local logs for the reaction time analysis.

Completion Time and Error Rates: Table 6 shows the time taken and error rates to play the games for each game type by different participants. Unlike our usability study, many game instances timed out, i.e., the participants were not able to always complete these game instances within the time out of 60s. In this light, we report two types of timings: (1) *successful time*, which is the time only corresponding to the games that the participants were able to complete successfully within the time out, and (2) *overall time*, which is the time corresponding to both the game instances completed successfully within the time out and those which timed out (in which case we consider the timing to be 60s). The overall time therefore will effectively be higher.

All games turned out to be quite slow, and much slower than that of the usability study where the games lasted for less than 10s on an average (Section 4). As in our usability study, we found that users took longest to solve the Animals (overall average: 46.51s), whereas the other games took slightly less time. This might have been due to the increased semantic load in the Animals game due to the presence of 3 target objects. We observed that the error rates were the highest for the Animals game (40%), and the least for the Shapes games (9%)

although the corresponding per click error rates were high (56%). The Ships and Parking games had comparable overall error rates between 20-30%. We analyzed and further compared the mean time for different game categories. Using the ANOVA test, the games showed statistically different behavior from each other ($F = 12.85$, $p < 0.0001$). On further analyzing the data, we found the following pairs of games to be statistically different from each other: Shapes and Ships ($p = 0.027$) and Animals and all other games ($p < 0.001$).

To analyze errors better, we investigated error rates per click, i.e. for each drag attempt whether the object being dragged was dropped at the correct position or not. The error rate per click was the least for the Ships game (17%), much lower compared to all other games (50-70%), the latter itself being much higher than observed during the usability study. This suggests that the server could prevent the relay attack against Animals, Parking and Shapes games by simply capping the number of drag/drop attempts.

Table 6: Error rates and completion time per game type

Game Type	**Overall Time (s)** *mean (std dev)*	**Successful time (s)** *mean (std dev)*	**Error Rate** *mean*	**Error Rate Per click** *mean*
Ships	30.92 (5.91)	22.25 (5.04)	0.26	0.17
Animals	46.51 (5.05)	37.93 (4.91)	0.40	0.65
Parking	28.16 (7.36)	20.45 (5.04)	0.22	0.66
Shapes	26.19 (1.59)	22.94 (1.74)	0.09	0.56

Reaction Time: We now analyze the reaction time corresponding to different games during the relay attack experiments. We consider two types of reaction times, one corresponding to all clicks made by the participants, and the other corresponding to only the correct clicks (i.e., those that resulted in a correct drag and drop). The averaged results for the two types of reaction times for each game type are summarized in Table 7. We can see that the average reaction time (all clicks) for all game categories was more than 2s and the least for the Shapes game (2.17s). The average reaction time (correct clicks) is slightly lower than reaction time (all clicks), but still higher than 1.5s and still lowest for the Shapes game (1.62s). Neither types of reaction times change significantly across different game categories. ANOVA test, however, did find significant difference between the mean reaction time (all clicks) of the four games ($F = 13.19$, $p < 0.01$). On further analyses using paired t-tests with Bonferroni correction, we found that there was a significant difference between the Animals and Parking games ($p < 0.01$). Similarly, using the ANOVA test, we found significant difference between the mean reaction time (correct clicks) ($F = 3.24$, $p < 0.027$). Further, we found a significant difference between the Shape and Ship games ($p < 0.005$) with respect to mean reaction time (correct clicks).

Table 7: Reaction times per game type

Game Type	**Reaction Time All Clicks (s)** *mean (std dev)*	**Reaction Time Correct Clicks (s)** *mean (std dev)*
Ships	2.27 (0.34)	2.06 (0.17)
Animals	2.58 (0.35)	1.85 (0.23)
Parking	2.50 (0.51)	2.00 (0.31)
Shapes	2.17 (0.2)	1.62 (0.11)

User Experience: We now consider the data collected via direct user responses during the post-study phase. The average SUS score from the study came out to be only 49.88 (std dev = 5.29). This is rather low given that average scores for commerical usable systems range from 60-70 [21], and suggests a poor usability of the system. This means that it would be difficult for human users to perform well at the relay attack task and implies that launching relay attacks against DCG captchas can be quite challenging for an attacker.

Table 8 shows the 5-point Likert scores ('1' is "Strong Disagreement"; '5' is "Strong Agreement") for the visual appeal and pleasurability of the games. Although the former average ratings are on the positive side (more that 3), the latter ratings are low, suggesting the participants did not find the games to be pleasurable. In our games, we made use of visual and audio stimuli to which the users had to respond. In order to understand what type of stimulus worked best for the participants, we asked them to what extent the audio, visual or both stimuli together was useful as an indicator to respond fastest to the game. These ratings are depicted in Table 8. The responses were on average in favor of the visual stimulus, followed by the two stimuli together, and finally the audio stimulus. 35% participants found audio stimulus and visual stimulus to be sufficient whereas 45% participants agreed or strongly agreed with the statement that both visual and audio stimulus are necessary to play the game. We further performed the ANOVA test for responses corresponding to the three – visual, audio and visual+audio – stimuli, but did not find a statistically significant difference. Finally, 80% of the participants felt that training will help them play the games better with an average score of 3.95. This suggests an attacker might improve success in relay attack through advance training of human solvers.

Table 8: Participant Feedback Summary

Features	**Likert Mean (std dev)**
Visually Attractive	3.20 (0.92)
Pleasurable	2.85 (0.99)
Visual Stimulus	3.20 (1.17)
Audio Stimulus	2.95 (0.93)
Both Audio and Visual	3.10 (1.25)
Need Training	3.95 (1.01)

Summary of Relay Attack Analysis: Our analysis suggests that subjecting the DCG captcha to relay attacks poses certain challenges in practice. Specifically, for the Static Relay attack to succeed, the human solvers have to perform a reaction time task (average reaction time is more than 2s). This task, except for the Shapes game, takes much longer (> about 30s on average), is significantly more error prone (error rates more than 20%; per click error rates more than 50%), and much harder for the users *when compared* to directly playing the games by honest users under a non-relay attack setting. In real life, where the communication delays between the bot and solver's machine will be non-zero and average solver population samples are used (unlike our attack set-up), the timings and error rates might be higher and launching a relay attack might be even more difficult. Although our experiments were conducted on our 4 DCG captcha instances, we believe that our analysis is generally applicable to other DCG captcha types involving moving answer objects.

7. CONCLUSIONS AND FUTURE WORK

This paper represents the first academic effort towards investigating the security and usability of game-oriented captchas in general and DCG captchas in particular. Our overall findings are mixed. On the positive side, our results suggest that DCG captchas, unlike other known captchas, offer *some* level of resistance to relay attacks. We believe this to be a primary advantage of these captchas, given that other captchas offer no relay attack resistance at all. Furthermore, the studied representative DCG captcha category demonstrated high usability. On the negative side, however, we have also shown this category to be vulnerable to a dictionary-based automated attack.

An immediate consequence from our study is that further research on DCG captchas could concentrate on making these captchas better resistant to automated attacks while maintaining a good level of usability.[8] Moreover, our paper focused on "pure automated" and "pure

[8]The modifications made to the original DCG captchas to resist automated attacks, such as a dynamic background, may further make relay attacks more difficult.

relay attacks" (in line with traditional captchas). However, hybrid attacks can also be envisioned, which combine the computing power and human knowledge. Future research is necessary to investigate how well hybrid attacks work, and how they alter the economics of captcha-solving (following up [23]). Finally, the results of our user study on reaction-time task performance may have general applications in human-centered computing (security and non-security) domains. For instance, these results may rule out the possibility of usable captcha schemes themselves based on reaction-time tests.

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APPENDIX

A. ADDITIONAL FIGURES AND TABLES

(a) A star indicating correct object match (b) A cross indicating incorrect object match

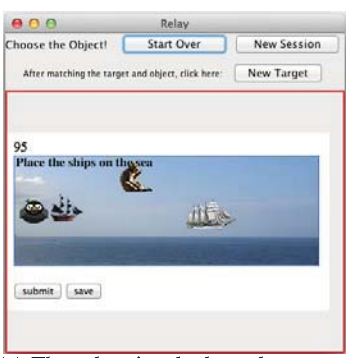
Figure 6: User Feedback per Game Interaction

B. TARGET AREA DETECTION USING THE EXCLUSION METHOD

A design alternative for target area detection, called the *exclusion method* is to detect the target area by simply removing foreground object pixels accumulated from all the sample frames. However, while this alternative is slightly faster but still at about the same time efficiency as the MBR-based method, it is less robust than the latter especially when the objects are moving slow such that the remaining area, i.e., the detected target area, may include too much of the foreground object moving area that has not had a chance to be covered by the footprints of foreground objects extracted from the limited set of sample frames. Figure 8 shows our experimental results for this design alternative applied to four different challenges, where the blue dots represent the detected target area centers. This alternative method failed to detect the correct target center in all four cases.

(a) The solver is asked to choose a target object

(b) The solver is asked to choose the next answer object, if any



(c) The solver is asked to select a new target object, if any

Figure 7: User interface implementing the reaction time relay experiment (95 represents the User ID; the red rectangle in (c) represents our visual stimulus)

Table 9: Usability Study Participant Demographics

	N=40
Gender	(%)
Male	50
Female	50
Age	(%)
18 - 24	80
25 - 35	20
Education	(%)
Highschool	45
Bachelors	27.5
Masters	22.5
Ph. D.	5
Profession / field of study	(%)
Computer Science	60
Engineering	5
Science, Pharmaceuticals	10
Law	2.5
Journalism	2.5
Finance	2.5
Business	5
Others	12.5

Table 10: Relay Attck User Study Participant Demographics

	N=20
Gender	%
Male	70
Female	30
Age	%
18 - 24	35
25 - 35	60
35 - 50	5
Education	%
Highschool	25
Bachelors	45
Masters	30
Ph. D.	0
Profession / field of study	%
Computer Science	90
Engineering	5
Medicine	5

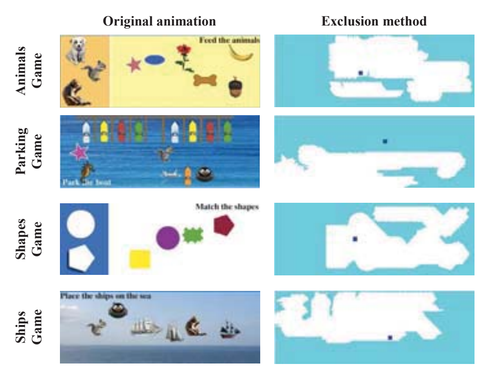


Figure 8: The target area centers (blue dots) detected by exclusion method