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Quantizing and Characterizing the Variance of Hand Postures in a Novel Transformation Task

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Abstract— **This paper presents a numerical approach using principal component analysis (PCA) to quantize and characterize the variance of hand postures in a novel posture transformation task. Five subjects were tested in two tasks in which a cursor can be moved by varying the hand posture. This was accomplished by weighted linear combination of 14 sensors of a data glove. The first task was to move a cursor on computer screen in one dimension horizontally, by posing various hand postures. To increase the complexity of control, in the second task, subjects were asked to move a cursor on computer screen in two dimensions. Joint angles were measured during the experiment by the data glove. In both tasks subjects participated in multiple trials until they achieved smooth cursor movement trajectories. PCA was performed over the postures obtained during the multiple trials of the two tasks. Across the trials, in both the tasks a gradual decrease in the number of principal components was observed. This implies that the variance in the postures decreases with learning. Additionally this might indicate that through learning, subjects adapted postural synergies (or eigen postures) in this novel geometrical environment. Postural synergies when visualized revealed task specific synergies.**

I. INTRODUCTION

SYNERGIES can be defined as common or shared patterns which combine in time and space to form more complex or compound patterns. These patterns can be either movements (kinematics and dynamics) or muscle activities. Synergies were observed experimentally in movement kinematics (position, velocity and acceleration), dynamics (joint torque and joint force), muscle activities and also postures [1]. Synergies are hypothesized as building blocks of movement. Muscle activities of several muscles of frogs across a large number of movements were expressed as a linear combination of only four muscle synergies in [2]. Joint movement of hand across a number of reach and grasp tasks were decomposed into a small set of joint synergies in [3]. Grinyaginl et al. [4] reported that synergies were found in velocities as well as accelerations across joints. One possible solution to biological complexity of the motor system is probably the concept of synergies.

Synergies are viewed as common or shared patterns that can be generalized over a large set of movements. Over repeated trials of new movements, one learns these synergies across the distinct movements. A musician displays a consummate coordination or synergistic pattern across multiple fingers of the hand. A novice although struggles to perform such coordinated movements, learns through practice over training and learning. One possible reason for performing better over practice is that new task specific synergies are learned over time. If this is true, for learning involving any novel task certain task synergies will be learnt over training. This formed the motivation behind the current paper.

The coordination patterns of the hand have been examined with multivariate statistical techniques [5]. These techniques have been used to search for synergies in hand movements at several levels of investigation. Based on the principal component analysis (PCA), [6] found support for the existence of static postural synergies of angular configuration: The shape of human hand can be predicted using a reduced set of variables and postural synergies. Similarly, Santello and Soechting [7] showed that a small number of postural static synergies were sufficient to describe how human subjects grasped a large set of different objects. Mason et al. [1] used singular value decomposition (SVD) analysis to demonstrate that a large number of hand postures during reach-to-grasp can be constructed by a small number of principal components or eigen postures. Here we adapted a similar approach using PCA for obtaining eigen postures or postural synergies in a novel transformation task.

In this paper, the design of the experiment of novel transformation from glove coordinates or hand postures to geometric coordinates of cursor was inspired from [8]. In [8] it is reported that variance of the postures decreases over repeated trials. By using PCA we first quantized the reduction in the variance across trials while subjects progressed in learning. Can PCA help beyond measuring variance? Can PCs or the eigen vectors lead to physiologically meaningful eigen postures? If so, are these postural synergies learnt in this novel task? We attempted to answer the above questions in this paper. Results indicate that the number of PCs decrease across trials. One possible reason for decrease in the number of PCs is that subjects attempted to reduce the variance by avoiding unwanted postures which did not help them in moving the cursor

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forward. Elimination of unwanted postures led to learning of common and shared postures or in other words, synergies.

II. Materials and Methods

A. Materials

The experimental setup consists of a 5DT data glove equipped with 14 sensors that can measure angles at ten finger joints including proximal interphalangeal and metacarpal interphalangeal joints and four sensors to measure abduction and adduction between fingers. A typical setup for the experiment is shown in Fig.1. Starting point and destination are represented by green and red colored cubes respectively. Blue colored sphere is the cursor which subjects can control by their right hand posture. By varying the hand posture subject can move the cursor.

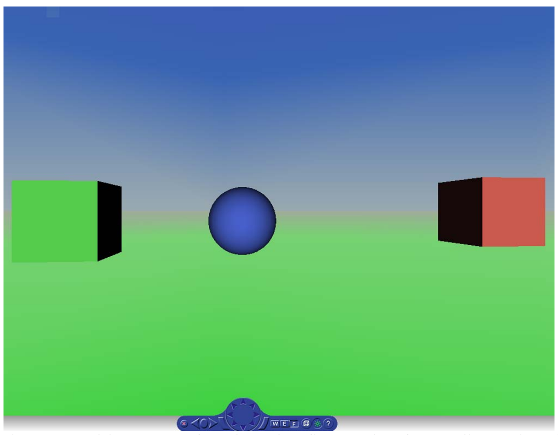

Fig. 1. Subject 1 performing the first task of one dimensional cursor movement. Starting point and destination are represented by green and red colored cubes respectively. Blue colored sphere is the cursor.

B. Methods

The experiment consisted of two tasks. First task is moving the cursor in one dimension along the horizontal axis. Five subjects (including 3 male and 2 female, all right hand dominant) were asked to perform this task by varying the hand postures. Each trial was limited to 5 minutes. In the second task, complexity was relatively increased by asking the subjects to control the same cursor in two dimensions. Each trial here was limited to 5 minutes. In both tasks cursor reaching the destination is considered as success. Subjects were instructed that successful completion of the task corresponded to smooth trajectories of the cursor from starting point to destination.

During the task subjects wore the data glove on the right hand. Sensor values of the glove were sent through MATLAB engine into MATLAB®SIMULINK where they were transformed into cursor coordinates. In the first task of moving the cursor in one dimension, a weighted summation of sensors was used. This linear combination of the sensors will enable a desired posture by assigning positive weights to desired fingers and negative weights to undesired fingers. Similarly, in the second task two such linear combinations guided the cursor coordinates in two dimensions.

C. Data Analysis

In both tasks, hand postures (say N in number) were collected along the trial time. Each posture consisted of 14 joint angles corresponding to 14 sensors. One dimensional horizontal cursor movement needed a maximum of two trials for each subject. For each trial a matrix of dimensions 4xN was obtained. Two dimensional cursor movements needed a maximum of three trials for each subject. Similar matrices as in the first task were obtained here. Please note that the number of trials in which the subjects learnt the novel transformation is lesser when compared to [8]. Two possible reasons for this are (i) trial times were longer (about five minutes) (ii) number of glove sensors used in this paper are lesser when compared to [8]. Finally, PCA was performed over the obtained matrices.

D. Principal Component Analysis

The above matrices were normalized such that their mean equals 0. This was done by subtracting mean of each row from every element of the row. For each of the normalized matrices covariance matrices were calculated. The eigen values and eigen vectors of covariance matrices were computed. The number of synergies or the number of principal components (PCs) was computed using the following equation:

$$\frac{\lambda_1+\lambda_2+\ldots+\lambda_r}{\lambda_1+\lambda_2+\ldots+\lambda_m}, \tag{1}$$

where λ_1, …, λ_r correspond to first r largest eigen values written in the descending order of any covariance matrix, and r is no greater than m, the total number of eigen values. If this fraction exceeds 90% for least possible number of largest eigen values, then the number of eigen values is equal to number of PCs. Our computation behind PCA roots from [9].

E. Rendering Eigenpostures

To render the eigenpostures, numerical method presented in [10] was used. According to this method, contribution of eigen vector to the eigenposture/ postural synergy can be formulated using the following equation: $S_i = A + \alpha e_i$, where S_i is the i^{th} postural synergy associated with i^{th} eigen vector e_i, A is the average posture in the trial, and α represents a weight to constrain the obtained postures to be biologically meaningful. Each postural synergy thus obtained is of dimensions 14 x 1, corresponding to 10 joints and 4 abduction sensors as discussed in Materials. These postures were rendered using a custom made virtual hand in virtual reality tool box in MATLAB.

III. RESULTS

In each subject, five posture matrices were obtained, two for two trials of the first task (1D) and three for three trials of the second task (2D). PCA was performed on all these matrices. Detailed variation between percentages of variance accounted by PCs across increasing number of PCs averaged across all the subjects are shown in Figs. 2 and 3. Error bars indicated the standard deviation across subjects.

As observed from Fig. 2, in the first task, from first trial (Fig. 2. Top) to second trial (Fig. 2. Bottom), the number of PCs required to accommodate 90% of variance decreased from four to two. Note that the percentages of variance are numerically equal to the fraction given in equation (1). This implies that variance was reduced from first trial to second trial as subjects learned to avoid unwanted postures. The two eigen postures of the second trial might correspond to learnt postural synergies in this novel 1D transformation task.

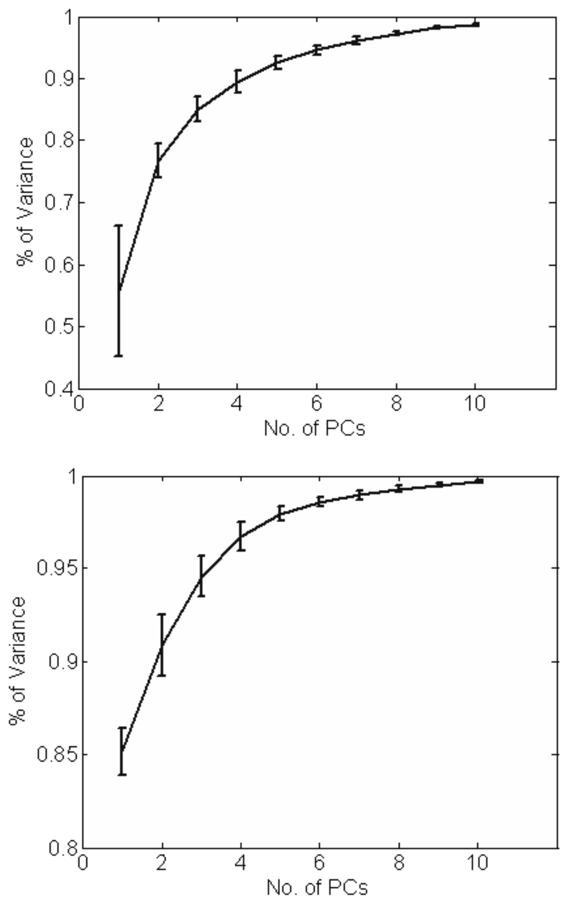

Fig. 2. Percentage of variance changes vs. No. of PCs averaged for all subjects for 1D cursor control task. Error bars indicate standard deviations across subjects. Top and Bottom plots corresponded to first and second trials respectively.

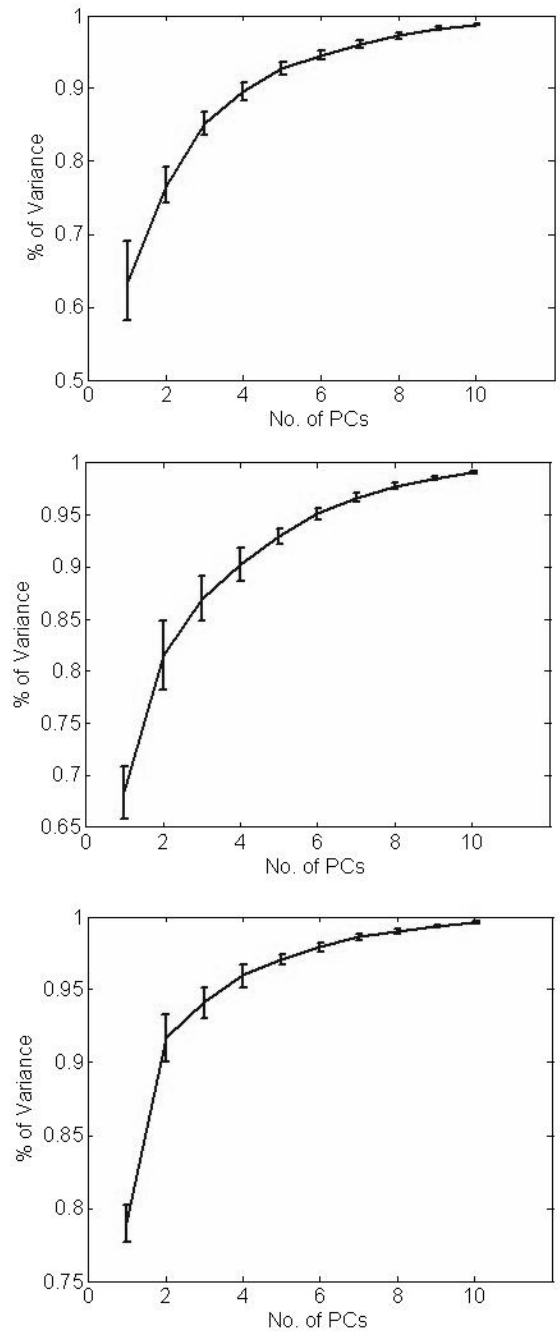

Fig. 3. Percentage of variance changes vs. No. of PCs averaged for all subjects for 2D cursor control task. Error bars indicate standard deviations across subjects. Top, Middle, and Bottom plots corresponded to first, second, and third trials respectively.

In Fig. 3, the results from PCA for the second task are shown, from first trial (Fig. 3. Top), second trial (Fig. 3. Middle) to third trial (Fig. 3. Bottom). As mentioned earlier, for 2D cursor control task, subjects took more trials to learn the glove transformation. As observed from Fig. 3. from first trial (Fig. 3. Top) to third trial (Fig. 3. Bottom), the number of PCs required to accommodate 90% of variance decreased from five to two. This suggests that variance of the postures was reduced from first trial to third trial as subjects learned new postural synergies which are shared across a large number of postures, thus reducing the variance. Note that number of PCs in the first trial of 2D task were more than the number of PCs in the first trial of 1D task, indicating the complexity of the task which led to increase variance.

In Fig. 4 and Fig. 5 postural synergies or eigen postures for Subject 1 are illustrated. Five most significant synergies corresponding to five largest eigen values were depicted. For both the tasks, the synergies were obtained from the last trials as subjects achieved smooth control of cursor movement in last trials (second trial in the 1D task and third trial in the 2D task). Hence during last trials subjects will have learnt synergies and probably recruiting them for smoother movement.

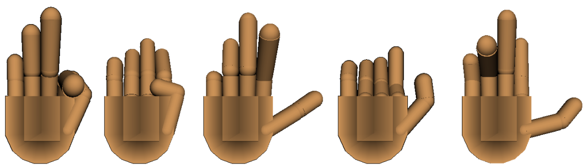

Fig. 4. Synergies from Subject 1 performing the first task of one dimensional cursor movement, arranged in decreasing order of their significance from left to right.

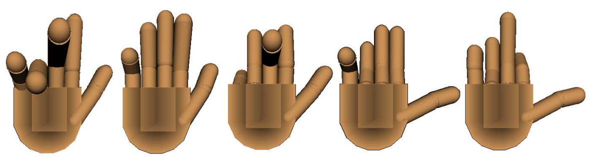

Fig. 5. Synergies from Subject 1 performing the second task of two dimensional cursor movement, arranged in decreasing order of their significance from left to right.

IV. Discussion

We investigated the postural synergies in a novel learning task involving finger coordination. Since the map from fingers to cursor motion is unknown to the subjects, they need to learn based on trial and error. After training, the subjects developed novel patterns of coordination of fingers to handle smooth cursor trajectories. Over all, the results from PCA suggest that by learning, variance across the postures decreases gradually with increasing trials. This is in consistence with the findings in [8].

The experiment was designed to investigate whether the learning involves the formation of new postural synergies. Figures 4 and 5 depict the postural synergies obtained for Subject 1. In both tasks, the first synergy was very similar to the desired hand posture. Note that subjects do not have the knowledge of this desired hand posture and they learned it with training. The other synergies although not related directly to the desired hand posture might have been used to eliminate the ambiguities between the desired and undesired postures.

V. Conclusion and Future scope

In this paper we presented a method using PCA to quantize and characterize the variance of hand postures in a novel transformation task. Quantization of variance was achieved using PCA and decrease in the number of PCs suggests decrease in variance with learning. To characterize decrease in the variance, eigen postures were rendered. Eigen postures indicated the presence of task specific synergies.

A comparison of postural synergies across the trials might lead to demonstration of progressive development of synergies. A comparison of synergies across the subjects can give information about a generalized set of synergies which can further be used in rehabilitation purposes. We view these as future scope.

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