Keystroke Inference using Smartphone Kinematics

Oliver Buckley[1], Duncan Hodges[1], Melissa Hadgkiss[2] and Sarah Morris[2]

[1] Centre for Electronic Warfare, Information and Cyber,
Cranfield University, Defence Academy of the United Kingdom,
Shrivenham, Swindon, SN6 8LA, UK
o.buckley@cranfield.ac.uk
d.hodges@cranfield.ac.uk
[2] Cranfield Forensic Institute,
Cranfield University
m.hadgkiss@cranfield.ac.uk
s.l.morris@cranfield.ac.uk

Abstract. Port hornswaggle loot aft hands heave down no prey, no pay spirits strike colors snow crack Jennys tea cup topmast jib man-of-war trysail gun marooned bilge water hogshead scuppers. Cat o'nine tails wherry schooner rigging topgallant topmast chase gun hornswaggle boatswain topsail grog blossom Davy Jones' Locker Brethren of the Coast Corsair bilged on her anchor gangplank Pirate Round clap of thunder execution dock. Jack Ketch Gold Road six pounders gaff brig poop deck Pirate Round chandler gunwalls clipper mizzen keel pink line jury mast main sheet booty stern Sea Legs maroon. Fathom Jolly Roger Barbary Coast crow's nest aft hearties scuttle nipper overhaul gun schooner run a rig jolly boat barkadeer cog scuppers Corsair smartly tack line. Chain Shot careen wherry lass stern line man-of-war bring a spring upon her cable hang the jib smartly rope's end Plate Fleet clipper ahoy poop deck ye warp me brigantine rigging.

1 Introduction

Smartphones are becoming an increasingly significant part of our everyday lives as their popularity continues to grow. Research conducted by the Office of Communications (Ofcom) [1] shows that two thirds of all adults in the UK own a smartphone, compared to only 39% in 2012. The research also highlights just how essential smartphones are becoming in our everyday lives as they are now considered to be the most important device for connecting to the Internet, ahead of a laptop. However, this trend of increased smartphone ownership is not limited to the UK as research by the Pew Research Centre [2] shows the global median for smartphone ownership is at 43%.

The increasing popularity of smartphones means that they are now used to manage nearly every aspect of our daily lives. A survey conducted by the Pew Research Centre [3] shows that smartphones are being used for a wide variety of tasks ranging including online banking, education, social interactions, obtaining information about medical conditions, submitting a job application and using key government services. The result of this is that a high proportion of our day-to-day lives are handled using a smartphone, including very sensitive applications such as banking and healthcare through to the more mundane. Given the very personal nature of these devices it is important to understand the way in which our data and information can be leaked from these devices.

In this paper we hypothesise that the motion sensors, such as the accelerometer and gyroscope, within a smartphone can be used to infer keystrokes. We posit that it will be possible to infer the keystrokes on a virtual smartphone keyboard based on the movement of the phone, as recorded by the accelerometer and gyroscope. Additionally, the way in which a user holds and interacts a smartphone will provide an identifiable motion signature for a particular user.

The remainder of this paper is structured as follows: Section 2 provides a review of the related work, focusing on keystroke and swipe analysis in smartphones and the use of motion sensors in user identification. Section 3 details the methodology used to conduct the experimentation. Section 4 provides an analysis of the collected data and the results of the study. Finally, in Section 5 we conclude by providing a reflection on our analysis and a discussion of further work in this area.

2 Background

Modern smartphones will typically contain a variety of motion sensors, including a gyroscope that is capable of tracking the rotation of the device and an accelerometer to monitor the movement and orientation of the phone in space. These sensors can be exploited to determine certain information about the user of the phone. For example this might include: recognising the activities that are being performed by the user [4] or identifying an individual based on analysis of their gait [5]. One of the interesting benefits of using these sensors is that they will typically run as a background process, normally without the need for explicit approval; therefore it can be possible to covertly capture smartphone motion data without the express permission of the user. In essence, it is entirely possible for a malicious application on a mobile device to be able to freely gather motion data without first requesting permission from the user. In turn the captured motion data could be used to probabilistically infer the users keystrokes without their knowledge.

The sensors in smartphones have been used to good effect to infer a wide range of information about an individual solely based on the way that they interact with the smartphone's touchscreen. For example, Bevan et al. [6] used swiping gestures to infer the length of the individual's thumb. The length of the thumb can then be used to infer other physical characteristics. Similarly, Miguel-Hurtado et al. [7] analysed the swiping gestures of users to predict the sex of the individual.

Motion sensors within smartphones have previously been used to attempt to infer a user's keystrokes with some promising results. Cai and Chen [8] developed TouchLogger, a smartphone application designed to infer the keystrokes on a soft (or virtual) keyboard based solely on the vibrations recorded by the smartphone's motion sensors. The research was capable of successfully inferring more than 70% of the keys that were typed using only the device's accelerometer. However, the work focused specifically on inferring the keystrokes from a soft keyboard that contained only numbers. The work we present in this paper will look to infer the keystrokes of an individual that use a standard soft keyboard, which contains both numbers and letters.

Owusu et al. [9] extend the work of Cai and Chen to use a smartphone's accelerometer to infer the characters, both letters and numbers, contained within a user's password, although with a relatively small set of only four participants. The work was capable of extracting the 6 character passwords in as few as 4.5 attempts (median). The work of Owusu et al. focused only on the use of accelerometer readings, in contrast to our own work with also includes analysis of rotational data using the smartphone's gyroscope.

3 Method

In this paper we focus on the use of Tetris to identify individuals based on the way in which they interact with the game. Tetris was chosen as it is a game that is both simple and intuitive for someone who does not have experience with videogames. However, Tetris also provides a consistent challenge that allows players to continually develop and refine their skills and strategies. Despite the depth of complexity of the demonstrable behaviours, the game board itself has a finite and manageable set of states and there is a limited set of pieces available to the player, as shown in Figure **??**.

To conduct this study a website was developed and deployed to play a modified version of Tetris, the modifications are required to allow data collection; the aim of the game and way the game is played remain entirely unchanged. During the study there were four key data dimensions that were collected:

- Current board state
- Current piece
- Next piece
- Keystrokes for the current piece

The study comprised of two experiments, the first required participants to simply play a game of Tetris with a random selection of pieces (i.e. there was no predetermined ordering to the shapes). Participants were required to play the game until they 'lost' the game, by the height of the pieces exceeding the height of board, or until they had played for three minutes. The second experiment again required participants to play the game for three minutes, or until they 'lost' the game but in this instance all participants were using a fixed set of pieces. That is to say, all of the participants would have exactly the same set of pieces, appearing in the same order, where the order was: 'S', 'S', 'T', 'Z', 'O', 'J', 'J', 'L', 'S', 'T', 'Z', 'Z', 'O', 'J', 'O', 'I', 'L', 'I', 'I'. This sequence of shapes was randomly generated prior to the start of the second experiment and remained constant throughout, with the sequence beginning again once the player had reached the end.

Recruitment for the survey was carried out using social-media networks as well as making use of the student population at Cranfield University. In total there were 50 unique participants who played 73 games during the first experiments and 75 unique participants who played 117 games during the second experiment.

4 Analysis and results

It was hypothesised that there were two top-level approaches to playing Tetris: one approach only considers solving shorter-term problems whilst the other is based on longer-term problems. In the short-term approach the user only considers the current piece and the profile of the top of the current board state, however in the longer-term approach the user also considers the next piece in addition to any 'holes' that are trapped in the current board state. In the research presented in this paper the focus is on the short-term approach, in essence, the state of the game (i.e. the stimulus to the user) is entirely characterised by the board state and the current piece.

Initially the board state is characterised as the gradient of the profile of the pieces in the board, an example is shown in Figure **??** along with the array defining this board state.

As can be seen there is some discrete structure in the first component, which can be expected given the discrete nature of the elements of the state vector. As expected the states associated with random play demonstrate a greater spread of states, the unconstrained nature of the piece order enabling a broader set of profiles.

The variance described by each of the first 7 components is shown in Figure **??**. As is consistent with Figure **??** the first component describes around 25% of the variance, however there is also significant variance contained in the other components. This implies that dimensionality reduction techniques will loose a significant amount of information within the state vector and the board state should be used as complete vector as the information content of the higher dimensions is significant.

The previous analysis considered each 'turn' in the game as an individual discrete state, given that a game is a time-ordered flow of these game states it is intuitive to plot the users 'journey' through these states as the game is played. Intuitively this can be represented as a directed graph, with the board states represented by the nodes and the type of the current piece representing the edges.

One game from each of the participants was randomly selected and the directed graph of the board states associated with the experiment with ordered play is shown in Figure ??. In this graph the width of the transitions is proportional to the number of times an edge is used in play, with all edges that are used by one or more different users coloured red.

As can be seen the graph in Figure ?? there are a number of common approaches to the early game phase — this is not surprising given the ordered nature of the pieces and the initial empty board state. There are two main approaches most users took for the first three or four pieces at which point the graph begins to diverge quickly. Once the graph has begun to diverge there are only three times a users' game reaches the same board state as that of another user, at which point the games immediately diverge again (i.e. the indegree of the node is greater than 1 and the indegree and outdegree are identical). Two examples of this are shown in Figure ?? which shows a cropped and zoomed area of Figure ??.

This implies that even in the ordered play experiment within a few pieces the games become relatively unique, the same graph analysis is shown in Figure ?? for the random play experiment. Due to the more unconstrained nature of the game it is clearer that the board state diverges quicker than the ordered play, also of note is that the number of times board states are revisited is also small.

In addition to the uniqueness between users it is also important to assess the repeatability of users' play. In order to examine the repeatability of users behaviour the graphs associated with users who played multiple games were extracted from the ordered play experiment.

The first interesting characteristic is that it is apparent that a number of users exhibit little repeatable behaviour, with every game effectively taking a unique path, examples are shown in Figure ?? and Figure ??. The games are also relatively short with few pieces placed during the three minute length of the game. This can be contrasted with other users such as those in Figure ??, Figure ?? and Figure ?? which demonstrate significantly more repeatable strategy for much longer. It is also notable the number of pieces placed in the same time-frame is significantly higher.

This difference in overall strategy is maybe not surprising as, although Tetris is a popular and common game, there will be differing degrees of experience with the game. This implies the users whose games are shown in Figure ?? and ?? have not yet had enough experience in order to develop strategies for play. This also implies that an individual's strategies will evolve over time — in the same way that over time other behavioural biometrics (such as keystroke dynamics) will evolve, although the rate of this change is likely to decrease as the user becomes more experienced and their strategies stabilise. In solo games these strategies are likely to be more stable than in adversarial games where a users' strategy will evolve with respect to an opponent's.

Moving to a 'piece-centric' view it is possible to explore whether certain pieces result in more unique behaviours. In order to explore this question the board state at a given time is less important, what is more important is the change in the board state caused by a given piece. In this study the board state transition caused by a given piece is simply the change in the height of the board, as demonstrated in the two examples shown in Figure **??**.

These board state changes were assessed for all participants and for all pieces, before calculating the number of times each board state change was seen for each piece. This highlighted very common board state changes which were seen per piece, the Cumulative Distribution Function (CDF) of these counts are shown in Figure **??**. As can be seen in both the graphs in Figure **??**, the commonality between the board state changes associated with the 'O' piece[3] is much higher — this indicates that the 'O' piece is less useful for discriminating between users. In this case the piece commonality will also be affected by rotational symmetry being greater than the other pieces.

Also of note in Figure **??** is the similarity between the curves associated with pieces that are mirror images of each other (e.g. 'J'/'L' and 'S'/'Z'). The 'J'/'L' pair also represent pieces that have a wider diversity of use than other pieces, this implies that using these pieces to discriminate between users will potentially provide more discriminatory power than other pieces.

Considering the ordered play, where the order of pieces is predetermined and all players receive the same pieces in the same order, the same analysis results in the plot shown in Figure **??**. This plot shares several characteristics with that from random play, most notably that the 'O' piece has the greatest commonality in use. However, a number of the profiles for pieces differ from that of random play.

This indicates that by controlling the order of pieces it is possible to control the discriminatory power of individual pieces, in this example the 'J' piece has become less discriminatory whilst the 'Z' piece has become more discriminatory. The ability to control the discriminatory power of individual pieces by changing the order in which they appear is key to creating a system that can leverage gaming to aid user identification.

5 Conclusion and Future Work

In this paper we have investigated the use of videogames, specifically Tetris, and the associated strategies as a means of user validation. The findings have shown that some individuals exhibit repeatable strategies, although conversely there are those who appear to exhibit no notable, repeatable strategies. We posit that the degree of strategy that a player displays is linked to their experience with Tetris and is something that will be investigated in future work.

The other key finding from this work is that within Tetris there are certain states of the game board that are more divisive than others when trying to validate the identity of individuals. Similarly, some of the pieces are more useful when trying to discriminate between users, for example, it was discovered that the 'O' piece (as seen in Figure **??**) is less useful for determining individuals. This suggests that it will be possible to manufacture scenarios that allows users

[3] The 2×2 square piece

to exhibit more unique behaviours. Further experimentation will allow this idea to explored in more depth, and will help to determine those board states and pieces that are better suited to discriminating between individuals.

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