Enhancing Input On and Above the Interactive Surface with Muscle Sensing

Hrvoje Benko[1], T. Scott Saponas[1,2], Dan Morris[1], and Desney Tan[1]

[1]Microsoft Research
Redmond, WA, USA
{benko, dan, desney}@microsoft.com

[2]Computer Science and Engineering Dept.
University of Washington,
Seattle, WA, USA
ssaponas@cs.washington.edu

ABSTRACT

Current interactive surfaces provide little or no information about which fingers are touching the surface, the amount of pressure exerted, or gestures that occur when not in contact with the surface. These limitations constrain the interaction vocabulary available to interactive surface systems. In our work, we extend the surface interaction space by using muscle sensing to provide complementary information about finger movement and posture. In this paper, we describe a novel system that combines muscle sensing with a multi-touch tabletop, and introduce a series of new interaction techniques enabled by this combination. We present observations from an initial system evaluation and discuss the limitations and challenges of utilizing muscle sensing for tabletop applications.

Author Keywords

Surface computing, tabletops, muscle sensing, EMG.

ACM Classification

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

INTRODUCTION

Interactive surfaces extend traditional desktop computing by allowing direct manipulation of objects, drawing on our experiences with the physical world. However, the limited scope of information provided by current tabletop interfaces falls significantly short of the rich gestural capabilities of the human hand. Most systems are unable to differentiate properties such as which finger or person is touching the surface, the amount of pressure exerted, or gestures that occur when not in contact with the surface. These limitations constrain the design space and interaction bandwidth of tabletop systems.

In this paper, we explore the feasibility of expanding the interaction possibilities on interactive surfaces by sensing
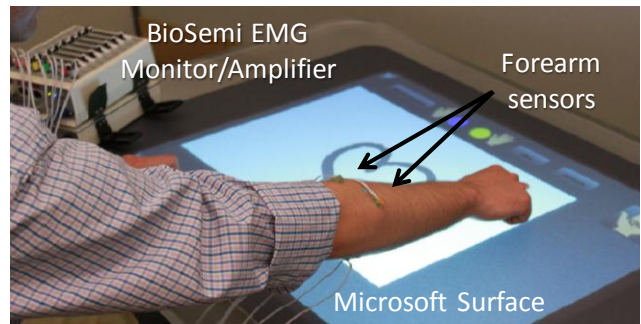
Figure 1. Our system uses electromyography (muscle activity) sensors placed on the forearm to infer finger identity, estimate finger pressure, and allow off-surface gestures.

muscle activity via *forearm electromyography* (EMG). EMG allows us to infer additional information about each contact with an interactive surface, and provides novel information about hand and finger movement away from the surface. We employ muscle sensing in combination with the contact sensing of a standard multi-touch tabletop (Microsoft Surface) and introduce novel interactions that emerge from this combination of sensor streams.

As demonstrated in previous sensor fusion work, the combination of multiple complementary streams can often be greater than sum of the parts [8,10,15]. For example, in our work, we use muscle sensing to determine which finger is in contact with a surface, assess the level of pressure exerted by the user while they are pressing down, and even detect activity when a user's hand is not in contact with the surface. Combining these sensing modalities allows us to explore finger-specific input, pressure-sensitive interaction, and free-space gestures that complement traditional on-surface interactions.

The contributions of this paper are: (1) a novel multimodal system that combines muscle-sensing with interactive surface input; (2) four proof-of-concept interaction techniques that make use of finger identification, pressure detection, and free-space hand movement in conjunction with surface contact information; (3) a preliminary system evaluation demonstrating the feasibility of our approach; and (4) a discussion of the benefits and limitations muscle

sensing offers as a complementary technology to those employed by the tabletop community.

BACKGROUND AND RELATED WORK

We briefly review relevant work on interactive surfaces and provide background on muscle-sensing and its use in human-computer interaction.

Interactive Surface Sensing

While most available multi-touch systems are capable of tracking various points of user contact with a surface (e.g., [5]), the problem of identifying particular fingers, hands, or hand postures is less well solved. Existing approaches to solving this problem include camera-based sensing, electro-static coupling, and instrumented gloves.

Several camera-based interactive surface systems have demonstrated the capability to image the user's hands, either above the display (e.g., [22]) or through the display (e.g., [2,20]), but none of these explore contact identification or freehand interactions in the space above the surface. Malik et al. [13] used two overhead cameras to detect hand postures as well as which finger of which hand touched a surface, but required a black background for reliable recognition. In general, camera-based approaches have two shortcomings: fingers and hands can easily be occluded and contact pressure is not robustly observable.

Techniques such as frustrated total internal reflection (FTIR) [7] are able to estimate contact pressure by detecting changes in the shape of a contact that are often indicative of pressure changes; however, this approach has limited precision, and FTIR systems cannot reliably discriminate contact shape changes due to posture adjustments from those due to pressure variation. FTIR systems also cannot reliably identify contacts as belonging to particular fingers.

Benko et al. [1] demonstrated a multi-finger interaction technique which required users to wear instrumented gloves for finger identification. Gloves have also been extensively used in virtual reality research. For example, Cutler et al. [4] used gloves for above-the-surface 3D interactions. While simple and reliable, gloves suffer from many issues, including hygiene, comfort, access time, and a reduction in the directness offered by "direct touch" interfaces.

Interaction in the space *above* the interactive surface has also been explored with styli [12], video cameras [21, 22, 23], and depth-sensing cameras [2,24]. The use of depth-sensing cameras is particularly of interest, as it facilitates precise 3D hand positioning and gesture-tracking without requiring the user to wear on-body sensors. However, low sensing resolution, finger visibility, and occlusion issues make such approaches potentially more error-prone than the approach described in this paper. In addition, neither depth-sensing or standard video cameras are able to directly sense contact pressure and require gestures to be "within sight" of the surface. Other technologies such as Izadi et

al.'s SecondLight [9] permit projection onto objects held in the space above the surface. While supporting an interesting set of interactions, this does not allow input away from the surface, only output.

While not in the domain of surface computing, Sugiura and Koseki [19] demonstrated the concept of finger-dependent user interface elements and interactions. They relied on a standalone fingerprint reader to determine which finger was used and assigned data and specific properties to each of the user's fingers.

Muscle Sensing

In an independent line of work, researchers have demonstrated the feasibility of using forearm electromyography (EMG) to decode fine finger gestures for human-computer interaction [17,18]. EMG measures the electrical signals used by the central nervous system to communicate motor intentions to muscles, as well as the electrical activity associated directly with muscle contractions. We refer the reader to [14] for a thorough description of EMG.

EMG has conventionally been used in clinical settings for gait analysis and for muscle function assessment during rehabilitation. More recent research has explored the use of EMG for direct input, specifically for controlling prosthetic devices (e.g. [6,16]). Work in this area has demonstrated experimentally that such a system can be used to differentiate among finger and hand gestures performed by hands resting on a non-interactive table [20,25,26]. Furthermore, these gestures extend to scenarios in which the user's hand is not constrained to a surface, including gestures performed when holding objects [18].

COMBINING MUSCLE AND TOUCH SENSING

Touch-sensitive surfaces and EMG provide complementary streams of information. Touch-sensitive surfaces provide precise location and tracking information when a user's hand is in contact with the surface. They can also precisely record temporal information about the arrival and removal of contacts. EMG can detect which muscle groups, and consequently which fingers, are engaged in the current interaction. It can also approximate the level of activation of those muscle groups, which allows the estimation of contact pressure. Furthermore, EMG can provide information about an interaction even when a user's hand is no longer in contact with a surface. However, EMG cannot provide spatial information, and is not as reliable as touch-sensing for temporally-sensitive gestures. We thus introduce a multimodal system that relies on surface input for spatial information and muscle sensing for finger identification, pressure, and off-surface gestures.

Hardware and Setup

Our system is implemented using a Microsoft Surface (http://microsoft.com/surface) and a BioSemi Active Two EMG device (http://biosemi.com). The EMG device samples eight sensor channels at 2048 Hz.
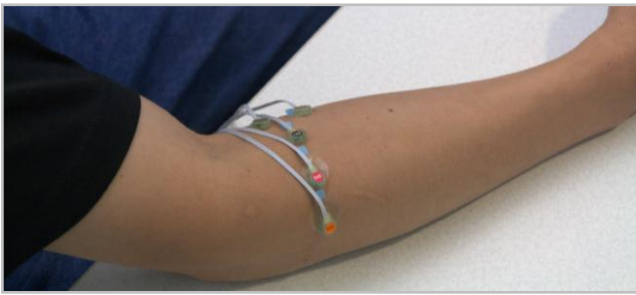
Figure 2. EMG sensors on a user's arm.

We placed six sensors and two ground electrodes in a roughly uniform ring around the upper forearm of the user's dominant hand for sensing finger gestures (Figure 2). We also placed two sensors on the forearm of the non-dominant hand for recognizing coarse muscle activation. We chose this configuration to minimize setup complexity while allowing us to demonstrate the feasibility of bimanual interactions. The current asymmetric setup was a constraint of only having 8 sensor channels, and beyond this, more sensors on both arms would yield finer resolution of muscles and touches.

In general, our approach was to place EMG sensors in a narrow band on the upper forearm, which we believe is relatively unobtrusive while allowing us to sense finger movements accurately. Our current system utilizes a wired connection between the sensors and an amplifier, but wireless EMG systems such as that made by ZeroWire (http://zerowire-emg.com) have recently become commercially available. We envision our system eventually becoming a thin wireless band worn just below the elbow.

Interpretation of Muscle Signals

Our system uses the EMG signals to provide four primitives to applications on the interactive surface.

Level of pressure. The *pressure* primitive is a smoothed, down-sampled representation of the raw level of muscle activation on the dominant hand. This feature requires no
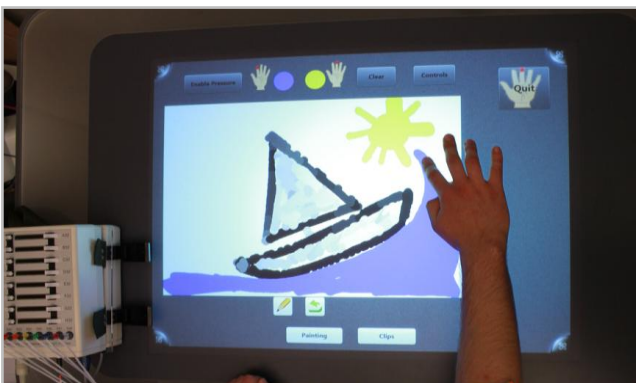

Figure 3. An example drawing demonstrates both pressure-painting and finger-dependent painting. A different color is mapped to each finger, and pressure controls stroke saturation.

training, but only a ten-second calibration procedure that allows the system to scale pressure values appropriately. The latency of pressure reporting is approximately 150ms.

Contact finger identification. This primitive is based on a machine learning methodology demonstrated in the work of Saponas et al. [17,18]. Specifically, we use a support vector machine to analyze frequency and amplitude information in the EMG signal and determine which finger is applying pressure to the surface. This primitive requires about two minutes of training for each user. In prior work, users have typically been asked to respond to various controlled stimuli while the arm is in a fixed position in order to collect labeled data. This can be tiring and boring. In our training, we instead prompt users to use each of their fingers to draw freely on the surface. At the end of the training period, the system analyzes the training data to build a real-time classifier. Building the classifier requires less than five seconds. The latency of finger identification is approximately 300ms.

"Pinch" and "Throw" gestures. A "pinch" gesture consists of bringing a finger rapidly against the thumb, and lifting away from the surface, the way one might pick up a small object from a table. The "throw" gesture consists of rapidly opening the fingers from the pinched state, as one might do when throwing an object held between pinched fingers. The "pinch" and "throw" gestures are detected by looking for characteristic changes in the muscle activation level of the dominant hand. *Detecting* these gestures requires no training, but *identifying* the fingers performing these gestures currently requires a two-minute training procedure identical to that described for contact finger identification, except that instead of drawing on a surface, the system asks the user to pinch specific fingers against his or her thumb in mid-air for five seconds at a time during a two minute training period. The latency of pinch detection and identification is also approximately 300ms.

"Flick" gesture. The "flick" gesture consists of a simple wave of the hand. The "flick" gesture is detected by looking for characteristic changes in the muscle activation level of the hand. This primitive requires no training other than a ten-second calibration procedure that allows the system to scale pressure values appropriately. The latency of "flick" detection is approximately 50ms.

Due to the equipment constraint of having only 8 EMG sensor channels and the resulting asymmetric setup, we bound each of the gestures to a specific hand. The dominant hand, with the larger number of sensors, could sense pressure, contact-finger identification, as well as the pinch and throw gestures. The flick gesture was restricted to the non-dominant hand.

Calibrating and training our system for all four primitives requires approximately five minutes per user. We discuss incorporating these primitives into hybrid interaction techniques in the next section.

Figure 4. Performing the *finger-dependent pick and throw* interaction: A user picks up a virtual object by pinching it on the surface and lifting his hand away from the surface. Releasing the pinch return the object the current canvas.

Hybrid EMG-Surface Interactions

We have prototyped four interaction techniques to demonstrate and evaluate the utility of EMG sensing for interactive surfaces. These interactions are all prototyped within a simple painting and image-manipulation application.

Pressure-sensitive painting: To demonstrate our system's ability to estimate contact pressure, we associate different saturation levels in our painting application with different levels of finger pressure (more pressure results in darker strokes) (Figure 3).

Finger-aware painting: To demonstrate our system's ability to associate surface contacts with specific fingers, we associate different brush colors with the index and middle fingers (Figure 3). When the interactive surface detects a contact, it immediately queries the EMG system for the identity of the active finger, and uses that color for the brush stroke associated with this contact. Because we have independent processing streams for touch and muscle sensing, we begin to draw a translucent stroke to maintain the sensation of responsiveness, and only fill in the color when the EMG system has returned with the finger it detects.

Finger-dependent pick and throw: To demonstrate our system's ability to detect gestures more complex than simple touches, and to persist the state of those gestures even when the hand leaves the surface, we map the "pinch" and "throw" gesture primitives to "cut/copy" and "paste" operations on a simple photo canvas. Thus the user is able to *pick* a photo up from the table and *throw* it back onto the canvas. Picking is initiated on the surface, by placing two fingers on the desired photo and then performing a pinch gesture (Figure 4). By pinching with the index or middle finger, the user can specify whether to initiate a cut or a copy operation, respectively. A user holds on to a copied or

cut photo by maintaining the pinch posture, even after the hand has left the surface, and pastes the object back onto the surface by executing the throw gesture. The user can perform arbitrary actions (e.g., switch between canvases) while she is holding the object and has not thrown it back.

***Undo flick*:** To demonstrate our system's ability to facilitate bimanual, off-the-surface interaction, we map the "flick" gesture performed by the non-dominant hand to the undo operation in our painting application. This action removes the most-recently-created stroke.

EXPLORATORY SYSTEM EVALUATION

To gather initial feedback on our system, we recruited 6 participants (3 female) from within our organization. Each participant spent approximately 90 minutes interacting with our system and was provided with a $10 compensation for their time. The goals of our evaluation were to validate the basic feasibility of our system and interaction techniques, to assess their robustness and reliability, and to gather anecdotal responses from novice users about our proposed interaction techniques.

Tasks

At the beginning of each participant's experimental session, we applied EMG sensors to the participant's arm as described in the previous section. We then asked the participant to make a tight fist and then relax, allowing calibration of the signal level for each hand. Introduction and the initial setup took approximately 15 minutes. Participants then completed the following five tasks (in order):

Task 1: Copy an image from a given paper template (Figure 5a) using the pressure-sensitive painting technique. The image was presented on paper and contained varying
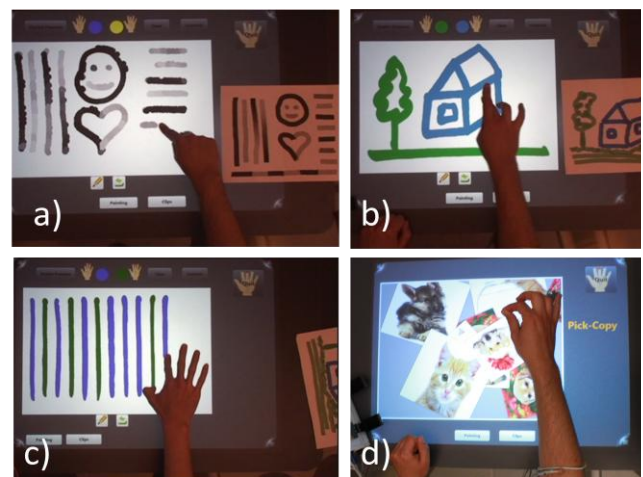

Figure 5. Four tasks from our user evaluation: (a) *Task 1:* copy an image using contact pressure to control saturation; (b) *Task 2*: copy an image using index and middle fingers to paint two separate colors; (c) *Task 3*: draw lines with alternating colors; and (d) *Task 5*: move three images and copy three images to a different canvas.

levels of light and dark strokes.

Task 2: Copy an image from a given paper template (Figure 5b) using the finger-aware painting technique. The image was presented on paper and contained blue and green strokes, which were mapped to the participant's index and middle fingers, respectively.

Task 3: Make a series of vertical lines across the surface, changing color with each vertical line (Figure 5c). Each participant filled two canvases with vertical lines.

Task 4: Write the numbers from 1 to 10 on the surface, executing the "undo flick" gesture after each even number, but not after odd numbers. Correct execution of this task would leave only the odd numbers written on the surface. If an even number contained multiple strokes, participants executed the "undo flick" gesture as many times as was necessary to erase the number completely.

Task 5: Presented with a pile of six images on a canvas, either copy or move each image to another canvas, depending on the image category. Specifically, they had to copy images of cats and move images of dogs (Figure 5d). Participants picked up images using our "pick" gesture, where the index finger initiated a "move/cut" operation and the middle finger initiated a "copy" operation. While the image was held in their dominant hand, participants pressed an on-screen button with their non-dominant hand to switch to the target canvas, and used the "throw" gesture to place the image on that canvas.

There were two additional training sessions: First, before performing Task 2, participants spent two minutes training the system to recognize finger-specific contacts. Second, participants spent another two minutes training the finger-specific "pinch" gesture before Task 5. Training in both cases consisted of repeated activation of a desired hand pose or gesture using a stimulus-response training method, i.e., the user was prompted with a particular pose/gesture on the screen, they performed it for 2 seconds, and then they relaxed their hand muscles.

Before performing each task, participants were given time to practice each interaction and ask questions. This practice session took no longer than 5 minutes. When comfortable with the interaction, participants proceeded to complete the specific tasks, which were untimed. On average, participants completed each task within one minute.

At the conclusion of the session, each participant completed a questionnaire that solicited feedback about each interaction.

Results

In this section, we present quantitative results from each of our tasks. Discussion of the implications of these results is presented in the following section.

Task 1: We analyzed Task 1 (copying an image using pressure-sensitive painting) by defining 22 features, such as "line 2 is lighter than line 1", and "line 3 demonstrates the correct brightness gradient", and coding errors on each of these features for each participant. The resulting drawings can be seen in the top row of Figure 6. Across our six participants, the mean accuracy was 93.9% (sd = 4.7%). In short, *all participants were able to effectively manipulate pressure to control brush darkness in a drawing task.*

Task 2: The task of copying a multi-color image is more open-ended and therefore difficult to formally analyze, as participants used different numbers of strokes to complete the image. Anecdotally, success on task 3 (vertical lines) was indicative of users' ability to perform task 2: *while all six participants completed the target drawing* (middle row of Figure 6), *one had some difficulty reliably selecting the finger color.*

Task 3: We analyzed Task 3 (finger-aware drawing of alternating blue and green vertical lines) by computing the percentage of lines drawn in the correct color for each participant (see bottom row of Figure 6). Across our six participants, the mean accuracy was 90.9% (sd = 11.1%). This includes one participant for whom finger classification did not perform at a level comparable to the other participants. In this errant case, the classification was biased toward one finger, resulting in an accuracy of only 71%. Without this participant, the mean accuracy overall was 94.8%. In short, *five out of six participants were able to effectively specify brush colors by painting with different fingers.*

Task 4: We analyzed Task 4 (writing numbers and selectively erasing half of them with the "undo flick" gesture) by counting the number of false-positive and false-negative "undo" operations performed by each participant. All participants but one completed this task with no errors. The one participant had two false positive errors. In short, *five out of six participants were able to reliably execute and control the "undo flick" gesture without any false positives.*

Task 5: We analyzed Task 5 (picking and throwing images) by counting the number of "mis-triggers" and "mis-classifications." Mis-triggers were instances where the system detected a pinch or throw gesture that the user did not intend, or failed to detect an intended gesture. Mis-classifications were instances where the system correctly detected the presence of a "pick" gesture but failed to correctly identify the gesturing finger. Three of our six participants performed this task without any errors of either type. Two of the remaining three participants experienced no mis-triggers, but had 2 and 3 mis-classifications, respectively. The remaining participant experienced 2 mis-triggers and 1 mis-classification. In short, *this was the most difficult of our interactions, but the three perfect executions of this task support its basic feasibility*. In the following section, we will discuss hypotheses surrounding the classification errors experienced by the other participants.

In summary, while it is important to keep in mind that we base our observations on a very limited set of six participants, only one experienced difficulties getting reliable recognition, while five performed all tasks without problems.
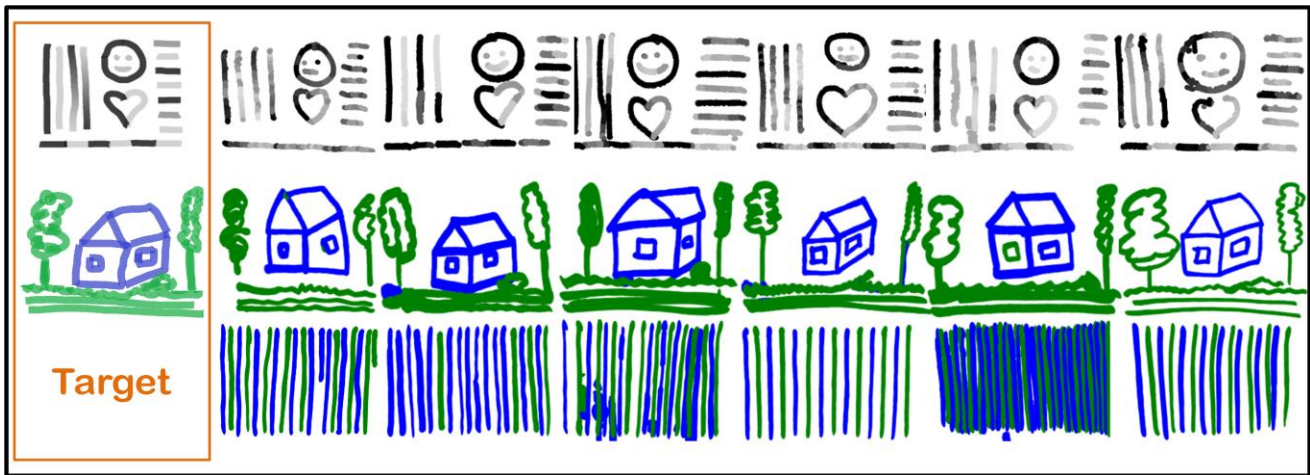
Figure 6. Pictures painted by participants in our exploratory system evaluation, where rows 1, 2, and 3 show the results of Tasks 1, 2, and 3 respectively. Task 1: copy the leftmost image using pressure-sensitive painting. Task 2: copy the leftmost image using index and middle fingers to paint in blue and green, respectively. Task 3: draw alternating blue and green lines using index and middle fingers, similar to task 2. The leftmost target images were provided to our participants on paper.

DISCUSSION AND FUTURE WORK

Here we discuss the lessons learned from developing our system and testing our interaction techniques, and present opportunities for future work.

Calibration and Training

One goal when developing sensing and recognition systems is to construct an accurate model that requires minimal calibration and training. Our system currently requires gross calibration each time a user dons the EMG device. This comes in the form of a making a tight fist and then relaxing each of the hands. Because of the variance in muscle activity across users and the inconsistency in sensor placement, even for repeated use on the same user, this is necessary to normalize the raw amplitudes and find the basic working range of the signal. This calibration provides sufficient information to model pressure gestures, pick and throw gestures, as well as our flick gesture, since these function based on thresholds set on the signal amplitude.

Other gestures such as distinguishing between different fingers require more training since the relationship between the raw signal and the desired recognition result is less obvious. In these cases, we have users perform tasks in which we collect labeled data that can be used by machine learning techniques to dynamically build the classification model.

We believe that this training exercise must be carefully designed in order to collect data that is representative of real use scenarios. For example, traditional EMG training methodologies have largely employed a stimulus-response paradigm, in which the user is told exactly which gesture to perform and when. In the case of finger identification, we could have had the user press down with each of their fingers when we told them to. This is not only potentially boring and annoying to perform, but also provides data that is quite different from that which has to be recognized.

In our tests, we had users paint images of their choice while using fingers of our specification, which was a much more compelling exercise that provided better training data. Even then, some users performed the training very differently than they did the task. While we cannot quantify this, our informal observations of the user that had poor recognition results leads us to believe that they were trying so hard to train the system correctly that their arm might have been abnormally tense when they did this, leading to the construction of a poor model.

These issues point toward a limitation of our current system. We did not explicitly tell users that they had to perform the tasks and gestures in any given way, and we found that users who deviated most from the way they trained the system generally had the worst recognition results. This is hardly surprising, but most users were able to naturally self-correct after the training phase, and with a few minutes of practice, quickly learned how to perform the gestures in a way as to get reliable classification.

Classification Limitations

The recognition rates achieved by our system – for example the 90% mean accuracy for finger identification – might be considered low when compared to the error rates of standard input devices such as mice and keyboards. However, our accuracies are comparable to other "non-traditional" input modalities such as speech and gesture, both of which have achieved success in a variety of applications where the benefits of alternative modalities compensate for reduced accuracy. In addition, we believe that a more synergistic combination of touch sensing and muscle sensing would probably yield better recognition results. For example, we could consider the changes in the

touch contact area as well as the outline of the hand in the hover zone to further aid our recognition system.

The present work also did not explore the long-term performance of our classifiers, and finding techniques that create models that are robust to variations in sensor placement and user performance remains future work. The need to individually place electrodes on a user's arm limits the reusability of training data and thus the long-term robustness of our system, but we are currently investigating a novel, dry-electrode armband form factor which allows the user to quickly attach sensors to their arm. This approach shows potential in facilitating calibration data reuse across multiple sessions for each individual user.

Gesture Sets

In this work, we only classify a single contact at a time. This is not an intrinsic limitation of the approach, but rather one of implementation. It remains future work to develop recognition techniques that deal with compound gestures, whether through training explicitly for these gestures or by inferring them from models of the individual gestures. If multiple digits are touching the surface at the same time, the system could also use the relative position and ordering of the fingers and the information about which fingers are currently touching the surface to infer which finger is which. Even minute changes in pressure and finger flex could be correlated with minute changes in finger contact area and relative position to other contacts to precisely identify each finger in contact with the surface.

One of our explicit design decisions was to utilize only the index and middle fingers. This was a simplification since we sought to explore modality fusion rather than explicit EMG system performance. That said, [17] and [18] have shown that the recognition accuracy does not degrade drastically even when people use all five fingers. This work demonstrated that the little finger was the least reliable for EMG classification, which we believe is acceptable since the little finger is typically the least comfortable to design gestures around. It should be noted that we expect that the natural way to use the thumb on a surface is probably not equivalent to the best-case scenario tested in that work and we would likely see slightly degraded performance there as well; the muscles controlling the thumb, are less accessible to a forearm EMG sensor than the muscles that drive the other fingers.

Interaction and Interface Considerations

A slightly more opportunistic idea is to make use of a unique property of muscle-sensing: it is sometimes possible to detect a physical movement event before it actually occurs. This is because before we make a motion, we have preparatory muscle activation that can be sensed by EMG. Hence, it may be possible to detect actions such as pressing a button slightly before the physical event actually occurs, which could perhaps be integrated into interaction techniques for tabletops to, for example, begin animating a change to an object that will be affected on screen.
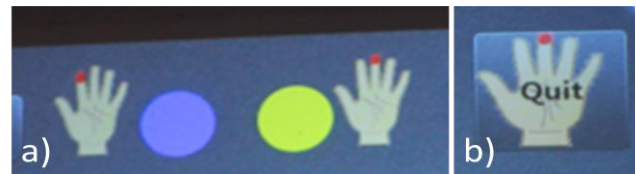

Figure 7. Finger-dependent UI elements: (a) finger ink wells for choosing the brush color of index and middle fingers, and (b) middle-finger quit button to reduce accidental activation.

In our prototype system, we implemented and evaluated each of our interaction techniques separately. However, these can obviously be integrated into a single system. Pressure sensing can be done simultaneous with finger identification and the surfaces ability to sense contact shape for hybrid interactions such as simultaneously controlling, stroke shape, color, and saturation. Similarly, finger identification on the surface (e.g., painting) and finger identification off the surface (e.g., pinching) can be inferred simultaneously through separate classifiers while using surface contact information to determine how to use the results.

In addition to our hybrid interaction techniques, we explored the concept of finger-dependent user interface elements (Figure 7), i.e., on-screen elements that can be activated only when touched with a specific finger (similar to the concept introduced in [19]). We prototyped finger-dependent ink-wells for selecting the finger brush color, and middle-finger quit button for exiting our application. Such elements are harder to activate by mistake than standard widgets, which could be useful for actions with high cost of accidental activation (e.g., delete or quit).

CONCLUSION

We have presented a novel fusion of complementary sensing modalities: touch sensing via an interactive surface and muscle sensing via EMG. Our approach enhances the existing tabletop paradigm and enables new interaction techniques not typically possible with standard interactive surfaces. Our exploratory system evaluation provides important insights into the feasibility, reliability and effectiveness of our approach. We believe that with the future development of miniaturized, wireless, and wearable EMG sensing devices, our techniques will provide useful interaction capabilities for the next generation of interactive surfaces.

REFERENCES

1. Benko, H. & Feiner, S. Balloon Selection: A Multi-finger Technique for Accurate Low-fatigue 3D Selections. In *Proc. of Symp. on 3D User Interfaces '07*. 79–86. 2007.

2. Benko, H. & Wilson, A. DepthTouch: Using Depth-Sensing Camera to Enable Freehand Interactions On and Above the Interactive Surface. *Microsoft Research Technical Report MSR-TR-2009-23*. 2009

3. Costanza, E., Inverso, S.A., Allen, R., & Maes, P. Intimate Interfaces in Action: Assessing the Usability and Subtlety of EMG-based Motionless Gestures. In *Proc. of ACM CHI 2007.*

4. Cutler, L.D., Fröhlich, B., & Hanrahan, P. Two-handed Direct Manipulation on the Responsive Workbench. In *Proc. of Symp. on Interactive 3D Graphics (I3D '92).* 107-114, 1992.

5. Dietz, P. & Leigh, D. DiamondTouch: A Multi-user Touch Technology. In *Proc. of ACM UIST '01.* 219–226, 2001.

6. Farry K., Walker I., & Baraniuk R.G. Myoelectric Teleoperation of a Complex Robotic Hand. In *Proc.of IEEE Intl Conf Robot Autom*ation '96. 775-788, 1996.

7. Han, J. Low-cost Multi-touch Sensing through Frustrated Total Internal Reflection. In *Proc. of ACM UIST '05*, 115–118, 2005.

8. Harada, S., Saponas, T.S., & Landay, J.A. VoicePen: Augmenting Pen Input with Simultaneous Non-linguistic Vocalization. In *Proc. of Intl. Conf. on Multimodal Interfaces*, 2007.

9. Izadi, S., Hodges, S., Taylor, S., Rosenfeld, D., Villar, N., Butler, A., & Westhues, J. Going Beyond the Display: A Surface Technology with an Electronically Switchable Diffuser. In *Proc. of ACM UIST '08*, 269–278, 2008.

10. Ju, P., Kaelbling, L.P., & Singer, Y. State-based Classification of Finger Gestures from Electromyographic Signals. In *Proc. of ICML '00*, 439-446, 2000.

11. Julia, L. & Faure, C. Pattern Recognition and Beautification for a Pen-based Interface. In *Proc. of Intl. Conf. on Document Analysis and Recognition* (Vol. 1), 58, 1995.

12. Kattinakere, R.S., Grossman, T., & Subramanian, S. Modeling Steering within Above-the-surface Interaction layers. In *Proc. of ACM CHI '07*, 317-326, 2007.

13. Malik, S., Ranjan, A., & Balakrishnan, R. Interacting with Large Displays from a Distance with Vision-tracked Multi-finger Gestural Input. In *Proc. of ACM UIST '05*, 43–52, 2005.

14. Merletti, R. & Parker, P.A. Electromyography: Physiology, Engineering, and Noninvasive Applications. John Wiley & Sons: Hoboken, New Jersey, 2004.

15. Oviatt, S., Cohen, P., Wu, L., Vergo, J., Duncan, L., Suhm, B., Bers, J., Holzman, T., Winograd, T., Landay, J. A., Larson, J., & Ferro, D. Designing the User Interface for Multimodal Speech and Pen-based Gesture Applications: State-of-the-art Systems and Future Research Directions. *HCI 15*, 263–322, 2000.

16. Peleg, D., Braiman, E., Yom-Tov, E., & Inbar G.F. Classification of Finger Activation for Use in a Robotic Prosthesis Arm. *Trans. Neural Syst. Rehabil Eng.*, 10(4), 2002.

17. Saponas, T. S., Tan, D. S., Morris, D. & Balakrishnan, R. Demonstrating the Feasibility of Using Forearm Electromyography for Muscle-Computer Interfaces. In *Proc. of ACM CHI '08*, 515–524, 2008.

18. Saponas, T. S., Tan, D. S., Morris, D, Balakrishnan, R., Landay, J.A., & Turner, J. Enabling Always-available Input with Muscle-Computer Interfaces. In *Proc. of ACM UIST 2009.*

19. Sugiura, A. and Koseki, Y. A user interface using fingerprint recognition: holding commands and data objects on fingers. In *Proc. of ACM UIST '98*, 71–79, 1998.

20. Tenore, F., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, R., & Thakor, N. Towards the Control of Individual Fingers of a Prosthetic Hand Using Surface EMG Signals. In *Proc. of IEEE EMBS 2007.*

21. Wilson, A. TouchLight: An Imaging Touch Screen and Display for Gesture-based Interaction. In *Proc. of ICMI '04*. 69–76, 2004.

22. Wilson, A. PlayAnywhere: A Compact Tabletop Computer Vision System. In *Proc. of ACM UIST '05.* 83–92, 2005.

23. Wilson, A. Robust Computer Vision-Based Detection of Pinching for One and Two-Handed Gesture Input. In *Proc. of ACM UIST '06*. 255-258., 2006.

24. Wilson, A. Depth-Sensing Video Cameras for 3D Tangible Tabletop Interaction. In *Proc. of IEEE Tabletop '07*, 201-204, 2007.

25. Wheeler, K.R, Chang M.H., & Knuth K.H. Gesture-Based Control and EMG Decomposition. *IEEE Trans on Systems, Man, and Cybernetics*, 36(4), 2006.

26. Yatsenko, D., McDonnall D., & Guillory, S. Simultaneous, Proportional, Multi-axis Prosthesis Control using Multichannel Surface EMG. In *Proc. IEEE EMBS 2007.*