A NATURAL HAND GESTURE SYSTEM FOR PEOPLE WITH BRACHIAL PLEXUS INJURIES

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Abstract. This paper focuses on a design case study of a natural hand gesture system for users with intact motion control of the metacarpophalangeal joint and thumb basal joint of the hand after brachial plexus injuries. The lexicon of hand gestures had eight entries and was demonstrated to be natural and ergonomic with the limited hand motions. A cooperative multi-cue system was proposed for the key hand posture recognition of the proposed hand gestures. We utilized the designed system into a remote smart car control and electric wheelchair control. Experimental a results demonstrated the robustness and potential feasibility of the system in human-computer interaction for the proposed users.

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1 INTRODUCTION

Vision-based hand gesture interfaces are increasingly popular in a variety of application domains, such as medical assistance, entertainment, human-robot interaction, etc. There are a number of factors that affect the design methodology, including accuracy, intuitiveness, comfort, lexicon size, availability, and responsiveness [1]. And human gestures can be described in different levels of representation [2].

To be accurate, hand gesture systems must operate at an almost zero error rate, especially in medical assistive systems, to guarantee the safety of users. Considering the users' errors, additionally techniques [3] such as automatic obstacle detection and avoidance, have been developed to enhance the reliability of systems. In order to ensure a good user experience, the following requirements should be addressed:

- System latency has to be close to 45 ms for practical applications [4].
- Designed lexicons must be ergonomic, to avoid the "Gorilla arm" syndrome.
- The provided lexicon size should allow a variety of device control, at the same time, prevent the high mental load of gesture recall and low learnability.

In the domain of human-robot interaction, e.g., electric wheelchair control, many systems have been proposed for intelligent wheelchair control [1, 3]. Here we only review the recent systems classified as vision-based gesture systems for intelligent wheelchair control, summarized in Table 1 (more details can be referred to [1, 3]).

The traditional control interfaces for motorized devices include joysticks, keypads, etc. But it is important to develop natural interfaces that allow users control devices adapted to their abilities, especially for the disabled with limited physical abilities, e.g., peoples with brachial plexus injuries. Brachial plexus injury is an generous term for a variety of conditions with disabled functions of the brachial plexus nerve network which originates in the fifth (C5), sixth (C6), seventh (C7) and eighth (C8) cervical, and first thoracic spinal nerves (T1), and branches off to form most of the other nerves that control movement and feeling of the shoulder, arm, forearm, and hand. Obstetric brachial plexus palsy and other trauma may cause the injuries [15]. According to different injured nerves, symptoms of the injuries may vary greatly, e.g, an injury of the upper brachial plexus nerves (C5 and C6) may lead to loss of motion around the shoulder and ability to flex the elbow, while an injury of the lower brachial plexus nerves (C7, C8, and T1) may attribute to loss of motion in the wrist and hand.

In this paper, we focused on a natural hand gesture system design for users with brachial plexus injuries. The types of motor impairments restricted on the disabled

System	Gesture component	Motion pattern	Lexicon size
The proposed system	Hand	Limited finger movement	8
H. Jiang, et al. (2012) [5]	Hand	Hand movement	8
G. C. Lee, et al. (2012) [6]	Head	Head movement	5
Y. Zhang, et al. (2011) [7]	Hand	Hand movement	5
J. S. Ju, et al. (2009) [3]	Face and mouth	Face-inclination and mouth-shape	7
I. Yoda, er al. (2007) [8]	Head	Head movement	7
K. Posada-Gomez, et al. (2007) [9]	Hand	Hand movement	4
P. Jia (2007) [10]	Head and nose	Frontal face movement	5
C. Shan, et al. ((2007) [11]	Hand	Hand movement	5
S. P. Kang, et al. (2004) [12]	Hand	Finger and wrist movement	4
S. P. Kang, et al. (2003) [13]	Hand	Finger and wrist movement	9
I. Moon, et al. (2002) [14]	Head	Head movement	4
SIAMO(2001)[15]	Head	Head movement	5

Table 1. Vision-based gesture systems for intelligent wheelchair control

functions of shoulder, arm, forearm, and even wrist, with intact motoric control of the metacarpophalangeal joint and thumb basal joint of the hand, which are commonly caused by the injury of the upper brachial plexus nerves. In order to offer a more available and convenient interface for this purpose, a natural and ergonomic hand gesture vocabulary was designed with the consideration of factors including limited hand motions, user-friendly design, and distraction detection. The multi-cue (i.e., color, motion and shape cues) system was utilized to detect and classify the words in the hand gesture vocabulary. A customized motion history image technique with the adaptive time segmentation was used to accurately calculate motion direction and motion area size of the hand gestures. The shape cues employed in the system included statistical moments, silhouette perimeter, and shape aspect ratio information. Each cue served as an efficient classifier with a low computing load and high accuracy in specific lexical entries in the system, and the whole multi-cue system could acquire great performance on recognition of all lexical entries.

2 HAND GESTURE VOCABULARY

The designed hand gesture vocabulary consisted of eight commands with five key hand postures and three compound ones, as shown in Figure 1. The corresponding commands of each lexicon entry for motorized device control might be "Go",

"Left turn", "Right turn", "Keep", "Stop", "Back", "Right turn and go", and "Left turn and go". The hand motion in the vocabulary was limited to the abduction and adduction of the thumb, index finger, ring finger, and little finger. In our previous research [16], the proposed hand gesture vocabulary was demonstrated to have the characteristics including intuition, comfort, low mental load, and the high learnability. Considering atypical capabilities for motor control and hand gestural expression of patients with upper brachial plexus injuries, the motion joints involved in the vocabulary were reduced to the metacarpophalangeal joint (MCP) and the thumb basal joint (TBJ).
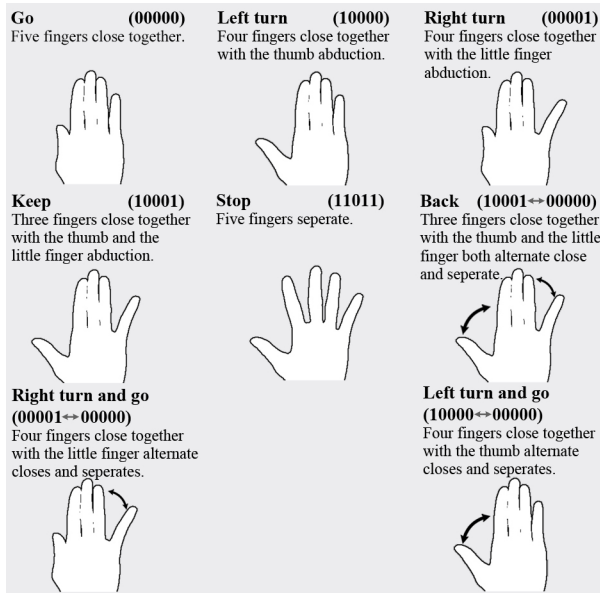

Figure 1. The designed hand gesture vocabulary

3 AN COOPERATIVE MULTI-CUE SYSTEM FOR HAND GESTURE RECOGNITION

In order to efficiently and accurately detect and recognize the words in the vocabulary, a multi-cue based system was proposed, which used features covering the hand-like color, finger motion, and hand shape information. The system was deployed with a fixed hand-top mounted web camera and a fixed background using a coarse black cotton cloth. The descriptors of the motion and the shape were used to detect and recognize the hand gestures. The schematic diagram of the proposed multi-cue system is shown in Figure 2, where CS indicated the operation of color segmentation and SG_i $(i = 1, \ldots, 5)$ represented one of the five key hand postures in

the system. MG and SG meant the gestures derived from the motion and shape information respectively. And MSG was the gesture concluded both from the motion and the shape descriptors.
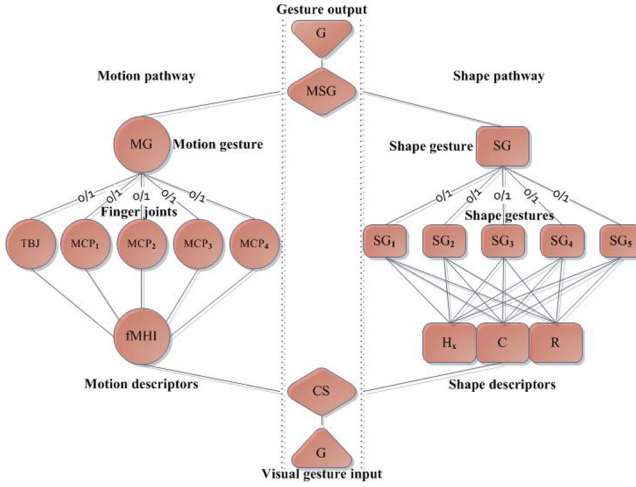

Figure 2. The proposed multi-cue system for hand gesture recognition

The operation in the SG, MSG were as follows:

$$SG = \begin{cases} i, & \text{if } C(SG_i) \cap R(SG_i) \cap H_x(SG_i) = 1 \\ NULL, & \text{otherwise,} \end{cases} \tag{1}$$

$$MSG = \begin{cases} MG \text{ or } SG, & \text{if } MG \text{ is equal to } SG \\ NULL, & \text{otherwise.} \end{cases} \tag{2}$$

In the motion pathway of the multi-cue system, the method of frame-based motion history images was used to calculate the motion states of finger joints. The motion direction, motion location, and motion area size were adopted to distinguish each finger motion. For example, the radial abduction of the TBJ had features including:

1. motion direction was close to 150 degrees,

2. motion was located in the leftmost of all motion blobs.

In the shape pathway, three shape descriptors i.e., the horizontal mass center (H_x), circumference (C), and aspect ratio (R) of hands, were employed to classify the gestures. In order to acquire 100% accuracy, each descriptor could vote for from one to up to four candidates depending on its distinctness in the gestures.

3.1 Color Segmentation

Skin color based hand segmentation is a popular method because of its ease of implementation and speed, but it also has limitations with respect to strong lighting change and accuracy [17]. In the system, a novel single-threshold segmentation method in the red channel of the RGB color space was proposed to accurately discriminate the hand from the fixed black background. The red channel was employed because of its maximal similarity to skin color in the RGB color space. The problem of the background color selection was studied in our previous research [16] and the results demonstrated that the pure black acquired the best performance in segmenting hands because of its robustness to lighting change and shadows. The simplified design of the background made the system robust to strong illumination change with a high performance, as shown in Figure 3.
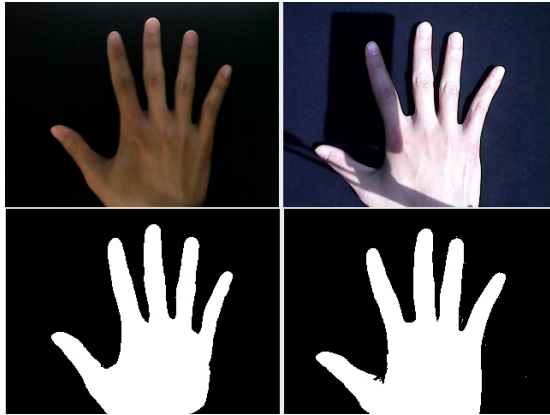

Figure 3. Hand segmentation from the weak and strong lighting conditions respectively

3.2 Motion Pathway

Each finger joint has its typical motion range. For example, the normal motion range of the MCP abduction and adduction is 30 degrees, and the radial abduction of the TBJ is 60 degrees [18]. The heuristic prior knowledge of the finger motion offers a convenient and accurate way to detect and classify hand postures. The motion history image (MHI) method is a good choice to motion analysis [19]. In this paper, we proposed a customized motion history image technique with the adaptive time segmentation to calculate the motion direction and the motion size.

3.2.1 Silhouette Generation

Suppose that $R_f(x, y)$ was a frame in a video sequence or a web camera with the frame number of f. The thresholding frame $T_f(x, y)$ was determined as follows:

$$T_f(x, y) = \begin{cases} 255, & \text{if } R_f(x, y) \leq \varsigma \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The silhouette $S_f(x, y)$ was generated according to Equation (4).

$$S_f(x, y) = \begin{cases} 255, & \text{if } T_f(x, y) - T_{f-1}(x, y) > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

3.2.2 Frame-Based Motion History Images

In this paper, the frame number was used as the timestamp in the motion history image $fMHI_f(x, y)$ which was updated as follows:

$$fMHI_f(x, y) = \begin{cases} 0, & \text{if } (f - fMHI_f(x, y)) < \xi \\ f * \tau, & \text{if } (S_f(x, y)) > 0, \end{cases} \tag{5}$$

where ξ is the maximum memory time of motions, and τ is the time duration constant of a frame.

3.2.3 Finger Motion Segmentation and Gradient Calculation

To improve robustness to user differences in the motion duration between two successive hand gestures, each motion duration $\Psi(\Psi \leq \xi)$ was counted for further finger motion segmentation. The customized motion history image with adaptive time segmentation $(TfMHI_f(x, y))$ was calculated as follows:

$$TfMHI_f(x, y) = \begin{cases} 255, & \text{if } (f - fMHI_f(x, y)) \leq \Psi \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Each finger motion blob was then calculated in the $TfMHI_f(x, y)$ according to the algorithm in [20]. In order to handle problems of the surrounding boundary of the $fMHI_f(x, y)$ and small amounts of noises, an erosion operation was applied to shrink the $fMHI_f(x, y)$ before finger motion segmentation. There were distinct borders among timestamps in $fMHI_f(x, y)$. The gradient orientations Δ_i of the boundary points was calculated as follows [21]:

$$\Delta_i = \arctan \frac{D_{xi}}{D_{yi}}, \tag{7}$$

where D_{xi} and D_{yi} are the spatial derivatives in the X and Y directions of the boundary points.

3.2.4 Finger Motion Direction

Motion direction of each finger motion blob was calculated as follows:

$$\Lambda = \sum_{i \in \Gamma} \frac{\Delta_i}{n}, \tag{8}$$

where Γ is the set of the valid boundary points with non-zero gradient orientations, and n is its element number. We must be careful when summing the elements with gradient orientations closing to 0 degree or 360 degrees. The frequencies of the Δ_i existing in the first quadrant F_1 and the fourth quadrant F_4 were counted. Then the Δ_i and Λ were revised as follows:

$$\Delta_i = \Delta_i + 360, \text{if } (F_1 + F_4)/n > \upsilon \text{ and } F_1/n > \omega \text{ and } F_4/n > \omega, \tag{9}$$

$$\Lambda = \begin{cases} \Lambda, & \text{if } \Lambda < 360 \\ \Lambda - 360, & \text{otherwise,} \end{cases} \tag{10}$$

where υ is a minimal proportion of the sum of F_1 and F_4 in Γ, and ω is minimal proportion of the F_1 and F_4 in Γ. One example of the finger motion calculation of the hand gesture changing from "Go" to "Stop" is shown in Figure 4. Motion direction of each finger appears to have a fixed mean with a small deviation with respect to the heuristic prior knowledge of the finger motion.
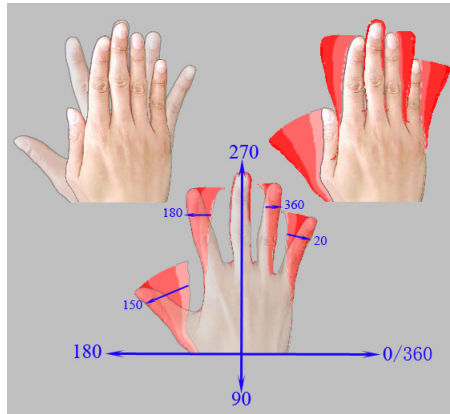

Figure 4. An example of the finger motion calculation of hand gesture changing from "Go" to "Stop"

3.3 Gesture State Transition Network

In order to classify the hand gestures basing on the motion information, a full-connected state transition network of gestures was maintained in the system, as

shown in Figure 5. For example, for the transition from "Go" to "Keep", only the abductions of the TBJ and the MCP of the little finger were expected.
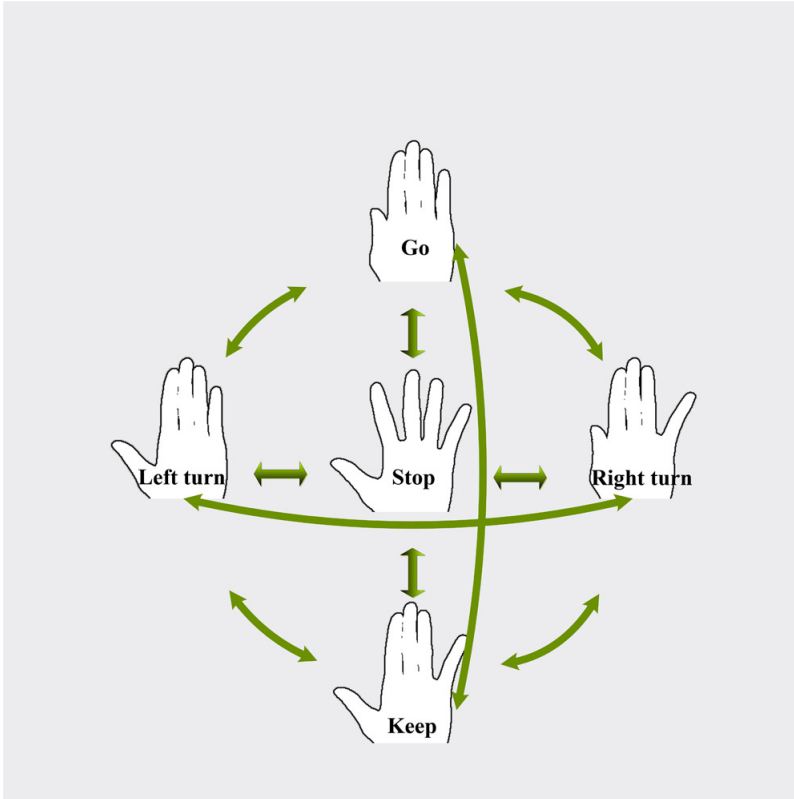

Figure 5. The state transition network of the hand gestures

3.4 Shape Pathway

3.4.1 Hand Shape Normalization

In our system, some simple but distinctive descriptors were used, i.e., the horizontal mass center, circumference, and aspect ratio of hands. The hand region was normalized to a fixed height so as to get a common basis for multi-cue based hand posture recognition. The computing method was defined as follows.

1. According to the method in [20], contours were computed in the image $T_f(x, y)$ defined in Equation (3). The one with maximum area was selected as the hand contour HC.

2. Let the height and the width of the HC be HC_W and HC_H respectively, and the finger tip of the middle finger get a maximum Max_y in the y axis of the image $T_f(x, y)$. $HC(x, y)$ was one of the elements in HC. The normalized hand contour was redefined as Equation (11).

$$HC = \{HC(x, y)|y \geq Max_x - H\}, \tag{11}$$

where H is the normalized height of hands. It could be set according to anthropometric data of hands, or based on the individual.

3.4.2 Shape Descriptions

The shape descriptors were computed in the normalized hand contour. The horizontal mass center H_x and the aspect ratio R were calculated as follows:

$$H_x = \frac{\sum_{x,y}(HC(x, y) \times x)}{W \times \sum_{x,y} HC(x, y)}, \tag{12}$$

$$R = \frac{HC_W}{H}. \tag{13}$$

The circumference C is defined as the pixel number of the most outer contour of the HC. The typical values of the H_x, C, and R in the five key hand postures of the vocabulary are shown in Table 2.

Gesture descriptor	H_x	C[points]	R
"Go"	0.517	568	0.621
"Left turn"	0.635	627	0.882
"Right turn"	0.422	656	0.785
"Keep"	0.549	729	1.030
"Stop"	0.544	1 096	1.065

Table 2. The typical values of the H_x, C, and R in the five key hand postures of the vocabulary

As shown in the Table 2, the shape descriptor of the H_x is distinct among "Left turn", "Right turn", and the other words, the R has noticeable differences among the gestures except for "Keep" and "Stop", and the C has a clear boundary between "Stop" and the other gestures.

3.5 Gesture Spotting

The gesture recognition was executed only in the first static frames fsf which were defined as follows:

$$fsf = \{f|(W_{f-1} - W_{f-2} > \kappa) \text{ and } (W_f - W_{f-1} \leq \kappa)\}, \tag{14}$$

where W_f is the width of the normalized hand region in the $f-th$ frames and κ is the maximum amount of the width change in the static frames. The compound gestures in the system are determined unless two successive fsf satisfy Equation (15):

$$fsf_i - fsf_{i-1} \leq \Theta, \tag{15}$$

where Θ is the maximum time constant between fsf. For example, the "Back" gesture is determined when the following conditions are met:

- The result of gesture recognition is "GO" in the fsf_{i-1} frames;
- The result of gesture recognition is "Keep" in the fsf_i frames;
- Equation (15).

4 THE EXPERIMENTAL RESULTS

The proposed hand gesture interface was implemented in the intelligent wheelchair control and smart car control. The experiments were carried out in the indoor and outdoor environments in our campus. The frame size of the camera was 320×240. The system was running on a computer with an Intel Core 2 Duo CPU P8400 @ 2.26 and 1.92 GHz under Windows XP. The implemented system operated as about of 15 frames per second without parallel implementation.

4.1 Experiment I: Remote Control of the Smart Car

In the control of the smart car, only five key hand postures were used, i.e., "Go", "Left turn", "Right turn", "Keep", and "Stop". Their corresponding control commands of the smart car were "Go ahead", "Turn left", "Turn right", "Go back", and "Stop". The designed hand gesture platform, smart car, and test map are shown in Figure 6. The smart car was navigated to run the test map 10 times. Five able-bodied subjects (five male), ranging in age from 23 to 27, participated in the experiment. The performance is shown in Table 3.

Lexicon entry	Recall	Precision
"Go"	1	1
"Left turn"	1	1
"Right turn"	95 %	1
"Keep"	96 %	1
"Stop"	1	1

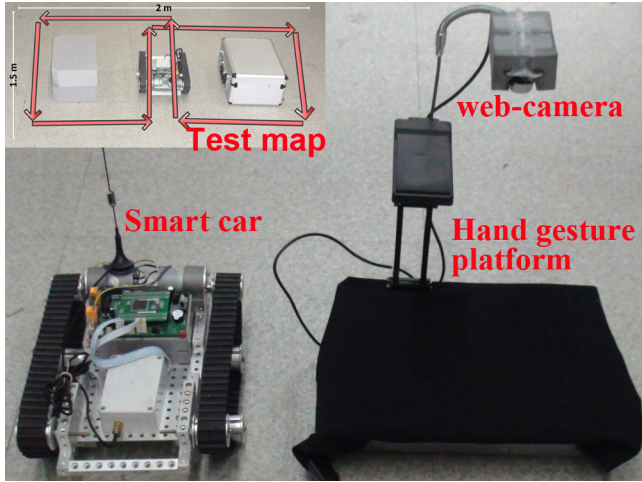Table 3. Performance of the remote control of the smart car

Figure 6. The designed hand gesture platform, the smart car, and the test map

4.2 Experiment II: Intelligent Wheelchair Control

In the condition of the intelligent wheelchair control, the hand gesture platform was mounted into the right armrest of the wheelchair. We tested the system in the outdoor environment with strong lighting changes as shown in Figure 7. The wheelchair was freely controlled for almost half an hour. The control commands

Figure 7. Intelligent wheelchair control in the outdoor environment

Lexicon entry	Recall	Precision
"Go"	1	1
"Left turn"	1	1
"Right turn"	1	1
"Keep"	1	1
"Stop"	1	1
"Back"	0.92	1
"Right turn and go"	0.96	1
"Left turn and go"	0.94	1

Table 4. Performance of the intelligent wheelchair control in the outdoor environment

covered each lexicon entry in the vocabulary for 50 times at least. The performance is shown in Table 4.

5 DISCUSSIONS

The advantages of the system can be summarized in the following:

1. The computer vision based interface

   Vision-based interfaces have the advantages such as nonintrusion, passive sensing, low cost, etc. They can be served to many applications aside from hand gesture interfaces, e.g., identification and attention monitoring [22].

2. The hand gesture interface

   Comparing to other gesture-based interfaces, such as the head-based, the mouth-based, and the body based, hand gesture interfaces make heads unoccupied which is important for multi-task operation in dairy life.

3. Limited hand motions

   The hand motion in the designed vocabulary is limited to the abduction and adduction of the thumb, index finger, ring finger, and little finger. The involved motion joints are reduced to the MCP and the TBJ. The above features make the system more available and convenient to most of users.

4. The user-friendly design

   The lexicon size in the system is 8 which is various enough for device control and is just easy for users to remember and to perform. The system can run in real-time with good experiences for users as "no delay".

5. The multi-cue system

   The system combines the motion and the shape features in the key hand posture recognition. Each descriptor acts as a weak classifier with the high accuracy and low computing load. The whole multi-cue system is robust to users' differences

and environment changes. When considering other shape descriptors, for example, hand finger tip detection, our proposed three shape descriptors are more simple and distinct in classifying the hand gesture in the system.

People with upper brachial plexus injuries usually reserve the ability of motoric control of their fingers, but not the shoulders, arms, or elbows. The proposed hand gesture system only requires the limited hand motions as mentioned above. In addition, our system offers a comfortable platform for patients to perform the gestures. The multi-cue system guarantees the recognition accuracy and robustness to strong lighting changes and users' errors. The proposed system offers a feasible and natural interface for users with intact motoric functions of hands to interact with external environments.

6 CONCLUSIONS

The natural and ergonomic vision-based hand gesture interface system was proposed for intelligent human-computer interaction aiming at a special group of people. The multi-cue system was designed for accurately recognition of the designed hand gesture vocabulary which had the characteristics of limited finger joint motion and the user-friendly priority. The fMHI technique was used in the motion pathway for motion information calculation. The shape pathway included the descriptors of the horizontal mass center, circumference, and aspect ratio of silhouettes. The proposed hand gesture interface was tested in the applications of the intelligent wheelchair control and smart car control, and got the good performance under the environments of strong lighting changes and users' errors.

Acknowledgements

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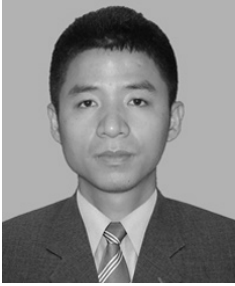
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