local muscle fatigue during sustained isometric constant force muscle contractions. The reliability and accuracy of the AIF was statistically compared with the most commonly used frequency variables (MDF and MNF), in terms of their robustness against the size of the analysis window. The results suggest that the AIF method is a better choice for the estimation of the slope and p.o.i. of the regression line, a process commonly used to quantify myoelectric manifestations of muscle fatigue.

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Biological Constraints Simplify the Recognition of Hand Shapes

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***Abstract*—This study sought to identify constraints that might lead to a concise system of recognizing fingerspelling hand shapes. Previous studies of grasping suggested that hand shape is controlled using combinations of a small number of neuromuscular synergies, but fingerspelling shapes appear to be more highly individuated and, therefore, might require a larger number of degrees of freedom. Static hand postures of the American Sign Language manual alphabet were recorded by measuring 17 joint angles. Principal components (PCs) analysis was compared to the use of subsets of individual variables (i.e., joint angles) for reduction in degrees of freedom. The first four PCs were similar across subjects. Classification using weightings from these four components was 86.6% accurate, while classification using four individual variables was 88.5% accurate (thumb abduction, as well as flexion at the index and middle finger proximal interphalangeal joints and the ring finger metacarpalphalangeal joint). When chosen for each subject, particular four-variable subsets yielded correct rates above 95%. This superior performance of variable subsets over PC weighting vectors suggests that the reduction in degrees of freedom is due to biomechanical and neuromuscular constraints rather than synergistic control. Thus, in future application to dynamic fingerspelling, reasonable recognition accuracy might be achieved with a significant reduction in both computational and measured degrees of freedom.**

***Index Terms*—American Sign Language (ASL), Cyberglove, gesture recognition, postural synergy, principal components analysis.**

I. INTRODUCTION

Communication in American Sign Language (ASL) typically relies on hand shapes placed in or moved across particular locations relative to the signer's body, in addition to movements of the head and arm, and facial expression. However, proper names and words with no unitary sign are spelled, letter by letter, in English, and students of ASL often begin their studies by learning the 26 hand shapes that constitute the manual alphabet.

Translation of sign language into artificial spoken language has been approached in two ways. First, several studies have developed algorithms to classify features of video images of manual alphabets [1], [2]. This approach has met with some success, although it suffers from the typical image processing problems of occlusion of key elements and complexity of the input signal. A second approach involves the use of an instrumented glove to measure the angular positions of the joints of the hand [3], [4]. Previous studies along these lines of investigation have used a neural network architecture and a classification scheme employing multiple pixel-based features or the full set of joint angles for a robust system of recognition.

The present study used an instrumented glove to measure 17 joint angles of the hand, but developed a somewhat different approach to letter recognition. With the goal of reducing the dimensionality of the hand, we looked for evidence of either synergistic control strategies or

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biomechanical/neuromuscular constraints. We sought to evaluate the potential for limiting the number of input channels (i.e., degrees of freedom) to a recognition algorithm, and how the degrees of freedom should be reduced. We report evidence to suggest that the inputs could be limited to just four individual joint angles.

II. Methods

Experimental Task

Subjects were instructed to produce the sign for each letter according to the ASL manual alphabet. These signs are unimanual and contain extremes of hand posture designed to offer highly visible contrast between letters. However, because there are so many letters (26), several letter pairs are similar except for one discriminating feature, such as wrist orientation or thumb position.

Subjects began each trial from a relaxed hand position, with the elbow resting on a flat surface. Subjects were given the letter cue before each trial. Upon hearing the "go" command they produced the sign, and held that hand position for three seconds. Each of the 26 letters was presented a total of five times; the order of the 130 trials was randomized.

Eight subjects (seven females and one male) participated in the experiment. Seven were right-handed and one was ambidextrous. All had normal hearing. Four subjects (subjects 1–4) were naive, with little experience in fingerspelling, while the others (subjects 5–8) were fluent signers recruited from an interpreting service. All subjects gave informed consent and the experimental procedures were approved by the Institutional Review Board of the University of Minnesota.

Data Acquisition

A right-hand glove (Cyberglove, Virtual Technologies, Palo Alto, CA) with embedded sensors was used to record joint angles. We recorded data from 17 degrees of freedom: metacarpal phalangeal (MCP) and proximal interphalangeal (PIP) joint angles for the thumb and four fingers; abduction (ABD) of the thumb (T), middle (M), ring (R), and little (L) fingers; thumb rotation (ROT); wrist pitch (WP); and wrist yaw (WY), with a spatial resolution $<0.5^\circ$, and a temporal resolution of 12 ms (see [5] and [6]). Static hand postures were defined by averaging the last 60 samples of each trial (i.e., the last 720 ms). Images of hand shapes for letter postures and principal components (PCs) were later modeled and rendered using Persistence of Vision Ray Tracer (POV-Ray, copyrighted freeware).

Discriminant Analysis

We used a discriminant analysis to classify the postures into letter categories. This classification scheme maximizes the ratio of between groups variance to within groups variance, and can be used to categorize a trial according to a training set of grouped data. As previously described [5], calculation of discriminant functions allows data to be mapped into a multidimensional discriminant space, in which the best axes for maximum separation of data can be defined. For each trial vector $\mathbf{y}$ (composed of joint angle data for up to 17 variables), Mahalanobis distances along these axes to each group mean vector $\mathbf{u}$ (from the training set) were computed

$$d_{ij}^2 = (\mathbf{y}_i - \mathbf{u}_j)'\mathbf{A}^{-1}(\mathbf{y}_i - \mathbf{u}_j)$$

where $\mathbf{A}$ is the pooled covariance matrix. Each trial vector was classified into the letter category for which this distance was smallest.

Reducing Degrees of Freedom

In this experiment, when all recorded variables were used in the discriminant functions, each vector contained measurements for 17 degrees of freedom. However, any number of variables can be omitted from the function, resulting in a lower dimensionality discriminant space. Because of biomechanical and neuromuscular constraints, a small reduction in the number of joint angles might not result in great impairment of classification. However, further reduction might significantly degrade classification accuracy; the severity of degradation indicates the relative importance of the variables discarded and retained. As described in Section III, one approach to assessing this phenomenon was backward elimination, a technique that, at each iteration, removes the parameter that contributes least to successful classification.

PC Analysis

PC analysis provides a different way to reduce the degrees of freedom used in the discriminant analysis. Computed for each subject from the eigenvalues and eigenvectors of the covariance matrix of the 26 averaged letter postures, the PCs are linear combinations of all the variables that when summed together with the proper weights can exactly reconstruct any of the original samples. There are as many PCs as there are variables, but they are ordered by the amount of variance they account for in the data, so that by summing the first several weighted components, most of the variability is accounted for. Every trial is given a weight (w) for each of the 17 PCs

$$w_{mn} = \frac{\mathbf{y}_m \bullet \mathbf{c}_n}{(\mathbf{c}_n \bullet \mathbf{c}_n)^{1/2}}$$

where $\mathbf{y}$ is the trial vector and $\mathbf{c}$ is the PC vector. Each weight corresponds to a particular PC, or degree of freedom, measuring the contribution of a particular linear combination of all the variables. Therefore, the weights can be used in place of individual variables in the discriminant function. If the control strategy involves the use of a small number of synergies [6], we would expect a high degree of accuracy in classification using a relatively small number of PCs.

Information Content

In order to evaluate the information content, we performed the discriminant analysis using various numbers of PCs, and using various numbers of individual variables (i.e., joint angles), and then compared these results. Using a jack-knifed classification procedure (i.e., omitting the trial being classified from the training set), we plotted the discrimination results in confusion matrices [7], and calculated the correct classification rates. We also used information theory [8] to quantify the amount of information transmitted. The sensorimotor efficiency (SME) is defined by the ratio of information transmitted (T) by hand shape about target letter, to the maximum possible transmitted information (see [5]). The size (in number of letters) of an alphabet that would contain an equivalent amount of information is given by 2^T.

III. Results and Discussion

PCs

Because each PC is a linear combination of all 17 variables, they can be represented visually as hand shapes. The first four PCs for all subjects are shown in Fig. 1. Because the PCs were rendered using the maximum weighting coefficients from each subject, the images represent each PCs greatest contribution to overall hand shape, across all of the letters. There are similarities across subjects, which might be explained by the fact that the hand postures formed by the subjects were all targeted to conform to the same ideal (an alphabet designed to emphasize individual finger positions). However, these similar hand shapes might also reflect common synergistic control strategies such as those previously found for grasping [6]. Identification of these synergies would simplify hand shape recognition.

To evaluate whether a small number of PCs could adequately reconstruct the experimental data, we examined the percent of the total variance accounted for by subsets of PCs. Using data from all subjects,

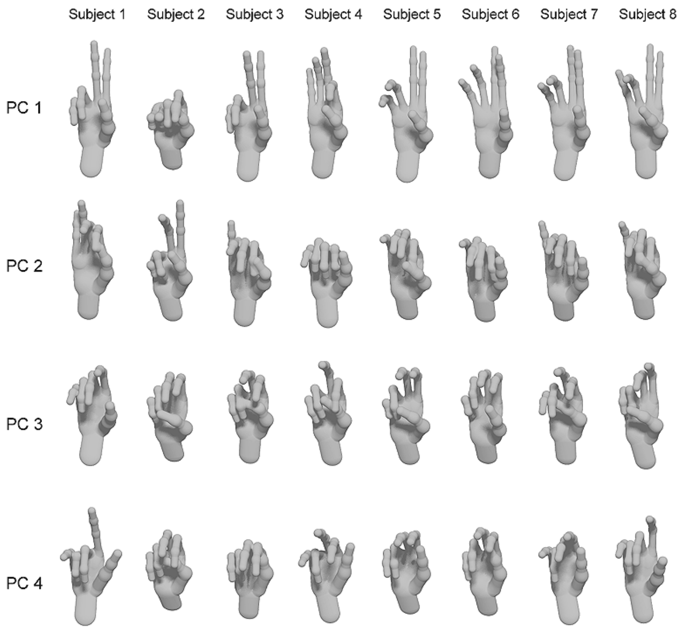

Fig. 1. Hand shapes equivalent to the heaviest weighting of the first four PCs for each subject.

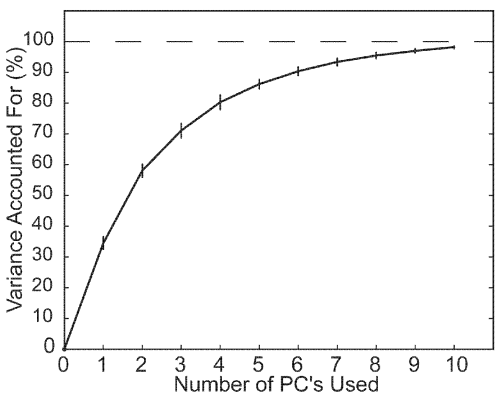

Fig. 2. Mean proportion of variance accounted for plotted against the number of PCs used in reconstruction.

in Fig. 2 we show the mean cumulative percentage of the total variability accounted for, as PCs are added to the reconstruction. Because the PCsare ordered, the first four (out of 17) components account for approximately 80% of the variability. This is in contrast to our previous study of grasping [6] where only two PCs were needed to account for more than 80% of the variance. In complicated hand postures like fingerspelling, a small amount of variability can be crucial to the distinguishability ofletter signs. We, therefore, addressed the question of classification by computing discriminant functions using weights of the PCs.

We found that reconstructions from weighted combinations of PCs transmit a great deal of information (Fig. 3). For a discriminant function including the first four PCs, the mean correct rate across subjects was 86.6% [Fig. 3(A)], and the SME indicated that 92% of the possible information was transmitted [Fig. 3(B)], for an equivalent alphabet size of 20.1 letters—a loss of less than six letters' worth of information. Using data from a representative subject, Fig. 3(C) shows that classification errors were rare, and were restricted to highly similar hand shapes (such as the signs for U and H, which differ mainly in wrist position). This demonstrates that the last 13 components were relatively unimportant for the classification of hand posture. The small number of required components, together with the similarity in PC shape across subjects, im-

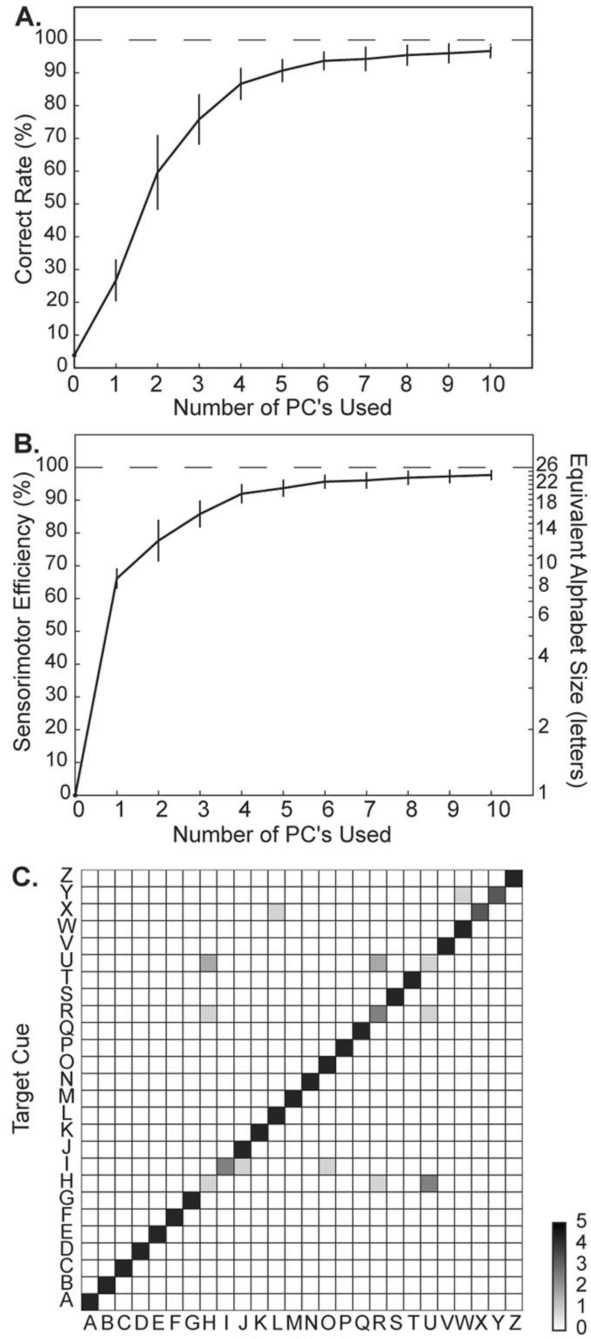

Fig. 3. (A) Mean percentage correct classification plotted against the number of PCs used in the discriminant function. (B) Mean information transmitted plotted against the number of PCs used in the discriminant function. The axis on the left measures SME, a percentage of the total possible information transmitted. The axis on the right shows the number of letters in an alphabet encoding an equivalent amount of information. (C) Jack-knifed confusion matrix for a representative subject (subject 6). Classifications were computed based on weightings for the first four PCs.

plies a reduction in the degrees of freedom and might suggest synergistic control. However, this does not necessarily mean that synergies are the over-riding control strategy. Although the fingerspelling postures are designed to accentuate individuation of fingers, they may still allow for enough covariation in finger positions that the biomechanical and neuromuscular constraints of human hand posture [9], [10], in conjunction with the task demands, might be responsible for the apparent synergies.

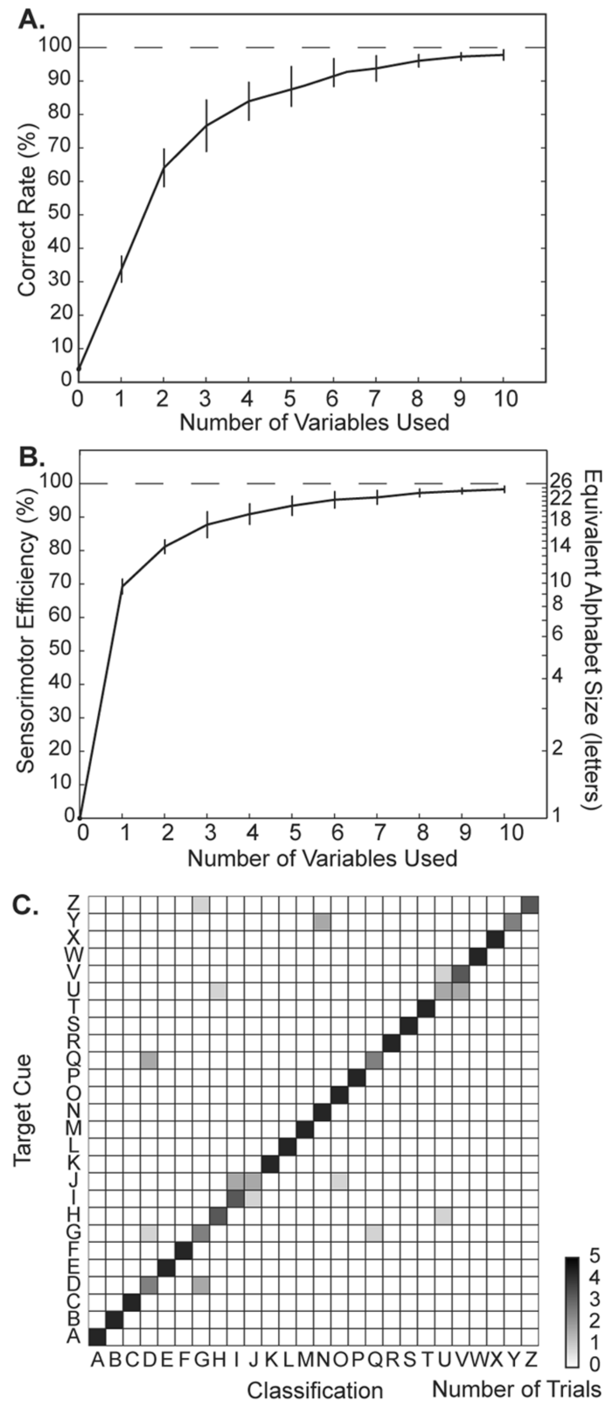

Fig. 4. (A) Mean percentage correct classification plotted against the number of variables used in the discriminant function. (B) Mean information transmitted plotted against the number of variables used in the discriminant function. See Fig. 3 for an explanation of the vertical axes. (C) Jack-knifed confusion matrix for a representative subject (subject 6), using a four-variable subset for classification. In this figure, all classifications were computed based on subsets determined from the backward-stepping process (Table I).

TABLE I

INITIAL RANKING OF VARIABLES BY BACKWARDS ELIMINATION (THE BOTTOM ROW WAS ELIMINATED FIRST). ABBREVIATIONS: THUMB (T), INDEX (I), MIDDLE (M), RING (R), LITTLE (L), METACARPAL PHALANGEAL (MCP), PROXIMAL INTERPHALANGEAL (PIP), ABDUCTION (ABD), ROTATION (ROT), WRIST PITCH (WP), AND WRIST YAW (WY)

Subject	1	2	3	4	5	6	7	8
	IPIP	**IPIP**	**IPIP**	**IPIP**	MMCP	**MPIP**	**IPIP**	**IPIP**
	MPIP	**MPIP**	RPIP	RPIP	IMCP	**IPIP**	**MPIP**	**MPIP**
	RPIP	LPIP	**MPIP**	**MPIP**	**MPIP**	IMCP	LPIP	IMCP
	TABD	MMCP	TMCP	LMCP	**IPIP**	MMCP	IMCP	MMCP
	TMCP	RMCP	TABD	TMCP	RPIP	RPIP	MMCP	RPIP
	WP	TMCP	LMCP	TABD	WP	MABD	TMCP	TABD
	RABD	MABD	MMCP	LPIP	TABD	TMCP	WP	MABD
	IMCP	TABD	WP	IMCP	TROT	TROT	MABD	TPIP
	RMCP	IMCP	WY	MMCP	MABD	LMCP	RPIP	LMCP
	LMCP	RPIP	MABD	MABD	LPIP	LABD	TABD	TROT
	TROT	WP	TROT	WP	LABD	RMCP	LABD	LMCP
	MMCP	TPIP	RMCP	RMCP	TMCP	TABD	LMCP	WP
	LABD	LABD	TPIP	RABD	LMCP	RABD	TROT	TMCP
	LPIP	RABD	IMCP	TROT	WY	WP	WY	WY
	TPIP	WY	RABD	WY	RABD	TPIP	RABD	RMCP
	MABD	LMCP	LPIP	LABD	RMCP	LPIP	RMCP	LABD
	WY	TROT	LABD	TPIP	TPIP	WY	TPIP	RABD

Comparing Subsets of PCs to Subsets of Joint Angles

In order to evaluate various means of reducing dimensionality, we directly compared the discriminant results from PC weights to results using subsets of individual joints (Figs. 3 and 4). Because the joints are not automatically ordered (as are the PCs), subsets must be chosen in other ways. We started by using backward-elimination to generate a rudimentary order of importance for the 17 variables for each subject (Table I). In most subjects, the flexions of the proximal interphalangeal joints of the index finger (IPIP) and the middle finger (MPIP) were identified as accounting for the largest portions of the variance (underlined in Table I). The results from discriminant analysis of subsets defined by these orders are shown in Fig. 4. The mean percent correct and SME rates are approximately equivalent to those found using PCs for discrimination, and in both cases the confusion matrix reveals few errors (compare Fig. 4 with Fig. 3). This is surprising because, although both analyses involved the same number of computational degrees of freedom, the variable subsets contained information only from individual joints, whereas each PC resulted from combinations of measurements from all joints.

Ranking of Subsets of Joint Angles

We found even stronger evidence for the superiority of joint subsets over PCs as we continued to investigate different possible subsets. We decided to focus on discriminant functions using four variables, since these appeared to lie on the lower boundary of good success rates ($>$80% correct). Since backward elimination does not necessarily yield an optimal solution, we ran the discriminant function using all possible subsets of four from the 17 variables ($_{17}C_4 = 2380$ subsets) for two representative subjects, one naive (subject 1) and one fluent (subject 5). We then ranked those subsets by correct rate and ran the top 300 for the rest of the subjects. The best-performing four-member subsets (in terms of correct rate) for each subject are listed in Table II.

We also ranked the subsets by average correct rate across all subjects. The top-ranking joint subset contained one joint from each finger, with the exception of the little finger. It was comprised of thumb abduction (TABD), and the flexion angles of the IPIP, MPIP, and ring metacarpal phalangeal joint (RMCP). The results for this subset are also shown in Table II. The average correct rate for this subset was 88.5%, with 93.1% of possible information transmitted for an equivalent alphabet size of 20.8 letters. The average rates across subjects when using the best subset for each individual subject were substantially better: 94.4% correct, 96.0% SME, and 22.8 letters. The difference in performance between the best overall subset and the best subset per subject indicates idiosyncratic favoring of certain joints for each subject.

TABLE II
SUMMARY OF THE PERFORMANCE OF THE DISCRIMINANT FUNCTIONS

Subject	1	2	3	4	5	6	7	8	mean
correct rate (%)									
4 PCs	83.1	90.0	83.8	84.6	86.2	89.2	80.0	96.2	86.6
4 variables (TABD, IPIP, MPIP, RMCP)	85.4	89.2	85.4	87.7	90.0	92.3	86.2	91.5	88.5
4 variables (best per subject)	90.8	96.9	93.1	93.1	96.9	98.5	88.5	97.7	94.4
SME (%)									
4 PCs	89.8	92.9	90.3	90.5	91.8	94.2	88.7	97.8	92.0
4 variables (TABD, IPIP, MPIP, RMCP)	92.1	93.3	91.8	92.1	93.5	94.5	91.0	96.2	93.1
4 variables (best per subject)	93.2	97.6	95.5	95.3	98.0	98.8	91.3	98.6	96.0
number of letters									
4 PCs	18.7	20.6	18.9	19.1	19.9	21.5	18.0	24.2	20.1
4 variables (TABD, IPIP, MPIP, RMCP)	20.1	20.9	19.9	20.1	21.1	21.7	19.4	22.9	20.8
4 variables (best per subject)	20.8	22.6	22.4	22.3	24.4	25.0	19.6	24.9	22.8
best variable subset per subject									
	TROT	TMCP	IMCP	TABD	TABD	TROT	TMCP	TABD	
	IMCP	IMCP	MMCP	IPIP	MMCP	TMCP	MPIP	IMCP	
	IPIP	IPIP	RPIP	MMCP	MABD	MMCP	MABD	MPIP	
	MMCP	RABD	WP	MABD	RMCP	MABD	LMCP	RPIP	

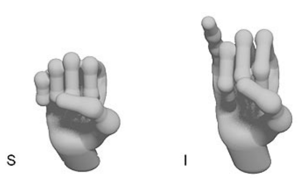

Fig. 5. The signs for S and I are ideally distinguishable only by the extension of the little finger, but biomechanical and neuromuscular constraints in the hand make it difficult to extend the little finger independently of other finger movements.

Implications and Future Directions

The high information content of subsets of four variables implies that covariation in joint angles allows changes in one angle to be reflected by the values of the other joint angles. This effectively spreads the information across the hand, so that while the angle of an unmeasured joint cannot be predicted by the angle of a measured joint, the target posture, nevertheless, can be accurately identified. This is true even in cases where the ignored joint angles appear to be crucial to the recognizability of the hand shape. For example, the signs for the letters I and S (Fig. 5) ideally differ only in the extension of the little finger. However, since it is difficult to extend the little finger without altering the angles of the other joints, subtle variations in the measured variables reflect "information leakage" across joints, which allows the analysis to discriminate between the letters I and S, even when the little finger is completely ignored [see for example, Fig. 4(C)].

The superiority of four-variable subset vectors over four-PC weighting vectors in transmitting information about fingerspelling hand postures suggests that synergies are not used as a primary control strategy for this task. In our previous study of grasping [6], we found that the first two or three PCs accounted for about 85%–90% of the variance, and we suggested that these PCs represented the main neuromuscular synergies used to control grasping. In contrast to grasping, in the present study subjects attempted to control the joints individually in order to generate the highly individuated postures of the ASL manual alphabet.

Future attempts to produce a "talking glove" [11] or to understand the control of hand movement [9], [10] may be facilitated by our conclusion that the number of measured joint angles can be greatly reduced. When the joint angles are properly chosen, just four are needed to produce an alphabet of about 20–25 letters. This is surprising because the manual alphabet is designed to produce letters that are as distinctly different from one another as possible. Therefore, one might expect that the 20 or so joints of the hand would be controlled as independently as possible. Instead, the high performance of small subsets of joint angles indicates that biomechanical and neuromuscular constraints produce a pattern of covariation in joint flexions consistent enough to allow fluctuations in one joint angle to be picked up reliably by others, effectively spreading the information across joints. The failure of PCs to carry as much information as individual joints suggests that fingerspelling hand shapes are primarily controlled by individuated finger movements subject to these mechanical constraints, rather than synergies.

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