Unified modules in muscle synergies during complicated point to point hand motions in vertical planes

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Abstract

Central nervous system (CNS) uses an abundant set of joints and muscles to ensure both flexible and stable movements while interacting the environment. How the CNS faces the complexity of control problem and solves the question of physiological and mechanical abundances is not still clear. Modular control is one of the most prevalent hypotheses in answer to these questions. According to this point of view, CNS combines a few building blocks, here this will be muscle activities, named as muscle synergies, to present a vast repertoires of movements. In this study the algorithm of sample-based nonnegative matrix tri-factorization (NM3F) is used to extract spatial and temporal muscle synergy modules from muscle EMG data for three different types of point to point reaching (simple straight, reversal and via-point) movement in the frontal and sagittal planes. After extracting different features of the muscle synergies, physiological interpretation of these decomposed parts has been discussed. The first temporal module coded the direction and type of movement, while the spatial modules describe some via postures. Also the extracted modules are not similar for subjects. The recruitment of the spatial and temporal modules are correlated due to the movement direction.

Keywords: modular control structure; temporal module; spatial module; muscle synergy; human motor control; EMG decomposition.

I. Introduction

It has been estimated that the human body has between 500 and 1400 degrees of freedom! Yet, he can generate an infinite variety of very precise, complicated and goal-directed movements in continuously changing and uncertain environments. Understanding how this is achieved is of great interest to both biologists and engineers [1]. Different researchers in the field of motor control have studied the subject with various approaches, e.g., applying standard feedback control theory based on continuous tracking of desired movement [2], or using weighted combination of pre-configured movement primitives or muscle synergies to generate the desired movement [1]. Therefore, a complex task is performed by combining synergy blocks with appropriate amplitudes and offsets. In fact, the idea of muscle synergies reduces dramatically the dimension of the parameter space and thereby, simplifies movement control of musclo-skeletal dynamics.

On the other hand, gathering large sets of data during natural movements is becoming increasingly easier, thus allowing us to characterize coordination across many variables at different levels of the motor system. However, interpreting such large data sets and analyzing them to test motor control hypotheses remains a challenge [3]. Component decompositions allow us to decompose large data set of EMG data and other variables into components that can interpret and depict the upstream organization of the neural control systems, and their functional biomechanical outputs downstream [3]. Decomposition techniques can help the researchers to find the relationship between the derived components and the original data and draw conclusions about the underlying neural mechanisms. It should be noticed that the extracted components must be interpreted in terms of the known underlying physiological mechanisms and biomechanical outputs [3]. Decomposition can also be useful for understanding the function of the underlying components. In this field, non-negative matrix factorization (NMF) methods are especially useful for examining neural and muscle activity signals that are inherently non-negative [1], [4]. One of the attractive features of components resulted from applying NMF methods is that they generate a parts-based type of representation that appears similar to both neurophysiological observations as well as to the predictions from “sparse-coding” algorithms in sensory systems [5].

Different algorithms implemented to decompose EMG data, among them we restrict ourselves to study and use the non-negative matrix factorization based decompositions. In fact, these methods result in components that are physiologically more

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relevant to EMG signals; because, non-negative signals reflect more concretely the “pull only” [5] behavior of muscles (i.e. muscles cannot be activated “negatively”). Other dimensionality reduction algorithms have been discussed with more details in [4].

It has been approved that the CNS uses a modular structure for human motion control. Thus the modules extracted from the EMG data could be recruited instead of controlling all muscle activities. In this way the abundances in the muscle activity space, could be simpler by recruitment of muscle synergies.

By applying NMF algorithm on the EMG data, it can be decomposed in spatial, temporal, spatio-temporal or hybrid (space by time [6]) manners using NMF algorithm. In this study, the method of space by time decomposition of EMG matrix [6] is used to extract the unified spatial and temporal modules. This decomposition method, in addition to reduction of degrees of freedom (DOF), requires less amount of memory for saving information of module compared to other methods mentioned above [7].

Space by time decomposition has already been used to extract synergy modules for simple reaching point-to-point in horizontal plane, and it has resulted in significant findings [6]. The main objective of this study is to apply this method to extract the unified spatial and temporal modules for compound tasks in vertical planes. The importance of this study lies in the fact that we will be able to evaluate also the effect of gravitational component of the arm movement. It should be noticed that moving in the horizontal plane with air sled, the arm does not endure its weight through the movement and more joint angles cooperate in the motion. The tasks we will investigate include simple reaching point-to-point, reversal and via point movements in the sagittal and frontal planes [8]. Unified muscle synergies will be extracted and analyzed from the EMG signal, for simple to more complex movements in two vertical planes. In this way, we will study encoding of the motion information in the extracted modules and their recruitments. The sequence of reaching point to point movement task execution could be analyzed through evaluating unified modules and their recruitment in compound task. These tasks could be reversal (start from a location then go to the center and back to the start point) or via-point (go from start location to the target location via center point). Thus, by scrutiny of the unified spatial and temporal modules in eight specified directions in the vertical planes, and their assessment in different types of simple and complex movements, a physiological interpretation of motion control and the decomposed parts of the EMG signal will be presented.

II. MATERIALS AND METHODS

A. Experimental data set

The data has been obtained from the research group at the Santa Lucia Foundation. Two right handed subjects took part in the test. The experimental apparatus and reaching task has been described in details in [8]. Briefly, two standing subjects gripped a 180 gr handle connected to a sphere. The center of sphere was aligned with the axis of the forearm at a distance of 12 cm from center of the palm. Participants were instructed to move the sphere between a central position and eight peripheral targets points located on a circle at 15 cm of distance in vertical planes (Sagittal and Frontal) while minimizing shoulder and wrist movements. In each trial, subjects were instructed to reach the target point with a movement of a duration shorter than 400 msec, and to hold there for at least 1 second. Unsuccessful trials were repeated. Each subject performed each movement successfully five times, the target points are 8 with 2 directions that are done in 2 planes. The subject would do the test for a total number of 160 point-to-point movements (2 planes × 8 targets × 2 directions × 5 repetitions). As the subject moves his arm in different types of reaching point to point movements, the marker’s position attached to his shoulder, elbow and wrist were recorded using an optic motion- tracking system (Optotrack 3020, Nothern Digital, Waterloo, Ontario, Canada) with a sampling frequency of 120 Hz and spatial resolution below 0.1 mm. 17 to 19 active bipolar surface electrodes (DE 2.1; Delsys, Boston,MA) recorded the EMG activity [8].

B. Arm model

Kinematic and kinetic model of the arm, incorporating geometrical and inertial parameters of the upper arm and forearm segments, was used to estimate shoulder and elbow joint angles from the recorded spatial position of the shoulder, the elbow, and the wrist markers. The kinematic model was developed using the Denavit-Hartenberg (D-H) [9] notation for shoulder joint with 3 degrees of freedom (Abduction/Adduction angle, Flexion/Extension angle and External/Internal

Rotation angle) and elbow joint with one degree of freedom (Flexion/Extension angle). The D-H parameters of human with 3 DoF shoulder and 1 DoF elbow are as follows. Where L_U shows upper arm link length and L_F shows the forearm link length.

The length of every segments of the body could be calculated as a function of subject's weight and height [10]. Also inertial parameters of these segments for the kinetic model could be calculated as a function of subject's weight and height according to regression equations [11].

Tablel: D-H parameters for 4 DoF arm model

Link	Joint angle	α_i	a_i	θ_i	d_i	Offset
1	Sh. Adduction	$\pi/2$	0	0	0	$-\pi/2$
2	Sh. Flexion	$\pi/2$	0	0	0	$\pi/2$
3	Sh. Ext. Rotation	$\pi/2$	0	0	L_U	π
4	El. flexion	0	L_F	0	0	$\pi/2$

Table2: Geometrical and inertial parameters for subject's arm model

Subject	1	2
Height (cm)	162	181
Weight (Kg)	58	78
L_U (cm)	3013	33.67
L_F (cm)	40.82	45.61
r_u (cm)	12.16	13.78
r_f (cm)	23.57	26.39
M_U (kg)	1.56	2.11
M_F (kg)	1.52	1.90
$I(lo)_U$ (kg cm^2 s^{-2})	28.54	42.61
$I(ap)_U$ (kg cm^2 s^{-2})	74.02	130.03
$I(tr)_U$ (kg cm^2 s^{-2})	84.74	144.65
$I(lo)_F$ (kg cm^2 s^{-2})	12.93	19.56
$I(ap)_F$ (kg cm^2 s^{-2})	295.87	445.74
$I(tr)_F$ (kg cm^2 s^{-2})	302.27	455.45

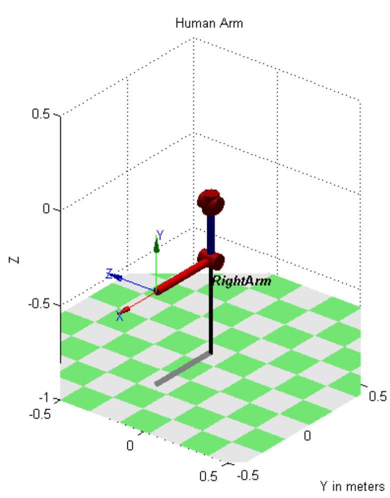

Fig. 1. Human arm model using subject's geometrical and inertial parameters.

Where index U and F represent upper arm and the forearm, respectively. R is the position of the link's center-of-mass along the link and I is the inertia along lo (longitudinal), ap (antero-posterior) and tr (transversal) axis of the link, respectively. It should be noticed that the mass of the forearm, hand, and handle was assigned to the 4th link, associated with the elbow flexion.

Using these parameters and Robotic toolbox, the four degrees of freedom arm containing three angles on shoulder joint and one angle on the elbow joint can be represented as Fig. 1.

C. Working hypotheses and terminology

An important aspect of this work is the assumption of concurrent existence of both temporal and spatial modularity. The temporal and spatial modularity is defined as follows. *Temporal modules* are some scalar functions of time, they represented temporal pattern of muscles activity. The decomposition approach in this algorithm is based on NMF, and is called as motor primitives, pre-motor drives/bursts or temporally fixed muscle synergies in other researches [12-15]. *Spatial modules* are some vectors that whose number of elements are the same as the number of EMG channels. These vectors describe the ratio of each muscle activation. This corresponds to time-invariant, synchronous, spatially fixed muscle synergies or muscle modes [16-18].

Two specific properties of modular control structure are 1) low dimensionality, and 2) hierarchical organization, to simplify control and learning in the human arm motion control. So, it is required to compare any decomposition algorithm for EMG data, considering these two facts [7].

The muscle activity matrix is decomposed as a linear combination of one-dimensional temporal modules, which are time-varying (Fig. 2A). This model considers a primitive as a temporal pattern that will affect selectively different muscles. The temporal decomposition has been used in [20].

In spatial decomposition a muscle activation matrix is decomposed during one sample, as a linear combination of a set of time-invariant weighted muscle activity across all muscles (spatial modules) that are multiplied by a time-varying activation coefficient (Fig. 2C). This model has been used in [17].

Another type of EMG matrix decomposition is time-varying synergies [8] [21-24], referred to as spatiotemporal decomposition and illustrated in Fig. 2B. It has one amplitude and one time coefficient as two free parameters for each synergy.

Later, a Hierarchical Alternating Least Squares (HALS) method used for NMF model which provides a very good convergence property and therefore results in to achieve both better accuracy and repeatability [25].

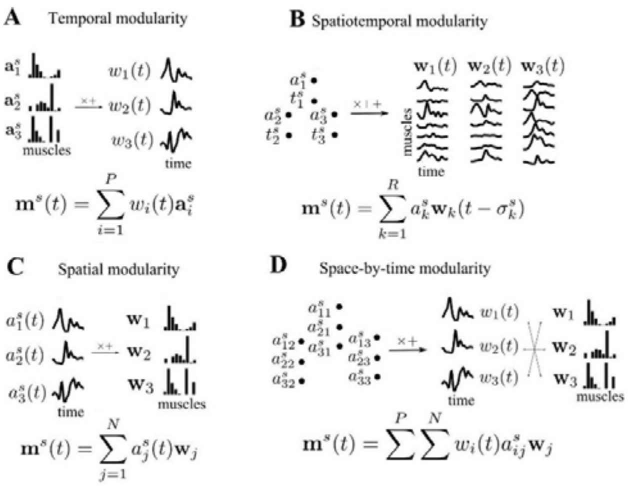

Fig. 2. Different algorithms used to extract modules from muscle activity matrix. *A*: temporal decomposition. *B*: spatial decomposition. *C*: spatiotemporal decomposition. *D*: concurrent spatial and temporal decomposition.

In this work, another model is used (referred to as space-by-time decomposition [7] [26], illustrated in Fig. 2D) to extract separately but concurrently spatial and temporal modules from muscle activity data matrix. The decomposition can be viewed as a generalization and unification of existing models and expresses any muscle pattern $m^s(t) \epsilon R^{T\times M}$ as the following double sum (*T* and *M* being the number of time frames and muscles, respectively):

$$m^s(t) = \sum_{i=1}^{P}\sum_{j=1}^{N} w_i(t) a_{ij}^s w_j + residual \quad (1)$$

Where $w_i(t) \epsilon R^{T\times 1}$ and $w_j(t) \epsilon R^{1\times M}$ are the temporal and spatial modules respectively, and $a_{ij}^s \epsilon R$ is a scalar activation coefficient.

Where *P* and *N* are the number of temporal and spatial modules respectively. To extract these concurrent spatial and temporal modules in practice, a specific algorithm is developed that seeks an approximate low-dimensional representation for all the input matrices called sample-based nonnegative matrix tri-factorization (sNM3F). This algorithm takes the parameters *P* and *N* as input and is designed (like the three previous ones) to iteratively minimize the total reconstruction error expressed as follows, where the Frobenius norm is calculated:

$$E^2 = \sum_s \left\| m^s(t) - \sum_{i=1}^{P}\sum_{j=1}^{N} w_i(t) a_{ij}^s w_j \right\|^2 \quad (2)$$

In this way by using sNM3F algorithm the temporal and spatial modules could be extracted concurrently from rectified EMG data. While in some works the EMG matrix decomposition had been applied on the phasic part of muscle activity, by decreasing the tonic part from the rectified EMG signal [8][17][21-24]. The most important variant attempts to capture variability in time, which may be inherent to the CNS's modular control strategy, or which may simply be caused by the time-normalization procedure of the data or by any intrinsic fluctuation (e.g., sensorimotor noise).

III. Criteria to evaluate modular decompositions

A. Avoiding local minima

Although as the number of temporal and spatial modules increase, the reconstruction error decreases, but the degree of freedom for motion control will increase. So achieving the optimized number of modules, in that the number of DOF is low enough while the error rate of reconstruction is as low as possible, would be very important. For this purpose it is necessary to increase the number of temporal and spatial modules from 1 to 9, and calculate the reconstruction error through the number of modules. To avoid labelling local minima as the global minimum when reconstructing the EMG signal, it is necessary to specify the number of modules, the algorithm of finding temporal and spatial modules according to the amount of the initial conditions should be repeated several times. Thus, the amount of reconstruction error minima in the 50 times repetition, is the global minima of the reconstruction error through the number of temporal and spatial modules.

B. *Variance accounted for (VAF)*

The VAF which is a metric typically used in studies investigating modularity in muscle activations, is defined as the residual reconstruction error normalized by the total variance of the dataset. The VAF shows similarity between the original EMG patterns and the reconstructed data using a limited number of temporal and spatial modules and can be used to validate or falsify the decomposition.

C. *Selection of the number of modules*

It should be considered that the inclusion of an additional module must lead to reliably some task-related EMG variations not described by other already included modules. When applied to spatial or spatiotemporal decompositions, this formalism was shown to be able to select reliably and robustly the smallest set of modules that describe all task-related information in the EMG data [6] [26].

Extension of the method for the space-by-time decomposition is as follows. After evaluating decoding performance with (N, P) = (1,1), it is considered adding either a spatial or a temporal dimension. i.e., increasing either N or P by one. The selected dimension increases the most the decoding performance. Accordingly, the number of modules is increased step by step, until the increase of modules does not gain any further statistically significant increase of decoding performance. This procedure ensures the detection of modules that explain only the “task- relevant” variability and the exclusion of other sources of noise that produce “task-irrelevant” variability.

IV. Results And Discussion

A. Number of modules

The VAF changes through different number of spatial and temporal modules is shown in Fig. 3 It can be seen that increase in the number of modules can affect the reconstruction error and VAF in a restricted manner. To maximize the VAF and at the same time minimize required memory capacity, three temporal and four spatial modules are chosen. The number of synergies is selected considering for further analysis as a compromise between model parsimony and accuracy [27].

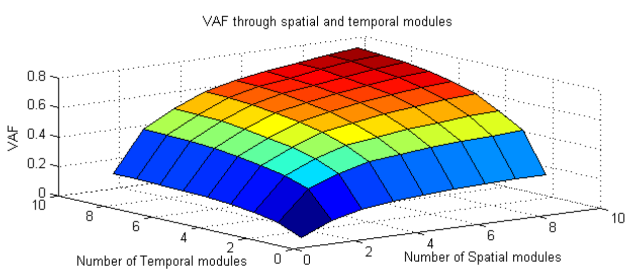

Fig. 3. VAF through different number of spatial and temporal modules.

B. Similarity in the same number of modules

To compare different spatial modules extracted with the same number, the modules should be extracted through different number of temporal modules. Therefore N=1,2,…,9 different spatial modules correlations that are extracted with M=1,2,…,9 temporal modules in nine different decomposition, could be represented in a 9×9 matrix. The ith row of this matrix shows the correlation of N spatial modules that are extracted with i temporal modules, compared with N spatial modules that are extracted with j=1,2,…,9 temporal modules. Each N spatial modules would create an N×N matrix of correlation that the average of its elements is determined as the similarity between these two sets of N spatial modules. Fig. 4 shows the similarity between spatial modules (N is the number of spatial modules), while the number of temporal modules changes.

As shown in Fig. 4(left top) if only one spatial module is extracted, this spatial module does not change when the number of temporal modules changes. That is when there is one spatial module and change the number of temporal modules from 1 to 9, the extracted spatial module in any of nine decompositions are similar to each other. The average value of similarity in these nine decompositions, that is more than 75%, is shown in the bar plot (Fig. 4 down).

Thus when number of spatial module considered constant, by changing the number of temporal modules, there would be no significant change in the spatial modules. This arises because what is varying in each movement is encoded in temporal modules and the related coefficients. So the temporal modules and related coefficients would change through different motions, and this variation is independent of the number of temporal modules. Due to this fact it can be concluded that the spatial information of the EMG signal is encoded as spatial modules that are independent from the number of temporal modules.

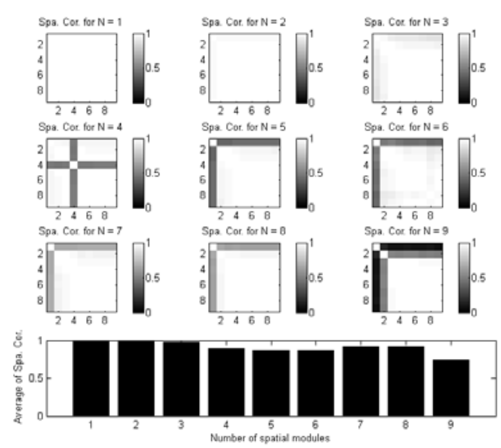

Fig. 4. Spatial modules correlation through different number of temporal modules.

Like what explained for spatial modules similarity, the correlation between the same numbers of temporal module extracted with different number of spatial modules could be calculated. Thus 9 matrix of correlation and the average value of the correlation could be shown in Fig. 5.

Considering the number of temporal modules fixed, the spatial modules and related coefficients would change through different motions, and this variation is independent of the number of spatial modules. Due to this fact it can be concluded that the temporal information of the EMG signal is encoded as temporal modules that are independent from the number of spatial modules.

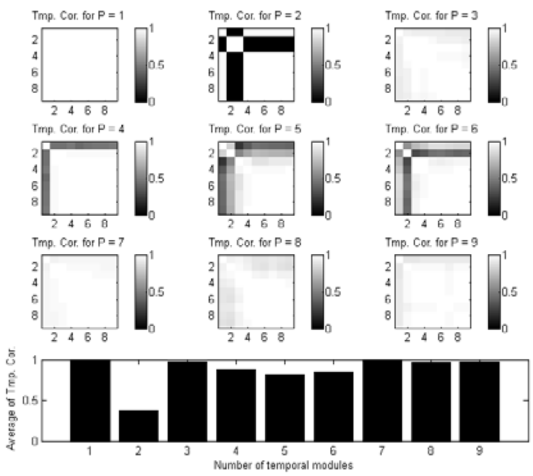

Fig. 5. Temporal modules correlation through different number of temporal modules

C. Spatial modules in different types of motion

Three extracted spatial modules for different types of subject2's motions are nearly similar to each other. Table. 1 has represented comparison of these three spatial modules in straight simple movement, reversal movement and via-point movement. The average value of the correlation between these extracted spatial modules in different types of motions for subject2, is 0.9823.

Table3: similarity comparison in extracted spatial modules for subject2

	Simple straight vs. reversal	Simple straight vs. via-point	via-point vs. reversal
1st Module (W1)	0.9728	0.9866	0.9931
2nd Module(W2)	0.9529	0.9911	0.9760
3rd Module (W3)	0.9780	0.9962	0.9941
4th Module (W4)	0.9732	0.9862	0.9891

On the other hand, it seems that the extracted spatial modules are different for different subjects. As what some other researchers have suggested, the number and pattern of muscle synergies configured in an adaptive process. The morphology and experience of each individual may interact in unexpected ways over time [28], resulting in a unique set of muscle synergy patterns. More subtly, these adaptive processes themselves may vary depending on context [29][30].

Thus each spatial module could be considered as a specific configuration in joint space that relies to a distinctive state of subject's upper extremity. Therefore if the decomposition of the EMG data has i number of spatial modules, then there would be i distinctive postures in the subject's upper extremity, which could be used as i stable points in the work space of human arm. The temporal modules and their related coefficients could form the transition between these postures in movements. To acquire these distinctive stable points it is required to calculate the related joint angles due to the muscle activation in each spatial module through neural network identifier (NNI). Thus a Neural network with one hidden layer, 17 input elements (as the number of EMG channels from 17 different muscle in upper extremity), and 4 output elements (as the number of joint angles: three angles (3DoF) for shoulder joint: adduction/abduction angle, flexion/extension angle and external/internal rotation angle, and one angle (1DoF) of flexion/extension in elbow joint) has been used.

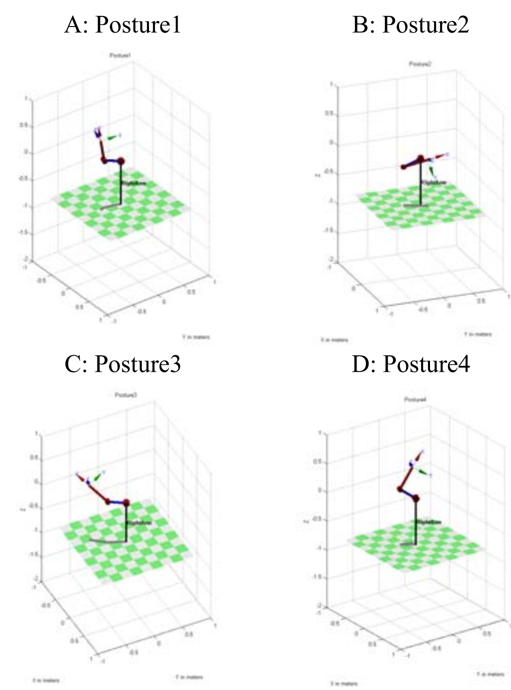

Fig. 6. Postures related to 4 extracted spatial modules of subject1.

The network would be trained with 70% of the data measured from simple movements of each subject. Remaining 20% and 10% of the data used for testing and evaluating the neural network, respectively. In the progress of training, the Epoch number is 676, was feed to the network randomly. Scaled conjugate gradient algorithm was used for training. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

By using a nonlinear function of neural network that projects the 17-19 muscle activity to the shoulder and elbow angles, the appropriate posture of the specified spatial modules could be extracted. Thus, the arm model can be used to show different postures related to the different spatial modules. In Fig. 6 and Fig. 7, the postures corresponded to 4 extracted spatial modules of subject1 and subject2 are shown respectively. As shown in these figures, the spatial modules of different subject are not the same. This would strengthen the idea that the muscle synergies are subject dependent.

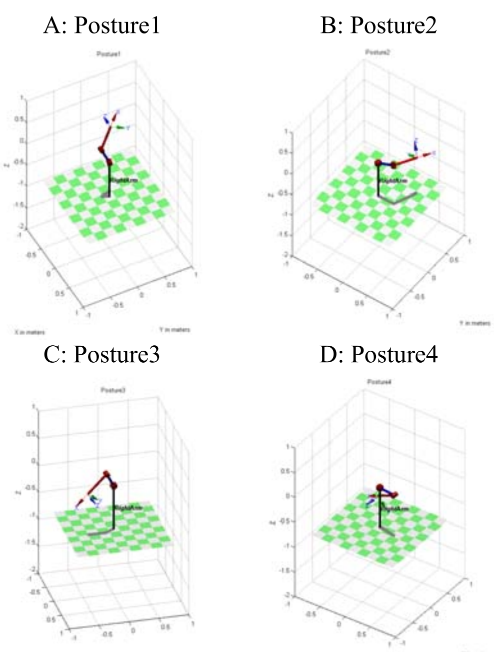

Fig. 7. Postures related to 4 extracted spatial modules of subject2.

D. *Temporal modules in simple straight motion*

By extracting the spatial and temporal modules from EMG matrix decomposition in any simple straight point to point reaching movements in sagittal or frontal planes, the motion information such as direction or start or stop positions would be encoded in the coefficients of the specified modules. Thus the coefficients for the recruitment of the modules vary through the task information. Fig. 8 shows three temporal modules extracted in simple straight point to point reaching movements in sagittal and frontal planes for both subjects.

As shown in Fig. 8 extracted temporal modules for simple straight motions are almost the same for both subjects. The first temporal module in both subjects have a positive bias at the beginning and end of the motion, with one minimum followed by one maximum through these biases. In two remaining temporal modules, the initial value is approximately zero. Also they have two peaks in their active region. The second temporal module has a zero value between its two peaks, but in the third one there is no zero value between its two peaks.

E. *Sequence of point to point movements in complicated motions*

Subject2 performed, in addition to the basic set of point-to-point movements, reaching movements from one start location (either central or peripheral) to a target location and back to the same start location in a continuous movement (reversal) and from a peripheral start location to a different peripheral target location through the central location (via-point).

The tangential velocity profiles for reversal and via-point movements had two distinct peaks (Fig. 9). The movement duration was approximately two times the duration of point to point movements, and the maximum tangential velocity of both peaks was close to the maximum of the tangential velocity of point-to-point movements. The averaged, phasic muscle activation waveforms for reversal and via-point movements generally showed a complex sequence of peaks and valleys that, by a first qualitative analysis, resembled the superposition of the waveforms of the muscle patterns of the corresponding point to point movements, each shifted in time to align the tangential velocity peaks. However, many of the muscle activation waveforms were modulated in amplitude and timing with respect to the point-to-point waveforms, and these changes were different across muscles.

A fast single-joint arm movement is characterized by a similar tri-phasic muscle pattern of sequential bursts of activity (for a review see [31]). The first agonist muscle bursts initiates the motion, the antagonist burst decelerates the movement toward the intended end position, and finally the second agonist burst stabilizes the limb after movement termination by dampening oscillations.

As shown in Fig. 9 the tangential velocity in reversal movements, reaches to zero near the center point. That is because of the direction change in motion. At the first stage the movement is out-center and after reaching to the center point, the direction of movement changes and in the second stage, the movement is center-out. During reaching center point, the tangential velocity becomes zero. It can be concluded that the reversal movements are sequence of two point to point reaching movements with zero velocity in start and stop points. According to [32], each point to point reaching movement is characterized by a similar tri-phasic muscle pattern of sequential bursts. The reversal motions consist of two fast point to point reaching movement, in each stage there are three sequential burst of acceleration, deceleration and stabilization [33]. In reversal motions during reaching the center point, the stabilization sequence takes place.

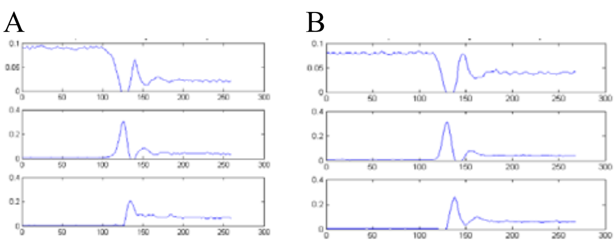

Fig. 8. Three Temporal modules extracted for simple straight point to point reaching movements A) for subject1. B) for subject2.

In via-point motions, the tangential velocity during reaching the center point closes to zero as the target point closes to the start point. As shown in Fig. 6 the tangential velocity at the center for via point motions from position2 to position1 or position3 are closer to zero than the tangential velocity at center in via point motions from position2 to position4 or position8. As the target position in via point movements goes far from the start position, the tangential velocity at the center point moves away from zero. It seems that as the target position goes far from the start position, two stages of point to point reaching movement merge more to each other. Referring to [34], each point to point reaching movement is characterized by a similar tri-phasic muscle pattern of sequential bursts. The via-point motions consist of two fast point to point reaching movement, in each stage there are three sequential burst of acceleration, deceleration and stabilization [35]. During reaching the center point as the target position goes far from the start position, the deceleration and stabilization sequence of the first stage merge more to the acceleration of the second stage. That is why the tangential velocity at the center goes away from zero. As mentioned in [36] [37] the merging of stages in complicated motions is to some extent subjective. But if the subject knows the target position, he could merge these two stages while crossing the center point.

F. *Temporal modules in complicated motion*

To compare temporal modules in simple and complicated motions, it is required to extract temporal modules of reversal and via-point motions in two vertical planes. As shown in Fig. 8 the second and third temporal modules in reversal and via-point motions has the same features as the features in the second and third temporal modules in simple motions (Fig. 10). They have two peaks in the active region of first module.

The first temporal module shows the type of motion. In simple straight point to point reaching movements, the first temporal module have a positive bias at the beginning and end of the motion, with one minimum followed by one maximum through these biases. As mentioned above the reversal and via-point motions could be represented as the combination of two simple straight motions. This could be represented in the first temporal module pattern. For example in via-point motion there exist one out-center motion followed by one center-out motion.

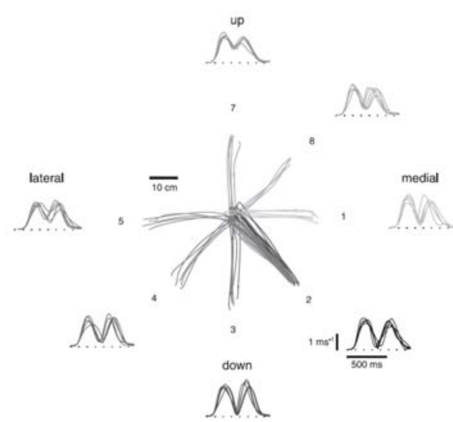

Fig. 9. Trajectories and tangential velocity profiles of the endpoint for five repetitions of reversal movements from point2 to center an back to point2 (black line) and via-point starting from point 2 to points 1, 3, 4, 5, 7 and 8 via center point (gray line). All movements are in the frontal plane.

As shown in Fig. 10 the first temporal module could be considered as the first module in simple straight motion repeated two times after each other. In reversal motion it seems that the pattern of first temporal module is as the first temporal module followed by its inverse. In the first stage of motion the pattern has a minimum followed by a maximum, and in the second stage the pattern has a maximum followed by a minimum. According to the above discussion and [35] [38] [39], the complicated motions are combination of simple tasks. That the type of task is represented in the first temporal modules of the complicated motion.

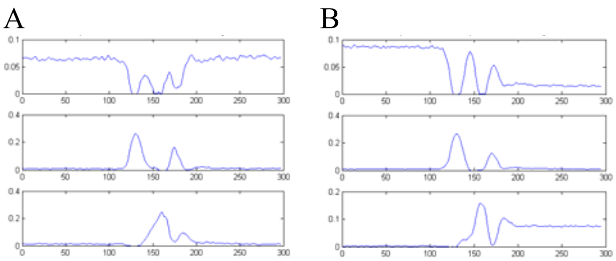

Fig. 10. Three temporal modules extracted for subject2 in A) reversal movements. B) via-point movements.

G. Coefficients Correlation analysis

Due to extracting three temporal and four spatial modules for the human arm reaching point to point motions, the coefficient matrix has 12 elements in three rows and four columns. By averaging the coefficient matrix for five trials in each motion, the correlation of the coefficient matrix for different motions could be calculated. As we have 8 peripheral target points in each plane, assuming center-out and out-center motion, we would have 16 different simple motions in each plane for each subject.

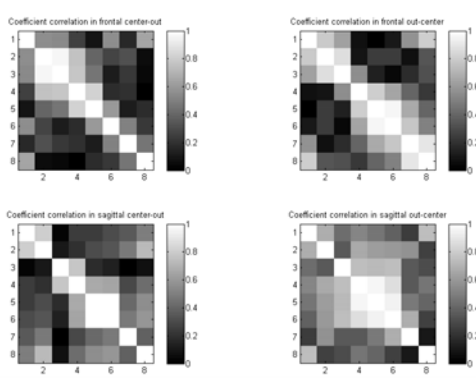

Fig. 11. Coefficient correlation for simple straight motions of subject1, left column for center-out and right column for out-center motions. Above row in frontal and bellow row for sagittal plane

As shown in Fig. 11 each motion has its own coefficient matrix due to its direction. But in some motions (like 0-to-2 and 0-to-3 motions or 5-to-0 and 6-to-0 in frontal plane, and also 0-to-5 and 0-to-6 motions or 0-to-4 and 0-to-5 motions in sagittal plane), the coefficient correlation is high. This means the recruitment of spatial and temporal modules in these motions are to some extent the same with high correlation.

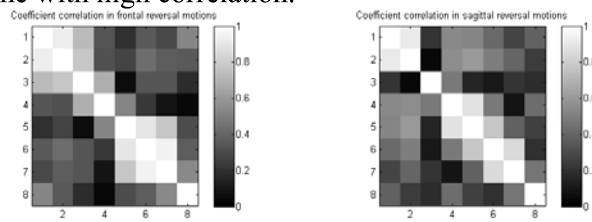

Fig. 12. Coefficient correlation for reversal motions of subject2, left in frontal and right in sagittal plane.

The coefficient correlation for the reversal motion of subject2 is shown in Fig. 12. As seen, the recruitment of spatial and temporal modules in the reversal motions (1-0-1 and 2-0-2) and (6-0-6 and 7-0-7) in the frontal plane, and the reversal motions (1-0-1 and 2-0-2) and (4-0-4 and 5-0-5) in the sagittal plane, are highly correlated.

It could be concluded from these similarities, that the recruitment of spatial and temporal modules is due to the motion direction or the distance of target points from each other in different motions.

V. conclusion

Decomposition of matrix data can be useful for understanding the function of the underlying components. In this study, we used sNM3F algorithm to extract unified spatial and temporal modules from recorded muscle activities. NMF-based decompositions are physiologically more relevant to EMG signals, since non-negative signals reflect well the "pull only" behavior of muscles [5].

Thus, the sNM3F algorithm seeks an appropriate low dimensional representation for input matrix of EMG data from simple and compound types of point-to-point reaching motions. The evaluated motions are simple straight, reversal, and via-point movements of human hand in sagittal and frontal planes, with motion in each plane leading into a four DOF movement (one DOF in the elbow and three DOF in the shoulder joint). Since the movements were performed in the vertical planes, effects of the gravitational component of arm movement are included in the results.

The extracted spatial modules are different for different subjects. According to [28], the number and pattern of muscle synergies are configured in an adaptive process. The morphology and experience of each individual may interact in unexpected ways over time [28], resulting in a unique set of muscle synergy patterns and yielding to distinct postures. To acquire these distinctive stable points it is required to calculate the related joint angles due to the muscle activation in each spatial module through neural network identifier (NNI). Our results show that extracted postures that are related to the spatial modules are also subject-dependent.

Three temporal and four spatial modules are extracted to minimize the reconstruction error and at the same time to reduce the DOF. The spatial information of the EMG signal is encoded in spatial modules, which are independent from the number of temporal modules. Moreover, each one of spatial modules can be considered as a specific configuration in joint space that corresponds to a distinctive posture of subject's upper extremity.

According to [35], [38], and [39], complex motions are combinations of simple tri-phasic tasks. The type of the task is represented in the first temporal module of the complex motion. As mentioned in [36]-[37], merging of stages in complex motions is to some extent subjective.

It could be concluded from coefficient similarity analysis that the recruitment of spatial and temporal modules is due to the motion direction or the distance of target points from each other in different motions.

Our results for activation or inactivation of muscles in the spatial modules were matched to our previous expectations due to physiological knowledge. Extracted modules are applicable for clinical evaluation and rehabilitation of movements [40].

All our conclusions are based on the data collected from two subjects, who performed 320 trials in total. To be able to generalize these results, certainly we do need to record data from more subjects.

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VI. References

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