

# Sensorimotor Control by Reverse Engineering the Biological Modalities

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## Abstract:

A robotic model is designed to reverse engineer the sensorimotor control functions of human itch-scratch behavior patterns. The unique elements of the system are: a) neurological somatotopic topographic mappings are used to generate a coordinate frame, b) The mechanoreceptors operate as a feedback mechanism that enable monitoring the body, locate all itch-type activations and c) measure all the reaction forces exerted on the body by the external environment. The significance of the system is that it reverse engineers neurological brain modules for a) biological perception by means of "tactile sensory monitoring", b) "self awareness" by locating and identifying all parts of the body, c) "self-knowledge" by programming/teaching the robot the location of all bodily parts associated with all possible itch-scratch trajectories, and d) "Tactile-sensorimotor control" by executing itch-scratch trajectories for all possible itch-points. The connectivity of the Controller may shed light on the neurophysiology of the brain.

**Keywords:** Sensorimotor, Sensorimotor control, Robotic neurobiology, Mechanosensory, Motor control, Movement [Motion; Motor Activity], motor-skill automation, Motor learning

## List of symbols used in mathematical formulas:

- $p$  = The control signal output of a neural network.
- $q$  = The input signal to a neural network.
- $P_x, P_y, P_z$ : The control signal output of a neural network directed to each of the three motors associated with a 3-degree of freedom joint.
- $P_{3d}$  = The vector sum of  $P_x, P_y$ , and  $P_z$  (for 3-degrees of freedom).
- $F_{ri}$  = The output of each of the  $r$ -neurons in a neural network (Ritter et al, 1991).
- $W_{rl}$  = The synoptic weight between neuron- $r$  and neuron- $l$ .
- $G_{rr'}$  = The coupling strength between the neuron- $r$  and all the internal  $r'$ -neurons.
- $\sigma_r$  = The threshold of neuron- $r$ .
- $V_i$  = The input to plane  $A_i$ , and the output of plane  $A$ .

## I. INTRODUCTION

Neural network models for the sensorimotor control functions of the brain have been studied by Stephen Grossberg (1987), Teuvo Kohonen (1988), and many others (Ritter et al, 1992; Guenther et al 2001). A new approach, presented in this paper, is a proposed connectivity of a sensorimotor control system by reverse engineering the biological modalities of mechanoreceptors<sup>1</sup>. The reverse engineered robotic system is designed to respond to the modality of "itch-type" activations. The motor response of the system is designed to generate a "scratch-type" trajectory for all possible end joints and all possible activation itch points.

The significance of this new approach is that it utilizes an experimentally observed neurological topographic mapping, sometimes referred to as an homunculus (Kandel, Schwartz, Jessell, 2000; Gazzaniga, Ivry, Mangun, 2002; Bear, Connors, Paradiso, 2001; ) to design coordinate frames within the controller. Such a coordinate frame may lead to the robotic design of:

- a. Biological-type perception by means of "tactile sensory-monitoring" of the external world.
- b. A form of mechanical "self awareness" by locating and identifying all parts of the robotic body.

- c. A form of mechanical "self-knowledge" by programming/teaching the robot the location of all bodily parts and the coordinate location of the space in the vicinity of the body parts that is associated with all possible itch-scratch trajectories.

- d. "Tactile-sensorimotor control" of all end-joints by executing itch-scratch trajectories for all possible itch-points.

- e. A Neuronal Correlate of a Modality (NCM)-circuit that reverse engineers the biological receptor modality, often defined in terms of the "subjective experience" or sensation evoked by the receptor (e.g. itch-type feeling). (Guyton, 1991; Kandel, Schwartz, Jessell, 2000).

In the design of a NCM-circuit, it is particularly significant that the modality of biological receptors is described in all medical and neuroscience textbooks (Guyton, 1991; Kandel, Schwartz, Jessell, 2000; Gazzaniga, Ivry, Mangun, 2002; Bear, Connors, Paradiso, 2001) in terms of the subjective experience evoked by the receptor. Modalities of receptors, studied in the field of psychophysics since 1840<sup>2</sup>, couple subjective experiences

with neuronal activity, and thereby lead to the possibility of designing a “thinking” Turing machine (Rosen and Rosen, 2007a,b; Turing, 1950)<sup>3</sup>.

In this paper, mechanoreceptors and nociceptors are reverse engineered by means of pressure transducers distributed on the robotic body. The pressure transducers and their connectivity is assumed to adhere to the connectivity of the biological receptors. The modality of the biological receptors and their connectivity to the brain is assumed to adhere to the biological “labeled line” principle (Guyton, 1991), or the “Law of Specific Nerve Energy” (Haines, 2002), which ensures that each type of sensor responds specifically to the appropriate form of stimulus that gives rise to a specific sensation. In the biological system the specificity of each modality is maintained in the central connections of sensory axons. Thus the term stimulus modality encompasses the receptor, afferent axons, and the central pathways that are activated by the stimulus. It is noted that the central connections associated with sensory modalities often form neurological topographic mapping in various regions of the brain (Kandel, Schwartz and Jessel, 2000; Purves et al, 1997). In this paper, it is proposed that those topographic mappings may form a coordinate frame in the brain that is utilized to design a functional biological sensorimotor control system. The building path presented in this paper, for the itch modality, is expandable to the modalities of the visual sensors (Rosen and Rosen, 2007c,d) the vestibular sensors, and ultimately to a multi-tasking sensorimotor control system (Rosen and Rosen, 2006b).

## II. METHOD

Topographic mappings and patterns of organization within the brain are suggestive of the formation of coordinate frames. Purves et al (1997) writes that “Patterns of organization within the sensory cortices may be a fundamental feature of the cerebral cortex, essential for perception, cognition, and perhaps even consciousness.” In this paper the pattern of organization associated with the homunculus is used to form a portion of a coordinate frame within the controller. The coordinate frame within the controller is utilized to generate a form of robotic “perception”, robotic “self knowledge,” robotic sensorimotor control, and a robotic form of mechanical modalities. The method for utilizing patterns of organization of neurons to design a sensorimotor control system is described in this section-II.

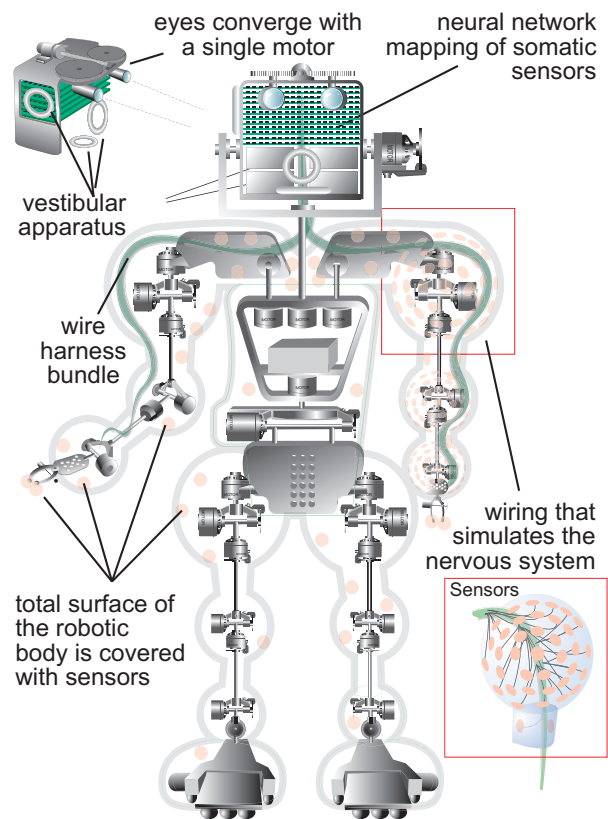
### 1. THE REVERSE ENGINEERED BODY AND BRAIN

This paper presents a model of selected elements of the human body and brain. The reverse engineered model consists of a) a mechanical robotic body, b) a neural network based robotic controller, c) an array of pressure transducers uniformly distributed along the peripheral surface of the robotic body (simulating biological mechanoreceptors), and d) thin electrical, low voltage wires (simulating the afferent and efferent somatic pathways) between the pressure transducers and the controller and between the controller and the motors. The total system is illustrated in Figure 1 and described in Rosen & Rosen (2006b).

### 1.1 The Selected Building Path

Caveat-A specified building path with simplified components: The task of reverse engineering a biological adaptation is often much simpler than design-engineering the adaptation itself. The specifications for the reverse engineered model may be selected to merely specify a building path for the biological functions. The human body and brain is viewed, in this paper, as a biological adaptation. Thus, the description of the robotic body and controller adheres to Daniel Dennett's reverse engineering requirement: “No functional analysis is complete until it has confirmed that a building path has been specified” (Dennett, 1997).

The objective of this paper is to specify a building path for the robotic controller and for the robotic body controlled by the controller. Therefore we have selected the simplest possible complete system consisting of a controller controlled by simplified, very basic neural network equations (Ritter, Thomas, & Schulten, 1992; Kohonen, 2001), and a simplistic robotic body controlled by motors with one torque generating motor per degree of freedom. The mechanical building path for the reverse engineered body and brain is illustrated in Figure 1. Numerous different, and always more modern, approaches



**Figure 1.** A reverse engineered building path for the major muscles and sensors that are used to control locomotive functions. The mechanoreceptors and nociceptors, the proprioceptors, and the vestibular sensors, are reverse engineered by pressure transducers uniformly distributed on the robotic (skin) surface, the angle measuring transducers associated with each motor, and the circular rings on the controller (head) section of the robot, respectively. The nervous system is reverse engineered by thin wires that connect all the sensors, via cable wire bundles, to the controller (see insert). The modalities of the camera/eyes (not discussed in this paper), have been studied by Rosen and Rosen (2003c), and the study report is available for viewing at [www.mcon.org](http://www.mcon.org).

to the design of the robotic body are rampant in the science and engineering literature. For example: “An overview of current research in the field of biped locomotion” by Westervelt & de-Wit (2007) and “Interlimb coordination: Neural, Dynamical, and Cognitive Constraints” (Swinen, et al, 1994).

### *1.1.1 The parts of the robotic body applicable to the design of the controller*

The following aspects of the robotic body and controller, shown in figure 1, are applicable to the design of the controller:

a) The robotic body: There are 21-joints in the robotic body. There are 3-motors and 3-angle measuring transducers associated with each joint (39-motors associated with the 21-joint body shown in Figure 1).

b) Angle measuring transducers: The biological proprioceptors are reverse engineered by the angle measuring transducers, located on the shaft of each motor. For each joint of the robotic body, the angle measuring transducers may be used to determine the angular location of the shaft-end emanating from that joint.

b) The Controller: The controller is a hybrid circuit made up of electronic neural networks and microprocessors that execute sequential algorithmic programs. The controller is a giant parallel processing unit that simultaneously controls all the joints present in the mechanical body. The controller described in this paper is a copy of the Relational Robotic Controller (RRC) designed by MCon Inc. (see the acknowledgement section).

c) The Reverse Engineered Somatic Sensors and the “Robotic self” of the System: The nociceptors and mechanoreceptors of the human body are reverse engineered by pressure transducers that are uniformly distributed on the surface of the robotic body.

d) Definition of robotic “self”: The robotic “self” of the system is defined to be the internal space and internal structure bounded by the pressure transducers uniformly distributed about the robotic body. The region external to the “robotic self” is defined to be the environment in which the robot operates.

e) The wiring of the reverse engineered nervous system adheres to The Law of Specific Nerve Energy: The wiring between the pressure transducers and the controller, and the controller to the motors, consists of thin electrical, low voltage-wires that reverse engineer the human nervous system. The connectivity of the system is assumed to adhere to the biological “labeled line” principle (Guyton, 1991), or the “Law of Specific Nerve Energy” (Haines, 2002).

## **1.2 The Constraints Imposed on the Operation of an itch-scratch Robot Controlled by the Modalities of Mechanoreceptors**

The following operational constraint may be imposed on a robotic system that is controlled by the itch-type activations of pressure transducers and designed to perform a scratch-type trajectory to alleviate the itch-activation: a) The system must perform tactile sensory monitoring of all the pressure transducers (mechanoreceptors) uniformly distributed on the robotic body. In this paper “robotic self monitoring” may be analogous to biological perception of itch-type activations b) The controller must locate and identify all body parts. For example, all possible itch-points and all possible end-joints

used for scratching must be located and identified by the controller. In this paper, “robotic-self” location and identification may be analogous to biological “self-awareness” of itch-type activations. c) The robot must be programmed/taught to perform all possible itch-scratch trajectories. In this paper, a robot that learns all possible itch-scratch trajectories is said to exhibit a form of “robotic self knowledge” analogous to the biological knowledge of the itch-scratch operations.

## **1.3 Four engineering constraints derived from the biological itch-scratch response**

Engineering constraints are derived by reverse engineering the observed itch-scratch behavior pattern of biological organisms. They have been selected to yield quantitative design parameters for the sensory motor control of animal-like itch-scratch behavior patterns, without regard to their neurobiological basis. The human-itch scratch adaptive behavior pattern is an assumed constraint that is not discussed in the method section. The neurobiological basis for the engineering constraints are discussed in the discussion section IV-1.

### *1.3.1 Evaluating and testing the engineering constraints derived from the assumed biological analogues:*

Quantitative engineering constraints may be viewed as assumptions that are derived from the qualitative biological analogues listed above, and the modalities of receptors as they apply to biological itch-type activations and the biological scratch-type response. The connectivity of the receptors is assumed to adhere to the biological labeled line principle or law of specific nerve energy, as stated in most neuroscience text books (Guyton; Kandel; Bear; Gazzaniga). In order to accommodate obstacle avoidance, the itch trajectory of motion is assumed to be pre-planned and goal directed with the option of re-planning if an obstacle appears along the pre-planned trajectory. Note that the assumed quantitative engineering constraints need not be substantiated by any experimental neurobiological data at this point of the discussion. It is proposed that these characteristics may be evaluated in the discussion section (after the model has been fully described), and tested to determine whether the mechanical characteristics of the reverse engineered model are representative of the biological analogues that have been ascribed to the human biological system.

The following engineering constraints, expressed in the form of four engineering problems, have been selected to be representative of the biological system’s response to itch-scratch type activations.

### *1.3.2 Constraint Associated With Tactile Monitoring for Itch-scratch-type Activations:*

#### *A coordinate frame within the controller*

The activated tactile sensors that are uniformly distributed on the skin surface also activate the central connections in the brain. In this paper, the central connections are reverse engineered by a neural network located within the controller. This neural circuit must monitor, locate, and identify each itch-type activation and all the biological parts used to scratch each itch-point. The first step for achieving this goal is to design a coordinate frame within the controller.

**Problem 1.** How to build a neural network within the controller that includes a coordinate frame defined by the pres-



sure transducers distributed on the surface of the robotic body: The selected approach is to transform the layers of the mechanoreceptors distributed on the robotic body into a “homunculus” within the controller (similar to the transformed homunculus discovered in the somatosensory and motor cortexes (Penfield and Rasmussen, 1950)). The coordinate frame within the controller, associated with the region around the homunculus, is defined by electronic receiving neurons that sometimes receive signals from mechanoreceptors that are located on the flailing limbs of the robot.

### 1.3.3 Constraints Associated With the Location and Identification of all Body Parts: “Robotic self-identification and location”

**Problem 2.** How to program the robotic controller to control the trajectory of motion (scratch trajectory) of robotic limbs: The limb must move towards any identified itch-goal-point defined by an activated pressure transducer. The selected approach is to assume that a) off-body receiving neurons define the space surrounding the homunculus, b) that robotic limbs move through that space, and c) that a mechanical form of “self knowledge” is gained if the robot has the capability to move a robotic limb towards any and every other part of the robotic body. The robot is programmed to locate each of its surface parts (itch points) with respect to and related to the location and motion of other parts (the scratching motion of the scratch trajectory). The robot has the capability to perform an “itch-scratch” response, by moving a limb through a goal directed trajectory aimed at an “itch”-point on the robotic body.

**Problem 3.** How to design the RRC so that the trajectory of motion is pre-planned and goal directed with the option of re-planning (obstacle-avoiding) the pre-planned trajectory: This requirement, obstacle avoidance along the trajectory, assures that the designed itch-scratch trajectory of motion adheres to the biological characteristics of volitional motor control<sup>4</sup>. The constraint is satisfied by dividing the trajectory of motion into small transitions to adjacent “nodes”. During each frame period, the total goal directed trajectory is pre-planned by the RRC as a sequence of small (nodal) transitions. However, only the first small nodal transition is activated by the controller. Thus the trajectory may be re-planned during all subsequent frame periods.

**Problem 4.** How to train/program the RRC so that location and itch-scratch type actions executed in the internal coordinate frame correspond to movements in the “real” environment: This training or programming requires that the robot learn by means of repeated multiple itch-scratch activations the location of each of its surface parts with respect to and related to the other surface parts. This requirement may be satisfied by state of the art techniques for training/programming the neural networks system.

The following section presents a technical solution to each of the four problems. Other related aspects of the system are presented in referenced publications (Rosen and Rosen 2003a,b; 2006a,b; 2007a,b,c,d).

## 2. THE RELATIONAL ROBOTIC CONTROLLER (RRC): THE REVERSE ENGINEERED BRAIN

The following section is divided into 5-parts. Each of the first 4-parts describe the solution to one of the 4-problems enu-

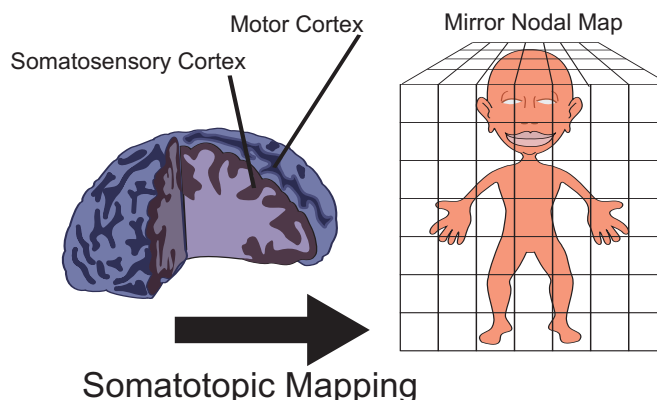
merated above. In each of the first 4-parts the design-solution is based on reverse engineering the connectivity of the assumed biological analogues (e.g. modality) of itch-scratch behavior patterns<sup>5,6</sup>. The fifth part is a summary description and solution to the neural network equations of the RRC circuits.

### 2.1 Problem 1. How to build a neural network within the controller that includes a coordinate frame defined by the mechanoreceptors distributed on the surface of the robotic body

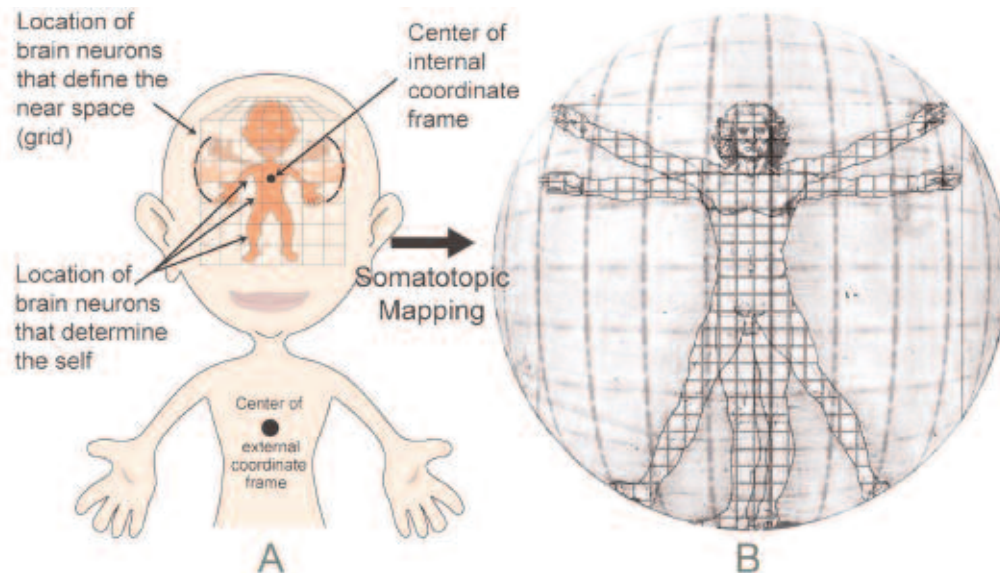
The coordinate frame within the controller may be represented by a topographic ordering of neural network neurons that are transformed into an homunculus as described by Kandel: “somatic sensory projections from the body surface and muscles are arranged in an orderly way in the cortex” (Kandel, Church, Jessell, 2000 p. 387). In the animal brain, the origin of the sensory signals, and the destination of the control signals is in the three dimensional space in which the robot/animal is located. This three dimensional external space, defined by the origin of the sensory signals and the destination of the control signals may be mapped onto a set of neurons within the controller, not by a conformal mapping or by self organizing neural maps, but by the direct connectivity between the pressure transducers on the 3-dimensional body and a neuronal coordinate frame within the controller defined and indexed by the location of the pressure transducers.

#### 2.1.1. A Biological Coordinate Frame in the Brain: Suggested by the observed topographic ordering of neurons in the brain

Figure 2 illustrates the transformation of the neuronal folds in the brain into the 3-dimensional external (mirror) nodal map containing the homunculus of the sensory self. Such transformations are suggested by the mapping of the neuronal folds of the somatosensory and motor cortex into an homunculus defined by the distribution of mechanoreceptors and muscle/motors throughout the body (Penfield and Rasmussen, 1950). Off-body neurons, used to define the flailing-limb’ space surrounding the homunculus, is not based on any neurobiological observation, but is assumed to be present in order to adhere to the constraint for the develop-



**Figure 2.** A somatotopic mapping: Transforming the cortical folds in the brain into a 3-dimensional external nodal mapping.



**Figure 3.** A coordinate frame within the controller. The neuronal coordinate frame (world map) shown in 3A, encompasses the total region of space (the near space) defined by flailing limbs shown in 3B. All motion of limbs, head, shoulders, and hip is determined relative to the origin-center of the internal coordinate frame, and the corresponding thoracic cavity-center in the external coordinate frame (see 3A).

ment of a sensorimotor coordinate frame within the controller.

### 2.1.2. A Biological Definition of the “Self” at the Center of the Topographically Ordered Neurons

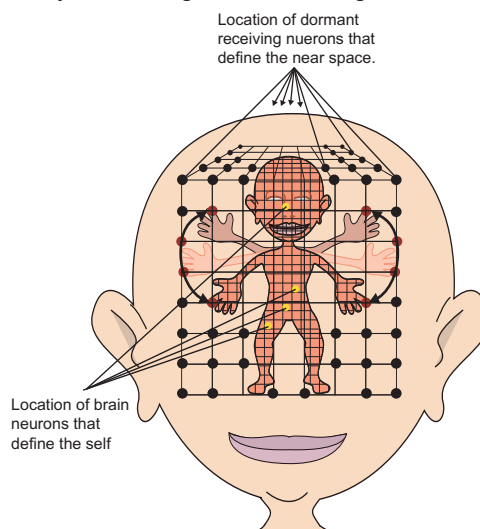
The somatic sensory system is different from other sensory systems in that its receptors are distributed throughout the body. Thus the system is well suited for the definition of the boundary between the “self” and the external world. The mechanoreceptors, embedded in the dermis under glabrous and hairy epidermal layers, have different axonal pathways and stimulate different regions of the brain (Haines 2002, p 46). The mechanoreceptors that define the boundary of the “self” in the external world may be used to define the “self” and the space around the self, in the brain.

### 2.1.3 The Robotic Self and the Robotic Near Space

The design of the “robotic self” in the RRC controller takes the form of somatotopic and topographical substructures made up of receiving neurons of a neural network. Each receiving neuron of the somatotopic organization maintains a one to one correspondence with a pressure transducer (mechanoreceptor) located on the somatotopic organization that makes up the “skin” surface. Those receiving neurons that define the “self” in the controller are shown in Figure 3. For visualization convenience the reverse-engineered input-internal receiving neuron array in the RRC controller is assumed to be configured in three dimensions similar to the external distribution of tactile sensors rather than being configured similar to the folds in the brain (see Figure 2). The arrangement of the array of electronic neurons in the RRC is illustrated in figure 4. Each node of the three dimensional internal coordinate frame is the indexed location of a receiving neuron, receiving data from a tactile body sensor. The origin of the system, shown in Figure 3, may be determined by sensory data from the thoracic cavity transformed into a receiving neuron at the center of the internal set of neurons defining the thoracic cavity. The motion of all body parts may then be determined relative to the internal center (origin) at the thoracic cavity.

The near space, the space surrounding the robot and

defined by the position of flailing limbs in the external world, may also be used to define the near space in the internal regions of the controller. This definition is not based on neurophysiological observations, but is assumed in order to extend the coordinate frame suggested by the homunculus to the near space surrounding the robot. Figure 3B illustrates the total 3-dimensional flailing limb region covered by receiving neurons in the internal space within the controller (see also Figure 3A and Figure 4). An electronic neuron may be assigned to a nodal position in the internal near space even though that position is unoccupied by a flailing limb. The receiving neuron at the corresponding node may have tactile data projected on it when and if the corresponding location in the external near space is occupied by a flailing limb. Regions of the external nodal map space unoccupied by flailing limbs are defined in the internal map shown in Figure 4 by dormant receiving neurons. The signal originating from each end-limb (associated with each robotic joint), and received by a receiving neuron is designated as the q-initial



**Figure 4.** Regions of the near space un-occupied by flailing limbs are defined by dormant receiving neurons. The positions of the robotic fingers in the near space is determined by the angle measuring transducers located on the shaft of each motor.

input signal. Thus, the current position-location of flailing limbs, head, and hips may be determined by all q-initial signals, relative to the origin of the coordinate system. All motion of robotic parts occurs relative to the fixed location of the thoracic cavity, flailing limbs, head and neck rotational motion, and hip rotational motion.

#### 2.1.4. Mathematical designation of the various coordinate spaces used in the design of the NCM-circuit.

Table 1 is a listing of the various spaces and sub-spaces located in the 3-dimensional space surrounding the robotic body, and the reflection of that space or subspace into a set of indexed receiving neurons located within the controller. In the following sections the various spaces will be referred to by the mathematical designators given in Table 1.

Coordinate frames in the 3-D space in which the robot is operating.

### 2.2 Problem 2. “Robotic self” Identification and Location: How to program the robotic controller to control the trajectory of motion (scratch trajectory) of the robotic limbs

The limb must move towards any identified goal-point defined by an itch-activated pressure-transducer. “Robotic self-knowledge” in the RRC-circuit consists of data relating to the location of the various bodily parts with respect to the origin of the coordinate frame located within the controller (see Figure 3 A ). The robotic controller is required to “learn” the location of each of its surface parts with respect to and related to the other surface parts. This “itch-scratch-knowledge” is gained by “learning” how to move, first the end-point of the robotic finger and then all other moveable body parts towards any and every other part of the robotic body. This “robotic self knowledge” requirement generates a “known” measure of the peripheral-surface space occupied by the robotic body and also a “known” measure of the space surrounding the robotic body (the near space defined by flailing limbs).

The motion of the robotic finger-calipers, illustrated in Figure 1, is a function of motion of at least 4 hinge joints; the motion of the fingers with respect to the hand, the motion of the hand with respect to the wrist, the motion of the wrist with respect to the elbow, and the motion of the elbow with respect to the shoulder. The locations of all the joints are simultaneously programmed by a combination of neural net-

works and inverse kinematics. When the motion of the robotic finger-joint is programmed by neural networks, the attached joints (hand joint, wrist joint, elbow-joint, and shoulder joint, etc.) are constrained by inverse kinematics and programmed by neural networks. For example, in order to scratch an itch point on the knee, the robot is trained to move the shoulder-joint, elbow-joint, wrist-joint, hand-joint, and finger-joint, in addition to the hip-joint and knee-joint, in order to achieve a trajectory from the q-initial of the end-finger to the knee-itch point. In order to achieve complete “robotic self knowledge” by means of itch-scratch trajectories, in addition to the itch-scratch finger training, the hand, wrist, elbow, and shoulder must be trained to perform itch-scratch type trajectories for the end-points of the hand, wrist, elbow, and shoulder respectively.

#### 2.2.1 The Biological Initial Position of a Flailing Limb

The initial position of a flailing limb is generally determined by signals received from the muscle and joint proprioceptor receptors. The perception of limb position and movement is mediated by three main types of peripheral receptor that signal the stationary position of the limb and the speed and direction of limb movement:

1. Mechanoreceptors located in joint capsules. The joint proprioceptors respond to changes in the angle, direction, and velocity of movement of the joint.

2. Muscle spindle receptors: Mechanoreceptors in muscles that are specialized for the detection of changes in muscle length (stretch).

3. Cutaneous mechanoreceptors from Golgi tendon organs monitor muscle tension, or force of contraction. There are 2-sub-modalities of limb proprioception: the sense of stationary position of the limb (limb position sense) and the sense of limb movement (kinesthesia), (Kandel, Schwartz, & Jessell, 1991)<sup>7</sup>.

#### 2.2.2 The Reverse Engineered Initial Position, q-initial, of a Robotic Finger in the RRC-near Space

In the robotic model, the muscles of the biological arm are reverse-engineered by a robotic arm with no more than three motors at each joint replacing each muscle set. The proprioceptors data are reverse-engineered by angle measuring transducers that measure the torque-generated angular displacement of the shaft of each motor. In order to connect a signal originating at a q-initial position at the tip of a robotic finger to its corresponding point in the near space of the internal nodal map, one must convert the signals received from a set of angle measuring transducers into the corresponding nodal position data within the controller. Figure 5 shows the corresponding position of a robotic finger, as measured by the angle measuring transducers, in the S-finger joint and S3-finger joint spaces. The internal nodal map position of q-initial is a function of the angle location readings that are transmitted to the RRC-controller at the rate of one set of readings per frame period.

In the design of the robotic arm, an intermediate circuit, associated with each joint on the robotic body, is required in order to convert all the angle measurements to a q-initial location in the S-finger joint space. The intermediate circuit then transmits the q-initial signals to the receiving neurons at the corresponding locations within the controller.

A complete and separate intermediate circuit is associated with each robotic joint. The range of motion of each end limb, and the possible q-initial locations covered by the end

Coordinate frames in the 3-D space in which the robot is operating

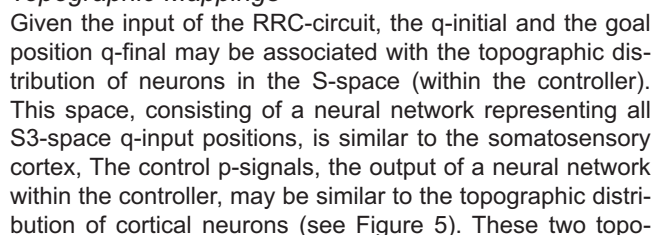
S3-self	The indexed location of mechanoreceptors distributed on the total robotic
S3-near	A set of indexed locations arbitrarily selected to cover the near space
S3-space	The S3-space is defined as S3-self + S3-near
S3-end joint	Defined by the indexed location of the range of motion of the end-joint in the S3-near space

Coordinate frames within the controller

S-self	A reflection of the S3-self space: indexed receiving neurons within the controller
S-near	A reflection of S3-near space
S-space	Defined as S-self + S-near
S-end joint	A reflection of S3-endjoint- Defined by the indexed location of the range of motion of the end-joint in the S-near space (within the controller)

**Table 1.** Mathematical designation of the various coordinate spaces used in the design of the NCM-circuit.





graphic distributions form an input/output neural network circuit within the controller, which is used to train the Nodal Map Modules, via the training path shown in figure 5.

## 2.2.4 The Design of the Nodal Map Modules

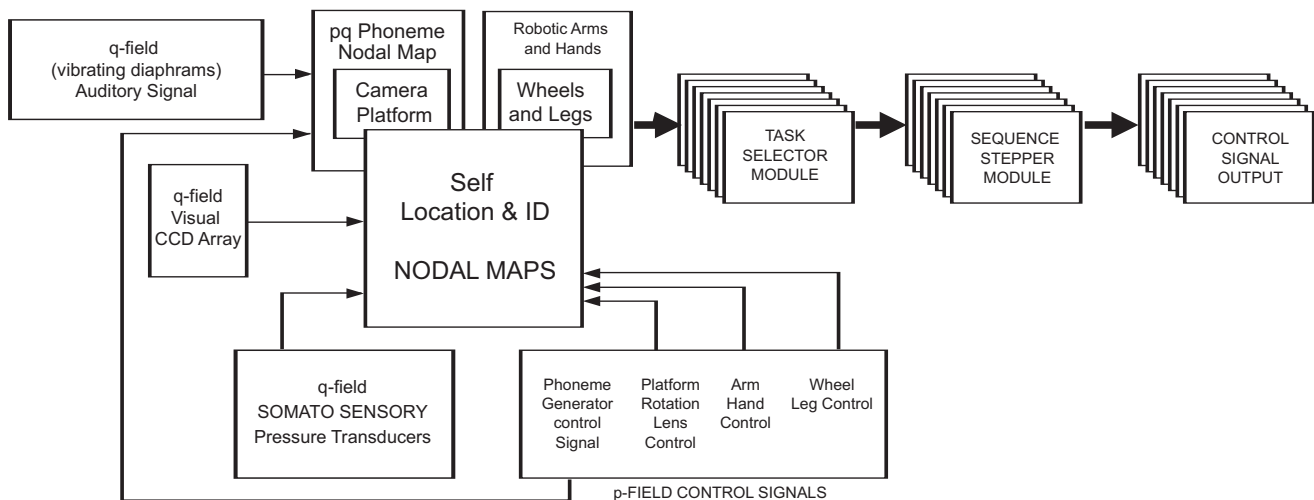
In the reverse-engineered design of the RRC these two topographic distributions are combined into a single unit called a Nodal Map Module. One Nodal Map Module is assigned to each joint and the associated S-end-joint space. The number of Nodal Map Modules in the RRC system is equal to the number of joints present in the robotic body. The combined sensory input and motor control output formed by a conjunction of topographic distributions (in a single S-end joint space) is shown in Figure 5. A set of p-signals known as table-line entries are assigned to each node of a Nodal Map Module. In a trained Nodal Map Module each table-line entry p-signal must represent an exact displacement of an end-joint to an adjacent node. The set of 8p-table line entries is shown in Figure 5 for the 2-dimensional Nodal Map Module that is associated with one robotic joint. The q-initial location of the end-joint is applied to only one node of the total number of nodes in the Nodal Map Module. The location of the q-initial signal is determined by the angle measuring transducers and all the intermediate circuits, and is applied to the corresponding q-initial position in the end-joint dedicated Nodal Map Module. When the end-joint location, q-initial is at a given nodal location, the correct p-signal table-line entry at that node, applied to the end-joint, generates an exact transition to an adjacent node. Training the Nodal Map Module to apply the correct set of p-signals (in the S-end joint space) to the motors in the S3-end-joint space is discussed in section 2.4.

The number of p-q Nodal Map Modules required to achieve “self” knowledge by the locomotive (itch-scratch) control of the total body, is equal to the number of joints in the body. Each joint in the body is associated with a set of motor control neurons in the brain that may control up to three degrees of freedom per muscle joint. For example, the muscles of the upper arm control the motion of the elbow with respect to the shoulder, whereas the muscle set of the lower arm controls the motion of the wrist with respect to the elbow.

In each case, two or three motors and angle measuring transducers are required at each joint (as shown in Figure 1). A p-q Nodal Map Module is required for each joint in the animal body. The q-initial position of the part associated with that joint is applied to the corresponding p-q Nodal Map Module associated with the S-end joint space.

The reverse-engineered brain is a giant parallel processing unit that simultaneously controls all the joints present in the body. Excluding all facial muscles and joints there are approximately 65-joints in the human body (34-arm, 26-leg and 5-hip shoulder and neck (Rosen & Rosen, 2003b)). Therefore, in order to model the locomotive actions of the human body 65-p-q Nodal Map Modules may be required in order to achieve “robotic self-knowledge” by the locomotive “itch-scratch” control of the robotic body. The output signals of each joint related Nodal Map Module consists of sets of signals that control each muscle set used to displace that particular joint-limb. The total reverse-engineered output of the RRC, generated by the total (21) S-end joint Nodal Map Modules, consist of all the outputs to all the robotic motor/joints associated with all the motor/muscle sets of the body.

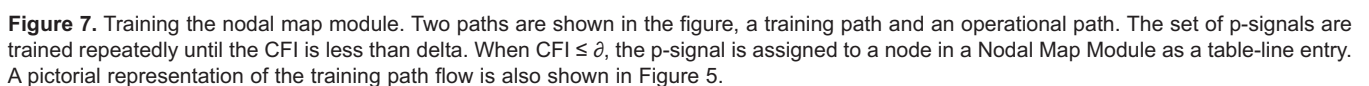
Figure 6 is a block diagram that shows an array of Nodal Map Modules and the central location of the large number of “self-location and identification” Nodal Map Modules that represent a topographic mapping of a 3-dimensional coordinate frame (the S3-space). Each Nodal Map Module consists of a conjunction of the q-input and p-output associated with the S-end joint space. The topographic mappings associated with the totality of Nodal Map Modules form a combined control and sensory signal model of the homunculus of the robot with the center of the homunculus located at the origin of the coordinate frame. Each node of each Nodal Map Module has a set of p-signals (table-line entries) associated with it. The q-initial location of each end-joint always appears at one node of the joint dedicated Nodal Map Module. The p-signals cause a displacement of the end-joint at q-initial to an adjacent node. For example in Figure 5, the displacement of the wrist (controlled by the elbow-joint Nodal Map Module) takes place between a set of three adjacent nodes, from q-initial to q-final.



**Figure 6.** A hierarchical array of RRCs. All the Nodal Map Modules, Task Selector Modules, Sequence Stepper Modules and Control Signal-output Modules (associated with each joint in the body), operate simultaneously during each frame period.



The Task Selector Module (TSM) generates the q-final “itch” location and motivates the robot to perform a “scratch” action aimed at the “itch”-point. For training purposes, the q-final “itch” location may be artificially generated by the TSM and applied to the appropriate q-initial-defined Nodal Map Module. The TSM-activated q-final “itch”-location becomes a

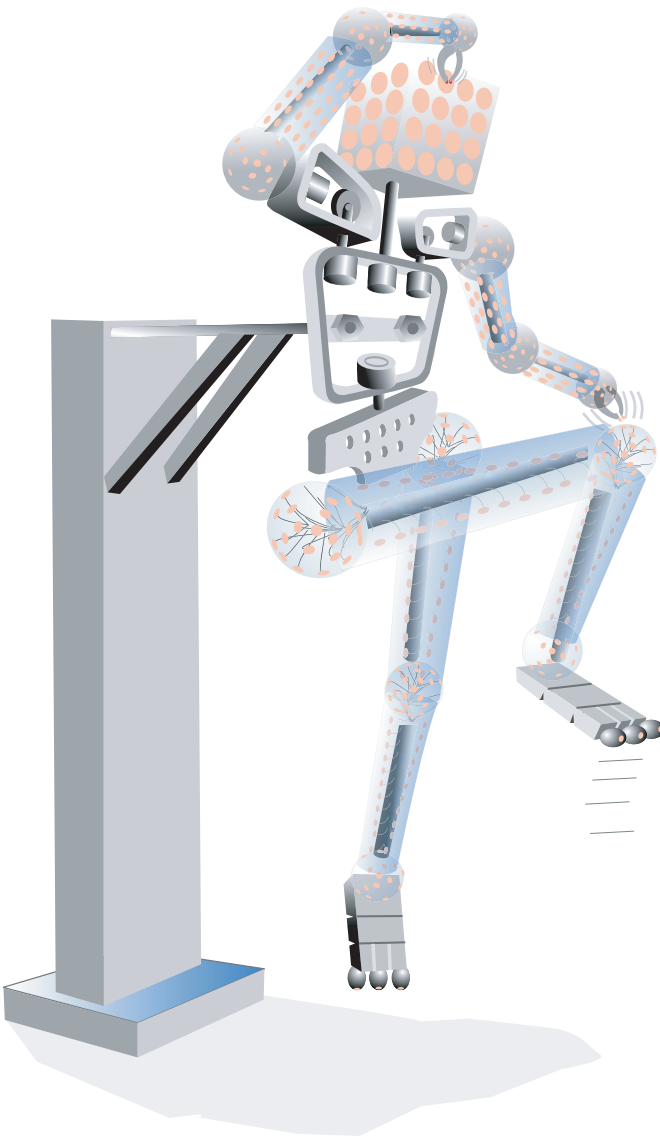


Task-initiating Trigger (TT) that activates the Sequence Stepper Module to examine the region in the Nodal Map Module, between q-initial and q-final, and select a pre-planned trajectory between q-initial and q-final.

#### 2.4.3 The Corrected Set of p-values Assigned to Each Nodal Map Module

The method of selecting the correct set of control signals (p-values for all the motors associated with the 21-robotic joints) required to move a robotic part from q-initial to q-final, is shown in Figure 7. The p-vector assigned to each node of each Nodal Map Module is first calculated, estimated and tested by the designer (the magnitude is designed to generate an exact transition to an adjacent node, and the directions, often determined by inverse kinematics, are calculated for each of the end-joints). Figure 7 shows that the estimated p-values are then corrected repeatedly until the correction factor increment ( $CFI < \delta$ ) approaches zero.

The correct table-line p-value at the initial node is that



**Figure 8.** A pictorial representation of a laboratory setup used to train an "itch-scratch robot. The robot is pictured with three trajectories of motion: scratching the head with the right hand calipers and scratching the knee with the left hand calipers while lifting the right leg.

value that generates an exact displacement from the initial node at q-initial to the adjacent node at q-final. Correction of the table line entry p-value proceeds by noting the displacement error generated by the set of p-initial and applying a correction factor so that the set of p-initial (corrected) leads to an exact transition to the final node defined by q-final (see Figure 7).

A Nodal Map Module is said to be "trained" if each nodal table, assigned to each node, is made up of a complete set of p-signal line entries. Each p-signal line entry causes an exact motor displacement to an adjacent external nodal position. The set of table line entries assigned to each nodal table consists of all the p-signals that lead to exact transitions to all adjacent nodal positions. At each node there are 27-p signal transitions to adjacent nodes in a three dimensional nodal map, and 8-p signal transitions to adjacent nodes in a two dimensional nodal map (see Figure 5).

#### 2.4.4 The Training Procedure

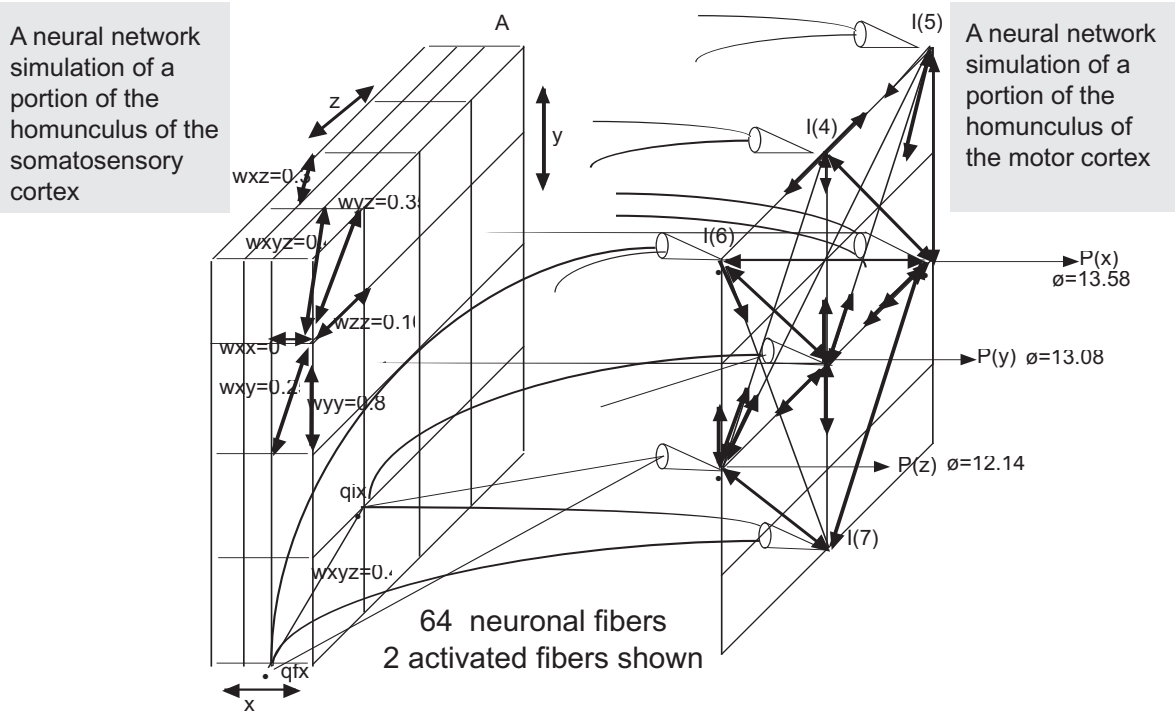
A pictorial representation of a laboratory set-up to train the itch-scratch robot is shown in Figure 8. The robot is attached at its center of mass, and all itch-scratch trajectories are performed relative to the center of mass. The robot is pictured with three coordinated and synchronized trajectories of motion: scratching the head with the right hand calipers and scratching the knee with the left hand calipers while lifting the right leg.

In order to train the robot to perform all possible itch-scratch trajectories, the q-final-itch point is initially selected at nodes that are immediately adjacent to a q-initial. For each nodal map, and for each node defined in that map, the training proceeds with the q-final location placed at distances of two, three, four, and more nodal distances from q-initial. When all the nodes of all the nodal maps associated with all the joints of the robotic body are fully trained, the RRC-circuit is said to exhibit "robotic self knowledge." The robot may have "learned" by this programming methodology how to move a robotic limb towards any and every part of the robotic body.

#### 2.4.5 An Example of Programming the Configured Neural Network

Training the Nodal Map Modules is performed by following the training path shown in Figures 5 and 7. The first step in the process is to select a Nodal Map module devoted to the control of the end-joint used for the scratch motion. Initially all the goal-defined itch-points and all the q-initial of the end joint are restricted to all the nodes defined by the S-and S3-end joint space. The next step is to solve only that small portion of the neural network (A subset of sensory neurons and motor neurons illustrated and labeled as, A, and, A', in Figure 5) that covers the S-and S3-end joint space. The solutions to the equations consist of a set of control p-signals, table line entries, assigned to each node of the S-end joint Nodal Map Module. In this case, given the input to a portion of the somatosensory topographic distribution of the configured neural network shown in figure 5, and the output of a portion of the configured motor distribution of p-generating neurons (Figure 5), a complete solution to the training of the Nodal Map Modules may be obtained.

A pictorial representation of the configured neural net surface layers associated with the somatosensory cortex and the motor cortex is shown in Figure 9. The planes A and A', shown in Figure 9, have been selected to be parts of the



**Figure 9.** A pictorial representation of neural networks applied to a single joint-Nodal Map Module. The structure of the neural networks, the location of all activated “world map” receiving neurons, and the magnitude of the input and output signals are known quantities. Plane A shows the configured input layer, the location of the qi and qf inputs, and the V-vector outputs of plane A. Plane A' shows a portion of the configured output layer, the V-vector input, the location of the Px, Py, Pz, output neurons, and the outputs of plane A'.

Nodal Map Module that is devoted to a single joint of the robotic body. The plane, A, shows the neural network's nodal positions of q-initial of the end-joint, qix, and the q-final, qfx, generated by the TSM (in this case, qfx is selected by the designer to fall within the S3-finger space). The primary activation of qix and qfx generate secondary activations (coupling) between all the neurons located in plane A. All activations (primary and secondary) of all neurons in pane A, may activate the control signal generating neurons located in the neural network of plane A'. However, in the solution to the neural network equations, the threshold,  $\emptyset$ , and the coupling strength,  $Grr'$ , have been selected so that secondary activations do not contribute to the input of plane-A' (see equations numbered 1, 2 and 3).

The equations for plane A': For a joint with 2 or 3 degrees of freedom (2 or 3-motors per joint), the output of Plane A' may be given by either Px, Py (2-motors) , or Px, Py, Pz (3-motors). For each joint, the set of P-signals generated during one frame period, cause a single nodal displacement of the end joint associated with the joint-motors. The displacement generating total torque may be specified by

$$P2d = aFr1 + bFr2 \quad (\text{for 2-degrees of freedom})$$

$$P3d = aFr3 + bFr4 + cFr5 \quad (\text{for 3-degrees of freedom})$$

Where the components Fri, the output of each of the i-neurons is given by Ritter's equation (Ritter et al, 1992)

$$Fri = \mu(\sum Wrl Vi + \sum Grr'Fr' - \emptyset r).$$

The neuron-r denotes the receiving neuron of the external input to plane A'. The term Wrl is the synoptic weight between neuron-r and neuron-l and the summation is carried

out over all l-neurons, from 1 to N (N is the total number of neurons that represent the range of motion of the end-joint that defines the Nodal Map Module). The term  $Grr'$  is the coupling strength between the neuron-r and all the internal r'-neurons, activated by  $Fr'$ . The term  $\emptyset r$  is the threshold of neuron-r. Vi represents the input to plane A', and is the output of plane A, determined by a solution to Ritter's equation applied to plane A.

The equations for plane A: The total input to plane A, associated with the somatosensory cortex illustrated in figure 5, activates only 2-input neurons, q-initial and q-final, denoted as qi and qf respectively. If the threshold  $\emptyset$ , and coupling strength  $Grr'$  are chosen so that

$$\text{Equation 1:} \quad \sum Grr'Fr' \leq \emptyset r,$$

then there are only 2-output solutions of plane A, given by the output of the qi-neuron, and the qf-neuron. The solutions, representing the inputs to plane A', are

$$\text{Equation 2:} \quad Vi = qi + Gif - \emptyset i$$

$$\text{Equation 3} \quad Vf = qf + Gif - \emptyset f$$

Solving the equations for plane A': There are now only two V-inputs to plane A'. Ritter's equations for plane A' may thus be written as

$$\text{Equation 4:} \quad Px = WixVi + Wfx Vf - \emptyset x$$

$$\text{Equation 5:} \quad Py = Wiy Vi + Wfy Vf - \emptyset y$$

A sixth equation may be obtained by noting that the magnitude of each displacement is measured to be exactly one nodal length, and the direction must be one of 8 or 27 differ-



ent directions, depending on whether the joint is a 2-dimensional or 3-dimensional degree of freedom joint. For example, for a 2-degree of freedom joint, the sixth equation may be written as:

**Equation 6:**  $Px = f(Py)$

The numerical solution of the 6-neural network equations with 6-unknowns, is presented in detail in a publication by Rosen and Rosen (2003b), titled "The engineering design of an NCC-circuit for the sensory motor control of a robotic arm." For example, numerical solutions for

***Px, Py, Vf, Vi, W, and  $\phi$ , are obtained by setting***

$$Wij = Gij = W, \text{ and } \phi i = \phi f = \phi.$$

Some numerical solutions, The thresholds,  $\phi$ , associated with Px, Py, Pz, are also shown in Figure 9 (Rosen and Rosen, 2003b).

The equations presented above follow Ritter's development of an electronic neural net layer in the form of a two dimensional sheet (Ritter et al, 1992). The layers A and A' are surface layers configured as receiving neurons shaped like a portion of a homunculus (see Figure 3, Figure 4, and Figure 5). However, in the case presented above, the Ritter equations are solved at exact neural locations rather than at spatially localized region of the layer (Kohonen, 1982a). The mapping/transformation of somatic locations into the controller determines exactly which neurons on the arrays are activated. This direct-wire method of mapping the somatic sensors and motors into topological maps and patterns reverse engineers the connectivity of the biological central nervous system. Most other published neural network models make use of mathematical analyses of self-organizing processes (Kohonen, 1982b) and analyses and transformations of topographical maps and processes (Kohonen, 1982c).

## 2.5 Overview of the Design of the RRC Circuit

The RRC-circuit consists of a hybrid set of circuits wherein a portion of the input and output layers (shown in Figure 5) are neural net based and intermediate subsystems are based on algorithmic sequential programming. The input circuit to the RRC is a configured neural network where the "robotic self" is at the center of the coordinate frame. Un-configured neural network circuits have been applied to the study of the adaptive brain by Stephen Grossberg and his associates at Boston University (Grossberg, 1987a,b.)<sup>8</sup>.

The detailed solution to the neural network portion of the RRC and the electronic design of the Nodal Map Module, the Sequence Stepper Module, and the Control Signal-output Module is described by Rosen and Rosen (2003 a, b) in a papers titled a) "The design of a Volitional, Obstacle Avoiding Multi-tasking Robot", and b) "Engineering Design of an NCC circuit for the Sensory-motor Control of a Robotic Arm control of the somatic motor system."

## III. RESULTS

### 1 FUNCTIONAL SIMILARITY BETWEEN THE ROBOTIC CONTROLLER AND THE BIOLOGICAL BRAIN

The previous sections presented a well-defined building path for a robotic model consisting of a robotic body controlled by a robotic controller. The robotic body and controller are designed to have some functional and mechanical characteristics similar to the human body and brain. The functional similarities of the controller to the operation of the brain include:

1. The controller is a giant parallel processor that controls all the motors and joints of the robotic body simultaneously with a response time of 1/30 second and with synchronization and coordination of all body parts.

2. The pressure transducer-sensory system constantly monitors the peripheral surface of the robotic body for tactile activations. Two types of activation are designed into the system, low-pressure and high-pressure thresholds of activation. The low-pressure threshold of activation is analogous to the biological modality of "touch-feel". Whereas the high-pressure activation threshold is analogous to the biological modality of "touch-pain."

3. Similar to the biological brain, the controller has within it a reflection of the robotic self, defined by pressure transducers (surface distribution of mechanoreceptors), that lead to a definition of a coordinate frame that is the origin of the input signals (mechanoreceptors) and the destination point of the output signals (muscle/motors).

4. The coordinate frame defined by the origin of the sensory signals and the destination of the control signals, is transformed into a configured neural network within the controller (simulating the neuronal folds of the somatosensory and motor cortex), not by a conformal mapping or by self organizing neural maps, but by the direct connectivity (afferent and efferent axons) between the 3-dimensional body and the central connections in the brain. All perceived tactile-activation data originating in the external frame are transformed and mapped, by means of direct connections associated with the nervous system, into a coordinate frame located within the RRC-controller.

5. The measure of the internal coordinates is calibrated with the measure of the 3-dimensional space in which the robot is operating.

6. The "robotic self" and the motion of the mechanical limbs of the robot with respect to the center of mass of the "robotic self" are fully defined and controlled in the internal coordinate frame as well as the external coordinate frame.

7. Similar to the biological brain, the controlled trajectories of motion are pre-planned and goal directed with the option of re-planning any planned trajectory. The control of "itch scratch" motion is goal directed and the robot has the option of re-planning (within 1/30-seconds), a pre-planned trajectory of motion in the midst of the action.

8. All the motors of the NCM-robot are trained simultaneously by means of neural networks that are initially programmed by inverse kinematics, whenever training is performed on a single end-joint associated with a Nodal Map Module.

9. The NCM-robot has the capability to be trained to perform a diverse set of actions guided by the goal directed output of the Task Selector Module, and limited only by the design of the sensory system, the sophistication of the neural networks in the controller and the design and the range of motion of all robotic moveable parts (Rosen & Rosen, 2006,a, b).

10. The tactile NCM-system has been expanded to a visual NCM (Rosen & Rosen, 2007 c,d) and into a multi-tasking NCM-robot that can walk, jump, and dance, and perform any set of multi-tasks defined by the designer in a Hierarchical Task Diagram (HTD) (Rosen & Rosen, 2006 a, b).

## IV. DISCUSSION

The discussion is divided into 4-parts. Part 1 discusses the neurobiological basis for the assumed engineering constraints imposed on the NCM-system. Part 2 compares the overall robotic sensorimotor control functions with the sensorimotor control functions of the human brain. Part 3 compares the connectivity of the robotic sensorimotor control system the neurophysiology of the brain. And Part 4 compares the connectivity of a biological modality with a “mechanical modality.”

### 1. THE NEUROBIOLOGICAL BASIS FOR THE ASSUMED ENGINEERING CONSTRAINTS IMPOSED ON THE NCM-SYSTEM

The first 3 sections of this paper present a robotic model of a robotic body and controller that reverse engineers some functional characteristics of the human body and brain. The design approach is aimed at reverse engineering the connectivity associated with the itch-modality (the subjective experience of “itch-feeling”) of the mechanoreceptors that are distributed on the skin surface of the human body. The system is designed to mimic the itch-scratch behavior patterns of humans. Operational engineering constraints on the design of the itch-scratch robotic system are selected so that they could be related to assumed biological analogues of itch-scratch behavior pattern of biological organisms. They are quantitative functional constraints imposed on the robot controller, and do not imply that the proposed implementation of each constraint is similar to the biological implementation actually present in the human body and brain. In the following sections, the neurobiological basis for the selected implementation is discussed in terms of the functional and structural (physiological) similarities between the itch-scratch robot and a biological itch-scratch organism.

#### 1.1 The neurobiological basis for a coordinate frame within the controller

The activated tactile sensors that are uniformly distributed on the skin surface also activate the central connections in the brain. In this paper, the central connections are reverse engineered by a neural network located within the controller. This neural circuit within the controller forms a coordinate frame that monitors, locates, and identifies each itch activation and all the biological parts used to scratch each itch-point. What is the neurobiological basis for such a coordinate frame?

a) A coordinate frame defining the homuncular body, and the

center of mass (CM-origin) of the homuncular body: The directly-wired transformation of the mechanoreceptors distributed on the robotic body into a mechanical “homunculus” within the controller is suggested by the discovery of a biological homunculus in the somatosensory and motor cortices (Penfield and Rasmussen, 1950). There is no biological evidence that the homunculus functions as a coordinate frame in the brain. However, the existence of such a coordinate frame is suggested by the comparison of the overall robotic sensorimotor control functions with the sensorimotor control functions of the human brain (section IV-2).

b) The coordinate frame within the controller, associated with the region around the homunculus, is defined by electronic receiving neurons that sometimes receive signals from mechanoreceptors that are located on the flailing limbs of the robot: The choice of dormant (indexed) receiving neurons within the controller for the definition of the near space was made by extending the coordinate frame of the homuncular body and the center of mass in the body to the region of space, the near space, around the homuncular body. This extension is not based on neurobiological observations of such dormant receiving neurons.

##### 1.1.1 Is there any neurobiological evidence for a coordinate frame in the biological brain?

First, There is no biological evidence that suggests that the topographic distributions that give rise to the homunculus (Penfield and Rasmussen, 1950), or the topographic structures called “brain modules (Purves et al.) are functionally or physiologically, a coordinate frame located in the brain. However, the homunculus, which is a “way of illustrating the location and amount of cortical area dedicated to a particular function” (Kandel et al 2000, p. 344), is suggestive of a mapping or transformation within the brain that is based on the conclusion of Kandel et al, (2000, p.387) that “somatic sensory projections from and to the body surface and muscles are arranged in an orderly way in the cortex.”

Second, The reverse engineered coordinate frame, and in particular the dormant receiving neurons that define the near space, is one of a number of possible alternative implementations of a coordinate frame within the controller.

The following relates to the question of how is the coordinate frame implemented in the biological brain? First, the authors are not committed to the simplified extension of the homuncular mapping to dormant receiving neurons that form a near space. Alternative views such as Francisco Varela (1991), Scot Kelso (1995), Rodney Brooks (1989a,b), Walter Freeman, (2000) and Gerald Edelman (1989), do not favor the existence of a coordinate frame within the brain, and Bressler and Kelso (2001) have not established the existence of off-body receiving neurons in the brain.

Second, the authors have not discovered any biological observations that rule out the existence of a coordinate frame in the brain. And although an alternative implementation different from the off-body dormant receiving neurons, may exist in the human brain, the authors favor additional research that includes the possibility of a dormant receiving neuron type coordinate frame, among the other possibilities.

Third, although the authors do not wish to argue that the connectionist reverse engineering approach is the “most biologically veridical.” They do present evidence in section IV-2, and IV-3 that it is biologically competitive with other approaches that compare the robotic and biological sensory motor control functions.

### 1.1.2 Alternatives to a coordinate frame in the brain

Alternatives to a coordinate frame in the biological brain have been presented by Varela, et al, (1991), among many others. It should be noted that Varela (1991), Edelman (1989), Freeman (2000), and to some degree Kelso (1995), approach the study of the brain by modeling symbolic representations and coordination dynamics<sup>6</sup>, rather than the connectivity of the brain (the approach favored in this paper<sup>5</sup>). For example, symbolic representations lead Varela et al (1991) to seek common ground, and develop a dialogue between cognitive science and Buddhist meditative psychology. Bressler & Kelso (2001), utilize synergistic concepts of self organization and the mathematical tools of non-linear dynamical systems (mainly coordination dynamics) to model observations of cooperative phenomena in the body and brain. When applied to the dynamical properties of cortical areas and their coordination, these symbolic representations yield inter-area pattern constraints that are postulated to underlay all cognitive operations of the brain. However, coordination dynamic<sup>6</sup> relates the interaction between different cortical areas, it does not address the detailed internal operation (The connectionist data) of these individual areas<sup>5</sup>. The approach presented in this paper is a connectionist approach wherein both the detailed connections and the coordinated inter-relationship between the different modules is designed into the system ( see "The approach of physical reductionism" (Amit, 1989, Chapter 1)).

None of the symbolic representational studies, listed above (and in footnote 6), invalidate the connectionist approach of mapping motor nodes or mechanoreceptors into a 3-dimensional space. On the other hand, they also do not validate this approach. It should be noted, however regardless of whether a connectionist or symbolic implementation is used, it is shown in section IV-2, that the existence of an internal coordinate frame in the brain leads to a sensory motor control system that is biologically as veridical or possibly more veridical than symbolic representational sensory motor control models.

## 1.2 Reverse engineering Proprioceptive control and inverse kinematics control by means of angle measuring transducers and an inverse kinematics intermediate circuit

Angle measuring transducers and inverse kinematics intermediate circuits are used to reverse engineer the biological proprioceptive position measuring sensors. There is no biological evidence for the existence of angler measuring transducers in the human body, or a set of intermediate circuits in the brain that generate precise biological proprioceptive position data. The angle measuring transducers and the inverse kinematics intermediate circuits were selected as relatively simple building paths that yield robotic self knowledge of the position of all end-limbs with an accuracy equivalent to the biological proprioceptive position-knowledge (Kandel et al, 2000)<sup>7</sup>.

### 1.3 Constraints Associated With Mechanistic-Volitional Control of all itch-scratch trajectories.

The mechanistic constraint applied to the NCM-circuit is that the itch-trajectory must be pre-planned and goal directed with the option available for re-planning the pre-planned trajectory if the sensory system detects an obstacle along the

pre-planned path. This constraint is a mechanical analogue of biological volition<sup>4</sup>.

### 1.3.1 Is there any neurobiological evidence for these constraints?

a) Goal directed representation of movement plans: Neurobiological evidence for end-point planning and goal directed representations of movement plans is presented in the 1998 edition of Cognitive Neuroscience (Gazzaniga et al, 1998, p. 381-382). Experiments performed by Bizzi et al (1984) support end point planning and goal directed action. However, cellular activity experiments in the primary motor cortex also reveal correlation with movement direction, movement location, and movement distance. In addition Kandel (2000, p.350) also discusses goal directed action observed in the multimodal association areas of the cerebral cortex.

b) Planning the goal directed action: Motor planning activity has been observed in different areas of the cortex. Kandel, (2000, p.470) writes, "Each pre-motor area contributes to different aspects of motor planning. Different areas of the cortex are activated during simple, complex, and imagined sequences of finger movement." The cortical activity of imagined sequences of finger movement may be associated with pre-planning the sequence of finger movements (Roland et al, 1980).

c. Re-planning a pre-planned trajectory: The possibility of re-planning is illustrated by the experiments of Libet et al (1982) that demonstrate a 550 millisecond gap in the readiness potential preceding unrestricted "spontaneous" versus pre-planned voluntary acts. The observed gap allows for pre-planning neuronal activity preceding the initiation of movement action, since the frame period of the NCM-robot is 31 milliseconds, less than one tenth the gap observed by Libet et al (1982). Note that in the NCM-robot, the gap, if it represents the cortical activity associated with re-planning or pre-planning, does not support the "free will" hypotheses put forth by Libet (1985)<sup>4</sup>.

## 2. A COMPARISON OF THE OVERALL ROBOTIC SENSORIMOTOR CONTROL FUNCTIONS WITH THE SENSORIMOTOR CONTROL FUNCTIONS OF THE HUMAN BRAIN

### 2.1 The symbolic representational approach to interlimb coordination and dynamics<sup>6</sup>

Most modern publications in robotic engineering generally study the design of isolated cognitive simulators (Brooks, 1989a)<sup>9</sup> (see for example Westervelt & Canudas-de-Wit (2007) and Bekey, 2005). Turvey (1990), for example presents a symbolic representational approach to inter-limb coordination and dynamics, rather than the study of how objects move under the action of forces (the force-mass-acceleration approach). Coordination dynamics deals with changes in systems, and tries to express its existing and evolving states. Scott Kelso (1995), utilizes the symbolic logical approach of coordination dynamics (synergistic concepts of self organization and the mathematical tools of non-linear dynamical systems) to model observations of cooperative phenomena in the body and brain.



## 2.2 The connectionist approach<sup>5</sup>

The distinguishing characteristics of the NCM-sensory motor control system is that the authors have embraced the reductionist approach (connectionism) rather than modeling the brain by use of symbolic representations of cooperative phenomena in the body and brain. Symbolic representations generally lead to the design of a conglomerate of isolated cognitive simulators, whereas the connectionist approach described in this paper, leads to the design of a robot that may be regarded as a “complete creature” (Brooks, 1989a). The NCM-robotic system consists of:

1. A giant parallel processor that controls all the motors and joints of the robotic body simultaneously with a response time of 1/30 seconds and with synchronization and coordination of all body parts.”

2. Bypasses the representational coupled nonlinear dynamical system. All couplings of all joints are constrained by inverse kinematics, whenever training is performed on a single end-joint associated with a nodal map module (see Section III-1).

3. The multi-tasking NCM-robot is a “complete creature” rather than a conglomerate of isolated cognitive simulators (Brooks, 1989)<sup>9</sup>.

4. The coordinate frame within the NCM combines all movement representations by learning (programming) the total system rather than a separate isolated cognitive simulation for each movement plan.

### 2.3 Contrasting the coordinate frame within the controller with coordination dynamics

The NCM-circuit, and the connectionist approach in general, does not reflect modern notions of coordination which center on coupled non-linear dynamical systems (Swinnen et al, 1994). The coordinate frame within the controller, a) incorporates all sensory signals and motor signals into that coordinate frame, b) the training and operation of the total robotic body (all 21 joints) is performed in the coordinate frame located within the controller and c) the volitional characteristics of the NCM-circuit, allows the authors to dispense with the mathematics of nonlinear dynamical systems to describe coordinated and synchronized movements, and avoid multiple designs of isolated cognitive simulators (see references listed above). Thus the NCM-robot a) may be taught (programmed) to perform synchronous and coordinated hand, foot, and body movements, b) is a multi-tasking robot (Rosen & Rosen, 2006) that may learn to walk, run, jump and dance in all terrains and in multiple orientations, and c) may even exhibit malfunction/recovery characteristics that are analogous to brain plasticity observed in recovering stroke victims (Schwartz and Begley, 2002 )<sup>10</sup>.

## 3. A COMPARISON OF THE CONNECTIVITY OF THE ROBOTIC SENSORIMOTOR CONTROL SYSTEM WITH THE NEUROPHYSIOLOGY OF THE BRAIN

What does the NCM-circuit contribute to the study of the small and large scale organization of the biological motor system?

### 3.1 The neurophysiology of motor control

The NCM-circuit offers a complete functional sensory motor

control system that integrates all the sensory functions and all the motor control functions by means of a single coordinate frame located within the controller. The building path of the integrated coordinate frame compared with the study of the cortical areas involved in the sensory motor control functions may shed light on the hierarchical and redundant organization of the biological motor system. Kandel et al (2000) says: “the processing of sensory inputs and commands to motor neurons and muscles is distributed in hierarchically interconnected areas of the spinal cord, brain stem, and forebrain”. In addition, M1 and many brain regions, including the Cerebellum and Basal Ganglia play crucial roles in the implementation of coordinated movement by the brain and body. Each of these regions takes sensory input, and their output may descend either through the hierarchy or in some cases directly to the spine. Of crucial importance is that lesions to each of these areas produce different behavioral deficits (Kandel et al 2000). Bressler and Kelso (2001) say: “Movement attributes at the extrinsic kinematic, internal kinematic, and dynamic levels have been found to be controlled by locations distributed over several motor cortical areas, suggesting that multiple areas must coordinate their activities during normal motor behavior”.

### 3.2 The contribution of the NCM-sensorimotor control circuit to brain physiology for motor control

The NCM-sensorimotor control circuit is not hierarchical, nor do the electronic modules bear any functional relationship to the various motor-brain locations distributed over the several motor-cortical areas described above. However, the NCM-sensorimotor control system is an integrated system with a functional flow that relates a) an input coordinate frame of all the sensory signals, b) via an intermediate circuit that is functionally similar to the biological functions in the brain, with c) an output coordinate frame of the set of motor control signals that control a biological behavioral adaptation. This NCM-circuit offers the neurobiologist and neurophysiologist a set of constraints that may guide their research. For example The NCM-circuit may guide the research into questions such as a) How does the sensory input of each set of sensors (tactile, visual etc) fit into the hierarchical organization of the brain?

b) What portion of the functional flow is implemented by each level in the motor control hierarchy? And c) How are the input and output coordinate frames implemented in the brain?

## 4. A COMPARISON OF THE CONNECTIVITY OF A BIOLOGICAL MODALITY WITH A “MECHANICAL MODALITY”

A biological modality is defined in terms of a subjective experience or “conscious” sensation that is quantitatively related to the receptor, the transduction process within the receptor, and the specificity of the afferent axons and the central connections in the brain activated by the receptors. The observed modalities of the various sensory receptors is the only case (known to the author) wherein a large body of psychophysical data<sup>2</sup> supports the transformation of “a subjective experience” or “conscious” sensations (Nagel, 1974)<sup>11</sup> into action potentials and bioelectric currents that activate specific areas of the brain. This is important because it may

also transform subjective experiences into computer code<sup>3</sup> (analogous to action potentials and bioelectric currents). It implies the existence of a Neural Correlate of Consciousness (NCC)-circuit (Metzinger, 2000) in the brain that is a biological Sensation Generating Mechanism (SgM) (Rosen & Rosen, 2007 a, b). The following comments are based on the assumption that a biological NCC-circuit exists in the brain, and explores the question of whether a mechanical NCC-circuit may also exist in the NCM-robot. However, there are two preliminary notes that need to be established:

1) The subjective experience (modality) of the receptor, now regarded as a transducer, is always associated with the incident energy (input) to the receptor (transducer). The output of the receptor (via a transduction process) converts the incident energy into action potentials and bioelectric currents. The design of the itch-NCM robot is dependent only on the action potentials and bioelectric currents at the output of all the biological receptors in the system. The design is totally independent of the subjective experience, which is associated with the incident energy to the receptor.

2) The design of the itch NCM-circuit generates a reverse engineered emulation of itch-scratch behavior patterns that depend only on the activated action potentials and bioelectric currents at the output of all biological receptors of the system. The reverse engineered behavior pattern is unchanged regardless of whether the robotic NCM has, or does not have, a modality-type sensation associated with it.

The somatotopic coordinate frame of the NCM-robot constantly monitors the state of the skin-surface pressure transducers for itch-type activations. The mechanical itch-type activation is similar to the biological itch type activation in that: a) The mechanical central connections emulate the biological central connections. They both are represented by the connectivities of neural-network-based mappings suggestive of a coordinate frame. b) Robotic location, identification and "self knowledge" are similar to biological self-knowledge of itch type activations. c) The itch-scratch motor control response of the robotic system is similar to the response of a biological system.

*The following philosophical questions are posed to the reader:*

a) In a mechanical NCM-circuit is there a mechanical-type of subjective experience, analogous to the biological itch-sensation, correlated with the mechanical "itch-type" activation of the pressure transducers?

b) Based on the similarities enumerated above, if the biological NCM-circuit gives rise to a modality-sensation and if the connectivity of the biological NCM-circuit is functionally similar to the mechanical/electronic NCM-circuit; then may it be hypothesized that electronic NCM-circuits may also give rise to a mechanical type modality-sensations? (Rosen & Rosen, 2007a,b)

## NOTES

1. Overlapping papers were presented at IEEE-IJCNN WCCI-Vancouver and ICONIP-2006 Hong Kong, and published in the proceedings of the conferences (Rosen & Rosen, 2006a,b). All the data is based on internal MCon publications and research, much of it available for viewing on the MCon website [www.mcon.org](http://www.mcon.org).

2. Psychophysics is often regarded as a sub-discipline of psychology dealing with the relationship between physical stimuli and their

subjective correlates. The modern study of sensation began in the 19th century with the pioneering work of E.H. Weber (1846) and G. Fechner (1860) in sensory psychophysics. Despite the diversity of sensations we experience, all sensory systems convey four basic types of information when stimulated, modality, location, intensity and timing. These four attributes of a stimulus yield sensation. An early insight into the neuronal basis of sensation came in 1826 when Johanne Müller advanced his "laws of specific sense energies." The specificity of response in receptors underlies the "labeled line code," the most important coding mechanism for stimulus modality (Kandel et al, 2000)<sup>3, 11</sup>.

3. In two philosophical papers (Rosen and Rosen, 2007a,b), the authors utilize the modalities of receptors to convert subjective experiences (members of a S-set), into computer code (the domain of variable defined by a Universal Turing Machine (UTM)) (members of the T-set).

4. This is a mechanistic definition of "volition". The robotic controller is said to be a volitional controller if the controlled trajectory of motion is goal directed and pre-planned, with the option available for re-planning the pre-planned trajectory if an environmental contingency is detected prior to reaching the pre-planned goal. Re-planning is always a function of the contingency that appears in the region of the pre-planned path. It is never functionless or random, as hypothesized by Libet (1985).

5. The approach of modeling the connectivity of the brain rather than the mind's symbolic representation of the world was inspired by D. O. Hebb (1949) and Frank Rosenblatt (1958, 1962 p.386). During the decades of 1980 and 1990, this approach was pursued by many research scientists. Some notable examples are the works of Stephen Grossberg (1988), Gail Carpenter (1991), Teuvo Kohonen (Kohonen, 2001), William Bechtel (Bechtel, Abrahamson, 2002), Paul Churchland (Churchland, Sejnowski, 1996) and Helge Ritter (Ritter et al, 1992). In the past decade the connectionist methodology has blossomed with the development of powerful neural network-based computational techniques that emulate a large variety of brain functions. For example, the work of Teuvo Kohonen (2001) and Helge Ritter (1992) applied to self Organizing Maps and micro-structural connectivity in the biological brain, and the work by authors of the Dept. of Cognitive and Neural Systems at Boston University (see note 8).

6. One of the motivations for performing symbolic representational studies, and abandoning the connectionist approach, is the presence of very large numbers of neurons and possible neural networks, in the human brain (numbers in the range of 100 billion). For example in this paper, only 10,000 connectionist neurons, forming the neural network portion of the NCM-circuit, are required to generate the input to the coordinate frame in the controller. Connectionists may reconcile those low numbers, when claiming that the neural connections reverse engineer some brain function, by noting that the brain is a highly redundant organ, where each neuron in a neural network is likely to be represented by thousands of neurons in the brain. Furthermore, each neural network is likely to be redundantly located in multiple regions of the brain. Thus, statements by Kalasky and Crammond (1992) that "sensory motor transformations of the CNS are population functions to which a single cell makes only a fragmentary contribution," is consistent with a connectionist approach wherein a single electronic neuron may be related to thousands of neurons in the human brain. Or the similar statement of Scott et al (1995) "The discharge of many motor cortical cells is strongly influenced by attributes of movement related to the geometry and mechanics of the arm and not only by spatial attributes of the hand trajectory." This statement is also consistent, on two counts, with the reverse engineered coordinate frame presented in this paper. First the motor control signals of the NCM-circuit involves many motor neurons (at least 3-per joint), and the movement of all joints (the hand, for example) is related to the geometry and mechanics (by inverse kinematics) of the joint (hand), and not only by the spatial attributes of the hand trajectory.

7. In discussing proprioceptive sensations, Kandel, Schwartz & Jessell (1991, p. 337) show that the brain determines precise knee position (in the absence of voluntary muscle contraction). At rest, the angle of the knee can be evaluated to within 0.5-degrees.

8. Stephen Grossberg, Boston University director of Adaptive Systems and colleagues and staff at the Department of Cognitive and Neural Systems, are responsible for prolific publications in neural networks applied to cognition, memory, motor control, speech, and pattern recognition. Stephen Grossberg is especially known for his studies of the brain by means of Pattern Recognition by Self Organizing Neural Networks (1982); Studies of Mind and Brain (1980); How Does the Brain Build a Cognitive Code (1980); Adaptive Resonance Theory (ART) models; The Adaptive Self-organization of Serial Order in Behavior Speech Language and Motor Control (1985); The Adaptive Brain vol. I & II (1987a,b) and many other sensorimotor control publications (Grossberg, 1988, 1998; Guenther et al 2001; Pack et al 1988; Cameron et al 1997).

9. Rodney Brooks of the MIT artificial Intelligence Laboratory has published extensively studies of "how to Build Complete creatures Rather than Isolated Cognitive Simulators" (Brooks, 1989a,b). However, having rejected reductionism (connectionism), Brooks and company, in all their publications, design robotic subsystems made up of a conglomerate of isolated cognitive simulators (Brooks, 2000a,b, 1985; Lorigo, Brooks & Grimson, 1997). For example, "A Robot that Walks; Emergent Behaviors from a Carefully Evolved Network" (Brooks, 1989b); A Robot Layered Control System for a Mobile Robot (Brooks, 1986); The Role of Learning in Autonomous Robots" (Brooks, 1991); "The Cog Project: Building a Humanoid Robot" (Brooks, et al, 2000b); and "Visually-Guided Obstacle Avoidance in Unstructured Environments (Lorigo, Brooks, & Grimson, 1997). Other noteworthy representational studies of isolated cognitive simulators are Kalaska and Crammond (1992) "cerebral Cortical Mechanisms of Reaching Movements; Scott and Kalaska (1995) Changes in Motor Cortex activity during reaching Movement with similar Hand Paths but different arm postures"; And Brooks (1986, 1989b) description of robotic ambulation. Kelso (2002) also presents a general representational approach that utilize synergistic concepts of self organization and the mathematical tools of non-linear dynamical systems to demonstrate that basic forms of biological coordination arise from changes (in state) due to self-organizing synergistic processes.

10. The nodal map module of the RRC-robot exhibits some characteristics of human plasticity as observed in human stroke victims (Schwartz & Begley, 2002). If the damage to the brain of a stroke victim is analogous to nodal malfunctions in the in the Nodal Map Module, then the recovery of the RRC-robot may be analogous to the recovery of the human stroke victim. For example, when the Sequence Stepper Module (SSM) searches for a pre-planned path between the initial position and the goal position, if it finds a few malfunctioning nodes along the path, the SSM would automatically generate a new pre-planned trajectory that avoided the malfunctioning nodes. (The first time this happens, the action of the robot would be more error prone than after it had been trained to implement this new trajectory. That is, the robot would be required to re-learn how to move that limb through the proper trajectory.)

11. The authors prefer to avoid the term "conscious" or "consciousness" in discussing the modalities of sensors, (Nagel's (1974) equivalence of subjective experiences with consciousness, notwithstanding). At this time there is no scientific concurrence on a definition of "consciousness, whereas the modality of a receptor is well defined in terms of the subjective experience or sensation that is evoked by the receptor and the central connections associated with it. Thus the authors defer (in section IV-4) to the philosophers any connection between modality-sensations and "consciousness."

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