

# Left and Right Hand Distinction for Multi-Touch Tabletop Interactions

Zhensong Zhang<sup>1</sup> Fengjun Zhang<sup>1,2\*</sup> Hui Chen<sup>1,2</sup>

<sup>1</sup>Beijing Key Lab of Human-Computer Interaction  
Institute of Software  
Chinese Academy of Sciences  
zsz@iel.iscas.ac.cn  
{fengjun, chenhui}@iscas.ac.cn

Jiasheng Liu<sup>3</sup> Hongan Wang<sup>1,2</sup> Guozhong Dai<sup>1,2</sup>

<sup>2</sup>State Key Laboratory of Computer Science  
Institute of Software  
Chinese Academy of Sciences  
{wha, dgz}@iel.iscas.ac.cn  
<sup>3</sup>Information Center, Guodian Finance Co., Ltd.  
liujiasheng@cgdc.com.cn

## ABSTRACT

In multi-touch interactive systems, it is of great significance to distinguish which hand of the user is touching the surface in real time. Left-right hand distinction is essential for recognizing the multi-finger gestures and further fully exploring the potential of bimanual interaction. However, left-right hand distinction is beyond the capability of most existing multi-touch systems. In this paper, we present a new method for left and right hand distinction based on the human anatomy, work area, finger orientation and finger position. Considering the ergonomics principles of gesture designing, the body-forearm triangle model was proposed. Furthermore, a heuristic algorithm was introduced to group multi-touch contact points and then made left-right hand distinction. A dataset of 2880 images has been set up to evaluate the proposed left-right hand distinction method. The experimental results demonstrate that our method can guarantee the high recognition accuracy and real time performance in freely bimanual multi-touch interactions.

## Author Keywords

Left-right hand distinction; multi-touch interaction; bimanual interaction.

## ACM Classification Keywords

H.5.2. Information interfaces and presentation: User Interfaces-*Ergonomics, Interaction styles, User-centered design.*

## General Terms

Human Factors; Design.

## INTRODUCTION

Over the past years, computer-vision based multi-touch surfaces are becoming prevalent in our daily life [2, 7, 8, 11,

21]. Multi-touch interactions extend traditional desktop interactions through allowing direct-touch with bare fingers. Therefore, designing natural interactions with multi-touch interactive surfaces has attracted increasing attention in recent years.

The advantage of interactive surfaces provides new opportunities for freely bimanual interactions. Moscovich and Hughes [18] demonstrated that usually one-handed input and two-handed input are not exchangeable since they have different meanings. Especially, their studies indicated that unimanual multi-touch manipulation is suitable for moving, rotating, and stretching an object, while two hands perform better than one at tasks which require separate control of two points. According to Guiard [13], asymmetric but bimanual interactions are among humans' most skilled manual activities. In fact, we are quite familiar with using both our hands in very different manners in our daily lives, such as playing violin and using scissors.

However, most existing multi-touch tabletop systems relied only on contact locations and the movement of fingertips; they provided little information about which hand was touching the display, hence limited the naturalness of the interactions. The limited scopes of information without left-right hand distinction constrain the interaction vocabulary and narrow the potential natural input bandwidth of bimanual interactions.

Since quite few hardware devices or software frameworks provide handedness information, the objective of our work is to group multi-touch contacts into a user's left or right hand to fully explore the potential of bimanual interactions. The observations show that finger orientation [8, 15, 25, 26, 30] may be a potential input dimension for detecting finger handedness and extending the design space for natural interactions on interactive surfaces. Besides, ergonomics, especially work area [3, 12, 23], should be taken into account when designing touch gestures [19, 29]. Surprisingly, although there have some researches on bimanual interactions [2, 8, 11, 25], very few exploit the work area for interactions.

In this paper, a new left and right hand distinction method is proposed based on both the finger orientation observation

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Note: \*Corresponding author. Tel.: +86-10-62661574

and natural ergonomics work area design principles. It is a simple but effective method of multi-touch tabletop interactions that can detect multiple touches, group the touch points, and further map the touch points to their associated joined hand without resorting to additional hardware. Left and right hand distinction can assign different work to different hands, enable asymmetric bimanual interaction [13], enrich semantic information, enhance user-friendliness of multi-touch screens and enrich the gesture vocabulary. The main contributions of our work are summarized as follows:

- A body-forearm triangle interaction model was proposed based on the human anatomy, normal comfort work area and ergonomics principles of gesture designing;
- A heuristic algorithm clustering multiple finger touches into groups, and distinguishing between left hand and right hand even when not all of the fingers from a given hand are placed on the surface;
- A dataset of multi-touch gestures with 2880 images was set up. The recognition accuracy and time performance of our method were tested on the dataset. The results demonstrated that one-handed or two-handed multi-touch gestures composed by arbitrary fingers can be identified in real time by the proposed method.

## RELATED WORK

Computer vision-based interactive tabletop techniques are most popular because of their scalability, low cost and ease of setup. However, in most vision-based techniques [21], such as Laser Light Plane Illumination (LLP), frustrated total internal reflection (FTIR) [14] and diffused illumination (DI), touch areas are recognized as blobs of light, therefore, touch discrimination is essential in multi-touch interactions.

Current available solutions to touch discrimination rely mostly on hardware. One of the earliest commercially available tabletop systems that supported discriminating touches was DiamondTouch [9], which used a technique where a circuit was capacitively closed when a user touched the surface, by which it associated touch regions to a specific user. This technology supports user identifications and bimanual interactions. Dohse et al. [10] distinguished and identified users by using skin color segmentation with a peripheral overhead camera. Ackad et al. [1] used the Kinect sensor and mobile phones to continuously track and identify different users, however, it didn't make hand discrimination of users. Some other hardware-based methods also require that the users wear the necessary devices, for example, both Meyer and Schmidt's IdWristbands [17] and Roth et al.'s IR ring [22] emitted a coded signal as identifiers. Marquardt et al. [16] employed the gloves equipped with fiducials that enabled recognition of markers together with their orientations, hence finger

orientations were derived. Hand and user detection were also achieved in this way. However, these methods rely on external devices, which impede the compactness of the setup and also introduce additionally heavily processing to the pipeline [10].

Software-based systems with the existing hardware of a common vision-based tabletop are also proposed. Considering the positional information for the fingertips, distance based distinction methods are most widely used. Ewerling et al. [11] developed an approach for finger identification and hand distinction on optical multi-touch devices, their approach relied on the Maximally Stable Extremal Regions algorithm for detecting user's fingertips. Nevertheless, their method is more computationally intensive than common blob detection methods. Bojan et al. [5] proposed a biometric method which was based only on the touch coordinates for user identification on multi-touch displays. Au and Tai [2] presented a simple finger registration method, which could distinguish which hand and fingers were touching the interactive surface directly from the positions of the contact points. While this method only works when all the five fingers are touching the surface in a natural pose, and it cannot tackle two hand distinctions.

Several other systems employed finger orientations to extend natural interactions. Malik et al. [15] firstly explored finger orientations in their Visual Touchpad system, the entire hand of the user was tracked by two overhead cameras, hence the finger orientations were derived. Considering the dynamics of the finger landing process, Wang et al. [26] proposed an algorithm for detecting finger orientations from contact information in real time. Zhang et al. [30] used the orientations of the touching fingers for discriminating user touches on vision-based tabletop systems. Dang et al. [8] developed heuristics based on constraints applied to the touch position with finger orientations and mapped fingers to their associated joined hands. Walther-Franks et al. [25] proposed a decision tree to classify fingertip configurations on optical interactive surfaces. Their system provides fingertip registration with less than five fingers present. However, their detection rate is only 80%, which is still too low for tabletop interaction.

Besides using the positions of the contact regions and finger orientations, researchers have also developed methods that extract additional context information for new interactions. Boring et al. [6] and Benko et al. [4] explored the use of contact size to enable rich interactions. ShapeTouch presented by Cao et al. [7] directly utilized contact shape to manipulate objects. Wilson et al. [28] leveraged the contact contours to expand the interaction vocabulary, with which they could manipulate digital objects. Wang and Ren [27] empirically investigated and evaluated several finger properties using a FTIR-based multi-touch surface, they concluded that the shape of the finger contact area, the size

of the contact area and the orientation of the contact finger are useful for designing natural multi-touch gestures.

Rather than rely on additional hardware or consider finger properties individually, in this work, we utilize the three aspects together for left and right hand discrimination: 1) both finger orientations and touch positions; 2) the anatomy of human hands and fingers; and 3) natural comfort work areas [3, 12, 23] when interacting with multi-touch tabletop.

### LEFT AND RIGHT HAND DISTINCTION ALGORITHM

In this section, we will introduce left and right hand distinction algorithm in detail. First, we will present the basic assumptions used in the algorithm. Second, we will describe a method that detects the orientation of finger contact based on the shape of the contact area. Third, several constraints in grouping finger contacts will be explained. Finally, based on the two groups, we can then perform left and right hand distinction.

#### Basic Assumptions

Based on existing ergonomics researches [3, 12, 13, 20, 23, 24] and observations of interactions on multi-touch tabletop, three assumptions of our left and right hand distinction method are proposed.

The three assumptions are derived from the movement of kinematic chain of upper limb [13], including angular movement of the wrist, natural work area considering movement of elbow and shoulder. The ergonomics normal range of the angular movements of the wrist [24] is given in assumption 1. Then the normal area [3, 12, 23], which can be reached easily in natural interactions, is given in assumption 2. After that, body-forearm triangle model is proposed based on the observations in assumption 3.

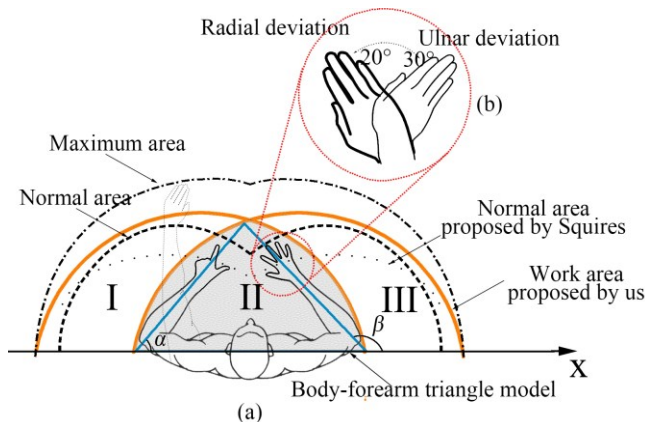


Figure 1. Basic assumptions: (a) working areas; and (b) the angular range of wrist movements.

**Assumption 1 (Ergonomics forearm movements assumption):** The user naturally places his/her hand(s) on the surface, with his/her wrist(s), elbow(s) and shoulder(s) relaxed, the angular range of wrist movements [24] is shown in Figure 1(b), the orientation of forearm is estimated by the average orientation of finger contacts.

This assumption is in accordance with ergonomics [20]. Nielsen et al. [20] pointed out that the human based gesture approach should be ergonomic, i.e. not physically stressing when used often. They furthermore concluded six main principles in ergonomics, among which are avoiding outer positions, relaxing muscles and avoiding internal and external forces on joints that may stop body fluids. According to these principles, when designing touch interactions, the human hand cannot be utilized beyond the limits of its inner structure despite its dexterity.

**Assumption 2 (Work area assumption):** According to Barnes and Squires's theory, we divide the work area into three parts (in Figure 1(a)) : I) the left work area, only left hand can reach this area; II) the public work area, both hands can reach this work area; and III) the right work area, only right hand can reach this area. Obviously, these parts depend on the length of the user's hand as well as his/her position, therefore the users are asked to identify their work areas before interaction with the multi-touch tabletop when he/she moves or uses our system for the first time.

Figure 1(a) shows the maximal and normal areas proposed by Barnes [3] and Squires [23], and work area proposed by us. Farley [12] and Barnes [3] proposed maximum and normal areas in horizontal work surface area. Maximum area is defined as the area that could be reached by extending the arm from the shoulder, shown in dash-and-dot line. Normal area is defined as the area which can be conveniently reached with a sweep of the forearm while the upper arm hangs in a natural position at the side, shown in dashed line. Squires [23] also took into account the dynamic interaction of the movement of the forearm as the elbow also is moving, and the normal area proposed by Squires is shown in dotted line. In practice, the user will not fully extend his/her arm(s) or fix his/her elbow(s) when interacting with tabletop, therefore we define work area as the area which both include normal area and can be easily reached, shown in orange solid line.

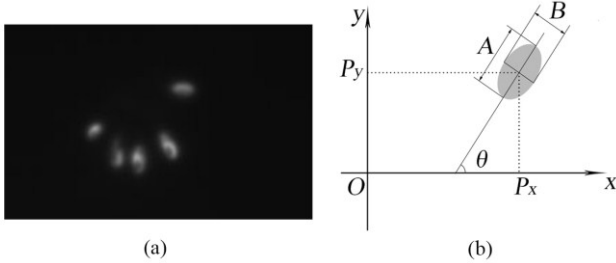
**Assumption 3 (Body-forearm triangle assumption):** According to our observation, we suppose that the body and the forearms form a triangle, termed as body-forearm triangle, in the public area during natural interactions, shown as the blue triangle in Figure 1(a)).

In Figure 1(a),  $\alpha$  and  $\beta$  are the orientations of the left forearm and the right forearm, respectively. When a user interacts with the tabletop using two hands, it is always true that  $\beta > \alpha$ . Hence if we can calculate the orientations of two forearms, we can easily tell left hand from right hand by comparing their orientations, the hand that has the smaller orientation is left hand, and the other one is right hand. When a user interacts with the tabletop using only one hand, there are three cases: 1) if the touch contacts occur in the left work area, then these touch contacts belong to left hand; 2) if the touch contacts occur in the right work area, then these touch contacts belong to right hand; and 3) if the touch contacts occur in the public area, the orientation of

the hand is estimated as  $\theta$ , if  $\theta > 90^\circ$ , then these contacts belong to right hand, otherwise, they belong to left hand.

### Finger Orientation Detection

Despite various multi-touch hardware systems, computer-vision based multi-touch technologies are considered in this paper, such as LLP-based multi-touch table (Laser Light Plane). Depending on the particular LLP-setup, only the finger contacts are visible. The captured image in Figure 2(a) stems from a LLP-based table. Since our left-right hand distinction algorithm depends highly on the orientation of finger contact, it's very important to calculate right orientations for all contacts.



**Figure 2. Finger orientation: (a) image captured by a camera from the LLP-based table; (b) finger contact region fitted to an ellipse.**

The position and orientation of a detected finger contact area is defined in Figure 2(b). The major axis  $A$ , minor axis  $B$  and slant angle  $\theta$  ( $0^\circ \leq \theta \leq 180^\circ$ ) describe the shape of the ellipse; and  $(P_x, P_y)$  is the center coordinate of the finger contact. The finger contact blob appears as an elliptic shape which can be perfectly fitted to an ellipse using least-square fitting, as in Figure 2(a). Equation (1) describes the fitted ellipse, where  $a$  and  $b$  are one-half of the ellipse's major axis  $A$  and minor axis  $B$  respectively [26].

$$\left( \frac{(x-P_x)\cos\theta + (y-P_y)\sin\theta}{a} \right)^2 + \left( \frac{(y-P_y)\cos\theta - (x-P_x)\sin\theta}{b} \right)^2 = 1 \quad (1)$$

As explained in [26, 27], only oblique touches are considered in our algorithm. Hence we need to determine whether the finger is currently in an oblique touch state to generate reliable finger orientation, similar to [26], area and aspect ratio are used to identify an oblique touch. The identification criteria is shown in Equation (2), where  $t_a$  and  $t_b$  are empirical thresholds of touch area, and  $t_s$  is empirical threshold of aspect ratio.

$$\begin{cases} t_b > \text{area} > t_a \\ \text{aspect ratio} = \frac{A}{B} > t_s \end{cases} \quad (2)$$

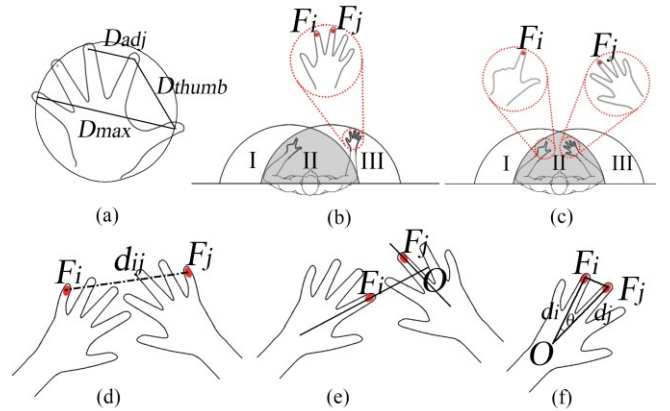
An oblique touch should meet both criteria in Equation (2), otherwise the touch contact will be discarded. Based on pilot experiments and ergonomics [26],  $t_a$  is set to be  $100 \text{ mm}^2$ ,  $t_b$  is set to be  $500 \text{ mm}^2$ , and  $t_s$  is set to be 120% in our

prototype system. For an area smaller than  $t_a$ , we consider the contact to be vertical or accidental touch; for an area bigger than  $t_b$ , we consider that user's fingers are placed too close together; in this case, the finger contacts are merged to one contact area resulting in unreliable detection.

In this step, positions and orientations of all touch contacts as well as their distance between each other are calculated.

### Finger Contacts Grouping

Due to the fact that thumb always has the largest spanning angle and its orientation is of large difference with other four fingers, it's hard to tell whether a contact belongs to left hand or right hand solely from its orientation. As a result, when more than one contacts are detected, we have to cluster the finger contacts first, all the contacts from one hand should be clustered in the same group. Both finger orientation and the distance between two contacts are used for clustering the contacts from the same hand into one group.



**Figure 3. Finger grouping constraints: (a) some thresholds; and (b-f) constraints of touch contacts.**

To better describe our algorithm, as depicted in Figure 3, we denote  $D_{adj}$  as the maximal distance of adjacent fingers (except thumb) from same hand,  $D_{thumb}$  as the farthest distance a thumb can have to the other fingers from same hand,  $D_{max}$  as the maximal distance of any two fingers from same hand,  $O$  as the intersection point of finger contact  $F_i$  to  $F_j$ ,  $d_{ij}$  as the distance from contact  $F_i$  to contact  $F_j$ ,  $d_i$  as the length of  $OF_i$ ,  $d_j$  as the length of  $OF_j$ . Based on prior trials,  $D_{adj}$  is empirically set to be 40 mm,  $D_{thumb}$  is empirically set to be 80 mm,  $D_{max}$  is empirically set to be 100 mm in our system. Nevertheless, these thresholds are user specific, in fact, these thresholds may be unreasonable for a child. One potential solution is to register hand before interactions as in [2, 11]. In registration, the user is asked to open his/her palm and his/her fingers fully stretched apart as shown in Figure 3(a), then places his/her hand on the interactive surface,  $D_{adj}$ ,  $D_{thumb}$  and  $D_{max}$  can be easily derived when five fingertips are detected. Different from [2, 11], the user only has to register his/her hand once before his/her first interaction in our system. All contacts during

interactions are clustered into two groups according to the following four constraints:

**Constraint 1 (Consistent area constraint):** For contacts  $F_i$  and  $F_j$ , based on Barnes and Squires's theory, if both contacts are in the left part of the user's work area as explained in **Assumption 3**, these two contacts belong to the same group, furthermore, they belong to left hand. This is also true when both contacts are in the right part of the user's work area, shown in Figure 3(b).

**Constraint 2 (Maximum distance constraint):** If  $d_{ij} > D_{max}$ , the two touch contacts are certainly from different hands. When two hands are far away from each other, this step can effectively cluster contacts belonging to the same hand into one group, as shown in Figure 3(c). When two hands are close enough, fingers can be partly divided into two groups. Such as in Figure 3(d), finger  $F_i$  and finger  $F_j$  are from different hands.

**Constraint 3 (Minimum distance constraint):** The distance ( $d_i$  and  $d_j$ ) from the intersection point  $O$  to finger contacts ( $F_i$  and  $F_j$ ) should all be larger than a minimum finger length threshold  $\lambda$ . That is if one is smaller than the threshold  $\lambda$ , i.e.  $d_i < \lambda$  or  $d_j < \lambda$ , then finger contact  $F_i$  and finger contact  $F_j$  come from two different hands. Generally, the threshold  $\lambda$  is set to be the minimum of the average length of thumbs and that of pinkies. In our system,  $\lambda$  is empirically set to be 50 mm. Figure 3(e) sketches this case.

**Constraint 4 (Angle constraint):** If  $d_{ij} < D_{adj}$ , the interior angle  $\theta$  between the orientations of the two fingers is taken into consideration. The basic idea behind this constraint is to estimate a proper angle range of two fingers in the same hand. According to the law of cosines, Equation (3) can be derived (in Figure 3(f)),

$$\theta = \arccos\left(\frac{d_i^2 + d_j^2 - d_{ij}^2}{2 \times d_i \times d_j}\right) \quad (3)$$

where  $d_i \in [a_0, a_1]$  and  $d_j \in [b_0, b_1]$ .

If the range of  $d_i$  and  $d_j$  are known, given a specific  $d_{ij}$ , the range of  $\theta$  can be estimated according to Equation (3). The range of  $d_i$  and  $d_j$  are estimated using Equation (4), then the proper angle ranges of two fingers from the same hand ( $\theta_0$  and  $\theta_1$ ) are estimated by Equation (5).

We can easily figure out the range of  $d_i$  and  $d_j$  are the same, i.e.  $a_0 = b_0$  and  $a_1 = b_1$ . As explained in **Constraint 3**,  $d_i \geq \lambda$  and  $d_j \geq \lambda$ , hence  $a_0 = b_0 = \lambda$ . In a vision-based tabletop system, if two fingers are too close when interaction, then these two finger contacts may merge into one big contact area, which violate the area criterion in Equation (2), thus finger orientation cannot be detected. In our observation, in order to correctly detect finger orientation, the centers of adjacent fingertips should be at least 20 mm apart,  $d_i$  and  $d_j$  are supposed to reach the upper length boundary in this

situation. To estimate the value of  $a_1$  and  $b_1$ , we let both  $d_i$  and  $d_j$  be  $x$  in Equation (3), thus:

$$x = \frac{d_{ij}}{\sqrt{2 \times (1 - \cos(\theta))}} \quad (4)$$

Our prior experiments show that  $\theta$  is at least  $5^\circ$  when  $d_{ij}$  approximates 20 mm. Hence we set  $d_{ij}$  to be 20 mm and  $\theta$  to be  $5^\circ$  in Equation (4) to estimate the upper bound of  $d_i$  and  $d_j$  (i.e.  $a_1$  and  $b_1$ ) to be 230 mm.

In our prototype system,  $a_0$  and  $b_0$  are empirically set to be 50mm,  $a_1$  and  $b_1$  are empirically set to be 230 mm. Furthermore, the range of  $\theta$  has

$$\theta_0 = \arccos\left(\frac{a_1^2 + b_1^2 - d_{ij}^2}{2a_1b_1}\right) \leq \theta \leq \arccos\left(\frac{a_0^2 + b_0^2 - d_{ij}^2}{2a_0b_0}\right) = \theta_1 \quad (5)$$

It won't be hard for us to derive that  $F_i$  and  $F_j$  are from different hands if  $\theta < \theta_0$  or  $\theta > \theta_1$ .

Based on these constraints and heuristics, the touch contacts are divided into two groups.

#### Left and Right Hand Distinction

Wobbrock and Colleagues [29] outlined 27 different gesture commands performing on a tabletop interactive surface. Murugappan et al. [19] further studied these hand poses, and concluded that 1) the majority of gestures are performed with one, two, three or five finger touch points; 2) almost all the one-finger interactions are performed using the fore-finger; 3) for two-finger interactions, the fingers used are thumb-fore fingers and fore-middle fingers; 4) for three-finger interactions, the finger combinations used are thumb-fore-middle and fore-middle-ring; and 5) for four-finger interactions, the finger combinations are thumb-fore-middle-ring and fore-middle-ring-and-little. Based on the above observations, and taking bimanual and asymmetric interactions into account, we propose 80 gestures including  $(1 + 2 + 2 + 2 + 1) \times 2 = 16$  one-handed gestures and  $(1 + 2 + 2 + 2 + 1)^2 = 64$  two-handed gestures to be detected in our system.

The clustered groups are then used to distinguish left hand contacts from right hand contacts. Since there are only two groups of touch contacts, if one group of them is recognized, the remaining group is determined. The left and right hand distinction steps are as follows:

**Step 1:** Figure out the centroid of the either group of touch contacts. According to our body-forearm triangle model, if the centroid locates in the left work area, then this group of touch contacts belongs to left hand; if the centroid locates in the right work area, then this group of touch contacts belongs to right hand; if both centroids locate in the public work area, then go to **Step 2**.



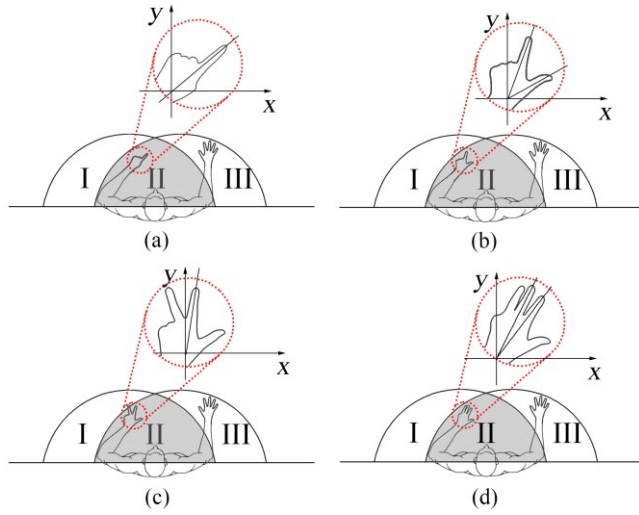


Figure 4. Hand orientation estimation.

**Step 2:** Compute the orientation of the group while the centroid of the group of touch contacts locates in the public work area. When there is only one contact in the group (Figure 4(a)), the orientation of the group equals to that of the contact; when there are two contacts in the group (Figure 4(b)), the orientation of the group equals to the mean orientation angle of contacts; when there are more than 2 contacts in the group (Figure 4(c-d)), the group orientation is the mean orientation angle of the contacts without the maximum and minimum orientations.

**Step 3:** Make left and right hand distinction based on the **body-forearm triangle assumption**. If there is only one group, the orientation of the group is estimated as  $\theta$ , if  $\theta > 90^\circ$ , then these contacts belong to right hand, otherwise, they belong to left hand. If there are two groups of contacts,  $\alpha$  and  $\beta$  are the orientations of group one and group two, respectively. If  $\beta > \alpha$ , then the contacts of group one belong to the left hand, while the contacts of group two belong to the right hand, and vice versa.

A concrete example of our left and right hand distinction algorithm is shown in Figure 5. Figure 5(a) is a raw image captured by Flycap, the image is firstly preprocessed by background removal and image binarization (Figure 5(b)). Secondly, finger orientations are calculated by detecting contacts blobs and fitting the blobs into ellipses, as shown in Figure 5(c). Thirdly, the contacts points are classified into two groups in Figure 5(d), where the finger grouping result is represented by the colored digits, yellow digits belong to one group, while purple digits belong to another group. Finally, we perform left and right hand distinction (Figure 5(e)), the left and right hand distinction result is indicated by the colored ellipses, red ellipses indicate that this group of contacts belongs to left hand, while green ellipses indicate that this group of contacts belongs to right hand.

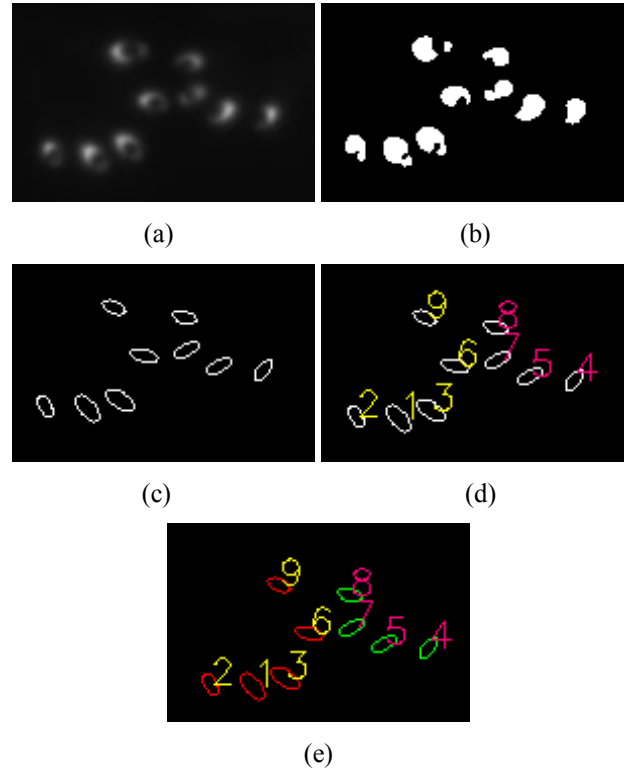


Figure 5. A concrete example of our left and right hand distinction algorithm.

## EXPERIMENTS

Experimental evaluations were conducted to assess the performance of our proposed left and right hand distinction algorithm.

### Apparatus

We conducted the experiment on LLP (Laser Light Plane Illumination, LLP) based multi-touch interactive tabletop, shown in Figure 6. The tabletop device rear-projects images with a resolution of  $1024 \times 768$  pixels onto a surface with size  $140 \text{ cm} \times 104 \text{ cm}$ . The tabletop was connected to a personal computer with 2.4 GHz processor and 2GB RAM, the operating system is 32-bit Windows XP Professional 2002 Service Pack 3.

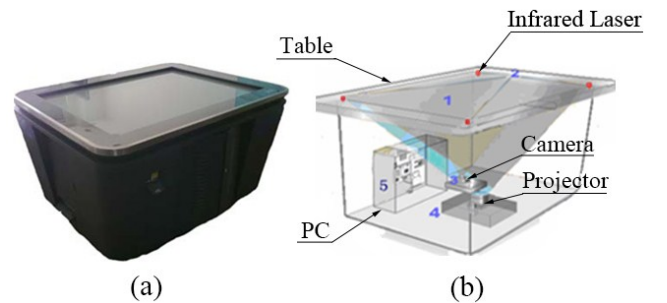


Figure 6. LLP-based multi-touch table: (a) appearance; (b) internal components.

### Participants

12 graduate students (6 males and 6 females, aged between 23 and 29) with a mean age of 25.2 (std. dev. = 3.1) were involved in this study. 2 participants were left-handed (1 male and 1 female). All of the participants had experience in using multi-touch user interfaces. None of them had used the system we developed in this work prior to the experiments.

### Task & Design

At the beginning of experiments, all of the participants were given a brief demonstration of how the task could be done using various finger gestures. The participants stood in front of the tabletop and were asked to adopt a position that felt natural and comfortable for them. Since detecting finger orientations was a component of our left-right hand distinction system, we didn't provide any visual feedback; hence the participants had to rely on their subjective perception of the finger orientation completely.

The participants were asked to perform the proposed 80 gestures and were reminded to touch the screen in a natural and comfortable way. When they posed a gesture, the user input image was recorded via software named Flycap. At the same time, the actual gestures were recorded by a camera to verify our left-right hand distinction result. The participants had to lift their fingers before performing the next gesture. Participants performed each gesture with three repetitions, and in one of which they were reminded to put their fingers closer.

Thus a dataset consisting of multi-touch gestures was set up, and the total images consisted of: 12 participants  $\times$  80 gestures  $\times$  3 repetitions = 2880 images in total.

### Criteria

The hand discrimination accuracy and time performance are assessed with the following criteria:

- 1) **Grouping Accuracy (GA):**  $GA = (\text{the number of correctly grouped fingers}) / (\text{the number of all contacts});$
- 2) **The Precision in left-right hand Distinction after Grouping contact points (PDG):**  $PDG = (\text{the number of contacts that are successfully mapped to their joined hands}) / (\text{the number of correctly grouped fingers});$
- 3) **The Overall Handedness Identification Accuracy (OHIA):**  $OHIA = GA \times PDG = (\text{the number of contacts that are successfully mapped to their joined hands}) / (\text{the number of all contacts});$
- 4) **Execution Time (ET).**

### Results

Several experimental cases are shown in Figure 7, for every subfigure, the original image is shown in the left, while the results of finger contacts grouping and left-right hand distinction are shown in the right. The finger grouping result is represented by the colored digits, white represents

no group information, yellow represents one group, while purple represents the other group; the left and right hand distinction result is represented by the colored ellipses, red ellipse represents that this contact belongs to left hand, while green ellipse represents that this contact belongs to right hand. Even when there is only one finger touching the tabletop, as shown in Figure 7(a)(b), our algorithm can effectively provide the handedness information. Figure 7(c) shows the case that two touch contacts from the same hands, while Figure 7(d) shows the case that two touch contacts come from the different hand. Similarly, Figure 7(e-o) indicates some possible combinations of input gestures from three to ten fingers. Besides, our method support both unimanual gestures, such as in Figure 7(a-c)(e)(i), and bimanual gestures, such as in Figure 7(d)(f)(g-h)(j-o). The results show that one-handed or two-handed multi-touch gestures composed by arbitrary fingers can be identified by our proposed method.

We collected  $12 \times 80 \times 3 = 2880$  images in the experiment, seven of which were discarded because of the mis-operation by the users. In experiment, we manually annotated 2873 images with 15501 touch contacts, during which 14759 contacts were grouped correctly by our algorithm, the precision in clustering contacts was 95.2%; Based on correctly grouping, 14165 contacts were correctly mapped to their associate joined hand, the accuracy rate was 96.0%; The average recognition rate of our proposed method was about 91.4% which improved dramatically comparing to that of decision tree-based method [25], whose detection rate was 80%. Figure 8 shows the precision in correct clustering contacts (GA), the precision in left-right hand distinction after correctly grouping contact points (PDG) and the precision in mapping contact points to the associate joined hands (OHIA) from 1 finger to 10 fingers. Our result reveal accuracy rate as high as 97.2% when there is only 1 contact, comparing to Literature [19], we can not only map single contact to its associate joined hand, but also have a higher success rate, which supports our body-forearm triangle interaction model; as expected, when it comes to 2 contacts, we achieve a lowest precision of 90 % in correctly clustering fingers (GA), and a lowest precision of 86.4% in mapping contact points to the associate joined hands (OHIA); along with the increase of the number of contacts, the precision in correctly clustering the contacts and mapping contacts to their associate joined hands increase. When it comes to 10 contacts, we observe 98.9% recognition rate for grouping fingers (GA) and 98.3% for left-right hand distinction (OHIA).

Figure 9 shows the execution times with respect to the simultaneous number of contacts. The reported execution times include all steps of our proposed method as well as image preprocessing. We started measuring just after loading the images into memory and stopped when all processing steps had been executed. In order to minimize the influence of external factors, the record images were processed three times and we took the average times as

performance measures. It took 11.55 ms on average (std. dev. = 2.30 ms) with a maximum of 16ms to detect handedness, which met the requirement of real-time interaction on tabletop.

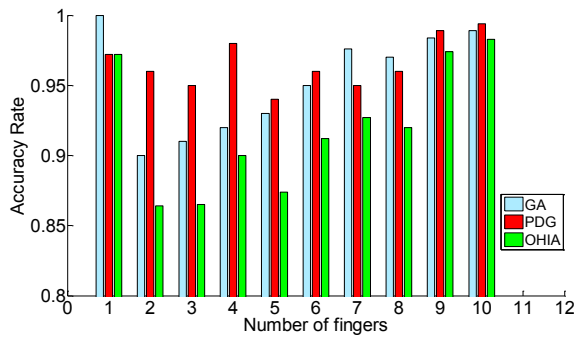


Figure 8. The precision in clustering contacts and mapping contacts to their associate joined hands.

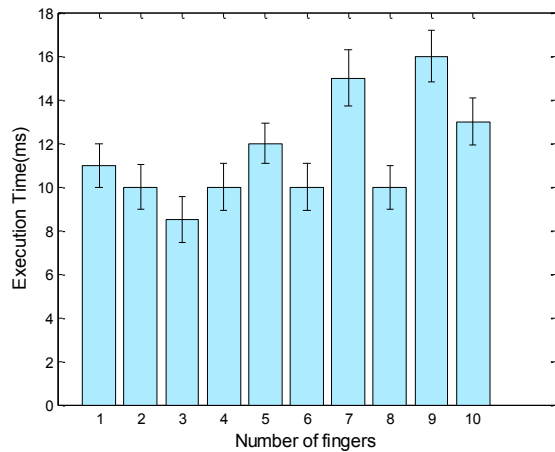


Figure 9. Execution times with respect to the simultaneous number of contacts involved in the processing.

### Discussion

When the number of contacts is less than five, there is relative less information for us to use to group fingers, therefore most of our errors stemmed from false finger orientation. There is no overlapping and adhesion when there is only one contact, resulting in correct finger orientation at high recognition rate. In the case of 2 contacts, contacts grouping usually failed in the presence of overlapping and adhesion when user performs fore-middle finger gestures. The case that mistaking one hand's fore-finger as the thumb of the other hand didn't happen. One possible reason might be that this posture is not natural or comfortable for the users. We also observed that the accuracy increases as the number of finger contacts increases. When there are many contacts, the accuracy of handedness detection (OHIA) may be affected by adhesion, when contacts points are too close, our algorithm may fail. The major reason is that it will cause wrong finger orientation detection. In order to generate reliable finger

orientation, we adopt Equation (2) to avoid the situation when two contacts points are too close. In our experiment, this situation happened very few, about less than 10 times in our collected dataset with 2880 images. One potential solution to this problem is to consider continuous frames. Because the contacts points may be too close in current frame, but they may be far enough to be distinguished in next frame.

Our proposed method has several limitations, it only deals with one user, and it may be desirable to consider collaborative use with the multi-touch systems and moving scenarios. Our method only deals with one image in our current study; it may also be interesting to consider multiple frames in our future work. What's more, our algorithm relies heavily on the detection of finger, especially finger orientation, hence a false detection for finger orientation may result in a false left-right hand distinction. Future studies are needed to explore reliable finger orientation detection.

### CONCLUSION

In this research work, we designed and implemented a simple but robust software-based method for finger handedness distinction on optical interactive surfaces. We take both the contacts and the complete arm-hand-chain into consideration. Using data gathered from 12 users on an LLP multi-touch display, our system reported an accuracy of 91.4% in detecting finger handedness. Our prototype system demonstrates that it is possible to provide finger handedness distinction capabilities on every multi-touch display, and we also believe that detecting handedness of fingers will enrich designs of multi-touch interactions.

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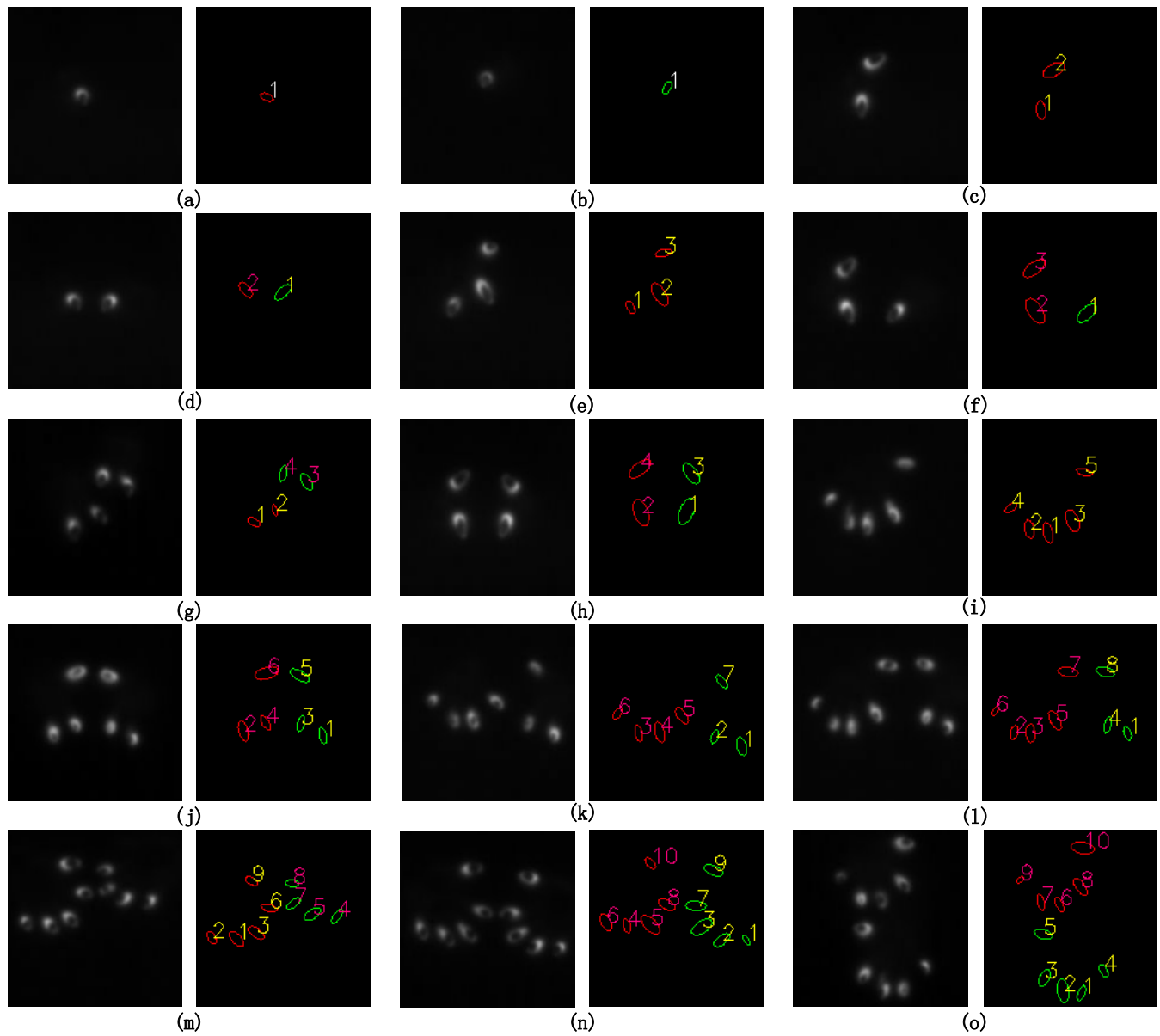


Figure 7. Experiments of finger grouping and left-right hand distinction.