Recruitment of Small Synergistic Movement Makes a Good Pianist*

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***Abstract*— Time-varying synergies from kinematic data can be used to discern fundamental patterns of movement. We show through simultaneous extraction of synergies from both novice and experienced pianists that movement common to both groups can be identified. The extracted synergies successfully allow for the majority of the variability of the data to be accounted for by a limited number of components. Furthermore, classification of the weightings representing the recruitment of each of the synergies accurately distinguishes between the piano playing of the two groups of subjects. However, the major differences between the two groups lie not in the synergies representing the majority of the variance of the data but in the recruitment of smaller synergies.**

I. INTRODUCTION

The dexterity and coordination exhibited by the human hand gives it the capability to produce a wide array of precise detailed movements. As such, the hand is a highly complicated and also redundant system [1]. With such large numbers of degrees of freedom, how the central nervous system implements a control strategy for this system is of interest in numerous different fields, from robotics to rehabilitation. The concept of synergies, that is, common patterns of movement across multiple joints which can be reused and serve as building blocks to produce detailed movements [2], has been gaining traction in recent years. Synergies provide an approach which reduces the number of degrees of freedom to be controlled individually, with studies indicating that only a few components are required to be able to represent finger movement [3].

Understanding detailed coordinated movement requires knowledge of how the fingers move - not only within themselves (individual joints) but also in relation to each other (simultaneous movement) and independently of each other (sequential movement). Physiological constraints mean that complete independence of fingers is not possible, with the thumb and index finger having greater independence than the other fingers. A high degree of correlation between fingers has been observed with spillover movement between fingers being noted to increase with the frequency of the finger movement, with the greatest amounts seen in the middle and ring fingers [4]. At the same time coarticulation of the movement of fingers means the sequence in which fingers move has an effect on the overall movement; with the movement of one finger impacting on how both the preceding and subsequent fingers move. For example in sign language, when spelling out words it has been shown that the sequence of letters in the word had an effect on the hand shape of the current letter [5].

As a skill which requires control and precision of both simultaneous and sequential finger movement, piano playing requires both coordination and dexterity. Previous investigation of the covariation of joint kinematics for experienced pianists during piano playing showed time-varying synergies with distinct patterns of movement [6]. Unlike other studies, the pianists displayed limited spillover between the fingers, however, as the study considered only experienced players this may be an implication of practice and exercise. With physiological constraints leading to the optimization of piano playing having a set of feasible solutions, which can limit what can be achieved through practice [7], of interest is how improvements caused by such exercise manifest.

In this paper we investigate the differences in synergistic movement between a group of novice and experienced pianists for sequential single finger piano playing. We extract synergies from all subjects simultaneously to identify the patterns of movement common to both groups rather than individual subjects. Classification of the weightings of these common patterns reveals how the recruitment of these patterns differs between the novice and experienced groups of pianists.

II. EXPERIMENTAL PROCEDURE

A. Subjects

10 right-handed subjects (3 female, 7 male, 22.1 ± 2.3 years old) participated in the experiment. Participants gave informed consent to the experimental procedure, which was approved by the ethics committee at City University of Hong Kong. Of the 10 subjects 5 were novices with little or no piano playing experience. The other 5 were all experienced players having at least passed a grade seven exam[1] (1×G7, 3×G8, 1×Diploma/Concert level) with an average of 12 ± 6.20 years experience.

B. Music

The selected piece of music was Exercise No. 11 from Practical Exercises for Beginners Op. 599, Carl Czerny.

*This work was supported by the Research Grants Council of the Hong Kong Special Administrative Region, China [Project No. CityU110813].

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Czerny's Op. 599 is a well known set of exercises used to improve the fingering technique of novice pianists. The exercise selected was a static hand, five finger exercise which contained no repetitions of the same key press. Subjects were provided with the score of the music and first allowed to familiarize themselves with the piece. To aid the novices they were told where on the keyboard to position their hand and the score was annotated with the number of the finger which was to play the note, 1 to 5 for thumb to little finger respectively. For the recordings, subjects were asked to play at their own pace and complete two separate repeats of the music with a break in between.

C. Data Collection

The subjects' hand kinematic data was recorded with a 5DT Data Glove 14 Ultra (5th Dimension Technologies, Pretoria, South Africa), with 12 bit resolution recording at 64Hz. The glove contains 14 flex sensors, 1 sensor for each of the metacarpophalangeal (MCP) joints, 1 for each proximal interphalangeal (PIP) joint (interphalangeal (IP) joint in thumb) and the remaining 4 sensors measure the abduction between each of the fingers. The music was recorded to MIDI files using a Yamaha PSR-E333 61-key touch response keyboard. The MIDI data stores the note played, onset and offset of the key press and the velocity (loudness) of the key press. Simultaneous video recordings of the subjects hands were also taken for reference.

III. Data Analysis

A. Preprocessing

For the purposes of the analysis, the kinematic data was segmented into sequences of 3 consecutive notes using the key press timings from the MIDI files. The middle note of each sequence was considered the key press of interest with each sequence spanning from the start of the key press prior to it to the release of the one following. From the music score 21 distinct sequences were identified, each repeated between 1 and 7 times, these sequences were grouped according to the finger used to play the middle note of interest. After incorrect key sequences were removed and the data from both recordings for all 10 subjects combined, the total key sequences for each finger were $N = [253, 212, 409, 115, 175]$ from thumb to little finger respectively.

To allow the comparison of different key sequences the time length of each key sequence was normalized. As the coordination of the movement was the factor of interest the overall length of the key sequence rather than the inter-key interval was standardized. This was done in order to preserve the dynamics of the transitions between the key press of interest and the notes preceding and subsequent to it. For each key sequence the rate of flexion, calculated from the data glove sensor data as a rate of change of flexion per second, were interpolated to give a normalized time vector with a standardized number of samples $K = 186$.

B. Synergy Extraction via Principal Component Analysis

Previous studies have shown similarities when comparing the synergies extracted from different subjects performing the same task [8]. Therefore, by extension, the aim of our study was to find generalized fundamental patterns in sequential finger movement by extracting synergies from all the subjects simultaneously. By grouping the key sequences according to the finger playing the middle note of each trio, the intention was to identify movements specific to each finger independent of the fingers moved prior to and subsequent to the current finger. To achieve the simultaneous extraction, principle component analysis (PCA) was applied to each of the 5 groups (one for each finger) of key sequences. Following the approach from [3] the elements of the covariance matrix of each data set are given by

$$C_{ij} = \sum_{k=0}^{K} \sum_{l=1}^{L} \left(\dot{\theta}_i(l,k) - \bar{\dot{\theta}}(l) \right) \cdot \left(\dot{\theta}_j(l,k) - \bar{\dot{\theta}}(l) \right), \quad (1)$$

where $\dot{\theta}_i(l,k)$ is the rate of flexion for trial i, joint l at sample k and $\bar{\dot{\theta}}(l)$ is the average rate of flexion of joint l across all trials. The principle components (PCs) are then constructed from the covariance matrix such that each trial can then be precisely reconstructed as a weighted version of the PCs plus the mean rate of flexion

$$\dot{\theta}_i(k) = \bar{\dot{\theta}} + \sum_{n=1}^{N} w_i(n) PC_n(k). \quad (2)$$

The weighting of each component $w_i(n)$ is a constant term for each time-varying synergy and indicate the proportion each component contributes to the overall trial signal.

C. Classification

Having extracted synergies for each finger from the data of all the subjects and trials together, the next step was to identify any differences in their recruitment between novice and experienced pianists. An expectation-maximization (EM) algorithm [9] was used to fit a 2 component Gaussian mixture model (GMM) to classify the weightings of the synergies. Selection of the subset of synergies which achieved the greatest degree of separability was achieved via a forward selection strategy. That is, the synergy whose weightings achieved the greatest separation between the two groups was selected first and at each subsequent iteration all remaining weightings were tested in conjunction with the already selected weightings until the maximum possible classification accuracy was achieved.

IV. Results

The results of the synergy extraction indicated the variance accounted for (VAF) by the first ten extracted components, shown in Fig. 1, account for the majority of the variance across all the fingers. The first 4 components account for greater than 60% of the variance, which is inline with results from previous piano playing studies, where the synergies were extracted for each subject individually [6]. Having successfully extracted synergies which could represent the

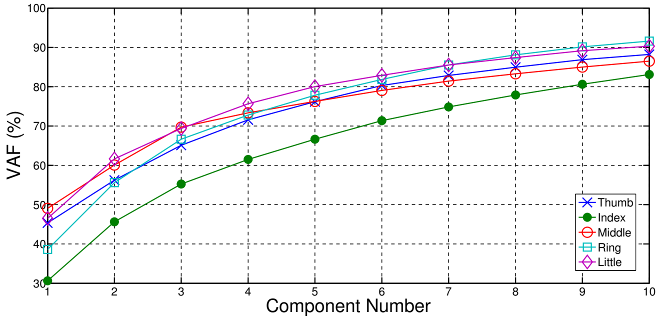

Fig. 1. The variance accounted for by the first 10 components extracted from the key sequences centered around each finger.

TABLE I

CLASSIFICATION ACCURACY FOR KEY SEQUENCES CENTERED AROUND EACH OF THE FINGERS, THE NUMBER OF COMPONENTS REQUIRED TO ACHIEVE THE ACCURACY, THE RANGE OF AND VARIANCE ACCOUNTED FOR BY THE SELECTED COMPONENTS.

	Accuracy (%)	Number of Components	Component Range			VAF (%)
			Largest	Smallest	Total (N)	
Thumb	93.68	15	17	253	253	1.38
Index	94.81	14	55	211	212	0.11
Middle	93.40	17	8	408	409	2.70
Ring	96.52	18	9	111	115	5.97
Little	98.29	17	19	175	175	0.96

TABLE II

AVERAGES OF THE INTRA-TRIAL VARIANCE FOR EACH JOINT AND EACH SET OF KEY SEQUENCES CENTERED AROUND ONE OF THE 4 LONG FINGERS FOR NOVICE AND EXPERIENCED PIANISTS.

		Index		Middle		Ring		Little	
$\times 10^{-3}$		Nov.	Exp.	Nov.	Exp.	Nov.	Exp.	Nov.	Exp.
Thumb	MCP	0.07	0.06	0.05	0.09	0.08	0.14	0.07	0.09
	PIP	0.13	0.12	0.09	0.15	0.14	0.24	0.11	0.16
Thumb/Index		0.30	0.31	0.19	0.39	0.38	0.84	0.32	0.55
Index	MCP	3.79	3.69	1.41	2.93	6.73	16.5	3.25	3.91
	PIP	4.33	4.02	1.09	2.83	7.14	11.2	2.60	4.24
Index/Middle		***14.0***	10.8	***5.16***	***11.4***	20.8	32.3	***16.5***	***26.5***
Middle	MCP	1.77	1.27	1.28	2.25	2.91	3.97	2.90	3.55
	PIP	6.28	5.68	4.01	7.93	11.4	23.3	8.83	14.9
Middle/Ring		11.3	***11.8***	2.62	7.98	***29.8***	***50.2***	9.61	10.4
Ring	MCP	0.50	0.44	0.12	0.34	1.32	1.59	0.77	1.20
	PIP	7.00	4.11	0.58	1.94	20.2	21.4	4.16	7.14
Ring/Little		4.07	4.51	1.55	5.30	13.4	23.7	13.2	16.9
Little	MCP	1.05	1.03	0.34	0.90	3.56	4.88	3.23	2.33
	PIP	0.17	0.20	0.09	0.26	0.43	0.94	0.44	0.65

* Bold values indicate the joint with maximum average variance for each finger

movement data of both the novice and experienced pianists, the weightings of each component for each trial were used to classify the key sequence trials according to whether they were played by either a novice or experienced pianist. Table I lists the maximum classification accuracy achieved for each finger and the number of components required to achieve it.

While the weightings of only a small number of components were required to distinguish between the movement of the novice and experienced pianists, of particular interest is the fact that the components selected were not those which accounted for the majority of the variance. The range of components selected for classification are given in Table I, the component numbers range from 1 being the component which accounted for the most variance to N which accounted for the least. It should be noted the largest selected components were not necessarily selected first in the forward selection strategy and conversely for the smallest. The VAF of the selected components was less than 6% for all fingers yet achieved greater than 90% classification in all cases.

To investigate how the selected components related to the movement, the signals for each trial were reconstructed according to (2) using only the selected components. Fig. 2 shows the average reconstructed signals for novice and experienced pianists from the key sequence trials with the middle finger as the centre key press. The reconstructed signals for each joint, based on the synergies used for classification, show the largest range of motion in the abduction between the index and middle fingers (Fig. 2 bottom row 2^{nd} from left). This trend was observed in all 4 of the long finger reconstructions indicating abduction was significant to the classification.

To further understand how the different joints contributed to the reconstructed signals the variance of each joint for each trial was calculated. Table II lists the average intra-trial variability of the key sequences centered around each of the 4 long fingers for novices and experienced piano players. The average variance of each joint shows that for all 4 fingers the maximum variance occurs in one of the abduction measurements. In particular the abduction between the index and middle fingers was largest in 5 of the 8 groups and in all but one case (novice middle finger movement) the top two average inter-trial variances for each finger's set of key sequences occurred in the abduction. Following abduction, the next largest movements were PIP joints. In contrast the MCP joints did not appear in the top 5 variances for any of the fingers, indicating a generally greater degree of similarity between the two groups in the MCP joints.

V. DISCUSSION

Our results show that in line with previous studies the synergies extracted for piano playing movement can account for the majority of the variance in the movement using only relatively few components [6]. Since the synergies extracted from different subjects for the same movement have been shown to have a high degree of similarity [2]; rather than compare the profiles of the synergies extracted from different subjects, our approach extracted synergies from the data of all the subjects simultaneously. Combining the data and extracting the synergies simultaneously allows us to identify the fundamental components of the movement which exist across subjects. To reduce effects observed due to the order

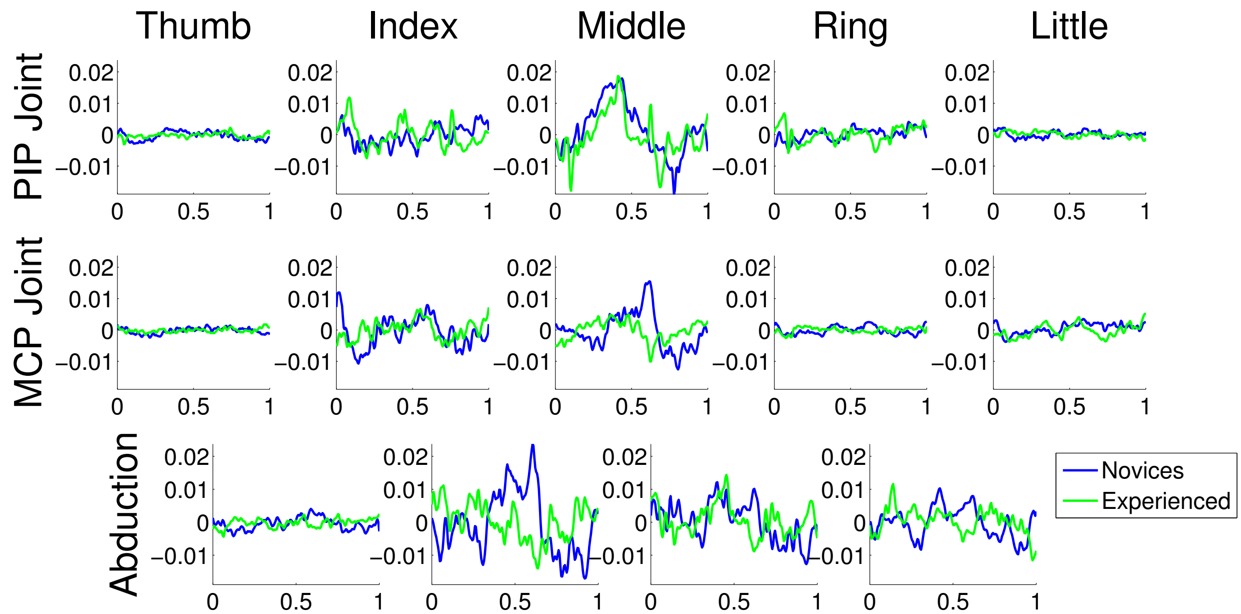

Fig. 2. Reconstructed signals for key sequence trials centered around the middle finger. Each plot shows the average rate of flexion for novice and experienced pianists for one joint. Top row: PIP joints thumb to little finger from left to right. Middle row: MCP joints. Bottom row: abduction between Thumb/Index, Index/Middle, Middle/Ring, Ring/Little.

of the sequence of finger movement [5], key sequences with the same finger playing the note at the centre of the trial were combined into one data set for analysis.

This approach allowed direct comparison of the recruitment weightings of the synergies from different subjects and for different movements. We demonstrated that accurate distinction between novice and experienced pianists based on the weightings of their shared synergies could be achieved. Further, the results indicated the groups were most distinguishable in their recruitment of the smaller components, whereas the weightings of the synergies which accounted for the majority of the variance displayed similar recruitment across the subject groups. For sequential finger movement with a static hand position, as investigated in this study, the most significant differences between the novice and experienced subjects occurred in the abduction between the long fingers. Although the thumb showed a less distinct pattern in the joints when reconstructing the data from the synergies used to classify the key sequences.

From the results obtained in this study the differences in the experience levels of the subjects appear to be most noticeable in the relationships between the fingers and their neighbours, rather than the flexion of the finger in question. We can hypothesize that the training of the experienced pianists may lead to a greater degree of independence and more efficient coarticulation between the fingers, resulting in the observed differences in the abduction between the fingers of the novice and experienced pianists. However, physiological constraints of individual hands may differ, impacting the degree to which independence of fingers can be trained and hence, constraining the optimization of the movement [7]. As such, understanding how training affects performance requires greater study of the learning process. It is also worth considering whether these observations remain consistent when extended into coordinated movements which involve sequences with simultaneous finger movement, such as sign language or when playing more complicated pieces of music. Finally, if we want to produce systems that can represent detailed coordinated movement using synergistic approaches, the results presented here suggest we need to consider whether extracting synergies which account for the majority of the variance is a sufficient requirement.

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