Simple Touch Prediction with Built-In IMUs

Benedict Steuerlein
University of Stuttgart
Stuttgart, Germany
st111340@stud.uni-stuttgart.de

Felix Bühler
University of Stuttgart
Stuttgart, Germany
st117123@stud.uni-stuttgart.de

ABSTRACT

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CCS CONCEPTS

• **Human-centered computing** → **User studies**; **Ubiquitous and mobile devices**;

KEYWORDS

Smartphone; IMU; touch prediction; LSTM; regression.

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1 INTRODUCTION

Touch is the preferred input method on smartphones today. Current research and manufacturers are constantly trying to improve and enhance the interaction on smartphones. Enhancing smartphones with new, rich interaction methods allows users to operate their phone faster and more accurate, thereby increasing the usability and user-experience. One way can be the extension of interactable space with interaction possibilities on the devices' backside [1, 7, 9, 15]. E.g. unlocking the phone by using gestures on the backside, or explicit touches on the backside to reach for unreachable targets on the front side may be possible applications of this technique. However, some of these solutions do not conform with the form factors and weights of ordinary phones [2, 3, 13, 14]. Another way to extend interaction is the introduction of additional touch gestures and touch recognition on touchscreens [5, 6, 8].
Previous work tried predicting touch positions on the touchscreen based on sensor data from either built-in or additional sensors [4, 10, 11]. Accurately predicting touch positions could offer many use-cases:

> **Preloading Content**: Preloading certain content that a user might request in the near future, e.g. a web page, reduces the waiting time and thus improves the user experience. Removing the latency and thereby getting rid of the delay between certain actions greatly enhances the usability of a system. However, when navigating on websites and preloading content from small links a high and precise accuracy is required. Inaccurate prediction would require to preload more data around the predicted point.
>
> **Highlighting Objects**: When navigating through folders, predicted future positions of a touch can be used to highlight information about the to be touched folders. Navigation through a picture gallery on the phone can slightly enlarge the to be touched pictures to give a small preview, maybe showing picture information of where and when the picture was taken. The accuracy required for this approach does not necessarily have to be very high as elements are usually larger than small weblinks.

Despite its novelties, accuracy of some of these solutions has been low.

Motivated by related work and its unexploredness we present a machine learning model for predicting touches on smartphones using only the phones' built-in sensors.

Device	Release	Weight (g)	Screen Diagonal (in)	Height (cm)	Width (cm)	Depth
Samsung Galaxy S3 Mini	2012	113	4.	12.16	6.3	0.99
Samsung Galaxy S4	2013	130	5.	13.7	7.0	0.79
Google Nexus 5X	2015	136	5.2	14.7	7.26	0.79
Motorola Nexus 6	2014	184	6.	15.93	8.3	1.01

Table 1: Data about the smartphones that were used in the study.

2 RELATED WORK

In this paper we are building on a regression model for touch prediction based on smartphones' inertial measurement units. We therefore structured our related work in the following parts: (1) existing solutions and research about touch prediction, and (2) **who the hell knows**.

3 DATA COLLECTION STUDY

We conducted a data collection study to gather IMU data while performing touches on a smartphone. Our collected data set consists of 6 smartphone sensors that were sampled while participants performed successive touches on the smartphones front side.

Design

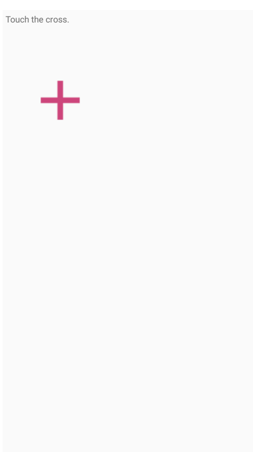
We used a repeated-measures design with one independent variable: PHONE, which was counterbalanced using Latin Balanced squares. To total amount of conditions was: PHONE = 4.

Apparatus

Our dataset was generated using four different sized smartphones on which participants had to perform a certain amount of touches (for further information see Section 3). Our used phone sizes range from 4″ (S3) to 6″ (N6). Using phones of these sizes we were able to cover the sizes of everyday smartphones, including some high-end devices and create a generalizable machine-learning model. For more technical details about the used devices see Table 1.

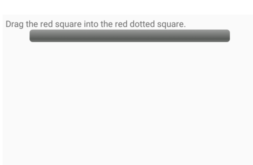
Tasks

For our data collection study participants had to perform a series of touches on the smartphones' touchscreen. We aligned the touch points displayed as crosses in a 16×9 grid. In order to achieve a



[-5cm]

Figure 1: Touch task with one cross displayed.



high variance across the whole screen, we randomized the positions of the crosses within all the cells. To avoid sequential effects, we randomized the order in which the crosses were displayed. There were a total of 3 repetitions, resulting in a total of $16 \times 9 \times 3 = 432$ touches on one device.

Between two touches our study participants had to perform a simple *Fitts' Law task*. Here participants had to drag a filled rectangle into a dashed contour of a rectangle. This task was mainly implemented to reset the participants grip to the bottom half of the device. Because a previous shifted grip of the hand to the upper half of the phone influences the recorded sensor data when reaching for the next target in the lower half and vice versa. See **??** for a more detailed view of the tasks.

Procedure

Participants were either invited within the course *FIS'18* or orally. All appointments were discussed orally. After participants have arrived they signed a consent form. We then continued measuring their hand length. We asked the participants to take a seat on a chair without armrests and explained the study procedure and its sense. We started carrying out the study and handed out the first phone accordingly to the balanced Latin Square order. After participants finished the tasks (see Section 3) on the first phone, we asked them if they need a short recovery break and then continued with the next phones. Additionally, we allowed participants to rest and put away the phone during the *Fitt's Law task* because we specifically deal with this task in our preprocessing step (see Section 4). The study duration was **X** minutes on average.

Participants

UPDATE ON STUDY FINISH

We invited 20 participants (14 male, 4 female). Their age ranged between 21 and 27 ($M = 24.28$, $SD = 1.67$). All participants were fellow students. We only invited right-handed people. We measured the hand length of participants. The size was measured from the tip of the middle finger to the wrist crease with fingers stretched out. Hand lengths ranged from $16.0cm$ to $21.3cm$ ($M = 19.44cm$, $SD = 1.4cm$). Our measured data covers samples from the 5th and 95th percentile of the anthropometric data reported in previous work [12].

4 RESULTS

Report about your model. No source code!

Report about the validation dataset / validation study.

5 DISCUSSION

Disuses why it is still not awesome and how this could be improved. Why this is still awesome? Think about: Nobody has done this before.

Preprocessing - either sidebar, or subsection

We recorded a total of X minutes of sensor data from the *touch* and *Fitt's Law task* task. Since we are only interested in sensor changes during the process of reaching for a target and touching it and the purpose of the *Fitt's Law task* was only for reseting the participants grip to the lower half of the phone our first step in our preprocessing pipeline was `cutting` out the sensor fragments of the *Fitt's Law task*.

6 CONCLUSION

Two sentences wrap up what you have done. Than report what you achieved.

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