An Electromechanical Neural Network Robotic Model of the Human Body and Brain. Sensory-Motor Control by Reverse Engineering Biological Somatic Sensors.

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Abstract. This paper presents an electromechanical robotic model of the human body and brain. The model is designed to reverse engineer some biological functional aspects of the human body and brain. The functional aspects includes reverse engineering, a) biological perception by means of "sensory monitoring" of the external world, b) "self awareness" by means of monitoring the location and identification of all parts of the robotic body, and c) "biological sensory motor control" by means of feedback monitoring of the internal reaction of the robotic body to external forces. The model consists of a mechanical robot body controlled by a neural network based controller.

1 Introduction

This paper presents a functional design of an electromechanical robotic model that is based on human biological functions. The reverse engineered model is shown in Figure 1. The portrayed robotic system is designed as a humanoid, volitional, multitasking robotic system that may be programmed to perform any task from mail delivery postman to a expert basketball player. However the system is not a high level design that even comes close to the present day state of the art standards.
Caveat: Our goal was to reverse engineer a biological adaptation, which requires merely a building path[1] [1] for a humanoid robot. Thus the robotic body is a simplistic design (19th- 20th century technology) of motors and sensors with one simple torque generating motor per degree of freedom, operating on a simplified structure that has not been calculated to carry even the weight of the robot. The robotic controller, known as a Relational Robotic Controller (RRC)[2], is a hybrid circuit made up of neural networks and microprocessor based components. The neural network portion is controlled by simplified, very basic neural network equations (vintage 1980 generated by Teuvo Kohonen [2] and Helge Ritter [3]). However, the engineering design of the controller is complete albeit inefficient and cumbersome by present day standards.
The system is unique because the RRC-robot reverse engineers the human brain, the muscles of the human body, and is designed to perform humanoid actions with its body and limbs (see Figure 1).

1 The description of the robotic body adheres to Daniel Dennett's reverse engineering requirement: "No functional analysis is complete until it has confirmed that a building path has been specified"[1].

2 The RRC has been designed, reduced to practice and patented (Patent no. US 6,560,512B dated May 6, 2003). A more detailed description of the RRC may be viewed at the MCon site www.mcon.org [4].

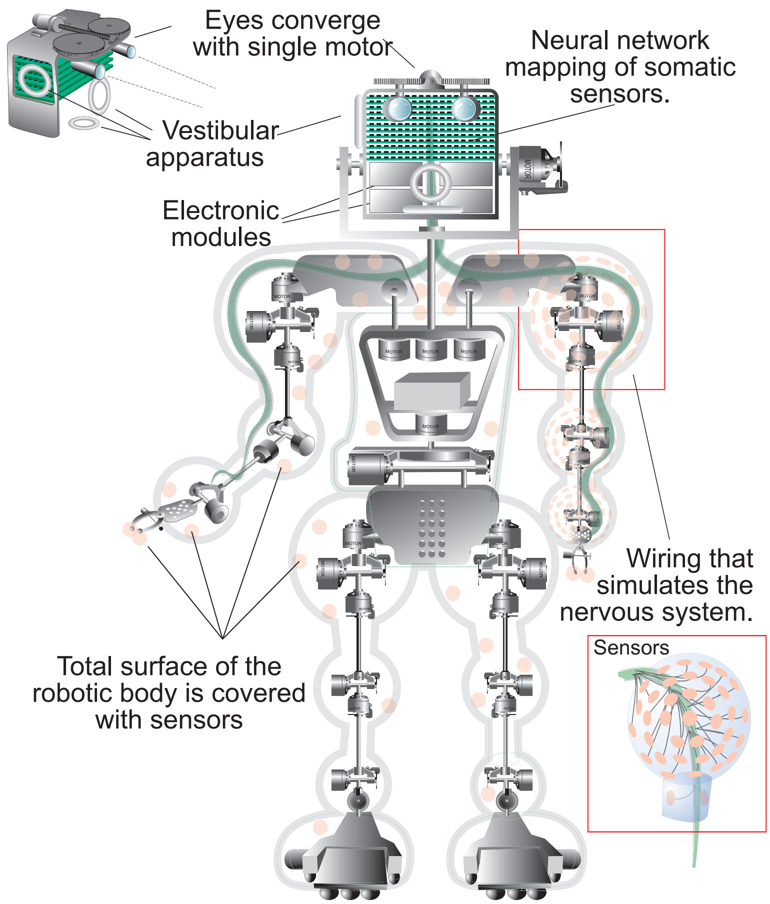

Fig. 1. A reverse engineered building path of a humanoid mechanical robotic body controlled by a hybrid neural net based Controller (RRC). The mechanoreceptors and nociceptors are reverse engineered by pressure transducers uniformly distributed on the robotic (skin) surface. The proprioceptors are reverse engineered by angle measuring transducers that are associated with the angular position of the shaft of each motor. The vestibular sensors are reverse engineered by circular rings on the controller (head) section of the robot. 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 [5]. The connectivity of the system is assumed to adhere to the biological "labeled line" principle[3] [6].

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-seconds and with synchro-

[3] The 'labeled line' principle [6], and the "Law of Specific Nerve Energy" [7], 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, so that stimulus modality is represented by receptors, afferent axons, and the central pathways that it activates. In the biological case, the labeled line principle is often used to explain the unique "conscious sensation" that each modality generates [6][7]. In this case, low level and high level activation thresholds in the pressure transducers simulate the modalities of "touch-feeling" and "tactile pain," respectivly.

nization and coordination of all body parts. The pressure transducers, uniformly distributed on the robotic body, simulate the tactile sensory system that constantly monitors the peripheral surface of the body for tactile activations. In the following sections, we shall show that the RRC-robot shares the following four characteristics of the human body and brain.

1. Similar to the biological brain, the controller has within it a reflection of the external coordinate frame in which the robotic motors are operating. The perceived tactile-activation data originating in the pressure transducers in the external frame are transformed into the coordinate frame located within the RRC-controller.
2. The measure of the internal coordinates is calibrated with the measure of the 3-dimensional space in which the robot is operating.
3. 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.
4. The robot has the capability to be trained to perform a diverse set of actions limited only by the sophistication of the neural networks in the controller and the design and the range of motion of all robotic moveable parts. for example a RRC-model may be programmed (trained) to perform multitasking sequences that range from digging ditches to playing basketball.

2. Main Results

The main results consist of four sections, sections 2.1 to 2.4, showing that the RRC-robot shares the four characteristics of the human body and brain enumerated above.

2.1 Similar to the Biological Brain. The Controller has within it a Reflection of the External Coordinate Frame.

Figure 2A illustrates the transformation of the neuronal folds in the brain into the 3-dimensional external (mirror) nodal map containing the homunculus of the robot. Validation of such transformations may be obtained by reference to most textbooks in

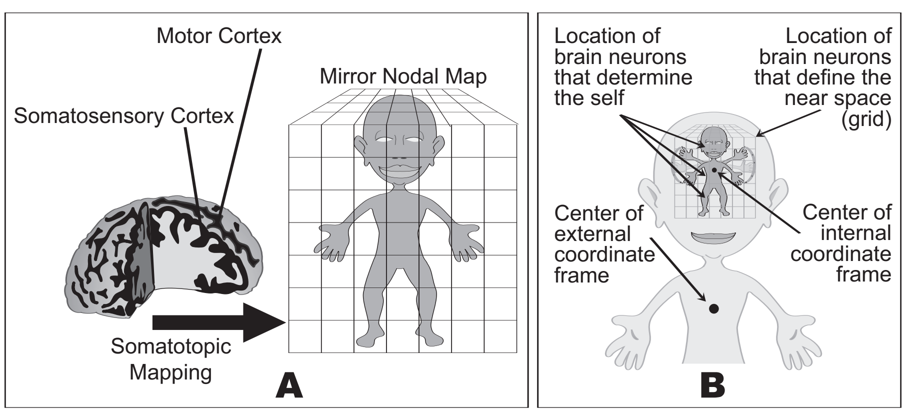

Fig. 2. A coordinate frame within the controller. A: Transforming the cortical folds in the brain into 3-dimernsional nodal mapping. B: A neuronal world-mapping: An indexed coordinate frame within the brain. The positions of flailing limbs are also shown.

cognitive neural science [8][10]. The mapping of the folds of the brain into an homunculus is shown in figure 2A. In the reverse engineered controller, the pressure transducers located on the robotic surface (skin), are mapped onto electronic receiving neurons identified by indexed locations determined by the 3-d coordinate location of the pressure transducer. Those indexed locations form the internal nodal coordinate frame within the controller. Thus, each electronic neuron, located at each of the indexed coordinate locations, forms a a portion of a neural network configured by the indexed locations of all pressure transducers.

2.2 The Measure of the Internal Coordinates is Calibrated with the Measure of the 3-dimensional Space in which the Robot is Operating.

Figure 2A shows the indexed locations of the electronic neurons (part of the neural network) that define the robotic self. The primary constraint imposed on the design of a world map-coordinate frame is that the topographic ordering of neural network neurons within the controller form a one to one correspondence with the external world space that defines the boundaries (skin-surface) of the robot.

2.3 The "Robotic Self" is Fully Defined in the Controller.

Figure 2B shows that the "robotic self" is fully defined in an indexed coordinate frame within the controller. The "near space" around the robotic self is defined by flailing limbs. Regions of the near space unoccupied by flailing limbs are defined by dormant receiving neurons. For example, the positions of the robotic fingers in the near space is determined by the angle measuring transducers located on the shaft of each motor.
A configured neural network is located within the controller with individual neurons of the neural network located at indexed locations that form a map of the robotic body (the configuration of neurons may be like the folds in the brain or like the 3-d homunculus shown in the figure). The configured neural network is that part of the RRC that facilitates reverse engineers the connectivity of the biological brain.

2.4 The Robot has the Capability to Be Trained to Perform a Diverse Set of Actions.

This section is divided into 5 parts: part 2.4.1-The flow through the configured neural network (neurons located at indexed locations) and the RRC, part 2.4.2-The block diagram of the RRC, part 2.4.3-Training a Nodal Map Module with robotic self knowledge, part 2.4.4 The solution to the neural net equations (for the neural network portion of the RRC), associated with a single joint Nodal Map Module, and part 2.4.5-Training a volitional Multitasking robot.

2.4.1 The Flow through the Configured Neural Network (each neuron located at an indexed location) and the RRC: In this paper, the RRC-robot is trained to perform itch-scratch type actions. The indexed location of an end joint, such as a robotic finger, used for scratching, is called q-initial. The itch-point, possibly an indexed location of a pressure transducer is labeled q-final. Figure 3 shows the flow of q-signals emanating from the pressure transducers, and the control pulse signals, p-signals, that are transmitted from the controller to the motors. The itch scratch trajectory from q-initial to q-final is shown in Figure 3 as a sequence of control signals, po. p1, p2.
A dedicated Nodal Map Module is associated with each robotic joint, and the indexed

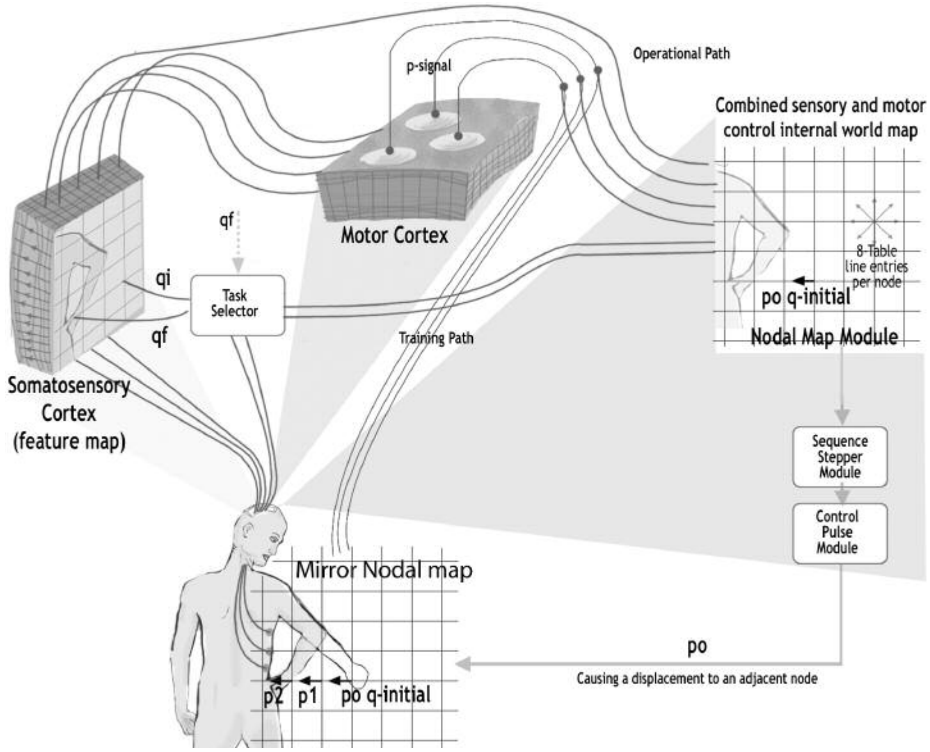

Fig. 3. A flow diagram of the q-vector and p-vector through a configured neural network and thence to the RRC that simulates the functionality of the human brain. The output of the Nodal Map Module goes to the external mirror nodal map via the Sequence Stepper and the Control-signal Output Module.

location of the end-joint, q-initial, is always recorded in the dedicated Nodal Map Module.

To satisfy the volitional constraint (motion must be pre-planned and goal directed), the trajectory of motion of any end-joint is divided into small nodal transitions. The total trajectory is a sequence of nodal p, q-initials between the first and final, q-final, node in the trajectory. Only the first of a pre-planned sequence of nodes may be activated during any frame period. Thus, the maximum speed of operation is one nodal transition per frame period (with all joints (q-initial nodes) activated simultaneously)

2.4.2 Block Diagram of the RRC (Hybrid Circuit). The RRC is a hybrid circuit made up of a set microprocessor based modules, programmed by sequential algorithmic programming (takes up approximately half the physical space of the controller), and a set of neural network modules, that take up the remaining physical space within the controller. A microprocessor based module is dedicated to each joint of the robotic body (21-joint require 21-modules). The q-initial motion of the end-joint is controlled in each module, during each frame period.

All the programming of the Nodal Map Modules, Task Selector Modules, Sequence Stepper Modules, and Control-signal Output Modules, is based on indexed locations in the 3-d space, determined by the programming/training of the configured neural networks shown as the top half of the physical space within the controller (see Figure 4). A Nodal Map Module associated with each joint, is made up of index locations covering the range of motion of the end-joint. Twenty one Nodal Map Modules are required

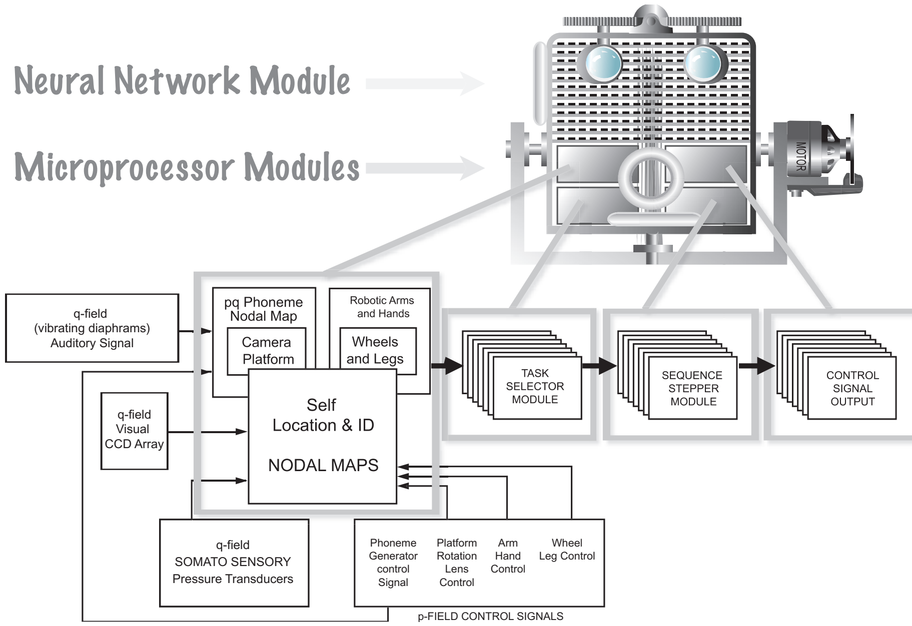

Fig. 4. Hierarchical array of RRCs. All the Nodal Map Modules, Task Selector Modules, Sequence Stepper Modules and Control Signal-output Modules (associated with each joint in the body), operate simultaneously during each frame period.

to control all the joints of the robot shown in Figure 1. Figure 1 shows the 21-joints and the motors present at each joint (a total of 39 motors with one p-signal per motor). Thus, given a q-initial position located at an indexed location of a Nodal Map Module, the Task Selector Module generates a q-final location. The Sequence Stepper Module is activated by q-final to search the region between q-initial and q-final and generate an obstacle avoiding p-q sequence that represents the pre-planned trajectory between q-initial and q-final. The Control-signal Output Module may then (conditionally) transmit all 39-p-signals to all the motors in order to generate the first nodal transition of the pre-planned sequence of p-signals (that control motion from q-initial to q-final).

2.4.3 Training A Nodal Map Module. Robotic Self Knowledg: A block diagram explaining the training proicedure is shown in Figure 5. Two paths are shown in the figures, a training path and an operational path. Training is performed on all twenty one Nodal Map Modules simultaneously.
The itch-scratch trajectory is used repeatedly to train the robot with a “self identification and location” form of knowledge. This form of knowledge is also called “robotic self-knowledge”. Robotic self knowledge is implemented by training the robot to identify and locate any and every body part of the robot by means of the itch-scratch trajectory of motion. The training consists of teaching first the Nodal Map Module associated with the end-joint of the robotic finger to scratch all possible itch points that can be reached by the end-joint. Then training the remaining twenty Nodal Map Modules to scratch, with the aid of each associated end-joint, all possible itch points.
In the training path of the end-joint Nodal Map Module, the set of p-signals (39-p-signals one to each motor of the robot) are trained repeatedly until the displacement error CFI<∂ (see Figure 5). When the CFI<∂, then up to 3-corrected table line entry p-signals are assigned to the end-joint Nodal Map Module, and the remaining corrected table line entry p-signals are assigned to all the other end-joint Nodal Map Modules.

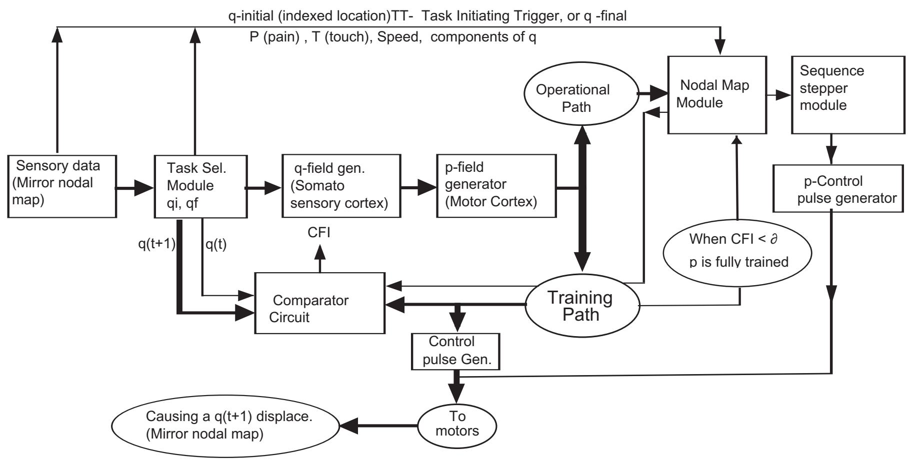

Fig. 5. Training the Nodal map module: Two paths are shown in the figure, a training path and an operational path. The set of p-signals are trained repeatedly until the CFI is less than delta. When CFI ≤ ∂, the p-signal is assigned to a node (indexed location) in a Nodal Map Module as a table-line entry. A pictorial representation of the training path flow is also shown in Figure 3.

Since the designer may calculate the magnitude of the set of p-values (all the table-line entries) in all the Nodal Map Modules, required to move a robotic end-joint from q-initial to q-final, the training process is a refinement and correction of the calculated indexed-table-line entries, so that the robot generates an exact transition from q-initial to q-final.

When training one end-joint of the robotic finger Nodal Map Module by the itch scratch method, all remaining twenty Nodal Map Modules are trained simultaneously (by inverse kinematic techniques) with the measured and corrected displacement of the robotic finger. Note that there may be multiple inverse kinematic displacements of the other Nodal Map Module for any fixed displacement in the end-joint Nodal Map Module. The end-joint Nodal Map Module is said to be fully trained when each indexed-node has a correct and complete set of table line entries assigned to it. In a 3-d space the complete set per node consists of table line entries representing 27-displacements to adjacent nodes. Each displacement may be represented by a 3-component vector (p=px + py + pz), and each component represents the input/torque to one of the three motors that may be present at that joint.

2.4.4 The Solution to Neural Net Equations Associated with a Single Joint Nodal Map Module: A complete solution to the equations of motion of an RRC- circuit for the sensory-motor control of a robotic arm has been developed by Rosen & Rosen [9]. The solutions to the neural net equations applied to a joint-dedicated Nodal Map Module, and represented by thresholds and the synoptic weights of interconnections are shown in Table 1. The equations are based on the work of Teuvo Kohonen [2] and Helge Ritter [3]. The two most important factors in obtaining the solution to the neural net equations are:

1. For each joint-dedicated Nodal Map Module the required p-signals and required displacements are known quantities that are determined by the physical design of the system. All the displacements may also be observed (by inverse kinematics) when the p-signals act on all the motors of the robot. Thus the training process is a refinement and correction of the calculated indexed-table-line entries, so that the robot generates an exact transition from q-initial to q-final.

2.The equations and solution of one joint-dedicated Nodal Map Module of a given dimensionality is applicable to all the other joint-dedicated Nodal Map Modules of the same dimensionality (the same number of motors per joint).

2.4.5 Training a Volitional Multitasking Robot: The emphisis of this paper is on reverse engineering the connectivity of the somatic sensors in the body and brain. Our goal is not to design a multitasking robot-but to show that the reverse engineered building path of the human brain, described in the previous sections, is applicable to the design of a volitional multi-tasking robot that has the biological locomotive characteristics of walking, dancing or even playing basketball. The only difference between a itch-scratch robot and a basketball playing robot is in the training of the Nodal Map Modules, not in any re-design of any of the electronic or mechanical components.
The robot is first trained to visually detect obstacles by means of a Nodal Map Module designed with a q-visual field configured "world map" within the controller, as described by Rosen & Rosen [5]. The itch-scratch robot may then be trained to visually detect an obstacle along a pre-planned itch-scratch trajectory and to generate a re-planned obstacle avoidance trajectory (by means of the Sequence Stepper Module) whenever an obstacle appears along the pre-planned trajectory.
Training an obstacle avoiding multitasking robot is performed by means of an Hierarchical Task Diagram (The top level specification for an RRC-robot) shown in Figure 6. Training the robot to move a limb through a single scratch trajectory, called a chunk (see figure), is represented by a sequence of p-signals that guide the robotic limb from q-initial to q-final. A sequence of chunks may be called a daisy chain or a line dance. Teaching/training a robot to walk is analogous to teaching the robot to perform a repetitive sequence of daisy chains. A non-repetitive, but artistic goal directed sequence of chunks may be called a line dance. A trained basketball playing robot performs a goal directed, obstacle avoiding, sequence of line dances, interspersed with daisy chains (associated with running and dribbling the basketball).

Table 1. The solution to the neural net equation applies to a single joint/nodal-map-module.

EACH NODAL MAP MODULE (associated with one joint) CONTAINS • Only the control signal (p-signal) output of the motor neurons associated with that joint • Only the q-initial position of the end-joint associated with that joint. • The q-final positon is common to all nodal map modules
PLANE A' (See diagram) THE OUTPUT OF MOTOR NEURONS (assoiciated with the motor cortex (figure 6) • The output for 3-degrees of freedom is given as Px,Py,Pz (see A') • Total output P_{3D} = a Fr3 + bFr4 + cFr5 • Where Fri is given by Ritter's equation: Fri= μ($\sum$Wrl Vl + $\sum$Grr' Fr' -Ørr')
PLANE A (See diagram) THE INPUT SOMATIC RECEIVING NEURONS (associated with the somatosensory cortex (figure 6) • The threshold Ø, and the coupling strengths Grr' may be chosen so that Equation 1: $\sum$ Grr' Fr' $\leq$ Ørr' • Thus there are only 2 activated outputs of A, applied to A' Equation 2: Vi = qi + Gif -Øi Equation 3: Vf = qf + Gif - Øf
PLANE A' RITTER' EQUATION MAY THUS BE WRITTEN (with only 2 Vi inputs) Equation 4: Px = Wix Vi + Wfx Vf -Øx Equation 5: Py = Wiy Vi + Wfy Vf - Øy Equation 6: Px = f(Py) Direction dependence for the 2D case
SOLUTION TO A SET OF 6 EQUATIONS WITH 6 UNKNOWNS(See Rosen, 2003b): • Set Wij = Gij = W • Set Øi = Øj = Ø • Solution achieved by adding a sixth equation (for the 2D case): Equation 6: Px = f(Py) • Solutions shown in figure 9 are for Px, Py, Vf, Vi, W, Ø

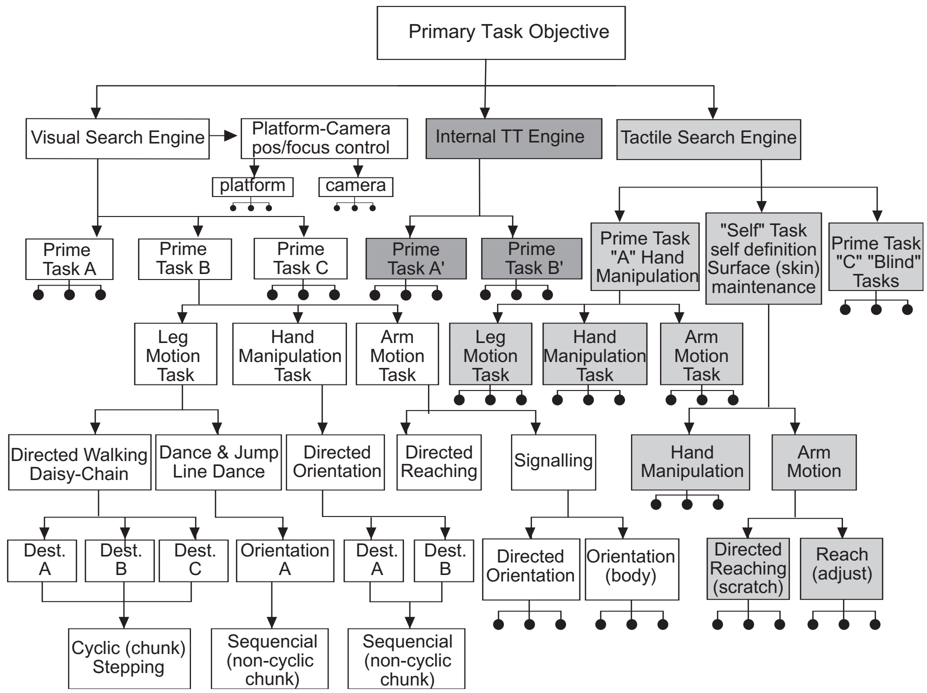

Fig. 6. A Hierarchical Task Diagram (HTD). The HTD is the top level specification for training a multitasking RRC-robot.

3.0 Similarities to the Biological Brain

The previous sections presented a well defined reverse engineered building path of the connectivity of the tactile sensors and the topographic characteristics of the human brain. A byproduct of the reverse engineered connectivity is the design of a locomotive RRC-robot programmed to perform itch-scratch-“self location and identification” type actions. Some philosophical issues arise from the functional similiarity of the RRC to the functions of the human brain.

1. A philosophical issues associated with the trainability of the RRC-robot: The robot has the capability to be trained to perform a diverse set of actions. Does the reverse engineered RRC shed light on how the brain controls complex locomotive behavior? What are the implications of neural net based robotic memory and robotic learning on the biological procedural learning and procedural memory?
2. Is it possible to compare the robotic self and robotic self knowledge with the human psychological perception of self knowledge? 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. The measure of the internal coordinates is calibrated with the measure of the 3-dimensional space in which the robot is operating. But the most important characteristic of the RRC-robot is “self awareness” of the reaction forces exerted on the pressure transducer of the robotic body, by the external environment. Thus the robot, may have “self knowledge” or “self awareness” of the forces exerted on the pressure transducers of the robotic feet as the robot leaps walks or runs.
3. Is it possible to compare robotic monitoring with biological perception (such as tactile feeling, psychological “seeing”, or psychological hearing)?

The internal coordinate frame of the robot constantly monitors the state of the pressure-transducer/tactile sensors. In connection with biological tactile monitoring, the modality of the biological tactile receptors are defined in medical and neuroscience textbooks [10], in terms of the conscious sensation that they evoke. What is the modality of the robotic pressure transducers that are connected to the controller in the same manner as the biological receptors (adhering to the law of specific nerve energy)?

4. In Conclusion, we propose that the modality of the robotic pressure transducers is a “conscious sensation”, similar to the modality of biological mechanoreceptors and nociceptors. The RRC-circuit is thus a Conciousness-generating Mechanism (CM). It may be the reverse engineered analogue of the long sought after Neuronal Correlate of Consciousness-(NCC)-circuit in the brain [11]. Thus, the biological “conscious sensations” of “touch-feeling” or nociceptic “pain” may be correlated with a neuronal “self identification and location”-circuit. The RRC-circuit is also a neuronal correlate of consciousness circuit within the controller, for subjective experiences analogous to “touch feeling,” and “tactile pain. ”

This proposal may be generalized as follows:

1.For all the biological sensors, the biological "self location and identification circuit" in the brain, coupled with self knowledge and self awareness, represents the philosophically, long sought Neuronal Correlate of Consciousness (NCC)-circuit in the brain (see www.mcon.org)[4].

2.The biological NCC-circuit and the RRC-circuit may give rise in addition to a biological/machine-like form of tactile “consciousness,” other forms of “consciousness” such as biological/machine-like visual “consciousness (the sensation of “seeing”), “hearing”, “smelling” and “tasting.”

[4] All the data and figures for this article are based on patents and publications relating to the Relational Robotic Controller (RRC)-circuit that have been published in the MCon Inc. website www.mcon.org. The authors are particularly grateful for the financial support and permission to publish the MCon data and Figures, received from Machine Consciousness Inc

References

1. D. C. Dennett, Artifact Hermeneutics, or reverse Engineering p. 194 in Evolution edited by Mark Ridley Oxford University Press: New York 1997.
2. T. Kohonen, Self Organizing Maps (3rd ed.) Berlin: Springer-Verlag, T. (2001.
3. H. Ritter, M. Thomas, & K. Schulten, Neural Computation and Self Organizing Maps. New York: Addison Wesley Pub. Co., 1992.
4. D. B. Rosen A., & A. Rosen, The Application of the NCC Circuit to Sensory-Motor Control of the Somatic Motor System. Machine Consciousness Technical Journal. 1, 41-56, 2003 (available for viewing at www.mcon.org)
5. A. Rosen A., & D. B. Rosen, The Design of the NCC-circuit for Visual Perception. Machine Consciousness Technical Journal. 1, 19-40, 2003 (available for viewing at www.mcon.org)
6. A. C. Guyton, Textbook of Medical Physiology. Philadelphia: W.B. Saunders 1991.
7. D. E. Haines, Fundamental Neuroscience 2nd ed. Churchill Livingston: Phil. PA, 2002.
8. D. G. Purves, A. D. Fitzpatrick, L.C. Katz, A. S. La Mantia, & J. O. McNamara, Neuroscience. Sunderland Mass: Sinauer Assoc. Inc., 1997.
9. D. B. Rosen A., & A. Rosen, The Engineering Design of a NCC Circuit for the Sensory-Motor Control of a Robotic Arm. Machine Consciousness Technical Journal. 1, 41-56, 2003 (available for viewing at www.mcon.org)
10. E. R. Kandel, J. H. Schwarts, & T. M. Jessell, Editors, Principles of Neural Science. Norwalk Conn:Appleton and Lange, 1991. (See also Chapter 26: “Touch”)
11. T. Metzinger (Ed). Neural Correlare of Consciousness. Cambridge Mass:MIT Press, 2000