

EavesDroid: Keystroke recovery using mobile phone accelerometers

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Abstract—[to - fill]

I. INTRODUCTION

Mobile phones [1] are becoming increasingly powerful devices. In addition to being able to run applications ranging from email clients to web browsers, a progressively sophisticated set of sensors are enabling these devices to more actively interface with the world around them.

Unfortunately, the array of sensors in these devices can also be used in unintended ways. As many have suggested, malware could potentially gain access to a mobile phone's camera to take photos or video of the owner and their surroundings [2]. In cases where the camera may not be pointed at an interesting target, a malicious application could instead attempt to activate the device's microphone and record ambient sounds or syphon GPS data to track the target's location [3], [4], [5], [6]. Recognizing the potential for the leakage of sensitive information, many modern mobile phone operating systems provide mechanisms by which access to such sensors is protected by explicit permission from the user. For instance, the manifest files included with every Android application provide an unambiguous list of all of permissions an application may ever request at installation time. Should an application not request access to these resources or the user deny the application such rights, the application will not be able to potentially abuse these resources. However, access to all of the sensors contained in these devices are not so tightly controlled.

In this paper, we demonstrate that unfettered access to the accelerometers available on many mobile phones can allow for significant unintended leakage of information from a user's environment. We show that a malicious application with access to the accelerometer feed can record and reconstruct the keypresses made on a nearby keyboard based solely on the observed vibrations. We

develop profiles for keypress events using boosted Random Forests, which creates an abstract representation of the relationship between the keystroke signal and the alphabet typed. We then recover the typed content by translating from our intermediary form to English words using a number of different dictionaries. Such tasks are not a trivial application of standard techniques, especially when compared to previous efforts in this space. Specifically, we must overcome much lower sensor sampling rates than has been experienced in the related acoustic and electromagnetic-based eavesdropping attacks, which makes deciphering individual keypresses extremely difficult.

Through this, we make the following contributions in this paper:

- 1) **Develop an infrastructure for characterizing keypress vibrations:** We capture, analyze and develop profiles of keypress events on a nearby keyboard based on the vibrations created when they are pressed. Our inputs are then processed using a set boosted Random Forests to create an intermediary representation, which is combined with candidate dictionaries to successfully recover words at rates as high as —
- 2) **Dataset made publicly available:** To the best of our knowledge, there does not exist a dataset with the keystrokes for the vibrations recorded using an accelerometer. In this paper, we demonstrate we construct the dataset of keystroke vibrations, recorded using the accelerometer, present in a smartphone and make the dataset publicly available to enhance further research on this topic. Given the widespread about security breaches and email leaks, we perceive this to be of great importance in motivating the mobile operating system manufacturers to restrict the usage of accelerometers to permitted applications only.

Note that our approach is greatly influenced by the work of Marquardt *et. al* [1] and we present key differences with our approach.

II. RELATED WORK

Researchers have studied malicious code on mobile devices that learn information about the device owner using other embedded sensors. In the most closely related work to our paper, Marquardt *et. al* [1] propose *(sp)iPhone* which uses motion sensors in the iPhone 4 to infer keystrokes of nearby laptop users. *(sp)iPhone* uses 3 labels for each pair of keystrokes in order to determine the correct identification for the letters of the word. The location of the key is modelled using a neural network trained on 150 keystrokes for each letter of the English alphabet. A profile is then constructed for each pair using the neural network and determines and models the distance between the two events. The predictions of the neural network are matched against a dictionary to determine the top matches. The accuracy achieved is roughly 80% but this decreases to 40% as the size of the dictionary increases.

In a very similar, but orthogonal, use case, Owusu *et. al* [7] present the threat of applications which extract the keystrokes of the user's typing on the smartphone screen itself. Again, due to no restrictions on the usage of the accelerometer, they are able to extract 6-character passwords in as few as 4.5 trials (median). TouchLogger [8] uses orientation of the smartphone device to infer the keystrokes.

III. THREAT MODEL

Our attack is based upon two observations:

Many users like to place their smartphone close to their laptop while working, so that it is easily accessible and notifications are not missed.

Furthermore we note that while smartphones offer a broad range of sensors such as microphone, GPS, gyroscope and accelerometer, the accelerometer is the only sensor to which access is not protected in any current mobile phone operating system. That is mainly due to the frequent usage needs of the accelerometer to determine window orientation and update screen orientation, a feature any app can make use of.

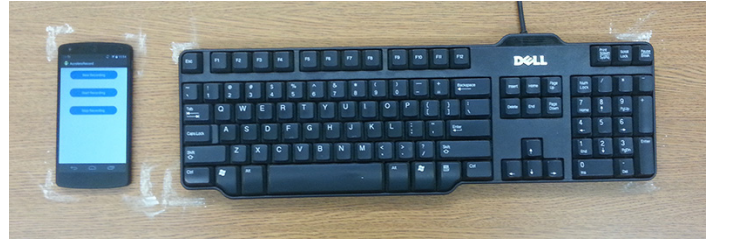


Fig. 1. Threat model of a smartphone placed next to a keyboard. Used in our experimental setup to capture the dataset.

IV. FRAMEWORK DESCRIPTION

A. Dataset Capturing

Our experimental setup is shown in fig.1. We placed a Dell USB keyboard and a LG Nexus smartphone on a wooden table. No other items were placed on or were touching the table. All keys were pressed with the index finger of the right hand. The hands do not touch the keyboard or table, and the fingers do not pause on the keyboard but only touch it during the brief duration of the key press.

We recorded 1000 datapoints in 40 sessions with 25 letters in each sessions. For each session we generate a sequence of 25 random letters and display the letters in 3 second intervals to ensure an even recording of the letters and to ensure that there is no bias towards a specific letter. For the data capturing we developed an Android app that reads from the hardware accelerometer and syncs with our laptops, where we further process the data. The raw accelerometer data as returned by Android contains the x , y and z -direction components of the acceleration of the vibration received. We calculate the G-force magnitude as $\sqrt{x^2 + y^2 + z^2} - g$ where $g = 9.81$ is the acceleration due to gravity.

The original recording will contain a large spike at the beginning and end due to the pressing of "Start" and "Stop" on the recording app. We cut off these noise signals and further segment the data into 25 individual data points. An example of a plot of one such signal is shown in fig.2.

B. Feature Extraction

We use a combination of time-domain and frequency-domain features to construct our feature vector.

V. ANALYSIS & IMPLEMENTATION

In [1], Marquardt *et. al* use a neural network to build the signal profiles of the letters typed by the user. We

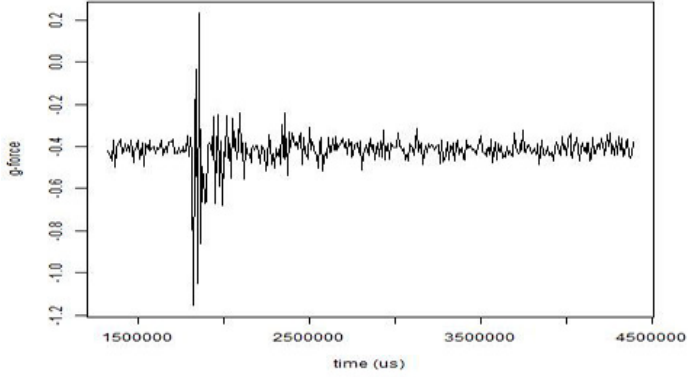


Fig. 2. Sample Recording for letter 'a'

present the implementation details of the algorithms used in order to best generate a prediction model on the training. The given dataset is broken into training (66%) and testing (33%) sets. We then generate the prediction model by 10-fold cross-validation on the training set. We use AdaBoost with Random Forests as the weak learner, AdaBoost with Decision Stumps as the weak learner, and Neural networks to determine the accuracies of the respective models on the testing set (shown in Table I). The results corresponding to Random Forests are using 10 decision trees. The accuracy of using Decision Stump is better than that of Random Forests because of overfitting happening taking place in the Random Forests. When the number of the number of trees in the Random Forests was increased, the training error decreases and the test error increases. Since Random Forests represent a multitude of decision trees, the higher number of trees increases the testing error. On the other hand, Decision Stumps are one node trees and are less prone to overfitting on the training data and provide the similar accuracies as Random Forests with less complex hypotheses/model. Neural Networks achieves almost similar accuracies as the AdaBoost implementations, but we do not use this as our choice of algorithm for the experimentations (Section VI). This is because firstly we do not have the MFCCs features extracted from the keystroke signal and these which provides better representation of cepstral information about the signal and capture by the neural network. Secondly, Marquardt *et. al* have presented a solution to the threat model using neural networks and in order to benefit the research community, we attempt to provide an orthogonal analysis with less features and using a different machine learning approach.

The cepstral features corresponding to the FFTs have significant impact on the predictions of the model. Table II shows the test accuracies using AdaBoost with Decision Stumps. FFTs alone provide 10% higher correct predictions compared to the rest of the features in the case of LR dataset. The combined prediction accuracy when using all the features is better than when using just the FFTs and this demonstrates that the frequency of the vibration signal received from the different keystrokes has significant impact in making correct alphabet predictions.

In addition to LR and UD datasets, we compute the predictions of the algorithms on the Triads dataset. Table I shows that the models generated make poor predictions about the triad to which a keystroke belongs. This is, firstly, due to the assumption that the alphabets grouped into the same triad do not necessarily have similar keystroke vibrations. Careful triads construction is expected to give better predictions but this is analysis is beyond the scope of this project study and we leave it as future work in the interest of limited time for this project. Therefore, for the purpose of experimentation, we use LR and UD label predictions only for determining the keystrokes of the user. Section VI will demonstrate that good triad predictions, in addition to LR and UD predictions, will increase the accuracy with which the words typed by the user are identified.

Dataset	Algorithm	Test Accuracy(%)
LR	AdaBoost (RandomForests)	68.67
	AdaBoost (DecisionStumps)	69.82
	Neural Networks	68.10
UD	AdaBoost (RandomForests)	56.60
	AdaBoost (DecisionStumps)	58.68
	Neural Networks	58.62
Triads	AdaBoost (RandomForests)	16.37
	AdaBoost (DecisionStumps)	13.21
	Neural Networks	14.65

TABLE I. TEST ACCURACIES ON $1/3^{rd}$ OF DATASET

Dataset	Features Picked	Test Accuracy(%)
LR	FFTs	69.54
	non-FFTs	59.48
UD	FFTs	56.89
	non-FFTs	59.48
Triads	FFTs	19.54
	non-FFTs	15.22

TABLE II. TEST ACCURACIES WITH AND WITHOUT FFT FEATURES USING ADABOOST WITH RANDOMFORESTS.

[table with all combinations of accuracies]

LR predictor and Up down predictor .

Mention triads did not give too good accuracies

A. Appendix Subsection

VI. EXPERIMENTAL RESULTS

[Box sentence: exact matches and possible choices for non-exact matches]

[Negative analysis, word watch, many potential matches when dictionary size increases]

VII. CONCLUSIONS

A. Future Work

Mobile browsers having allowing access to accelerometer data,

<http://blogs.adobe.com/cantrell/archives/2012/03/accessing-the-accelerometer-and-gyroscope-in-javascript.html>

<http://isthisanearthquake.com/>

<http://isthisanearthquake.com/seismograph.html>

VIII. ACKNOWLEDGMENTS

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