RESEARCH-ARTICLE

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PalmGesture: Using Palms as Gesture Interfaces for Eyes-free Input

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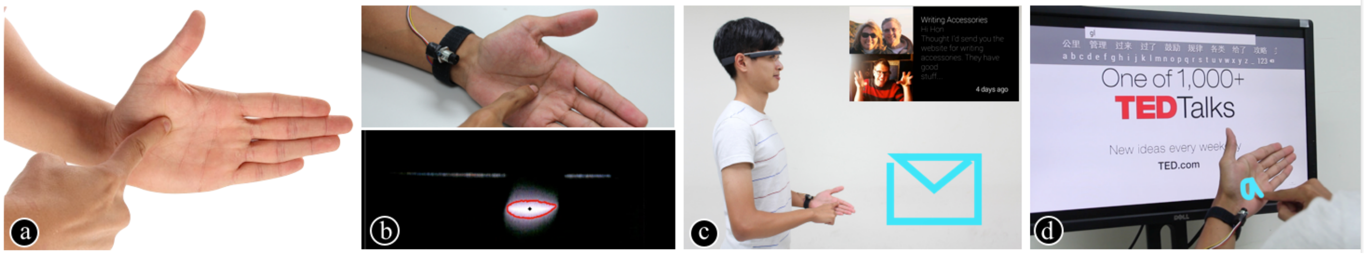

Figure 1. (a) Leveraging the palm as gesture interface. (b) EyeWrist prototype tracks bright regions in the infrared camera image. (c) Drawing an email symbol to check emails on Google Glass. (d) Handwriting the titles to search for videos on smart TV.

ABSTRACT
In this paper, we explored eyes-free gesture interactions on palms, which enables users to interact with devices by drawing stroke gestures on palms without looking at palms. We conducted a 24-person user study to understand how users draw gestures on the palm with varying characteristics including regions, orientation and starting points. Based on the findings, we proposed two new interaction techniques for palm-based gesture interface. To explore and demonstrate the feasibility of the interaction, we implemented EyeWrist, a wrist-mounted prototype which detects gestures on palms by using an IR camera and laser-line projector. The preliminary evaluation revealed that EyeWrist enabled users to draw graffiti letter and multi-stroke gestures with above 90% accuracy and that both the concept of using palms as gesture interfaces for eyes-free input and the proposed two interaction techniques were appealing to users.

Author Keywords
Palm-based interaction; Gesture input; Stroke gestures; Eyes-free input; Wearable

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation (e.g. HCI): User Interfaces - Interaction styles.

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INTRODUCTION
Eyes-free input techniques are important for lack-of-attention scenarios (e.g., walking) and operation with lower cognitive/physical effort [37]. For example, when users are walking(i.e., in mobile scenarios), eyes-free input techniques allow them to pay attention to the environment without looking at the input interface, which could reduce distraction and danger [9]. Also, users can immerse themselves in watching smart TV without switching their attention between the input interface and the content on TV.

The human palm exhibits unique affordances that have been considered highly beneficial for eyes-free interaction. The human sense of proprioception enables the palm surface to be leveraged as an eyes-free remote control [32]. Plenty of natural tactile feedback allows people to interact effectively without visual feedback [27]. However, previous studies on palm-based interaction only mentioned standard touchscreen gestures like tap, swipe and pinch. Stroke gestures, which are also used in a variety of applications [4, 23, 25], have the potential to lower cognitive load and the need for visual attention and thus could be suitable for eyes-free input.

In this paper, we aimed at designing gesture interactions that don't require visual attention to the palm. For example, users draw an email symbol to check emails on Google Glass or handwrite the titles to search for videos on smart TV without looking at palms or retrieving remote controls as shown in Figure 1. To understand user behavior when users draw gestures on palms and how characteristics of palms affect the gestures on palms, we conducted a 24-participant user study. The result of the study showed that (1) users preferred using the whole palms as the gesture interfaces with 3 categories of hand orientations. (2) With proprioception on palms, users tended to draw different gestures from the same starting region even without looking at their palms. (3) Palm interface has potential for eyes-free Graffiti input with high accuracy. The accuracy of eyes-free Graffiti input and multi-stroke gesture recognizer on palm interface reached as high as 98% and 95% respectively in our gesture sets.

Derived from Digits [18], we implemented EyeWrist, a proof-of-concept prototype which embeds a micro-camera and an IR laser line generator on the wristband, and used computer vision algorithms to sense finger movements. We further applied recognizer to recognize gestures on palms. The preliminary evaluation revealed that EyeWrist enabled users to draw graffiti letter and multi-stroke gestures with above 90% accuracy.

Based on the findings of user studies, we proposed two new interaction techniques for palm-based gesture interface: gesture recommendation by starting regions and returning to a drawn feature to start a specific function of an application. The users' positive feedback showed their interests in the concept of eyes-free and palm-based gesture interaction.

In summary, the main contributions of this paper are as follows:

- Conduct a user study to understand characteristics of stroke gestures on palms and further suggest a number of guidelines for designing palm-based gesture sets and recognizers.
- Implement a proof-of-concept prototype, EyeWrist, which embeds a micro-camera and an infrared laser line generator on the wristband to explore and demonstrate the feasibility of gesture interaction on palms.
- Propose and design eyes-free gesture interaction techniques that are especially suited for palm interface on the basis of characteristics of gestures on palms.
- Provide web-based visualization tool [1] and dataset for the HCI community to foster more research on palm-based gesture interaction.

RELATED WORK

With abundant tactile cues and proprioception on palms, the palm can be leveraged as a gesture interface for eyes-free input which decreases visual attention to interfaces and minimizes cognitive/physical effort. Our work builds on research in eyes-free input, palm-based interaction and gesture input.

Eyes-Free Input

Eyes-free input has received much attention from the human-computer interaction community. Although many eyes-free input techniques for mobile phones have been proposed [30, 7, 35], users usually still have to find and take out their phones from pockets, bags just to access basic functionality, which demands a high level of attention both cognitively and visually and is often socially disruptive.

The availability of the users own body for always-available eyes-free input has also been explored in previous research. Chan et al. proposed input methods by exploring human fingers for eyes-free and private interaction with low cognitive loading [5]. Touching a particular part of the ear could also be used to control functions according to EarPut from Lissermann et al. [24]. Other interface concepts have explored users' intimate familiarity with their peripersonal space and their proprioceptive abilities. Folmer et al.s proprioceptive displays [8] combined proprioception with spatially triggered vibrotactile feedback to allow eyes-free exploration of the featureless space in front of the user. Similarly, Motion Marking Menus [31] used proprioception to enable eyes-free input for handheld devices, and Virtual Shelves [22] allowed users to invoke mobile phone functions by pointing at representative locations in the hemisphere in front of them.

Eyes-free interaction typically involves proprioception and taction working together since proprioception alone is not precise enough to enable fine-grained interaction [9] . In this paper, we leveraged the palm as gesture interface and studied how the characteristics of palms help users input without visual attention.

Palm-based

Skinput [16] and OmniTouch [15] combine on-body interaction with visual feedback from body worn projectors. Skin buttons [21] uses tiny projectors integrated into the smartwatch to project touch-enabled interface elements on the skin. Weigel et al. investigated skin input modalities and preferred locations [34]. Because of humans' high proprioceptive sense of palms, hands and arms as well as convenience in interacting with these surfaces, a number of projects have appropriated them for always-available input interface. PalmRC [6] used palm as a remote control for TVs with a small set of buttons, and numeric pads have also been proposed [10]. Gustafson et al. designed an imaginary phone interface that directly mapped a phone's UI to users' palms [13], which enabled users to interact with their mobile phone by recalling and touching locations on their palms that corresponded to the app icons on the phones. In addition, studies on palm-based imaginary interfaces showed that people can interact effectively without visual feedback [14].

Compared with previous studies on palm-based interaction that only mentioned standard touchscreen gestures like tap, swipe and pinch, we focus on characteristics of stroke-gestures on palms and present a set of guidelines to help design gesture sets and recognizers for palm interface.

Gesture Input

The continuing rise of ubiquitous touchscreen devices highlights both needs and opportunities for gesture-based interaction. In addition to standard swipe, flick, and pinch gestures, stroke gestures, defined by their trajectories (e.g., a circle, an arrow, a spring, each character in an alphabet), can be used in many applications. Gesture strokes have been employed as shortcuts for invoking commands [4, 11, 19, 20, 28, 38]. Gesture shortcuts allow a user to easily articulate a command by drawing strokes without having to find the command within a menu hierarchy. Gestures are also easy to input and rich in semantics. Users can associate a gesture with a target data item

[1] http://palmgesture.herokuapp.com

and then activate the item by drawing a similar gesture later (e.g., [23]). In addition, variations in stroke gesture articulation have been studied in different ways in the literature, including examining the consistency between and within users [1], differences between user populations [17], and the impact of input devices [33].

In this paper, we leveraged the palm as gesture interface and proposed interaction techniques that particularly suit for eyes-free and palm-based gesture interaction based on the findings of our user studies.

USER STUDY: DRAWING SHAPES AND GESTURES

The goal of the study is to explore user behavior when they draw gestures on palms and to understand how characteristics of palms affect the gestures on palms. Participants were asked to reproduce a series of predefined sketches.

Participants

We recruited 24 participants (12 male, 12 female) between the ages of 20 and 29. All participants were right-handed and drew with their right index fingers on left palms. Participants received a small compensation for their time.

Apparatus

The apparatus is shown in Figure 2. We used the Vicon 3D motion tracking system to avoid noise introduced by sensors when tracking the position of participants' hands. Three retro-reflective markers were placed on the plane of the participant's non-dominant hand and tracked by the Vicon system with 6 IR-cameras to define a 3D plane that corresponded to the palm surface. Moreover, one marker was placed at the tip of the pointing index finger. The system tracked the marker sets with 1mm accuracy.

Task and Procedure

In each trial, after the participant indicated his readiness, one of the drawings in Figure 3 appeared on a Keynote slide. The participant was asked an eyes-free input, that is, not to look at his left palm when sketching on it by right index finger; also, the starting point and stroke order of each drawing were provided. The trial was completed when the participant finished the sketch and dropped his right arm to get ready for the next trial.

During the trial, the participant needed to wear a partial blindfold modified from a sanitary mask to completely occlude the users view of his hand as shown in Figure 2.

The trials were divided into three tasks:

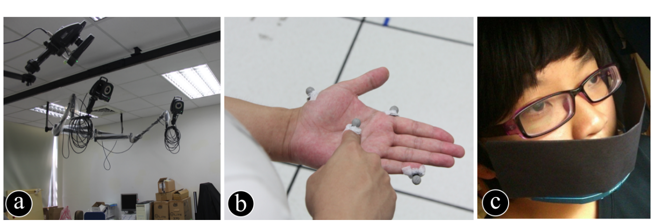

Figure 2. (a)Vicon motion capture system. (b)Markers on users' hands. (c)Occluding the user's view of the hand by a partial blindfold.

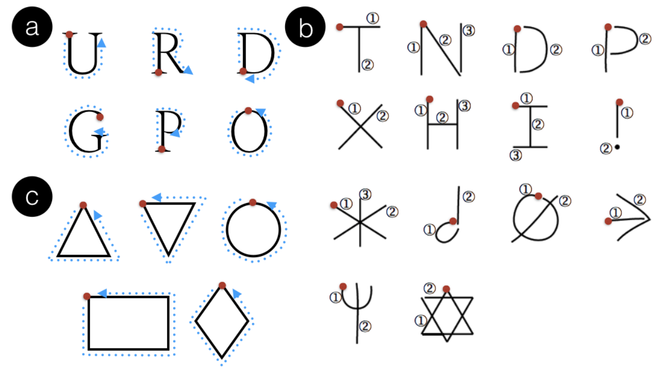

Figure 3. Stimulus drawings for the participants to reproduce. (a) Task 1: single-stroke Graffiti characters. (b) Task 2: simple shapes. (c) Task 3: multi-stroke gestures in MMG dataset [2].

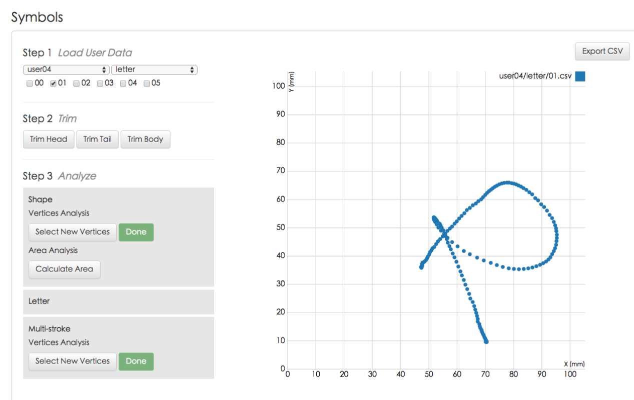

Figure 4. Web-based visualization tool.

Graffiti

The participants were asked to draw 6 Graffiti characters (Figure 3), which were selected from [29] because they are especially difficult for users to complete without visual attention; to obtain correct recognition, participants need to end the stroke of these characters at a proper position. Also, selecting these characters allowed us to compare the results with other related systems.

Shape

In this task, participants drew 5 simple shapes including circle, triangle, inverted triangle, rectangle, and diamond.

Multi-stroke drawing

Except for two unistroke gestures ("line" and "five-point star"), the other 14 gestures of Mixed Multi-stroke Gesture (MMG) corpus [2] were sketched by participants in this task, and each gesture was repeated 6 times.

Every participant completed all the three tasks and then had a 10-minute interview. The sequence of tasks was counterbalanced, and we used a DSLR camera to record participants' performances during the study. All participants completed the experiment session within 30 minutes.

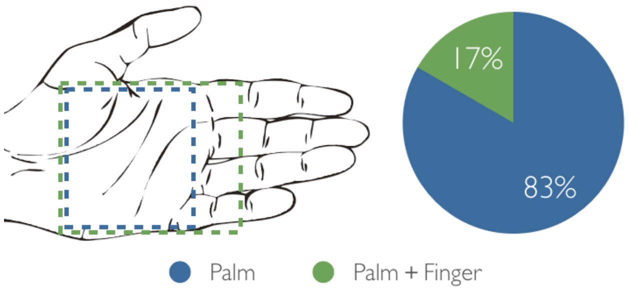

Figure 5. Users' preferred regions when users drew gestures on palms.

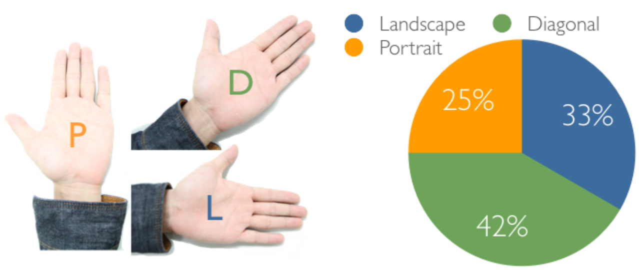

Figure 6. Users' preferred hand orientations when gestures were drawn on palms. L: landscape (0°-30° degrees), D: Diagonal(30°-60°), P: Portrait(60 90 degrees).

Data Processing

With 24 participants and 95 trials per participant, a total of 2280 trials were completed in the study. A finger's position on the palm is calculated by projecting the position of the fingertip's marker on the palm plane and measuring the distance. However, it's difficult to detect when a gesture begins by applying a fixed threshold for the vertical distance between the fingertip and the palm to all participants. Therefore, we filter out points greater than 5mm threshold for the vertical distance and then manually marked the beginning and the end of each stroke by the web-based visualization tool developed by us.

Web-based Visualization Tool

As shown in Figure 4, we provided the palm-based gesture dataset collected during the user studies for the HCI community through our web-based visualization tool. The tool contains a number of features, such as trimming the gestures and calculating the area and distance of vertices of a gesture. We believe that the dataset will encourage additional exploration in the field of gesture recognition and interactions.

Result

Region

From the recorded videos, we observed that all participants preferred using the whole palm as the gesture interface (see Figure 5). 17% of the participants also used the finger region by accident due to the restriction on seeing the palm, and all participants considered the gaps between fingers unfavorable to the drawing.

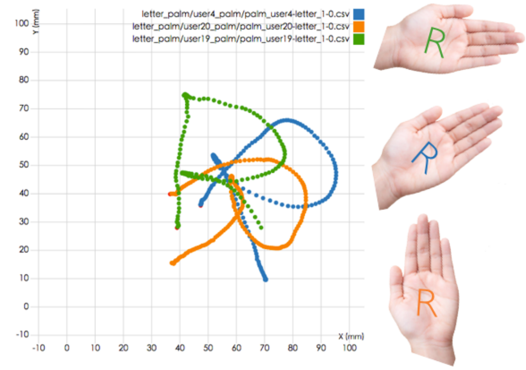

Figure 7. The orientations of captured drawings varied with hand orientations.

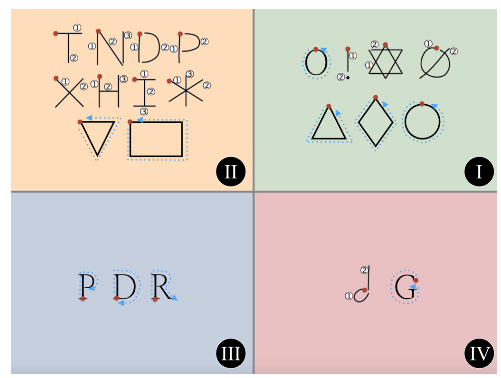

Figure 8. Gestures were classified into four groups by locations of starting points. (e.g., T starting from the top-left corner was in second quadrant.)

A user said, "because the fingertip is wider than a pen, I try to draw a bigger gesture to avoid mixing up the strokes." Another user viewed the entire palm as a grid and wanted to fill it up when drawing a gesture. The result suggested that people preferred using the palm region as the gesture interface rather than the whole hand. Therefore, the system's sensing range (e.g., a camera's view angle or an infrared proximity sensor's range) should cover the whole palm to carry out palm-based gesture interaction in future system implementation.

Hand orientations

The difference in users' hand orientations was observed. The hand orientations were classified into three postures by the angle between hand and body, including portrait (60°-90°), diagonal (30°-60°), and landscape (0°-30°). Figure 6 demonstrates that diagonal orientation was most used (42%) when participants drew gestures on their palms, and that 33% of the users drew with landscape orientation and 25% with portrait.

The result showed that every participant used different hand orientation ranging from 0°to 90°when drawing gestures on the palm. Besides, Figure 7 demonstrated that orientations of drawings would vary with hand orientations. Thus, rotation-invariant gesture recognizers would be more suitable to be palm-based gesture recognizers. Besides, when we design palm-based gesture sets, we should avoid designing gestures

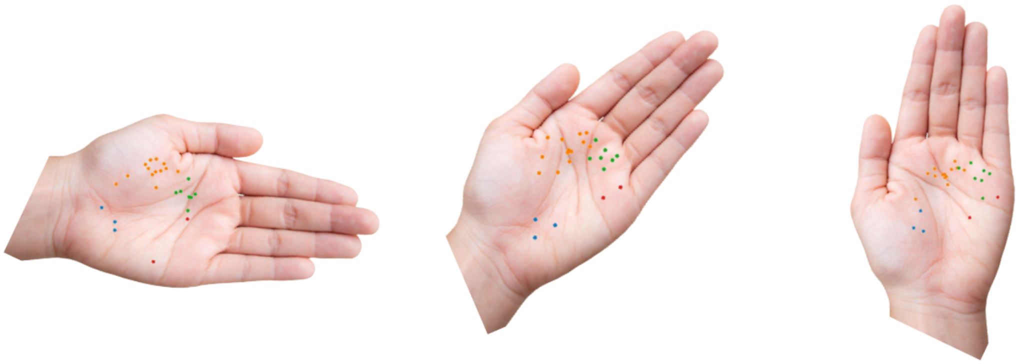

Figure 9. Starting points of classified gestures drawn by a user with different hand orientations. (blue: bottom-left group, orange: top-left group, green: top-right group, red:bottom-right group.)

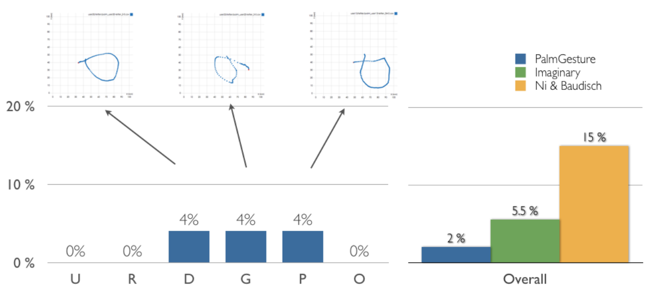

Figure 10. Graffiti recognition error rates compared with Ni and Baudisch's feedback-less gesture input [28] and imaginary interface [12].

that could be similar and confusing after rotation (e.g., 6 and 9 or P and b).

Supposing that people might use portrait orientation with longer gestures like diamond but use landscape orientation with wider ones like rectangle, we informed participants that they could change hand orientations during the trials to understand the relationship between hand orientations and gestures. However, no participants changed hand orientations during the study. They thought they couldn't draw gestures on palms accurately without visual attention because they needed to orient themselves after changing different hand orientations.

Starting points of gestures

Firstly, we classified gestures used in the study by locations of their starting points (see Figure 8). For example, both T and N start from the top-left corner and thus are classified into second quadrant. Secondly, after normalizing all gesture data with the average size of participants' palms (10.04 x 7.9 cm), we extracted and plotted starting points of all gestures.

PalmRC [6] has shown that when users touch the landmarks of palms without visual attention, the diameter necessary to encompass 90% of all touches is 28mm. As shown in Figure 9, the distance between the starting points of some gestures is less than 28mm, which implies that different gestures can start from the same region due to the proprioception of palms.

Graffiti

We analyzed the captured graffiti drawings through a Graffiti recognizer, which have been used in previous study [29, 12]. However, as shown in Figure 7, the orientations of captured drawings were varied with users' hand orientations, and rotational graffiti letters couldn't be correctly recognized by Graffiti recognizer. Thus, we manually calculated the angle formed between the centroid of the gesture and the origin for all 144 trials of Graffiti tasks by our web-based visualization tool. Because the rotation angles of all gestures were between 0°-120°, we rotated each candidate gesture by +1°for 120°and searched all possible angles to find the best recognition result, which is the same technique used in $1 unistroke gesture recognizer [36].

As shown in Figure 10, only 2.2% of the gestures were unsuccessfully recognized versus 15.0% for the same subset of 6 Graffiti characters from [29] and 5.5% from [12]. Also, palm-based interaction, even without eye engagement, reached the accuracy as high as Graffiti text entry on pen devices(2.9% error rate for the same subset of characters by first-time users with 5-minute training [26]). Although more data is needed for statistical analysis, the result suggested that palm interface has potential for eyes-free Graffiti input with high accuracy.

Multi-stroke

We collected a total of 2016 samples, i.e., 14 gestures x 24 participants x 6 repetitions. As mentioned earlier, different hand orientations affected the rotation angles of stretched gestures, so we analyzed the captured drawings of multi-stroke tasks through a $N recognizer [2] for rotation invariance.

The users were classified into three groups by hand postures: portrait, diagonal, and landscape. Since the least number of users in one group was 6 in portrait group, we randomly selected 6 gesture datasets from one group as training samples, and datasets of the remaining 2 groups was used as testing samples. From Table 1, the average accuracy can reach above 90% even with only one group of gesture data as training samples, which implied that an accurate gesture recognizer

	Portrait	Diagonal	Landscape	All(leave-one-out)
Accuracy	92.43%	93.67%	90.01%	95.7%

Table 1. The accuracy of $N recognizer with different training samples.

Tested gesture	Confused gesture	No. of confusions	% tests confused
N	H	1	0.6%
H	N	1	0.6%
P	D	8	5.6%
P	Half note	20	13.9%
D	P	8	5.6%
Half note	P	28	19.4%
X	Pitchfork	3	2.1%
Pitchfork	X	1	0.6%
Arrow	X	3	2.1%
Null	Half note	5	3.5%

Table 2. Gestures in the MMG dataset are most highly confused by $N-recognizer(144 per tested gesture).

for palm-based gesture interaction could be generated without collections of gesture data in different groups. Besides, we ran a 10-fold subject-independent (leave-one-out) cross-validation of randomized gesture datasets, and the overall average accuracy could reach 95.7%.

The most highly confused pairs are given in table 2. Since half note symbol is close to the letter P which is rotated by 90 counterclockwise, 19.4% of half notes were wrongly recognized as P, and 13.9% of P were confused with half notes, which results from limitations of the rotation invariant gesture recognizer. As a result, we shouldn't design gestures whose identities depend on specific orientations for palm-based gesture interaction.

Different from the findings of Ni & Baudisch [29], problems with closing shapes were minimal and the alignment within multi-stroke gesture was good as well. We believed this was because the tactile cues of palms, especially the passive tactile sensing by the palm, allows users to orient themselves, which was proven in prior work [14].

DESIGN AND IMPLEMENTATION

In the user study, the accuracy of eyes-free Graffiti input and multi-stroke gesture recognizer on palm interface reached as high as 98% and 95% respectively in our gesture sets, which suggested the potential of palm-based gesture interface for eyes-free input. Therefore, we implemented EyeWrist, a proof-of-concept prototype to explore and demonstrate the feasibility of the interaction.

EyeWrist used the similar approach in Digits [18] to detect finger movements, and we further applied recognizer to recognize gestures on palms rather than recovering the 3D pose of the users hand.

System Hardware

The EyeWrist hardware is worn on the anterior side of the wrist as shown in Figure 11. An IR laser line generator (Gated Cameo 1260 from Global Laser) operating at 850nm with 105 angular spread is attached to a wristband. On top of the laser generator is the combination of a micro-camera module (640x480 resolution capturing frames at 60Hz) which has a radius of 1.5mm and a length of 15mm and a 850nm IR filter lens which covers the camera to block visible light. To avoid occlusion by the bottom part of the palm (the thumbs thenar muscles), we attached a micro-camera to the top of the laser generator.

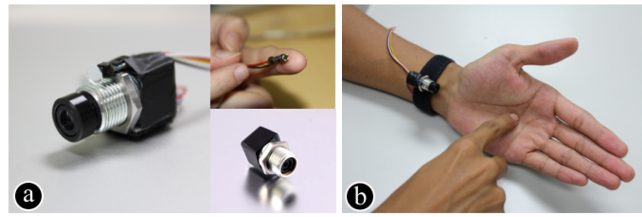

Figure 11. (a) EyeWrist embeds a micro-camera and an IR laser line generator. (b) EyeWrist prototype on the wristband.

Tracking Finger Movements on Palms

An IR laser line generator projects across the user's palm a thin IR line which intersects with the other hand's fingers that are moving on the palm. These intersections are clearly observed as bright elongated ellipsoids which are filtered by size and shape as shown in Figure 12. When the finger moves toward the wrist, the bright region in the IR image is shown at the lower position of the finger and at the upper position as the finger moves away. Therefore, we can calculate a finger's relative movement (e.g., moving forward or backward) on the palm by tracking the centroid of the bright region. With this tracking approach, the camera doesn't need to image the users' fingertips on palms, which could lower the camera height and make the whole device more portable.

In the beginning, because the palm surface seen by the camera is a quadrilateral, the user needs to touch the four corners of the palm surface to define the space of interactive area. When the finger moves on the palm, the system applies homography transformation to convert the finger's position on palm to the rectangular coordinate system for gesture recognition. In order to detect when a gesture ends, the end of gesture is defined when the finger remains at a position more than 1.5s. After a gesture ends, all the fingers positions of the gesture would be sent to computer via Wi-Fi for gesture recognition, as shown in Figure 13.

Gesture Recognition

We used the same study design as our user study to conduct a preliminary evaluation with 6 participants (3 male, 3 female) between the ages of 20 and 27, but only Graffiti and multi-stroke tasks needed to be completed. Overall, we collected 540 samples, including 36 samples in Graffiti and 504 samples in multi-stroke task, and analyzed gesture data sets by the same method in the user study. We observed that the accuracy of eyes-free Graffiti was 92.8%, and that the accuracy of 10-fold subject-independent (leave-one-out) cross-validation was 81.3% in multi-stroke tasks. Because of the noise between strokes of multi-stroke gestures, the accuracy was less than the one reported in the user study. However, the within-subject (leave-one-out) cross-validation that took 5 trials as training samples and tested the remaining one could reach 90.3% accuracy, which implies that our proof-of-concept implementation can recognize the graffiti

Figure 12. (a) Tracking bright regions in the infrared camera image. (b) Fingers positions were sent to computer for gesture interaction.

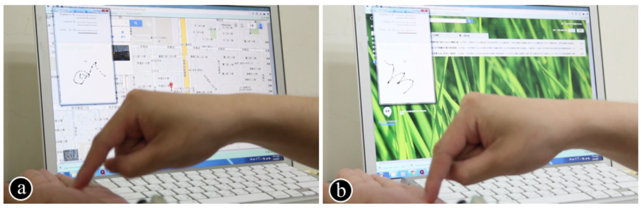

Figure 13. Applying the gesture recognizer to identify gestures:(a) Drawing a note icon to open Spotify. (b) Drawing m to open Google Map.

and multi-stroke gestures reliably under certain circumstances.

INTERACTION TECHNIQUES

Inspired from the Gesture Search [23], we developed a gesture shortcut application that allows users to open applications on a web-based smart TV interface by sketching the defined gestures on palms, such as P for Pinterest, N for CNN and D for Dropbox.

Based on the two user studies, we further proposed two new interaction techniques for palm-based gesture interface, which takes advantages of palm characteristics and could be easily combined with "Gesture Shortcut" techniques. To explore these interaction techniques, we developed two applications for smart TV and Google Glass with EyeWrist prototype. The recognition result would be sent to applications via socket for gesture-based interaction.

Gesture recommendation by starting regions

In order to help users sketch gestures without remembering a large number of gestures, we provide a gesture recommendation application. Based on the result of our user study which demonstrates users' inclination to draw different gestures from the same starting region even without looking at their palms, we can immediately provide candidate gestures of the same starting region when users start drawing. As shown in Figure 14, we chose some popular applications on the web and paired each one to a gesture shortcut according to starting regions of gestures in the user study. For instance, Pinterest(P), CNN(N), Dropbox(D), Hulu TV(H), Yahoo(!), and Outlook(O) are all started from the top-left region of the palm.

Returning to a drawn feature to start a function

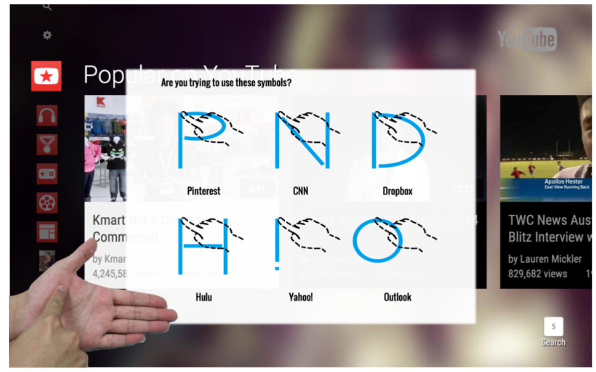

Figure 14. By analyzing the point that the user first touched on the palm, the system provides stroke suggestions on the screen of smart TV or smart glasses.

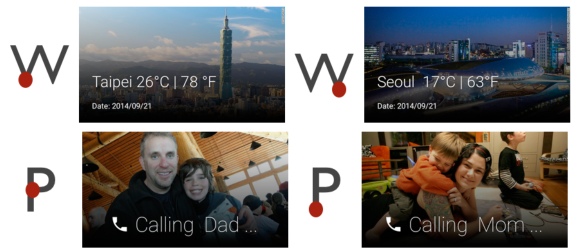

Figure 15. Assigning functions to the drawn features in Google Glass app.

In the user study, we observed that problems with closing shapes were minimal and the alignment within multi-stroke gesture was good as well with the help of tactile cues of palms. Therefore, we proposed a new interaction technique that extends gesture shortcuts from application level (e.g., contact app) to function level (e.g., calling someone) by assigning a specific function to a drawn feature.

We developed an application on Google Glass that allows users to draw P (phone) and touch the starting point to call dad or the end point to call mom. Users can also draw W (weather) and return to the specific point to check local weather or to the other specific point for the weather at the travel destination (see Figure 15).

EARLY USER FEEDBACK

In order to get initial user feedback on the 3 interaction techniques, we conducted a user study composed of 5 participants (3 male, 2 female) between the ages of 18 and 25. None of them had participated in our first study. After a brief introduction to both of the concept and interaction techniques, the participants explored the interaction with EyeWrist prototype while thinking aloud. During the discussion with participants, we received some positive feedback:

Feedback on gesture shortcuts

Participants considered gesture shortcuts very useful to open an application quickly. A participant said, "the link between gesture shortcuts and application names makes it easy to memorize the defined gestures." A participant also hoped to use symbols to open applications, such as drawing a mail icon to open Gmail.

Feedback on gesture recommendation

A participant commented, “It is convenient for me as a first time user to know all the usable gestures because the recommendation system will show me.” Another participant said, “When I have no idea what to draw as the gesture shortcut, I hope to see the gestures designed by others to help me think.”

Feedback on returning to a drawn feature

A participant said, “I want to bind the function with the position I like, such as the corner of the drawing.” The interaction technique could also be applied to other applications. One participant commented, “For now, i can listen to my favorite music list quickly by drawing note symbol and returning to the starting point.” However, according to some participants, it may be difficult to remember more than 3 functions. One participant presented a possible solution that combined gesture recommendation, that is, the recommended gestures and the defined drawn features of them were shown at the same time.

The above feedback suggested that participants were interested in the concept of drawing gestures on palms and the interaction techniques were appealing.

DISCUSSION

Stroke Gesture Articulation

Although we had provided the starting point and stroke order of each drawing so as to understand the recognition rate of gestures on palm by the same standard, some users reported that they would like to perform different stroke gesture articulation, such as stroke direction or stroke order. A user said, “Its difficult to draw a bottom-to-top stroke such as the third stroke of a rectangle. I prefer using 3 strokes rather than the bottom-to-top one.” Another user considered, “I feel uncomfortable when drawing the bottom-to-top stroke of a Graffiti-styled D due to the friction or the raised fleshy area on palm, so I prefer drawing D by two strokes.” Since the current popular gesture recognizers like $1 [36] and $N [2, 3] require an explicitly-defined template for each gesture articulation to be recognized, we could generate all possible permutations of a given gestures to design a reliable gesture recognizer for palm-based gesture interaction in real situations.

Helping blind users learn gestures

Kane et al. [17] investigated the preference and performance of usable gestures for blind people. According to their design guidelines, blind people, with possibly limited knowledge of symbol-based gestures, should learn how to draw symbol-based gestures before performing them. From the result of our user study, problems with closing shapes were minimal and the alignment within multi-stroke gesture was good as well. Therefore, it could be suggested that the palm can be leveraged as an interactive surface to improve gesture learning especially for visually impaired users. However, this claim obviously requires a substantial amount of additional research.

A wider variety of applications

According to the feedback from users, sketching gestures on palms could apply to more scenarios than just the interaction with smart glass, TV and phone. A user narrated that he could use gestures to jump to another slide or to circle a certain part of the slide, which could improve the smoothness of his presentation. Also, some users hoped to connect to other smart home devices quickly by drawing gestures on palm. For example, a bulb symbol could be sketched to connect to smart bulbs (e.g., PHILIPS Hue), or the user could draw a circle to connect to Nest to adjust colors or temperature. It is suggested that using the palm as a gesture interface appeals to users and could suit for a wider variety of applications.

LIMITATION AND FUTURE WORK

System Limitation

Our proof-of-concept implementation consists of a micro-camera and an IR laser line generator on the wristband, and computer vision algorithms are used to calculate the fingers position on the palm. However, the finger posture will affect the calculated fingers position. We consider replacing the single line laser len with a multiple lines to estimate finger poses and calculate fingers positions more precisely in the future.

Two-handed usage

Two-handed usage of the drawing gestures on palms may not be appropriate for some scenarios such as holding a glass with the other hand while watching TV. We believe that this issue will become less severe by extending the palm-based gesture input to the surface of other parts of the body such as thigh, which affords one-handed interaction.

In addition, we will explore the consistency of users' finger stroke gestures on palms to help the design of gesture recognizers and gesture sets for palm-based interaction. The future work should also investigate the effectiveness of helping blind people learn gestures by sketching those gestures on their palms.

CONCLUSION

In this paper, we explored the concept of leveraging the palm as gesture interface for eyes-free input. To understand user behavior when they draw gestures on palms and how palm characteristics affect gestures, a 24-participant user study was conducted. The result showed that users not only preferred using the whole palm region as the gesture interface with 3 categories of hand orientations but tended to draw different gestures from the same starting region due to proprioception on palms. Furthermore, the palm can be leveraged as a gesture interface for eyes-free input with high accuracy. The accuracy of eyes-free Graffiti input and multi-stroke gesture recognizer in our gesture sets reached as high as 98% and 95% respectively.

We implemented a proof-of-concept prototype, EyeWrist, which embeds a micro-camera and an infrared laser line generator on the wristband to explore and demonstrate the feasibility of the interaction. Besides, based on the results of studies, we proposed two interaction techniques: gesture recommendation by starting regions and returning to a drawn feature to start a specific function of an application. The users' positive feedback suggested their interests in the concept of eyes-free palm-based gesture interaction. Finally, we provided web-based visualization tool and dataset for the HCI community to foster more research on the palm-based gesture interaction.

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