FlickBoard: Enabling Trackpad Interaction with Automatic Mode Switching on a Capacitive-sensing Keyboard

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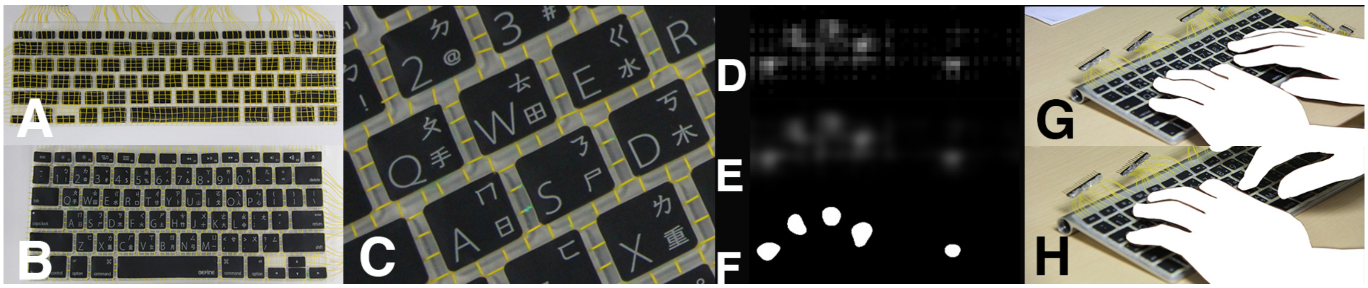

Figure 1. We present a keyboard cover with capacitive touch sensing capability which automatically disables itself while typing. Sensing wires are embedded into a typical keyboard cover (A), the modified cover is then put on an off-the-shelf keyboard (B). The sensing grid is all over the keyboard with 0.5cm grid size (C). This results in a low-resolution raw intensity image when hands are near the surface of the keyboard (D). The image is then processed to obtain touched areas (E+F). The raw image can also be used to robustly recognize whether user wants to type on the keyboard (G) or to control cursor with touchpad (H) using a machine learning-based classifier.

ABSTRACT
We present FlickBoard, which combines a touchpad and a keyboard into the same interaction area to reduce hand movement between a separate keyboard and touchpad. Our main contribution is automatic mode switching between typing and pointing, and the first system capable of combining a trackpad and a keyboard into a single interaction area without the need for external switches. We developed a prototype by embedding a 58x20 capacitive sensing grid into a soft keyboard cover, and used machine learning to distinguish between moving a cursor (touchpad mode) and entering text (keyboard mode). We conducted experimental studies that show automatic mode switching classification accuracies of 98% are achievable with our technology. Finally, our prototype has a thin profile and can be placed over existing keyboards.

Author Keywords
Keyboard; Touchpad; Co-located input devices;

ACM Classification Keywords
H.5.2. User Interfaces - Input devices and strategies: User Interfaces

INTRODUCTION
Operating a computer requires both pointing devices and text input devices. However, most of the commercially available computers present these as two separate devices, which require hand repositioning while switching between mouse and typing actions. Therefore, previous studies had explored how to co-locate touch sensing and regular typing. There are two main issues of the dual functional keyboard: 1) How to enable touch sensing capability on the keyboard? [1, 2, 5] provided different sensing approaches to combine gesture interaction and typing on the same area. 2) How to automatically switch between trackpad mode and typing mode? To our knowledge, this issue has not been resolved yet. We present FlickBoard, a keyboard cover with a smart capacitive touch sensing film with an automatic mode switching algorithm that recognises the user's intention based on the recorded usage data of 30 participants. In this work, we focus on automatic mode switching between typing and pointing, and the design of our sensing cover is based on the work, SmartSkin [3], which recognizes multiple hand positions and shapes by using capacitive sensing grids. Furthermore, we modified the software implementation provided by Type-hover-swipe in 96 bytes [5], which uses Motion Signature approach [5] to do gesture recognitions. We conducted experimental studies that show automatic mode switching classification accuracies of 98% are achievable with small amounts of training data per user.

RELATED WORK
Previous research has shown that co-locating two devices will improve user performance [1]. ThumbSense [4] helps users

keep their fingers on the home row by using keyboard keys as mouse buttons when it detects a movement of the thumb on the touchpad. TypeHoverSwipe [5] implemented a modified keyboard with infra-red proximity sensors that recognizes in-air hand gestures and obtains coarse finger positions. The depth map generated by the infrared range finder is fast and stable, but the finger positions obtained by the system are too rough to control a mouse cursor because the sensors were interspersed between the key caps. DGTS [2] uses capacitive sensing technology, in contrast, to obtain a higher resolution image to control the cursor. However, the integrated device still requires manual mode switching to avoid false triggering of the pointing device.

SYSTEM OVERVIEW

Our system consists of four parts: 1) sensing film, 2) capacitance-to-digital converters and 3) automatic mode switching predictor.

Sensing Cover

We built a capacitive sensing grid on a commercially available silicone keyboard cover. The modified cover was placed over an Apple wireless keyboard. We connected the ground of the grid to the body of the Apple keyboard to stabilize the readings. The grid consists of 58 vertical and 20 horizontal 30 AWG copper wires. With mutual capacitance sensing techniques, each cross point of vertical and horizontal wires can be a single sensing point, so the film can capture a 58x20 frame. The sensing resolution could be higher if the conductive pattern would be printed directly on the cover with higher line density. With this modified keyboard cover, we can enable touch sensing capability on any keyboard by simply putting it over an unmodified keyboard.

Capacitance To Digital Converters(CDC)

We adopted the CDC design of SmartSkin [3] to measure the change of mutual capacitances at the sensor grid intersections. Here we briefly highlight our changes cover [3]. The main idea of this design is to measure the signal reduction of the square wave signal passed through the sensor film, which can be viewed as a very small capacitor. The square wave signal generated by a programmable clock generator is passed into sensor films through analog demultiplexers, so we can raster scan through all the 58 vertical wires by switching between the channels. 20 OP-Amps are connected to the horizontal wires of the sensor grid, amplifying the weakened signal by a factor of 5 for further processing. The CDC also has an analog subtractor for hardware-based background substraction. The CDC currently is capable of raster scanning through the sensor grid at 13 Hz. Calibration of the sensor is done by sampling through the sensor grid for 10 times. The data generated by the CDC can form a 58x20 pixels resolution. Each pixel has 10-bit intensity value ranging from 0 to 1023. The sensor grid only responds to conductive objects in a very short range($<$0.2cm).

Signal Processing

The 58x20 10-bit intensity image is scaled up to 464x160 10-bit image with nearest-neighbor interpolation to provide a more accurate cursor positioning capability. (Figure 1.D) A Gaussian filter is then applied to the image for smoother blob images. Each row of the filtered image is subtracted with the mean of the row since we found that the sensor value will be interfered when there are some other touch points on the same horizontal sensing wire.(Figure 1.E) The image is binarized with a simple local adaptive thresholding algorithm. Finally, the system detects blobs in the binarized image as touched points. (Figure 1.F) Calculated blob positions are filtered with a Kalman filter to stabilize blob position and make cursor controlling possible.

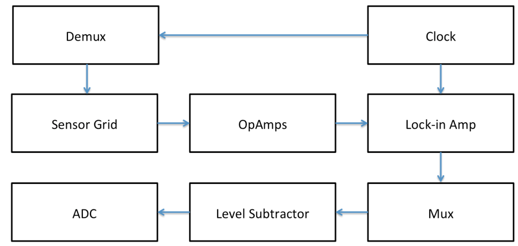

Figure 2. CDC circuit diagram. The switch and RC low-pass filter are the main components of the lock-in amplifier.

AUTOMATIC MODE SWITCHING PREDICTION

After co-locating the touch sensing and typing device, automatically switching between the touching and typing modes becomes an important issue. We classified the calculated MHIs with Random Decision Forests(RDF) into *keyboard mode* and *trackpad mode* to recognize which mode the user intends to use.

Task Design for collecting training data

We designed the tasks to meet the following criteria: 1) The tasks must be using both keyboard and touchpad alternately. Switching between two devices occurs frequently. 2) The task was extracted from the regular use of the keyboard and touchpad, and must be simple enough for the users to perform while they also need to operate an extra foot pedal to record their actual intention (see Figure 3.A). 3) The individual usage times of the keyboard and the touchpad should be as close as possible to each other. This would result in a more balanced dataset, which is better for building a classifier.

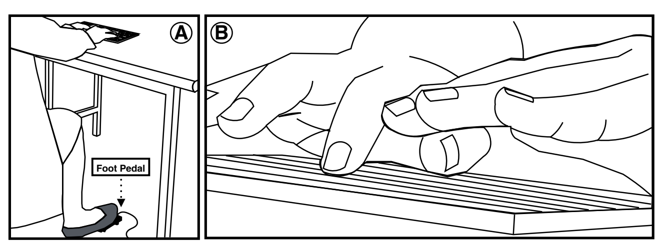

Figure 3. (A) Participants switched between typing and pointing by operating the foot pedal manually during the procedure of ground truth collection. Meanwhile, the system labeled each frame according to the current foot pedal's state. (B) A majority of the participants raised their left hand and used one finger of the right hand to perform cursor movements in the trackpad mode.

Procedure

We recruited 30 participants (15 females, 15 males, mean age 21) with an on-line form. All participants are right-handed. In the training session, participants were asked to fill in a questionnaire and learned how to use the foot pedal to switch modes. In the testing session, participants were asked to use FlickBoard to perform the following tasks: 1) Type a specified sentence in the text processing software. 2) Change the font size of the sentence by moving the mouse cursor to select a different size on the menu bar. 3) Continue typing another sentence and their own name. 4) Insert a picture in the document with the menu button, and resize the picture with the cursor. 5) Close the text processing software and open a web browser. 6) Type ”www.facebook.com” in the location bar. 7) Browse the social network site, comment on one of the posts in the news feed. 8) Scroll back to the top of the page and upload a photo. 9) Add some comment on the uploaded photo. Participants were not allowed to use hot keys. They can only type and control the cursor or use a scrolling gesture(two finger swipe).

All of these tasks were very common tasks for a modern PC user, and should be performed without any difficulties. Videos of the hand postures and its interaction with the keyboard were recorded for further analysis. The total operating time of the recorded data is 187.36 minutes, average operating time is 6.24 minutes per user.

Labeling

The ground truth of whether the user is trying to use the keyboard or touchpad is collected with a foot pedal (see Figure 3.A) switch operated by the participant during the data collection session. Pedal down means pointing and pedal up means typing. We collected 150007 frames from the training data collection session, 25739 were *keyboard frames*, 61896 were *touchpad frames*. The remaining 62372 frames were frames without any touched blobs, we call them *blank frames*. Since those frames didn’t contain any touched blobs. We could safely assume that no user operation was being executed at that moment, so we could classify it into neither keyboard nor touchpad frames. The blank frames were removed from training data while building a classifier, and directly skipped while running on a real-time interactive system, so there would not be any output from our system.

Classification Method

We also implemented Motion Signature [5] to recognize whether the user is trying to use the pointing device or not. Since our sensor’s sampling rate of 13Hz is much lower than the sensor used in [5](325Hz), we only used 30 frames of raw signal to build MHIs. Also, we removed binary-MHI(bMHI) from the original MHI implementation because intensity-MHI already provides enough accuracy for recognizing user intention. We classify the calculated MHIs with Random Decision Forests(RDF), the same classifier used in TypeHoverSwipe [5]. With our hardware system, we can extract touch areas from the image collected with the capacitive sensor grid. Therefore, our system can recognize where the moving touch point is even if the second hand rests on the keyboard.

SYSTEM EVALUATION

We evaluated our system by running various cross-validation tests with usage data collected with 30 participants. In this section, we describe the details of the validation process and result.

Preprocessing Raw Data

After analyzing the raw data, we found all pointing operations are performed on the right side of every *touchpad frames*, because all of our participants are right-handed. This user behavior indicates we can build our classifier, which enables automatic mode switching, with right half of raw images. So we used a 29x20 10-bit image instead of a 58x20 10-bit image as input data for our RDF classifier to speed up the classification process.

Testing Parameters

The forest size improves the performance of RDF classifier at a linear cost of time, to build a real-time interactive system, we set the number of trees to 50 and the maximum depth per tree to 25 for more accurate recognition. While running the experiments, we found the number of frames referenced while building Motion Signature (N_f) can strongly affect the performance for recognizing user intention, so we need to find out a good parameter for the number of frames referenced. We run a 5-fold cross validation with 1-20 frames referenced. The results are shown in Figure 4. We can find that the recognition rate is very low when N_f is 1. Then gradually rising while N_f is increasing. The recognition rate stabilized around 98% when N_f = 30. This means we only need to remember 30 frames to achieve a good recognition rate, and we can recognize the user’s intention with about 2.3 seconds of previous surface action. We found this parameter can have a great impact on the performance of the system, but previous work did not mention this. [5] According to the result, we set N_f = 30 in the following experiments.

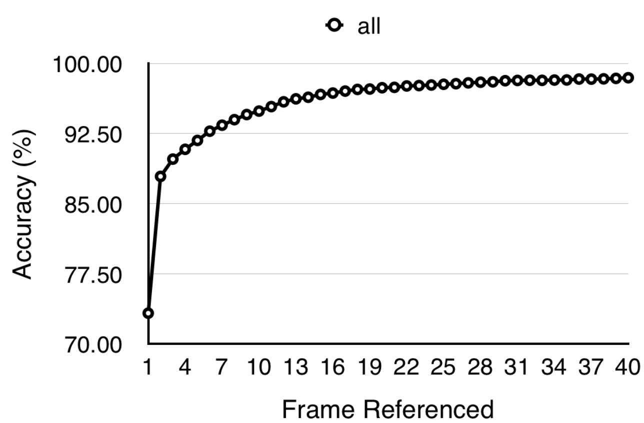

Figure 4. Classification accuracy of 5-fold cross validation for each user and leave-one-user-out cross validation. X axis is number of frame referenced while building Motion Signature (N_f)

Performance

We ran a 5-fold cross validation with each participant’s own data with parameters shown above. The averaged overall

	Keyboard (Predicted)	Touchpad (Predicted)	Keyboard (Predicted)	Touchpad (Predicted)
Keyboard	98%	2%	78%	22%
Touchpad	2%	98%	14%	86%

Table 1. Confusion matrix in a 5-fold cross validation(left) and leave-one-user-out cross validation(right)

recognition rate is 98.83%, with maximum 99.52% and minimum 96.91%. We also conducted a leave-one-user-out cross validation, the averaged overall recognition rate is 83.71%, with maximum 94.62% and minimum 49.53%. Accuracy of leave-one-user-out cross validation strongly depends on users' behavior. If a user's behavior is very similar to another one, his/her accuracy will be relatively higher. When we built a shared classifier with all participant's data, the performance was 98.42% recognition rate in a 5-fold cross validation. The confusion matrix of the shared classifier is shown at Table 1.

DISCUSSION

The performance evaluation of FlickBoard shows a satisfying result with usage data collected from a variety of participants. Because our implementation is based on RDF, it is very easy to adapt to new user behavior with a small amount of training data. In this section, we discuss user behavior, limitations and possible improvements of this prototype.

Observation of User Behavior

All of the participants used only one finger to move cursors without any instructions. Participants reported that they directly adapted their previous experience of using a traditional touchpad, so they used only one finger to touch on the surface of FlickBoard. While we expected most of the users would rest their fingers on the surface of the keyboard, we observed that a large part (19 out of 30) of the users lifted their left hand while using touchpad function(see Figure 3.B). None of the participants could explain the cause of this behavior. Our explanation is that users may treat the whole keyboard as a long touchpad so they remove all the obstacles before using it. Although one-third of the participants did not lift their non-dominant hands while using trackpad, the overall correctness of our classifier remain high (98%), so it is believed that the classifier can distinguish touch from typing whether users rest their non-dominant hands on the keyboard or not. In the meanwhile, most of the users tried to use the touchpad in a very small area, about 3x3 cm for shorter movement. 20 of 30 users operated the cursor on the center area of the keyboard, 9 users operated on the center of the right side, the other 1 user operated on the bottom of right side.

Uneven Touch Surface

Many users reported that the surface of FlickBoard is too uneven to perform smooth cursor pointing operations. The user's fingers may get stuck between the key caps, which make it harder to move his finger to the desired position. This drawback can be solved with some physical modification, such as adding a mechanical structure to lift the case of a Chiclet keyboard to the top of key caps, forming a flat and smooth platform for users to perform a surface operation.

Higher Frame Rate and Resolution

The frame rate of the current prototype may be too low for some time-critical interactions. There are two major bottlenecks of current implementations: sampling speed of the lock-in amplifier and the speed of MCU. Currently, sampling speed of the lock-in amplifier is bounded by two factors: the RC time constant of RC low-pass filter and sampling speed of ADC. Both of them can be improved by using better implementation options, which require modification of the hardware design. On the other hand, we can save more MCU computing power by dividing the raster scanning process into two stages. We can scan a lower resolution image first, calculate possible touch blobs position with it, and perform a higher resolution raster scanning around touched blobs. This modified process is faster in most of the cases (the number of touched blobs < 5), and does not sacrifice precision. As a result, the frame rate can be higher without modifying the hardware setup.

CONCLUSION

We built a prototype to combine a trackpad and a keyboard into a single interaction area and designed a system that can automatically switch between trackpad mode and typing mode with very high accuracy. Furthermore, our system can be adapted to a new user only with small amount of training data (about 6 minutes). Currently, we only enable pointing and 2-finger scrolling gestures in trackpad mode. In the future, we are planning to implement a gesture recognizing system to recognize more multi-touch gestures, such as, swipe, and pinch to enable more functions on our system.

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REFERENCES

1. Fallot-Burghardt, W., Fjeld, M., Speirs, C., Ziegenspeck, S., Krueger, H., and Lubli, T. Touch&type: a novel pointing device for notebook computers. In *NordiCHI'06* (2006), 465–468.
2. Habib, I., Berggren, N., Rehn, E., Josefsson, G., Kunz, A., and Fjeld, M. Dgts: Integrated typing and pointing. INTERACT '09, Springer-Verlag (Berlin, Heidelberg, 2009), 232–235.
3. Rekimoto, J. Smartskin: An infrastructure for freehand manipulation on interactive surfaces. CHI '02, ACM (New York, NY, USA, 2002), 113–120.
4. Rekimoto, J. Thumbsense: Automatic input mode sensing for touchpad-based interactions. CHI EA '03, ACM (New York, NY, USA, 2003), 852–853.
5. Taylor, S., Keskin, C., Hilliges, O., Izadi, S., and Helmes, J. Type-hover-swipe in 96 bytes: A motion sensing mechanical keyboard. CHI '14, ACM (New York, NY, USA, 2014), 1695–1704.