Simple Touch Prediction with Built-In IMUs

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ABSTRACT

Touch on smartphones is a momentary snapshot of the 2D position of the user's finger on the screen. However, the genesis of touches comes from events on the screen itself and can be traced until the moment of touch throughout the movement and rotation of the wrist and the fingers. In this paper, we present an approach for making use of the genesis of touches and the associated movements in order to predict the actual touch with the help of phones built-in sensors. The benefits offered by this approach can be preloading content based on future touches or enhance information gathering by highlighting to be touched objects. Related work in this field of interaction enhancement relied on additional equipment like capacitive sensors, self-capacitance touchscreens, or user-mounted sensors. For this purpose, however, neither the availability nor the applicability is given for ordinary smartphone use. We conducted a study with 20 participants to gather internal phone sensor data for a number of touches on four different smartphones. We built a neural network that was able to predict touches up to 66ms into the future with an average accuracy of 18.05*mm*.

CCS CONCEPTS

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

KEYWORDS

Touch prediction; smartphone; sensors; regression; machine learning; deep neural networks.

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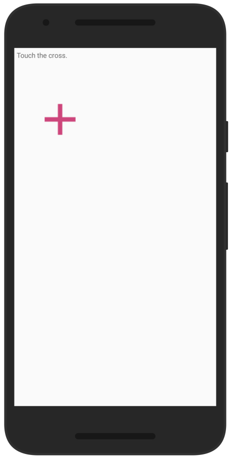
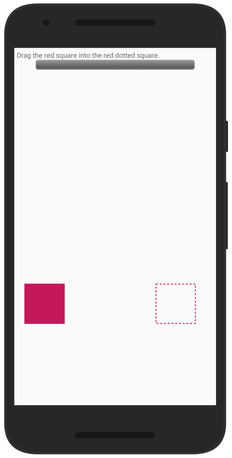


Touch the cross.

Figure 1: Touch task with one cross displayed.



Drag the red square into the red dotted square.

Figure 2: Fitts Law task with a progress bar displaying the current progress.

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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 phones faster and more accurate, thereby increasing usability and user experience. One way can be the extension of interactable space with interaction possibilities on e.g. the back of device (BoD) [2, 8, 10]. 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 [3, 4, 14]. Another way to extend interaction is the introduction of additional touch gestures and touch recognition on touchscreens [6, 7, 9]. Previous work tried predicting touch positions on the touchscreen based on sensor data from either built-in or additional sensors [11, 12].

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 predictions 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, e.g. 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, the accuracy of some of these solutions has been low. In this paper, 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 (mm)
S3 Mini	2012	113	101.6
S4	2013	130	127.
Nexus 5X	2015	136	132
Nexus 6	2014	184	152.4
	Height (mm)	**Width (mm)**	**Depth (mm)**
S3 Mini	121.6	63	9.9
S4	137	70	7.9
Nexus 5X	147	72.6	7.9
Nexus 6	159.3	83	10.1

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

	S3M 0ms	S4 0ms	N5X 0ms	N6 0ms
RF	28.11	34.76	36.38	41.4
DT	28.81	35.58	37.03	42.56
kNN	28.67	34.61	36.36	42.91
GP	53.35	66.83	69.53	79.06
	S3M 33ms	**S4 33ms**	**N5X 33ms**	**N6 33ms**
RF	27.91	34.29	36.05	40.45
DT	28.39	35.1	35.03	41.52
kNN	28.41	34.31	35.92	42.13
GP	52.89	66.82	69.52	79.05
	S3M 66ms	**S4 66ms**	**N5X 66ms**	**N6 66ms**
RF	27.54	33.58	35.24	40.18
DT	27.9	32.74	34.67	39.54
kNN	28.1	33.99	35.93	41.62
GP	44.65	64.83	67.88	76.18

Table 2: Average euclidean distances (mm) for baseline regressors.

2 RELATED WORK

This paper explores the applicability of touch prediction on smartphones with built-in sensors. We considered related work that extends or improves everyday interaction and therefore looked into work that tries to adapt touch interaction in the field of mobile interaction.

An addition to the interaction enhancement through e.g. BoD elements could be the integration of the internal sensors of smartphones, as modern telephones are shipped with them by default. Goel et al. [5] presented *GripSense*, a system that can imply pressure and infers hand postures on phones based on inertial sensor measurements by the gyroscope with an accuracy of 84.3%. To reduce the noticeable latency of continuous motion on touchscreens, Le et al. [11] introduced *PredicTouch*, a system consisting of three external IMUs attached to the wrist, the finger, and to a stylus in order to predict where users will continue their motion on touchscreens in the near future. Using a combination of IMU and a multi-layer feedforward neural network for regression, which was trained on touch coordinates with preceding data from the IMU, they were able to accurately predict touches 33ms and 66ms into the future. Additionally, the user’s throughput for finger input was increased by 15% and 17% for stylus input. Support was found for Banks et al. [1] approach of using self-capacitance touchscreen displays as a means for mobile interaction. Self-capacitive touchscreens capture fingers and their distance from the screen before touching it. Their contribution covers the applicability of multi-touch hover and grip, which is enabled by self-capacitance touchscreens, in common interaction scenarios. Motivated by overcoming the lack of input modalities, Mohd Noor et al. [12] presented *28 Frames Later*, a system that predicts future touch positions on smartphones. Based on grip data they gathered from a total of 24 capacitive sensors built inside the BoD and on the laterals while performing touches on the touchscreen they built a basic machine learning model that was able to predict touch positions 200*ms* before the actual touch with an average offset of 18*mm* to the actual touch position. However, their system required the 24 built on sensors which are not feasible for ordinary usage.

Some of the presented work require additional features for their approach to work. This includes, for example, having additional sensors mounted to the telephone or having special touch-sensitive displays. The normal use of today’s smartphones does not support this kind of interaction elements. However, the use of internal sensors is a promising solution for this limitation as smartphones nowadays are equipped with them as standard. Confirmation of this can be found in the approaches mentioned above. We present a combination of a neural network and the internal sensors to predict where touches will happen in the near future.

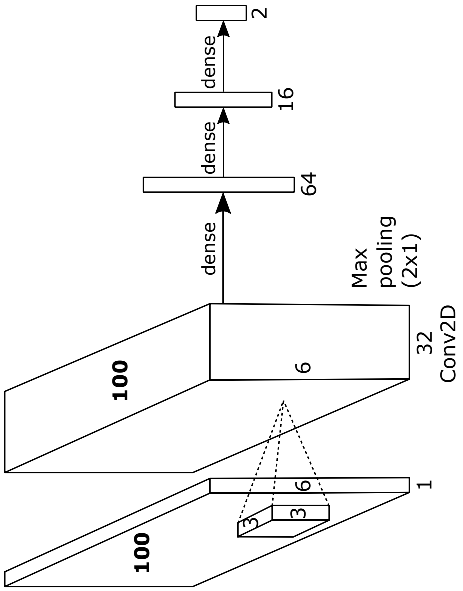

Figure 3: Model architecture of the neural network of general models for predicting touches based on phones’ IMU.

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. For our data collection study, we used a repeated-measures design with one independent variable: phone, which was counterbalanced using Latin Balanced squares. The total amount of conditions was: phone = 4.

3.1 Apparatus

Our data set was generated using four different sized smartphones on which participants had to perform a certain amount of touches (for further information see Section 3.2). The phones we used were a Samsung S3 Mini, a Samsung S4, a Google Nexus 5X, and a Motorola Nexus 6. For more details about the devices used in the study see Table 1. 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.

3.2 Tasks

For our data collection study participants had to touch points displayed as crosses in a 16×9 grid on the touchscreen (see Figure 1). We decided to create the crosses the same as the aspect ratios of the mobile phones. To achieve a high variance, 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* (see Figure 2). Here participants had to drag a filled rectangle into a dashed contour of a rectangle. This task was mainly implemented to reset the participant’s grip to the bottom half of the device. Because a previously 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.

3.3 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, and we 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 handed out the first phone accordingly to the balanced Latin Square order. After participants finished the tasks (see Section 3.2) on the first phone, we asked them if they need a short recovery break and then continued with the next phones. The study duration was 54 minutes on average.

Model	Phone	0ms	33ms	66ms
single	S3	12.50 (7.36)	13.17 (7.82)	14.40 (8.24)
	S4	17.25 (9.94)	18.77 (10.76)	19.41 (10.78)
	N5X	17.01 (9.76)	18.09 (10.39)	19.96 (10.93)
	N6	18.87 (11.4)	19.78 (12.15)	21.52 (12.7)
general	S3	12.95 (7.57)	13.48 (7.92)	14.52 (8.38)
	S4	16.79 (10.61)	17.69 (10.99)	18.70 (11.21)
	N5X	17.39 (10.61)	18.02 (10.88)	19.46 (11.60)
	N6	17.53 (11.59)	17.75 (11.94)	19.53 (12.72)

Table 3: Average test euclidean distances (mm) and standard deviations (brackets) for single and general models for all configurations.

3.4 Participants

We invited 20 right-handed fellow students as participants (5 female). Their age ranged between 21 and 27 ($M = 24.25$, $SD = 1.58$). 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 ($M = 19.3cm$, $SD = 1.47cm$). Our measured data covers samples from the 5th and 95th percentile of the anthropometric data reported in previous work [13].

4 RESULTS

4.1 Data Set & Preprocessing

We recorded a total of 1079 minutes of sensor data from the *touch* and *Fitt’s Law task* task. The duration for touches was on average 664.56ms (SD = 300.69ms). The fastest touch was performed within 181ms. During the study, we sampled the linear accelerometer, gyroscope, magnetometer, gravitational sensor, and the orientation sensor. Due to the high sampling rate of the sensors, we first removed occurring duplicates by keeping the last sensor value and timestamp. We then up-sampled the sensors to 333.33 Hz, resulting in 1 sample given every 3ms. Finally, we saved 100 samples before each touch resulting in a total of 3.456.000 samples. After testing we only kept the accelerometer and the gyroscope, as using all sensors led to overfitting. Up-sampling the sensors to 1 sample every 3ms resulted in a discontinuous function for each sensor axis. We have therefore tried applying several smoothing procedures, including a Butterworth lowpass-filter and a moving average filter. Both approaches, however, did not lead to an increase in accuracy, so we kept the unsmoothed data of the sensors. We have split the data set randomly into 14 training and 6 testing participants.

4.2 Baseline

We explored basic regressors from scikit-learn [1] as a baseline to test whether using novel machine learning techniques achieve better touch predictions with IMU than standard machine learning algorithms. The used regressors are abbreviated as follows: RandomForestRegressor (RF), Decision Tree Regressor (DT), *k*-Nearest Neighbors Regressor (kNN), and Gaussian Processes Regressor (GP). We performed a grid search for the different regressors to find the best hyperparameters for each regressor. The results for all phones with different time configurations of all regressors can be seen in Table 2. Light green highlighted values in phone columns represent the regressor that performed the best for this configuration of phone and prediction time. Green highlighted values in the first column represent the overall best regressor for each prediction time.

[1] https://scikit-learn.org/stable/supervised_learning.html#supervised-learning

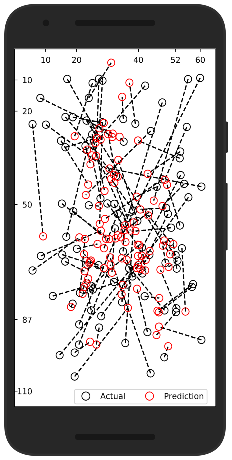

Figure 4: Predictions and true points for the single model of the N5X. Units are depicted in mm.

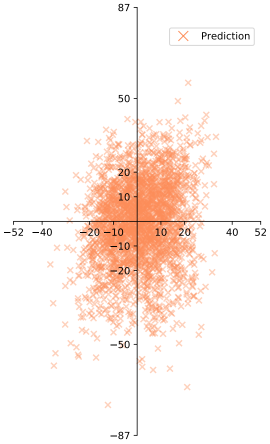

Figure 5: Origin heatmap plot for the single model of the N5X after each true point with the corresponding prediction is shifted by the distance from origin to actual point.

4.3 Neural Network

We implemented our neural network using *Keras* 2.2.4 which is based on the TensorFlow backend. We trained two model types, one which we call *single* and one which we call *general* model. Single models were trained on sensor and touch data of single phones; general models were trained on sensor data and normalized touch data of all phones. We trained each model for approximately 2000 epochs. The network architecture differs for single and general models. Due to place restrictions and the fact that general models performed better than the single models, we only report about our general model architecture. The final architecture is shown in Figure 3. The input consists of values from the 3 accelerometer and 3 gyroscope sensor axis. The input length varied based on the prediction time. As mentioned above, we saved 100 samples before each touch. We varied between 3 prediction times: *0ms*, *33ms*, and *66ms*. If we wanted to predict 0ms in the future, i.e. predict the point of contact directly at a touch, we provided the neural network with 100 sensor samples for each touch. If the prediction was 33ms in the future we only fed in 89 sensor samples, and for 66ms predicting into the future, we only used 78 samples. The bold written 100 in Figure 3 therefore varied between 100, 89, and 78 for the different prediction times. The input then goes through one Conv2D layer on which a L2 regularizer with a factor of .001 is applied. The same L2 regularizer is applied to the first dense layer. We used a .25 dropout after the Conv2D layer and a .5 dropout after each dense layer to prevent overfitting. We used the MSE (mean squared error) as the loss function and initialized the learning rate with .001. We trained our model using an Adam optimizer with an epsilon value of $1e$-08. The output layer consists of 2 values *(x,y)* coordinates that represent the predicted touch for the given prediction time.

4.4 Predictions

For each point prediction we converted its unit from pixels to mm based on the pixel sizes of the mobile phones. The average Euclidean distances between actual points and predictions for both the single and the general model can be seen in Table 3. Figure 6 visualizes the errors of the general model grouped by phones for each prediction time. Figure 4 shows 100 random taken predictions for the N5X single model. For Figure 7 and Figure 8 we have shifted each prediction with its corresponding true point by the distance from the true point to the origin, thus resulting in a heatmap around the origin representing the scattering of the prediction points. Such an origin heatmap can be seen in Figure 5. For each phone and each prediction time, we have fitted an elliptic envelope with a contamination parameter of .0261 inside the heatmap. This value can be explained that .261% of all predictions have a higher RMSE than the mean RMSE + .5 $*$ RMSE std. For each ellipse of single and general models, we have approximated the area in mm^2 by calculating the percentage of points of a rectangle with known size falling within the ellipse. The areas are listed in Table 4. Light green highlighted cells depict which model resulted in a smaller ellipse area for its predictions.

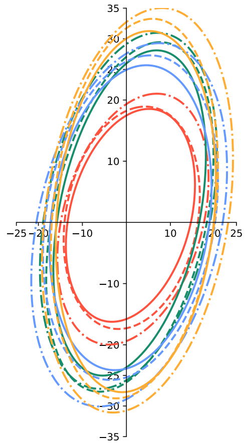

Figure 7: Elliptic envelope plot for single models.

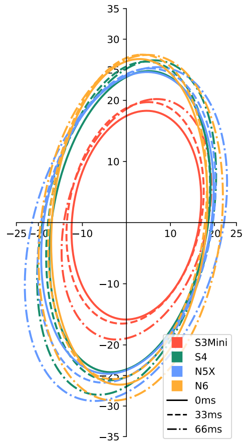

Figure 8: Elliptic envelope plot for general models.

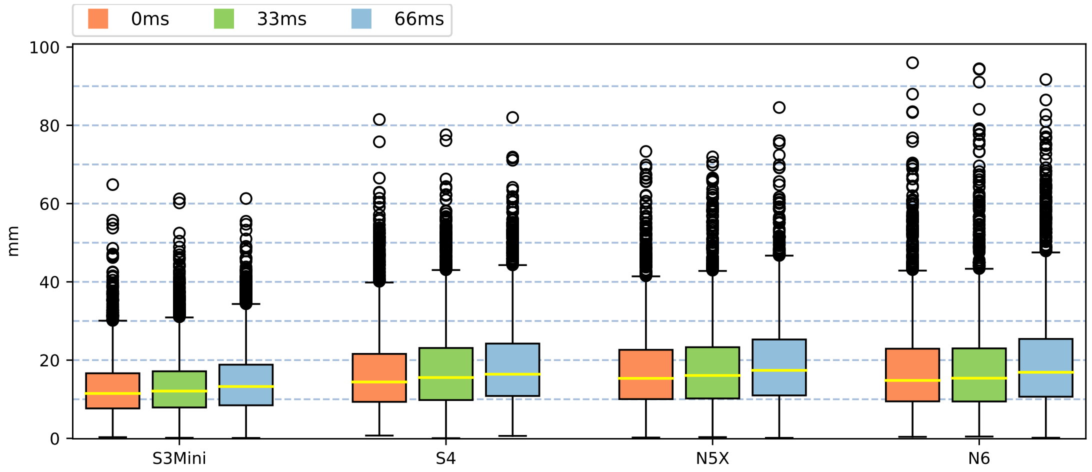

Figure 6: Boxplots for the prediction errors of the general model. The groups are based on the phones with each prediction time as one box.

5 DISCUSSION

Motivated by related work, we conducted a study where participants performed touches on smartphones during which we sampled the internal sensors. A combination of a neural network and accelerometer and gyroscope values from the internal sensors allowed us to predict future touches on the smartphone. We have focused on showing the possibility of the applicability of our approach as using the IMU is feasible for ordinary usage.

Our results show that touch prediction with neural networks based on internal sensor values is possible, with fairly high precision accuracy. For increasing prediction times prediction errors increase, e.g. for the N5X the single model for a prediction time of 0ms average prediction errors were 17.01*mm* while for 66ms the errors increased to 19.96*mm*. This trend can be observed for all telephones, whether single or general model. Same holds for the elliptic envelope areas where the enclosed area increases for increasing prediction times. This suggests that the data we collected during our study is either not feasible for predicting touches into the future or that the amount of sensor movement patterns did not differ too much, meaning looking at the times to complete the touches (see Section 4.1) participants tried to perform the touches as fast as possible to end the study leading to data consisting of a fairly high amount of fast touches and to an occlusion of slow touches. The fact that the general model performed better than the single models might be due to a better generalization of the data, leading to overall lower errors. To return to the use cases from Section 1, our average errors (single models: 16.67mm$_{0ms}$ (SD = 2.47mm) to 18.82mm$_{66ms}$ (SD = 2.67mm) ; general model: 16.17mm$_{0ms}$ (SD = 1.88mm) to 18.05mm$_{66ms}$ (SD = 2.07mm)) will not allow content to be preloaded which requires clicking small icons or weblinks. However, our results could be applied to highlighting larger elements or preloading content from larger elements.

	Model	0ms	33ms	66ms
S3	**S**	766.92	864.35	1049.42
	G	778.93	869.17	1002.76
S4	**S**	1354.96	1588.03	1733.1
	G	1376.14	1482.92	1656.89
N5X	**S**	1413.76	1612.83	1972.12
	G	1477.92	1573.48	1871.57
N6	**S**	1661.86	1814.29	2176.2
	G	1462.5	1479.93	1826.55

Table 4: Ellipse areas (mm^2) from single models seen in Figure 7 and from general models seen in Figure 8.

Limitations

In this paper, we focused on one specific use task where users touched randomized targets on smartphones while sitting on a chair without armrests. The sensor samples generated during our study are specific for this use case and thereby do not cover ordinary smartphone usage and implied phone movement when e.g. walking, lying in bed, or operating the phone in a train. An In-The-Wild study is open for future work, where participants are handed out phones which relentlessly record touches and sample the IMU. The variety of touches during different activities would lead to a more generalizable data set for touch prediction. The participants tried to complete the tasks as fast as possible because the study was exhausting for both the hand and the eyes. This led to a high amount of sensor data from fast touches and a low percentage of slow touches. Future work could explore the variety of different touches ranging from slow to fast touches while sampling the IMU.

6 CONCLUSION

In this work, we have investigated the feasibility touch prediction with built-in IMU. We conducted a study where we recorded a series of touches participants had to perform and meanwhile sampled the phones' internal sensors which were later on fed into a neural network which enabled us to predict touches that lied up to 66ms in the future.

We have shown that it is possible to predict future touches on smartphones only with the built-in sensors and the help of neural networks. The accuracy of our approach does not yet reach the accuracy of more related work. Mohd Noor et al. [12] could predict 200ms with an accuracy of 18mm into the future, whereas for our general model we achieve an accuracy of 18.05mm for predicting 66ms into the future with increasing errors the further we predict away from touches. However, these results could be improved by enhancing the data set with touches specifically aiming for predicting hand movements and subsequent touches on smartphones.

Touch events on smartphones are only single snapshots of a long concatenation of grasping and movement events of the fingers around the phone. The genesis of these motions, however, comes much earlier and can be predicted when observing the movements and rotations of the hand. This offers an efficient way to enhance future interaction on smartphones and should be taken into consideration by researchers and developers.

The code used to generate the results for this work is provided under https://05.jupyter.interactionlab.io/user/beneste/notebooks/fapra-imu/.

REFERENCES

[1] Richard Banks, Gavin Smyth, William Buxton, Michel Pahud, Hrvoje Benko, Seongkook Heo, Abigail Sellen, Kenton O'Hara, Christian Holz, and Ken Hinckley. 2016. Pre-Touch Sensing for Mobile Interaction. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16*. ACM Press, New York, New York, USA, 2869–2881. https://doi.org/10.1145/2858036.2858095

[2] Patrick Baudisch and Gerry Chu. 2009. Back-of-device interaction allows creating very small touch devices. In *Proceedings of the 27th international conference on Human factors in computing systems - CHI 09*. ACM Press, New York, New York, USA, 1923. https://doi.org/10.1145/1518701.1518995

[3] Christian Corsten, Bjoern Daehlmann, Simon Voelker, and Jan Borchers. 2017. BackXPress. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI '17*. ACM Press, New York, New York, USA, 4654–4666. https://doi.org/10.1145/3025453.3025565

[4] Alexander De Luca, Emanuel von Zezschwitz, Ngo Dieu Huong Nguyen, Max-Emanuel Maurer, Elisa Rubegni, Marcello Paolo Scipioni, and Marc Langheinrich. 2013. Back-of-device authentication on smartphones. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '13*. 2389. https://doi.org/10.1145/2470654.2481330

[5] Mayank Goel, Jacob Wobbrock, and Shwetak Patel. 2012. GripSense. In *Proceedings of the 25th annual ACM symposium on User interface software and technology - UIST '12*. 545. https://doi.org/10.1145/2380116.2380184

[6] Anhong Guo, Robert Xiao, and Chris Harrison. 2015. CapAuth. In *Proceedings of the 2015 International Conference on Interactive Tabletops & Surfaces - ITS '15*. 59–62. https://doi.org/10.1145/2817721.2817722

[7] Christian Holz, Senaka Buthpitiya, and Marius Knaust. 2015. Bodyprint. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15*. 3011–3014. https://doi.org/10.1145/2702123.2702518

[8] Huy Viet Le, Patrick Bader, Thomas Kosch, and Niels Henze. 2016. Investigating Screen Shifting Techniques to Improve One-Handed Smartphone Usage. In *Proceedings of the 9th Nordic Conference on Human-Computer Interaction - NordiCHI '16*. ACM Press, New York, New York, USA, 1–10. https://doi.org/10.1145/2971485.2971562

[9] Huy Viet Le, Thomas Kosch, Patrick Bader, Sven Mayer, and Niels Henze. 2018. PalmTouch: Using the Palm as an Additional Input Modality on Commodity Smartphones. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (2018-04-21) *(CHI'18)*. ACM, New York, NY, USA, 360:1–360:13. https://doi.org/10.1145/3173574.3173934

[10] Huy Viet Le, Sven Mayer, Patrick Bader, and Niels Henze. 2017. A smartphone prototype for touch interaction on the whole device surface. *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '17* (2017), 1–8. https://doi.org/10.1145/3098279.3122143

[11] Huy Viet Le, Valentin Schwind, Philipp Göttlich, and Niels Henze. 2017. PredicTouch. In *Proceedings of the Interactive Surfaces and Spaces on ZZZ - ISS '17*. 230–239. https://doi.org/10.1145/3132272.3134138

[12] Mohammad Faizuddin Mohd Noor, Simon Rogers, and John Williamson. 2016. Detecting Swipe Errors on Touchscreens using Grip Modulation. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16*. ACM Press, New York, New York, USA, 1909–1920. https://doi.org/10.1145/2858036.2858474

[13] Alan Poston. 2000. Human engineering design data digest. *Department of Defense Human Factors Engineering Technical Advisory Group Washington* (2000), 82. https://www.acq.osd.mil/rd/hptb/hfetag/products/documents/HE_Design_Data_Digest.pdf

[14] Katrin Wolf, Christian Müller-Tomfelde, Kelvin Cheng, and Ina Wechsung. 2012. PinchPad. In *Proceedings of the Sixth International Conference on Tangible, Embedded and Embodied Interaction - TEI '12*. ACM Press, New York, New York, USA, 103. https://doi.org/10.1145/2148131.2148155