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MODULATION OF ANTICIPATORY POSTURAL ACTIVITY FOR MULTIPLE CONDITIONS OF A WHOLE-BODY POINTING TASK

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Abstract—This is a study on associated postural activities during the anticipatory segments of a multijoint movement. Several previous studies have shown that they are task dependant. The previous studies, however, have mostly been limited in demonstrating the presence of modulation for one task condition, that is, one aspect such as the distance of the target or the direction of reaching. Real-life activities like whole-body pointing, however, can vary in several ways. How specific is the adaptation of the postural activities for the diverse possibilities of a whole-body pointing task? We used a classification paradigm to answer this question. We examined the anticipatory postural electromyograms for four different types of whole-body pointing tasks. The presence of task-dependent modulations in these signals was probed by performing four-way classification tests using a support vector machine (SVM). The SVM was able to achieve significantly higher than chance performance in correctly predicting the movements at hand (Chance performance 25%). Using only anticipatory postural muscle activity, the correct movement at hand was predicted with a mean rate of 62%. Because this is 37% above chance performance, it suggests the presence of postural modulation for diverse conditions. The anticipatory activities consisted of both activations and deactivations. Movement prediction with the use of the activating muscles was significantly better than that obtained with the deactivating muscles. This suggests that more specific modulations for the movement at hand take place through activation, whereas the deactivation is more general. The study introduces a new method for investigating adaptations in motor control. It also sheds new light on the quantity and quality of information available in the feedforward segments of a voluntary multijoint motor activity. © 2012 IBRO. Published by Elsevier Ltd. All rights reserved.

Key words: motor control, support vector machines, EMG, anticipatory postural activities, anticipatory activation, anticipatory deactivation.

Postural adjustments accompany any oriented movement in which there is a displacement of a focal module such as an arm. They are largely thought to be involved in the maintenance of equilibrium and to compensate for shifts in the center of mass due to limb movement (Gahéry and Massion, 1981; Massion, 1992; Cordo and Gurfinkel, 2004). Anticipatory postural adjustments (APAs) take place before the movement is observed. They are feedforward in nature and therefore offer insights into the neural commands that initiate and control movement without the benefit of feedback sensory signals that might correct the movement. Feedback due to postural disturbances can take place through the somatosensorial, visual, or auditory systems (Horak and Macpherson, 1996; Nashner, 1977; Ting and Macpherson, 2004; Fautrelle et al., 2010b). In this study, we investigate the collective modulation of electromyographic (EMG) activities in the anticipatory feedforward activities of several postural muscles during a whole-body reaching task. How discriminating are these muscle activities for the different conditions of whole-body pointing? We present, in particular, machine learning as an innovative method that can be used to address this question, that is, study the adaptation of signals involved in complex movement planning and execution. In this introduction, we will first have a brief presentation of previous studies on the tuning of anticipatory postural EMG activities followed by a section on the potential contributions that machine learning might make to the field.

Several investigators have now found APAs to be tuned to the requirements of the voluntary activity to be performed. For example, Tyler and Karst (2004) found that APA onset occurred progressively earlier as the target distance was increased during a reaching task. Bouisset et al. (2000) had found that the amplitude and duration of the APAs showed a linear relationship to the work performed during a shoulder flexion task. A linear relationship between the anticipative postural adjustments and the magnitude of self-initiated perturbation in a shoulder abduction task was also found by Aruin and Latash (1996). Leonard et al. (2009) demonstrated a direction tuning in the feedforward activities of various postural muscles during a pointing task.

All these studies have in common that they only investigated how APA is modified as the task variables are altered one or at most two at a time. The relationship between the EMG signal and a task variable was established with the use of linear correlation (Tyler and Karst, 2004; Bouisset et al., 2000; Aruin and Latash, 1996). Those that have examined a wider variety of activities have only conveyed a qualitative report of the differences in the

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Abbreviations: APA, anticipatory postural adjustments; BD1, near target; BD2, distant target; CD1, imposed semicircular finger trajectory pointing movement; EMG, electromyographic; KD1, straight knee pointing movement; LDA, linear discriminant analysis; SEM, standard error of the mean; SVM, support vector machine.

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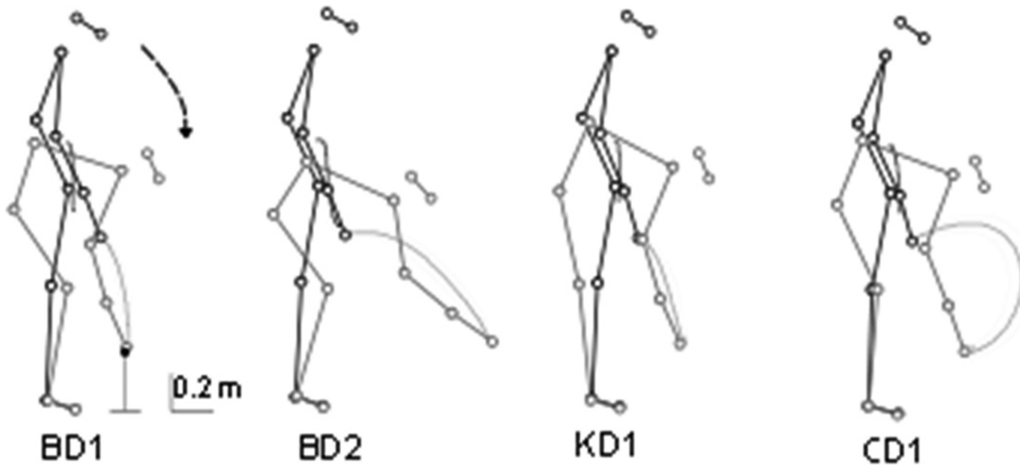

Fig. 1. Stick diagrams of whole-body pointing. Stick diagrams of the reaching tasks investigated for this study. These were an unconstrained reaching to a near target (BD1), an unconstrained reaching to a distant target (BD2), reaching with knees extended to a near target (KD1), and finally reaching with an imposed semicircular trajectory condition to near target (CD1).

anticipative muscular activity before these movements. Crenna and Frigo (1991) had reported on the anticipative postural activities before diverse movements such as walking, rising on tip toes, throwing, and standing up. No attempt was made to quantify the differences of the feedforward postural activities for these diverse requirements. Indeed, classical univariate techniques are not ideal for this task. We propose in this study the use of a classification paradigm to investigate the modulation of APAs for several variants of a multijoint movement, that is, movements that vary along several dimensions. Using the anticipatory portions of several postural muscle EMGs, we attempted to classify the type of movement at hand. A capacity to classify would indicate the presence of discriminating information in the APA. Poor classification would result from EMG activities with too much overlap.

We investigated four different variants of a whole-body pointing task—a totally unconstrained movement toward a near target (BD1), a distant target (BD2), a straight knee pointing movement (KD1), and an imposed semicircular finger trajectory pointing movement (CD1) (Fig. 1). These tasks represent various adaptations at the postural or focal level that could be called into play as the result of environmental constraints. Detailed studies on the kinematics of these movements (Berret et al., 2009; Fautrelle et al., 2010a) and the triphasic organization of their underlying EMG activities (Chiovetto et al., 2010) have been previously published. The state space in which such a classification must be performed reflects the complexity of a multijoint task. The target distance is only varied for the BD2 task. The CD1 task involves an imposed constraint on the hand path, whereas it is completely free for the other conditions. Finally, the KD1 condition is the only movement with an imposed postural constraint. Placing a point correctly in this space hence involves decisions along at least three different axes that represent different task constraints.

A Support Vector Machine (SVM) was used to carry out the four-way classification. The algorithm works by using part of the data as a training set to find the surface that best separates the various classes of data. The remaining test set is then used to verify whether the constructed surface is also able to correctly classify data that had not been used for training, that is, to detect automatically to which type of movement the feedforward EMG data belong to. The inability to correctly categorize the test data sets indicates the lack of sufficient differences between the data sets being classified, in other words, a lack of discriminative modulation and too much overlap. In the case of a four-way discrimination task, this would lead to a chance discrimination performance which is 25%. A larger separation between the data sets would lead to a greater ease and successfclassification. The capacity of SVMs to discriminate EMG data in a binary task involving whole-body reaching was reported in a previous study (Tolambiya et al., 2011).

Other than investigating the discriminatory capacities of all the postural muscle EMGs, we also investigated these capacities in two postural muscle subsets. These were the postural muscles that activated before movement onset and those that had deactivated (Chiovetto et al., 2010). A four-way classification with these two muscle subsets helped us to identify the postural groups that are better modulated for the task at hand.

EXPERIMENTAL PROCEDURES

General

Data from ten healthy male volunteers (ages 29±4 years) with no previous history of neuromuscular disease were used in this study. The experiment conformed to the declaration of Helsinki. Informed consent was obtained from all the participants according to the protocol of the local ethical committee.

Participants were required to point with both their index fingers at the extremities of a wooden dowel located in front of them. It was positioned horizontally with respect to the ground, parallel to the subjects' coronal plane, and with its center intersecting the subjects' sagittal plane. For each participant, for the BD1, KD1, and CD1 conditions, the extremities of the dowel had a vertical

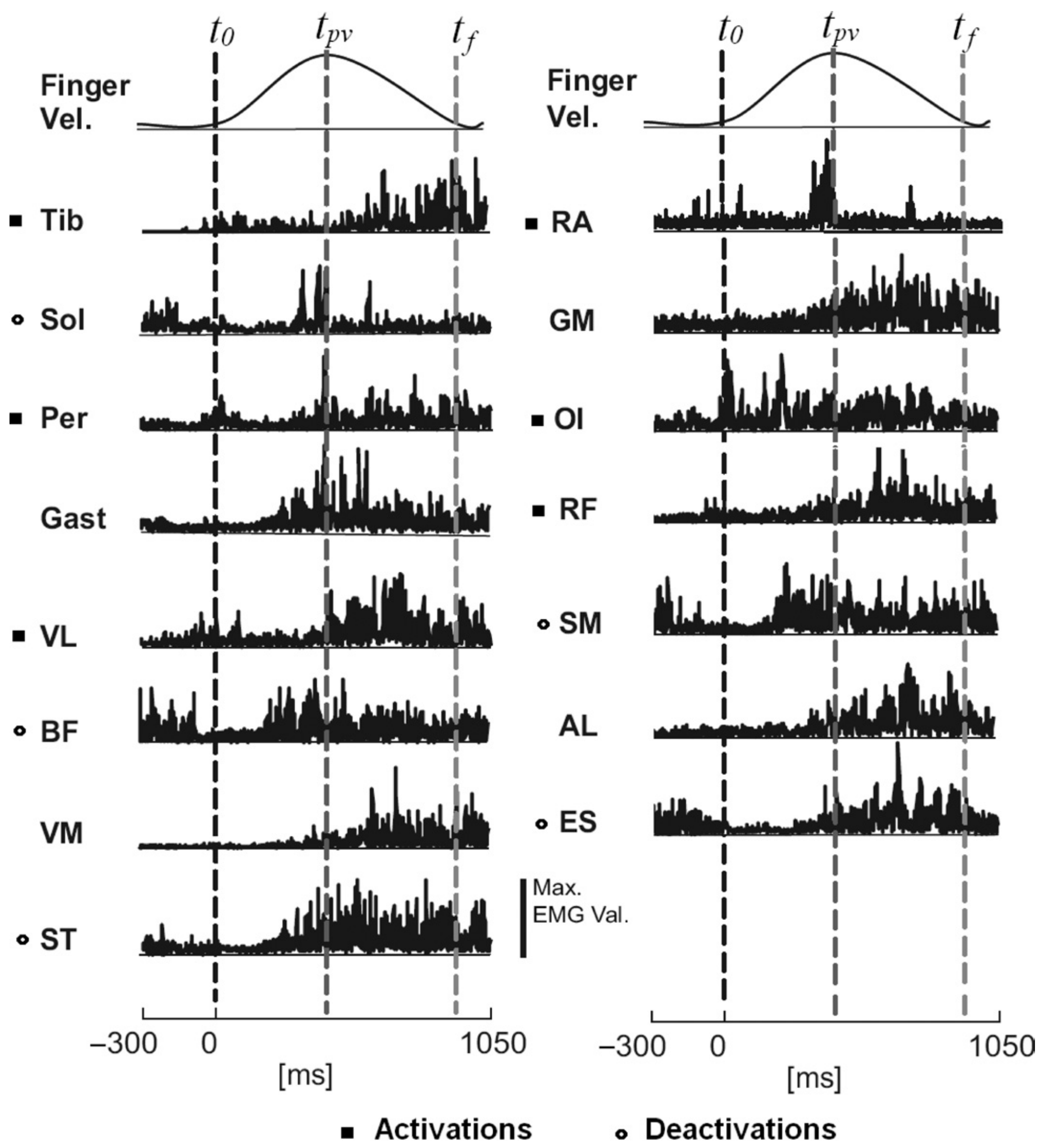

Fig. 2. EMG recordings from postural muscles during whole-body pointing task. Individual traces of the 15 postural muscles recorded during a whole-body pointing task. Muscle abbreviations are explained in the Experimental procedures section. The rectified EMG signals presented in the figure were low pass filtered at 5 Hz for the analysis. The first trace in each column represents finger velocity. Finger movement onset is indicated by t_o, the instant of its maximum velocity by t_{pv}, and the instant of finger movement termination by t_f. The segment analyzed in this study consisted of the time series between −300 ms and t_o.

distance from the ground equal to 15% of their body height. In the BD2 condition, the greater target distance corresponded to 30% of participants' height. The B movements were the only ones performed without any constraints. Postural constraints were imposed for the K condition in which subjects were instructed to point to the target without flexing the knees. Focal constraints were applied for the C conditions. Participants were requested to reach the targets with large finger path curvatures (semicircular finger trajectory). The imposed path was concave in the sagittal plane (Fig. 1). All movements were self-paced. Six repetitions were made of each kind of movement. During trial executions, kinematic and EMG data were simultaneously monitored. Body kinematics was recorded by means of a Vicon (Oxford, UK) motion capture system. Finger kinematics was used to define basic parameters in the finger pointing. These parameters have been well defined in a previous study of arm-pointing (Papaxanthis et al., 2005). Finger movement onset time t_o was defined as the instant at which the linear tangential velocity of the index fingertip exceeded 5% of its peak (Papaxanthis et al., 2005).

Collection of electromyographic data

The following 15 postural muscles were recorded on the right side of each of the 10 subjects: tibialis anterior (Tib); soleus (Sol); peroneus longus (Per); gastrocnemius (Gast); vastus lateralis (VL); vastus medialis (VM); rectus femoris (RF); semitendinosus (ST); semimembranosus (SM); biceps femoris (long head) (BF); adductor longus (AL); gluteus maximus (GM); rectus abdominis, superior portion (RA); internal oblique (OI); and erector spinae, recorded at L2 (ES) (Fig. 2). For all these muscles, electrodes were placed to minimize crosstalk from adjacent muscle contractions following Ivanenko et al. (2005) guidelines. The interval between a pair of electrodes for one recorded muscle was set to 2 cm. To check the goodness of electrodes location, the subjects were instructed on how to selectively activate each muscle (Kendall et al., 1993), and the experimenter could verify the signal response on a computer screen. During preparation, subjects' skin was shaved and cleaned with alcohol to ensure low resistance. Then the surface EMG activities were recorded at a sampling frequency of 1000 Hz (ZERO WIRE EMG system, AURION S.r.l., Milano, Italia). Each electrode was equipped with a little unit for signal processing and six tele-transmitters. The EMG signals were smoothed using a low-pass filter with a cutoff frequency at 5 Hz (Winter, 2005). Stored trials for each subject consisted of EMG activities 300 ms before movement onset and ended 100 ms after the movement termination t_f. Finger movement onset time t_o was defined as the instant at which the linear tangential velocity of the index fingertip exceeded 5% of its peak. Conversely, t_f was defined as the instant at which the index finger velocity had dropped to 5% of its peak value. These parameters have been well defined in a previous study of arm-pointing (Papaxanthis et al., 2005). The EMG segments used in this study corresponded to the segments between (t_o-300) and t_o. This segment was normalized to 50 points.

Using the same data set that is under investigation in this study, Chiovetto et al. (2010) had reported that several of these muscles underwent anticipative modifications before movement onset. Some of the alterations involved deactivations, whereas others involved activation. An activation or deactivation onset had been determined from the full-wave rectified EMG (rEMG) that had been recorded during the reaching movements. Anticipative activation activity was noted when the rEMG amplitude exceeded its mean level (computed between -300 and -100 ms before movement onset) plus two standard deviations (in the case of activation) or decreased below the mean level minus one standard deviation (for deactivation) for at least 30 ms. For activations, two standard deviations instead of one were chosen to avoid confusing actual muscle activations with noise and slight changes of the tonic activity level (Stapley et al., 1999). Using these criteria, the muscles that underwent anticipative activation were Tib, Per, VL, RF, RA, and OI. Anticipative deactivation had been observed in the Sol, BF, ST, ES, and SM (Fig. 2).

Four-way classification

A four-way classification task was carried out using the SVM. In the section Support vector machines, we describe how SVMs can be used to carry out a multiclassification. This is followed in section Linear discriminant analysis by a brief description of linear discriminant analysis, which is an older more classic classification algorithm. The manner in which the input vectors for the classification were prepared is described in section Construction of the input vectors, and the data sampling for the training and testing of the machine learning algorithms is described in Data sampling and testing section. The efficiency of a multiclassification is usually evaluated using a Kappa coefficient (κ). We provide a brief description of this coefficient in section The κ coefficient. When necessary the significance of each four-way classification was also tested using a χ^2 statistic with the required Bonferroni correction.

Support vector machines. SVMs are powerful methods for solving classification problems on large data sets. In a binary classification task, they aim to find an optimal separating hyperplane between the data sets by first transforming the data into a higher dimensional space by means of a kernel function. This permits the construction of a linear hyperplane between the two classes in feature space. Thus, although it uses linear learning methods, it is in effect a nonlinear classifier. Support vector machines were first developed by Vapnik and coworkers in the early 1990s. A complete formulation of Support Vector Machines can be found in a number of publications (Vapnik, 1995, 1998; Cortes and Vapnik, 1995; Theodoridis and Koutroumbas, 2003). In particular, a full description of the SVM algorithm in a study on EMG classification was published by Tolambiya et al. (2011).

For the multiclassification, we used one of the most widely used algorithms for multiclass SVM—the "one against all" strategy. For an M-class problem, M-SVM classifiers that separate a particular class from all the remaining classes are constructed (Rifkin and Klautau, 2004). To make the final decision, the classifier that generates the highest value from its decision function f is selected as the winner, and the corresponding class label is assigned. Because the highest value of f can belong to any one of four classes during the one against all strategy, the chance level with a random distribution would be 25%. Multiclass machine learning techniques are now being increasingly applied in the field of Neuroscience. Several of these techniques involve strategies similar to the one being applied here for picking the "winner" class, and chance levels were placed at 1/M, where M is the number of categories (Hohne et al., 2011; Xu et al., 2011; Sitaram et al., 2011). After having tested several kernel functions, the linear function was chosen as the most efficient for the task. Each SVM was created using Matlab and run on a PC. The same SVM program had been employed in several previous investigations (Tolambiya and Kalra, 2009; Tolambiya et al., 2010, 2011).

Linear discriminant analysis. Linear discriminant analysis (LDA) invented by Fisher (1936) is a technique that uses a linear combination of features to create a separating hyperplane between multivariate data. Unlike the SVM, no kernel is used to project the data to a higher dimensional space. As a technique that is older than SVM, several complete descriptions may be found on the algorithm (Manly, 1992; Duda et al., 2000; McLachlan, 2004). The LDA algorithm was implemented using the function "classify" available in Matlab. The diaglinear option was used to avoid restrictions on the structure of the covariance matrix that was used during the computation.

Construction of the input vectors. The construction of the input vectors for the SVM depended on the comparison at hand. The anticipatory EMG data from each muscle constituted a vector of 50 elements. A comparison using n muscles was therefore done using an input vector of size (nx50), where the input vectors of the muscles were linked together from end to end. This manner of constructing the input vectors for a classification of EMG data has already been described in previous publications on the use of the kernel method for classifying EMG data (Nair et al., 2010; Tolambiya et al., 2011). The specific input vector constructed depended on the question at hand. In some cases, we were investigating the predictive capacities of the anticipatory segments of all the postural muscle. We called this the full anticipatory postural vector. In other cases, we only used the anticipatory segments of the activating or deactivating muscles to construct in the manner described earlier in the text, the activating or deactivating anticipatory postural vector. At times, it was necessary to compare the classification obtained from the anticipatory EMG segments with what could be obtained from the entire movement, that is, from (t_o-300) to t_f. We will call these vectors the entire movement postural vectors to contrast them with the anticipatory segments.

Other than the standard normalizing along the time axis that is described in the Experimental procedures section, the input vectors for the SVM were also normalized for amplitude. This normalization was carried out over each muscle for each individual so that the differences in the EMG amplitudes between individuals or muscles were not taken into account. Without such a normalization, information from individuals and muscles with EMGs of higher amplitude would dominate the classifications results. Information concerning the amplitude differences between movements for each muscle however was incorporated by carrying out the normalization for each muscle of each individual over all the conditions. The decision to incorporate this information came from our previous study that had shown amplitude to be one of the parameters that the muscles modulate for the different types of whole-body pointing (Tolambiya et al., 2011).

Data sampling and testing. For each type of movement, each subject accomplished six trials. The classification tasks were carried out using cross validation. Cross validation is a technique that examines whether the results of a statistical test generalize to an independent data set. For this technique, the data are partitioned into subsets. The training is performed on one subset, and the remaining subset is then used for testing. Multiple rounds of testing are performed with different subjects in the testing subset each time. The reported results are then averaged over all the test rounds (Dejivar and Kittler, 1982; Geisser, 1993; Kohavi, 1995). As training is started anew for each test set, the results from each test set are independent. For our study, we used five-fold cross validation, that is, for each study we divided all the subjects with their associated trials into five folds (The input vectors from two subjects in each fold). Four folds were used for training and the last fold kept for testing. At no point in these studies was the data from individuals that were used for training, used in testing. This process was repeated five times, leaving one different fold for evaluation each time. The percentage of correct classification was verified for each subject when they were in the test case. In this manner, the data from each subject were tested once.

Taking any particular type of anticipatory vector for an individual, we report the percent of predictions in each category. For example, taking all the BD1 anticipatory EMG segments from an individual, what percentage of them would be classified as a BD1, BD2, CD1, or KD1 movement? This is done for each subject when they are in the test set. The results are reported as the mean±standard error of the mean (SEM) for all 10 subjects.

The κ coefficient. The κ coefficient is a measure of the agreement between two judges concerning the label to be assigned to the data. It quantifies how well the classification had been performed by comparing the results obtained from the SVM with the correct answers (Carletta, 1996). The calculation is based on the difference between how much agreement is actually present ("observed" agreement) compared with how much agreement would be expected to be present by chance alone ("expected" agreement). This difference is standardized to lie on a -1 to 1 scale, where 1 indicates perfect agreement, 0 is exactly what would be expected by chance, and negative values indicate agreement less than chance, that is, potential systematic disagreement with correct answers. The following values of κ have been taken to indicate various levels of agreement between the automatic classifier and the correct answer. Values of $\kappa<0$ no agreement, $0<\kappa<0.2$ slight agreement, $0.21<\kappa<0.4$ fair agreement, $0.41<\kappa<0.6$ moderate agreement, $0.61<\kappa<0.8$ substantial agreement, and $0.81 < \kappa < 1.0$ almost perfect agreement. The value of κ is defined as follows:

$$\kappa = (P_o - P_e)/(1 - P_e)$$

Where P_o is the observed level of agreement between the two classifiers, and P_e is the agreement that could be expected from two individuals flipping a coin to assign a class label.

The χ^2 test. The significance of each classification was also verified using a χ^2 test. Results were judged to be significant when $P<0.05$. In the case of multiple χ^2 tests, the necessary Bonferroni corrections were made.

RESULTS

In this section, we report the results that were obtained from attempting to classify the feedforward EMG segment as coming from a BD1, BD2, KD1, or CD1 movement (Figs. 3–5). As the classification to be performed was a four-way classification, a chance performance would yield a prediction of every type of movement for 25% of the cases. The quality of a classification was also judged using the χ^2 test and the value of the κ coefficient. The figure legend indicates the type of data that had been used for the testing. The black bar in each case represents the percentage of correct responses for the class mentioned in the figure legend, whereas the hatched bars indicated erroneous predictions in the remaining three categories. We will first report the results from attempting a movement prediction using the full anticipatory postural vector. This will first be done with an SVM. In the same section, we will also report the results obtained using the LDA technique. This will allow for a comparison of classification accuracies using two different algorithms. Finally, we will report the results obtained by using the SVM to classify activating or deactivating anticipatory postural vectors.

Movement prediction using the full anticipatory postural vector

In Fig. 3, we display the success obtained by using the full anticipatory postural vectors to predict the movement at hand. The SVM was asked to classify the input vector as belonging to a BD1, CD1, KD1, or BD2 movement. Fig. 3a–d display the percentage of correct and erroneous predictions made when using the BD1, CD1, KD1, or BD2 full anticipatory postural vectors, respectively. The dark bars represent the percentage of correct answers made for each type of feedforward EMG segment, whereas the hatched bars represent wrong answers. The figure shows a higher than chance performance for each type of movement classification. A χ^2 comparison was carried out to determine whether the distributions were significantly different from a random one. It was found to be significant in each case ($P<0.01$, χ^2 test with Bonferroni correction). The total mean classification success was 62±3% (mean±SEM) or on average 37% above chance. The κ score for the classification was 0.5. This reflects moderate agreement between the automatic classifier and the correct answer. Our results indicate that some information for these multiple conditions is present in the feedforward postural adaptations of these whole-body pointing movements.

Although the categorization success above chance levels in the case of each type of movement suggests some measure of multidimensional modulation, errors were also made in each case. Were these due to overlap in the feedforward activities of each type of movement or due to shortcomings in the SVM classification algorithm? To provide some answers to this question, we carried out a four-way classification using the entire movement postural vectors, that is, postural EMGs recorded from the full pointing movement. The four-way classification improved to 75±3% or 50% above chance. The κ score in this case was 0.65 indicating substantial agreement between the algorithm and the correct answer. This result with the entire movement postural vectors supports the conclusion that any shortcoming in the classification using the anticipatory segments was, in fact, partly due to their overlap in different conditions.

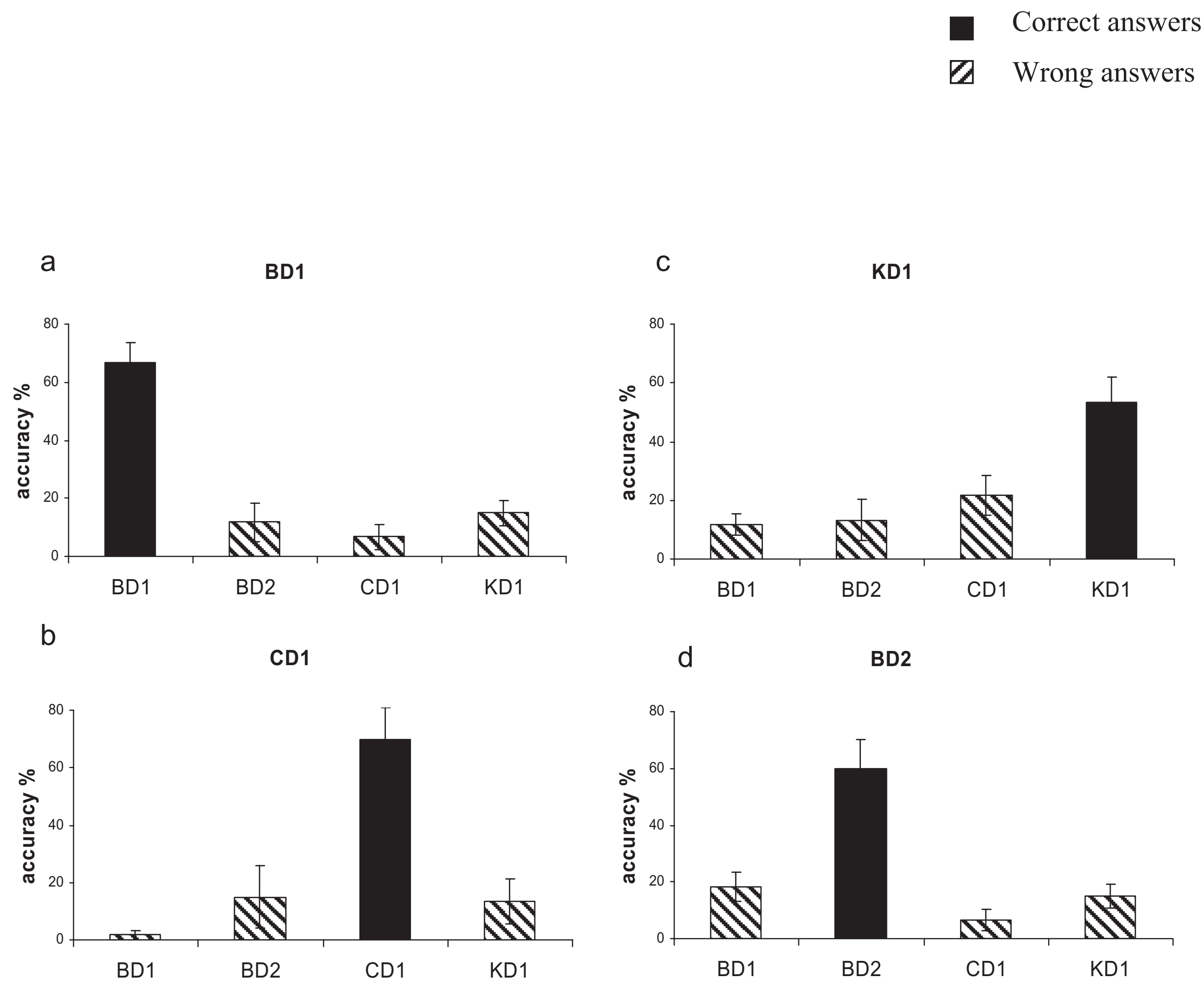

Fig. 3. Prediction by SVM of movement at hand by using the anticipatory EMG data from all recorded postural muscles. Prediction of movement at hand by using the anticipatory EMG data from all 15 recorded postural muscles, that is, the full anticipatory postural vectors of (a) BD1, (b) CD1, (c) KD1, and (d) BD2 movements. In each case, the figure shows the percentage-wise distribution of correct (black bars) and wrong answers (hatched bars). Each bar represents the mean±SEM for the ten individuals in the study. For any particular movement, the correct prediction could only be for one category, whereas the errors made could fall into any of the three remaining classes.

A final test involved investigating the capacities of an older algorithm, the LDA for performing the same type of four-way classification. The results of this test are displayed in Fig. 4a–d. Although LDA is capable of discriminating the CD1 and BD2 movements at approximately the same level of success at the SVM, there is significantly less selectivity for the BD1 and KD1 anticipative postural vectors. The difference in the results obtained with the two algorithms was found to be significant ($P<0.01$, χ^2 test). The less efficient performance by the LDA algorithm was also reflected in its lower κ score of 0.35.

Prediction of movement conditions using the activating or deactivating anticipatory postural vectors

We next attempted to predict the movement at hand by using the activating or deactivating anticipatory postural vectors. This would then give us some insight into which muscle types or activities undergo more discriminatory modulations for the movement at hand during the open-loop segments of the EMG activities. For the activating muscles, the rectus abdominus was identified after checking the classification capacities of the individual muscles, as a muscle contributing relatively little to the classification. It was hence left out of further tests in which we compared the discriminatory capacities of the activating and deactivating muscles. This then permitted us to have an equal number of both types of muscles. Fig. 5 compares the classifications using the activating and deactivating segments. The overall mean classification obtained in the activating case was 56% or 31% above chance levels (Fig. 5a–d). In the case of the deactivating muscles, it was 33% or only 8% above chance (Fig. 5e–h). This difference between the activating and deactivating muscles was found to be significant ($P<0.01$, χ^2 test). The difference between the two muscle groups was also clearly indicated by the difference in

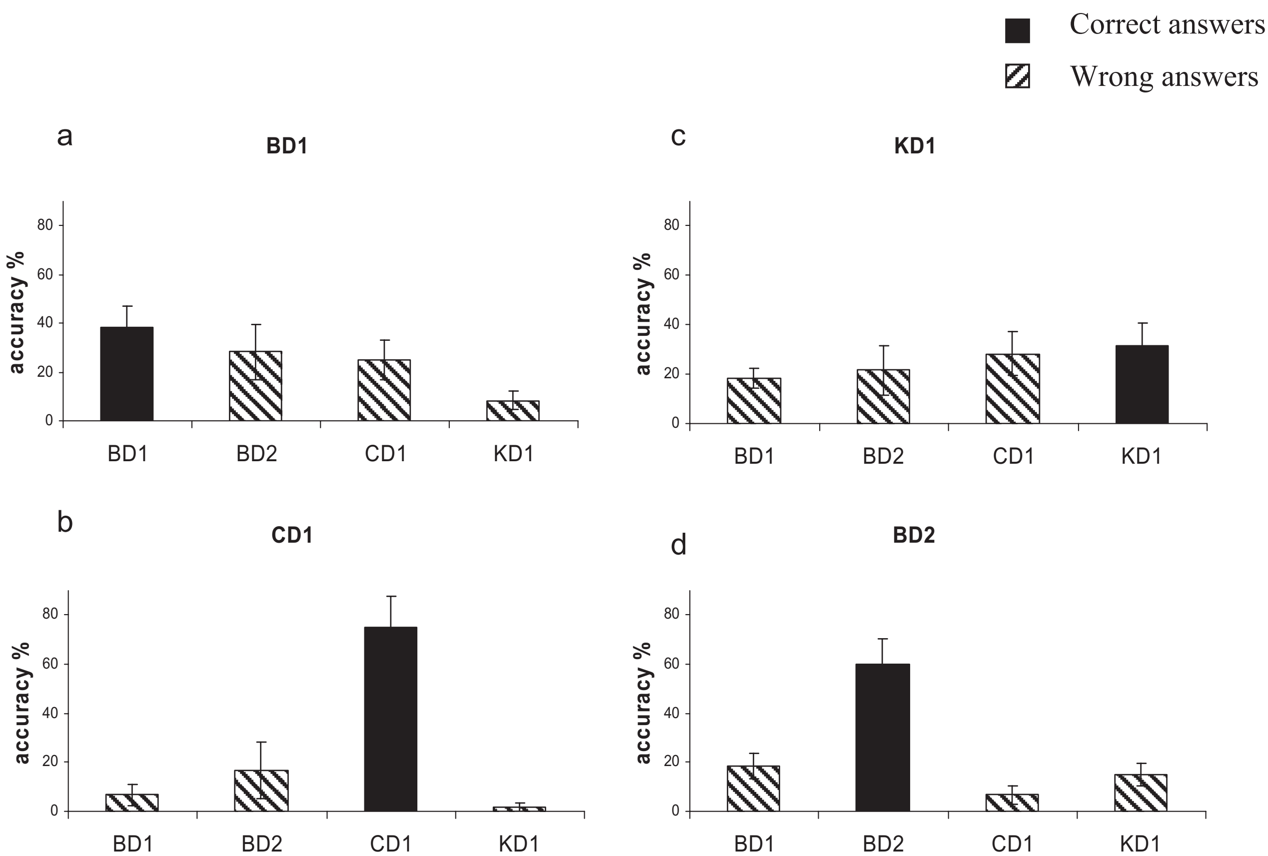

Fig. 4. Prediction by LDA of movement at hand by using the anticipatory EMG data from all recorded postural muscles. Prediction of movement at hand by using the anticipatory EMG data from all 15 recorded postural muscles, that is, the full anticipatory postural vectors of (a) BD1, (b) CD1, (c) KD1, and (d) BD2 movements. In each case, the figure shows the percentage-wise distribution of correct (black bars) and wrong answers (hatched bars). Each bar represents the mean$\pm$SEM for the ten individuals in the study. For any particular movement, the correct prediction could only be for one category, whereas the errors made could fall into any of the three remaining classes.

their κ scores. It was 0.1 indicating slight agreement in the case of the deactivating muscles and 0.41 indicating fair agreement in the case of the activating muscles.

It should be clearly noted that the differences in prediction by the activating and deactivating feedforward postural vectors were not due to lower EMG amplitudes in the latter. The normalization procedures that had been undertaken had ensured that the amplitude difference between muscles had been eliminated. Still present however was the amplitude differences of each type of movement for any given muscle.

Unlike the BD1, BD2, and CD1 conditions where there was clearly a better performance when using the activating EMG segments, such a distinction was not observed for the KD1 group. The performance was relatively poor using both subgroups indicating that in the KD1 case, the category preferences observed in Fig. 3 could only be obtained by combining the information present in the activating and deactivating subgroups.

DISCUSSION

The classification paradigm in motor control studies

In this study, we used machine learning techniques to gain insights into the quantity and quality of information available in the feedforward segments of a multijoint movement, namely whole-body pointing. As a task that integrates equilibrium as well as oriented aspects of movement, it is representative of the sort of movements commonly used in daily life. Although the study of complex movements can yield much insight concerning motor control (Cordo and Gurfinkel, 2004), one of the obstacles to using this approach is the analysis of data from such studies. In our study, these refer not only to physiological variables, in this case 15 EMGs, but also to several task variables—namely, focal and equilibrium constraints. Based on environmental obstacles, whole-body pointing tasks can vary in the hand trajectories used for reaching, the manner in which the knees are held, and the distance to which one reaches. How well does the motor system plan for these multiple constraints?

We used a classification paradigm to demonstrate the presence of postural muscle adaptation for these diverse task constraints. A machine learning algorithm that was correctly able to classify EMGs as belonging to BD1, CD1, BD2, or KD1 movements was taken as evidence of a four-way modulation. Currently used univariate regression techniques are unable to accomplish this. Classical multivariate regression techniques are

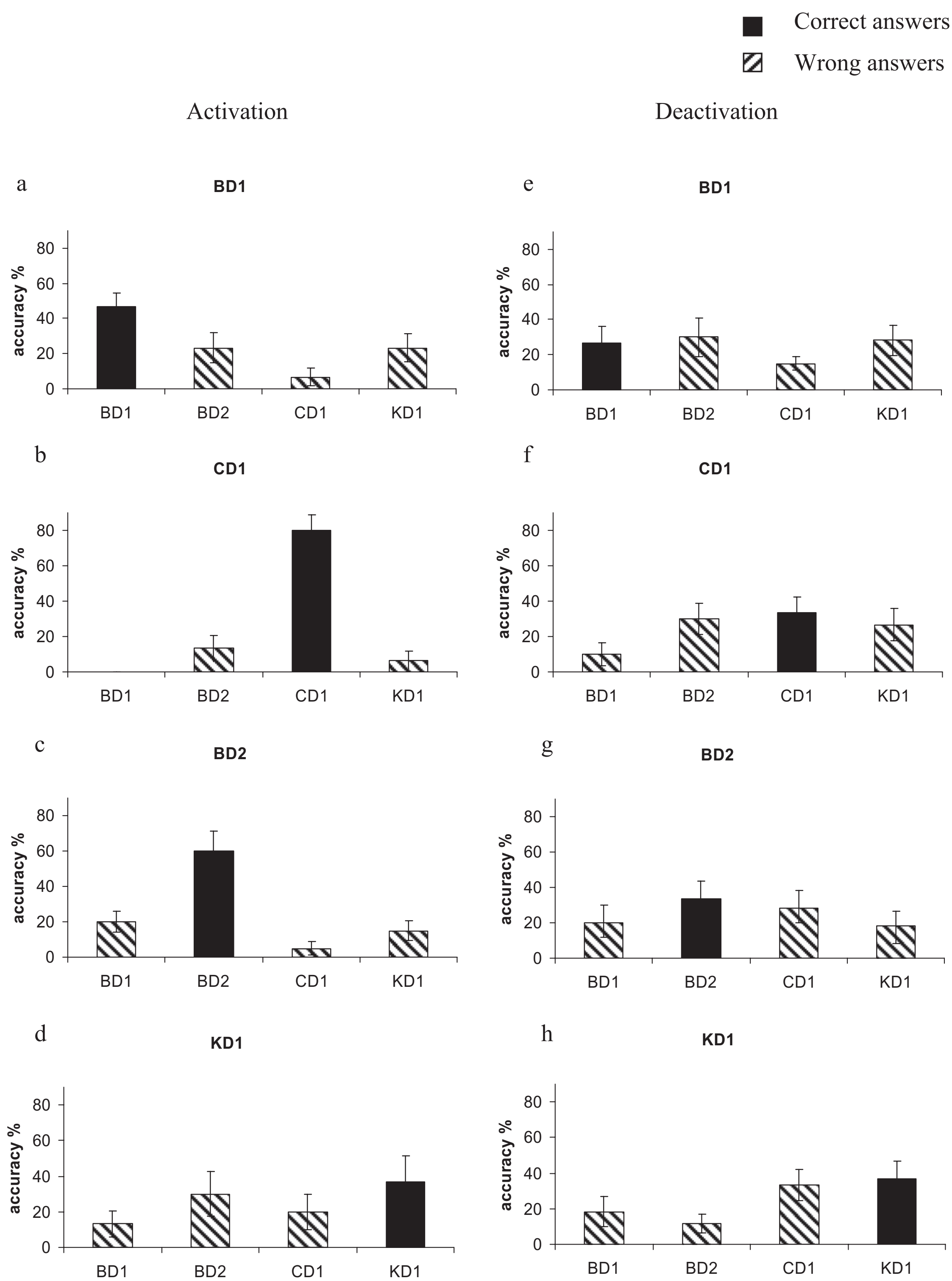

Fig. 5. Prediction by SVM of movement condition by activating vs. deactivating anticipatory EMG data. Prediction of movement condition by using the anticipatory postural EMG data of activating (a–d) and deactivating (e–h) muscles. The anticipatory postural EMG data had been used to predict whether the recording had come from a BD1, BD2, CD1, or KD1 movement. In each case, the figure shows the percentage-wise distribution of correct (black bars) and wrong answers (hatched bars). Each bar represents the mean ± SEM for the ten individuals in the study. For any particular movement, the correct prediction could only be for one category, whereas the errors made could fall into any of the three remaining classes. The distribution of responses in the activating case was found to be significantly different from those in the deactivating case ($P<0.01$, $\chi 2$ test).

linear and require that the data be normally distributed (Howell, 1992; Wonnacott and Wonnacott, 1990). These two conditions may be extremely difficult to fulfill in a situation with multiple motor constraints. Another advantage to using the classification paradigm is that it preempts the need for defining particular EMG features if this knowledge is not explicitly required. By permitting the use of the entire EMG segment, arbitrary definitions of features such as EMG onset times can be avoided. The classification paradigm has already seen limited applications in the field of neural encoding (Ghazanfar et al., 2000; Thomas et al., 2000). For obvious reasons, they also represent important steps in the field of brain machine interface (Nicolelis and Lebedev 2009).

The classification paradigm algorithm used in this study was the SVM. This technique, which is a type of kernel method, was chosen over other machine learning techniques, as previous studies have demonstrated their higher classification capacities over techniques such as neural networks and linear discriminant analysis when analyzing EMGs (Chan et al., 2002; Begg and Kamruzzaman, 2005; Nair et al., 2010). The previous studies, however, were carried out on binary classifications tasks. Our results with LDA in this study show that the earlier conclusions with the algorithm in question can also be extended to the multiclassification situation.

Modulation for multiple conditions in postural anticipatory adaptation

Feedforward segments in an EMG are interesting due to the insights they offer concerning the open-loop aspects of movement control, that is, aspects of movement control that are not rectified based on feedback and error messages. Movement execution during these phases must therefore depend on a combination of hard-wired elements in motor control and prior motor learning. This has been referred to as the internal model of movement planning (Jordan and Rumelhart, 1992; Miall et al, 1993; Wolpert et al, 1995; Saltzman, 1979; Hollerbach 1990). Previous research has demonstrated that feedforward postural adaptations are tuned to the particular demands of the task at hand. These previous studies, however, only examined cases in which the task demands were altered along one dimension (Leonard et al, 2009; Tyler and Karst 2004; Bouisset et al., 2000; Aruin and Latash 1996). In these studies, careful changes in a task parameter allowed for a description of how the body then adjusted itself for these changes. In other words, they traced a stimulus response curve for a particular task parameter. Our daily tasks, however, require an adaptation to several constraints. How different is the whole-body pointing internal model for distance, hand trajectory, and constraints of the knee? Perhaps the internal model for these variants of whole-body pointing is quite general, and feedback is an important part of the specifications in muscular activation patterns. We attempted to gain insight into this question by probing whether a classification algorithm was able to distinguish when presented with four possible choices, whether the feedforward postural EMGs belonged to a BD1, BD2, KD1, or CD1 movement. Too many features in common for these EMGs would have led to poor classification or in other words, a chance level classification of 25% for each type of movement. Our result of a mean classification that is 37% above chance suggests that there is some multidimensional modulation in the open-loop activities of postural adaptations. These adaptations would then help with the maintenance of equilibrium in the movement and is also thought by some to help in actively positioning the hand close to the target (Pozzo et al, 2002, Kaminski and Simpkins 2001).

Neuronal activity in the premotor and motor cortex before movement is interesting in the context of discussions concerning the internal model for movement. Neurons in the reach system of the premotor and motor cortex have been found to fire before movement onset. This activity has been found to be tuned to the direction of movement (Wise 1985), movement extent (Fu et al, 1993; Messier and Kalaska, 2000), and hand path curvature (Hocherman and Wise, 1991). Adaptations in these studies have only been investigated along one dimension at a time. Our results indicating multiple adaptation at the effector level (muscles) suggest that the same may take place at the cortical level. The classification paradigm provides a means for investigating this question.

A classification performance of 37% above chance still means that several errors were made as we attempted to predict the source of the feedforward EMG segments. Was this due to shortcomings in the classification algorithm? Or is there a significant overlap in the activation patterns of these 15 postural muscles specified by the internal model? Some insight into this can be attempted by performing a four-way classification with the entire movement postural vectors. The substantial improvement that was obtained in this case indicates that the SVM is able to classify better in the presence of more information and that the shortcomings in the classification obtained when using the feedforward segments are indeed due to the limits in the information content of the feedforward EMG. In other words, the results suggest that there is a fair amount of overlap in the early feedforward segments of the postural adaptations in a whole-body pointing task. This is not altogether unexpected. Many of the stability and planning requirements may be common for the early parts of all the different classes of whole-body movements.

Modulation for multiple conditions in activating or deactivating postural muscles

Electromyographic activities in the anticipatory segments of postural muscle activities involve both activating and deactivating patterns. The former refers to a phasic increase in the activity of a muscle, whereas the latter is a decrease in its activity. The former is related to the muscular contraction that is necessary for the movement, whereas the latter is thought to be a decrease in activity in preparation for movement (Agostino et al., 1992; Aoki et al., 1989; Berardelli et al., 1996; Berret et al., 2008). Indeed, inhibition in the antagonist muscle is the first activity that is observed before the commencement of movement (Hufschmidt and Hufschmidt, 1954).

Are both excitatory and inhibitory activities of the neuromuscular system equally modulated in the open-loop phases of movement control? We probed this question by comparing the prediction capacities using the activating or deactivating anticipatory postural vectors. Some measure of success was observed in the four-way predictions using the activating muscles. The mean categorization success using the activating anticipatory postural vectors from the normal (BD1), distant (BD2), or hand curved trajectories (CD1) was 31% above chance, whereas it was only 8% above chance for the deactivating muscles. This difference as explained in the Result section was not due to higher EMG amplitudes in the activating muscles, as the EMG maximum amplitudes were normalized to be equal for each muscle. Note that for each muscle, information concerning amplitude differences between each type of movement was present. Previous work has shown that the latter variable is pertinent to the classification of the different variants of whole-body pointing (Tolambiya et al., 2011). Our results suggest that movement planning for whole-body pointing takes place to a greater extent via the activating muscles. In comparison, a poor classification with feedforward inhibitory activities suggests that they are more general and share many features between the several variants of whole-body pointing. This may be because deactivation is usually associated with the disruption of an erect posture, which may be common to several movements.

It is interesting to compare the contrast we observed between activating and deactivating muscles with previous studies on the subject. First of all, no direct comparisons can be made as previously used techniques such as correlation analyses have not permitted an analysis of a population adaptation to multiple task requirements. Nevertheless, it is interesting to observe what previous studies have shown concerning the comparative modulation of these two types of activity in postural muscles. Although several studies exist on this topic and arm movements (Hallet et al., 1975; Berardelli et al., 1996; Hoffman and Strick, 1990; Berret et al., 2008), we will restrict ourselves to postural muscles for the sake of simplicity. Aruin and Latash (1996) report a positive correlation between anticipative activation in postural muscles before a task that involves arm extension. They did not, however, find this task-dependant correlation in the anticipatory inhibitions of the dorsal postural muscles. Some researchers have, however, demonstrated a correlation between the anticipatory inhibitory activities of an antagonist and the activation of the agonist (Cheron et al., 1997; Crenna and Frigo, 1991) during tasks involving postural adjustments. This would seem to imply a tuning in the anticipatory inhibitory activities of the postural muscles. There are several possible explanations for the contrast between these results and ours. The most simple might be that anticipatory deactivation is sufficient for a binary separation but not well enough tuned for a four-way task. Another possible explanation is that timing rather than amplitude was found to be the correlated variables in the last two cited studies. In contrast, amplitude rather than timing seems to be the pertinent variable for distinguishing several variants of whole-body pointing (Tolambiya et al., 2011).

CONCLUSION

This study introduces the use of classification as a means of probing the modulation of muscular activity in multijoint movements. Anticipatory postural EMGs were used to predict which one of four different variants of whole-body pointing was to be performed. The support vector machine algorithm was used to carry out the aforementioned task. An average classification success of $62\pm3\%$ (mean$\pm$SEM) or 37% above chance in this task provides an idea of the information available in the open-loop segments of motor control. The results suggest that there is some measure of population modulation for multiple conditions in the feedforward phases of whole-body pointing. A comparison was made of the classification capacities of the anticipatory activating and deactivating postural EMGs. Better prediction results using the activating muscles imply that motor planning is adapted to the various conditions to a greater extent via the activating muscles. Deactivating anticipatory postural EMGs associated with the rupture of an erect posture in whole-body pointing are more general and share more common features across several variants of the movement.

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