Chapter 3

Dactylology: An Outcome of User Evaluation Study

The proposal of the interactive system involves three inter-connected research—design of interaction space, development of dactylology and recognition unit. We have already discussed the user interface design in Chapter 2. The development of dactylology is presented in this chapter while the recognition unit will be discussed in Chapter 4 and Chapter 5. This chapter details the user evaluation study performed with blind and visually impaired users. Further, the proposal of the dactylology using which blind and visually impaired can interact with computers is discussed in this chapter.

3.1 Background

As stated in Chapter 1, gestures have a great potential to create more intuitive, creative and productive experience. Research has already confirmed that vision is not responsible for the production of gesture [91]. Every human being—even those blind by birth—produce hand gestures during interaction [24]. They produce gestures almost similar to the gestures produced by sighted users. But, their gestures are limited and are less detailed. Recent evolution in gesture recognition algorithms and low-cost hardware development had made it possible to use gesture commands for interacting with computer and other consumer electronics. Gesture-based interaction can offer them a new vista of computer interaction. However, one needs to consider their performance and preference towards hand gestures and understand the difficulties faced by them. To understand their problems and to overcome their difficulties, a user evaluation study is conducted with them and optimal gesture set is devised.

3.2 User Evaluation Study

The user evaluation study is performed out to devise optimal gesture set with lower biomechanical and ergonomics risk. The gestures are rated on four subjective criteria using a Likert scale (strongly disagree = 1, disagree = 2, neutral = 3, agree = 4 and strongly agree = 5). The outcome of the gesture rating analysis indirectly indicates the complexity level of gestures in the set and their suitability for users. More than 12,400 questions are asked and analysed in this user evaluation study. Further details are briefed in the next sections.

3.2.1 Related Literature

The design of gestures plays an important role from the perspective of system usage. If a gesture is painful, users will not enjoy the experience of using it. So, it is important to consider their comfort. Most of the studies in vision-based hand gesture recognition system are focused either on technical design and implementation or usability and human factors. Only a few researchers [36–48, 122] have considered the usability and human factors related issues of hand gestures. Majority of the research concentrates on hand gestures recognition aspects [80, 82, 88, 123, 124]. Gestures selected in [36–39, 41, 45, 47, 48, 82, 88, 122–124] are based on two different approaches: technical and human. In the technical approach of choosing gestures is to select a set of gestures which is easy to recognize. However, this approach sometimes leads to a gesture set that is difficult to pose by some group of users. In the human-based approach, gestures are selected on the basis of gesture elicitation study performed on target users. Such a user-centered approach increases users performance and satisfaction.

Earlier research work with a user-centered approach while designing gesture set is presented here. A gesture elicitation study is performed in [36] to propose a gesture vocabulary which includes human factors. A unified approach of selecting a gesture by quantifying its guessability and agreement score is presented in [37]. This elicitation study has been widely adopted by a number of researchers and recently, it is extended to create a user-defined gesture set for augmented reality [41]. Selection of gestures through an analytical modeling of performance measures such as intuitiveness, comfort and recognition accuracy is presented in [38]. A hand gesture set developed with sighted users on the basis of usability and effort ratings is presented in [45]. A gesture set especially aimed for people with cognitive disabilities is developed in [47]. Open gestures and their usability for older people are investigated in [39]. A similar study is done with upper limb motor impaired users to make gesture interfaces usable by them [48]. Several usability and human factors are studied in [122] for arm–and finger–based gestures with sighted users.

Gesture elicitation study [44] suggests that including users in interactive technologies is not only advantageous but also a necessity. Despite this, no study has been performed so far with the inclusion of blind people as target users. It is equally important to consider their preference and opinion towards the formation of hand gestures. It was found that the decision made by them were significantly different from the sighted person [125]. Apparently, a designer without any visual impairment can hardly think about the requirements of the blind users. They have their own requirements which could be understood by involving them in the design process. To achieve this goal, we have performed a study with blind people. The focus of this chapter is to obtain a gesture set suitable for blind users. Preference and performance measures are used to find out the optimal gestures from the possible set. Two important metrics—performance and preference—are considered to devise optimal gesture. Illustration of gesture selection method is shown in Figure 3.1. Further details about the gesture selection methodology are explained in the next section.

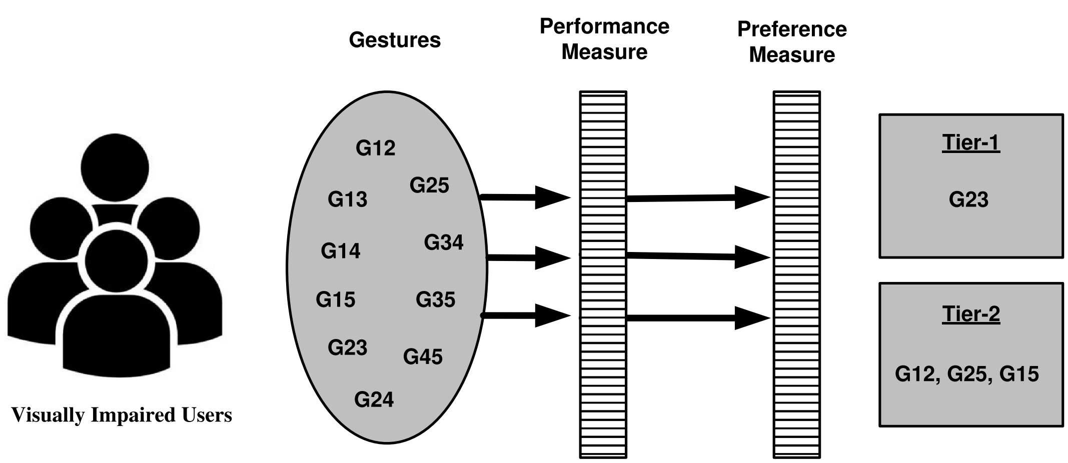

FIGURE 3.1: Illustration of gesture selection method (Example of a class 2 gestures).

3.2.2 Proposed Methodology

The usability of a gesture-based interactive system depends on the choice of gestures used. Studies have suggested that arm-based gestures cause more fatigue and appear less natural than that of the finger-based gestures [122]. Blind users also feel arm-based gestures are difficult to pose because there is no haptic feedback. Additionally, there is no/minimal support to the arm. This reduces the stability of hand. Hence, only finger-based gestures are considered in this work.

In this user evaluation study, a finger is deemed to be either in extension- or flexion-state. We assigned a number to each finger, i.e. thumb→ 1, index→2, middle→3, ring→4, little→5. The naming convention of gesture used in the study consist of letter 'G' that resembles gesture followed by the finger(s) in the extended state, e.g. G15, G2345, etc. G15 means a gesture with the thumb (1) and little (5) finger is in the extended state. Similarly, G2345 means a gesture with index (2), middle (3), ring (4), and little (5) fingers in the extended state. With the help of 5 fingers, a maximum of 31 gestures can be formed as shown in Figure 3.2. However, one needs to identify gestures that are optimal from the user's perspective. Therefore, a series of study is conducted with 25 blind users (congenital: 23, acquired: 2). These participants were the blind students and staff members of Banaras Hindu University, Varanasi, India. All participants were male (average age = 21.36 and SD = 2.33).

Usually, a user can remember 7 ± 2 items in short-term memory [126]. So, it is a difficult task to remember all 31 possible gestures and rank those on an ordinal scale. Additionally, we wanted to find out the most preferred gesture with the same number of fingers in preference measure study. Therefore, we have classified the gesture set into different classes based on the number of extended fingers. Class-wise gesture are listed in Figure 3.2.

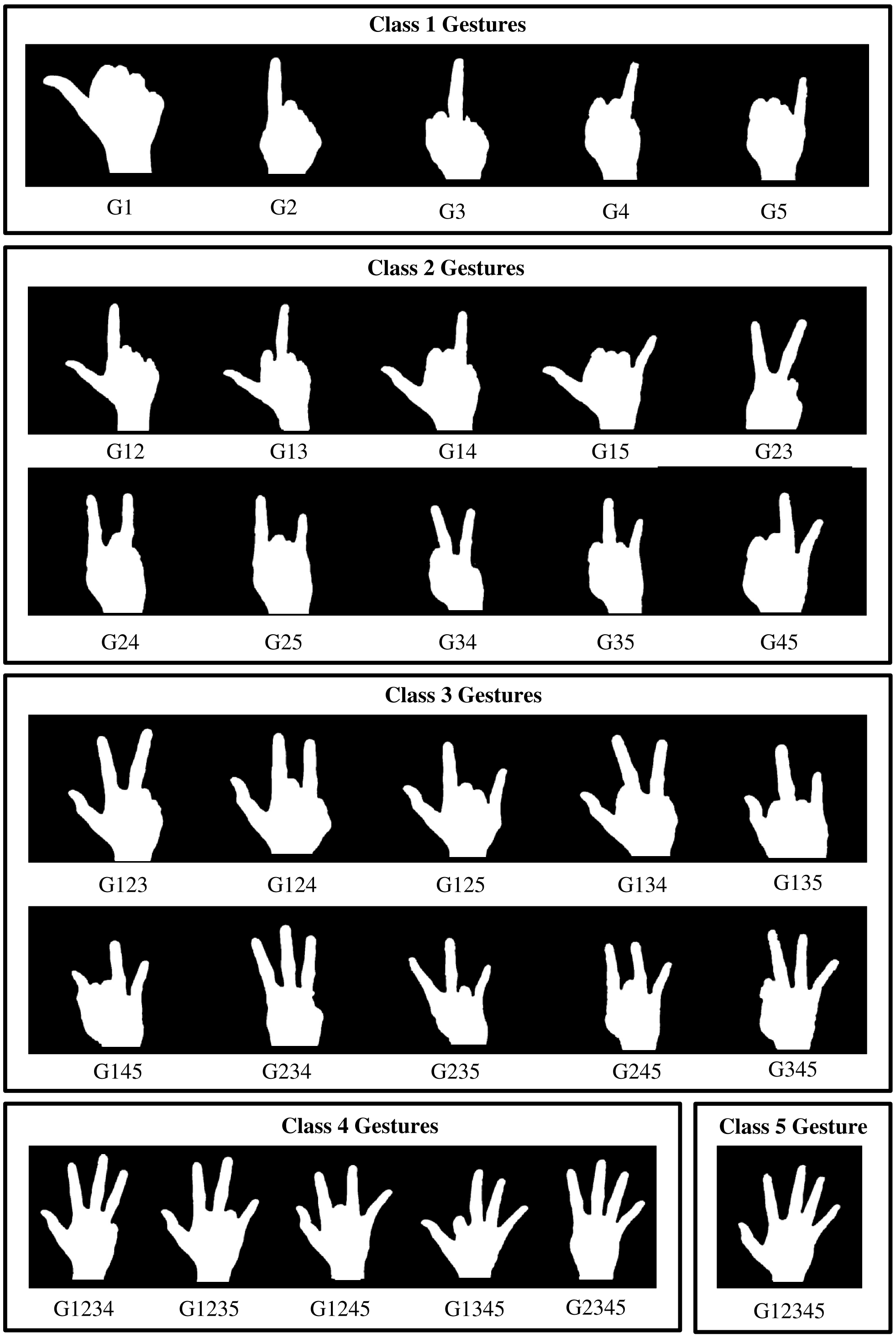

FIGURE 3.2: Class-wise illustration of possible gestures.

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Performance and preference measure are considered to identify suitable gestures. Performance measure includes ratings of gestures on the basis of easiness, naturalness, learning, reproducibility. Preference measure considers popularity and preference of gestures among users. Finally, a dactylology is proposed using optimal gestures obtained from this user evaluation study.

3.2.2.1 Gesture Performance Measure

From the user's perspective, the gesture set needs to be optimal in terms of posing, easiness, etc. We conducted a gesture rating analysis of all the possible gestures to fulfil this requirement. This gesture rating analysis indirectly reveals the information about the complexity levels of the gestures in a set and their suitability for the target users.

Three important design aspects—articulatory, cognitive, and technical—are suggested for the selection of gesture [127]. Articulatory aspect is used to find how easy it is for a user to pose a gesture. Using cognitive aspect one can determine how easily a gesture can be learned and recalled; while the technical aspect relates to the recognition accuracy of a gesture. This chapter is focused on articulatory and cognitive aspects only. With respect to both the aspect two criteria are selected, as shown in Table 3.1. Through easiness and reproducibility, we try to figure out the articulatory aspect of hand gesture. Cognitive aspect is obtained by considering naturalness and learning of the gesture. These subjective criteria are defined as below.

- Easiness: A parameter to figure out the fatigue [127] while executing/posing hand gestures.

- Naturalness: It is a parameter which considers the likeness of the gesture being used in natural everyday human behaviour [128].
- Learning: We try to figure out whether a gesture can be learned and adopted using this [127] criterion.
- Reproducibility: A parameter to measure the reproduction ease of a gesture. We considered fist to be neutral pose and asked participants to repeatedly (4 times) produce the gesture from fist and finally, rate the gesture based upon its reproduction easiness.

Twenty-five blind people participated in this study. Participants were seated in a relaxed position with their forearm flexed with elbow at 90°. A total of 31×2 gestures of both hands were analyzed through the proposed gesture rating. Verbal cues were given to the users to perform each gesture and rate it. All gestures were rated on four subjective criteria mentioned in Table 3.1. A Likert scale (strongly disagree =

TABLE 3.1: Sample questionnaire

Subjective Criteria	Questions / Statements	Gesture Rating
Easiness	Gesture is easy to pose.	
(C_1)	Gesture is difficult to pose.	
Naturalness	Gesture is natural.	
(C_2)	Gesture is unnatural.	
Learning	Gesture is easy to learn.	
(C_3)	Gesture is difficult to learn.	
Reproducibility	Gesture is easy to re-produce.	
(C_4)	Gesture is difficult to re-produce.	
Preferences among class (Rank):		

Table 3.2: Performance metric

Class / No. of fingers	Gesture/ Posture	Thumb 1	Index 2	Middle 3	Ring 4	Little 5	(P_m) Left hand	(P_m) Right hand
1	G1	✓	–	–	–	–	40.00	40.00
	G2	–	✓	–	–	–	40.00	40.00
	G3	–	–	✓	–	–	25.00	25.00
	G4	–	–	–	✓	–	14.00	19.00
	G5	–	–	–	–	✓	35.00	36.00
2	G12	✓	✓	–	–	–	36.00	34.00
	G13	✓	–	✓	–	–	23.00	20.00
	G14	✓	–	–	✓	–	14.00	12.00
	G15	✓	–	–	–	✓	35.00	34.00
	G23	–	✓	✓	–	–	40.00	40.00
	G24	–	✓	–	✓	–	14.00	22.00
	G25	–	✓	–	–	✓	36.00	32.00
	G34	–	–	✓	✓	–	22.00	24.00
	G35	–	–	✓	–	✓	16.00	25.00
	G45	–	–	–	✓	✓	24.00	29.00
3	G123	✓	✓	✓	–	–	35.00	34.00
	G124	✓	✓	–	✓	–	15.00	14.00
	G125	✓	✓	–	–	✓	33.00	33.00
	G134	✓	–	✓	✓	–	16.00	18.00
	G135	✓	–	✓	–	✓	16.00	19.00
	G145	✓	–	–	✓	✓	22.00	22.00
	G234	–	✓	✓	✓	–	40.00	40.00
	G235	–	✓	✓	–	✓	26.00	30.00
	G245	–	✓	–	✓	✓	20.00	24.00
	G345	–	–	✓	✓	✓	33.00	32.00
4	G1234	✓	✓	✓	✓	–	30.00	31.00
	G1235	✓	✓	✓	–	✓	26.00	28.00
	G1245	✓	✓	–	✓	✓	22.00	23.00
	G1345	✓	–	✓	✓	✓	22.00	25.00
	G2345	–	✓	✓	✓	✓	40.00	40.00
5	G12345	✓	✓	✓	✓	✓	40.00	40.00

Note: Tick mark represent finger in extended state.

1, disagree = 2, neutral = 3, agree = 4 and strongly agree = 5) is used to rate each gesture. However, sometimes a user might be acquiescence biased. Therefore, the proposed questionnaires included a mix of 'positively-keyed' and 'negatively-keyed' items. Questions on subjective criteria as well as the order of gesture analysis were randomly sampled to avoid further biasing. Eight questions were asked corresponding to each gesture. Thus, a total of $8 \times (31 \times 2) \times 25 = 12,400$ questions were asked during this gesture rating analysis. Data record form is attached as Appendix B.

In the process of analyzing questionnaire responses, negatively-keyed items of each criterion are reverse-scored before computing the overall score. This score is obtained by taking the sum of positively-keyed items rating and reversed-scored negatively-keyed items of all the criteria. Next, the performance metric (P_m) of a gesture is obtained by taking the median of these overall scores by all the 25 users. The entire process is repeated for all possible gestures (i.e. 31×2) and the result is presented in Table 3.2. Finally, gestures whose performance metric (P_m) is greater than thirty-two are selected. Gestures of both hands satisfying this condition are treated as optimal gesture set and those are listed in Table 3.3.

TABLE 3.3: Optimal gesture set

Class	Optimal gestures
1	G1, **G2**, G5
2	G12, G15, **G23**, G25
3	G123, G125, **G234**, G345
4	**G2345**
5	**G12345**

* Tier-1 gestures are boldfaced

3.2.2.2 Gesture Preference Measure

Understanding of user preference in an elicitation study provides the knowledge of their likes and dislikes. Comprehension of their preferences will increase the usability of the targeted system. Although the performance measure (P_m) indirectly indicates the preferences of users, it does not provide any information about the most preferred gesture within each class. Hence, a preference index was formulated and proposed to explicitly consider the popularity and the preference of a gesture among blind users.

Few studies [129, 130] with consideration of user preference have been proposed in the literature. In previous studies [44, 130], each participant was asked to select one referent for a symbol among the available options based on their preference/choice. Referent with the highest number of choice is selected as the choice of the participant group for a symbol. Inspecting such cases, it can be found that we have not considered the remaining choices of all the participant. It is quite possible that two referents in the set of available referent for a symbol S are almost of equal priority. However, the participant needs to choose only one between them. But, ignoring the remaining choices (i.e. $2^{nd}, 3^{rd}$ and so on) may lead to unfavourable choice.

To understand it in a better way, let there be 5 referents and 25 users ranked their preference for a symbol S. The rating of two best referents is shown in the Table 3.4. If we choose based on the largest number of referent choice, both the referent-A,

Table 3.4: An example case

	Rank-1	Rank-2	Rank-3	Rank-4	Rank-5
Referent-A	11	7	4	2	1
Referent-B	11	7	3	3	1

referent-B have the same number of rank 1 choice. If we choose either referent-A or referent-B, without any further information may lead to unfavourable choice. Further, inspecting closely, we can observe that the number of second and fifth choice (i.e. rank-2 & rank-5) are also the same. Referent-A has more number of rank-3 choice and less number of rank-4 choice as compared to referent-B. Observing the number of rank-3 and rank-4 choices, one can deduce that referent-A is a better choice as compared to referent-B. Hence, to do so, we proposed to obtain the ranking of all the referents instead of only the most preferred (i.e. rank-1) and use these relative ranking to select the final referent. These ranking explicitly represent the relative preference of all referent among a group of participants. All the ranking obtained should be taken into account to get the actual preference instead of considering the highest number of referent choice only.

The same 25 blind people participated in this study. They were seated in a relaxed position with their forearm flexed with elbow at 90°. They posed all the gestures of each class and ranked those gestures according to their preferences. Based on their responses, the preference count of each rank for a particular gesture is calculated by performing a frequency analysis. However, we need a formulation to quantify these gesture preferences using a single parameter. Let us consider two cases:

1. All the 25 users ranked a gesture to be at the first position.

2. All the 25 users ranked a gesture to be at the last position.

Both the cases represent 100% agreement in their preferences. However, case-2 is not a favourable choice. The formulae proposed in [37, 44, 131] are not able to differentiate these two cases as the authors of [37, 131] only consider agreement among the users while that of [44] consider only the highest number of referent choice. Here, we introduce a new parameter termed as preference index (P_i) to quantify and

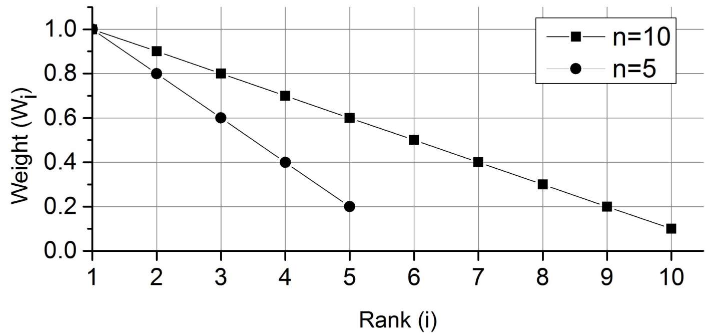


FIGURE 3.3: Relationship between gesture rank and its weight.

differentiate these cases. This, preference index (P_i), considers preference ranking as well as its agreement among users. The following expressions are used to capture this.

$$P_i = \sum_{i=1}^{n} \left(W_i \times \frac{N_i}{N} \right) and \tag{3.1}$$

$$W_i = \left[1 - \frac{(i-1)}{n} \right], \tag{3.2}$$

where 'n' is the number of gesture/s in that particular class, 'N' is the total number of participants and N_i is the preference count of i^{th} rank for a particular gesture among its class. Weights (W_i) are assigned as shown in Figure 3.3. The first position is given the highest weight, whereas the last is given the lowest weight.

A gesture with a preference index score of unity suggests that it is the most preferred gesture with full agreement. For a 5 referents case (class 1 gestures) nearly 23751 permutations of user ranking frequency are possible with N=25. Two of its case are shown in Table 3.4. The proposed index is capable of differentiating each case on the relative scale of preference index. Data obtained from 25 users in preference analysis

TABLE 3.5: Popularity index calculation of class 1 gestures

Gestures	Rank	Frequency	Percent	Popularity index
G1	1	4	16	0.76
	2	20	80	
	3	1	4	
G2	1	21	84	0.97
	2	4	16	
G3	3	1	4	0.40
	4	19	76	
	5	5	20	
G4	4	5	20	0.24
	5	20	80	
G5	1	2	8	0.616
	2	1	4	
	3	21	84	
	4	1	4	

of class 1 gestures is furnished in the Table 3.5. Further, preference index (P_i) is obtained using Equation 3.1 and 3.2. The same is shown as bar plot in Figure 3.4.

It was expected that complex hand shapes which involve the movement of joints far from their neutral positions will have a low preference index. The preference index also represents similar observation. For example, ring finger cannot be extended without the little finger, if tried causes fatigue. Figure 3.4(a) also reveals the same fact and it is observed that the value of the preference index is the least for $G4$.

Optimal gestures obtained using performance measure (shown in Table 3.3) are divided into two groups: tier-1 and tier-2. A gesture with the highest preference index is referred as a tier-1 gesture. Among class 1 gestures G1, G2 & G5 have performance rating greater than thirty-two. However, the preference index shows that G2 is the most preferred gesture within its class. Please refer to Figure 3.4. Hence, G2 is categorized as a tier-1 gesture of class 1. Similarly, G23, G234, G2345,

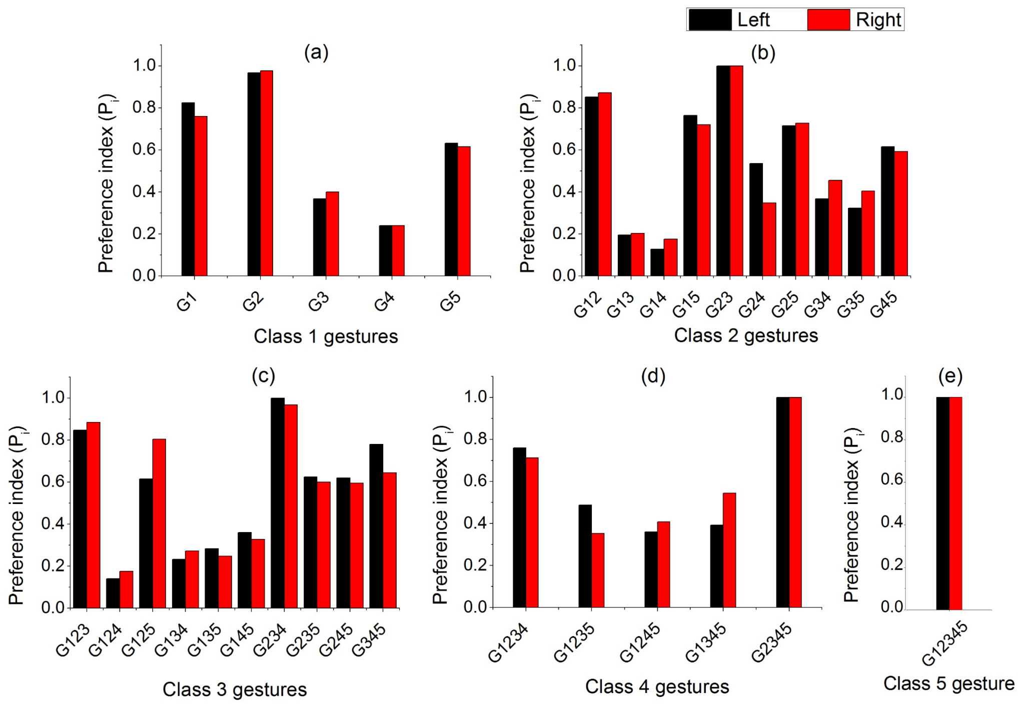


FIGURE 3.4: Preference index of (a) Class 1 gestures (b) Class 2 gestures (c) Class 3 gestures (d) Class 4 gestures (e) Class 5 gesture.

G12345 are the tier-1 gestures from the other classes. Rest are treated as tier-2 gestures.

3.2.3 Mapping of Gestures

There is no standard method using which gestures can be mapped to commands. A standard QWERTY keyboard contains a large number of keys (e.g. alphabet, number as well as special keys). In order to perform one-to-one mapping of its functionality, large numbers of gestures are required. Additionally, remembering such a large gesture-command pairs will be difficult to learn at the same time it will be difficult to recall too! Work [45] has suggested to consider user's expectation in order to minimize learning and maximize cultural transparencies. Additionally, the mapping should be as such that it should have less effort (cognitive load) in recalling the gesture-task pair. One suggestion to reduce the cognitive load is to make reuse of the similar gesture under different contexts. Such reuse of gestures permits users to form a larger set of task with fewer gestures. According to [132] common tasks should be mapped to gestures that are rapid and comfortable to form.

Gesture mapping in the proposed dactylology is inspired from the deep-rooted concept of cryptography. An ancient Greek historian and scholar, Polybius, proposed a method to encode Greek alphabets (plaintext characters). He proposed a cipher called the Polybius cipher (also commonly known as the Polybius square). It consists of a 5×5 matrix with the alphabet placed in the grid. A 5×5 matrix can accommodate a maximum of 25 letters. Hence, two letters—usually I and J —are combined to encode all the 26 letters. Each letter is coded by its coordinates in a grid. For example, A as 11, B as 12 and so on.

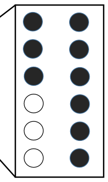
The concept of Polybius square was adopted and modified by Barbier—a captain in Napoleon's army —to send messages which could be read even during night time (also known as night writing). He used a 6×6 grid (i.e. 36 cells) for French letter and their combinations. Each cell contains two columns of six dots. The rightmost column represents the row number of the grid and the leftmost column represents the column number. The intersection of these two number on the grid represents the code for a character. The corresponding code of the character is encoded by raising the dot of the cell. For pictorial representation, the raised dots in a cell are shown by filled circles. So, to represent 'Z', which is numerically encoded as '36' can be coded as shown in Figure 3.5.

Louis Braille in 1824—at the age of 15—simplified and modified this night writing system and proposed a tactile reading system for the blind. He overcame the shortcomings of the Barbier's system, such as use of a clumsy 12-dot cell and the

	1	2	3	4	5
1	A	B	C	D	E
2	F	G	H	I/J	K
3	L	M	N	O	P
4	Q	R	S	T	U
5	V	W	X	Y	Z

(a)

	1	2	3	4	5	6
1	a	i	o	u	é	è
2	an	in	on	un	eu	ou
3	b	d	g	j	v	z
4	p	t	q	ch	f	s
5	l	m	n	r	gn	ll
6	oi	oin	ian	ien	ion	ieu



(b)

Figure 3.5: Encoding matrix (a) Polybius square (b) Barbier night writing grid

phonetic basis. He found that he could not feel all the dots of a 12-dot cell without moving fingers. He modified this large dot matrix and proposed something that was functional and superior to the existing system. His original code consisted of six dots arranged in a rectangle comprising of 2 columns of 3 dots each. Due to this smaller cell, it was easier to feel the dots. This configuration was simpler but still versatile enough to allow up to 63 characters. Braille is written using a device known as Brailler. There are six mechanical keys corresponding to each dot and dots in one column are controlled by one hand. A desired combination of dots is formed by pressing these keys simultaneously which engage both hands. The proposed dactylology also make use both hands, but the user only needs to pose finger/s instead of pressing the keys. Furthermore, compared to the Braille large numbers of symbols (~ 1023) can be produced. For a proper analogy, think of a Braille cell containing 5×2 matrix of dots. Here, every dot combination can be represented by using the fingers of both hands. However, due to physiological constraints, all gestures are not comfortable to pose. Only few of them are optimal (refer Table 3.3 and Table 3.2). Additionally, we don't need 1023 gesture commands. Hence, the mapping of gesture commands with alphabets is done based on the visualization matrix which is further modification of Polybius square.

3.2.4 Proposed Dactylology

The proposed dactylology can be presented in terms of a visualization matrix as shown in Table 3.6. This matrix is a modified Polybius square where I and J have been encoded differently. Here, alphabets from A to Y are arranged in a 5×5 matrix. Character A is represented as an element of the first row and the first column. If left-hand fingers represent row number, and right-hand fingers represent column number, then the symbol for A can be formed, as shown in Figure 3.6(a).

Similarly, a symbol of other alphabets can be formed as shown in Figure 3.6(a). Ten more symbols can be added in this set by posing only one hand. In this case, the number of finger(s) represents a numeric character. Left hand represents '1' to '5' numbers, as shown in Figure 3.6(b) and rest of the digits are represented using right hand. It should be noted that tier-1 gestures are assigned to the most frequently used keys of a keyboard, i.e. alphabets and numbers. Total 35 (25+10) symbols are formed with the help of these tier-1 gestures. Tier-2 gestures are proposed to incorporate more symbols. Symbols created using tier-2 gestures (G12, G15) are shown in Figure 3.6(c) and Figure 3.6(d). A large number of such combinations can

TABLE 3.6: Visualization matrix for alphabets and numbers

	Col-0	Col-1	Col-2	Col-3	Col-4	Col-5
Row-0	*Ready*	*6*	*7*	*8*	*9*	*0*
Row-1	*1*	A	B	C	D	E
Row-2	*2*	F	G	H	I	J
Row-3	*3*	K	L	M	N	O
Row-4	*4*	P	Q	R	S	T
Row-5	*5*	U	V	W	X	Y

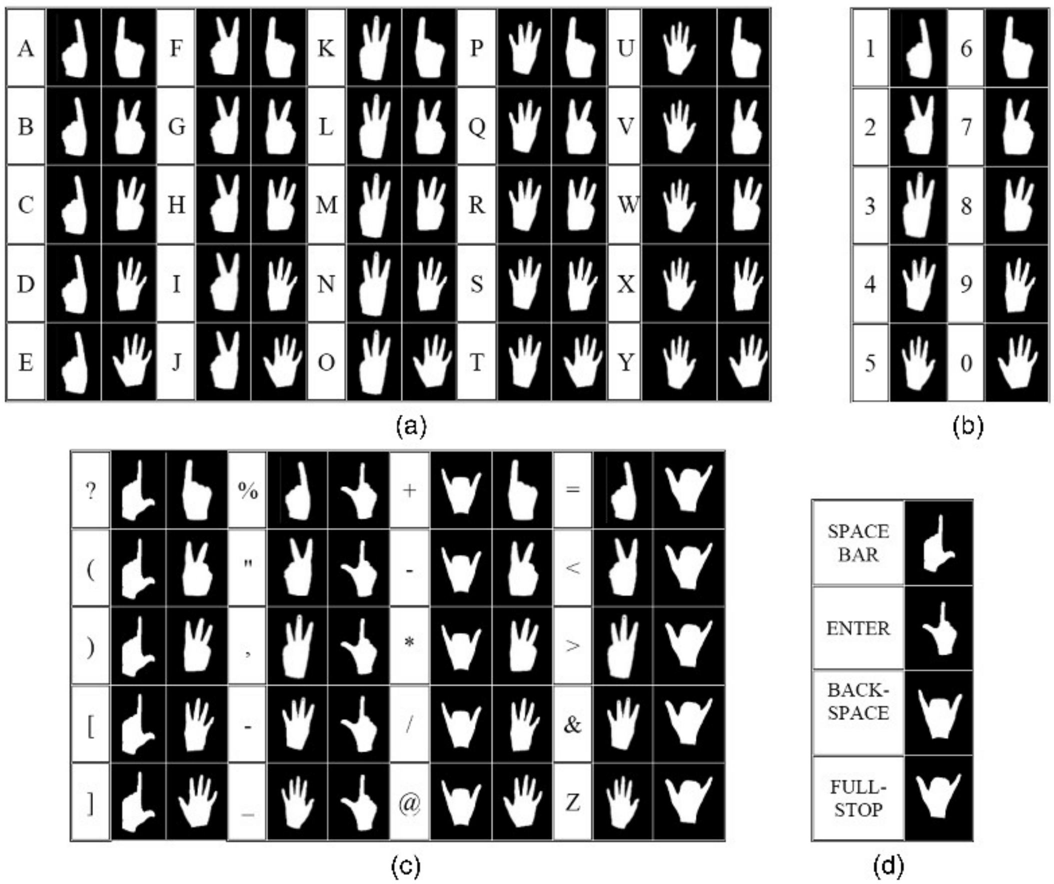


FIGURE 3.6: Proposed Dactylology (a) Double handed symbols using tier-1 gestures (b) Single handed symbols using tier-1 gestures (c) Double handed symbols using tier-2 gestures (d) Single handed symbols using tier-2 gesture.(© 2017 Kishor Prabhakar Sarawadekar and Gourav Modanwal. All rights reserved)

be formed using rest of the tier-2 gestures. With the inclusion of 'm' number of tier-2 gestures, a total of $(m+5+1)^2-1$ gesture combinations can be formed. It is estimated that by using G1, G5, G12, G15, G24, G123, G125 and G345 along with highly rated and the most preferred gestures of each class, about 195 symbols can be formed. However, one needs to find a perfect match among these combinations which can be mapped to keys targeted on the computer keyboard.

3.3 Result and Discussion

In this chapter, we've considered visually impaired as target users and performed a study to find out an optimal gesture set for them to interact with computers. They felt arm-based gestures are difficult to pose. So, only finger-based gestures are studied. With the help of 5 fingers, a maximum of 31 gestures can be formed using each hand. However, one needs to find out optimal gestures from the user's perspective. Therefore, a series of study is conducted with 25 blind users (congenital: 23, acquired: 2). Performance and preference measure are used for this purpose.

In performance measure, a total of 12,400 questions are queried and results of this study are shown in Table 3.2. Further, multi-constraints are applied and optimal gestures of both hands which satisfy these criteria are shortlisted. The results of this step are presented in Table 3.3. From Table 3.2 and 3.3 it is conjectured that although several gestures can be formed using fingers, only a few of them are optimal for posing. Rest of the gestures cause fatigue due to the constrained relationship between individual joints within the finger as well as between neighbouring fingers. For example, the pinky finger cannot be bend without bending the ring finger; if tried, causes fatigue. Performance metric in Table 3.2 also reveals this fact wherein the rating of gesture G4 is very low. Further, it is observed that ratings of left and right hand are different. This difference and variance in performance metric indirectly tell us that the constrained relationships between joints and fingers are different in both hands of the same participant as well as among all other participants. In the preference measure, a new parameter termed as preference index is proposed in this work. A gesture with preference index score of unity suggest it is the most preferred gesture with full agreement. From Figure 3.4 it is observed that the most preferred gesture of each class is nothing but the highly rated gesture obtained through performance measure. A positive correlation is observed in both the studies.

The optimal gesture presented in Table 3.3, are further divided into two groups: tier-1 and tier-2. A gesture with high-performance metric as well as preference index is treated as tier-1. Otherwise, it is a tier-2 gesture. Tier-1 gestures are boldfaced in Table 3.3. A new dactylology is proposed using these gestures. The most frequently used commands—alphabets and numbers—are encoded with tier-1 gestures, whereas tier-2 gestures are used to create additional commands. The advantage of mapping tier-1 gestures to the most frequently used commands will reduce the biomechanical and ergonomics risks in using the system. Additionally, the mapping of commands using the visualization matrix will reduce the cognitive load and increase the learning and recall.

3.4 Concluding Remarks

Research has already revealed that every human being—even those who are blind from birth—produces hand gesture during the interaction. The gestures produced by them are almost similar to the gesture produced by sighted users. But, their gestures are limited and are less detailed. Recent evolution in gesture recognition algorithms and low-cost hardware development has made it possible to use gesture command for interacting with computer and other consumer electronics. Gesture-based interaction can offer visually impaired users a new vista of computer interaction. But, one needs to consider their performance and preference toward hand gesture. To understand their problem and overcome the difficulties faced by them in using hand gesture, a user evaluation study was conducted and its outcome is

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presented in this Chapter. In this study, an optimal set of hand gesture was devised. This optimal gesture set was obtained based on two measure—performance and preference. Further, a dactylology was proposed using these optimal gestures wherein, Polybius square is modified and the mapping of gestures to commands is done. Visually impaired users can use this dactylology to interact with computers.