Tuning for Pointing Direction in Phasic Muscular Activity: Insights From Machine Learning

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Abstract

Arm movements in our daily lives have to be adjusted for several factors in response to the demands of the environment, for example, speed, direction or distance. In this study we will focus on muscular adjustment for pointing direction. Much is known about how single muscles adapt and tune for pointing direction. Movement however, is not accomplished by single muscles but by groups of muscles. The effort in data collection to ensure synchronized collection from multiple muscles reflects this reality. In this study we propose the use of Machine Learning as a method which is able to analyze the ensemble activities of multiple muscles recorded during pointing in various directions. The primary goal of the analysis was to characterize multimuscle tuning for pointing direction. By providing an index of multimuscle activity, the Machine Learning analysis brought to light several features of tuning for pointing direction. In attempting to trace tuning curves, all comparisons were done with respects to pointing in the horizontal, gravity free plane. Firstly, we demonstrated that counter to intuition, tuning for pointing in the downward direction is greater and takes place with a greater gain than for pointing in the upward direction. Secondly, we demonstrated that tuning for direction does not take place in a uniform fashion but in a modular manner in which some muscle groups during some phases of the movement play a primary role. The antigravity muscles were more finely tuned to pointing direction than the gravity muscles at all phases of movement. Of note, was their tuning during the first half of downward pointing. As the antigravity muscles were deactivated during this phase, it showed that deactivation is not an on-off function but tuned to pointing direction. Tuning was poorest in the deceleration phase of upward movement for the gravity muscles. Finally, we demonstrated that muscular activation differences scale more efficiently for pointing direction than the activation means themselves, hence suggesting that this could be a useful measure to exploit in order to reduce the quantity of information that has to be stored in motor control.

1 Introduction

There is a significant amount of research on muscular activation underlying reaching movements. Much has been written on the basic triphasic pattern of muscular activation for reaching. This refers to a firing pattern during reach which begins with a burst from the agonist muscle during the acceleration phase of the reach, followed by a burst in the antagonist muscle which serves to decelerate the arm. The third phase refers to a second burst by the agonist muscle which helps to brace the limb in its final limb. [Hallett et al., 1975, Hannaford and Stark, 1985]. Our daily activities require that our arm movements be modulated in accordance with the context in which the movement takes place. This then requires adaptations for conditions such as speed, direction and distance. Gottlieb et al described how these adaptations could be divided into speed sensitive or insensitive categories [Gottlieb et al., 1989, Corcos et al., 1989, Gottlieb et al., 1990]. The manner in which specific characteristics of this triphasic activation give rise to different ratios of acceleration versus deceleration in the pointing movement have also been described [Brown and Cooke, 1990, Cooke and Brown, 1990].

The above studies however were done on a very small number of muscles. Investigations in this field have gone on to include data coming from the simultaneous recording of several muscles. There are several reasons for this. One is conceptual – movement after all, is the result of the contraction of more than 3 or 4 muscles. The second is our ever growing capacity to collect data. As an example of investigations on pointing involving more than 5 muscles, we can look into the research from the Flanders group. especially has shown that reaching movements which are slower and multijoint may not be characterized in such a simple manner but can nevertheless be described by common waveforms from which muscular activation patterns for reaching in different directions at different speeds can be derived [Flanders, 1991, Flanders and Herrmann, 1992, Flanders et al., 1994, Flanders et al., 1996]. They showed that the EMG activity can be decomposed into two components – the tonic and the phasic. The former is primarily involved with counteracting the force of gravity and does not scale with speed while the latter is altered by movement duration. A very detailed description of the activities of 16 arm and trunk muscles during the acceleration and deceleration phases of pointing in various directions was also published by [Mira et al., 2021].

An investigation on the role of gravity finds a natural place in any study involving pointing direction. Research on the phasic EMG component during pointing, especially with regards to gravity was conducted by Gaveau *et al.* [Gaveau et al., 2021]. They demonstrated that the existence of the negative portions of the phasic EMG are in keeping with the idea that gravity is incorporated as part of an effort minimization strategy during pointing movements. This is in contrast to a view in which movement is constructed around the need to compensate for the torques created by gravity. The use of gravity to optimize energy expenditure in movement was found to persist in aging subjects [Poirier et al., 2020]. These researchers make the case that the differences in the

activity patterns of antigravity and gravity muscles fit into the idea of movement optimization through the integration rather than compensation of gravity. The former especially turns off at the acceleration phase of downward movement and at the deceleration phase of upward movement.

The current study seeks to extend on our knowledge of muscular adaptations for pointing direction. In particular it seeks to find tuning curves which highlight major trends in muscular adaptation for pointing direction. Are the tuning curves symmetric in the upward and downward directions? Is the strategy employed for adaptation to different directions one in which uniform adjustments are made to the involved muscles and phases? Or does the nervous system have a more modular tuning strategy. By this, we mean one in which some muscle groups or phases are left relatively invariant as other modules bear the primary responsibility for muscular differentiation as a function of pointing direction.

An important point of departure in this investigation compared to previous studies will be the use of Machine Learning techniques to investigate groups of muscles or movement phases rather than single muscles or single moments in time like the time to peak or onset time. The field of Machine Learning is vast. More specifically, we used binary classification in which EMG time series from groups of muscles are automatically classified as coming from a movement of horizontal pointing or from pointing at another angle. Information on the separation of the EMGs is obtained from the classification accuracy of the Machine Learning algorithm. Poor separation in the EMGs would lead to poor classification accuracy while EMGs which are very different would lead to high accuracy. Classification is achieved through the construction of models of each category by the Machine Learning algorithm. The manner in which this is done differs from one algorithm to the other. In our case we used Linear Discriminant Analysis, an algorithm which utilizes information on the mean and variance of each category to build a representation of each category [Grimm and Yarnold, 2000, Johnson and Wichern, 2007, Izenman, 2008]. One of the reasons for choosing this algorithm is the greater ease finding the factors which are critical in classification success – what is now referred to as explainable AI [Murdoch et al., 2019, Arrieta et al., 2020]. This technique of using Machine Learning to probe the modifications of muscle groups rather than single muscles for adaptation to task constraints has been utilized before. [Tolambiya et al., 2011] demonstrated that postural muscles underwent greater changes than the focal muscles for several Whole Body Pointing tasks. Once again, using Machine Learning, the same group showed that activating rather than deactivating EMG signals during the anticipatory phase of Whole Body Pointing were able to predict which type of movement was about the occur [Tolambiya et al., 2012].

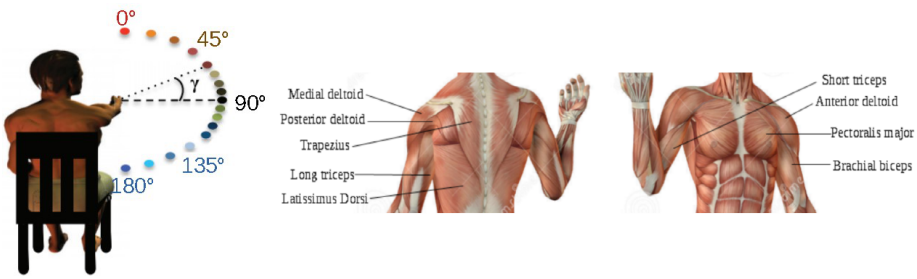


Figure 1: Illustration of the task (on the left, adapted from ©2016, Gaveau et al.) and the muscles of the shoulder from which the EMGs are recorded (on the right)

2 Method

2.1 Subject, task and recording

The data used in the current investigation comes from a previous study by [Gaveau et al., 2016]. To briefly summarize the task : adults were asked to execute a pointing task. Participants started at an initial position (shoulder elevation 90°, shoulder abduction 0°, arm completely stretched) then proceeded to rapidly point at specific directions rotating only the shoulder (see Figure 1, left). The EMGs from nine muscles of the shoulder were recorded during the pointing tasks (see Figure 1, right). The EMGs were then processed to extract the phasic part of the movement. To do so, the EMG signals were integrated from 1 and 0.5s before movement onset and from 0.5 to 1s after movement stop and averaged. The linear interpolation between those two values was used as an estimate of the tonic component which was removed from the original EMG to keep only the phasic component. Then, all the trials were uniformised to 1000 points using linear interpolation and smoothed using a moving mean with a window of 100 points.

The next step was a normalization step to prepare the input signals for the LDA algorithm. The EMG signals were normalized using a Z-score transformation. It was done separately for each individual. This reduced the variability which would be caused by inter individual differences in EMG amplitudes. It was also done separately for each muscle, hence ensuring that muscles with small EMG amplitudes were not eliminated from playing a role in classification The normalization was done over all the angles so that information concerning differences in EMG amplitudes for pointing at different angles remained available in the data.

2.2 Linear Discriminant Analysis

Linear discriminant algorithm (LDA) is a classification algorithm which tries to find the best linear hyperplane (hence the name) in the feature space to separate

different classes of objects [Johnson and Wichern, 2007]. This then allows to classify new observations depending on which side of the hyperplane they are. Traditionally, LDA was reduced to an eigenvector problem, with the objective of finding a subspace in the original data space that maximize the separability between classes along the first axis of this subspace. However, computational power allow for a more direct approach to classify new data.

To achieve this, the algorithm tries to estimate the probability distributions of the different classes, following certain assumptions about those distributions. Knowing this information, it is then possible to infer the probability of a new observation to belong to a certain class thanks to Bayes' theorem. This probability is pondered by a cost function to bias the results for particular applications if needed.

In practicality, the class $\hat{y}$ of a new observation is determined by the following equation :

$$\hat{y} = \underset{y=1,\ldots,K}{arg\,min} \sum_{k=1}^{K} \hat{P}(k|x)C(y|k) \tag{1}$$

with y and k being class numbers among the K different classes of object. $C(y|k)$ represent the cost function, *i.e.* how much is penalized the misclassification of an observation. This function can be tweaked for particular usage (*e.g.* to increase sensitivity of the algorithm at the expanse of specificity) but the general approach used here is :

$$C(y|k) = \begin{cases} 0 & \text{if } y = k \\ 1 & \text{if } y \neq k \end{cases} \tag{2}$$

Thus, Equation (1) tries to determine, for an observation x, the class k that maximizes $\hat{P}(k|x)$ as it is the probability of the observation x to belong to class k. It is determined thanks to the Bayes' theorem :

$$\hat{P}(k|x) = \frac{P(x|k)P(k)}{P(x)} \tag{3}$$

$P(k)$ is the prior probability and is determined empirically using the labels distribution from the training set. What the algorithm learn from the data are actually the likelihood distributions $P(x|k)$. In the case of LDA, those distributions are assumed to be multivariate Gaussian distributions all with the same variance matrices. Thus, the main part of the computation is to find the variance matrix and classes means. Those distribution being Gaussian distributions, $P(x|k)$ is entirely determined by the Mahalanobis distance of x in the distribution of the class k. Finally, $P(x)$ is the normalization factor calculated pooling all the estimated $P(x|k)$ distributions :

$$P(x) = \sum_{k=1}^{K} P(x|k) \tag{4}$$

Having all the elements needed, $\hat{y}$ can then be determined for any new observation using Equation (1).

2.3 Generalized Procrustes Analysis

The Generalized Procrustes Analysis (GPA) is derived from a topographic method to measure the resemblance of two shapes. This method aims to fit a shape on the other using only linear transformations (translation, scaling and rotation) then measure the remaining differences [Gower, 1975]. The GPA follows this principle but fits multiple data sets together. The main interest of this method is to objectively assess the shape resemblance between two EMG curves, as well as give the operation to go from one to another.

To do so, the matrices describing the shapes are first normalized. Then, we consider the operation to transform the matrix X of the reference shape into the matrix Y of a target shape. The best linear approximation of this transformation is obtained by singular value decomposition. The result of this decomposition then allow us to retrieve the different components of the linear transformation.

Let X and Y be the matrices describing two shapes. Each line of the matrix corresponds to a point of the shape and contains its coordinates with each row corresponding to a dimension of the considered space. First, both matrices are normalized following the equation :

$$X_0 = \frac{X - \overline{X}}{||X - \overline{X}||_F} \quad \text{and} \quad Y_0 = \frac{Y - \overline{Y}}{||Y - \overline{Y}||_F} \tag{5}$$

where $\overline{X}$ and $\overline{Y}$ are the coordinate vectors of the centroids of the shapes X and Y respectively. Additionally $||X - \overline{X}||_F$ and $||Y - \overline{Y}||_F$ are the Frobenius norm of the matrices $X - \overline{X}$ and $Y - \overline{Y}$ respectively. The next step is the singular value decomposition of the matrix :

$$X_0^* Y_0 = U \Sigma V^* \tag{6}$$

where X_0^* and V^* the complex conjugate transpose of the matrix X_0 and V. From this decomposition can be derived all the values of interest for the GPA to fit Y on X :

$$\begin{cases} \text{Rotation matrix :} & R = VU^* \\ \text{Scaling factor :} & s = Tr(\Sigma)\frac{||X-\overline{X}||_F}{||Y-\overline{Y}||_F} \\ \text{Translation matrix :} & T = \overline{X} - s\overline{Y}R \end{cases} \tag{7}$$

with $Tr(\Sigma)$ the trace of the matrix Σ. However, in this particular study, the data is one dimensional, thus, the rotation factor is reduced to $R = 1$ which corresponds to no rotation. Moreover, since the data has already been normalized using a Z-transform, all signals are already centered in 0, meaning the translation factor is essentially negligible (See Figure S1 for empirical evidence). Finally, the normalized distance between X and $sYR + T$ is :

$$d = 1 - Tr(\Sigma)^2 \tag{8}$$

For a visualization of the normalization process and get a feel for the sensitivity of the distance measure on actual data, see Figure S2.

2.4 Analysis

All analyses were performed offline using custom Matlab scripts [Mat, 2021]. The input data was constructed by concatenating the processed EMG signals of the nine muscles. This gave us one vector of 9000 points (1000 normalized time points multiplied by 9 muscles) per trial. These vectors were the samples fed to the LDA algorithms, without further feature selection. Thus, the LDA algorithms were trained on the entire EMG waveforms simultaneously. Further analyses involved focusing on certain parts of the signal. In that case, the input vectors were pruned of irrelevant information for the question asked before being fed to the LDA algorithm.

The training of the LDA algorithms was done using binary classification setups, *i.e.* an algorithm was trained to discriminate between EMGs of only two directions. In this analysis, one of the movement direction was always the horizontal plane (90°, gravity neutral, taken as reference) while the other class was any of the other angles.

In order to ensure the generalization of the results, a stratified five-fold cross-validation method was used. The data set was separated into training and testing sets using the known labels of the samples to ensure that both directions were equally represented in each training and testing set. The cross-validation approach allowed a better estimation of the efficacy of the algorithm by testing it on multiple data sets. Thus, we could compute an average accuracy of the algorithm on the testing sets.

From each trained algorithm we extracted the means of the two $P(x|k)$ distributions as well as the testing accuracy. The vector joining those two means will be referred to as the "difference vector" (the notation X°-90° signifying the vector joining the average EMG of angle X in the training set to the average EMG of the angle 90° in the training set) and its norm the "LDA distance" from now on. Therefore, the LDA distance measures the separation between the mean vectors of each class.

Since we used a relatively low number of folds for the cross-validation, statistics were obtained using non-parametric tests, namely the Wilcoxon rank sum test when comparing two conditions ; and the Friedman test to compare effects across multiple conditions.

3 Results

3.1 Collective muscular tuning for Pointing Direction

As described in the methods section, LDA is able to utilize the combined information from multiple muscles in order to predict if pointing had taken place in the horizontal gravity free direction or at a chosen angle. Using unlabelled EMG data, the LDA algorithm was used to perform binary classsifications and automatically detect if subjects had pointed in the horizontal gravity free direction or in the direction indicated on the x axis of Figure 2. Poor classification accuracies reflect small separation between data groups while a good accuracy

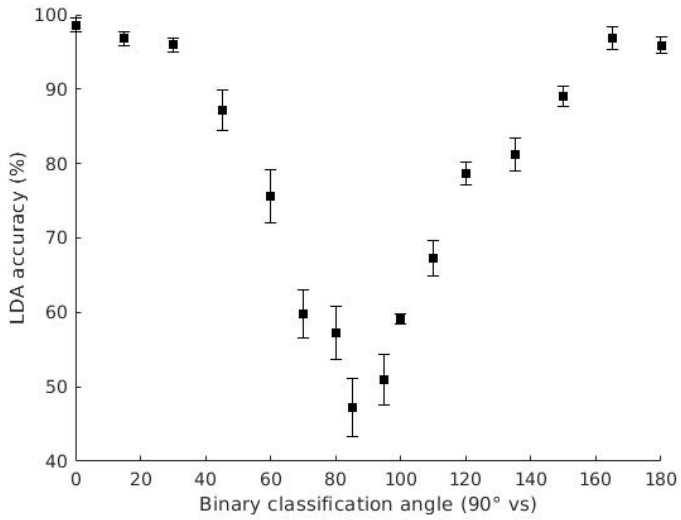


Figure 2: Accuracy of the binary classification between 90° and the other angles. Error bars indicate standard error.

is indicative of clear separation. The EMG tuning curves using this technique display adjustments which are mostly linear until approximately 60° from horizontal direction. Following this, classification accuracies took a non-linear trend. This however, may not be due to actual non-linear muscular modification but due to saturation in classification capacities. Verification as to whether this was the case, was done by further examining the model used by LDA to perform the classification.

The multivariate mean of each category is an important piece of information used to create these models. The distance between these means can also be exploited to measure muscular tuning for pointing direction. Figure 3 displays how LDA distance changes as a function of pointing direction. The figure confirms a linear trend in collective muscular tuning for pointing direction until about 60° from horizontal. However, unlike classification accuracy LDA distance is not subject to the effects of classification saturation. Muscular modification as reflected in the LDA distances continue increasing with a slightly nonlinear trend both upwards to 0° and downwards to 180°.

The LDA distance also reveals a very interesting and counter intuitive aspect of muscular tuning for pointing direction. It shows that adjustments for downward pointing are bigger than those for upward pointing when compared to pointing in the horizontal direction. The LDA distance for pointing at 0° upward was found to be significantly lower than the distance for pointing at 180° downward (Wilcoxon rank sum $W = 40$, $p = 0,0079$). Differences in the gain for tuning were also revealed by fitting a regression line for both sides of the EMG tuning curves. They revealed a value of 0.2839 ($R^2 = 0.9852$) for

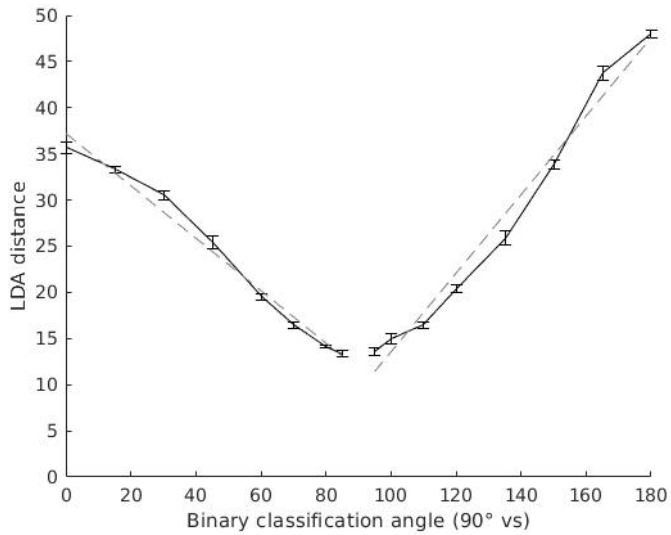
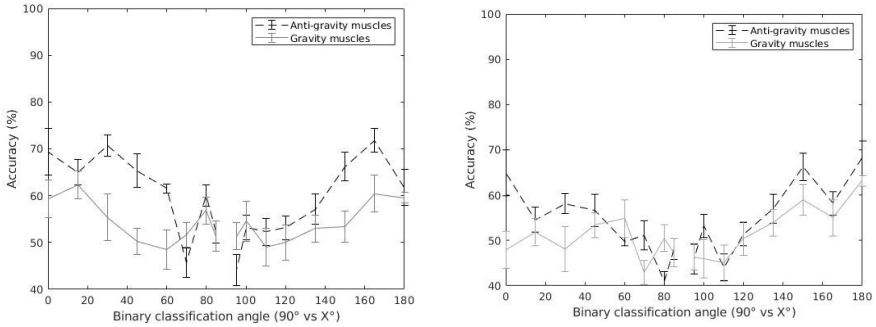


Figure 3: Accuracy of the binary classification between 90° and the other angles. Error bars indicate standard error. Gray dashed lines show the performed linear regressions.

upward pointing and 0.4257 ($R^2 = 0.9795$) for downward movements indicating once again that counter to intuition, movements were more finely tuned in the downward direction.

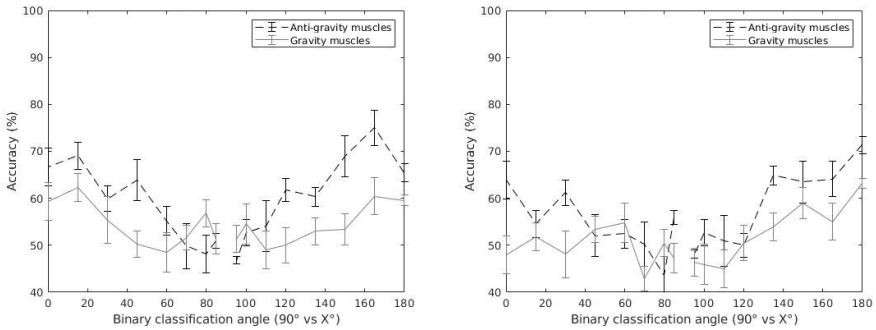
3.2 Modular EMG tuning for pointing direction

As the system adapts for tuning in various directions, what is the nature of this tuning? Does the entire system undergo modifications to bring the arm to a new direction i.e. a uniform tuning? Or is adaptation for pointing to the new direction primarily accomplished by a few muscles at particular moments i.e. modular tuning. In order to answer this question we examined the classification capacities of different groups of muscle at different moments. The muscle groups studied were the gravity and antigravity muscles. A finer grained analysis of modularity was obtained by examining the acceleration and deceleration halves of pointing for the aforementioned muscle groups. The gravity muscles in this study are the posterior deltoid, the latissimus dorsi and long triceps. The antigravity muscles are the anterior deltoid, medial deltoid, trapezius and biceps brachii. Figure 4 below demonstrates the classification accuracy of these muscle groupings. Taking the case of the acceleration phase (Figure 4.a) it can be seen that the antigravity muscles achieved a significantly superior performance at predicting pointing direction when compared to the gravity muscles (Friedman test, $\chi^2(1) = 13.32$, $p = 0.0003$).



(a) Acceleration phase (b) Decceleration phase

Figure 4: Classification accuracy using only the EMGs from either gravity or antigravity muscles during the acceleration phase of the movement (a) or the deceleration phase (b).



(a) Acceleration phase (b) Decceleration phase

Figure 5: Classification accuracy using only the EMGs from either gravity or antigravity muscles. Contrary to Figure 4, the biceps brachii is not included in the antigravity muscles here.

(a) Acceleration phase

	Upward movements	Downward movements
Antigravity muscles	0.2089 ($R^2 = 0.85$)	0.2425 ($R^2 = 0.76$)
Gravity muscles	0.09945 ($R^2 = 0.41$)	0.1040 ($R^2 = 0.60$)

(b) Deceleration phase

	Upward movements	Downward movements
Antigravity muscles	0.2030 ($R^2 = 0.51$)	0.2407 ($R^2 = 0.85$)
Gravity muscles	0.01788 ($R^2 = 0.02$)	0.1990 ($R^2 = 0.88$)

Table 1: Slope coefficients of the linear regressions for the classification accuracy of the different muscle groups.

As there were 4 antigravity muscles but only 3 gravity muscles, it was necessary to verify that the higher classification accuracies observed in the antigravity muscles was not due to more information. In order to do this we repeated the classification tests after having removed the biceps brachii from the group of antigravity muscles (this muscle showed the poorest tuning among the group of antigravity muscles, see Figure 9). Figure 5 demonstrates the results of this classification. The prediction capacities of the antigravity muscles remain significantly higher than those of the gravity muscles (Friedman test, $\chi^2(1) = 11.88$, $p = 0.006$). Complementary information on the nature of directional tuning in these two groups of muscles was obtained by fitting regression lines to the curves on either side of 90°. Table 1.a shows the values for the slopes of these lines for each group of muscles for upward and downward pointing. They reveal higher slopes for the antigravity muscles while pointing in the upward as well as downward directions. Of note, is the high slope of the antigravity muscles during the acceleration phase of downward movement. As this is a phase during which the antigravity muscles are deactivated, it indicates that the deactivation in these muscles is not an all-or-nothing function, but one which is graduated as a function of pointing direction.

The poorest tuning was seen in the deceleration phase of the gravity muscles for upward movement. The low values of the slope here demonstrate very little adjustment by this group of muscles for pointing angles.

3.3 Scaling of EMGs for pointing direction and the Procrustes Distance

In this section we will continue looking at the difference vector between the representations of each EMG category. Having found that the antigravity muscles, the anterior deltoid, the medial deltoid and the trapezius play a very important role in tuning for pointing direction, we will focus on these three muscles to characterize the tuning for pointing direction. Figure 6 displays the difference vectors obtained from subtracting the LDA EMG representations at 0°, 35°, 135° and 180° from those at the gravity free horizontal direction (see Methods

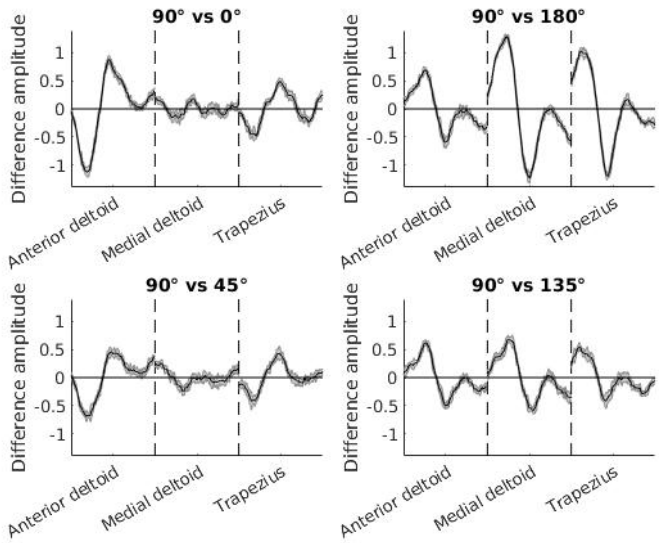


Figure 6: Visualization of the LDA_{diff} vector for the antigravity muscle group for different angles compared the gravity neutral angle.

section for explanation of LDA_{diff}). In studying these diagrams, we will comment on some aspects of these comparisons in a qualitative manner while other observations will be quantified.

First of all, qualitatively, many segments of the EMG differences in the upward direction appear to be the inverted versions of those in the downward direction for equivalent angular distances from 90˚.

Secondly, taking EMGs for pointing in the same direction i.e. upward or downward, the difference EMGs at smaller angular separations appear to be scaled versions of those at bigger angular separations. By this we mean that the LDA_{diff} at 35˚ appears similar to the LDA_{diff} at 0˚ while this variable at 135˚ appears similar to the one at 180˚. A quantification of this scaling was carried out using the Procrustes Distance ie We attempted to quantify how well the LDA_{diff} for the upward angles could be obtained for the LDA_{diff} at 0˚, while those for the downward angles were compared to the LDA_{diff} at 180˚. As explained in the Methods section, the Procrustes distance could range from 0 to 1. A value of 0 indicates very good scaling and 1 indicates very poor scaling. How would the scaling with these LDA_{diff} values compare with the simpler scaling of the mean of each category? Perhaps the mean EMG representations for all the downward pointing angles would scale well using the representation at 180˚, while the mean EMG representations for upward pointing would scale well with the mean representation at 0˚. Figure 7 displays the results of this analysis for the anterior deltoid, the medial deltoid and trapezius muscle. How would the scaling with these LDA_{diff} values compare with the simpler scaling

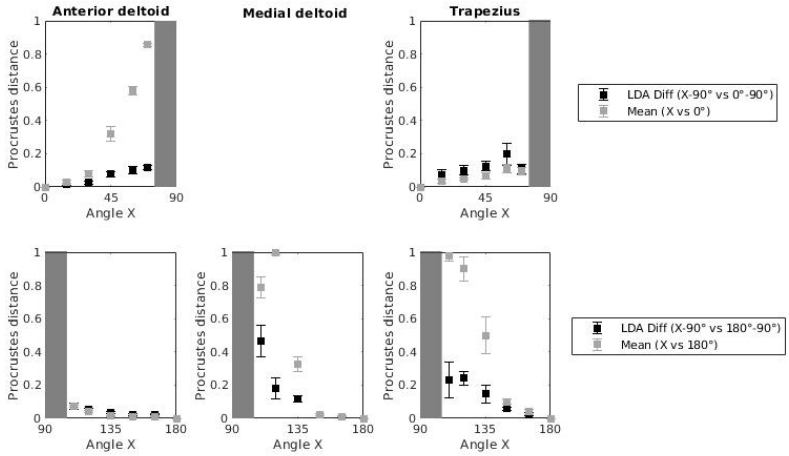


Figure 7: Procrustes distance between angles using either the LDA_{diff} (in black) or the simple mean (in gray).

of the mean of each category? Perhaps the mean EMG representations for all the downward pointing angles would scale well using the representation at 180°, while the mean EMG representations for upward pointing would scale well with the mean representation at 0°. In these graphs, the blue squares represent the Procrustes values for the LDA_{diff} vectors while the red squares represent those for the mean of each representation. The grey colored areas of the graph correspond to sections in which the LDA_{diff} had values close to zero due to its proximity with muscular activity at 90°. A meaningful Procrustes and scaling analysis could not be carried out for these angles that were very close to 90° and for which muscular adaptation was small.

Taking an overall view with all the muscles and angles together, the LDA_{diff} values have lower values for the Procrustes distance than the representation means (Friedman test, $\chi^2(1) = 6.47$, $p = 0.011$). This demonstrates better scaling for the LDA_{diff} of the EMGs than for their means. This was especially the case for the anterior deltoid. In the case of the trapezius muscle, this difference is much less marked. Prominently missing in this figure is a comparison for the medial deltoid in the upward direction. As in the case of the pointing angles close to 90°, the values of LDA_{diff} for this muscle were very close to zero at all upward angles. The poor tuning of this muscle for the upward direction is not only reflected in the extremely low values of the LDA_{diff}, but also in its poor classification accuracy in this direction (Figure 9).

The Procrustes Distance incorporates the use of a scaling factor as an integral part of the algorithm. This therefore provided us with the means to follow the scaling of the LDA_{diff} for each angular distance. The results of this analysis can be seen below in Figure 8. A qualitative look at the figure shows that the EMG activity of the individual muscles scaled in a nonlinear manner, beginning

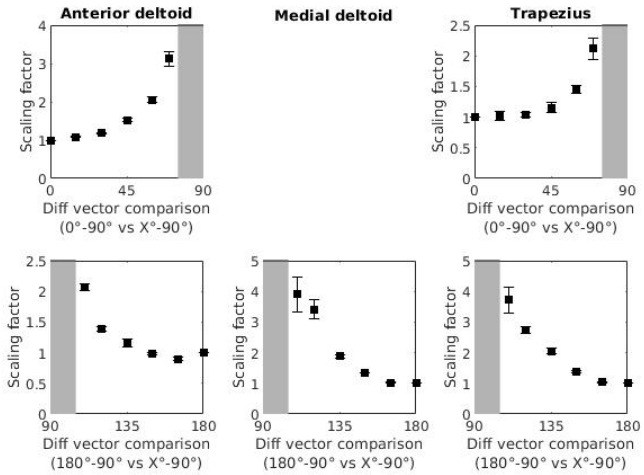


Figure 8: Procrustes scaling factor for antigravity muscles. The results of the medial deltoid for upward directions are not reported as this muscle doesn't show a good scaling in those directions (see Figure 7).

with small values for smaller angles before shifting in a nonlinear manner to higher gains for similar angular separations at bigger angular distances from 90°.

3.4 Not all muscles are created equal for tuning

In this section we compare the adaptations of each muscle for pointing in the upward and downward direction. It should be noted that once again, as opposed to traditional analyses in which a particular aspect of EMG activity is examined in isolation, we used the entire time series of the EMG as input for classification. Figure 9 displays the classification accuracies of each muscle for distinguishing upward or downward pointing in comparison to horizontal pointing. A most important thing to be noted when studying this figure is the low accuracy of the individual muscles when compared to the collective accuracies seen in Figure 2. This demonstrates the potential of this technique when diagnoses have to be made with multiple factors.

Other features of note, are that some muscles like the anterior deltoid, have relatively higher accuracies than the other muscles when pointing at 0° or 180°. This is not the case for a muscle like the medial deltoid which displays higher accuracies for distinguishing from the horizontal in pointing at 180°, but not for 0°. The triceps muscles in displaying poor accuracies in both directions, demonstrate a poor role in adjustments for either direction.

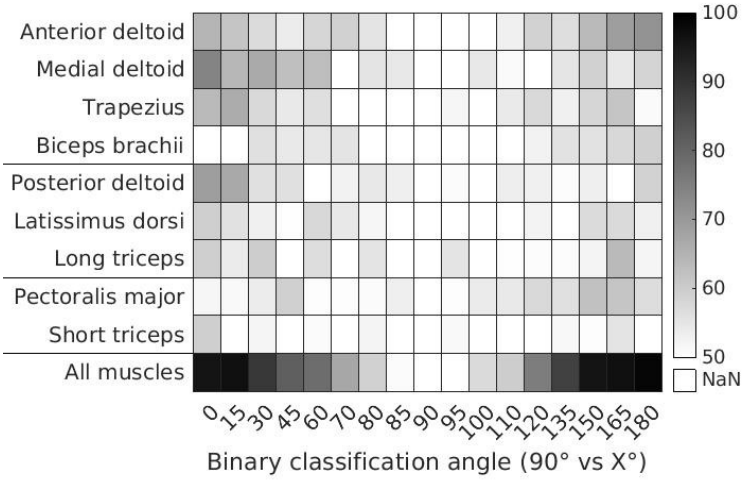


Figure 9: Maximum binary accuracy of individual and all muscles for different angles compared to 90°. The muscles are ordered by their type (anti-gravity, gravity and neutral) and lines separate the different types of muscles.

4 Discussion

In this study we examined the manner in which phasic muscular activity of the arm and shoulder are adjusted for pointing in different directions. It is an extension of a previous study in which [Gaveau et al., 2021] had demonstrated that effort optimisation leads to clear differences in phasic muscular activity for vertically upward or downward pointing. The current study does not only examine these two diametrically opposed directions but identifies trends in muscular tuning at several intermediate angles as well.

Another original aspect of the study is the use of Machine Learning in order to obtain an ensemble view of the adaptations. Tuning of muscles for pointing direction was analysed in terms of classification accuracy i.e. prediction of task constraints with a Machine Learning algorithm was done with combined muscular activity as input. This approach is interesting in view of the synergistic manner in which muscles achieve task goals. The term synergistic refers to the fact that movement is the result of the combined activities of several muscles in which the role of any one muscle in the group need not remain constant. The term Motor Equivalence also refers to this idea [Lashley, 1933, Morasso, 2022]. An ensemble analysis therefore has the potential to provide insight into group properties which may not be present at the single muscle level or worse yet, at the level of a single EMG parameter such as amplitude or onset delay. A single variable of this sort may not have sufficient power to reach statistical significance. This is clearly demonstrated in Figure 9 where the last line displays the classification accuracy obtained from the combination of all the muscles

recorded during the experiments. It is darker than any of the preceding lines hence indicating a higher discrimination power for the muscle population.

The technique used for ensemble analysis was Linear Discriminant Analysis for machine learning classification. This algorithm was used instead of more a more efficient classifier like Support Vector Machines [Han et al., 2018, Heung et al., 2016, Statnikov et al., 2008, Nair et al., 2010, Uddin et al., 2019] as the latter would have shown poor discrimination for pointing angles due to a ceiling effect. By this we mean a high classification accuracy even in the face of very minor muscular changes hence failing to provide any differentiation on data separation and muscular tuning. This effect can already be seen in Figure 2 where angular separations greater than about 60° from pointing in the horizontal direction lead to very high classification accuracies and a plateau effect. This problem was corrected by looking further into the models of each class used by the LDA algorithm for classification, in this case, the LDA distance, which is the distance between the multivariate mean of each class.

The first global aspect of the tuning of phasic EMGs for pointing direction can be seen in Figures 2 and 3. Figure 2 shows that the combined tuning for pointing direction was approximately linear uptil about 60° of separation from horizontal pointing. Following this, the classification accuracies begin to asymptote. This ceiling effect is due to the fact that once data separation reaches a certain level, classification accuracies stagnate at high accuracy levels. This problem was corrected in Figure 3. In this case, the models being used by the LDA algorithm was analysed directly to obtain information on the distance between the classes. The figure of the LDA distance as a function of angular distance from 90°, confirms that the prominent nonlinearities displayed in Figure 2 are partly due to a ceiling effect. Nevertheless, some small nonlinearity is still evident towards the extremities of Figure 3. Curve fitting with higher order polynomials showed slightly better fitting than linear functions. This is not unexpected as previous work on this data have shown that the Gravity Torque as well as the kinematic symmetry ratio show a sigmoidal trend as a function of pointing direction [Gaveau et al., 2016].

Another feature highlighted by this ensemble analysis, was the unexpected finding that discrimination in the downward direction had a higher gain than discrimination in the upward direction (Figure 3). This difference is quantified by the difference in the slopes of the regression lines fitted to the two sides of the LDA distance curve. Some caution has to be exercised in interpreting this result. It does not indicate greater muscular activity when pointing downwards but rather that there are more marked modifications as a function of downward angular separation than upwards. High amplitude activity that does not change very much from angle to angle would show poor tuning.

One possible explanation of this may be that both upward and horizontal pointing follow the classical triphasic burst pattern [Hallett et al., 1975, Virji-Babul et al., 1994]. In contrast to this, Gaveau et al had predicted (2016) and demonstrated (2021) a very different pattern of muscular activity for downward pointing. In accordance with the effort optimisation hypothesis they has shown that the antigravity muscles deactivate during the first half of downward

pointing. This reduction in muscular activity would allow for the exploitation of gravity toward an effort optimisation. This is in contrast to a view in which the internal model of gravity is used to compensate rather than exploit its presence. Our study sheds further insight into this reduction in phasic contribution to muscular activity. Table 1 and Figure 5 show that there is a progressive increase in classification accuracy of the antigravity muscles during the acceleration portion of downward pointing (phase of negative phasic activity). This indicates a growing separation between the muscular activity for downward pointing compared to pointing in the horizontal direction. An all-or-nothing deactivation function for this portion of downward pointing would have led to constant values for classification accuracies. This indicates a scaling in the decrease in phasic activity of these muscles and provides insights on the neural representation of gravity thought to be present in the brain stem, cerebellum, vestibular cortex and anterior thalamus.

Figure 6 opened up the question of scalability in the difference vector obtained from subtracting the model of each category created by the LDA algorithm (LDA_{diff}). While this had not been a primary goal of the project the presence of some scaling was evident from the figure and had to be investigated. Given the importance of scaling as a potential method of dealing with the huge number of degrees of freedom available for constructing movement [Bernshteĭn, 1967], it was important to look into it. A visual inspection (Figure 7) showed that the clearest scaling was between the pointing angles of one quadrant. By this we mean that EMG activities for pointing to all the angles in the upward direction might scale at a function of pointing in the vertically upward direction of 0°and pointing for all the downward angles, as a function of pointing vertically downwards at 180°. Using the Procrustes distance, Figure 7 shows clearly that the gravity muscles display some scaling as there are many angles for which the value of the Procrustes distance is very low. The figure compares the scaling for the mean of each group and the LDA_{diff} vector. The latter refers to the EMGs for a particular pointing direction minus a reference EMG. In the case of the current study, the reference EMG is the mean EMGs for pointing horizontally at 90°. Figure 7 shows that the LDA_{diff} has significantly better scaling properties than the mean EMGs for each group. Further theoretical work is required to understand why the LDA_{diff} would scale better than the mean EMGs of each group. Furthermore, if this computation is to be carried out by the nervous system, it would require that a memory trace of pointing in some key directions, is stored in the brain areas thought to represent gravity. The scaling reported here is of a limited nature compared to the scaling for both upward and downward directions reported by several researchers through the use of Principle Components Analysis [d'Avella et al., 2008, Muceli et al., 2010, d'Avella and Lacquaniti, 2013]. The goal of the current project was not to develop a framework for EMG vectors which would scale in all directions but to report and quantify some scaling which was observed. The development of LDA representations which would scale for both upward and downward directions would probably require the exploration of multiclass LDA classification which is outside the scope of the current paper.

Finally Figure 9 displays the accuracies of each muscle for pointing in different directions individually. It reinforces why machine learning is an interesting technique for studying EMG activities. The clearly higher accuracies on the bottom line of the figure shows that the information obtained from the combined activities of muscles is better than what is obtained using any individual muscle. The Figure 9 also displays the differences in tuning of each muscle. The higher accuracies of the anterior deltoid for example show that it is tuned in both directions. Its importance may stem from its role in setting the pointing direction. The trapezius shows a similar pattern of classification accuracies, though their smaller values would indicate smaller adjustments than the anterior deltoid. The tuning of these two antigravity muscles is most interesting as they deactivate for downward pointing. Once again, in keeping with the results of Figure 4, they show that the phasic activity decrease for downward pointing is scaled and not an on-off function. In contrast to the two aforementioned muscles, the phasic activity of the medial and posterior deltoids are more tuned for downward pointing, showing higher accuracies for distinguishing downward pointing angles. The importance of all these muscles in pointing have been highlighted by various studies [Flanders, 1991, Flanders et al., 1994, Flanders et al., 1996, Mira et al., 2021, Tokuda et al., 2016]. In contrast to the previous studies, the use of classification accuracy allows for a greater ease in comparing and contrasting the roles of individual muscles. A direct comparison with the previous studies is not possible, as the pointing protocols were often different, involving for example, mobility around the elbow joint. In contrast to the previously mentioned muscles, the short triceps display poor classification accuracies at all angles in both directions. Once again, this does not necessarily mean that the muscle is not active, but that it is poorly distinguishable from its activity for horizontal pointing, and hence does not play an important role in tuning for direction.

No discussion on ensemble methods would be complete without talking about Principle Components Analysis. This method has also been used by various researchers to examine multimuscle activity in a simultaneous manner [d'Avella et al., 2008, Muceli et al., 2010, d'Avella and Lacquaniti, 2013]. The data characteristics exploited by this technique are completely different from those of Machine Learning classification. The PCA method uses correlations between muscles to then reduce the dimensionality of the multimuscle space. In the complete opposite direction, the goal of Machine Learning is to look for and even emphasize differences. It should be noted that the two methods are sometimes used sequentially. The PCA is often used in the feature extraction step to first reduce spatial dimensionality before then going on to apply Machine Learning [Duda, 2000]. We could have reduced the multimuscle space with the PCA before going on to use LDA did not take this step as it would have made interpretation much more difficult.

We conclude by saying that the use of Machine Learning with muscle combinations allowed us to describe muscular tuning in a concise manner. It allowed us to bring to light certain trends in combined muscular tuning for direction. The higher gains in classification accuracy as a function of pointing angle showed

greater tuning in the downward direction when compared to horizontal pointing as a reference. Higher tuning gains were also observed in the antigravity muscles compared to the gravity muscles. The presence of tuning during the negative phases of antigravity muscle EMGs was especially interesting as it indicated that the decreasing implication of phasic activity in these muscles may be scaled as a function of pointing direction. Classification accuracy as a concise description of data separation between high dimensional EMG vectors also allowed for an easy comparison of the tuning characteristics of each muscle, some playing a bidirectional role, while others were involved in the adaptations for only one direction. We propose Machine Learning classification and LDA in particular as is a method which could complement the current univariate statistics which are primarily employed to study EMG adaptation for task constraints. Last but not least, higher classification accuracies with muscle combinations demonstrate the potential of this method in increasing the power of detecting physiological adaptations for task constraints.

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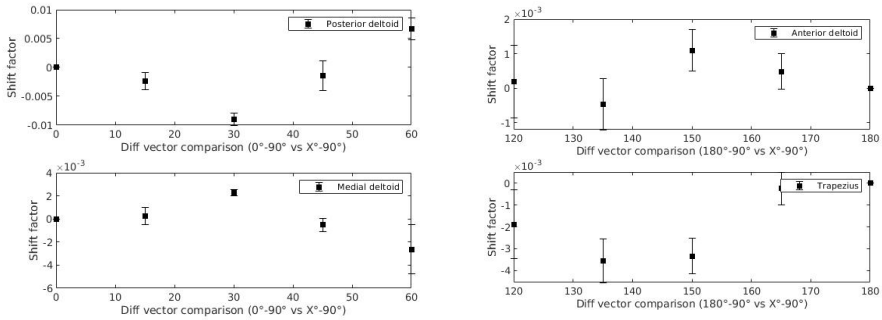

Figure S1: Procrustes translation factor between the 0˚-90˚ difference vector and other upper angles difference vectors for the posterior and medial deltoid (on the left) and between the 180˚-90˚ difference vector and other lower angles difference vectors for the anterior deltoid and the trapezius (on the right). Results are only reported for meaningful scaling values ($Distance < 0.3$, See Figure 7). Error bars indicate standard error. Since values appear in a range between -0.01 and 0.01, they represent a shift of at best 0.5% of the signals deviation and where therefore considered negligible.

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5 Supplementary Material

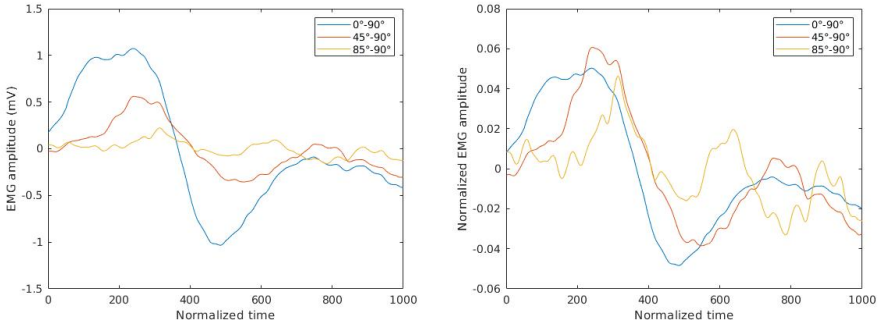

Figure S2: Difference vectors of the posterior deltoid for different angles, 90° taken as reference. On the left are the original smoothed EMG signals and on the right are the EMG signals after the normalization step of the Procrustes analysis. In this example, the Procrustes distance between the 0°-90° and 45°-90° difference vectors is 0.35 and the Procrustes distance between 0°-90° and 85°-90° difference vectors is 0.87.

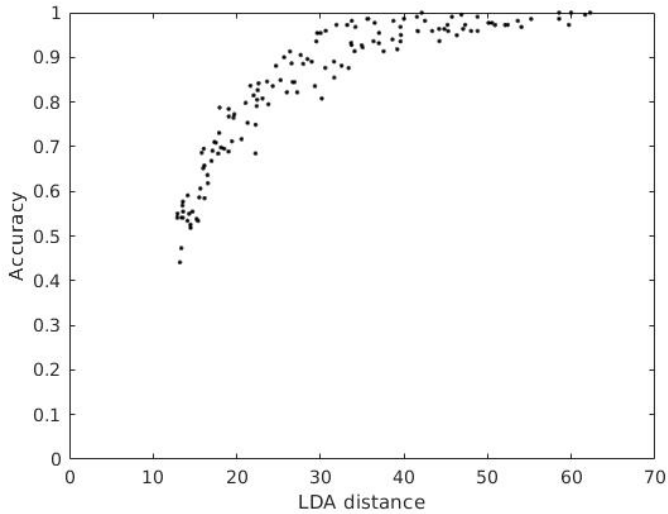

Figure S3: Accuracy as a function of the LDA distance.