Computational Model of the Role of Sensory Disorganization in Focal Task-Specific Dystonia

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Sanger, Terence D. and Michael M. Merzenich. Computational model of the role of sensory disorganization in focal task-specific dystonia. J Neurophysiol 84: 2458–2464, 2000. We present a new computational model for the development of task-specific focal dystonia. The purpose of the model is to explain how altered sensory representations can lead to abnormal motor behavior. Dystonia is described as the result of excessive gain through a sensorimotor loop. The gain is determined in part by the sensory cortical area devoted to each motor function, and behaviors that lead to abnormal increases in sensory cortical area are predicted to lead to dystonia. Properties of dystonia including muscular co-contraction, overflow movements, and task specificity are predicted by properties of a linear approximation to the loop transformation. We provide simulations of several different mechanisms that can cause the gain to exceed 1 and the motor activity to become sustained and uncontrolled. The model predicts that normal plasticity mechanisms may contribute to worsening of symptoms over time.

INTRODUCTION

Task-specific focal dystonia is a frustratingly complex disease that is often refractory to medical therapy. It includes diseases such as writer’s cramp or musician’s cramp, and it is characterized by involuntary movements that occur over seconds or minutes often involving co-contraction of antagonist muscles and leading to abnormal and frequently painful limb postures (Bressman 1998; Fahn et al. 1987, for review). Patients with dystonia may be severely impaired in their ability to perform common tasks or indeed to use the affected limb at all. The response to medical therapy including anticholinergic agents, dopamine depleting agents, or GABA agonists is frequently unsatisfactory, and patients may be left with prolonged or permanent deficits. An understanding of the mechanisms underlying dystonia would therefore be of potentially significant benefit.

There is evidence from studies in monkeys of disorganization of sensory cortical representations (Byl et al. 1996a, 1997; Merzenich and deCharms 1996). In particular, monkeys with focal hand dystonia were found to have neurons in primary sensory cortex that responded to tactile stimulation over more than one finger, or over both the palmar and dorsal surfaces of the fingers. Clinical studies in humans have shown abnormalities of tactile form perception (Byl et al. 1996b) and spatial and sensory processing (Bara-Jimenez et al. 2000). The central sensory cortical representations of individual fingers show closer spacing in focal dystonia (Bara-Jimenez et al. 1998; Butterworth et al. 1999; Byrnes et al. 1998; Elbert et al. 1998), and there is evidence of abnormal interactions between signals from median and ulnar nerve in writer’s cramp (Tinazzi et al. 2000).

It is not known whether the sensory abnormalities are a cause or a result of the motor abnormalities. Prolonged abnormal postures might lead to plasticity in sensory systems that result in the observed changes in sensory maps. It is more difficult to describe how the motor abnormality might be caused by the sensory changes. We seek to provide a model to explain how the sensory abnormalities could lead to the motor manifestations of dystonia. In particular, we will demonstrate that properties of a linear model predict that sensory de-differentiation may cause not only poor fractionation of movement, but also excessive contraction of the involved muscles.

We hypothesize that task-specific dystonia such as writer’s cramp or musician’s cramp is the biomechanical manifestation of an unstable sensorimotor control loop. The control loop includes motor cortex that produces an effect on muscles that is eventually transmitted through sensory systems to sensory cortex, which has projections back to the equivalent areas in motor cortex. If the gain of signals sent through this loop is >1, then motor cortical cells will continue to increase their firing rates until maximal muscle contraction occurs. In this paper, we will show that the loop gain can be analyzed in terms of a linear approximation to the motor to sensory transform. Several features of task-specific dystonia then arise as natural consequences of instability in this loop, including the following.

1) Symptoms may be present only during one task, but with progression may worsen to involve multiple tasks.

2) During a movement, muscle force may increase progressively until the task must be halted.

3) There is spread of activity into muscles normally unininvolved in or antagonistic to desired movements.

In this model, motor abnormalities can arise from sensory de-differentiation if the sensory changes lead to increased loop gain. Gain can be increased by increasing the relative sensory cortical representation of a limb. Sensory cortical increase could occur due to adaptation in response to the repetitive use of a limb, coupling of multiple sensory signals from the limb, or voluntary co-activation of muscles leading to correlated...
sensory activity (Allard et al. 1991; Jenkins et al. 1990; Kaas et al. 1983; Merzenich et al. 1983a,b; Wang et al. 1995). Only certain mechanical modes of the sensorimotor loop may be unstable, and as a result only focal or task-specific dystonia may be observed. Instability will occur as the gain approaches 1, and becomes more severe and persistent as the gain increases beyond 1. We further hypothesize that plasticity mechanisms in sensory and motor systems may contribute to the emergence or progression of symptoms. The onset of dystonia may be delayed until after many years of successful task performance if during those years the sensory representation is slowly changing and the gain is gradually increasing.

METHODS

Cortical representation

To use control-theoretic concepts to understand biological systems, a model for representation of signals in cortical neural populations is needed. The probability of firing for each neuron will be given by a Poisson process

\[ P(s \text{ spikes}) = \lambda^s e^{-\lambda} n! \] (1)

where \( \lambda \) is the expected or average firing rate. The behavior of a Poisson neuron is determined only by its rate, and loop instability will therefore be described in terms of an inappropriately high rate. We do not model the nonlinearities that limit the firing rate, but we note that a maximal rate exists. In the following discussion we consider the role of the sensory-to-motor loop through spinal cord and muscle actuators, but the same analysis can be applied to the loop through basal ganglia.

If \( \lambda(t) \) is the firing rate at time \( t \), then the loop gain for a single neuron \( i \) is given by

\[ g_i = \frac{\lambda_i(t + \Delta t)}{\lambda_i(t)} \] (2)

where \( \Delta t \) is the propagation delay through the muscle mechanical system and sensory processing. \( \lambda(t + \Delta t) \) depends on the transmission from motor cortex to the muscles, the effect of the muscles on the environment, the sensitivity of the sensory receptors, the transmission of information from the sensory receptors to sensory neocortex, and the link from sensory to motor cortex.

Now, consider a sensorimotor loop as shown in Fig. 1, which depicts the transformation from the motor cortical representation \( m \) through the external world to the resulting sensory cortical representation \( s \). \( C \) represents the map from sensory to motor cortex; \( W \) is the mapping computed by the external world, including motor neurons, muscles, physical plant, and sensory processing. In this figure, the boxes indicate the data representation in each component of the system.

![Sensorimotor loop](Image)

FIG. 1. Sensorimotor loop. \( s \) is sensory cortex, \( m \) is motor cortex. \( W \) represents the transformation from motor to sensory cortical activity including muscles, the external mechanical system, and the sensory receptors. \( C \) is the mapping between sensory and motor cortex.

\[ \lambda_s = W\lambda_m \] (3)

If the probability of any single motor cortical spike is small, then \( \lambda_m \) is small and we can approximate \( W \) with a linear mapping. We will

![Sensorimotor loop in detail](Image)

FIG. 2. Sensorimotor loop in detail, using control-theoretic notation. \( u \) is the initial motor command, \( m \) is the motor cortical activity, and \( s \) is the resulting sensory cortical response. \( n \) is external noise or uncontrollable components. \( M \) is the mapping from motor cortex to the muscles. \( P \) is the external plant including musculoskeletal dynamics and sensory receptor responses. \( \delta \) is a time delay. \( S \) is the mapping from sensory receptors to sensory cortex, and \( C \) is the mapping from sensory cortex to motor cortex. \( B \) represents feedback through the cortico-basal ganglia circuit back to motor cortex. \( S \) and \( C \) are assumed to be adaptive.

Figure 2 shows a detailed picture in more standard control-theoretic notation, in which the boxes represent transformations between signals. Here, motor activity \( m \) propagates to the physical muscles through the motor mapping \( M \), then through the musculoskeletal and external mechanical plant \( P \) to the sensory receptors, then through the sensory mapping \( S \) to sensory cortex. \( \delta \) represents the combined delays in motor to sensory information transmission. \( C \) represents the extracortical sensory to motor mapping that is assumed to connect sensations to the causative motor commands. \( n \) is an initial command issued to motor cortex to generate a desired voluntary movement, and \( n \) is an external source of sensory "noise" (that may include important but uncontrollable components of the environment). \( B \) is the internal mapping from motor cortex through basal ganglia and thalamus back to motor cortex. For simplicity, let \( W = Sn + \delta PM \) represent the complete nonlinear probabilistic transformation from motor cortex \( m \) to sensory cortex \( s \) including delays. \( m \) and \( s \) are vectors of integers indicating the number of spikes occurring during a short time interval \( \Delta t \). We define \( \lambda_m \) and \( \lambda_s \) to be the average rates of the Poisson processes generating the spikes for \( m \) and \( s \).

All the transformations \( M, B, P, S, C, \) and \( W \) are probabilistic, in the sense that they describe the average firing rate of an output neuron for each possible input firing pattern. For example, \( \lambda_s = Wm \) means that \( Wm \) gives the vector of average firing rates for each sensory neuron \( s \), when the motor firing pattern is given by \( m \). The resulting firing pattern \( s \) is generated randomly from the firing rate \( \lambda_s \) by spike generators modeled as independent time-varying Poisson processes. This formulation ignores information that may be encoded in details of timing of the spike train, since we are primarily concerned with understanding saturation of the average firing rate.

Loop gain

To understand the loop gain, consider the case in which the probability of a sensory spike is determined only by whether a motor spike occurred at some particular previous time. This is a special case of the general nonlinear mapping \( \lambda_s = Wm \), and it implies that \( m_1 \)'s effect on \( s_j \) is "time-locked" in the sense that \( m_1 \)'s effect on \( s_j \) is seen exactly at time \( \Delta t \) later. Taking expected values, we have

\[ \lambda_s = W\lambda_m \] (3)

Note that since the Poisson rates will be modulated by the output of other spike trains, we can distinguish the "instantaneous" rate from the "average" rate over longer periods of time. \( \lambda_s \) and \( \lambda_m \) refer to the average rates, which are well-defined since a Poisson process modulated by another stationary Poisson process continues to satisfy the independent increment property and therefore remains Poisson. See Sanger (1998) for further discussion.

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show that properties of this linear map are sufficient to predict several features of focal dystonia.

We can describe the sensory to motor transform $C$ in cortex the same way, and again assuming that sensory spike firing is rare, $C$ can be approximated linearly. In this case, we have

$$\lambda_s(t + \Delta t) = CW\lambda_s(t)$$

(4)

The gain for a single motor neuron $i$ is given by

$$g_i = c_i w_i$$

(5)

where $c_i$ is the $i$th row of $C$, and $w_i$ is the $i$th column of $W$. For the entire motor population, we can write the gain as

$$g = \sum_{i} g_i = \sum_{i} \lambda_s(t + \Delta t)^2 = \frac{\lambda_s(t + \Delta t)^2}{\lambda_s(t)\lambda_s(t)}$$

(6)

and the gain depends on the pattern $\lambda_s(t)$. Write the eigenvector decomposition $\lambda_s(t) = \sum \beta_i v_i$ where $v_i$ are the orthonormal eigenvectors of $W^T C^T W$ and $\beta_i = \lambda_i(t)v_i$ is the projection on each eigenvector. If $\alpha_i^2$ are the corresponding eigenvalues, we have

$$\gamma = \frac{\sum \alpha_i^2 \beta_i^2}{\sum \beta_i^2}$$

(7)

From Eq. 7 we see that instability occurs with $\gamma > 1$ if any of the $\alpha_i^2$s is $>1$ when $\beta_i$ is nonzero. The rate of increase in $\lambda_s(t)$ will be at least $(\alpha_{\text{max}}^2)^{1/\gamma}$. Instability will only occur if the initial motor cortex pattern $\lambda_s(0)$ contains a nonzero component $\beta_i v_i$ corresponding to an eigenvalue $\alpha_i^2$ that is $>1$.

In the following, we are concerned with enlargement of the sensory representation of different control modes, and without loss of generality we can simplify the discussion by assuming that each mode is represented directly by a discrete subpopulation of sensory cells that are uncorrelated with other populations. In the linear approximation, two cells firing at a rate $\lambda$ spikes per second have the same effect as one cell firing at a rate $2\lambda$ spikes per second. We will therefore represent the transform $W$ as the product $PGV$, where $V$ is an orthogonal matrix indicating the transformation of the pattern $\lambda_s$ into the pattern $\lambda_m$ into the pattern $\lambda_m$. $P$ is a diagonal matrix each of whose integer elements $p_i$ gives the number of cells representing a single mode, and $G$ is a diagonal matrix that gives the attenuation of each mode as it passes through the “world” transform $W$. In general, the elements $g_i$ of $G$ will be very small since most of the motor command will be seen only weakly reflected in the sensory response. If we assume that the sensory populations are uncorrelated as above, then $GV$ finds uncorrelated modes, and its output $GV\lambda_s$ must be uncorrelated. Therefore the expected value $E[GV\lambda_s^2 V^T G]$ is diagonal. This implies that $V$ is the matrix of eigenvectors of the covariance matrix $R_{\text{sn}} = [\lambda_s \lambda_s^T]$.

We hypothesize that the sensory to motor mapping $C$ forms links between sensory state and the motor commands that cause it, thereby completing the motor-sensory loop. This means that the cortical mapping $C$ is an inverse of the external mapping $W$. Since $C$ is the linear approximation to the mapping between the rates of sensory neuron firing $\lambda_s$ and the rates of motor neuron firing $\lambda_m$, each element of $C$ can be no greater than the maximum number of motor cortical spikes that can result from a single sensory cortical spike. Label this maximum number of output spikes per input spike $n_{\text{max}}$. Similarly, because the spike rate $\lambda_m$ is measured over a finite period of time, there is a minimum nonzero value of each element of $\lambda_m$ that can be measured. Since there is a maximum achievable spike rate for $\lambda_m$, there is an effective minimum value $n_{\text{min}} = \min (\lambda_m)/\max (\lambda_s)$ for nonzero elements of $C$. Ideally, $C = V^T G^{-1} P^{-1}$, but the limitation on $n_{\text{max}}$ and $n_{\text{min}}$ means that in reality we have $C = V^T N$ where $N$ is a diagonal matrix of gains $n_i$, with

$$n_i = \begin{cases} \frac{1}{p_i g_i} & n_{\text{max}} < \frac{1}{p_i g_i} < n_{\text{min}} \\ \frac{1}{p_i g_i} & n_{\text{min}} < \frac{1}{p_i g_i} < n_{\text{max}} \\ \frac{1}{p_i g_i} & n_{\text{max}} < n_i \end{cases}$$

(8)

In general, $g_i$ will be very small so $1/p_i g_i$ will be larger than $n_{\text{max}}$ for all modes, and $N$ will be equal to a diagonal matrix with identical elements $n_i = n_{\text{max}}$. The entire loop transformation can now be written

$$\lambda_s(t + \Delta t) = V^T N P G V \lambda_s(t)$$

(9)

and the gain through mode $i$ is given by

$$g_i = \frac{N_{\text{max}} P_{ig_i} < 1}{p_i g_i} \left( \frac{1}{n_{\text{max}}} > p_i g_i \right) > n_{\text{max}}$$

(10)

This means that either an increase in the gain $g_i$ through the external environment or an increase in the sensory cortical population size $p_i$ can potentially lead to instability in the sensory-motor loop.

If the command signal $u$ to the motor cortex is sustained during a prolonged movement, then the signal returning through the motor-sensory loop will add to the sustained command. In normal circumstances, this effect would be expected to be very small and not lead to significant changes in the force output. However, in the circumstance of pathologically increased loop gain, the feedback can become significant and lead to instability even at loop gains that are $<1$. In this case, we have

$$\lambda_s(t) = g \lambda_s(t - \Delta t) + u$$

(11)

which increases with time constant proportional to $-1/\log \gamma$ toward the steady-state

$$\lambda_s = \frac{u}{1 - \gamma}$$

(12)

If motor neuron firing saturates at a rate $\lambda_{\text{max}}$, then saturation occurs if

$$\gamma > 1 - u/\lambda_{\text{max}}$$

(13)

which will be $<1$. Note that as soon as the motor excitation $u$ stops, the activity will decay to zero with time constant proportional to $-1/\log \gamma$.

A further cause for instability can occur if the structure of the control modes changes. For instance, if two fingers are consistently co-activated, if they are sutured together, or if pressure is applied simultaneously and repeatedly to multiple fingers, then there may be a new combined mode representing the combined sensory stimulus to the two fingers. The combined sensory receptors and sensory cortical cells for the two original populations will lead to a larger total population, and a higher gain for the combined mode. This effect would be particularly severe if a combined mode involved a combination of agonist and antagonist muscle activation, since co-contraction may lead to increased correlated spindle fiber activation from both muscles, and the proprioceptive feedback gain will therefore be much higher. Plasticity mechanisms can worsen this effect, since the cortical representation for the two modes will fuse and possibly enlarge (Allard et al. 1991; Byl et al. 1996a, 1997; Dinsie et al. 1993; Jenkins et al. 1990; Wang et al. 1995; Xerri et al. 1996, 1999). This
leads to much more highly correlated distributed activity in sensory cortical areas (Recanzone et al. 1992; Wang et al. 1995) that can far more powerfully excite motor cortex neurons, given their relatively short integrative time constant.

**Simulations**

The simulation in Fig. 3 shows the effect of increased loop gain on neural firing rates. In each case, the initial motor command \( u = m(0) \) is a randomly chosen vector of spike counts, and \( C \) and \( W \) are random matrices normalized to a total gain of either 0.95 or 1.05. \( m(t + \Delta t) \) is defined as a vector of the integer number of spikes that occurred between times \( t \) and \( t + \Delta t \), and this vector is generated from Poisson statistics with rates given by \( CWm(t) \). The time-steps are in units of \( \Delta t \).

There are at least three mechanisms by which plasticity can lead to pathological increases in loop gain. Each mechanism corresponds to an increased gain through one element of the sensorimotor loop shown in Fig. 2. The first mechanism is caused by an increase in the size of the sensory representation of a particular movement mode. This is equivalent to increased gain through a component of the sensory transform \( S \), and it can occur as the consequence of plasticity that increases the cortical representation of sensory signals that occur frequently or have high power. The second mechanism is caused by cross-coupling through the external world so that two normally independent modes are mutually reinforced. This is equivalent to increased gain through \( P \) and can occur as the consequence of an altered mechanical environment such as would happen if two fingers were sutured together, or were otherwise systematically co-stimulated. The third mechanism occurs when two normally independently controlled modes are activated together by the command signals \( u \) and \( m \). This is equivalent to increased gain through the motor transformation \( M \) and can occur with repeated co-contraction of antagonist or normally uncorrelated muscles.

To illustrate the effects of plasticity on the loop gain, we simulate three different ways in which the sensory representation and the loop gain may increase. In the first, the sensory representation increases without any other change in behavior. In the second, there is external mechanical coupling between two modes of the system, as if two fingers had been sutured together. In the third, there is voluntary coactivation of two different modes, corresponding to a repeated task.

The second and third intervention lead to the creation of a new combined mode of the system and therefore de-differentiation of the sensory representation.

In the simulations, \( W \) is a random block-diagonal matrix of dimension \( m_1 + m_2 \) by \( s_1 + s_2 \) where \( m_1, m_2, s_1, \) and \( s_2 \) are the number of neurons allocated within motor and sensory cortex, respectively, to each of two different muscles. The total number of neurons used in the simulations is 40 (20 each in sensory and motor cortex). The linear sensorimotor mapping \( C \) adapts according to a Hebbian cross-correlational learning algorithm with \( \Delta C = \eta m(t)s(t) \) (Hebb 1949) in the simulations, the learning rate \( \eta = 0.01 \). To impose a threshold on motor neuron firing or gain \( n_{\text{max}} \) and \( n_{\text{min}} \) of the mapping \( C \), the system is trained with a small learning rate for only a finite number of steps. Therefore after 200 learning steps the mapping \( C \) is fixed and the system is tested by injecting a random motor cortical activation onto only the \( m_1 \) neurons at \( t = 0 \), and then iterating the motor-sensory loop for 200 time steps of length \( \Delta t \). The time \( T_p \) required for spontaneous neural activity to stop is then measured. The learning and testing process is repeated 10 times for each degree of abnormality, and results are averaged to produce the plots shown in Fig. 5. An important feature of the results is that there is a very rapid increase in sustained neural activity as the loop gain becomes 1.

Enlarging sensory area (shown schematically in Fig. 4A) is described by changing the ratio \( s_1/s_2 \) of the larger to the smaller (normal) digit representation in sensory cortex, for different values of this ratio from 0.2 to 2.0 (the total number of neurons is fixed, so that \( s_2 = 20 - s_1 \)). The number of motor cortical neurons are equal (\( m_1 = m_2 = 10 \)). The elements of \( W \) connecting \( m_1 \) to \( s_1 \) and \( m_2 \) to \( s_2 \) are chosen randomly with small values between 0 and 0.1. In this case there is no cross-coupling, so all elements in \( W \) that connect neurons in \( m_1 \) to neurons in \( s_1 \) (and from \( m_2 \) to \( s_2 \)) are set to zero. During learning, the motor command \( m \) randomly activates neurons in either group \( m_1 \) or \( m_2 \), but never both simultaneously.

External cross-coupling (Fig. 4B) is described by a correlation value that varies from 0 to 0.35. In this case, the number of neurons \( m_1 = m_2 = 10 \) and \( s_1 = s_2 = 5 \). Elements of \( W \) connecting \( m_1 \) to \( s_1 \) and \( m_2 \) to \( s_2 \) are again chosen randomly, but elements connecting \( m_1 \) to \( s_2 \) and \( m_2 \) to \( s_1 \) are nonzero and chosen randomly with normalization so that the column sums are all equal, and vary from 0 to 0.35. This means that the total additional input to any sensory neuron is 0.35. Again,
RESULTS

Figure 3 gives simulated examples of stable and unstable loops for neural populations that are described by the linear loop approximation $\lambda_m(t + \Delta t) = CW\lambda_m(t)$. The figure illustrates the increase or decrease in activity over a population of identical neurons in the loop. If $\Delta t \approx 50$ ms (Deuschl et al. 1989), then at a gain of 1.05, the simulation shows that saturation of firing will occur within 100 steps, or 5 s.

Figure 4 illustrates three causes of instability due to enlarged sensory representation (A), external cross coupling (B), or voluntary co-activation (C). Figure 5 shows simulations of the structures from Fig. 4, demonstrating the increase in activity decay time following a single motor command.

Figure 6 shows the time course of gain increase during Hebbian adaptation immediately following a change in the system. As before, time is indicated in units of $\Delta t$. For this simulation, at time 0 two previously uncorrelated modes start to be voluntarily activated entirely synchronously as illustrated in Fig. 4C. Parameters are the same as those described for Fig. 5C, with $e = 0.5$ in the range that leads to instability. As the cortical map from sensory to motor cortices $C$ adapts to the resulting increased sensory correlation, the loop gain to each of the motor neurons increases. As the gain approaches 1, the time for decay of firing rates $T_d \propto -1/\log(\gamma)$ becomes infinite, indicating sustained neural activity. This graph illustrates the rapid increase in sustained activity $T_d$ that occurs as the gain $\gamma$ nears 1.

DISCUSSION

The simulations show that changes in the sensory representation can lead to instability in the sensory-motor loop that may manifest as symptoms of dystonia. Task specificity is due to instability of only a single eigenvector. Worsening with prolonged activity occurs if continuing motor commands add to a nearly unstable loop gain. Co-contraction and spread of activity are the consequences of disordered or de-differentiated sensory-motor control modes. These properties arise as direct consequences of the linear approximation to the loop transformation $CW$.

To see this in more detail, if $CW$ is initially stable with maximum eigenvalue magnitude $<1$ and if the total gain increases slowly due to change in the motor-sensory gain $g_i$ or the sensory population size $p_i$, then one would expect that at first only one eigenvalue will become $>1$. Only this mode will be unstable, and unless triggered by a particular voluntary movement, ongoing motor command, or sensory input that matches its eigenvector, no instability will be seen. Since the motor system presumably has many different modes that are activated in a context-dependent way, dystonia will initially be very situation dependent. It may be possible to inhibit the dystonia by changing the context using a “sensory trick” (Hallett 1995) that changes the sensory pattern to be only slightly different from the unstable eigenvector. As the loop gain increases further, more modes will become unstable and it will become progressively easier to trigger dystonic postures and increasingly difficult to find sensory contexts in which these postures are inhibited.

Three regimes of behavior can be distinguished. If the largest eigenvalue $\alpha_{max}^2$ of $W^T C^T CW$ is $<1$, then the spontaneous neural activity will decrease toward zero unless a new motor
command is issued to motor cortex. This is the desired behavior of the system: movement occurs only in response to motor commands. However, if the gain is increased and the command is continued for the duration of an ongoing movement, then the combination of the command and the sensory feedback may lead to instability. If \( \sigma_{\text{max}}^2 \approx 1 \), there may be prolonged activity that may or may not saturate depending on random fluctuations in the Poisson statistics. Again, this sustained behavior will only occur if the pattern of activity matches the corresponding eigenvector. If \( \sigma_{\text{max}}^2 > 1 \), there will be sustained motor activity even in the absence of a triggering command, leading to dystonia at rest. The time to decay of neural activity (\( T_g \)) is proportional to \(-1/\log \gamma \). Figure 6 shows that \( T_g \) may increase much more rapidly than \( T_e \) even in the absence of a triggering command, leading to dystonia. In our model, dystonic symptoms are related to increased gain through a sensorimotor loop. The increased gain might decrease while the populations engaged by specific movements could increase due to progressive learning-induced changes that de-differentiate the cortical representations. Documentation of the progressive loss of representational topography may be an index of increase in the loop gain.

Direct measurement of the loop gain is possible in cortical myoclonus by correlating the somatosensory evoked potential and subsequent reflex electromyographic (EMG) response (Rothwell et al. 1984, 1986). However, this is not likely to provide a simple measurement for task-specific dystonia, since in dystonia the gain may only be increased during performance of the specific chosen task, and only particular sensory patterns may be able to excite the abnormal modes. In fact, the sensory response to a nonspecific vibration stimulus is reduced in dystonia on positron-emission tomography (PET) scanning (Tempel and Perlmutter 1990). Long-loop reflexes have been measured, and there are measurable increases in these reflexes in dystonia (Bressman 1998; Eisen 1987; Marsden and Rothwell 1987). There are also changes in the H-reflex recovery curve (Deuschl et al. 1989; Panizza et al. 1990), and prolonged EMG “tails” would be expected to follow rapid voluntary or reflex movements (Marsden and Rothwell 1987). Simultaneous activation of agonist and antagonist muscles is detectable as EMG “overflow” (Bressman 1998; Nakashima et al. 1989). Many of these effects might only be evident in certain postures or during performance of the affected task.

Conclusions

We have proposed a new model to explain the possibility of sensory disorganization as an etiology of focal task-specific dystonia. In our model, dystonic symptoms are related to increased gain through a sensorimotor loop. The increased gain leads to instability, which saturates the firing rate of motor cortical cells and causes a “high-output paralysis” of the affected muscles. Although we have proposed this model as a possible mechanism by which changes in the sensory representation could lead to dystonia, it is important to realize that dystonia might also be caused through a similar mechanism due to enlargement or de-differentiation of motor representations. Further, we have chosen to use a very simple model of the sensory representation that does not include lateral interactions within sensory or other cortices. This was done to demonstrate minimal requirements for the development of dystonia. In fact, a linear approximation to the sensory-motor loop is sufficient to predict an increase in tone resulting from sensory changes. The simulations show that, in addition, plasticity mechanisms can contribute to worsening symptoms. In this model, dystonia arises as a natural consequence of the normal behavior of the sensorimotor system in the face of abnormal sensory input. Much work remains to be done to validate the predictions and clinical relevance of this model, but it provides an initial structure to explain a possible etiologic role of sensory representations in the motor disorder of task-specific dystonia.

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