

Distinguishing Multiple Smart-Phone Interactions on a Multi-touch Wall Display using Tilt Correlation

William Hutama

Peng Song

Chi-Wing Fu

Wooi Boon Goh

School of Computer Engineering, Nanyang Technological University, Singapore
{hwilliam,song0083,cwfu,aswbgo} @ntu.edu.sg

ABSTRACT

While very large collaborative surfaces are already being widely employed to facilitate concurrent interactions with multiple users, they involve no personalization in the touch interactions. Augmenting them to identify the touch interactions with multiple smart-phones can enable interesting co-located communal applications with context-based personalized interactions and information exchange amongst users' portable devices and the shared wall display. This paper proposes a novel matching technique, called *tilt correlation*, which employs the built-in tilt sensor to identify smart-phones that make concurrent two-point contacts on a common multi-touch wall display. Experimental investigations suggest that the resultant error rate is relatively low; in addition, we also propose a quantitative measure, called the *Bourne Identity Index* to allow application designers to determine the reliability of each device identification.

Author Keywords

multitouch, accelerometer, personalized interaction

ACM Classification Keywords

H.5.2 : User Interfaces

General Terms

Algorithms

INTRODUCTION

Besides handheld devices, multi-touch interaction is also gaining popularity on surfaces with large form factors like the interactive tabletops, LCD display walls, and projector-based display surfaces. These surfaces [5, 4] are becoming more common as interactive exhibits in public settings, where people can reach and closely interact with the digital contents. While users can intuitively interact with the multi-touch wall, the interaction space is shared with other users without *personalization*. With recent proliferation of personal smart-phones equipped with multi-touch and accelerometer-based tilt sensing, we propose to extend users' interaction with a large multi-touch display to include personal smart-phones.

A number of novel and interesting personalized application scenarios can be realized, for example:

- **Interactive Music Shop Display.** A large multi-touch wall display in a music shop features user browsable song albums. Users can simultaneously interact with the wall; when their phones contact the visuals on the wall, the system can identify the phone and send purchased contents wirelessly to the identified phone. Likewise, audio samples could be downloaded for individual's preview.
- **Public Interactive Bulletin Board.** A large communal multi-touch wall display could be used for many users to simultaneously post advertisements, notices and comments by touching an unused space on the wall with their own smart-phones to upload their posts. Users at another locality of the same digital board could use his smart-phone to touch an existing post to download its content.

The main challenge of these scenarios is the capability to correctly identify the smart-phones that are simultaneously touching (or some may not be touching) the common multi-touch wall display. As for this, we propose to use the built-in tilt detector, i.e., the accelerometer. Since tilt detectors are already widely available on many smart-phones, our approach requires no extra hardware. Moreover, since tilt detectors can report the tilt condition at high sampling rate, we can analyze the devices' tilt condition dynamically during a touch interaction event. By augmenting the protective casing of smart-phones with two contact prongs, the device's orientation when touching the wall can be computed as the angle subtended by the two contact points relative to the wall's horizon. This touch-derived tilt angle can be correlated with the tilt sensor information from all active smart-phones registered in the vicinity. We analyze the identification error rate of the proposed tilt correlation algorithm for both static and dynamic situations, and propose a quantitative reliability measure, called the *Bourne Identity Index*, to accommodate infrequent but sometimes unavoidable mis-identifications.

Related Work. Tilt information provided by handheld devices was initially explored by Rekimoto [7] for developing various user-interaction applications. Rahman et al. [6] experimented with the ergonomics of human wrist when tilting handheld devices with a single hand, whereas Shirazi et al. [10] proposed an interactive card game running on a multi-touch table and personal cell phones; a number of tilting gestures are proposed for the game play.

There are some very recent works on synchronizing events between multiple handheld devices or objects: BumpApp [1] employs accelerometer on smart-phones to synchronize events

when smart-phones are bumped against one another. Wilson and Sarin [12] used vision-based handshaking by triggering infrared (IRDA) port to blink via Bluetooth. Schoning et al. [9] used a similar vision-based handshaking method with an additional camera to detect flash lights and to authenticate users' phone contacts on a large display. Cuypers et al. [3] employed the built-in camera and color-encoded patterns on surfaces to locate smart-phones. Strohbach et al. [11] used cooperative artefacts to track objects activities on a surface, while Schmidt et al. [8] observed the "bump" events between the surface's touch detection and the phone's accelerometer to identify the phone's contact on a common surface.

Comparing to this work, most previous works focus on a one-time authentication and require additional external hardware. Similar to [8], this work employs the built-in accelerometer available in most smart-phones to identify the phone's contact on a common surface. And further than that, this work is capable of observing temporal tilt changes over a longer period of time so that we can continuously identify dynamic contacts between the phones and the display.

TESTBED SYSTEM

Figure 1 depicts our testbed system. The multi-touch wall display is built using the standard laser-light-plane (LLP) method for finger touch detection. Since we propose to touch with a two-prong contact that emulates two rigid fingers in this testbed system, this technique can work on most standard multi-touch surfaces without hardware modification. Our custom-built experimental wall display is of size $120cm \times 80cm$ and is connected to the server PC (Dell workstation with dual CPUs). In our experiments, we employed an iPhone 3GS and two iPod touches as the tilt sensing mobile devices, and connected them to the server PC via wifi. Lastly, we used multi-threading on the server PC to send-and-receive real-time data with these sources.

WORKING SCENARIO

The following outlines the working scenario of our approach:

1. First, the user connects his/her smart-phone to the server PC via wireless so that the server can *continuously monitor* the 3D tilt orientation of all registered phones.
2. Then, the user touches the multi-touch wall display using the two-contact prongs located at the two corners on the front side of the smart-phone.
3. The multi-touch wall display detects the *two blobs* associated with the contact prongs and continuously sends the coordinates of the blob centroids to the server PC at 60Hz while contact remains, see Figure 1 (right).
4. At the same time, the server PC obtains 3D tilt conditions of all active smart-phones. Using the real-time an-

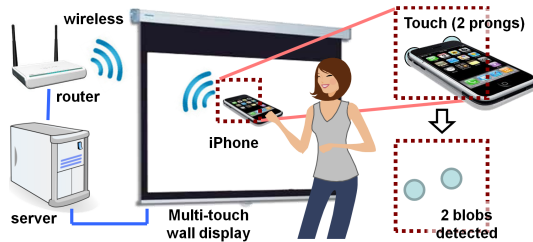


Figure 1. Overview of the testbed system setup.

gular data from these disparate sources, the *tilt correlation* method is then applied to determine the smart-phone that makes the particular touch contact with the wall display. The *Bourne Identity Index* is further computed to estimate the related reliability.

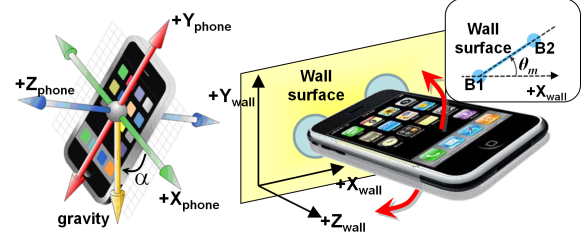


Figure 2. Coordinate systems: the phone (left) and wall display (right).

THE TILT CORRELATION METHOD

Before we discuss the procedural detail of tilt correlation, we first describe the coordinate systems involved:

- The *phone coordinate system* (see Figure 2 (left)) is defined by the built-in accelerometer, with axes aligned with the device; if we tilt the device, this coordinate system will still stay with the device's orientation, but after the tilt, its orientation relative to the wall will be changed.
- The *Wall coordinate system* (see Figure 2 (right)) uses the multi-touch screen coordinates as its coordinate axes, X_{wall} and Y_{wall} , and its surface normal as Z_{wall} .

Step 1) Compute multi-touch angle: θ_m . Given the blobs detected on the multi-touch wall, we compute θ_m , which is the angle measured anti-clockwise from the positive X_{wall} axis to the line segment joining the centroids of the two blobs, see Figure 2 (right). Note that we sort the two blobs so that the y -coordinate of blob B_1 on the wall is always less than that of blob B_2 . Thus, θ_m always ranges $[0^\circ, 180^\circ]$.

Step 2) Compute phone angle: θ_p . The accelerometer in the smart-phone reports the gravity direction from phone to Earth center, as a 3D vector in phone coordinates, see Figure 2 (left). This vector changes upon tilting the phone (up/down), and its components can tell us the angles between the gravity and each phone coordinate axis. Taking α as the angle between $+X_{phone}$ and gravity, and x_{acc} as the X component of gravity vector, we have $\alpha = \cos^{-1}(x_{acc})$.

When the phone's front side contacts the wall, both $+X_{phone}$ and gravity vectors of the phone lie on the wall's XY -plane. Thus we can compute the phone's contact angle on the plane, say θ_p , from α (and the sign of z_{acc} to determine the quadrant). Note that θ_p is measured anti-clockwise from $+X_{wall}$ axis like θ_m and ranges also $[0^\circ, 180^\circ]$. Moreover, we apply a low pass filter using moving-window average to smooth the accelerometer values like most smart-phone applications.

Pre-Step) Calibration. Since tilting sensing with accelerometer is non-linear, see [2], we need a calibration step on θ_p before the system is usable. Here we record time-series data, say $\theta_{m,t}$ and $\theta_{p,t}$ for θ_m and θ_p by slowly rotating the phone over the wall, and apply a degree-five polynomial to fit the mapping, say f , from θ_p to θ_m , to minimize:

$$\sum_t ||\theta_{m,t} - f(\theta_{p,t+t_s})||, \quad (1)$$

where t_s is the time delay shift and \ominus computes the angle difference while considering the wraparound in angular range, see Figure 3 for f . Note that the network latency for the server to receive multi-touch and tilting data is slightly different; we fit also t_s in the above minimization. This calibration process was repeated 5 times to obtain multiple time-series data pairs to improve the parameter estimation, and we compute also the standard deviation, say $\delta\theta$, of all gathered angle differences from the truly matched time-series pairs. The values of t_s and $\delta\theta$ are experimentally found to be around 20 milliseconds and 2.3 degrees, respectively. Note that this calibration is only done once for a particular system setup with the device, e.g., iPhone, and users are not required to do this when using the application.

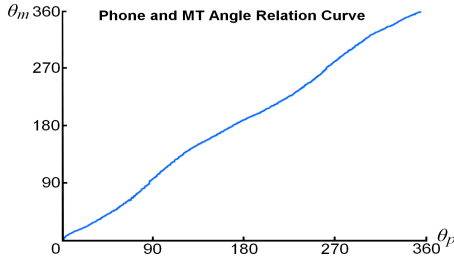


Figure 3. Angle calibration result, f : mapping θ_p to θ_m .

Step 3) Compute Identification Error. Given two time-series of calibrated angles, say $\theta_{m,t}$ and $\theta_{p_i,t}$ where i in p_i refers to the i th active phone, and time $t \in [0, T]$, where $t = 0$ indicates the time when the phone contact is first detected and $t = T$ refers to the present, we define the identification error between the touch event and the i th phone as:

$$E_i = \sum_{t=\max(0, T-T_w)}^T \|\theta_{m,t} \ominus f(\theta_{p_i,t})\|, \quad (2)$$

where T_w is the time window; in practice, T_w is set to be 5 seconds. The smaller the value of E_i , the better the given phone matches the given touch event.

Step 4) Bourne Identity Index. First, we normalize E_i against the standard deviation and the time window size:

$$\hat{E}_i = \frac{E_i}{\min(T_w, T) \delta\theta}. \quad (3)$$

If the k th phone gives the best match, all \hat{E}_i 's except \hat{E}_k are greater than 9, and their Bourne Identity Indices will be one, which indicates a perfect match. In general, we have:

$$R_i = \begin{cases} e^{-\hat{E}_i/10} & \text{if } \hat{E}_i < 9 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Bourne Identity Index (ith)} = R_i / \sum_j R_j.$$

Note that values 9 and 10 are empirical constants from experiments for controlling the cutoff and exponential drop, respectively.

PUTTING IT INTO PRACTICE

To evaluate the tilt correlation method, three tests were conducted with the testbed system. Ten participants (4 females and 6 males; aged 24 to 30 with mean 26.3) were involved, and they were randomly paired up into 5 groups. Each run of

test took around 5 minutes and was carried out with a group of two participants together.

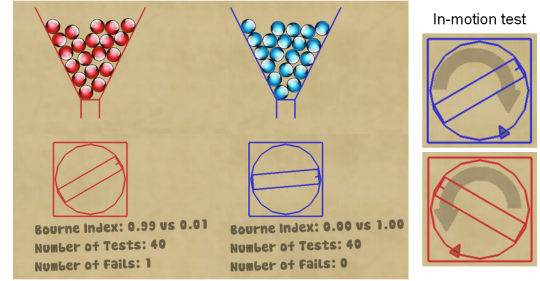


Figure 4. Static test (left); modified locks for in-motion scenario (right).

Static Scenario. After briefing the participants on how to contact a given handheld device with the wall display, i.e., with the prongs on device's front side, we started the graphical program shown on Figure 4 (left) on the wall. Here we had two sets of funnels (top) and door locks (bottom): red for the left and blue for the right. Each participant (in a group of two) was given an iPod touch (for the left) or iPhone 3GS (for the right) on his/her hand, and they were then asked to stand on the respective side of the wall and contact his/her device with the central bar of the door lock on his/her own side. If a multi-touch contact is detected, say on the left door lock, a red ball in the left funnel will pass down and go into the screen of the device identified by the tilt correlation method, and vice versa. Hence, if all identifications are successful, the iPod touch should receive only red balls whereas the iPhone should receive only blue balls.

In this test, each participant was asked to repeatedly touch his/her own door lock bar 40 times casually without coordinating with the other. Each static contact had to last for at least 2 seconds¹, and we randomized (with uniform distribution) the tilt angle of the bars after each touch on them. As a strategy to prevent mis-identifications in this static scenario, the randomization is constrained such that the two bars always maintain an angular separation of at least $3\delta\theta$. Note that this strategy is only needed in static case but not in in-motion scenario below because the dynamic movement in in-motion scenario can bring temporal changes.

Static	User (Left)	User (Right)	Bourne Identity Index	
			Mean (Success)	Failure Case
G1	40/0	39/1	0.950	0.518
G2	39/1	40/0	0.960	0.536
G3	40/0	40/0	0.959	-
G4	40/0	39/1	0.953	0.504
G5	40/0	40/0	0.954	-

Table 1. Identification results of static scenario.

Results. Table 1 shows the identification results. Though three failed cases were found among the identification events (success rate: 99.25%), they all come with a low Bourne Identity Index of around 0.5. In practice, we recommend 0.75 as a reliability cutoff for the Bourne Identity Index.

In-Motion Scenario. Rather than static contacts, we propose another identification strategy, with each door lock ran-

¹The contact time duration was selected arbitrarily; a shorter duration will also work, albeit with a minor fall in accuracy.

domized (also in uniform distribution) with a certain initial angular direction, see Figure 4 (right). In this test, each participant had to rotate his/her device while touching the wall display, mimicking the action of opening a door lock by hand. Since the tilt correlation method examines angles over time (see step 3 in previous section), this in-motion strategy is more accurate as compared to the static strategy.

In this test, the initial tilt angles for the door lock bars were also randomized as in the static test, and each participant was also asked to repeatedly touch his/her own door lock bar 40 times casually. But during the contact, they had to rotate their devices 90 degrees so that the door lock can be opened.

Motion	User (Left)	User (Right)	Bourne Identity Index	
			Mean (Success)	Failure Case
G1	40/0	40/0	0.978	-
G2	40/0	39/1	0.960	0.549
G3	40/0	40/0	0.982	-
G4	40/0	40/0	0.978	-
G5	40/0	40/0	0.971	-

Table 2. Results of in-motion scenario.

Results. Table 2 shows the corresponding results, again with the five groups of participants. This time, only one failed case was found and the resultant Bourne Identity Index for it was found to be relatively low as well.

Scalability Test. Lastly, we conducted a preliminary test on the scalability of tilt correlation. A group of three participants was recruited to do this test with two iPod touches (left and middle) and one iPhone 3GS (right). The in-motion strategy was employed and each participant had to perform the door open action 40 times as in the in-motion scenario.

User(Left)	User(Mid)	User(Right)	Bourne Identity Index	
			Mean(Success)	Failure Case
40/0	40/0	39/1	0.950	0.518

Table 3. Results of scalability test.

Table 3 shows the results; out of 40×3 identification events, there is one failed case, hence giving an accuracy of 99.33%. In general, we conjecture that a group of n users could roughly result in an error rate that is $n(n-1)/2$ times that in the case of 2 users. We leave this as a future investigation.

CONCLUSION

We have proposed a novel algorithm that applies the time-varying tilt information to distinguish multiple smart-phones when they interact with a common wall display. This approach is practical and easy-to-implement since it works on standard multi-touch wall displays and uses the built-in accelerometers that are already widely available in many smart-phones. Additionally, we proposed the time-dependent *Bourne Identity Index* to quantitatively measure the instantaneous reliability by which the tilt correlation algorithm identifies the device that makes the touch contact. Several experiments were devised to demonstrate the method's accuracy, performance, and scalability. As a future work, we envisage the two contact prongs that are used currently could be removed; we will explore the use of line tracking to detect the phone's edge on the multi-touch screen. Moreover, we will investigate the use of our system with children, where

they can use their smart-phones to adopt, deposit or pick up animated characters in a large virtual world shared on a common multi-touch display.

Acknowledgment. We thank comments from anonymous reviewers for improving the clarity of this paper; this work is supported by A*Star SERC grant (No. 092 101 0063).

REFERENCES

1. BumpApp, 2010. Bump Tech. Inc., <http://bu.mp/>.
2. M. Clifford and L. Gomez. Measuring tilt with low-g accelerometers. Application Note AN3107, Freescale Semiconductor, Inc., 2005.
3. T. Cuypers, Y. Francken, C. Vanaken, F. V. Reeth, and P. Bekaert. Smartphone localization on interactive surfaces using the built-in camera. In *Proc. Procams*, pages 61–68, 2009.
4. G. Jacucci, A. Morrison, G. T. Richard, J. Kleimola, P. Peltonen, L. Parisi, and T. Laitinen. Worlds of information: designing for engagement at a public multi-touch display. In *Proc. of Intl. Conf. on Human Factors in Comp. Sys.*, pages 2267–2276, 2010.
5. P. Peltonen, E. Kurvinen, A. Salovaara, G. Jacucci, T. Ilmonen, J. Evans, A. Oulasvirta, and P. Saarikko. It's Mine, Don't Touch!: interactions at a large multi-touch display in a city centre. In *Proc. of Intl. Conf. on Human Factors in Comp. Sys.*, pages 1285–1294, 2008.
6. M. Rahman, S. Gustafson, P. Irani, and S. Subramanian. Tilt techniques: Investigating the dexterity of wrist-based input. In *Proc. of Intl. Conf. on Human Factors in Comp. Sys.*, pages 1943–1952, 2009.
7. J. Rekimoto. Tilting operations for small screen interfaces. In *ACM Symp. on User Interface Software and Technology*, pages 167–168, 1996.
8. D. Schmidt, F. Chehimi, E. Rukzio, and H. Gellersen. PhoneTouch: A technique for direct phone interaction on surfaces. In *ACM Symp. on User Interface Software and Technology*, pages 13–16, 2010.
9. J. Schöning, M. Rohs, and A. Krüger. Using mobile phones to spontaneously authenticate and interact with multi-touch surfaces. In *Advanced Visual Interfaces (AVI) Workshop on designing multi-touch interaction tech. for coupled private and public displays*, 2008.
10. A. S. Shirazi, T. Döring, P. Parvahan, B. Ahrens, and A. Schmidt. Poker surface: Combining a multi-touch table and mobile phones in interactive card games. In *MobileHCI*, 2009. Article 73.
11. M. Strohbach, G. Kortuem, H.-W. Gellersen, and C. Kray. Using cooperative artefacts as basis for activity recognition. In *Proc. European Symposium on Ambient Intelligence*, pages 49–60, 2004.
12. A. D. Wilson and R. Sarin. BlueTable: connecting wireless mobile devices on interactive surfaces using vision-based handshaking. In *Proceedings of Graphics Interface*, pages 119–125, 2007.