Enhancing User Interaction With Smart Phone using Phalanx Bone

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ABSTRACT

Touchscreens are the most successful input method for smartphones. Despite their flexibility, touch input is limited to the location of taps and gestures. We present Phalanx Touch, an additional input modality that differentiates between touches of fingers and the phalanx. We present a use case for Phalanx Touch, including the use as a shortcut to open an application (for instance camera). To evaluate the use case, we have developed a model that differentiates between finger and phalanx touch with an accuracy of 98% in realistic scenarios. Results of the evaluation show that participants perceive the input modality as intuitive and natural to perform.

CCS CONCEPTS

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

KEYWORDS

Phalanx;capacitive image;machine learning; smartphone.

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INTRODUCTION & RELATED WORK

Smartphones have recently become the most successful mobile devices.Through a touchscreen, smartphones offer a wide range of functions that are used by millions of people. While most functions are accessible within a number of touches, some are used so frequently that shortcuts were introduced. Traditional devices offer volume buttons and a power button to enable users to change the device’s volume and state with just one press. With an increasing number of frequently used functions such as device assistants, cameras or music players, device manufacturers and developers look for new ways to integrate them for faster access.

Commercial devices, as well as previous research, presented a wide range of novel interaction techniques. Already in the first version of Android and iOS, they leveraged the time dimension to provide the long press. With the iOS 6s in 2015, Apple introduced 3D Touch which adds a pressure dimension the interaction. Both methods are used to modify the touch input and alter the action. Samsung also introduced a dedicated hardware button to call the Bixby assistant on the Samsung Galaxy S8. The HTC U11 incorporates Edge Sense, a pressure sensitive frame that launches a user-defined action when squeezing the device. While these additional input controls fulfill their purpose, they require additional hardware which leaves out the possibility to update already existing and older devices.

Touch gestures constitute a possible solution to the challenge described above. However, system-wide drawn gestures that are always accessible for user-defined actions may conflict with other applications. Previous work presented a number of alternative input modalities to support traditional multi-touch input. This includes using the finger’s contact size [1], 3D orientation [4], [6], [7], [8], pressure [3], or the shear force [2]. While these enrich the information of a finger’s touch, they also bring restrictions since specific finger postures may now trigger unwanted actions. One solution to lower the likelihood of triggering unwanted actions is to differentiate between fingers or parts of fingers, which prevents interference with the main finger for interaction.

Motivated by previous work, we applied this concept for smartphone interaction and as a result, we present Phalanx Touch, an additional input modality that enables people to use the phalanx to trigger pre-defined functions instead of simply rejecting phalanx input as recent smartphones do.

In this work, we propose Phalanx Touch, an additional touch input modality to trigger pre-defined functions by placing the phalanx on the touchscreen. Accordingly, we present a use case for Phalanx Touch and evaluate the input modality as a shortcut during smartphone interaction. To evaluate Phalanx Touch, we have developed a phalanx detection model that differentiates between finger touches and phalanx touches with a high accuracy. In contrast to previous work, we use the raw capacitive image of the touchscreen to classify the low-resolution fingerprint using a convolutional neural network. The contribution of this work is two-fold:
(1) *Phalanx Touch*, an additional input modality using the phalanx, and
(2) a high-accuracy phalanx detection model including a validation in realistic scenarios.

The described input modalities in previous works extend the touch input vocabulary, none of them focused on using different parts of the hand or finger for interaction using only off-the-shelf smartphones with a low likelihood of unintended activation.

Using capacitive images to distinguish between finger and phalanx, we close the gap between the field of rejecting phalanx detection by proposing palm input as an additional input modality for smartphone interaction.

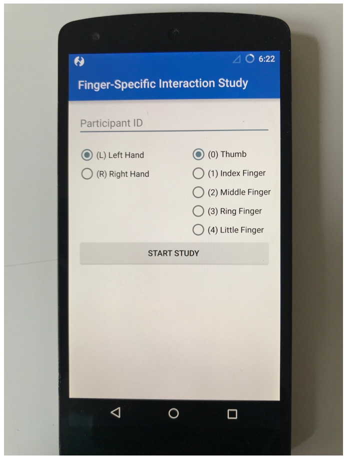


Figure 1: Android Application developed for Data Collection

Custom Actions and Applications

Smartphone manufacturers recently integrated simple and binary input modalities such as an extra button (Bixby button on the Samsung Galaxy S8) or a squeeze on the device's edge (Edge Sense on the HTC U11) to launch pre-defined applications. While these features require additional hardware, Phalanx Touch can be readily deployed onto recent and older off the-shelf smartphones, e.g., through software updates. Moreover,with the emergence of edge-to-edge displays on devices such as the iPhone X and Samsung Galaxy S8, the lack of a home button can be compensated with Phalanx Touch.

Instead of launching a single pre-defined action or application, a pie menu can be used to provide multiple options. Phalanx Touch can also be used for application dependent functions. For example, a phalanx touch could send away a message in a messaging application, while it accepts a call in the phone application or switch layers in different applications. Since Phalanx Touch can be used eyes-free similar to a hardware button or squeeze, actions such turning off the screen or accepting a call can be mapped to a phalanx touch. Phalanx Touch can also be used to unlock the smartphone by placing the phalanx on the touchscreen.

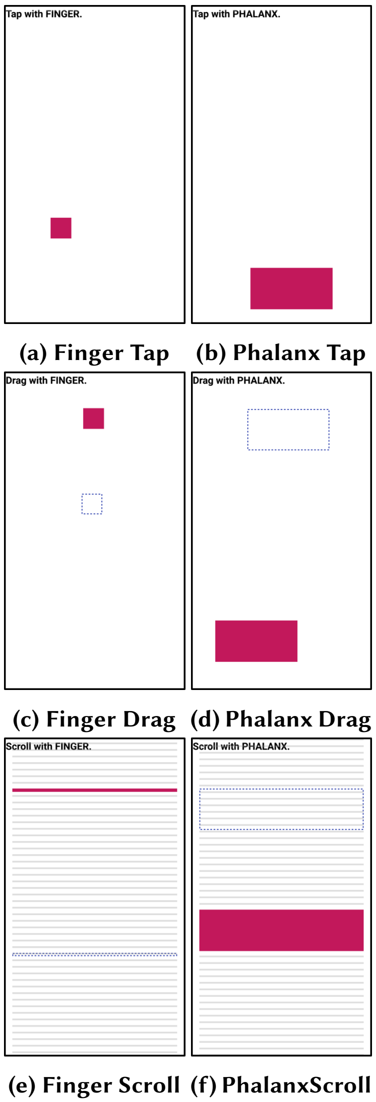


Figure 2: Screenshots of tasks performed by users in the data collection study

DATA COLLECTION STUDY

To implement the use cases presented in the previous section, the touchscreen needs to differentiate between finger and phalanx touches. We use capacitive images provided by the touchscreen which contain low-resolution fingerprints of the touch (e.g., finger or phalanx). Since we apply machine learning to classify the touch, we conducted a user study to collect labeled touch data of fingers and the phalanx while participants perform representative touch actions using an android application as depicted (see Figure 1). With this data, we train and evaluate a phalanx detection model to differentiate between touches from fingers and phalanx bones.

Apparatus

We used an LG Nexus 5 running Android 5.1.1 with a modified kernel to access the 15x27 raw capacitive images.The pixel values represent the differences in electrical capacitance (in pF) between the baseline measurement and the current measurement. We used a developed application and modified it as per our requirements for the tasks described above which logs a capacitive image every 50ms (20fps). Each image is logged with the respective task name so that every touch is automatically labeled.

Tasks

The purpose of this study is to collect a wide variety of finger and phalanx touch input. We designed six different tasks which instruct each participant to perform a total number of 36 representative touch actions for a single finger and resulting in 360 touch actions for all 10 fingers.These tasks are shown in figure 2

Procedure

After participants agreed to perform the study, we then explained the procedure including the phalanx input modality and handed them an instruction sheet which explains all tasks of the study. Participants performed all tasks in 30 minutes on average.

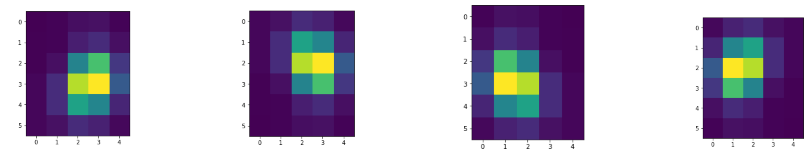
Participants

We conducted study with 25 participants [12 (Female) + 13 (Male)] between the age of 23 and 28 (M = 24.92, SD = 1.49). Participants were supposed to perform the tasks with both the hands.

RESULTS

Data Set & Pre-Processing

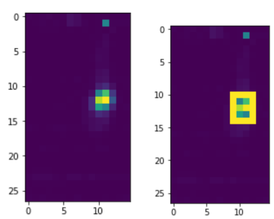
From our data collection study, we recorded total 6,22,726 Images. Then the first task was to pre-process data and filter noisy images. We used the OpenCV library in Python for blob detection. After



(a) Cropped finger input **(b) Up-Down(UD) Flip** **(c) Left-Right(LR) Flip** **(d) LR-Flip of UD image**

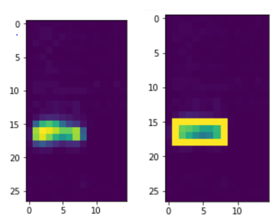
(e) Cropped phalanx input **(f) Up-Down(UD) Flip** **(g) Left-Right(LR) Flip** **(h) LR-Flip of UD image**

Figure 4: Outcomes of data augmentation



(a) **(b)**

Figure 3: Raw Capacitive(a) and blob detected(b) images of data collected from Participant 2 during finger drag task.



(a) **(b)**

Figure 5: Raw Capacitive(a) and blob detected(b) images of data collected from Participant 3 during phalanx tap task.

blob detection, we cropped the blobs from the original image and appended them as an extra column in the original data frame. Blobs with an area less than 5 and the images which have no touch area, were considered as noisy/empty images and were deleted from our dataset. So, after deleting noisy data we have total 3,38,723 useful images.

The sample input images from data collection are shown in figure (3a , 5a) and blob detection outcomes are shown in figure (3b , 5b).

Data Augmentation

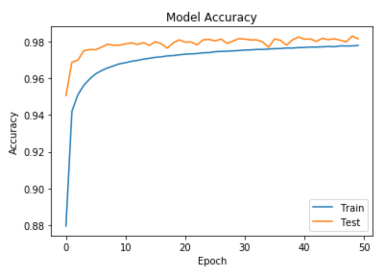
For training NN a good and extensive dataset is needed.So we performed data augmentation by flipping the original cropped images to up-down and left-right as shown in figure 4.

Data augmentation retains the orientation of phalanx and finger touch in all directions. Here we found the need of more finger touch data for all the orientations.So, we included dataset from the project - Capacitive Finger Orientation [5] which has such kind of data.

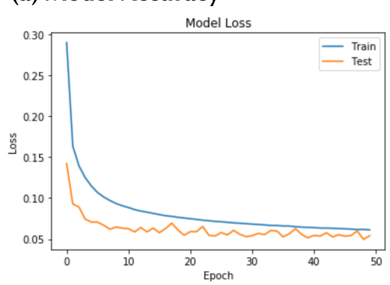
After augmentation, our dataset consisted of total 10,88,722 (Finger Images) and 7,95,820 (Phalanx Images).We then converted the cropped images to the size of the original image (27 x 15 pixels) to make them uniform.

Table 1: Architecture of CNN

	parameters	training acc	test acc
Input	27x15x1	97.79	98.15
Convolution	2x2x64 (ReLU)		
Convolution	3x3x64 (ReLU)		
Maxpooling	2x2		
Convolution	3x3x128 (ReLU)		
Convolution	3x3x128 (ReLU)		
Maxpooling	2x2		
FC Layer 1	256(ReLU)		
FC Layer 2	256(ReLU)		
Softmax (Output)	2		



(a) Model Accuracy



(b) Model Loss

Figure 6: Accuracy and Loss obtained after training the model

Phalanx touch using Convolutional Neural Network using Keras

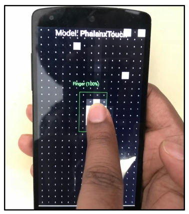
We have used state of the art Convolutional Neural Network techniques for classification between finger and phalanx. We trained and tested CNN with a participant wise split of 80-20 % (20:5). This is to ensure that samples from the same participant not to be in different sets.

The CNN architecture is summarized in the table 1. As seen from the table, we have achieved the test accuracy of 98.15% by training the model using SGD Optimizer with a constant batch size of 256 (results are shown in figure 6).

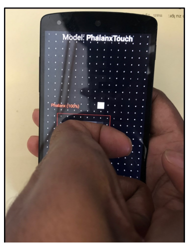
Validation Study

The validation of our project was done on an Android application which was developed by deploying the trained model into it by using tensorflow for Android. This app was used for detecting Phalanx touch in a realistic scenario. When the user touches the screen with random fingers and phalanx, the touch classification results were displayed on the bounding box of their touch area. The results for the validation study looks as shown in figure 7.

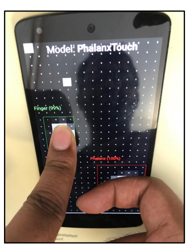
We presented another application which presents one of the use cases of the project. This application opens the camera on Phalanx scroll. This is one of the use cases which we can have with the Phalanx touch classification model.



(a) Finger classification



(b) Phalanx classification



(c) Multi-touch classification

Figure 7: Sample visualization images of Model deployed on Android phone

DISCUSSION

Though our model classification works well with most of the cases and in spite of very good results from our validation study we found that project can still be improvised on the following points-

1) The fingers placed on the screen occupying more area were being misclassified as a phalanx. These misclassification of fat finger touch as phalanx can be reduced with a more extensive dataset by collecting data for such kind of inputs and labeling them as fingers.

2) Our data collection study was conducted for ages between 23 and 28, this can be extended to more age groups for achieving a higher standard deviation and thereby generalizing the dataset.

CONCLUSION

We presented Phalanx Touch, an additional input modality on smart-phones using the phalanx to perform input. We proposed a use case and evaluated Phalanx Touch in a user study.

We implemented Phalanx Touch using capacitive images collected in a controlled study, and a convolutional neural network to differentiate between touches being made by fingers and phalanx bones. In contrast to previous work, our approach uses low-resolution fingerprints instead of heuristics that only work with multiple touch points (i.e., pen and palm) or that would introduce latency through temporal features. This enables us to build a model with an accuracy of 98% in a realistic scenario evaluation.Since we only modified the software of an off-the-shelf Nexus 5 smartphone, Phalanx Touch could be readily deployed onto recent smartphones, e.g., through software updates.

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