Neuroscience Letters 311 (2001) 97–100

Neuroscience Letters

www.elsevier.com/locate/neulet

Human elbow joint torque is linearly encoded in electromyographic signals from multiple muscles

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Received 28 June 2001; received in revised form 23 July 2001; accepted 24 July 2001

Abstract

When the central nervous system (CNS) develops a muscular activation pattern to accomplish a particular isometric task, it clearly uses information concerning the external task requirements. These task requirements serve as inputs to neural transformations that output muscular activations. However, the nature of the inputs is not exactly known. Electromyographic (EMG) signals from eight muscles spanning the human elbow, as well as the total joint torque, were collected during a submaximal isometric flexion/extension task at a single joint angle. The EMG data, without any torque information, were subjected to principal components analysis. We found that 98% of EMG data variation could be described by two principal components the first resembled the joint torque and the second resembled the sum of the EMG signals from all eight muscles. The findings suggest that the CNS encodes these two quantities during isometric tasks.

Keywords: Motor control; Electromyogram; Principal components analysis; Synergy

When the central nervous system (CNS) plans and executes an isometric task, physical properties that define the task requirements are very important pieces of information. The nervous system must have mechanisms for transforming task requirements into a set of muscular activations, although the rules or strategies behind such transformations are not well understood. Proposals for task requirements used by the CNS include the direction of movement, velocity, acceleration, posture, and joint torque (for a review see Ref. [14]). If the required joint torque for an isometric task is indeed used when choosing how to activate the set of muscles capable of causing that torque, then one might expect that the torque is somehow encoded in those muscular activations, measured with electromyographic (EMG). If this encoding does take place, then we may be able to explore the structure of multi-dimensional EMG data and find the torque.

Mappings between multiple EMG signals and the joint torque that they produce have been studied in recent years. Several researchers have used feed-forward neural networks to map EMG signals to either muscular forces or the corresponding joint torque [1,6,7,9,10]. These mappings can capture non-linearities arising from motor unit recruitment patterns [11] and muscular force-length and force-velocity curves [16]. However, for isometric tasks below roughly 50% of maximum effort, one may expect near linear EMG-force relations for many muscles, and therefore, linear EMG-joint torque relations [15]. Consequently, the process of encoding joint torque in a set of EMG signals may be quite linear.

The purpose of this study is to demonstrate that, for certain elbow flexion/extension tasks, the CNS embeds the joint torque, in a linear fashion, inside EMG signals from multiple muscles spanning the joint of interest. Data were collected from three subjects during isometric flexion followed immediately by isometric extension. This task was performed at approximately 50% of maximum, 90° flexion, and forearm neutral, with subjects seated and the elbow raised to the same horizontal plane as the shoulders. No feedback concerning task performance was given to the subjects. EMG was acquired from eight muscles using intramuscular fine-wire electrode pairs placed 2.5 cm apart: biceps short head, biceps long head, brachialis, brachioradialis, pronator teres, triceps medial head, triceps long head, and triceps lateral head; a set of muscles that has nearly all control over flexion/extension. EMG data were amplified and band-pass filtered (in analog) between

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0304-3940/01/$ - see front matter
PII: S0304-3940(01)02146-2

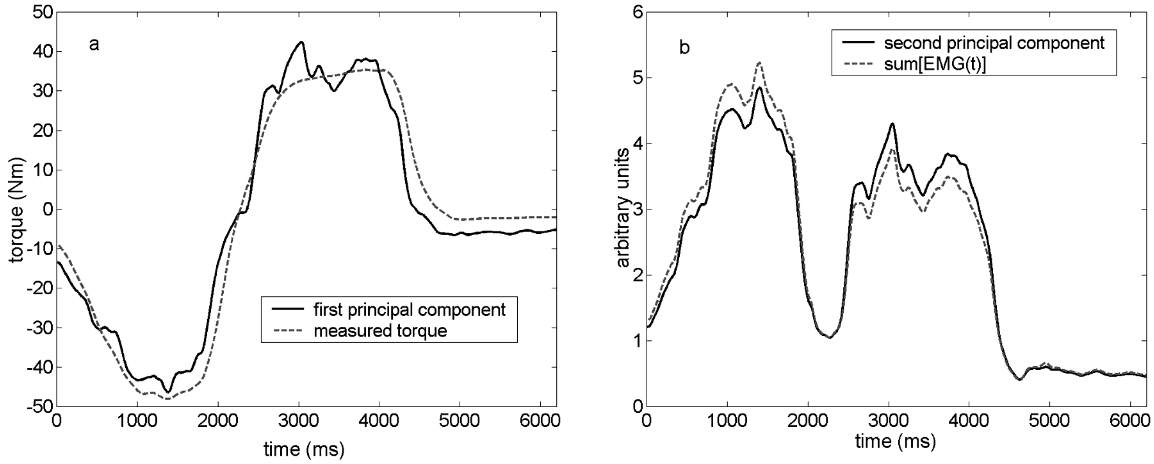

Fig. 1. Data from one subject during a time-varying isometric elbow flexion-extension task of up to approximately 50% of the subject's maximal torque. The subject was seated with the arm held horizontally (at an even level with the shoulders) while the forearm was in a neutral position and the elbow was at 90° flexion. (a) Scaled and shifted first principal component of EMG data from eight elbow muscles (solid line) compared to the measured torque (dotted line). (b) Scaled and shifted second principal component (solid line) compared to the sum of all eight normalized EMG signals (dotted line).

30–500 Hz prior to being digitally sampled at 1000 Hz for 6.2 s. They were subsequently rectified and low-pass filtered at 4 Hz to obtain linear envelopes. The total flexion/extension torque was simultaneously acquired at 1000 Hz, and then low-pass filtered at 4 Hz.

Principal components analysis is a commonly used technique that can find correlation in a multi-dimensional data set, and can show how a particular data set could be encoded in fewer dimensions without significant information loss. It accomplishes this by finding directions of maximum variance in the data set. To perform principal components analysis on an EMG data set, we first arranged the data into a 6200×8 matrix: rows corresponded to discretely sampled time points and columns corresponded to different muscles. We then found the covariance matrix of this data matrix, that is, the mean over time of the product of each possible pair of EMG values. The direction of maximum variance in the EMG data set is the covariance matrix eigenvector corresponding to the largest eigenvalue, the orthogonal direction of next largest variance corresponds to the next largest eigenvalue, and so on. For a further description and mathematical details, see Haykin [4].

When we perform principal components analysis on the EMG data set only, excluding all information about the measured torque, we find that the majority of the EMG data lies on a two-dimensional surface. That is, at each point in time, two numbers describe the EMG activity in the eight muscles more or less as well as all eight EMG values would. On this plane, one direction has more variance than the direction orthogonal to it. Let $z_1(t)$ denote the projection, or so-called first principal component, of the EMG from each of eight muscles at time t onto the line that characterizes the maximum amount of EMG data set variance, and let $z_2(t)$ denote the projection, or second principal component, of the EMG as a function of time onto an orthogonal line that characterizes the second greatest amount of EMG data set variance. We find empirically that $z_1(t)$ and $z_2(t)$ encode interesting physical quantities.

Fig. 1 shows example principal components of EMG data from one subject. Fig. 1a shows a linear function of $z_1(t)$ and compares it to the measured flexion/extension torque, where extension is positive. Here we have scaled and shifted the EMG projection using a linear function such that the difference between this function and the measured joint torque (in Newton-meters) has minimum sum-of-squares; therefore, the first principal component is actually plotted as $34.4z_1(t) - 2.7$. Fig. 1b shows a linear function of $z_2(t)$ and compares it to the sum of all eight EMG signals, at each time-point; the function $2.67z_2(t) + 2.36$ was also found by minimizing sum-of-squares. In Fig. 1a, the torque signal has been shifted forward in time 78 ms to account for electromechanical delay. The precise value of the shift was determined by temporally aligning the minima of the first principal component and the measured torque.

We see from Fig. 1a that the torque produced rather closely matches the first principal component of the EMG signals, implying that torque is encoded in the signal. Moreover, the torque occupies a special location in the EMG data set; namely, the torque is the projection of the EMG signals onto a line of maximum EMG variance. In other words, no single quantity is more important in determining the eight EMG signals than the desired total joint torque. This observation, of course, makes sense for isometric tasks, which are defined largely in terms of a torque requirement.

Fig. 1b is also of interest because it demonstrates that the sum of the EMG from each muscle is also important in determining the particular set of eight muscular activations to use. Many studies have employed optimization techniques in an attempt to predict muscular activation patterns (for reviews see Refs. [3,12]). These methods enforce an equality constraint that the sum of the products of muscular forces with their respective moment arms must equal the desired total joint torque. However, cost functions also have been employed to reduce a great multiplicity of possible solutions down to a single set of muscle forces. These cost functions combine the state of activation in several muscles into a single parameter to be optimized, just as the second principal component combines the EMG signals from all eight muscles studied. In this regard, the result presented in Fig. 1b may relate to a rule used by the CNS when transforming desired joint torque into an appropriate set of muscular activations.

There has been much discussion concerning the relation between EMG and muscular force during isometric contraction [5,8,11,15] and many studies explicitly assume a linear relationship [2,17]. One result of the present study, shown in Fig. 1a, demonstrates that it is possible to find a linear transformation that can map EMG to joint torque. That is, a weighted sum of the EMG signals from each of eight elbow muscles at each time-point can well approximate the total joint torque. If the muscular EMG-force were not approximately linear, this analysis based on principal components analysis would not work well.

We have found that, for the three subjects performing the task that was studied, an average of 98.16% of the EMG variance in eight muscles was accounted for by only two principal components. It has been previously reported that EMG data from multiple synergistic muscles can be explained with fewer principal components than the number of muscles [13]. We found that the first principal component explained 64.82% of the EMG variance and corresponded to the elbow flexion/extension torque produced. The second principal component explained 33.0% of the EMG variance and corresponded to the sum of all EMG signals. This finding implies that the CNS need only know these two pieces of information to control this task.

The findings presented in Fig. 1 provide some insight into how the CNS might create neural control signals capable of producing desired joint torques. Fig. 1 shows the two signals created when the CNS planned the necessary muscular activations for the given task. Did the CNS use this information a priori to construct the neural control signals that it did? If so, the CNS may use the torque requirements of a particular task, along with estimates of the total amount of muscle activity, as inputs to some type of transformation that creates specific activation patterns to complete the task. Since joint torque is the quantity most strongly encoded in the EMG signals, it is possible that the CNS could have determined the neural commands for this isometric task by focusing on the desired joint torque.

During the isometric task performed for this study, no feedback of task performance was provided to the subject. Other than the fact that the subject knew that the task should include elbow flexion followed by extension, the task was open-loop. It remains to be seen if the CNS encodes the joint torque during more complicated tasks in which sensory feedback is more directly involved. It also remains to be seen whether joint torque will be so prominently represented in a set of EMG signals during a dynamic task. Nonetheless, principal components analysis used in this manner will still provide a powerful tool to probe information coding in the human neuromuscular control system.

This work was supported, in part, by NIH grants AR40408 & AR46386.

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