Visualization of Trunk Muscle Synergies During Sitting Perturbations Using Self-Organizing Maps (SOM)

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***Abstract*—The purpose of this study was to demonstrate the use of the self-organizing map (SOM) method for visualization, modeling, and comparison of trunk neuromuscular synergies during perturbed sitting. Thirteen participants were perturbed at the level of the sternum, in eight directions during sitting. Electromyographic (EMG) responses of ten trunk muscles involved in postural control were recorded. The SOM was used to encode the EMG responses on a 2-D projection (i.e., visualization). The result contains similar patterns mapped close together on the plot therefore forming clusters of data. Such visualization of ten EMG responses, following eight directional perturbations, allows for comparisons of direction-dependent postural synergies. Direction-dependent neuromuscular response models for each muscle were then constructed from the SOM visualization. The results demonstrated that the SOM was able to encode neuromuscular responses, and the SOM visualization showed direction-dependent differences in the postural synergies. Moreover, each muscle was modeled using the SOM-based method, and derived models showed that all muscles, except for one, produced a Gaussian fit for direction-dependent responses. Overall, SOM analysis offers a reverse engineering method for exploration and comparison of complex neuromuscular systems, which can describe postural synergies at a glance.**

***Index Terms*—Balance, electromyography (EMG), muscle synergy, perturbation, self-organizing map (SOM), sitting, visualization.**

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I. Introduction

Trunk stability is responsible for maintaining upright posture of the spine during standing and sitting. Trunk stability relies on complex synergistic muscle activations, which play an important role during standing and sitting balance control. Previous analysis of trunk stability has examined over 40 muscles of the "spine system" [1], which are difficult to evaluate and interpret as a collective system using standard analysis methods. Consequently, there is a need to develop a technique which would allow one to quickly and intuitively analyze synergistic activity of many muscles that act in concert and to derive principles of their synergistic activity from the individual electromyography (EMG) recordings of the muscles of interest during a particular neuromuscular activity [2].

In postural control, gross movements that require a number of interdependent and simultaneous muscle responses are known as postural synergies. Postural synergies are control signals for groups of muscles that work together to assure stability of a certain joint or a body segment [3]. It is known that tonic muscle activation contributes to stability of the trunk during sitting balance [4]. It is established that tonic activation of the trunk muscles contributes to the stability of the trunk during sitting and standing balance [4]. It has also been established that phasic, feedback-driven, trunk muscle responses help maintain trunk stability during perturbed sitting [4], [5]. In this study, we analyzed postural synergy and the perturbation-induced phasic response of the trunk muscles that work collaboratively to ensure stability of the trunk during perturbed sitting.

The concept of synergy is related to the understanding of how the central nervous system (CNS) activates multiple muscles in order to perform complex movements [3]. Muscle synergies are analyzed by examining correlations between pairs of muscles [6]. However, correlation analysis is not sufficient when investigating tasks that involve more complex synergies [3]. Statistical methods using matrix factorization, such as principal component analysis [7], gradient descent [8], and cluster analysis [9], offer a solution for investigating more complex mechanisms by analyzing average performances over numerous repeated trials. Uncontrolled manifold (UCM) analysis method [10] evaluates the variability between trials in order to analyze synergies qualitatively. Though all these methods rely on extensive data analysis, which can often be difficult to interpret and conceptualize, they account for the complexities inherent in postural control, and can thus contribute to the understanding of how the CNS controls multiple muscles during complex movements.

Our study presents a self-organizing map (SOM) method for representing, comparing, and modeling complex postural synergies at a glance. The SOM is an artificial neural network (ANN) that uses an unsupervised learning algorithm to project large input datasets onto a 2-D representation known as a map [11]. The SOM produces an organized map in which similar patterns, discovered in the input data, are mapped onto nodes close to one another on the map. Thus, the map becomes a projection of the input data and allows visualization of large datasets on a 2-D display, while maintaining their topological order [11]. Consequently, visualization of numerous EMG responses following perturbations results in a method for representing and comparing postural synergies at a glance.

The SOM algorithm has been used as a robust method for classification of neuromuscular disorders based on EMG recordings [12] and for exploration of gait coordination based on locomotion kinematic data [13], [14] (see [15] for a review of other applications of SOM in biomechanics). To date, there have been limited applications of SOM for visualization of neuromuscular synergies in posturography. Moreover, postural muscle synergies represent a general construct used by the CNS [16] and may reveal insight into neural strategies used by healthy and impaired nervous systems [17]. The SOM presents topological relationships of high-dimensional, nonlinear data visually, thus making it an attractive tool for analyzing postural muscle synergies.

The objective of this study is to use the SOM method to represent and compare postural muscle synergies by producing a visualization of complex neuromuscular responses following perturbations. Furthermore, the objective is to produce response models of each muscle and compare the results obtained with the SOM analysis to the results obtained by Masani *et al.* [4] using curve fitting. Overall, the aim of this study was to demonstrate the use of SOM for visualization and comparison of neuromuscular synergies in posturography. The SOM analysis was expected to contribute to further understanding and aid the reverse engineering of the neural mechanisms responsible for sitting balance control, which relies on complex neuromuscular relationships [1].

II. Methods

The full experimental protocol is reported in our previous study [4], [5]. A brief description follows.

A. Subjects

This study included 13 healthy male adults (ages 21–39 years; mean height 178.0 (SD: 4.7) cm; mean body mass: 70.3 (SD: 10.0) kg; and all except one were right handed). Participants had no reported history of lower back problems. The experimental protocol was approved by the local ethics committee and all subjects gave written informed consent before participating.

B. Experimental Protocol

Subjects were seated in an upright position with legs unsupported, arms crossed over the chest, and eyes closed; subjects wore headphones to eliminate auditory cues. The experiment consisted of eight directional perturbations at the level of sternum, uniformly spaced at intervals of 45° around the subject. Perturbations were applied via manual pulling using a chest harness. The applied perturbation forces were in the range from 131 to 148 N [4]. Five trials were taken for each of eight directions (total of 40 perturbations) for each subject. The perturbations were randomly ordered to prevent any anticipation, with approximately 30 s between perturbations.

C. Data Acquisition

Surface EMG recordings were taken from ten muscle groups (five muscles recorded bilaterally) that were identified as relevant for posture and trunk stability. Ten disposable EMG electrodes (silver–silver chloride disposable electrodes, 10 mm diameter) were placed bilaterally, 18 mm apart, over the following muscles: 1) rectus abdominis (RA), 3 cm lateral to the umbilicus; 2) external oblique (EO), 15 cm lateral to the umbilicus; 3) internal oblique (IO), midpoint between the anterior superior iliac spine and the symphysis pubis; 4) thoracic erector spinae (T9), 5 cm lateral to the T9 spinous process; and 5) lumbar erector spinae (L3), 3 cm lateral to the L3 spinous process. A reference electrode was placed over the clavicle.

Data were acquired using two AMT-8 EMG recording systems (Bortec Biomedical Ltd., AB, Canada) with a preamplification gain of 2000 and a frequency response of 10–1000 Hz. All data were sampled at 2000 Hz using a 12-bit data acquisition system (NI6071E, National Instruments, TX). All recordings were rectified and low-pass filtered at 2.5 Hz using a fourth-order, zero-phase-lag Butterworth filter to compute the linear envelope of EMG signals [4], [18]. The phasic response was determined as the peak EMG value in the 0.5 s time window immediately following the perturbation [4]. Phasic responses of each muscle were selected as the features for analyzing postural synergies following perturbations.

D. Self-Organizing Map

An SOM was used to represent and compare postural muscle synergies, and to model the responses of each muscle. The SOM analysis method represented in Fig. 1 was implemented in MATLAB 7 (MathWorks Inc., MA) using the SOM Toolbox for MATLAB [19]. Acquired EMG signals were processed and the phasic muscle response feature was selected (see Section II-C). The SOM algorithm had two phases training phase and recall phase (visualization), which are shown in Fig. 2.

The input dataset consisting of trunk muscle phasic responses was encoded onto a 2-D map representation during SOM training. In the recall phase, the resultant map allowed visualization of postural synergies for each of eight directional perturbations. Each direction was assigned a cluster on the map corresponding to where the responses of that direction converged. The organized map contained similar responses grouped close together.

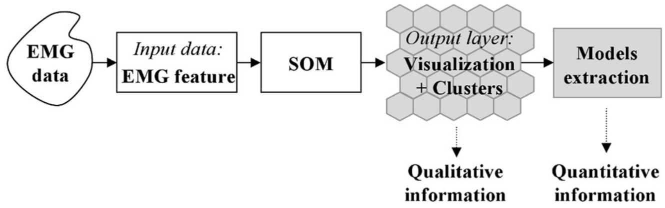

Fig. 1. Self-organizing map method for data mining, visualization, and model extraction of muscle synergies.

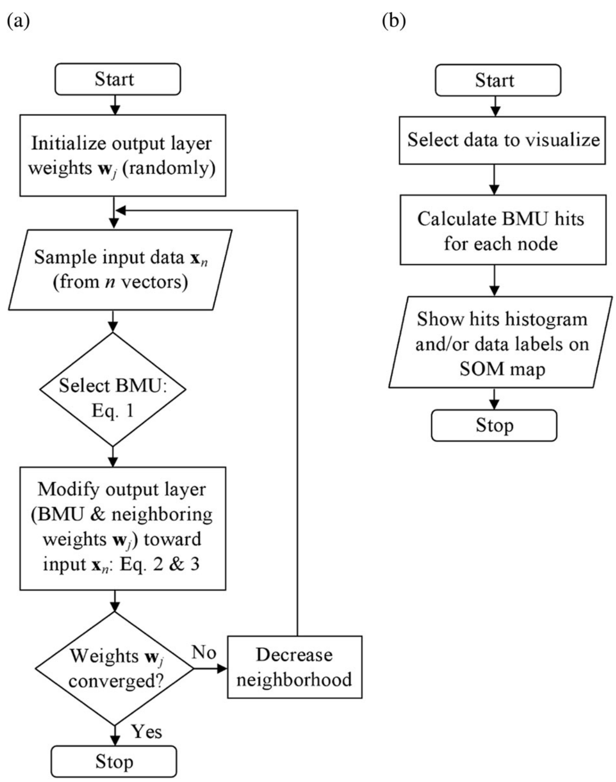

Fig. 2. Self-organizing map algorithm flowchart: (a) training and (b) Recall phase. BMU is the BMU in a Euclidian sense (1).

Comparison of the EMG response differences was done by analyzing the relative proximity of the clusters of each perturbation direction on the map. Clusters of perturbation directions that were close together had similar neuromuscular responses and clusters of perturbation directions that were far apart had dissimilar responses. Finally, from the clusters associated with each direction, an averaged response for each muscle was extracted. A direction-dependent model of the responses for each muscle was then constructed using Gaussian curve fitting, and compared to the results obtained using conventional EMG analysis. A detailed description follows.

1) SOM Training: During SOM training, the input data are encoded onto a 2-D output layer known as the map. SOM uses an unsupervised learning algorithm where the output layer nodes compete to encode the input data.

The input dataset contains a vector for each of eight perturbation directions for each participant (five trials were averaged for each participant) resulting in 104 input data vectors (13 participants $\times$ 8 directions). Each input vector contains ten points corresponding to the phasic responses of each analyzed muscle. The input vectors also contained a label with the corresponding direction of perturbation to allow comparisons of direction-dependent responses. The label was used only during the recall phase to show where the clusters for each direction converged on the resultant map, and was not used during the training phase. The input data were logarithmically normalized before SOM training. Training was performed in batch mode, which provided quicker execution of the algorithm [11].

The output layer was defined as a 5×5 hexagonal map. In the output layer, each node (indexed by $j = 1, \ldots, 25$) is represented by a weight vector $w_j = [w_{j1}, w_{j2}, \ldots, w_{j10}]^T$ with the same dimensionality as the vectors from the input space (i.e., ten points). Weight vectors were initially randomly assigned and during the training they were tuned to represent the input data.

During training, each iteration (indexed by n) proceeded by sampling a new input vector $x_n = [x_{n1}, x_{n2}, \ldots, x_{n10}]^T$ from the input data, which was matched against nodes in the output layer by calculating the Euclidian distance between a given input vector and each node on the map. The algorithm then selected the node that was the best matching unit (BMU), indexed by c. The BMU was the node whose weight representation ($\mathbf{w}_c$) was closest to the given input vector as measured by the Euclidean distance (1)

$$c = \arg\min_j (||x_n - w_j||). \tag{1}$$

The weight vector of the BMU node was then adapted toward the current input vector (2)

$$w_j(n+1) = w_j(n) + h_{cj}(n) \cdot [x_n - w_j(n)]. \tag{2}$$

Neighboring nodes were proportionally modified via the neighborhood function attempting to distribute knowledge locally around the BMU. A Gaussian neighborhood function $h_{cj}(n)$ which was centered on the BMU node controlled the region in the output layer over which training occurred; r_c and r_j are the positions of the BMU node and an arbitrary node j on the map (3)

$$h_{cj}(n) = \alpha_n \exp\left(\frac{-\|r_c - r_j\|^2}{2\sigma_n^2}\right). \tag{3}$$

The radius of the neighborhood (σ_n), as well as the learning rate (α_n), shrank monotonically as n increased. The algorithm sampled the input data randomly until the weight vectors converged to a stable projection of the input data [11], [19]. After SOM training, the map was encoded with the representation of the input data.

2) SOM Visualization: Visualization produced using the SOM-based method reduced dimensionality, yet maintained nonlinear topological relationships [11]. Visualization was generated by superimposing a histogram of BMU hits for a particular dataset onto the nodes of the map, indicating BMU locations. The resultant map contained groupings of similar patterns that were discovered in the input data mapped onto spatially proximal nodes, consequently forming clusters of input data. Visual-

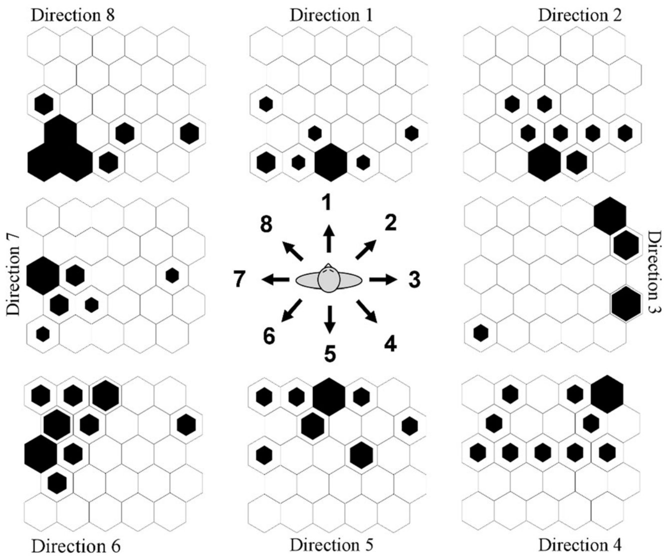

Fig. 3. SOM map visualization of postural synergy response for each perturbation direction. The plots show average responses for all subjects for each direction. The analysis represents postural synergies and compares the direction-dependent differences of perturbations by comparing the relative cluster locations.

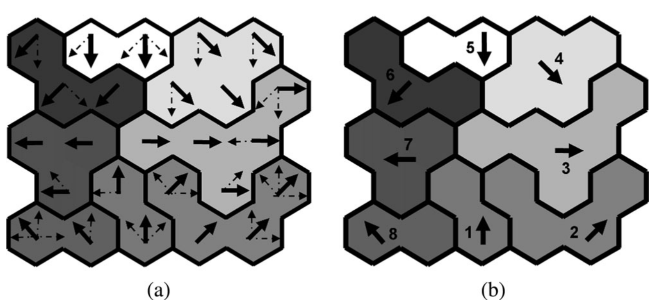

Fig. 4. SOM map visualization of mean cluster responses for all perturbation directions. (a) Directions of arrows on each node indicate perturbation directions 1–8; solid arrows represent the "winning" direction with the highest responses; dotted arrows represent all other directions with lesser responses on each node. (b) Each cluster is color coded and labeled with the associated direction number and the corresponding direction-indicating arrow.

ization of the hits histograms was produced for each perturbation direction (shown in Fig. 3). Such a method of data representation enabled us to compare complex neuromuscular responses caused by different perturbations (i.e., direction-specific postural synergies).

Visualization of all perturbation directions on a single map allowed rapid visual inspection of response differences. The arrows [shown in Fig. 4(a)] represent the label indicating direction of perturbation with the highest BMU hits frequency (solid line), and other BMU hits (dotted line), appearing on each node. Clusters of responses for each direction were obtained by assigning each node a "winning" direction based on the highest frequency of BMU hits in that direction (Fig. 4). Relative proximity of clusters on the map implies similarity or dissimilarity of the overall weight vectors associated with those clusters.

The Euclidian distance measure was calculated from the center of each cluster to the center of all other clusters on the map (4). The Euclidian distance between arbitrary clusters $a(x_a, y_a)$ and $b(x_b, y_b)$ is

$$d_{a-b} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}. \quad (4)$$

The average Euclidian distance shows the proximity between clusters, which infers similarity or dissimilarity of direction-dependent postural synergies.

3) Model Extraction: Models of neuromuscular responses were constructed from weight vector representations of the convergent clusters on the map. Each cluster contained several nodes and weight vector responses that corresponded to each perturbation direction. Average responses for each cluster were calculated to produce one overall response vector for each perturbation direction. The resulting weight vector for each direction (w_d, for $d = 1$–8) contained ten points representing the average phasic neuromuscular response of each muscle group. Gaussian curve fitting was used to build a continuous-direction model for each muscle. Each muscle response was analyzed with respect to the perturbation direction to extract direction-dependent models: the relationship between perturbation angle (x) and the EMG response (y), for each muscle, was described by a Gaussian function (5), where a, b, and c are the model coefficients

$$y = a \cdot \exp\left(\frac{-(x-b)^2}{c^2}\right). \quad (5)$$

III. RESULTS

A. Postural Synergy Visualization

Postural synergy representations for each direction were obtained and projected onto the SOM to produce visualization. Visualization based on BMU hits distribution shows the concentration of clusters for each perturbation direction (Fig. 3). The relative concentration of clusters on the map infers similarities (i.e., clusters closer together) and dissimilarities (i.e., clusters further apart) between direction-dependent postural responses. The same visualization also shows that perturbations to the front and back, as well as the right and left (directions 1 and 5, and 3 and 7, respectively), have symmetrical cluster locations relative to each other (Fig. 3). Although the absolute position of the clusters on the grid was arbitrary, cluster symmetry indicates that neuromuscular responses were dissimilar and opposite for opposing perturbation directions, and that the muscular reactions for front versus back and right versus left directions represented the most dissimilar and opposite postural synergies.

Visualizing the directions for which each node was active on a single SOM map using direction-indicating arrows allowed a comparison of postural synergies between perturbation directions (Fig. 4). It is possible for more than one direction to appear in the same node [represented as multiple arrow directions on a single node—Fig. 4(a)], indicating similarity of muscle responses for those directions. Each node could also be assigned to a particular cluster [grouped based on the "winning" direction of individual nodes—Fig. 4(b)] and projected on a single SOM

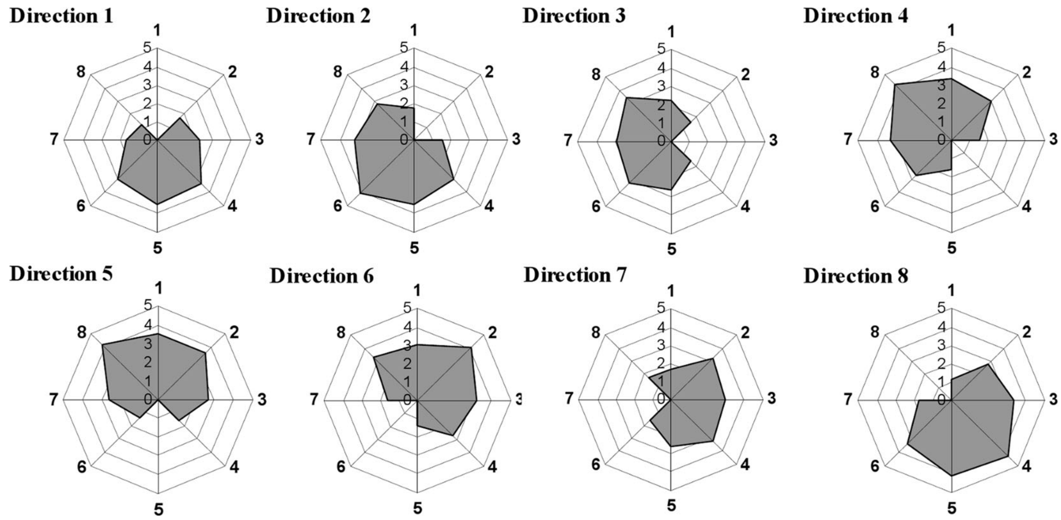

Fig. 5. Polar plots showing the Euclidian distances between clusters on the map. Distances between clusters imply neuromuscular differences between the corresponding clusters. Clusters of each perturbation direction are compared to all other perturbations to show the similarities and dissimilarities of direction-dependent neuromuscular responses.

map illustrating each of the eight perturbation directions clusters. Adjacent perturbation intervals are represented by clusters that were closest on the map [i.e., perturbation direction 5 appears between directions 4 and 6—Fig. 4(b)], indicating the most similar responses between these directions. In addition to similar input data converging to proximal clusters on the map, the size of the clusters is proportional to the size of data corresponding to those clusters [20]. Analysis of SOM cluster size (variability) was found to be valid for variability analysis [13]. Our analyses of the SOM map (Fig. 3) and the relative cluster size (Fig. 4) indicate that if the cluster size is smaller, less data are associated with that cluster (i.e., perturbation direction) [20] hence suggesting smaller variability of neuromuscular responses associated with that perturbation direction. The results suggest that neuromuscular responses to directions 1 and 5 (i.e., anterior–posterior directions) are less variable (average cluster size = 2) than other perturbations directions (average cluster size = 3.5).

The Euclidian distance measured between the central locations of two clusters on the map represents similarity (i.e., small Euclidian distance) or dissimilarity (i.e., large Euclidian distance) of synergistic postural responses associated with those two clusters. Each perturbation direction is presented on the polar plot (Fig. 5) showing similarities and dissimilarities of that perturbation to all other perturbation directions. As expected, the synergistic responses of each direction were most similar to the responses of those directions adjacent to it and got progressively more dissimilar as perturbations change. The responses were most dissimilar from the perturbations in the opposite direction to it. This analysis compared synergistic difference between direction-dependent postural responses using the SOM method.

B. Direction-Dependent Models

Gaussian regression models (5), for each muscle, were computed by extracting and analyzing the average response vector (w_d), for each direction (d = 1–8). Each direction vector contained ten points representing the average phasic neuromuscular responses of each corresponding muscle. The direction-dependent model for each muscle was computed to compare the results to previous studies, which used different approaches to analyze direction-dependent neuromuscular responses during sitting. The coefficient of determination (R^2) was used to assess the goodness of fit of each muscle model to be represented by the Gaussian function and the results obtained using the SOM method are presented in Table I. The R^2 values from Masani *et al*. [4] are used for the evaluation of the results obtained by SOM.

TABLE I
RESULTS OF GAUSSIAN CURVE-FITTING FOR EACH MUSCLE

Muscle		a	b	c	R^2	R^2 Masani et al. [4]
Rectus Abdominis (RA)	**L**	2.029	165.2	105.7	0.954	0.990
	R	2.350	178.0	101.2	0.967	0.988
External Oblique (EO)	**L**	2.636	156.2	133.1	0.978	0.977
	R	2.710	177.2	139.7	0.952	0.965
Internal Oblique (IO)	**L**	2.579	134.9	146.5	0.972	0.845
	R	2.210	221.9	193.6	0.728	0.953
Thoracic Erector Spinae (T9)	**L**	1.801	28.4	219.3	0.793	0.944
	R	2.533	341.4	316.9	0.886	0.924
Lumbar Erector Spinae (L3)	**L**	2.407	3.3	322.0	0.764	N/A
	R	4.141	348.7	878.7	0.415	0.969

Muscles are recorded bilaterally: left (L) and right (R); *a*, *b*, and *c* are the coefficients of (5); and R^2 is the coefficient of determination which is compared to R^2 obtained by Masani *et al.* [4].

In Fig. 6 the perturbation directions were converted from directions 1–8 into angles, where 1 = 0°/360°, 2 = 45°, 3 = 90°, 4 = 135°, 5 = 180°, 6 = 225°, 7 = 270°, and 8 = 315°. The responses were subdivided anatomically to abdominal and back muscle groups. The abdominal muscle (RA, EO, and IO) responses yielded a good fit suggesting that the relationship could be represented using a Gaussian function. The back muscle (T9 and L3) responses provided an acceptable fit using normal distribution, suggesting a tendency that the relationship fits a Gaussian function, with the exception of right L3. The models

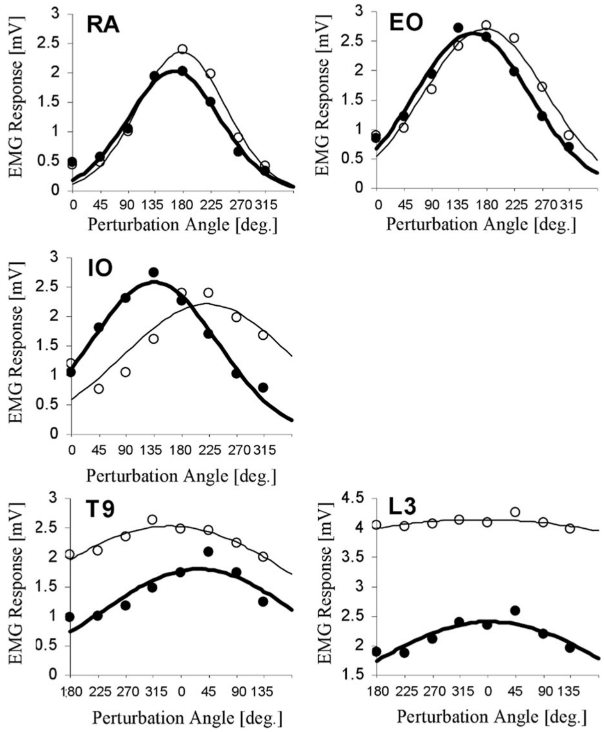

Fig. 6. Activation pattern for different directions of perturbation for left (thick line) and right (thin line) muscle group for all subjects. Abdominal muscles: rectus abdominis (RA), external oblique (EO), and internal oblique (IO); Back muscles: thoracic erector spinae (T9), lumbar erector spinae (L3).

obtained using the SOM method suggest that the amplitude of phasic response to direction of perturbation relationship during sitting may be quantitatively modeled using the Gaussian function. This finding confirms those of Masani *et al.* [4] and Preuss and Fung [21], who used standard analysis methods to quantify the relationship.

Coefficient "*b*" in Table I indicates where each muscle model had a maximal response. The abdominal muscles had maximal responses around 180° (back perturbation direction) suggesting that opposing muscles stabilized the perturbations. The maximal responses of back muscles were around 0° (front perturbation direction), suggesting that the opposing muscles also stabilized the perturbation. The anatomy of the back muscles, both of which are located around the spinal column, is consistent with the location of the peak responses.

IV. Discussions

The purpose of this study was to present and demonstrate an SOM-based method for representing, comparing, and modeling of trunk muscle postural synergies following direction-dependent perturbations during sitting. We used the SOM to project and represent the direction-dependent phasic responses of ten muscles on a 2-D map. Furthermore, the SOM method produced an organized visualization, where similar patterns were mapped close together, therefore allowing comparisons of the neuromuscular responses following eight-directional perturbations. Finally, we produced direction-dependent models for each of the ten muscles that were acquired using the SOM method.

A. Direction-Dependent Neuromuscular Responses

The results obtained by visualizations produced using SOM-based analysis provide important insights and allow quick comparisons of the neuromuscular system relevant to studies of complex mechanisms of sitting balance [1]. Using the SOM visualization cluster position analysis (Fig. 5) we have quantified direction-dependent differences of trunk muscle phasic responses during sitting, which are necessary to stabilize the trunk [4]. Our study found symmetrical and direction-dependent neuromuscular responses which are consistent with findings from the literature [4], [5]. In our study activation patterns for each muscle obtained from the SOM clusters were modeled using the Gaussian distribution (Fig. 6 and Table I) and demonstrate maximum EMG response in the anatomically opposite direction to the perturbation. The results indicate that opposing muscular reactions stabilize the body by stiffening the muscles that would provide the forces in the opposite direction to the perturbation. These results complement previous findings demonstrating the role of direction-dependent abdominal muscle responses that can be modeled using Gaussian distribution [4], [21]. Although our R^2 coefficients are not as high, the difference could also be attributed to the maximal voluntary contraction normalization by Masani *et al.* [4]. Moreover, the anatomy of back muscles (T9 and L3) extends vertically along the sagittal plane of the spine, whereas the abdominal muscles (RA, EO, and IO) extend along the sagittal and transverse planes of the trunk. This musculoskeletal geometry could explain why the back muscles exhibit less direction-dependent responses (i.e., have a more active role in stabilizing all perturbation directions), whereas abdominal muscles have more direction dependency. These results are consistent with the notion that the CNS may be tuning the activation level based on the musculoskeletal geometry [22].

Furthermore, analysis of variability based on the size of SOM clusters [20] (Figs. 3 and 4) and direction-indicating arrows [see Fig. 4(a)] offer some insights into the variability of neuromuscular responses during sitting. Our results suggest that the responses to anterior–posterior perturbations (i.e., forward and backward perturbations) are less variable than other perturbation responses, which include the mediolateral component. Variability of postural synergies is a result of neuromuscular redundancy [16] (i.e., the same movement can be executed by a variety of muscular patterns [1]) and does not necessarily reflect dysfunction [17]. Intertrial variations of individual muscles are known to be correlated, thus representing a general construct used by the CNS, and this variability may represent variations of neural commands that activate individual muscle synergies [16]. The smaller variability of neuromuscular responses in the anterior–posterior directions could be explained by the anatomy of the trunk muscles [23], which provides a greater mechanical advantage to resist perturbations in the anterior–posterior direction.

B. Muscle Synergy Visualization With SOM

The main advantage of SOM is the ability to represent the results pictorially [12]. An intuitive topological visualization of muscle synergies could aid clinicians in discriminating pathology, assessment of rehabilitation, and creating evidence-based interventions [17], by comparing responses of individuals (for example, with spinal cord injury) to established norms. Visualization of direction-dependent responses could also be used to assess symmetry of muscular responses of patients (with stroke, for example) or for biofeedback training. Furthermore, the capability of the SOM algorithm to encode redundancies in data [13], [20] and relative ease of interpretation [11]–[14], which have been cited as a limiting factor for clinical muscle synergy analysis [17], is another benefit of SOM over other muscle synergy extraction methods [6]–[10]. Foremost, the unsupervised, self-organizing structure of the SOM is an important feature of the SOM algorithm [20]. SOM generates classes of data automatically, consequently allowing discovery of subcategories of data, and making it suitable for exploratory analysis [11], [12], [14] or discovery of new patterns, perhaps justifying poorer goodness of fit obtained for the back muscles, and suggest that these muscles exhibit more uniform direction-dependent responses and should be modeled accordingly.

V. Conclusion

This study demonstrated the SOM-based analysis of postural synergies of trunk muscles during direction-dependent perturbed sitting. Complex neuromuscular synergies were visualized and compared by encoding large EMG datasets on a single map and quantitative models of each muscle were produced. The results obtained using SOM analysis are consistent with findings obtained by Masani *et al.* [4] and other studies [5], [21] therefore adding to the validity of the SOM visualization of postural synergies. Although computational methods and SOM analysis have not yet demonstrated their full potential [20], the presented method was capable of encoding, qualitatively comparing, and assessing variability of direction-dependent postural muscle synergies during sitting perturbations. The SOM-based analysis has revealed insights into mechanisms of trunk muscles during sitting perturbations, and can be used as a reverse engineering method for visualization of complex neuromuscular systems at a glance. The benefit of SOM-based analysis is the visualization, which has produced a way for summarizing and comparing postural synergies, despite of their complexity. Future applications will concentrate on encoding larger input sets with temporal information, including a larger selection of muscles, as well as a range of perturbation magnitudes. Comparisons to patient data and individual responses could provide a postural synergy classification method which can be clinically significant for trunk assessment and rehabilitation.

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