2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Generalizability of Hand Kinematic Synergies derived using Independent Component Analysis

Dingyi Pei, *Student Member, IEEE,* Tulay Adali, *Fellow, IEEE*, Ramana Vinjamuri, *Senior Member, IEEE*

Abstract— **In this paper, hand synergies were derived using independent component analysis (ICA) and compared against synergies derived from our previous methods using principal component analysis (PCA). For ICA, we used two algorithms — Infomax and entropy bound minimization (EBM). For all the methods, the synergies were extracted from rapid hand grasps. The extracted synergies were then tested for generalizability in reconstructing natural hand grasps and American Sign Language (ASL) postures that were different from rapid grasps. The results indicate that the synergies derived from ICA were able to generalize only marginally better when compared to those from PCA. Among the two ICA methods, Infomax performed slightly better in yielding lower reconstruction error while EBM performed better in sparse selection of synergies. The implications and future scope were discussed.**

I. Introduction

The central nervous system (CNS) plans, programs and executes a voluntary movement. How the CNS effortlessly coordinates and modulates many degrees of freedom (DoFs) independently or conjointly in a dexterous hand movement is still under investigation. Researchers have proposed models that can adequately describe the complexities of human motor control. A large number of DoFs allow tremendous movement flexibility but make motor control, especially neural control, exceedingly difficult. Nikolai Bernstein [1] proposed an idea of synergistic control, which provides a theory of low-dimensional DoF modulation in motor control. When a large diversity of actions could be combined and packaged into a functional module, synergy, motor control could be simplified.

Theoretically, hand synergies can be computed by dimensionally reducing the hand kinematics. A synergy-based hand movement generation model [2], as expressed in Equation (1), was proposed by us previously. Here the hand kinematics (joint angular velocities) were generated from kinematic synergies, containing both spatial and temporal characteristics of the hand movement.

$$v(t) = \sum_{j=1}^{m} \sum_{k=1}^{K_j} c_{jk} S^j\left(t - t_{jk}\right) \tag{1}$$

where v(t) denotes the joint angular velocities, S is the j^{th} (j = 1, 2, …, m) synergy, and c_{jk} represents the weights or coefficients of the j^{th} synergy at various time shifts t^{jk}. The spatial characteristics describe the coordination across multiple joints, and the temporal characteristics describe their activations and combinations across time. Thus, this model showed that the hand movements could be generated by linearly combining weighted and time-shifted synergies [2], [3].

Gradient descent algorithms were commonly applied to compute the weights or coefficients of synergies and their corresponding time-shifts [4] but they are not cost-efficient. A simplified method was proposed to reconstruct natural hand movement with the recruited synergies derived from rapid hand movements in [3] using principal component analysis (PCA). Several dimensionality reduction techniques have been used to determine hand synergies. A comparison of multiple dimensionality reduction techniques has been presented previously [5]. Previous study showed PCA is the best method to determine kinematic synergies because it captures physical constraints as well as global patterns, which represent the most common or shared patterns of the movements. After the dimensionality of the hand kinematics was reduced by using PCA, the top-ranked principal components accounted for the highest fraction of movement variance [6]. Each of these components could be considered as an empirical representation of a kinematic synergy. Therefore, researchers were able to reconstruct the hand movements by the first few synergies that accounted for a majority of the observed movement variance [6].

Other decomposition algorithms such as independent component analysis (ICA) were also used in deriving muscle synergies [7]. ICA belongs to the class of blind source separation methods and has been used extensively in several areas of signal processing. ICA can extract relatively useful information from whitened and compressed signals after reducing the dimensionality using PCA. However, rather than exploring the covariance among the large data, ICA prefers separating the statistically independent components, or source signals, underlying the data mixture. Additionally, ICA provides a method of capturing structure of signals in both amplitude domain and temporal domain.

II. Methods and analysis

A. Experiment protocol

This experiment was conducted under the approved IRB protocol at the of University of Pittsburgh. Ten right-handed subjects were recruited. The experiment contained two parts, training part and testing part. The training part included rapid grasp of 50 objects with two repetitions for each. The 50 objects spanned different shapes and dimensions found in

*Research supported by National Science Foundation (CAREER Award HCC-1845197).

D. Pei, T. Adali and R. Vinjamuri are with the Department of Computer Science and Electrical Engineering, University of Maryland Baltimore County, Baltimore, 21220, USA (e-mail: ramana.vinjamuri@umbc.edu).

activities of daily living (ADL). Testing part included a total of 100 natural grasps and 36 postural movements. Subjects were asked to grasp the same 50 objects in a natural speed (slower than rapid grasp) and repeated. Apart from the grasping actions, a broad scope of hand movement was considered. Subjects were asked to pose 36 American Sign Language (ASL) postures including ten numbers (0-9) and 26 alphabets (A-Z).

Hand movements were captured by the CyberGlove (CyberGloveSystems, San Jose, CA) [8] at a sampling rate of 125 Hz. Ten of the sensors were considered here. These sensors correspond to the metacarpophalangeal (MCP) and interphalangeal (IP) joints of the thumb and the MCP and proximal interphalangeal (PIP) joints of the other four fingers.

B. Derivation of Synergies

In this paper, synergies were derived from rapid grasps (training data). It was hypothesized that the reaction time in the rapid hand movement can be minimized and the synergies are constrained to combine simultaneously [3]. Then these synergies would be used to decompose natural hand movements and ASL movements (testing data), thus to test the generalizability.

$$v(t) = \sum_{i=j}^{m} c_j x_j(t) \tag{2}$$

First, the joint angular velocities from ten joints were derived from the differential of the recorded joint angles of the rapid grasps. Then, the first k (k = 2, 3, …, 10) principal components (PCs) were derived using singular value decomposition (SVD) (Equation 3).

$$V = \beta X = U \sum X \tag{3}$$

V denotes the angular velocity matrix with a dimension of $n\times m$, where n is the number the of the rapid grasps (n=100) and m is the number of samples (m=40). β ($n\times k$) represents the coefficients of PCs and $\boldsymbol{X}$ ($k\times m$) is the PC matrix. Then, the independent components (ICs) were separated from PCs by using independent component analysis (ICA) algorithm, as expressed in Equation (5).

$$X = AS \tag{4}$$

Since ICA is a generative model, both mixing matrix $\boldsymbol{A}$ and independent component (IC) matrix $\boldsymbol{S}$ need to be determined. Given PC matrix $\boldsymbol{X}$, a de-mixing matrix $\boldsymbol{W}$ was estimated and therefore the ICs can be estimated by:

$$\hat{S} = WX \tag{5}$$

In this part, for ICA, two algorithms were used, Infomax and entropy bound minimization (EBM). Infomax is one of the classic ICA algorithms [10] that demixes a set of statistically independent sources that have been mixed linearly using nongaussianity. In contrast, entropy bound minimization (EBM) ICA was used here, which depends on the maximum entropy principle. This is a much more flexible ICA algorithm able to deal with both super and sub-Gaussian sources [9].

Since both the ICs and mixing matrix cannot be directly observed, the best de-mixing matrix $\boldsymbol{W}$ was estimated using cross inter-symbol-interference (ISI). ISI is a simple and global metric that can be used for evaluating the performance of ICA algorithms and is given by Equation (6), where p_{ij} are the elements of matrix $\boldsymbol{P} = \boldsymbol{WX}$, and K denotes the number of ICs.

$$\begin{aligned} \mathrm{ISI} = \frac{1}{2K(K-1)} \Bigg[& \sum_{i=1}^{K} \left(\sum_{j=1}^{K} \frac{p_{ij}}{max|p_i|} - 1 \right) \\ & + \sum_{j=1}^{K} \left(\sum_{i=1}^{K} \frac{p_{ij}}{max|p_{kj}|} - 1 \right) \Bigg] \end{aligned} \tag{6}$$

After ICs were derived from PCs, the angular velocities of rapid hand movements can be expressed by Equation (6), where K synergies $s_k(t)$ were derived.

$$\begin{aligned} v(t) &= \sum_{k=1}^{K} \beta_k x_k(t) = \sum_{k=1}^{K} \beta_k a_k s_k(t) \\ &= \sum_{k=1}^{K} c_k s_k(t) \end{aligned} \tag{7}$$

Where $x_k(t)$ and $s_k(t)$, were considered synergies, which were also the PCs or ICs derived from rapid hand movements using PCA and ICA respectively, and β_k and c_k represent the subsequent weights of the synergies. As expressed in Equation (1), the hand kinematics can be represented as a weighted linear combination of time-shifted synergies. Now that we have computed the components or synergies, the weights needed to reconstruct a movement need to be determined.

C. Reconstruction of Natural grasps and ASL postures

We hypothesize that the CNS, being an intelligent controller, may employ only a small number of optimal selective recruitments of these synergies for a movement generation. After the synergies were derived from rapid hand movements using ICA and PCA, they were used as templates in reconstructing the natural hand grasps and ASL postures. Reconstructing the angular velocity profiles in terms of synergies involves linearly combining a selection of optimally and sparsely selected synergies that are stored in a large matrix, or bank. This bank, referred as $\boldsymbol{B}$, contains all possible time-shifted versions of these limited number of synergies. This synergy bank $\boldsymbol{B}$ was built using the PCs or ICs derived from rapid hand movements using similar methods discussed in [3]. The hand kinematics of natural hand grasps/ASL postures v were rewritten as a one-dimension array consisting of ten joints of angular velocities with 82 samples. The synergy coefficient vector c was estimated using l_1-minimization by solving the following Equation (8):

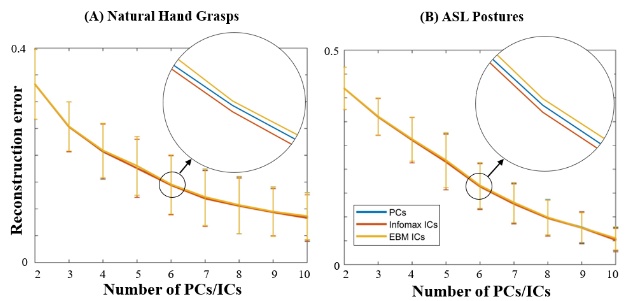

Figure 1. Reconstruction error. The natural hand grasps (A) and ASL postures (B) were reconstructed using k synergies (k=2, 3, …10). The performance of reconstruction using PC-synergies and IC-synergies were similar, while fewer PCs (k<6) provided a better reconstruction among all synergies. When more synergies were recruited (k≥6), infomax-derived ICs performed best. The standard deviation was calculated across ten subjects.

$$\text{Minimize } \| c \|_1 + \frac{1}{\lambda} \|cB - v\|_2^2 \tag{8}$$

where $\| \cdot \|_1$ represents the l_1 norm which allows to select a sparse number of synergies. $\| \cdot \|_2$ represents the Euclidian norm of a vector, minimizing the reconstructed angular velocity error. λ is a regulation parameter determined by:

$$\lambda = 0.01 \times \max(2|vB^T|) \tag{9}$$

To evaluate the reconstruction of natural hand grasps and ASL postures, the reconstruction error was determined for each task by using the difference between reconstructed angular velocities $\widehat{v_i}(t)$ and recorded angular velocities $v_i(t)$ of i^{th} (i =1, 2, …,10) joint for each task as show in Equation (10) below:

$$err = \frac{\sum_i^I \sum_t^T \left(\widehat{v_i}(t) - v_i(t)\right)^2}{\sum_i^I \sum_t^T v_i(t)^2} \tag{10}$$

III. Results

The synergies were extracted from rapid hand grasps using two ICA algorithms and compared with the synergies derived using PCA (implanted using SVD). For both natural hand grasps and ASL movements, reconstruction error gradually decreased when the number of synergies recruited increased (Fig.1). When fewer synergies (k<6) were recruited, PCs performed better in movement reconstruction. However, when more synergies (k≥6) were recruited, the lowest error was observed from the reconstruction using ICs derived using the Infomax algorithm. Similar reconstruction performance was observed among PCs, Infomax-ICs and EBM-ICs and no significant differences were observed among all the reconstructions.

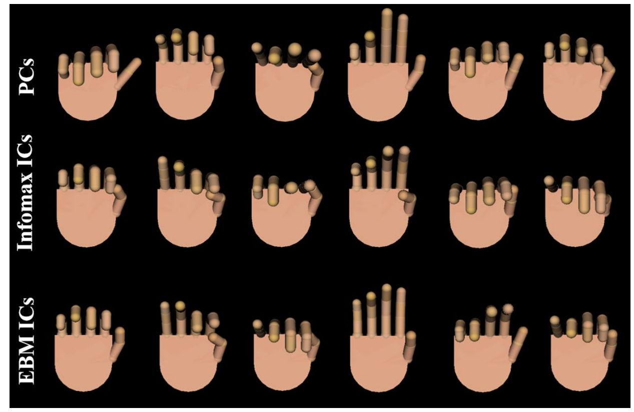

Figure 3. End-postures of synergies. Similar patterns were observed for PC-synergies and IC-synergies. For both PC-synergies and IC-synergies, the first posture was similar to a whole hand grasp and the second synergy was similar to a pinch grasp.

Similar results were observed in natural hand grasp and ASL posture reconstructions depicted in Fig. 2. The reconstructed hand kinematics of natural hand grasps and ASL movements from subject 1 are illustrated. A high similarity between the recorded kinematics and reconstructed kinematics was observed. The reconstructions using IC-synergies derived using two ICA algorithms were similar.

Furthermore, we graphically visualized synergies to see if we can find anatomical differences between the synergies derived from ICA and PCA. Only the final postures of the temporal postural synergies were depicted here (Fig.3). The end-postures of PC-synergies were listed in the order of decreasing variance from left to right. In contrast, ICs cannot be sorted by variance, since each IC represents an

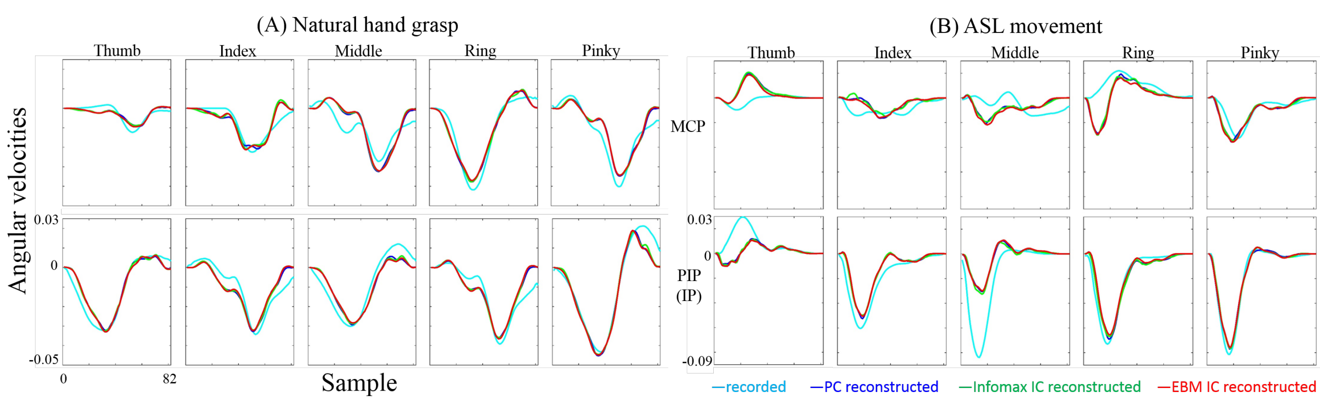

Figure 2. Recorded and reconstructed angular velocities of natural hand grasps (A) and ASL postures (B). Recorded and reconstructed angular velocities were similar for natural hand grasps. There are no significant differences among all reconstructions using PC-synergies and IC-synergies. The ASL postures were different from typical hand grasps and thus the reconstructions based on synergies derived from rapid hand grasps have limitations. These limitations were observed across all methods (PCA and ICA).

independent source of the movement. Nevertheless, some physiological significance and similarity can still be observed in Fig. 3. First and second synergies using either methods represent whole hand grasp and pinch grasp as observed from these end-postures. Higher similarities among the postural synergies of PCs and the ICs derived using Infomax and EBM is reflected in similar reconstruction errors illustrated in Fig. 1.

Furthermore, as proposed in Equation (1), the hand kinematics were modeled as weighted linear combinations of time-shifted kinematic synergies recruited at various time points. By using the l_1-minimization, the weights of the synergies and the time-shifts were determined. The pattern of recruitments of synergies varied for various movements. Since combinations varies across different tasks, the average number of synergy recruitments across tasks were calculated and shown in Fig. 4. One way to analyze these results is that if the synergies contain rich information about the movement then they don't have to be recruited multiple times. In this case, the PCs seem to have captured movement-related variability better than the ICs and thus were able to provide better reconstruction errors with fewer recruitments. Among the two ICA algorithms, EBM ICs might have captured more movement-related information than Infomax ICs.

IV. Discussion

This paper compared the generalizability of the hand synergies derived from ICA and PCA. For ICA we tested two different algorithms – one based on nongaussianity (Infomax) [10] and the other based entropy bound minimization (EBM), a more flexible algorithm that can separate both sub and super-Gaussian sources and multimodal distributed sources [9]. Results indicate that the synergies derived from ICA were able to generalize only marginally better when compared to those from PCA based on the reconstruction errors. Among the two ICA methods, Infomax performed slightly better in yielding lower reconstruction errors while EBM performed slightly better in sparse selection of synergies.

The goal of the PCA is to minimize the reprojection error from the compressed data by relying only on second-order statistics. Thus, the synergies derived using PCA may yield minimal reconstruction errors for the limited movements they were extracted from. However, the question remains whether they will be able to generalize for new movements that are different from the movements they were extracted from. Question arises, whether principal components that are orthogonal components based on uncorrelatedness (second-order statistics) can be regarded as synergies or as fundamental building blocks of movement. Independent component analysis (ICA), on the other hand, can effectively make use of higher-order statistical information to identify an independent set of synergies. The ICs are extracted purely on the basis nongaussianity, sample dependence, nonstationarity or other diversity and not based on the reprojection error. To explore this, we tested the generalizability of PCs and ICs on two different types of movements, natural hand grasp movements and ASL postural movements. While natural hand grasp movements are distantly similar to rapid hand grasps, ASL postures are dissimilar.

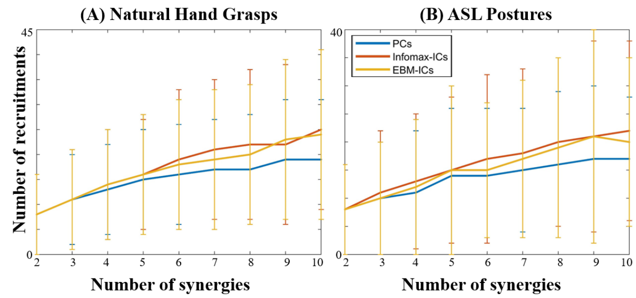

Figure 4. The number of recruitments of synergies for (A) natural grasps and (B) ASL postures. Each synergy maybe recruited multiple times at different time points. The recruitment numbers were averaged across all tasks and all subjects.

V. Conclusion

To test the generalizability of synergies derived from ICA, natural hand grasping movements and ASL postural movements were reconstructed and the results were compared with those from our previous methods based on PCA. The results indicate that the synergies derived from ICA were able to generalize only marginally better when compared to those from PCA. Among the two ICA methods, Infomax performed slightly better in yielding lower reconstruction error while EBM performed better in sparse selection of synergies. The results warrant further investigation on larger hand grasp datasets and we view this as immediate future scope.

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