REFERENCES

K. Fukunaga, "Introduction to Statistical Pattern Recognition," Academic Press, New York, 1972.

R. O. Duda and P. E. Hart, "Pattern Classification and Scene Analysis," Wiley, New York, 1973.

P. R. Devijver and J. Kittler, "Pattern Recognition: A Statistical Approach," Prentice-Hall, Englewood Cliffs, New Jersey, 1982.

A. K. Agrawala (ed.), "Machine Recognition of Patterns," IEEE Press, New York, 1977.

L. N. Kanal, Patterns in pattern recognition: 1968-1972, *Trans. IEEE Inform. Theory,* IT-20, pp. 697-722, 1974.

P. R. Krishnaiah and L. N. Kanal (ed.), "Handbook of Statistics 2: Classification, Pattern Recognition and Reduction of Dimensionality," North-Holland, Amsterdam, 1982.

T. Y. Young and K. S. Fu (ed.), "Handbook of Pattern Recognition and Image Processing," Academic Press, New York, 1986.

Richard R. Lippman, An introduction to computing with neural nets, *IEEE ASSP magazine,* pp. 4-22, April 1987.

3

SELF-ORGANIZING NEURAL NETWORK ARCHITECTURES FOR ADAPTIVE PATTERN RECOGNITION AND ROBOTICS

by Daniel Bullock[†]*, Gail A. Carpenter*[‡]*, and Stephen Grossberg*[*]*,*
Center for Adaptive Systems, Boston University

In this chapter, we discuss some recent results in neural networks relevant to adaptive pattern recognition and sensory-motor control problems. In biologically-oriented neural networks, whose fast dynamics are governed by slowly changing network transmission weights as well as by rapidly fluctuating external inputs, two major foci of research are (1) how to ensure that short-term dynamics are pattern preserving and (2) how to automatically regulate learning (transmission weight modification) in such a way that the system is guaranteed to develop along an adaptive trajectory. To exemplify these issues, we will quickly move through a series of network constructs. On the perceptual-cognitive end, we will discuss how recurrent competitive fields allow invariant pattern registration despite large fluctuations in input energies, and how an adaptive resonance module can learn a stable categorization/recognition code without an external teacher. On the motor-control side, results on variable-speed trajectory formation, sensory updating, learned anticipatory error compensation, and length-tension factorization illustrate networks that are applicable in several performance domains (planned arm and speech movements, ballistic eye-movements) and that help explain data on several distinct but cooperative neural regions (pre-central motor cortex, globus pallidus, cerebellum, spinal cord).

[†] Supported in part by the National Science Foundation (NSF ISI-87-16960).

[‡] Supported in part by the Air Force Office of Scientific Research (AFOSR F49620-86-C-0037 & AFOSR F49620-87-C-0018) and National Science Foundation (NSF DMS-86-11959).

[*] Supported in part by the Army Research Office (ARO-DAAL-03-88-K-0088) and the Air Force Office of Scientific Research (AFOSR F49620-86-C-0037 & AFOSR F49620-87-C-0018).

The primate nervous system has parsed the problems of perception, recognition, and sensory-motor control by distributing the computational task across a large number of specialized neural networks, many of which operate in parallel. Though the existence of a distributed solution has long been clear from the selective and partial effects of localized brain and spinal lesions, an understanding of the nature of the computations performed by distinct networks has been slower to develop. Recently, however, functionally oriented studies of simulated neural networks as analog, non-linear systems with coupled short- and long-term dynamics have begun to produce a powerful theoretical basis for making sense of the rich, but extremely ambiguous, physiological database (Grossberg, 1988a; Grossberg and Kuperstein, 1986).

1. AUTOMATIC GAIN CONTROL AND SENSORY FACTORIZATION OF PATTERN AND ENERGY

A paradigmatic study of short- and intermediate-term dynamics and their importance for non-distortive pattern registration and storage by a neuronal network was the paper by Grossberg (1973; reprinted in Grossberg, 1982) on feedforward and recurrent competitive fields. As shown in Figure 1A and 1B, each site in such fields recieves an excitatory input as well as inhibitory inputs branching from excitatory inputs to all other sites (in fully interconnected examples). To begin to analyze the real-time behavior of such a network, it is necessary to write differential equations for the activity x_i at each site v_i. Grossberg (1973) chose to analyze equations whose forms were closely related to the neural membrane equations of Hodgkin and Huxley (1952). A particularly useful formulation was

$$\frac{d}{dt}x_i = -Ax_i + (B - x_i)I_i - x_i \sum_{k \neq i} I_k \tag{1}$$

where A is a spontaneous decay rate, B is the maximum activity level, $\sum_{k \neq i} I_k$ is the total input to sites other than site i, and $i = 1, 2, \ldots, n$ for a neural field with n sites.

Grossberg showed that when the fluctuating activity at each site in such a field is governed by (1), then the inhibitory connectivity affords a kind of automatic gain control, which simultaneously prevents saturation and preserves information specified by the relative sizes of activities at different sites. In particular, let $\Theta_i = \frac{I_i}{I}$ where $I = \sum_n I_n$. Then the equilibrium activity at site v_i is:

$$x_i = \Theta_i \frac{BI}{A + I}. \tag{2}$$

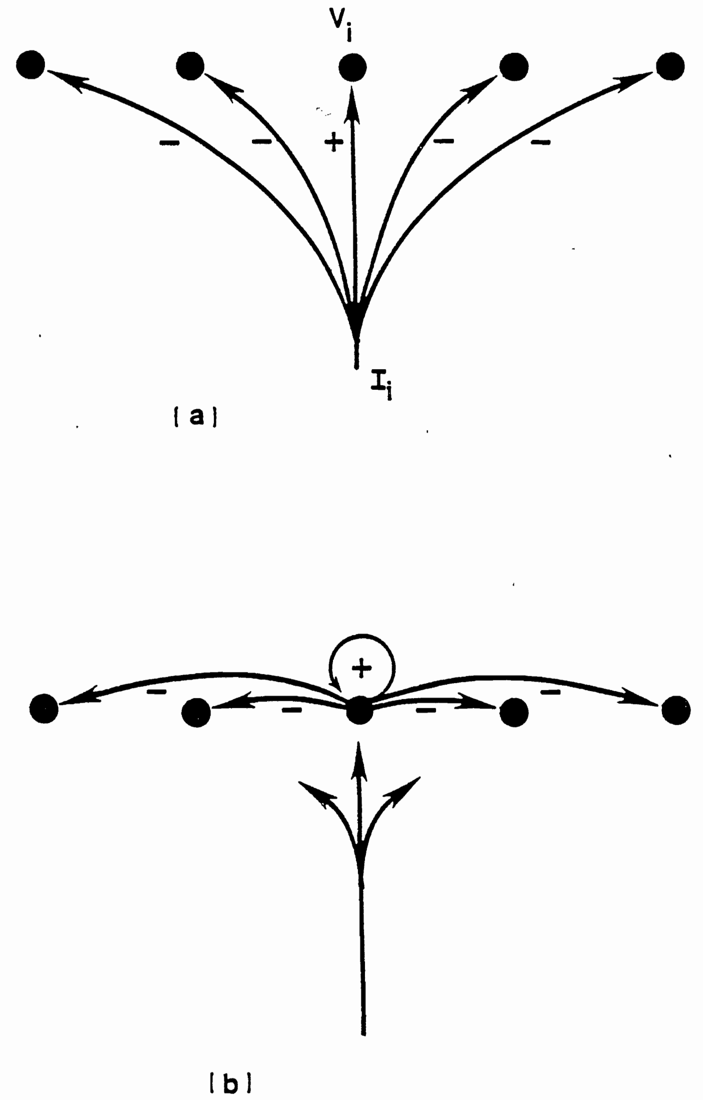

Figure 1. Schematic representations of two types of on-center, off-surround (competitive)networks. **(A)** A feedforward network, in which the input pathways define the on-center, off-surround interactions. For clarity, only inputs branching from channel I_i, which excites site v_i and inhibits other sites, are shown. The same, recentered, branching pattern holds for all indexes $k \neq i$. **(B)** A feedback network in which recurrent excitatory and inhibitory interactions can lead to various pattern storage and pattern transformation properties, e.g., choice of the site with the largest initial excitatory input.

Thus despite huge variations in I, the total input energy, the neural activity at each site remains proportional to the size of its excitatory input, I_i, relative to the excitatory inputs at all other sites. Such invariant ratio processing is a well-known operating characteristic of human perceptual systems, where it goes by the name "Weber's law". Besides explaining an important psychophysical law as a corollary of the need to factor pattern and energy, the model provides a rationale for a ubiquitous neural property, namely feedforward inhibitory connectivity within sensory and perceptual systems.

Further analyses concerned pattern processing in recurrent competitive fields, which, by virtue of excitatory feedback, are capable of indefinitely storing a pattern after the input is shut off. Sites in the simplest example of such a network obey equations of the form

$$\frac{d}{dt}x_i = -Ax_i + (B - x_i)[I_i + f(x_i)] - x_i[\sum_{k\neq i} I_k + \sum_{k\neq i} f(x_k)] \quad (4)$$

where $f(w)$ is generally a monotonic increasing function of its argument. Figure 2 (based on Grossberg, 1973) shows how the choice of this function can change the pattern-storage characteristics of the network. In particular, it shows that when the goal is to preserve initial activity ratios in a noisy environment, the best choice is a sigmoidal feedback function. Unlike a zero-threshold, linear feedback function, the sigmoid affords a tunable threshold that allows the suppression of small activities due to noise.

2. SELF-STABILIZING ADAPTIVE PATTERN CLASSIFICATION

A direct descendent of the work on recurrent competitive fields, and of related work on spatial pattern learning and classification (e.g. Grossberg, 1968) is the Adaptive Resonance Theory (ART) of Carpenter and Grossberg (1987a; 1987b) which itself has been under continuous development for more than a decade. This theory shows how to design a family of stable multi-layered neural networks, each member of which is capable of automatic, on-line category induction and rapid pattern classification. In particular the theory provides an autonomous solution to the stability problem inherent in all networks with coupled short- and long-term dynamics. The essential point of the solution is that the architecture responsible for the short-term dynamics—which constitute the computations in these systems where "the architecture is the algorithm"—must be parsed

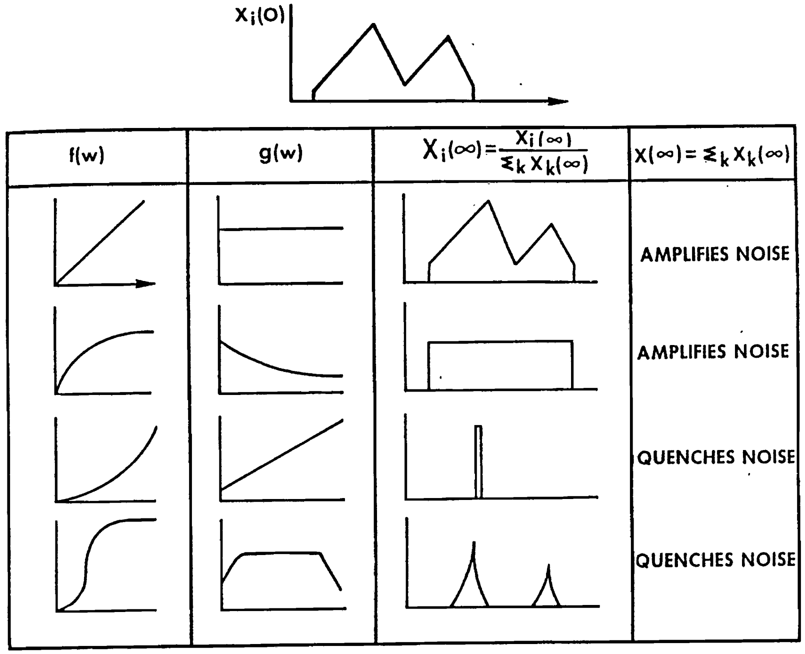

Figure 2. Influence of recurrent signal function $f(\omega)$ on input pattern transformation and short-term memory storage in a recurrent competitive field. Note that $g(\omega) = f(\omega)/\omega$. Based on Grossberg (1973).

into a relatively fixed regulatory component and an adaptive pattern-encoding component, which changes more slowly than the short-term dynamics. The fixed regulatory component then guarantees that the slower adapting pattern-encoding component cannot develop along non-adaptive trajectories. By contrast with ART networks, many recent neural network models have virtually no self-regulatory component, and hence depend on benevolent input schedules for their apparent adaptive trajectories (Grossberg, 1988a).

Figure 3 is a highly schematic representation of an ART module. Its first component is an input field, $F1$, whose distinct sites correspond to possible object features. Thus a distinct pattern of activity across $F1$ represents the set of features possessed by the object currently being presented for categorization by the ART module, and objects with disparate features will activate largely non-intersecting sets of sites in $F1$. In the maximal compression case, the task of the network is to learn to assign a single distinct site in field $F2$ for every distinct *class* of patterns that may be instated at $F1$. Furthermore, we desire a network that

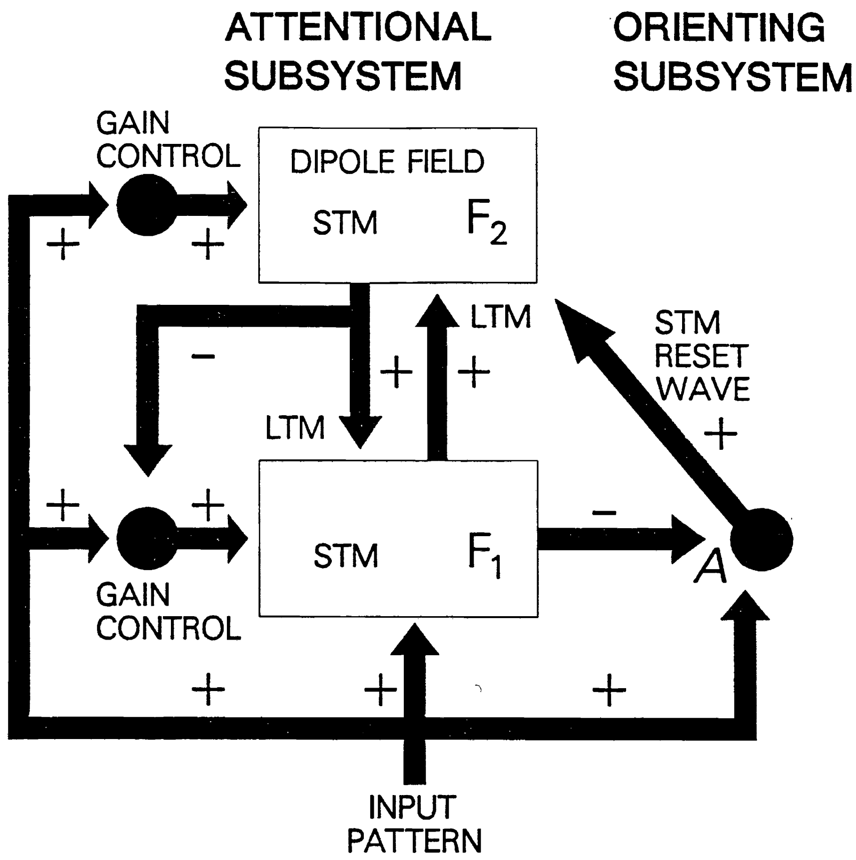

Figure 3. Anatomy of the attentional-orienting system: Two successive stages, F_1 and F_2 of the attentional subsystem encode patterns of activation in short term memory (STM). Bottom-up and top-down pathways between F_1 and F_2 contain adaptive long term memory (LTM) traces which multiply the signals in these pathways. The remainder of the circuit modulates these STM and LTM processes. Modulation by gain control enables F_1 to distinguish between bottom-up input patterns and top-down priming, or template, patterns, as well as to match these bottom-up and top-down patterns. Gain control signals also enable F_2 to react supraliminally to signals from F_1 while an input pattern is on. The orienting subsystem generates a reset wave to F_2 when mismatches between bottom-up and top-down patterns occur at F_1. This reset wave selectively and enduringly inhibits active F_2 cells until the input is shut off. Reprinted with permission from Carpenter and Grossberg (1987a).

can quickly stabilize its assignment, so that the *same* distinct site in $F2$ is always activated when a member of the pattern class is presented, despite large numbers of intervening presentations during which other pattern classes are learned. Finally, we want the network to induce and stabilize its categorization scheme autonomously, i.e. without an external teacher.

These properties can be realized if the pathways that connect all sites in $F1$ to all sites in $F2$ possess modifiable transmission weights (also called LTM, or long term memory, traces) that can be stably adapted over learning trials. To begin, suppose that during learning transmission weights z_{ij} on pathways arriving at a particular $F2$ site v_j, which is arbitrarily chosen to code exemplars of category j, become relatively *large* for all pathways from $F1$ feature-coding sites v_i that are diagnostic of category j, but relatively *small* for all pathways from features not diagnostic of category j. Suppose that upon instatement of any future feature set at $F1$, the total signal arriving at $F2$ sites v_j ($j = 1, 2, \ldots n$) is

$$T_j = \sum_i S_i z_{ij} \tag{4}$$

where, in the simplest case, $S_i = 1$ if the input contains the feature represented by $F1$ site v_i, and $S_i = 0$ if the input lacks this feature. Thus the fiber bundle projecting from $F1$ sites to $F2$ sites maximally activates that $F2$ site whose learned diagnostic feature pattern (encoded in the path weights) best matches the feature pattern of the new exemplar presented to the network. In effect, the adaptable filter connecting $F1$ to $F2$ computes, in parallel, the dot products between the input feature pattern and the distinct diagnostic feature patterns associated with all sites in $F2$. The site of the maximal dot product specifies the network class into which the current input exemplar falls.

If $F2$ is a recurrent competitive field (e.g., if it obeys equation 3), then its feedback function can be chosen such that after a short time the $F2$ site with the initially maximal activity will also be the *only* active site (Figure 2). Thus the "arbitrary choice" of a distinct coding site mentioned above can be made by the network itself on the basis of random initial differences in the strength of connectivity between $F1$ and $F2$ sites. Once such a choice is made, we have a distributed pattern across $F1$ and a single site active in $F2$ with activity x_j. During this interval of coactivation, pathweights z_{ij} are adjusted in accord with a learning law of form:

$$\frac{d}{dt} z_{ij} = f(x_j)[-\epsilon z_{ij} + g(x_i)] \tag{5}$$

Assuming that $f(x_j)$ and $g(x_i)$ are positive for positive arguments and zero otherwise, this law assures that weights on lines projecting to the active $F2$ site from active $F1$ sites grow toward positive value $g(x_i)$ while weights on lines projecting from inactive $F1$ sites shrink toward zero. As a result the active $F2$ site becomes more susceptible to future activation by input patterns possessing large featural commonality with the training pattern, and less susceptible to activation by disparate input patterns.

Grossberg (1976) noted that the scheme as so far described is unstable if learning continues beyond the time when categories are first established. This can be appreciated by noting that the *best* initial match need not be a *good* match. Because the simple feedforward scheme just described has no way of detecting whether the winning $F2$ site was activated by a pattern that matched the category's diagnostic feature pattern well or poorly, situations readily arise in which the weight vector associated with the winning $F2$ site begins to deform, in accord with (5), in the direction of a poorly matching input vector.

ART overcomes this problem by providing mechanisms whereby the network can compute the goodness-of-match between the *current* $F1$ pattern and that $F1$ pattern *expected* on the basis of prior input patterns that led to activation of the current $F2$ site. In the simplest case, such an expectation can be learned as a vector of weights on pathways projecting back from the chosen $F2$ site to all sites in $F1$, and the learning rule can be a variant of the form already described for the $F1$ to $F2$ adaptive filter. Then when an $F2$ site is activated, this causes the learned expectation to be sent as a second "input" to $F1$. A suitably designed $F1$ can then perform a feature-by-feature comparison between the bottom-up and the top-down inputs.

ART also provides a mechanism by which the $F2$ level can be reset whenever the degree of match between $F1$ inputs falls below an adjustable criterion. This reset prevents recoding of committed $F2$ sites by disparate exemplars and guarantees code stability. After reset, competition at $F2$ determines a *new* choice of site for coding the $F1$ input pattern, with the initial choice excluded from effective competition. This process iterates until an $F2$ node that has not learned a non-matching expectation is found. Its input weight vector and its output to $F1$ weight vector then begin to deform in the direction of the $F1$ pattern, and a resonance begins to occur between $F1$ and $F2$. This phenomenon gives the theory its name, "adaptive resonance theory."

By virtue of the reset-on-mismatch operation, ART performs an automatic serial search for an uncommitted $F2$ site when confronted by a member of a novel pattern class. Yet after learning, a serial search is unnecessary because the input directly addresses the correct $F2$ site as part of what is essentially a massively *parallel* search operation. ART systems thus exemplify a property we call *autonomous supercession of control:* the trajectory through system states utilized at an early stage of learning is autonomously superceded by a shorter, more efficient trajectory as learning proceeds. This is a critical feature of self-organizing systems, which must be capable of iterating to a solution when confronting novel problems, yet also capable of achieving high performance by directly instating learned solutions to familiar problems. In the second part of the chapter, we show that autonomous supercession of control has also been a major organizing theme in studies of neural networks for motor-control.

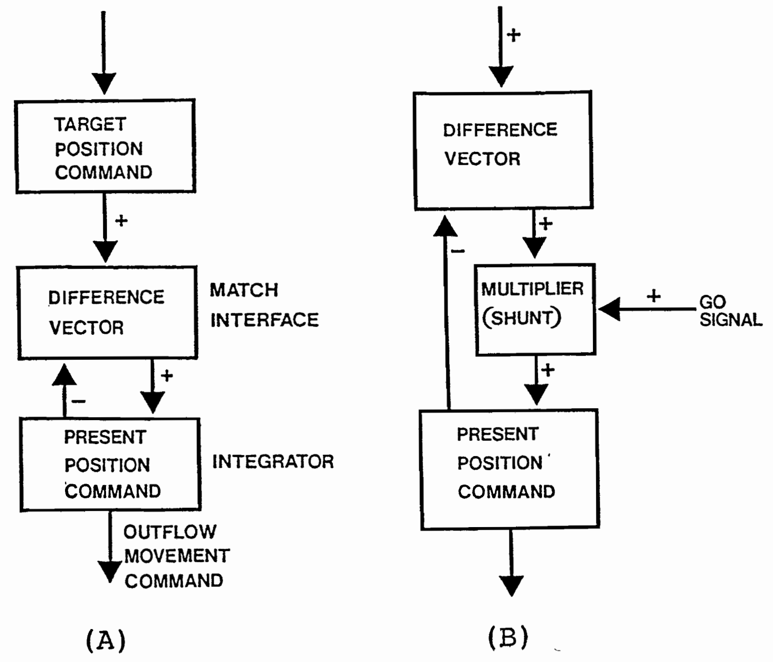

Figure 4. **(A)** A match interface within the VITE model continuously computes a difference vector (DV) between a target position command (TPC) and a present position command (PPC), and adds the difference vector to the present position command. **(B)** A GO signal gates execution of a primed movement vector and regulates the rate at which the movement vector updates the present position command. Reprinted with permission from Bullock and Grossberg (1988).

Detailed specifications of ART systems and explorations of the operating characteristics of several variants (e.g., versions for binary and for analog features) can be found in Carpenter and Grossberg (1987a; 1987b).

In the remaining sections, we will discuss four networks that have emerged on the motor-control side of neural networks research. Though different than the ART networks, each borrows from the same tradition of thinking within the neural networks field. In particular, these examples further illustrate the importance of coupled short- and long-term dynamics in these kinds of systems, and provide further evidence that autonomous match-regulated learning, automatic supercession of control, and automatic pattern-energy factorization are key organizing principles for the theory of neural networks.

3. TRAJECTORY GENERATION

First is a network model formulated by Bullock and Grossberg (1988; 1989) to explain trajectory formation in simple point-to-point arm movements. The theory proposes that sight of a desired object within reach can activate a distributed neural representation called the terminal position command, or TPC, an array of muscle-length (and therefore joint-angle) settings which, if instated in the arm, would position the hand near the object. This TPC is compared with a distributed representation called the present position command, or PPC, the array of muscle-length settings responsible for the arm's present posture. Subtracting the PPC from the TPC yields a difference vector, or DV, the array of muscle-length changes needed to bring the arm from its present position to the desired position coded by the TPC (see Figure 4A).

Thus the initial assumptions, apart from the parallelism, are fairly standard in a control-theoretic context, though not in the context of some recent physiological discussions of arm movements (e.g. Cooke, 1980). However, rather than merely adding the DV to the PPC, we propose that before being integrated by the PPC stage, outputs of the DV stage are multiplied in parallel by a widely broadcast, time-varying signal that grows faster-than-linearly during the movement interval. Thus the product of a declining DV and a growing "GO-signal" determine the momentary PPC updating rate (see Figure 4B). The widely-broadcast signal is called a GO-signal because until it becomes greater than zero the circuit can compute a DV but no PPC updating can occur—a motor act can be centrally primed then released by activation of the GO-signal. The GO-signal itself is

multiplied by a scalar that serves as a movement duration setting. Because the trajectory is formed by integrating multiplied DVs until the PPC equals the TPC and the DV stage activity is thereby zeroed, we call the model the vector-integration-to-endpoint, or VITE, model of trajectory formation. Equations for one component, corresponding to the controller for one of many muscles that may contribute to the movement, are:

$$\frac{d}{dt}V_i = \alpha(-V_i + T_i - P_i) \tag{6}$$

$$\frac{d}{dt}P_i = G[V_i]^+ \tag{7}$$

where α is constant, V_i is the DV stage activity, T_i is the TPC stage activity, and P_i is the PPC stage activity, for the component indexed by i. $G(t)$ is the current value of the GO-signal and $[V_i]^+ = \max(V_i, 0)$. Competitive (inhibitory) inputs to the PPC stage from antagonist muscle channels are omitted for clarity (see Bullock and Grossberg, 1988, 1989).

Despite its simplicity, the VITE model makes qualitatively and quantitatively correct predictions regarding a wide range of behavioral and neurophysiological data. On the physiological side, the key data are those of Georgopoulos, Schwartz and Kettner (1986) on precentral motor cortical cells (DV stage), and those of Horak and Anderson (1984) on the globus pallidus (GO-signal pathway). Among the well-documented kinematic properties explained by the model, several are common to both arm and speech-articulator movements, e.g., rate-dependent velocity-profile asymmetry, invariant ratio of maximum to average velocity, and a logarithmic speed-accuracy tradeoff (Bullock and Grossberg, 1988, 1989). Regarding the latter, note that energizing the movement by increasing the GO-signal scalar has relatively little effect on movement form (direction and distance) because of the way the GO-signal feeds into the loop that works to zero the DV. In particular, the multiplicative interaction of DV and $G(t)$ assures that PPC updating ceases whenever DV reaches zero, regardless of the size of $G(t)$. This is another example of a network design that ensures pattern-energy factorization.

Figure 5 illustrates that the circuit tends to guarantee that the different PPC command components influenced by a common faster-than-linear GO-signal will reach their terminal values (muscle-length settings) synchronously despite significant onset-time variability in DV component readout. This means that brief selective inhibition of some DV output components could be used to stagger action at different joints without sacrificing the

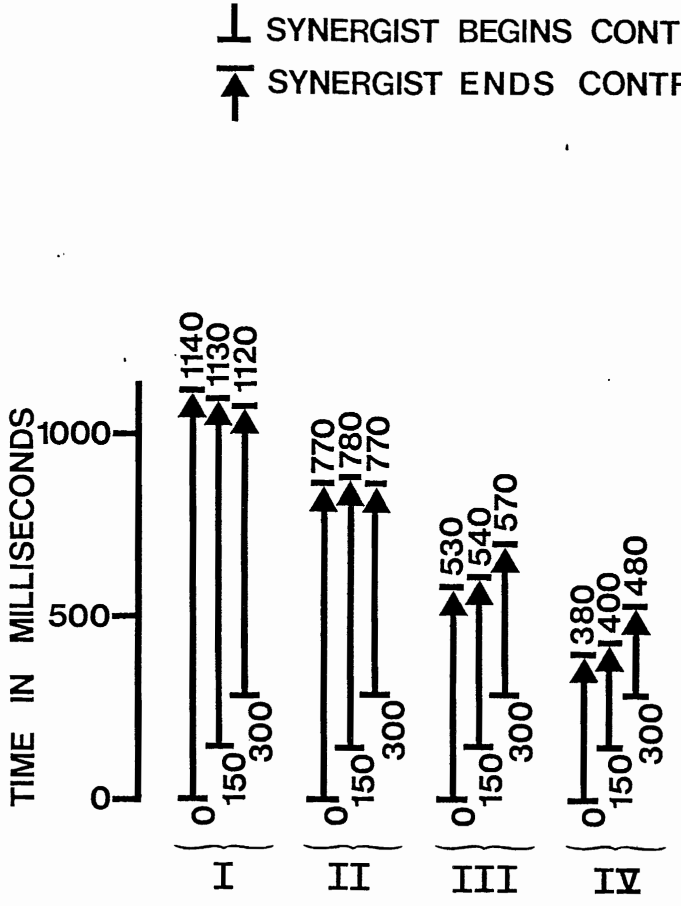

Figure 5. Simulation results showing automatic VITE circuit compensation for contraction-onset-time staggering across three components of a synergy. Each block (I, II, III, IV) of simulations shows results for a different value (10, 20, 40, and 80, respectively) of the GO signal scalar. The different lengths of bars within each block show that less time is needed to update those components whose onset times are most delayed. Offset synchrony begins to break down when earlier components have executed more than 50 percent of their trajectories before later components begin to move. Reprinted with permission from Bullock and Grossberg (1988).

desirable property of synchronous termination of muscle contractions. Hollerbach, Moore, and Atkeson (1986) have noted that such staggering could be used to linearize the Cartesian space hand-paths produced by linear-interpolative joint-space trajectory generators, of which the VITE circuit is one example, and have produced evidence that human arm movements do exhibit joint-space planning.

A closely related consequence of faster-than-linear GO-signal growth during movement emerges when we consider that TPCs frequently change during movement. For example, the projected position of the object to be reached may change, or a subject reaching for an object initially in the visual periphery may make a better estimate of object location after performing a saccade (ballistic eye movement) to foveate the object. The latter situation arises at least as frequently as the former (moving object), because saccades take much less time than the arm movements that may be unfolding in parallel. In a properly designed system incorporating the VITE module, the TPC is updated, after the saccade or after a target position change, by direct instatement via an eye-hand map; the TPC-PPC computation then updates the evolving DV, and this late-arriving information affects the arm's trajectory more quickly by virtue of the larger GO-signal value. Strong evidence that this operating characteristic is true of humans and perhaps many other mammals comes from experiments by Georgopoulos, Kalaska, and Massey (1981), Goodale, Pellisson and Prablanc (1986), and Gracco and Abbs (1985).

4. SENSORY UPDATING

A clearly delineated circuit like the VITE model provides clues to the brain's factoring strategy because it can only work well in connection with several complementary circuits. Of primary importance is a self-organizing associative map for eye-hand coordination, such as that developed by Kuperstein (1987). Such a map explains how seeing an object can directly instate a TPC.

Another likely circuit is the PUP (passive update of position) circuit shown in Figure 6 (Bullock and Grossberg, 1988). It ensures that when the GO-signal is off or small, the PPC is updated by sensory DVs arising from passive movements imposed on the arm. Such DV's are computed at a motor-sensory interface (DV_p stage in Figure 6), which includes modifiable transmission weights (symbolized by the semi-circular path-ending in Figure 6) whose long-term dynamics ensure that the motor signals used in the computation are correctly calibrated to the scale

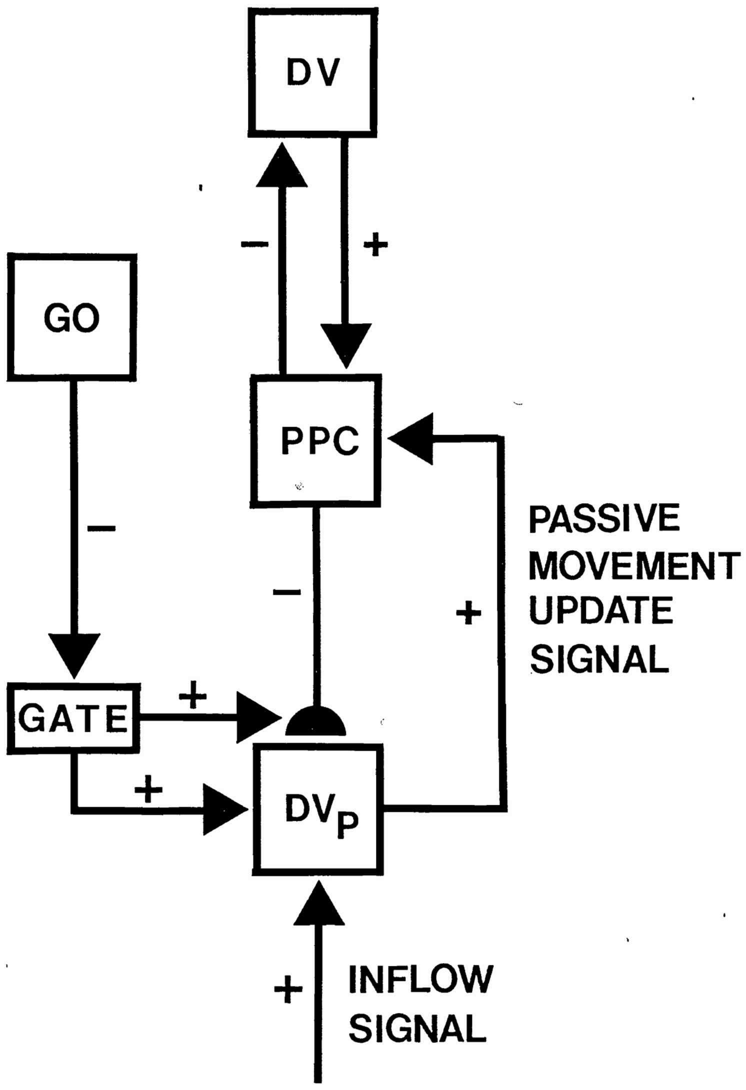

Figure 6. A passive update of position (PUP) circuit. An adaptive pathway $PPC \rightarrow DV_P$ calibrates PPC-outflow signals in the same scale as inflow signals during intervals of posture. During passive movements, output from GO equals zero. Hence the passive difference vector DV_P updates the PPC until it equals the new position caused by any passive movements that may occur due to the application of external forces. Reprinted with permission from Bullock and Grossberg (1988).

used by the sensory signals. A similar circuit was previously employed by Grossberg & Kuperstein (1986) in their multi-circuit model of the primate neural system for ballistic eye-movements. Note that the GO-signal gates, or switches on and off, not only the passive updating process, which occurs on a fast time-scale, but also the calibrative learning process (transmission weight modification), which occurs on a slower time scale. The gating prevents learning during fast movement, when feedback lags create spurious mismatches at the DV_p stage, mismatches that might force the transmission weights along a non-adaptive trajectory in the absence of the regulatory gating.

Typical equations for a PUP circuit component i are: present position command,

$$\frac{d}{dt}P_i = G[V_i]^+ + G_p[M_i]^+ \tag{8}$$

outflow-inflow interface,

$$\frac{d}{dt}M_i = -\beta M_i + \gamma I_i - zP_i \tag{9}$$

and synaptic transmission (learning) law,

$$\frac{d}{dt}z_i = \delta G_p(-\epsilon z_i + [M_i]^+) \tag{10}$$

where P_i is the PPC stage activity, M_i (for "match interface") the DV_p stage activity, G_p the output of the node inhibited by positive GO signals, and z_i the value of the learned transmission weight for a given component (muscle channel). With learning, z_i converges on a value such that $z_iP_i \simeq \gamma I_i$ when the arm has reached a given commanded posture. Constant coefficients δ and ϵ respectively control the overall learning rate and passive forgetting rate, both of which are slow relative to the dynamics governed by equations (8) and (9). Note that learning (change in synaptic weights z_i) proceeds faster when M_i, the discrepancy between inflow and outflow measures of present position, is large. Thus learning must be prevented when large discrepancies occur that are not due to miscalibration, e.g. during rapid movement. The active gating of sensory feedback pathways during rapid movement is well supported in the physiological literature (e.g., Evarts and Fromm, 1978).

5. ANTICIPATORY COMPENSATIONS

Because the VITE circuit uses feedback from the PPC stage to zero the DV during movements rather than sensory feedback, provisions must exist to ensure that the arm actually tracks the evolving PPC. In fact, such provisions are distributed across cortical and cerebellar networks in the brain, across spinal networks, and in the muscles themselves, which behave in some respects like springs. Figure 7 shows the overall design for a muscle linearization network (MLN) developed in Grossberg and Kuperstein (1986). Such a network autonomously learns to anticipatorily compensate for non-linearities in the muscle plant's response to changes in the PPC's length settings. In particular, whenever the measured response of the muscle (inflow signal) fails to match the commanded response (unconditional outflow signal), a mismatch is registered at the outflow-inflow interface (OII) and an error signal is sent to the adaptive gain stage (AG), where the strength of the transmission weight on a supplementary command-specific (position-dependent) outflow pathway is incremented or decremented depending on the sign of the error. Over time, the system comes to behave as if there were a linear relationship between PPC stage activities and muscle lengths, and errors no longer occur because they are pre-empted by the feedforward conditioned gain signals that arrive at the muscle plant via the supplementary pathway, or side loop, that passes through the AG stage. Prior to AG stage learning, errors must be compensated by reactive systems that operate *after* errors occur. Thus AG stage learning effectively creates new paths that allow direct instatement to supercede iteration—another example of autonomous supercession of control.

By virtue of the adaptive gain stage, the brain includes a powerful general purpose mechanism for learning arbitrarily conditionalized anticipatory compensations, and the broad usefulness of such a mechanism in motor skill acquisition (muscle linearization being only one of many applications) is attested by the large cranial volume displaced by the deeply convoluted cerebellum—almost certainly the site of the predictive adaptive gain stage (Grossberg and Kuperstein, 1986; Hore, 1987; Ito, 1984). Because the muscle linearization network of Figure 7 was developed as part of a neural system for moving the eye, which carries no loads and is subjected to few if any external pertubations, it can be much simpler than a functionally equivalent network for an arm. Assembling other components of the arm network, one of which is reprised in the next section, is one of the foci for our ongoing research.

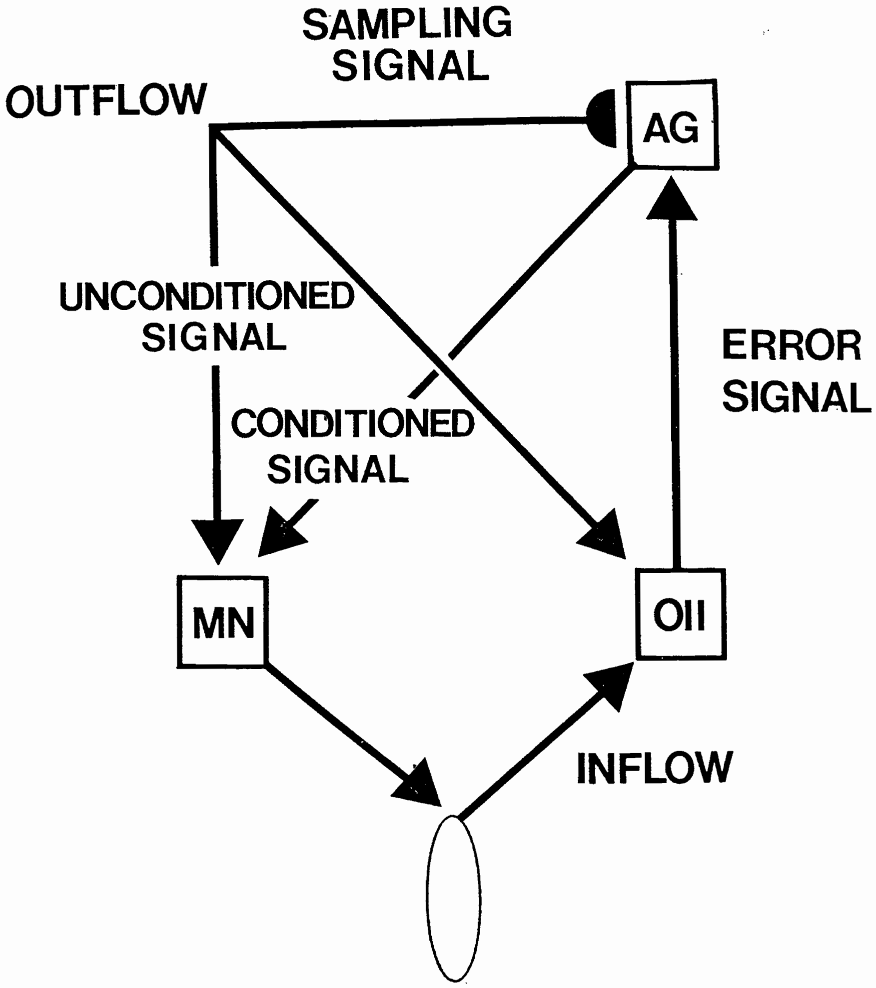

Figure 7. Some main features of the muscle linearization network, or MLN: The outflow-inflow interface (OII) registers matches and mismatches between outflow signals and inflow signals. Mismatches generate error signals to the adaptive gain (AG) stage. These error signals change the gain of the conditioned movement signal to the motoneurons (MN). Such an MLN adaptively linearizes the responses of a nonlinear muscle plant to outflow signals. The outflow signals can therefore also be used as a source of accurate corollary discharges of present eye position. Reprinted with permission from Grossberg and Kuperstein (1986).

6. SEPARABLE CONTROL OF JOINT ANGLE AND JOINT STIFFNESS

A remarkable property of the skeleto-muscular control system is the ability to hold arbitrary postures at various levels of stiffness: at any desired angle, we can vary the muscular forces acting on a joint such that the joint is either very compliant or very rigid. Thus muscles must be able to generate many levels of force at every possible length, and Bullock and Grossberg (1989) showed that this requirement leads to a self-similarity property, at the neuro-muscular interface, which had already been known empirically as the *size principle* of spinal motoneuron recruitment (Henneman, 1985) which ensures a faster-than-linear functional relation between neural inputs and muscle-force outputs. We also showed that the non-linearity introduced by the size principle complicates the spinal circuitry needed to provide higher motor centers with a simple method of achieving independent control of muscle length and muscle tension. This led us to propose a new quantitative model of the spinal-muscular system called FLETE, for **f**actorization of **le**ngth and **te**nsion. Simulations of this model show that the recurrent inhibition provided by spinal Renshaw cells enables a special kind of automatic gain control that compensates for posture-code distortions introduced by the size principle. This demonstration together with prior results shows that pattern-energy factorization by automatic gain control is a fundamental design feature at all points along the pathway from sensory transduction to muscular force generation.

7. CONCLUSIONS

These examples illustrate several basic themes in the recent neural network literature. Long term adaptive changes are accomplished by modifying transmission weights on signal lines, and the relatively slow weight modification process is regulated by the outcome of fast network processes, including critical comparison processes. In the work done at the Center for Adaptive Systems (e.g., Grossberg, 1988b) in Boston, it has often turned out that perceptual learning is driven by matches, whereas motor learning is driven by mis-matches. This correlation may reflect the natural asymmetry between perception, whose goal is to describe the existing world, and action, whose goal is to change the world in the direction of our desires. The ideal imposed by our interest in modeling the real brain is to design systems that can tune and even re-organize themselves on-line without external intervention, and that are robust in the face of the inherent non-linearities of neural systems, and the inherent non-stationarity of systems that grow, atrophy, and constantly create new adaptive challenges as unforseen consequences of their own activities. In this chapter, we have shown that match/mismatch-regulated learning, automatic pattern-energy factorization, and autonomous supercession of control have emerged as overarching principles in our evolving theory of such systems.

REFERENCES

Bullock, D. and Grossberg, S. (1988). Neural dynamics of planned arm movements: Emergent invariants and speed-accuracy properties during trajectory formation. *Psychological Review*, **95**, 49-90.

Bullock, D. and Grossberg, S. (1989). VITE and FLETE: Neural modules for voluntary control of movement speed and postural rigidity. In W.A. Hershberger (Ed.), **Volitional Action**, Amsterdam: North-Holland.

Carpenter, G.A., and Grossberg, S. (1987a). A massively parallel architecture for a self-organizing neural pattern recognition machine. *Computer Vision, Graphics, and Image Processing*, **37**, 54-115.

Carpenter, G.A. and Grossberg, S. (1987b). Art 2: self-organization of stable category recognition codes for analog input patterns. *Applied Optics*, **26**(23), 4919–4930.

Cooke, J.D. (1980). The organization of simple, skilled movements. In G.E. Stelmach & J. Requin (Eds.), **Tutorials in motor behavior**. Amsterdam: North Holland.

Evarts, E.V. & Fromm, C. (1978). The pyramidal tract neuron as summing point in a closed-loop control system in the monkey. In J.E. Desmedt (Ed.), **Cerebral motor control in man: Long-loop mechanisms**. Basel, Switzerland: Karger.

Georgopoulos, A.P., Kalaska, J.F., and Massey, J.T. (1981). Spatial trajectories and reaction times of aimed movements: Effects of practice, uncertainty, and change in target location. *Journal of Neurophysiology*, **46**(4), 725–743.

Georgopoulos, A.P., Schwartz, A.B., & Kettner, R.E. (1986). Neuronal population coding of movement direction. *Science*, **233**, 1416-1419.

Goodale, M.A., Pelisson, D., and Prablanc, C. (1986). Large adjustments in visually guided reaching do not depend on vision of the hand or perception of target displacement. *Nature*, **320**, 748–750.

Gracco, V.L. and Abbs, J.H. (1985). Dynamic control of the perioral system during speech: Kinematic analyses of autogenic and nonautogenic sensorimotor processes. *Journal of Neurophysiology*, **54**, 418–432.

Grossberg, S. (1968). Some nonlinear networks capable of learning a spatial pattern of arbitrary complexity. *Proceedings of the National Academy of Sciences*, **59**, 368–372.

Grossberg, S. (1973). Contour enhancement, short-term memory, and constancies in reverberating neural networks. *Studies in Applied Mathematics*, **52**, 217–257.

Grossberg, S. (1976). Adaptive pattern classification and universal recoding, I: Parallel development and coding of neural feature detectors. *Biological Cybernetics*, **23**, 121–134.

Grossberg, S. (1982). **Studies of mind and brain: Neural principles of learning, perception, development, cognition, and motor control**. Boston: Reidel Press.

Grossberg, S. (1988a). Non-linear neural networks: Principles, mechanisms, and architectures. *Neural Networks*, **1**, 17-61.

Grossberg, S. (1988b). **Neural networks and natural intelligence**. Cambridge, Mass.: MIT Press.

Grossberg, S. and Kuperstein, M. (1986). **Neural dynamics of adaptive sensory-motor control: Ballistic eye movements**. Amsterdam: Elsevier/North Holland.

Henneman, E. (1985). The size-principle: A deterministic output emerges from a set of probabilistic connections. *Journal of Experimental Biology*, **115**, 105–112.

Hodgkin, A.L. and Huxley, A.F. (1952). A quantitative description of membrane current and its applications to conduction and excitation in nerve. *Journal of Physiology*, **117**, 500–544.

Horak, F.B. & Anderson, M.E. (1984). Influence of globus pallidus on arm movements in monkeys, II. Effects of stimulation. *Journal of Neurophysiology*, **52**, 305-322.

Hore, J. (1987). Loss of set-dependent reactions during cerebellar dysfunction causes limb instability. In S.P. Wise (Ed.), **Higher brain functions**. New York: Wiley.

Hollerbach, J.M., Moore, S.P., & Atkeson, C. (1986). Workspace effect in arm movement kinematics derived by joint interpolation. In G. Gantchev et al. (Eds.), **Motor control**. New York: Plenum Press.

Ito, M. (1984). **The cerebellum and motor control**. New York: Raven Press.

Kuperstein, M. (1987). Adaptive visual-motor coordination in multi-joint robots using parallel architecture. Proc. IEEE International Conference on Robotics and Automation, Raleigh, N.C., March 31-April 3.