User-Centered and Analytic-Based Approaches to Generate Usable Gestures for Individuals with Quadriplegia

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***Abstract*—Hand gesture-based interfaces have become increasingly popular as a form to interact with computing devices. Unfortunately, standard gesture interfaces are not very usable by individuals with upper limb motor impairments, including quadriplegics due to spinal cord injury (SCI). The objective of this paper is to convert an existing interface to be usable by users with motor impairments. The key idea is to project existing patterns of gestural behavior to match those exhibited by users with quadriplegia due to common cervical SCIs. Two complementary approaches (a user-centered and an analytic approach) have been developed and validated to provide both subjective and quantitative solution to interface design. The feasibility of the proposed methodology was validated through user-based experimental paradigms. Through this study, subjects with upper extremity motor impairments preferred (gave a significantly lower Borg scale) the use of alternative constrained gestures generated by the proposed approach rather than the standard gestures.**

***Index Terms*— Assistive technologies, hand gesture-based interfaces, spinal cord injury, Laban space.**

I. Introduction

GESTURE recognition has been incorporated to design touch-free interfaces and to enhance users' experiences in many applications, such as mobile communication [1], smart home [2], robotics [3], entertainment [4], healthcare [5] and education [6]. For example, in the entertainment industry, gesture recognition based interfaces have been developed for Wii®, TLV® Play, Gesture Cube, Leap Motion®, and Xbox 360.

Gaming technologies (relying on gesture-interaction) is beneficial to users with quadriplegia due to spinal cord injury (SCI), since gestural commands can supplement users' hands off physical therapy [7]. Unfortunately, gesture recognition based interfaces have been developed without considering the motor limitations of users with upper extremity motor disabilities. Studies in the area of rehabilitation engineering and assistive technologies (AT) have investigated the design of hand-gesture based interfaces for users with quadriplegia [8]–[10]. These approaches provide off-the-cuff solutions that require redesigning the interface from scratch for each individual user. By "design from scratch", we mean that the user needs to select each gesture from the beginning and train them with enough samples. There is currently no existing methodology to convert commercial gesture-based[1] interfaces for people with upper extremity motor impairments.

For this reason, there is a need for a universal, generable approach to interpret gestures by quadriplegics due to high level (Cervical-1 (C-1) to Cervical-8 (C-8)) SCI that can work with existing sensors in the market with very little customization. To solve this problem, a user-centered approach and an automatic gesture projection approach concerning physical constraints are proposed to provide usable and effective gestural based interface for people with quadriplegia due to SCI. The user-centered approach consists of interviews with users with quadriplegia and determining a constrained gesture lexicon (set of gestures) based on their needs. In the analytic approach, Laban Movement Analysis (LMA) was applied to characterize gesture trajectories. LMA is a method proposed to describe all forms of human motion [11], including dance, music, and occupational therapy [12], [13]. LMA describes different aspects (direction, pathways, space used, and energy required) of human motion using four components: *Body*, *Space*, *Effort* and *Shape* [14], and has been applied to gesture analysis [15]. This theory plays a key role for determining the common patterns of gesture behaviors exhibited by users with motor disabilities [16], [17], [30], [31]. For the analytic approach, existing gestures designed for users without disabilities are encoded into a feature vector (using *Space*, *Shape* and *Effort* components of LMA, and components representing kinematic and geometric gesture characteristics). A pre-trained transformation function is then applied to the feature vector to obtain a candidate gesture set suitable for users with quadriplegia.

The contribution of this paper is three-fold: 1) two new approaches for gesture generation: a user-centered approach (through subjective interviews) and an analytic approach (based on gesture transformation between different manifolds, denoted as Laban Transform); 2) a solution to the problem of gesture projection from gestures designed for commercial consoles to suitable gestures for users with quadriplegia; 3) an assessment of the usability and effectiveness of the constrained gestures as an alternative for users with quadriplegia.

II. Problem Definition

The problem in the paper can be summarized as determining how to project standard gestures from a known manifold to a constrained (unknown) manifold that corresponds to the space where people with upper extremity motor impairments use. We refer to the term "standard gestures" as those gestures produced or designed for individuals without disabilities. A set of standard gestures used for a specific gesture-based interface is defined as "a standard gesture lexicon". Correspondingly, "a constrained gesture lexicon" represents the gesture set in the constrained space, which are usable for individuals with physical impairments. Let $\boldsymbol{G}$ denote a standard lexicon with N gestures. $\widetilde{\boldsymbol{G}}$ represents a constrained gesture lexicon corresponding to those gestures in $\boldsymbol{G}$. g_n and $\tilde{g}_n$ $(n = 1,2,\dots,N)$ denote the nth gesture in $\boldsymbol{G}$ and $\widetilde{\boldsymbol{G}}$, respectively (Eq. 1 and 2). Let $\mathcal{L}$ represents a mapping from a gesture trajectory to a feature vector, and $\breve{g}$ be an arbitrary gesture. $\boldsymbol{\Psi}$ denotes a pre-trained transform function set that maps the feature vector of a standard gesture to a set of feature vectors corresponding to constrained gestures. The problem can be represented as: finding a constrained gesture lexicon to satisfy Eq. 3 and 4 (Fig. 1).

$$\boldsymbol{G} = \{g_1, g_2, \dots, g_n, \dots, g_N\} \quad (n = 1,2,\dots,N) \tag{1}$$

$$\widetilde{\boldsymbol{G}} = \{\tilde{g}_1, \tilde{g}_2, \dots, \tilde{g}_n, \dots, \tilde{g}_N\} \quad (n = 1,2,\dots,N) \tag{2}$$

$$\tilde{g}_n = \arg\min_{\breve{g}} \|\mathcal{L}(\breve{g}) - \boldsymbol{\Psi}(\mathcal{L}(g_n))\| \tag{3}$$

$$\text{s.t. } n \le N, n \in \mathbb{Z}^+, g_n \in \boldsymbol{G}, \text{ and } \tilde{g}_n \in \widetilde{\boldsymbol{G}} \tag{4}$$

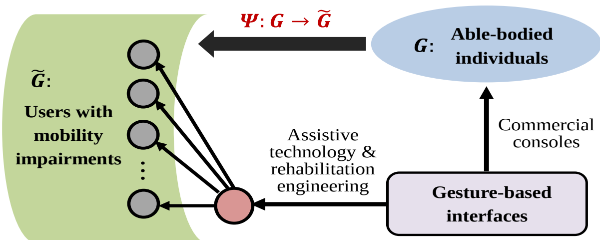


Fig. 1. Problem definition and the gap in knowledge

III. Methodology

A. User-centered Approach (UCA)

The *UCA* is a method that is used to tackle the problem using a human-centered approach. For a given standard gesture set $\boldsymbol{G}$, a constrained gesture set $\widetilde{\boldsymbol{G}}$ is obtained through interviews with human subjects and user-centered experiments. The interviewed subjects are individuals with quadriplegia due to SCI. A prototype trajectory of each gesture class g_n (Eq. 1) in the standard gesture set $\boldsymbol{G}$ was presented to the subjects using a slideshow [18], [19]. These subjects were then asked to provide a preferred gesture for the given gesture trajectory. The subjects can choose to use the presented gesture g_n or alternatively select a new gesture trajectory. Furthermore, the subjects could imitate sections of the given gesture trajectory, and replace the stressful segments of the gesture with a new sub-trajectory of their choice.

Each gesture $g_n \in \boldsymbol{G}$ was performed M times by the subject and each instance was recorded as $z_{n,j}(n = 1,2,\dots,N;\ j = 1,2,\dots,M)$, where M is the number of instances (M equals to 5 in this paper), and N the number of gestures in $\boldsymbol{G}$ (Eq. 5). The function $\oint$ maps the given gesture g_n to a gesture trajectory $z_{n,j}$ (a realization of a gesture, or instance). The acquired gesture trajectories are then preprocessed by two steps to reduce noise and the variability exhibited by users. First, outliers are removed (outliers are considered as those trajectory points further than three times the standard deviation from the mean). Then, the trajectories are smoothed using a Kalman filter [20] together with a Butterworth filter [21], resulting a gesture instance $\tilde{z}_{n,j}$ (Eq. 6). The function $\mathcal{F}$ maps the acquired gesture trajectory $z_{n,j}$ to a filtered trajectory $\tilde{z}_{n,j}$. The instances $\tilde{z}_{n,1}, \tilde{z}_{n,2}, \dots, \tilde{z}_{n,j}, \dots, \tilde{z}_{n,M}$ for each gesture in the lexicon are then aligned using dynamic time warping [22] and the mean gesture is computed. This mean gesture is assigned to the constrained gesture set, and referred as gesture $\tilde{g}_n$ (Eq. 7).

$$z_{n,j} = \oint(g_n) \ (n = 1,2,\dots,N, j = 1,2,\dots,M) \tag{5}$$

$$\tilde{z}_{n,j} = \mathcal{F}(z_{n,j}) \ (n = 1,2,\dots,N, j = 1,2,\dots,M) \tag{6}$$

$$\tilde{g}_n = \frac{1}{M}\sum_{j=1}^{M} \mathcal{A}(z_{n,j}) \tag{7}$$

where $\mathcal{A}$ is the function for gesture alignment. It results in an aligned trajectory $\tilde{\boldsymbol{g}}_{\boldsymbol{n}}$. This process is repeated for all gestures in the standard set (Fig. 2). After applying Eq. 7, a new gesture set is obtained. This method delivers a gesture set in the constrained space through a subjective approach. This approach generates one gesture set per user. Users might come up with different gesture sets based on their personal preferences and based on their functional degrees of mobility available. These types of gestures generated are user-centered, since the production process is built on the personal considerations.

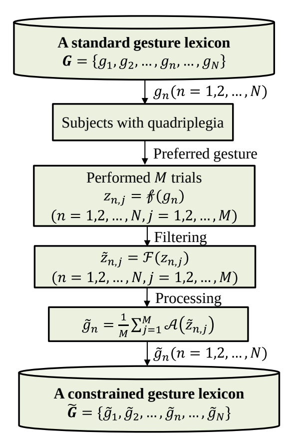


Fig. 2. Flow process for the user-centered approach

B. Analytic Approach (AA)

An analytic gesture generation approach [23] is proposed to address the problem of projecting standard gestures from a known manifold to a constrained manifold that corresponds to people with quadriplegia due to SCI. This approach consists of four steps: gesture trajectory acquisition and preprocessing, feature extraction, transformation, and constrained gestures generation.

The first step, *gesture trajectory acquisition and preprocessing*, collects two sets of gestures through interviews with individuals without disabilities and subjects with quadriplegia due to SCI, respectively. The process to obtain the two sets consists of requesting each subject (in each user group) to perform all the standard gestures. Each gesture instance is recorded, preprocessed, and collected leading eventually to a union set. Then, the *feature extraction* step consists of constructing feature vector, including the Laban space, kinematic, and geometric components, from each gesture trajectory. The Laban space features are good representations of the physical operational space of an individual. Features based on LMA components (*Space*, *Effort*, and *Shape)* are adopted to represent this operational space. The features representing the *Space* component are extracted using the symbolic representation developed in [24]. The *Effort* component is expressed by directness, inertia, and duration of a gesture trajectory [25], [26]. The *Shape* component is quantified by the volume of the gesture trajectory. For each pair of feature vectors extracted from gestures of subjects without disabilities and with quadriplegia, a *transform* function is obtained using regression trees. During the *gesture generation* step, for any given standard gesture trajectory, the acquired transform function is subsequently applied to project it and thus generate a candidate gesture set in the constrained manifold. A detailed description appears in [23] and is repeated here.

The gesture instance (j) obtained from each trial (i) is denoted as $x_{i,j} (i = 1,2, \dots, \mathcal{N}_{train};\ j = 1,2, \dots, M)$ for subjects without disabilities, and $y_{i,j}$ for subjects with quadriplegia (Eq. 8 and 9). $\mathscr{f}$ represents the mapping from the gesture $\bar{g}_i$ to the gesture trajectories. The corresponding training gesture set for each standard gesture is then denoted as $\boldsymbol{X}_i$ and $\boldsymbol{Y}_i$ (Eq. 10 and 11).

$$x_{i,j} = \mathscr{f}(\bar{g}_i) \tag{8}$$

$$y_{i,j} = \mathscr{f}(\bar{g}_i) \tag{9}$$

$$\boldsymbol{X}_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,j}, \dots, x_{i,M}\} \tag{10}$$

$$\boldsymbol{Y}_i = \{y_{i,1}, y_{i,2}, \dots, y_{i,j}, \dots, y_{i,M}\} \tag{11}$$

Let $\boldsymbol{\mathcal{I}}$ (Eq. 12) denote the set of gesture instances performed by individuals without disabilities, and $\tilde{\boldsymbol{\mathcal{I}}}$ (Eq. 13) be the set of gesture instances collected from subjects with physical impairments. The union is denoted as $\boldsymbol{\mathcal{S}}$ (Eq. 14).

$$\boldsymbol{\mathcal{I}} = \{\boldsymbol{X}_1, \boldsymbol{X}_2, \dots, \boldsymbol{X}_i, \dots, \boldsymbol{X}_{\mathcal{N}_{train}}\} \tag{12}$$

$$\tilde{\boldsymbol{\mathcal{I}}} = \{\boldsymbol{Y}_1, \boldsymbol{Y}_2, \dots, \boldsymbol{Y}_i, \dots, \boldsymbol{Y}_{\mathcal{N}_{train}}\} \tag{13}$$

$$\boldsymbol{\mathcal{S}} = \{\boldsymbol{\mathcal{I}}, \tilde{\boldsymbol{\mathcal{I}}}\} \tag{14}$$

Let the maximum and the minimum values of each feature be denoted as $\{u_1, u_2, \dots, u_j, \dots, u_K\}$ and $\{l_1, l_2, \dots, l_j, \dots, l_K\}$. An arbitrary feature (denoted as F) is then normalized using Eq. 15.

$$F' = \frac{F - l_j}{u_j - l_j}\ (j = 1,2, \dots, K) \tag{15}$$

Let $P_m^{i,j}$ denote a specific feature extracted from a gesture instance $(x_{i,j})$ collected from a subject without disability, and $Q_m^{i,j}$ be a specific feature extracted from a gesture instance $(y_{i,j})$ obtained from a subject with quadriplegia $(i = 1,2, \dots, \mathcal{N}_{train}; j = 1,2, \dots, M; m = 1,2, \dots, K)$. Let $\boldsymbol{\phi_{i,j}} \in \mathbb{R}^K$ denote a vector extracted from a gesture instance $x_{i,j} (i = 1,2, \dots, \mathcal{N}_{train}; j = 1,2, \dots, M)$, which consists of all features $(P_1^{i,j}, P_2^{i,j}, \dots, P_K^{i,j})$ (Eq. 16). Similarly, $\tilde{\phi}_{i,j} \in \mathbb{R}^K$ (Eq. 17) is a vector consisting of all the features $(Q_1^{i,j}, Q_2^{i,j}, \dots, Q_K^{i,j})$ extracted from a constrained gesture instance $y_{i,j}$. $\mathcal{L}$ represents the Laban transform.

$$\boldsymbol{\phi}_{i,j} = \mathcal{L}(x_{i,j}) \tag{16}$$

$$\tilde{\boldsymbol{\phi}}_{i,j} = \mathcal{L}(y_{i,j}) \tag{17}$$

For each given gesture, $\boldsymbol{\Phi_i}$ and $\tilde{\boldsymbol{\Phi}}_{\mathbf{i}}$ denote the set consisting of all feature vectors extracted from gesture instances of subjects without disabilities and subjects with quadriplegia, respectively (Eq. 18 and 19). The transform function (ψ_i) for $\bar{g}_i$ is obtained using regression trees [43] (Eq. 20). For each transform function ψ_i, a regression tree is obtained based on the input and output variables $\boldsymbol{\Phi_i}$ and $\tilde{\boldsymbol{\Phi}}_{\mathbf{i}}$. By applying this procedure for all the gestures, the set of transform function $\left(\boldsymbol{\Psi} = \{\psi_1, \psi_2, \dots, \psi_i, \dots, \psi_{\mathcal{N}_{train}}\}\right)$ is obtained.

$$\boldsymbol{\Phi}_i = [\boldsymbol{\phi}_{i,1}, \boldsymbol{\phi}_{i,2}, \dots, \boldsymbol{\phi}_{i,M}] = \begin{bmatrix} P_1^{i,1}, P_1^{i,2}, \dots, P_1^{i,j}, \dots, P_1^{i,M} \\ P_2^{i,1}, P_2^{i,2}, \dots, P_2^{i,j}, \dots, P_2^{i,M} \\ \vdots \\ P_K^{i,1}, P_K^{i,2}, \dots, P_K^{i,j}, \dots, P_K^{i,M} \end{bmatrix} \tag{18}$$

$$\tilde{\boldsymbol{\Phi}}_i = [\tilde{\boldsymbol{\phi}}_{i,1}, \tilde{\boldsymbol{\phi}}_{i,2}, \dots, \tilde{\boldsymbol{\phi}}_{i,M}] = \begin{bmatrix} Q_1^{i,1}, Q_1^{i,2}, \dots, Q_1^{i,j}, \dots, Q_1^{i,M} \\ Q_2^{i,1}, Q_2^{i,2}, \dots, Q_2^{i,j}, \dots, Q_2^{i,M} \\ \vdots \\ Q_K^{i,1}, Q_K^{i,2}, \dots, Q_K^{i,j}, \dots, Q_K^{i,M} \end{bmatrix} \tag{19}$$

$$(\tilde{\boldsymbol{\Phi}}_i)_{K \times M} = (\psi_i)_{K \times K} (\boldsymbol{\Phi}_i)_{K \times M} \tag{20}$$

Let $\breve{g}_n$ denote a seed gesture collected from subjects without disabilities. $\bar{\boldsymbol{\phi}}_{\boldsymbol{n}}$ $(n = 1,2, \dots, N)$ is the feature vector obtained for $\breve{g}_n$ (Eq. 21). The obtained feature vector $\bar{\boldsymbol{\phi}}_{\boldsymbol{n}}$ is then projected to a set of constrained feature vectors $\hat{\boldsymbol{\phi}}_{\boldsymbol{n,i}} (i = 1,2, \dots, \mathcal{N}_{train})$ using $\boldsymbol{\Psi} = \{\psi_1, \psi_2, \dots, \psi_i, \dots, \psi_{\mathcal{N}_{train}}\}$ (Eq. 22). For each gesture g_n, $\mathcal{N}_{\text{train}}$ constrained feature vectors $(\hat{\boldsymbol{\phi}}_{\boldsymbol{n,1}}, \hat{\boldsymbol{\phi}}_{\boldsymbol{n,2}}, \dots, \hat{\boldsymbol{\phi}}_{\boldsymbol{n,i}}, \dots, \hat{\boldsymbol{\phi}}_{\boldsymbol{n,\mathcal{N}_{train}}})$ can be obtained using the transform function $\boldsymbol{\Psi}$. Since the trajectories possess more information than their feature vectors, it is not analytically possible to obtain a gesture trajectory from its inverse Laban transform $\mathcal{L}^{-1}(\bar{\boldsymbol{\phi}}_n) = g_n$.

$$\bar{\boldsymbol{\phi}}_n = \mathcal{L}(\breve{g}_n)(n = 1,2, \dots, N) \tag{21}$$

$$\hat{\boldsymbol{\phi}}_{n,i} = \psi_i(\bar{\boldsymbol{\phi}}_n)(i = 1,2, \dots, \mathcal{N}_{train}) \tag{22}$$

To tackle this problem, a gesture generator is applied to generate a gesture instance $\breve{g}$. A feature vector $\breve{\boldsymbol{\phi}}$ (Eq. 23) is computed from the generated gesture and compared with the constrained feature vector $\hat{\boldsymbol{\phi}}_{\boldsymbol{n,i}}$. The mean trajectory that can minimize the distance metric (e.g. Euclidian) between $\breve{\boldsymbol{\phi}}$ and

$\widehat{\boldsymbol{\phi}}_{\boldsymbol{n},\boldsymbol{i}}$ is kept as a candidate gesture $\hat{g}_{n,i}$ (Eq. 24). For each gesture g_n, a candidate set including (denoted as $\widehat{\boldsymbol{G}}_n$) $\mathcal{N}_{train}$ constrained gestures are obtained (Eq. 25). The union of all the candidate set $\widehat{\boldsymbol{G}}_{\boldsymbol{n}}$ is denoted as $\boldsymbol{\Omega}$ (Eq. 26).

$$\breve{\boldsymbol{\phi}} = \mathcal{L}(\breve{g}) \tag{23}$$

$$\hat{g}_{n,i} = \arg\min_{\breve{g}} \left\| \breve{\boldsymbol{\phi}} - \widehat{\boldsymbol{\phi}}_{n,i} \right\| \tag{24}$$

$$\widehat{\boldsymbol{G}}_n = \left\{ \hat{g}_{n,1}, \hat{g}_{n,2}, \dots, \hat{g}_{n,i}, \dots, \hat{g}_{n,\mathcal{N}_{train}} \right\} \tag{25}$$

$$\boldsymbol{\Omega} = \{ \widehat{\boldsymbol{G}}_1, \widehat{\boldsymbol{G}}_2, \dots, \widehat{\boldsymbol{G}}_n, \dots, \widehat{\boldsymbol{G}}_N \} \tag{26}$$

IV. Experiments and Results

This research was approved by Purdue Institutional Review Board (IRB) and Rehabilitation Hospital of Indianapolis (RHI). The participants were recruited to this study using a flyer sent to the students e-mail list and distributed to the patients. The recruited subjects met one of the two criteria: 1) the subjects did not have any motor disabilities; and 2) subjects had quadriplegia due to C-1 to C-8 SCIs.

Gesture sets presented in Fig. 3 were used as the standard gesture sets (gestures in Fig. 3 (a)-(c) were used in [23], while Fig. 3 (d) were used in this paper). These selected gestures were developed for users without disabilities for different applications ranging from entertainment to education and were found in gaming console guides and products' manuals. The gesture lexicon shown in (a) have been used in [28] to help users with upper motor impairments with their rehabilitation.

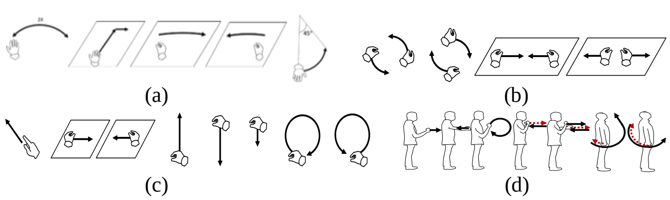


Fig. 3 Standard gesture lexicons (a) "Xbox" lexicon; (b) "PointGrab" lexicon; (c) "Win8" lexicon; (d) "Wisee" lexicon

A. Experimental Results for the User-Centered Approach (UCA)

Three male subjects (aged 29, 42, and 60) with quadriplegia (due to C-4/5, C-4/5, and C-5/6 SCI) were recruited to test *UCA*. The recruited subjects were able to perform coarse arm functions, but had limited fine motor function in the hands. The trajectories of the right arm were used for the testing procedure.

For each of these lexicons, a constrained gesture set was created including the mean trajectory of the corresponding constrained gestures (Fig. 4). The subjects were asked to perform each gesture for five trials. Each set of gestures in Fig. 4 represents the constrained gestures (with Fig. 4 (a)-(g) each corresponds to a standard gesture in Fig. 3 d) obtained from three subjects with motor impairments. The average variance between each execution for each subject is 52.3, 40.9, and 50.2, respectively (as large as 75.4, 44.7, 94.5, and as small as 27.9, 29.1, 29.2).

Using UCA, a constrained gesture lexicon $\widetilde{\boldsymbol{G}}$ is obtained based on the user's preference and performance. Thus, $\widetilde{\boldsymbol{G}}$ is useful for this user. However, the acquired gesture lexicon may not be applicable for users with different types of disabilities.

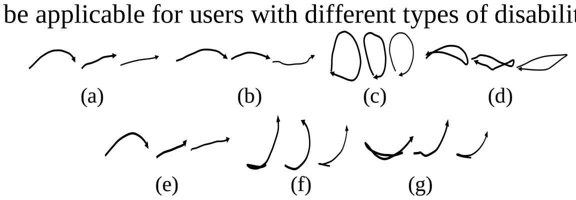


Fig. 4 The constrained gestures obtained by the user-centered approach for the "Wisee" lexicon through interviews with three quadriplegic subjects.

To understand how different the gestures performed by subjects with quadriplegia are from the standard ones, Mahalanobis distance [29] measurement between the gestures was adopted. The Mahalanobis metric addresses the limitation of Euclidean metric by accounting for the scaling of the coordinate axes. This distance metric assesses the separation (dissimilarity) of two groups of data, normalized so they are projected into the main distribution axis. We refer to this metric (the Mahalanobis distance) as a "Score" (Eq. 27). X and Y are the sets of points (from the trajectories) corresponding to gestures performed by subjects without disabilities and subjects with disabilities, and S is the covariance matrix.

$$Score = \sqrt{(X - Y)S^{-1}(X - Y)} \tag{27}$$

TABLE I illustrates the Mahalanobis distances between subjects with and without disabilities (or among subjects without disabilities). The level of the score measured the dissimilarity of gestures performed by subjects without disabilities and subjects with quadriplegia. A higher score indicated a larger dissimilarity between the two gesture groups, while a lower score indicated a smaller dissimilarity. The numbers in bold indicate the smallest Mahalanobis distance among a column (gesture). From the results, two (Subject 2 gesture d and Subject 3 gesture e, which are marked in bold) out of twenty-one constrained gestures obtained from subjects with upper extremity motor impairments were similar (has smallest Mahalanobis distance compared to the subjects without disabilities and other subjects with quadriplegia listed in the same column) to those gestures performed by subjects without disabilities. This indicates that the gestures selected by subjects with motor impairments were different from those gestures performed by subjects without disabilities. However, the score only measures the separation between the two gesture groups in a linear space. This means that this score does not necessarily indicate that the gestures are different in a non-linear space (e.g. such as the Laban space, which reflects better the user action space). To represent the gestures in a non-linear space, results using Laban transformation are provided in the following section.

TABLE I
MAHALANOBIS DISTANCE FOR THE "WISEE" LEXICON (MM)

Mahalanobis Score	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Subject 1	12.87	15.13	9.88	9.10	12.04	4.32	5.78
Subject 2	16.38	8.68	5.01	**7.07**	8.29	7.46	5.12
Subject 3	9.71	6.20	6.73	8.27	**7.64**	5.19	4.31
Able-bodied	**8.95**	**6.02**	**4.88**	8.45	11.35	**3.71**	**2.55**

B. Experimental and Gesture Generation for AA

Four (two male and two female) subjects without disabilities (aged 29, 31, 26, and 30) and four male subjects (aged 29, 42, 43, and 60) with quadriplegia (due to C-4/5, C-4/5, C-5, and C-5/6 SCI) were recruited to acquire a union of the gesture instances and train the transform function. The subjects with quadriplegia were able to perform arm functions within a limited space.

The constrained gestures obtained from the proposed approach are illustrated in Fig. 5. From these displaying figures, the present gestures demonstrate varied forms of the original gestures. In addition, most of the gestures exhibit more curvature than the ones in the standard lexicons ($g_i \in \boldsymbol{G}$). However, it is not possible to evaluate the effectiveness and usability of these gestures based purely on the appearance. To further assess these candidate constrained gesture sets, a subjective validation was conducted with subjects with quadriplegia in the next section.

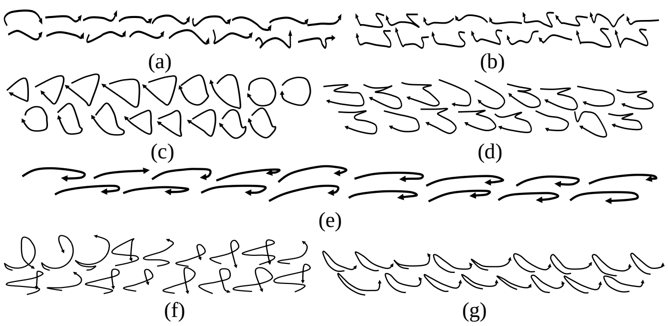
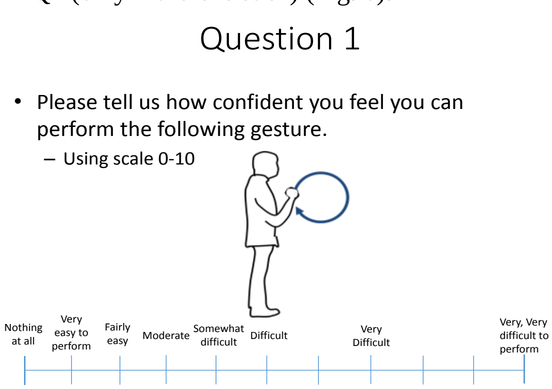


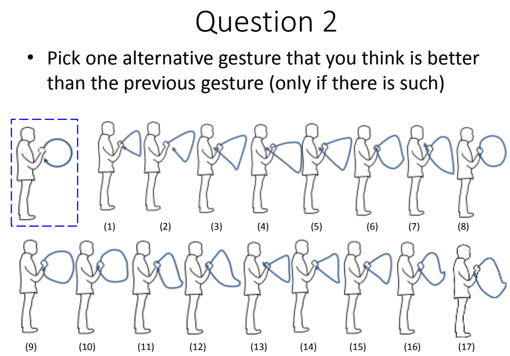
Fig. 5 Constrained candidate gestures for the "Wisee" lexicon.

C. Subjective Validation for AA

Six male subjects (aged 29, 30, 33, 42, 45, and 56) with upper extremity motor impairments (different from the subjects recruited for *UCA*) were recruited in a subjective validation experiment to evaluate the constrained gestures: five subjects with quadriplegia (due to C-4, C-4/5, C-7, C-6/7, and C-5/6 level of SCI) and one subject with Neurofibroma. The subjects were required to answer two questions: *Q1)* how confident you feel you can perform the given gesture? (Fig. 3(d)); *Q2)* choose one gesture from the candidate set that is better than the gesture given in Q1 (only if there is such) (Fig. 6).



(a)



(b)

Fig. 6 Slides for the user-based validation

For Q1, the subjects were asked to see a standard gesture in the "Wisee" lexicon (demonstrate via a slideshow) and rank the difficulty of the given gesture using the Borg scale (used to evaluate the effort the subjects experienced for a given gesture) [30] (0-10). A higher score indicates that the given gesture is more difficult to perform. For Q2, both the standard gesture (illustrated in Q1) and the corresponding constrained candidate gestures (all the gestures in Fig. 5) were shown to the subjects. The subjects can either select the standard gesture or an alternative gesture in the candidate set. The subjects were not aware whether the gestures were designed for healthy participants or the one generated for subjects with quadriplegia.

From the response of Q2, thirty six out of forty two preferred gestures selected by subjects with upper extremity motor impairments came from the constrained gesture sets generated by the *AA* (Fig. 7). The bar graph (upper part) illustrated the effort reported by each subject for each gesture in the "*Wisee*" lexicon (Fig. 3 d). The stem graph (lower part) indicated the index of the constrained gestures (Fig. 5) selected by the subjects. If there is no stem under the bar graph, it indicates that the gestures tend to keep the given gesture instead of selecting a gesture from the candidate set. From the results, even for the subject with C-7 quadriplegia, who has more residual hand/arm functions than the other subjects, three out of seven gestures were selected from the candidate constrained gesture set.

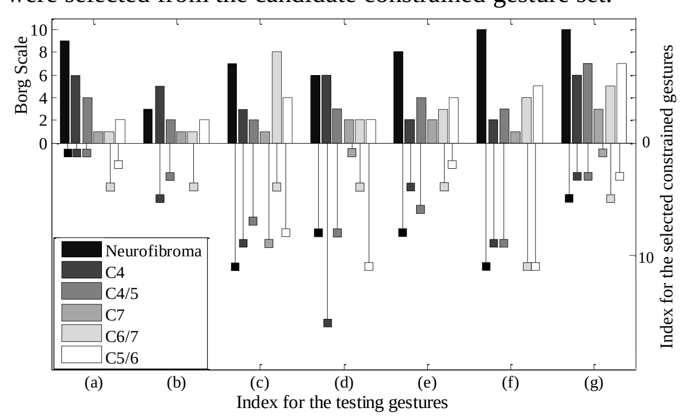


Fig. 7 Borg Scale and gesture selection results corresponding to the testing gestures.

D. Stability Validation for AA

For subjects with mobility impairments, a failure of one joint can be compensated by the remaining joints in their redundant motor system. Since different gestures allow for different level of redundancy, the goal is to pick those gestures that allow for the largest redundancy of the motor system to construct the final gesture set. A stability index (denoted as R_V) was computed for each standard and candidate gesture based on the Uncontrolled Manifold framework [21], [31]. This stability index is applied to identify differences in stability in joint configuration space for different gestures.

Four male subjects (aged 29, 33, 45, and 56) with quadriplegia (due to C-4/5, C-6/7, C-5, and C-5/6 SCI) were recruited to perform the standard (Fig. 3 d) and constrained gestures (generated by *AA*, see Fig. 5). The stability index R_V for the standard gesture (with gesture index "0") and constrained candidate gestures (with gesture index "1" to "17") are illustrated as in TABLE II. The goal was to select the gestures with the highest stability (largest stability index). From Table II, the gestures with the largest stability index were "9", "9", "11", "0", "11", "3", and "12", respectively. The corresponding average stability indices were 1.200, 1.132, 1.105, 1.482, 1.214, 1.035, and 1.006. The results revealed that six out of seven selected gestures (with the highest stability) were from constrained candidate gesture set (gestures with index "9", "9", "11", "11", "3", and "12"). This result was consistent with the subjective validation results.

TABLE II
STABILITY INDICES FOR STANDARD AND CONSTRAINED GESTURES

Index	(a)	(b)	(c)	(d)	(e)	(f)	(g)
0	0.943	0.929	0.846	**1.482**	0.977	0.665	0.774
1	0.659	0.829	0.701	0.995	0.886	0.677	0.670
2	0.860	0.870	1.042	1.126	0.989	0.865	0.607
3	0.709	0.973	0.651	0.863	0.976	**1.035**	0.692
4	0.803	1.095	0.745	0.886	0.898	0.667	0.680
5	1.096	1.113	0.739	0.836	0.782	0.942	0.648
6	0.899	0.849	0.731	0.789	0.848	1.002	0.843
7	0.802	0.887	0.660	0.756	1.015	0.946	0.770
8	0.721	0.964	0.701	0.834	0.720	0.532	0.579
9	**1.200**	**1.132**	0.834	0.569	1.007	0.708	0.556
10	0.925	0.918	1.100	1.051	0.785	0.710	0.790
11	0.538	0.674	**1.105**	0.786	**1.214**	0.682	0.827
12	0.601	0.884	0.973	0.813	0.795	0.861	**1.006**
13	0.703	0.940	0.887	0.888	0.874	0.661	0.706
14	0.601	0.818	0.879	0.771	1.073	0.610	0.789
15	0.799	0.901	0.872	0.921	0.750	0.962	0.735
16	0.733	0.886	1.096	0.841	1.081	0.903	0.782
17	0.673	0.792	0.984	0.725	1.043	0.961	0.676

V. DISCUSSION

The *UCA* and *AA* are two solutions for the same problem presented in Section II, and they are equally important, but different in nature. One is fundamentally based on subjective opinions, while the other is mathematically inspired. To further validate the usability of the proposed analytic method, a user-based and a stability-based validation were conducted with six and four subjects with quadriplegia, respectively. In the user-based validation, the standard gesture (Fig. 3 a) and all constrained gestures corresponds to each standard gesture were demonstrated to the subjects via slideshows (Fig. 7). Based on the informal feedback, this demonstration was effective to convey the gestures to the subjects. This may lead us to think that there are more chances to select a preferred gesture from the constrained set. Nevertheless, if the standard gesture is easier for users with mobility impairments to perform, they will still select it. The results (Fig. 6) revealed that subjects with upper extremity mobility impairments preferred to use the gestures generated by the analytic approach. Even for the subject with C7 quadriplegia, who has more residual hand/arm functions than the other subjects, three out of seven gestures were selected from the candidate constrained gesture set.

This study has a number of limitations: 1) Due to the difficulty of recruiting subjects with quadriplegia, this work includes a limited number of subjects in each experiment. Thus, further experiments are required in the future to provide more generable results. 2) It was assumed that users with the same type of disability will have a similar limitation when they perform a given gesture. This is true for most of the cases. However, for users with a variety of disabilities, the clinical conditions may be more complicated; thus, the pre-trained transform function may not be applicable and new data regarding to this user should be added for training. 3) The procedure described for the *AA* and *UCA* methods is the same for every user with C4-C5 mobility impairments. The only difference is the resulting gestures after applying this method; which represent the fact that different users will select different gestures that are more suitable. That is, the gestures obtained from the procedure described are generable for users with the same type of disability, however, they may not be adaptable for users with other types of disabilities. 4) Since there is no direct ways to measure the effectiveness of a gesture, a gesture is evaluated by the qualities such as desirability, total effort, and redundancy. We don't know whether these gestures are optimal, but they are better than the existing standard gestures.

This work could inspire and lead to clinical applications in the area of rehabilitation and cognitive and physical therapies. Video games are beneficial for cognitive and motor skill learning in rehabilitation science. Through our approach, existing gesture-based consoles can be adapted for people with motor impairments, and thus allowing this underserved population access to gaming based rehabilitation.

VI. CONCLUSIONS

In this paper, we studied the possibility of transforming gestures from standard lexicons to those that can be performed by users with motor impairments. Two new methods (UCA and AA) were proposed to address the problem of projecting standard gestures from a known manifold to an unknown constrained manifold that are usable for users with quadriplegia. The UCA provides a subjective solution through interviews with subjects with quadriplegia due to middle level (C4-C5) SCIs. For each standard gesture, one constrained gesture is acquired for each individual subject. This method is used to customize gesture-based interface for persons with motor impairments. However, it can only provide individualized solutions for a specific user rather than generalizable solutions. The AA is an analytic-based approach that builds the solutions based on a pre-trained transform function (coined the Laban Transform) and a gesture generator. The transform function is trained using the gesture instances collected from subjects without disabilities and subjects with quadriplegia due to mid-level (C4-C5) SCIs. For each gesture in the standard lexicon, seventeen constrained gestures are obtained with varied shape and curvature to constitute a candidate set. The generated constrained gestures were validated through a set of subjective experiments. Subjects with quadriplegia preferred to select the constrained gestures rather than the standard gestures (thirty-six out of forty-two constrained gestures were selected). This result is consistent with the stability-based validation (six out of seven gestures in the candidate were with higher stability index than the standard gesture).

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