Capacitive Fingerprinting: Exploring User Differentiation by Sensing Electrical Properties of the Human Body

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ABSTRACT
At present, touchscreens can differentiate multiple points of contact, but not who is touching the device. In this work, we consider how the electrical properties of humans and their attire can be used to support user differentiation on touchscreens. We propse a novel sensing approach based on Swept Frequency Capacitive Sensing, which measures the impedance of a user to the environment (i.e., ground) across a range of AC frequencies. Different people have different bone densities and muscle mass, wear different footwear, and so on. This, in turn, yields different impedance profiles, which allows for touch events, including multitouch gestures, to be attributed to a particular user. This has many interesting implications for interactive design. We describe and evaluate our sensing approach, demonstrating that the technique has considerable promise. We also discuss limitations, how these might be overcome, and next steps.

ACM Classification: H.5.2 [Information interfaces and presentation]: User Interfaces - Graphical user interfaces; Input devices and strategies.

General terms: Human Factors, Design.

Keywords: User identification; ID; login; collaborative multi-user interaction; swept frequency capacitive sensing; SFCS; Touché; touchscreens; finger input; gestures.

INTRODUCTION
Touch interaction is pervasive, especially on mobile devices. In a typical touch-sensitive interface, applications receive touch coordinates for each finger, and possibly contact ellipsoids as well. However, there is usually no notion as to who is touching – a valuable contextual cue, which could enable a wide range of exciting collaborative and multiplayer interactions [12,19,25,28,30].

There are two basic classes of touch-centric computing that could be enhanced with user identification and tracking. Foremost are large touchscreens, situated on desktops, mounted on walls, or placed horizontally, such as interactive tabletops [20]. These are sufficiently large to accommodate multiple users interacting simultaneously. Second are handheld mobile devices. Their small size and weight allows for them to be easily passed around among multiple users, enabling asynchronous co-located collaboration [16]. Tablet devices occupy the middle ground: portable enough to be easily shared among multiple users, while also providing sufficient surface area for two or more people to interact simultaneously.

In this paper we consider how the electrical properties of users' bodies can be used for *differentiation* – the ability to tell users apart, but not necessarily uniquely identify them. The outcome of our explorations is a promising, novel sensing approach based on Swept Frequency Capacitive Sensing (SFCS) [26]. This approach, which we call *Capacitive Fingerprinting,* allows touchscreens, or other touch sensitive devices, to not only report finger touch locations, but also identify to which user that finger belongs. Our technique supports single finger touches, multitouch finger gestures (e.g., two-finger pinch), bi-manual manipulations [5], and shape contacts [6], such as a palm press. Importantly, our technique requires no user instrumentation – they simply use their fingers as they would on a conventional touchscreen. Further, our technique could be made mobile and enhance a broad variety of mobile devices and applications. Our experiments show the approach is feasible. In a controlled lab study, touches from pairs of users were differentiated with an accuracy of 96 percent. Put simply, four touches in 100 were incorrectly attributed to the other user.

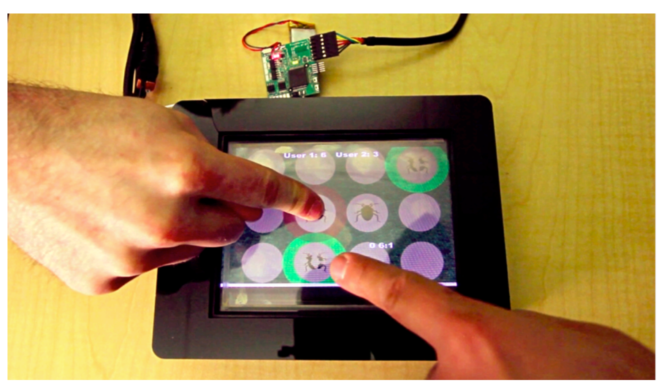

Figure 1. Example two-player "Whac-A-Mole" game. Red highlights indicate user one hits; green for user two. Individual score is kept and shown at top of screen.

RELATED APPROACHES

User identification has implications in many application domains, including security, personalization, and groupware. The fundamental goal of user identification is to understand *who is controlling the input at any given moment* and adjust interaction or functionality accordingly. Attempts to support co-located multi-user interaction on shared displays goes back to at least the late 1980's, with systems such as Boardnoter [29] and Commune [3]. The conceptual and social underpinnings of Single Display Groupware have been extensively researched by Stewart, Bederson, Gutwin and others (see e.g., [12,30]). More recently, there have been efforts to develop toolkits to facilitate "identity enabled" applications [19,23,25,28].

There are significant technical challenges in developing and deploying technologies for user identification, particularly on touchscreens. Foremost, and perhaps most challenging, is that the best techniques avoid instrumenting the user. Further, there should be minimal or no instrumentation of the environment, as external infrastructure is costly and prohibits mobility. Furthermore, the technique must be fast and robust, identifying a large number of users both sequentially and simultaneously. Additionally, it should be inexpensive, easily deployable, sufficiently compact, and have low power requirements, thus making integration into mobile devices feasible. Currently, we are not aware of any system that satisfies all of these requirements.

In attempting to answer this challenge, there has been significant effort put forth to develop technical solutions that can support user identification on touchscreens. One approach is to not uniquely identify each user per se, but rather distinguish that there are multiple users operating at the same time. For example, in Medusa [1], the presence of multiple users can be inferred by proximity sensing around the periphery of an augmented table. Touches to the surface can be attributed to a particular user by using arm orientation sensed by an array of proximity sensors on the table bezel. If users exit the sensing zone, knowledge of the user is lost; upon returning, the user is treated as new. Similarly, Dang et al. [8] used finger orientation cues to back-project to a user, achieving a similar outcome. In both systems, occlusion and users in close proximity (i.e., side by side) are problematic.

Another approach to user identification is to capture identifying features, such that each can be uniquely recognized. One option is to instrument the user with an identifying item, for example, fiducial markers [19] or infrared-code-emitting accessories [21,24]. Researchers have also considered biometric features, such as face [35], hand contour [27] and fingerprint analysis [15,31]. MultiToe [2] uses a series of down-facing Kinect cameras to segment users' shoes for identification purposes. DiamondTouch [9] and DT Controls [10] uniquely ground each user (e.g., through a chair or floor mat wired to the sensing electronics). Because the electrical path is unique to each user, touches on a large shared screen can be sensed quickly and reliably. All of these techniques require large, static setups and/or instrumentation of the user, increasing both cost and complexity, and not permitting truly mobile, ad-hoc interaction.

Finally, there are several systems that employ uniquely identifiable pens, such as in Wacom tablets [32], which use electromagnetic resonance sensing to identify several styli, which could be attributable to different users. TapSense [14] used pens with different tip materials, allowing for pen disambiguation through acoustic sensing. Although robust, these approaches do not support the highly popular direct touch interaction.

CONTRIBUTION

The salient distinguishing feature of our user differentiation approach is that it allows direct touch interaction without requiring instrumentation of either the user or environment – sensing electronics are fully contained within the device. This important property sets it apart from all previous techniques. Further, our technology is sufficiently compact, low-powered and inexpensive to enable integration into mobile devices and allow for truly mobile interactions. Additionally, user classification occurs in real time; the initial "first-touch" calibration takes less than a second. Finally, our approach is not sensitive to occlusion, orientation, lighting, or other factors that are problematic for computer vision driven methods.

At present, *Capacitive Fingerprinting* also has several drawbacks. Foremost, it can differentiate only among a small set of concurrent users. Further, users can only touch sequentially, not simultaneously. There are additional limitations regarding the persistence of identification. Finally, although our experimental results are promising, robustness needs to be improved for real world use.

Nonetheless, this work puts forward a novel and attractive approach for user differentiation that has not been proposed previously. This paper assesses and confirms the feasibility of the approach and expands the toolbox of techniques HCI researchers and practitioners can draw upon. Similar to any other user identification approach, *Capacitive Fingerprinting* offers a distinct set of pros and cons. Given that a sensor fusion approach might ultimately prove strongest for user identification, we believe that our approach may fill important gaps in the feature space used for classification. We hope this work will contribute to the ultimate goal of robust and unobtrusive technologies for differentiating and identifying users in a broad variety of applications.

CAPACITIVE FINGERPRINTING

Our approach is based on the fundamental observation that every human body has varying levels of bone density, muscle mass, blood volume and a plethora of other biological and anatomical factors. Furthermore, users also wear different shoes and naturally assume different postures, which alters how a user is grounded. As a consequence, the electrical properties of a particular user can be fairly unique, like a *fingerprint*, from which we derive our system's name. Therefore, if one can accurately measure the electrical properties of a user, it should be possible to identify, or at least differentiate, the person.

Humans have a multitude of electrical properties that can be measured, such as vital signs (e.g., EKG). In this paper, we estimate impedance profiles of users at different frequencies, by using recently proposed SFCS techniques [26]. The advantage of SFCS is that it is trivial to instrument devices, as only a single electrode and wire are needed. Furthermore, it is inexpensive, and it does not require user to wear or hold any additional devices. We are not aware of previous attempts to explore SFCS for user identification.

The fundamental physical principle behind *Capacitive Fingerprinting* is that the path of alternating current (AC) in a human body depends on the signal frequency [11]. This is because the opposition of body tissues, blood, bones, etc., to the flow of electrical current – or body electrical impedance – is also frequency dependent. For example, at 1 kHz bone has a resistivity of approximately 45 Ω•m, but at 1 MHz it's resistivity increases to ~90 Ω•m (Figure 2) [11]. Since the AC signal always flows along the path of least impedance, it is theoretically possible to direct the flow of the current through various paths inside the user's body by sweeping over a range of frequencies.

As the signal flows through the body, the signal amplitude and phase change differently at different frequencies. These changes can be measured in real time and used to build a frequency-to-impedance profile. Different people, by virtue of having unique bodies, should exhibit slightly different profiles. Although we do not specifically model this relationship, our fingerprint-based classification approach relies on it.

Importantly, *Capacitive Fingerprinting* is a non-invasive technique – we do not require a special purpose ground electrode be coupled to users (as in [9,10]). Instead, we use the natural environment as ground (i.e., the floor). This also means shoes influence the impedance profile. As shown in [2], users' shoes are also fairly unique and aid poster classification.

We should note that impedance measurements of the human body have been used since the 1970s in medical diagnostics, such as measuring fluid composition and BMI [11,17] and electro-impedance tomography imaging [7]. Despite a long history of such measurements, the correla-

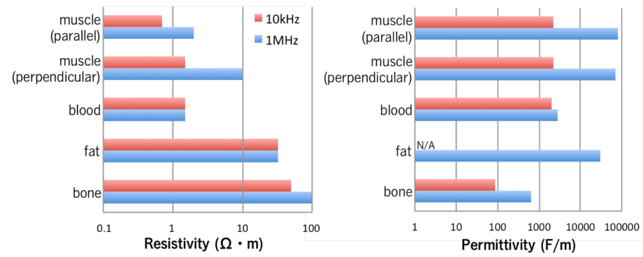

Figure 2. Mean permittivity and resistivity of different tissues (from [11]).

tion between measured body impedance and properties of the human body are still not fully understood [11]. Most often, just one or two frequencies are used for such measurements and we are not aware of any attempts to apply this technique in HCI applications. *Capacitive Fingerprinting* should not be confused with galvanic skin response (GSR), which measures the conductivity of the skin (see e.g., [18,22] for applications in HCI).

PROTOTYPE

We created a proof-of-concept system seen in Figure 1 and schematically described in Figure 3. To capture and classify impedance profiles among a small set of users, we employ Swept Frequency Capacitive Sensing (SFCS), introduced as Touché [26]. Beyond the Touché sensor board, our system consists of a 6.7" LCD panel, a 6.4" IR touch screen, and an Indium Tin Oxide (ITO) coated transparent plastic sheet.

The Touché sensor board generates a 6.6V peak-to-peak sinusoidal wave, ranging in frequency from 1KHz to 3.5MHz, using 200 steps. This signal is injected into an ITO sheet situated on top of the LCD panel. When a user touches the ITO sheet, an electrical connection to the Touché sensor is created (the user is also grounded to the environment). The current of the sine wave is significantly lower than 0.5 mA, safe for humans and on par with commercially available touchscreens [33]. Impedance profiles are sent over USB to a computer approximately 33 times per second. Note that our present sensor board does not measure the true impedance of the body, but rather measures the amplitude component. Specifically, it creates a voltage-divider circuit with a resistor and samples this with an AD converter. We leave measurement of the phase component to future work.

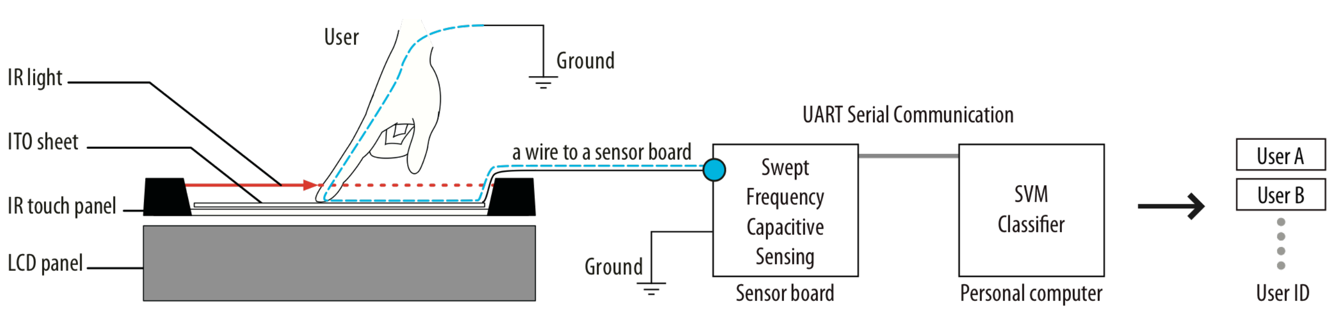

Figure 3. A cutaway view of the touchscreen layers, which are connected to a Touché sensor board. Here, when a user touches the screen; our classifier attributes the touch event to a set of users that have previously logged in.

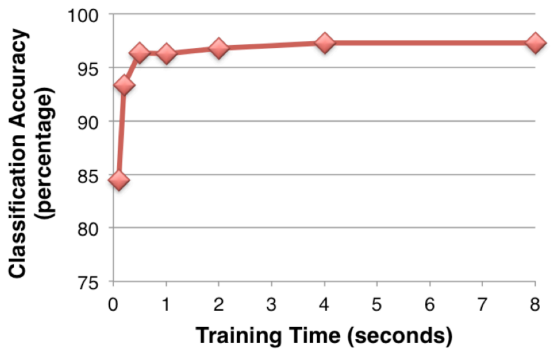

Figure 4. Impact on classification performance by varying classifier training data from 0.1 seconds (1 sample per participant) to 8 seconds (80 samples per participant).

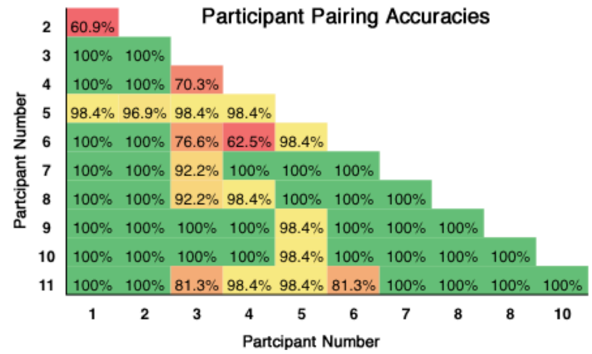

Figure 5. Classification accuracies for all trial participant pairings. Classifer was trained using 0.5 seconds of finger training data (5 samples per participant).

We first attempted to build our system on top of a capacitive touch input panel. However, we found that the conductive nature of the ITO sheet interfered with touch sensing. Simultaneously, the conductive layers inside capacitive and resistive touchscreens interfered with SFCS. This necessitated the use of an electrically passive sensing technology. We selected an IR-driven touch panel, though several other technologies are applicable (e.g., Surface Wave Acoustic). It is important to note, however, that with tighter hardware integration it may be possible to use e.g., a projective capacitive touchscreen for both touch and impedance sensing.

The final component of our system is a conventional computer running a classification engine. We use a Support Vector Machine (SVM) implementation provided by the Weka Toolkit [13] (SMO, C=2.0, polynomial kernel, e=1.0). We employ the same feature set used successfully in [26]. Our setup provides 200-point impedance profiles 33 times per second. When a user first touches the screen, ten impedance profiles are captured, taking approximately 300ms. Each profile is classified in real time; a majority-voting scheme is used to decide on the final classification. This improves accuracy, as the first 100ms of touch can be unstable due to the user not yet making full contact. This final classification result is paired with the last touch event.

EXPERIMENTAL EVALUATION

The first fundamental question that we aim to answer in this paper is: *can we use measured electrical properties of a user's body for differentiation*? To answer this question, we conducted an evaluation that included 11 participants (two female, mean age 28.1) recruited from our industrial research lab. Our evaluation consisted of two phases. First, we collected data for the purpose of training our classifier. The second phase collected independent data for the purpose of evaluating our classifiers. The experiment took approximately 20 minutes.

Procedure

During the *training data* collection, users were asked to touch a single point in the center of the screen for 8 seconds while rocking their finger back-and-forth and side-to-side (see Video Figure). This helped to capture variability in finger pose and pressure that might be naturally encountered through extended use, but unlikely reflected in a typical, single touch event. During the touch period, 10 samples were collected per second, yielding 80 data points per participant. We were also interested in evaluating how the technique scaled to other gestures beyond simple finger touches. The same procedure was used to collect data for a two-finger pinch (using one hand), a bi-modal two-finger touch, and resting the palm on the screen.

Note that we deliberately chose to collect data from a single touch (i.e., single point) on the touchscreen, as this best simulated a "login button" experience. Although multipoint collection would yield more data, and potentially stronger results, pilot testing suggested that this would be impractical for real world use and applications.

During *testing data* collection, a 4x4 grid of numbered crosshairs was provided as touch targets. Users were asked to touch, with a single finger, each crosshair in order. Two rounds were completed, yielding 32 touch events per participant. In addition, participants performed, in locations of their choosing, ten one-handed pinches, ten bi-modal two-finger touches, and ten palm touches. In total, this process provided 62 touch events, using four different gestures, distributed over the entire surface of the screen.

When investigating a new sensing technique, it is beneficial to control various experimental factors so as to best isolate the innate performance of the technique. Once this has been established, it is then interesting to relax various constraints to explore the broader feasibility. Following this mantra, during the experiment users were asked to stand with both feet on the floor, providing a relatively consistent connection to the floor.

Pairing Users

To assess our system's feasibility, we investigated user differentiation accuracy for pairs of users. Instead of running a small number of pairs live, we used train/test data from our 11 participants to simulate 55 pairings (all combinations of participants). For example, in a trial pairing participant 1 with participant 2, the system was initialized with training data from 1 and 2. The resulting classifier was then

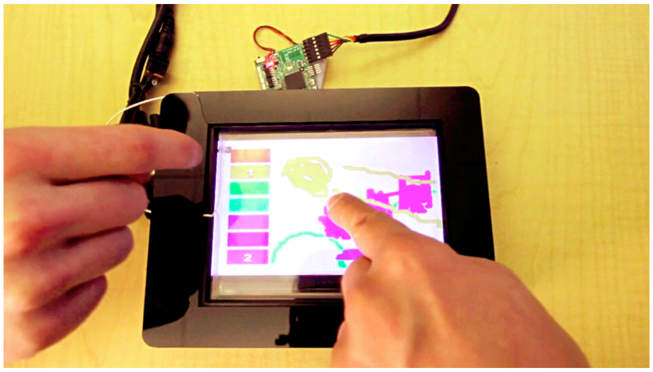

Figure 6. Example painting application. Two users can select colors from a palette on the left of screen. The system records each user's selection, allowing users to paint in a personalized color.

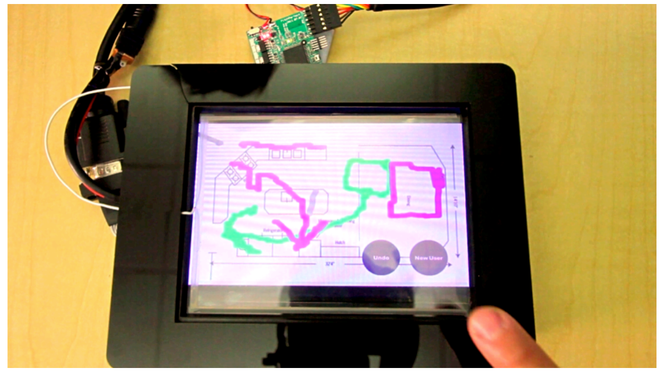

Figure 7. Example – sketching application. Each user has a different drawing color to attribute edits. An "undo" button is provided, allowing users to undo strokes from their personal edit history.

fed unlabeled testing data from participants 1 and 2 combined and in a random order. This simulated sequential touch events as if the users were co-located. From the perspective of the classifier, this was no different than real-time operation.

Results

Looking first at single finger touches, performance using all 8 seconds of training data yielded an all-pairs average accuracy of 97.3% (SD=5.9%). Figure 4 illustrates the classification performance with different volumes of training data, varying from 0.1 second (1 training sample per participant) to 8 seconds (80 training samples per participant). Performance significantly plateaus after 0.5 seconds of training data (5 training sample per participant), which achieves 96.4% accuracy (SD=9.0%). Figure 5 shows classification accuracies for all user pairings. Of note, two thirds of pairings had 100% differentiation accuracy.

These findings underscore two key strengths of our approach. Foremost, the fact the system is able to perform at 84.5% accuracy (SD=18.9%) with a single training instance from each user suggests the feature space we selected is highly discriminative between users. Second, 0.5 seconds appears to be a sweet spot, in particular, a nice balance between classification accuracy and training duration. Whereas an 8-second login sequence would significantly interrupt interactive use, 500ms is sufficiently quick to be of minimal distraction. Given that our current approach requires users to login each time they want the system to differentiate them, this interaction has to be extremely lightweight if it is to be practical.

We ran a second, post-hoc simulation that included all gestures: single finger touches, one-handed pinches, bi-modal two-finger touches, and palm touches. The goal was not to distinguish between different gestures, as demonstrated in [26], but rather to distinguish between users performing a variety of gestures. Our classifier was trained on 20 samples per participant (5 samples per gesture), representing 2 seconds of training data. Our testing data consisted of all 62 touch events from our testing data collection. Again using all 55 simulated participant pairings, average accuracy was 97.8% (SD=6.9%). This is very similar in performance to finger-touch-only performance using 2 seconds of training data (both classifiers were trained on 20 samples per participant).

We repeated the latter experiment using a single frequency in order to demonstrate the utility of employing a swept frequency approach. We used attribute selection to identify 753.5kHz as the single best frequency at which to differentiate users. It should be noted that in a real world system this ideal frequency depends on the set of users and environmental conditions, and thus cannot be known *a priori* – thus our estimate is idealized. On average, user differentiation was 87.3% accurate vs. 97.8% when all frequencies were used, or roughly six times the error rate.

EXAMPLE APPLICATIONS

The second research question that we would like to answer in this paper is: *what are the real-world implications of this technique*? To begin to address this question, we designed three simple exemplary applications based on *Capacitive Fingerprinting*. These applications demonstrate different interaction possibilities if user differentiation was available on touchscreens (see also the accompanying Video Figure).

For example, there are many games, especially for tablets, that allow two users to play simultaneously. When individual scoring or control is needed, interfaces most typically have a split view. However, this limits game design possibilities and decreases the available screen real estate for each player. Using *Capacitive Fingerprinting*, it is possible for two players to interact in a common game space. To demonstrate this, we created a "Whac-A-Mole" game [34], seen in Figure 1. Targets appear out of random holes; players must press these with their fingers before they return underground. Each time a player successfully hits a target, he gains a point; individual scores are kept for each player automatically and transparently for each user.

In another example, we created a painting application (Figure 6), where two users can paint with their own selected color. For example, User A can select red and paint in red, while User B can select blue and paint in blue without affecting User A's selection. This could be trivially extended to brush type, thickness, opacity, and similar features. In a general sense, *Capacitive Fingerprinting* ought to allow users to operate on the touch interface with personalized properties [25]. Further, because applications identify the owner of each stroke, it is possible to support individualized undo stacks – a feature we built into a simple sketching application (Figure 7).

LIMITATIONS AND CHALLENGES

The experimental results suggest that measuring the impedance of users is a promising differentiation approach. However, our study and exemplary applications brought to light several limitations and challenges. These include:

Persistence of identification: Calibration seems to be sensitive to changes in the human body over the course of the day. Thus, walking away and returning hours (or certainly days) later is not currently possible. We hypothesize that environmental factors, such as ambient temperature and humidity, as well as biological factors, such as blood pressure and hydration, cause impedance profiles to drift over time. This personal change variability can be larger than between-person variability. This suggests use scenarios where interaction is ad hoc and relatively short, or where the precision of recognition is not critical.

Because of this limitation, we instituted a login procedure for all of our example applications. Specifically, when a user wants to join a multi-user collocated interaction, he must first press and hold a "login button" (see Video Figure). This triggers the system to capture an impedance profile (of the finger pressing the button) and retrain the classifier. As discussed in the evaluation section, this interaction can be completed as quickly as 500ms.

Ground connection: The electrical properties of the user cannot be taken separately from the electrical properties of the environment. However, since the environment is typically the same for co-located users, per-user differences are detectable. The system is sensitive to how a user is connected to ground. For example, if a user logs into the system while seated and then attempts to use it standing, recognition can be poor. By changing the global impedance of a user so dramatically, the user variations are often obscured. The user must re-login so as to register a new impedance profile. Future work is required to study this in more detail, as well as to develop possible techniques to overcome this limitation.

Sequential touch: A further limitation is that our system currently uses a single electrode, covering the entire touch surface. As a consequence, our current prototype can only process a single touch at a time (i.e., two users cannot press the screen simultaneously and be differentiated). It is likely, though not tested, that a mosaic of electrodes, as seen in some forms of projective capacitive touchscreens, could be used to overcome this by sampling the smaller regions which are unlikely to fit two users.

Robustness: Our experimental results suggest a fairly robust system with paired-user accuracies in excess of 96%. However, we caution that a controlled lab study is not a good proxy for real-world use. Our experimental results should be viewed as evidence that the underlying technique is valid and may be a tenable way forward for supporting instrumentation-free, identity-enabled, mobile touchscreen interaction – the first technique to achieve this end. This opens up the possibility of future work, which we discuss next.

FUTURE WORK

Combining *Capacitive Fingerprinting* with other sensing techniques is of great interest. Sensor fusion approaches generally aim to merge multiple imperfect techniques to achieve a superior outcome. Our approach has a unique set of strengths and weaknesses that lend well to this approach. We are also interested in exploring adaptive classifiers, where the system could continuously collect training data from users and integrate changes, including natural drift.

It may also be possible to identify specific situations where the difference between two users is sufficiently dramatic, so that login is no longer necessary and a persistent general classifier can be used. One example application scenario is differentiation between parents and children, or teacher and young student, where games and educational experiences may be designed according to who is providing input. For example, in an educational application a teacher could draw a hint to help a student solve a math problem; the hint then would fade out after a few seconds, prompting the student to complete the problem him or herself.

Finally, we are also interested in exploring applications of *Capacitive Fingerprinting* in highly controlled environments or applications where exact user identification is not necessary - so called *soft biometrics*. In-car entertainment systems are a prime example. We are also curious as to how our approach could be applied to differentiating between humans and non-humans (e.g., bags, drinks) in ride systems and other applications.

CONCLUSION

In this paper we have described how sensing of humans electrical properties can be used for interactive user differentiation. We integrated this approach into a small, touchscreen device and built three simple demo applications to highlight some basic uses of user-aware interaction. The evaluation of our sensing technique demonstrated that the approach holds significant promise. We hope that the current research will encourage HCI researchers and practitioners to investigate this interesting and exciting technology direction.

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REFERENCES

1. Annett, M., Grossman, T., Wigdor, D., and Fitzmaurice, G. Medusa: a proximity-aware multi-touch tabletop. In *Proc. UIST '11*. 337-346.
2. Augsten, T., Kaefer, K., Meusel, R., Fetzer, C., Kanitz, D., Stoff, T., Becker, T., Holz, C., and Baudisch, P. Multitoe: high-precision interaction with back-projected floors based on high-resolution multi-touch input. In *Proc. UIST '10*. 209-218.
3. Bly, S.A., and Minneman, S.L. Commune: A Shared Drawing Surface." In *SIGOIS Bulletin*, Massachusetts, 1990. 184-192.
4. Burges, C.J. A Tutorial on Support Vector Machines for Pattern Recognition. *Data Mining and Know. Disc.*, 2.2, June 1998. 121-167.
5. Buxton, W., and Myers, B. A study in two-handed input. In *Proc. CHI '86*. 321-326.
6. Cao, X., Wilson, A., Balakrishnan, R., Hinckley, K., and Hudson, S.E. ShapeTouch: Leveraging contact shape on interactive surfaces. In *Proc. TABLETOP '08*. 129-136.
7. Cheney, M., Isaacson, D., and Newell, J.C. Electrical impedance tomography. *SIAM Review*, 41(1), 1999. 85-101.
8. Dang, C.T., Straud, M., and Andre, E. Hand distinction for multi-touch tabletop interaction. In *Proc. ITS '09*. 101-108
9. Dietz, P. and Leigh, D. DiamondTouch: a multi-user touch technology. In *Proc. UIST '01*. 219-226.
10. Dietz, P.H., Harsham, B., Forlines, C., Leigh, D., Yerazunis, W., Shipman, S., Schmidt-Nielsen, B., and Ryall, K. DT controls: adding identity to physical interfaces. In *Proc. UIST '05*. 245-252.
11. Foster, K.R. and Lukaski, H.C. Whole-body impedance - what does it measure? *The American Jour. of Clinical Nutrition, 64* (3), 1996. 388S-396S.
12. Gutwin, C., Greenberg, S., Blum, R. and Dyck, J. Supporting Informal Collaboration in Shared Workspace Groupware. HCI Report 2005-01, U. Saskatchewan, Canada. 2005.
13. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., and Witten, I.H. The WEKA Data Mining Software: An Update. *SIGKDD Explor*., 11(1), 2009.
14. Harrison, C., Schwarz, J., and Hudson, S.E. TapSense: enhancing finger interaction on touch surfaces. In *Proc. UIST '11*. 627-636.
15. Holz, C. and Baudisch, P. The generalized perceived input point model and how to double touch accuracy by extracting fingerprints. In *Proc. CHI '10*. 581-590.
16. Lucero, A., Holopainen, J., and Jokela, T. Pass-them-around: collaborative use of mobile phones for photo sharing. In *Proc. CHI '11*. 1787-1796.
17. Lukaski, H., Johnson, P., Bolonchuk, W., and Lykken, G. Assessment of fat-free mass using bioelectrical impedance measurements of the human body. *The American Jour. of Clinical Nutrition.* 41, 4 (1985), 810-817.
18. Mandryk, R.L. and Inkpen, K.M. Physiological indicators for the evaluation of co-located collaborative play. In *Proc. CSCW '04*. 102-111.
19. Marquardt, N., Kiemer, J., Ledo, D., Boring, S., and Greenberg, S. Designing user-, hand-, and handpart-aware tabletop interactions with the TouchID toolkit. In *Proc. ITS '11*. 21-30.
20. Matsushita, N. and Rekimoto, J. HoloWall: Designing a Finger; Hand, Body, and Object Sensitive Wall. In *Proc. UIST '97*. 209-210.
21. Meyer, T. and Schmidt, D. IdWristbands: IR-based user identification on multi-touch surfaces. In *Proc. ITS '10*. 277-278.
22. Moore, M.M. and Dua, U. A galvanic skin response interface for people with severe motor disabilities. In *Proc. ASSETS '04*. 48-54.
23. Partridge, G.A. and Irani, P.P. IdenTTop: a flexible platform for exploring identity-enabled surfaces. In *CHI EA '09*. 4411-4416.
24. Roth, V., Schmidt, P., and Guldenring, B. The IR ring: Authenticating users' touches on a multi-touch display. In *Proc. UIST '10*. 259-262.
25. Ryall, K., Esenther, A., Everitt, K., Forlines, C., Morris, M.R., Shen, C., Shipman, S., and Vernier, F. iDwidgets: Parameterizing widgets by user identity. In *Proc. INTERACT '05*. 1124-1128.
26. Sato, M. Poupyrev, I, and Harrison, C. Touché: Enhancing Touch Interaction on Humans, Screens, Liquids, and Everyday Objects. In *Proc. CHI '12*. 483-492.
27. Schmidt, D., Chong, M.K. and Gellersen, H. HandsDown: hand-contour-based user identification for interactive surfaces. In *Proc. NordiCHI '10*. 432-441.
28. Shen, C., Vernier, F.D., Forliens, C., and Ringel M. DiamondSpin: an extensible toolkit for around-the-table interaction. In *Proc. CHI '04*. 167-174.
29. Stefik, M., Bobrow, D. G., Foster, G., Lanning, S., and Tatar, D. WYSIWIS Revised: Early experiences with multiuser interfaces. *IEEE Transactions on Office Information Systems*, 5(2), 1987. 147-167.
30. Stewart, J. Bederson, B., and Druin, A. Single Display Groupware: A Model for Co-present Collaboration. In *Proc. CHI '99*. 286-293.
31. Sugiura, A. and Koseki, Y. A user interface using fingerprint recognition: holding commands and data objects on fingers. In *Proc. UIST '98*. 71-79.
32. Wacom tablet. http://wacom.com/en/Products/Intuos.aspx
33. Webster, J., Editor. *Medical instrumentation: Application and design.* 4th ed. 2008, Wiley. p. 641.
34. Whac-a-mole. http://en.wikipedia.org/wiki/Whac-A-Mole
35. Zhao, W., Chellappa, R., Phillips, P.J., and Rosenfeld, A. Face recognition: A literature survey. *ACM Comput. Surv.* 35(4), Dec. 2003. 399-458.