262

Computer networking for the robotic neural and sensory systems

Carol Niznik and Robert Newcomb describe a method for analysing the software and hardware structure of the robotic motor, visual and sensory systems

At the present time, robotic systems are composed mainly of mechanical functions connected for the purpose of achieving a specific form of automation. An overall plan for the robotic system computer architecture is described to investigate optimal, efficient and cost effective mimicking of human nervous system functions in the robotic system. The following component analogies are drawn between the computer network and the human nervous system: computer node to soma (cell body), input communication channels (links) to dendrites, output communication channels to axons and communications processor ports to buttons. The robotic nervous system therefore is structured as a larger internetwork (similar to the DARPA internetwork) of gateway nodes (controlling neuron cell bodies) which connect neuron intranetworks together. As in the human body, the robotic nervous system is the controlling system for visual and sensory functions.

Keywords: computer networking, robotics, human nervous system

ROBOTIC SYSTEM ARCHITECTURE COMPONENTS

Present robotic systems are quite primitive and they lack lifting, strengths and sensing accuracy because of the lack of sophistication in the marriage of software and hardware theory. The robotic architecture, required for development of a robotic controlling nervous system that closely emulates important intellectual nervous system functions which in turn control mechanical motion and sensing functions, is considered here. The implementation of the human nervous system will be described by the interconnection of a robotic brain to motor, sensory and visual functions via multi-network hardware representations of the human nervous system topology. The structure of the controlling software will be composed of the following three automata:

- learning automata (brain visualization and learning of the outside environment, decisions, functions and chaotic behaviour),
- interconnecting path automata (connection of learning automata functions via nervous function paths enabling muscle function control),
- function control automata (connection of nervous system path functions to limb, hand and finger controllers).

This overall architecture requires the interconnection of many microprocessors, and therefore includes the individual microprocessor architecture linked to an overall brain-controlling microprocessor system within a multi-network. The hardware implementation analogy will be between

- microprocessor and neural type cells,
- fibre optic links and dendrite or axon channels.

The probabilistic aspects of connections between the microprocessors will be realized by the existence of

---

[*] Department of Electrical Engineering, University of Pittsburgh, Pittsburgh, PA 15261, USA

[†] Department of Electrical Engineering, University of Maryland, College Park, MD 20742, USA

controlling centres of the human nervous system. These controlling centres (major gateways) are locations where large numbers of dendrites and/or axons respectively enter and leave a single or a few neuron cell bodies. Real time measures on the robotic system controlling hardware and software subsystems will be explored via the generating mathematical tools of queueing theory and optimization theory. The components required to form these automata structures determine the parameters of an overall robotization cost equation.

Robotic system overview

Figure 1 gives a general overview of the robotic system organization proposed, and Figure 2 shows the specifics of this human-mimicked robotic system. Figure 3a illustrates the brain to finger sensor path and Figure 3b illustrates the spinal cord to knee of the leg response neural paths in the human system, which will be designed for this robotic system under the constraints of the quantization theory.

ROBOTIC NERVOUS SYSTEM SOFTWARE THEORY AND IMPLEMENTATION: LEARNING AUTOMATON

Robotic vision

The computer vision utilized is based on image processing and scene analysis where distinctive features of an object are extracted to identify its location and orientation; a set of prototype patterns are assumed to be known and their features learned. The objective of the robotic vision hardware and software is to mimick the mammalian visual system[27], and thereby suggest ways of organizing the visually sensed information, properly processed, for the robotic nervous system. In

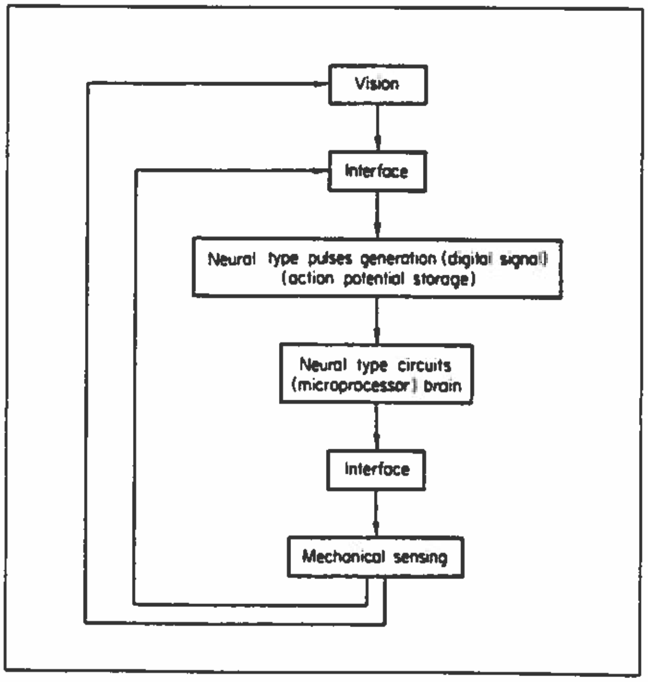

Figure 1. Robotic system flow chart

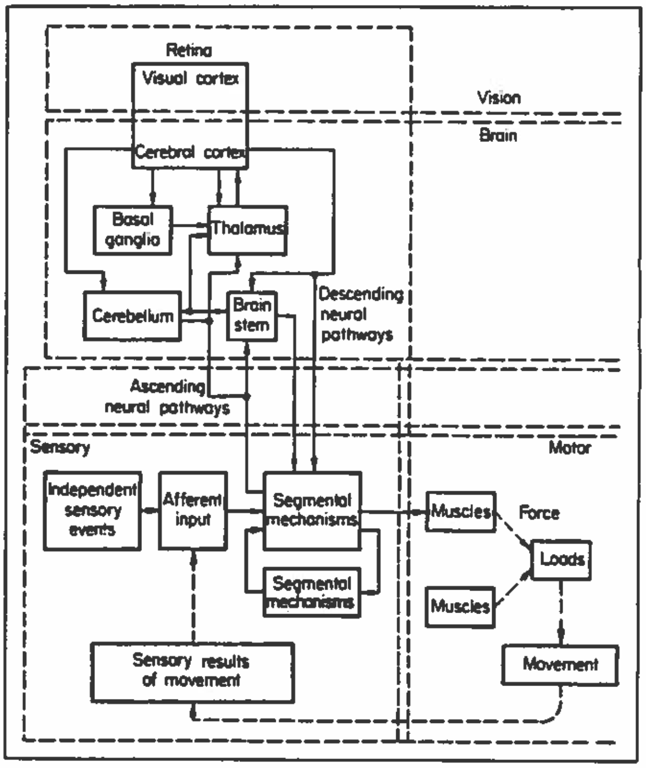

Figure 2. Robotic visual-sensing system overview with nervous system components

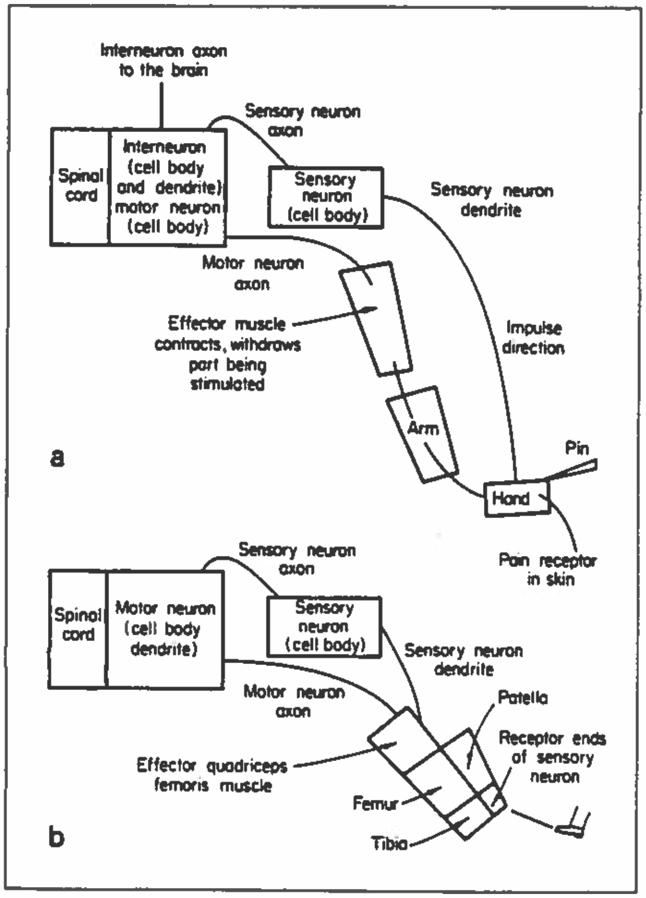

Figure 3 Robotic knee jerk response sensory and motor neurons

the mammalian visual system, the photo receptors in the retina, called rods and cones, sense the information in the visual field and send the coded signals to ganglion cells through bipolar neurons. The axons of ganglion cells exit from the eye and form the optic nerves. There are numerous fibres in each optic nerve. All the fibres from the nasal halves of the two retina cross to the opposite side. Fibres from the right nasal retina combine with fibres from the left temporal retina to form the left optic tract; the right optic tract is formed in symmetry. The fibres of each optic tract synapse in the lateral geniculate nucleus in the thalamus, as indicated in the block diagram of Figure 4.

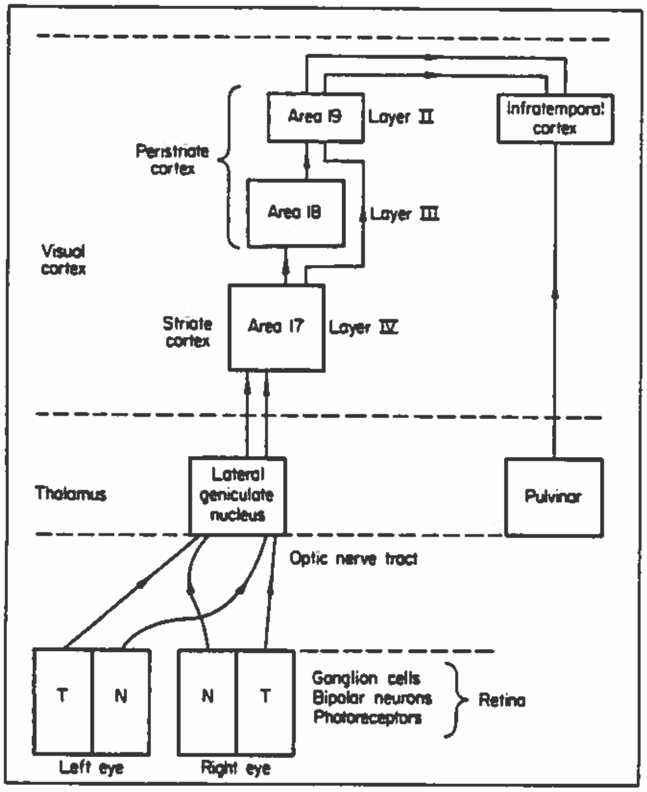

Figure 4. Block diagram of the robotic visual system mimicking the mammalian visual system

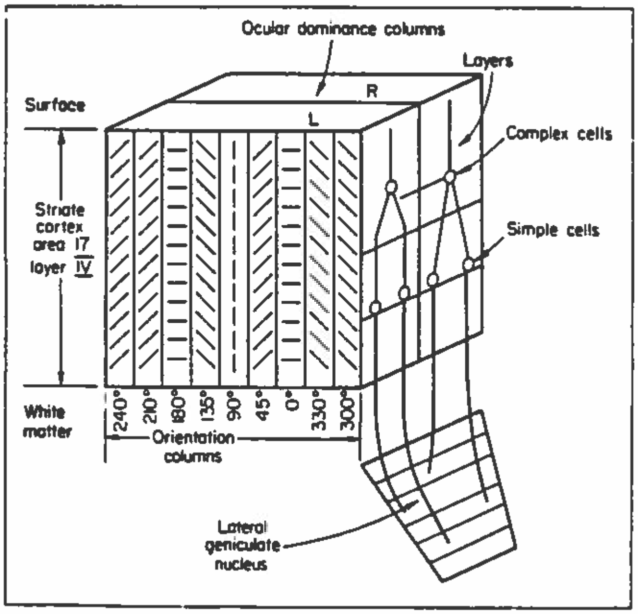

Figure 5. Development of robotic vision software based on the structure of the mammalian primary visual cortex

Axons of neurons in the lateral geniculate nucleus relay the information from each eye to the primary visual cortex (layer IV or striate cortex). The axons are clustered in patches within layer IV (area 17). Each patch represents a zone dominated by one eye, and the patches dominated by either eye alternate regularly with one another. Therefore, ganglion cells at different loci in the retina project upon distinct regions in the lateral geniculate nucleus, which in turn are mapped onto the striate cortex in a point-to-point manner, with some distortion, but preserving the topographical relations.

The cortical maps are distorted maps of the visual field in that the regions of high discimination or delicacy of function occupy relatively more cortical area. The processed information from layer IV is sent to layer III (area 18) and layer II (area 19) in the peristriate cortex, which in turn send the extracted information to the infratemporal cortex. The striate cortex is organized into narrow columns, containing many simple cells with identical axes or orientation and complex cells, which take inputs from a group of simple cells in the column and respond to edge information. Therefore, the striate cortex decomposes a visual scene into short line segments of various orientations. There are also orthogonal columns devoted to ocular dominance relating to binocular vision. Figure 5 illustrates the orientation columns of layer IV in the visual cortex on which the proposed robotic vision software structure is based and from which it will be developed. At the peristriate cortex, hypercomplex cells receive convergent inputs from two or three complex cells and respond to changes in boundaries and corners. The cells in areas 17, 18 and 19 appear to be the early building blocks of perception and they extract features by progressive convergence. At successively higher cortical levels, parallel processing may take place in the sense that each region simultaneously performs distinct feature abstraction and the combination of these abstractions forms the basis of image pattern recognition.

For identification and orientation determination of a simple object, ignoring the problem of binocular vision and depth measurement, we will be concerned only with two-dimensional image pattern recognition. The proposed robotic system will contain a camera–computer system for the above mentioned recognition task by structuring the system so that some well-known processes in the biological visual system are appropriately utilized. The visual scene will be restricted to a small field corresponding to a small array of picture points which are mapped, with equivalent topography, onto a hypothetical region of the lateral geniculate nucleus, which in turn, projects onto the visual cortical regions. Since the responses of various visual cortical cells are orientation specific, the object edge segments will be extracted and organized for the purpose of object recognition at successive layers in a hypothetical visual cortex. Subsequently, the object orientation and other pertinent features of interest can be computed.

ROBOTIC NERVOUS SYSTEM SOFTWARE THEORY AND IMPLEMENTATION: LEARNING AUTOMATA AND INTERCONNECTING PATH AUTOMATA

Robotic brain

The accurate establishment of the connection and synchronization of the robotic computer vision, the nervous system architecture, and arm, limb, hand, foot and fingers, will be made by the optimal determination of quantization encoded communicating pulses in the human body. The number of redundant pulses is large enough to take into account the constant death rate and possible damage to nervous system cells, to ensure function accuracy in the transmission of action potentials. According to Niznik[50], the optimal quantization interval ensuring accuracy in the representation of probability density functions (pdf), gave maximum accuracy. Further narrowing of this horizontal quantization interval, i.e. increasing the number of pulses representing the envelope of the pdf, causes a falling off of accuracy due to round-off error in the computer. Since the robotic nervous system will be an internetwork of microprocessors, the Niznik quantization approximation (QA) determines the optimal number of nervous system pulse transmissions of encoded action potentials to analogize the balanced number which the human nervous system maintains.

Experimentation in the robotic vision and robotic sensing functions is required in conjunction with the VLSI (very large scale integrated-circuit) circuitry implementing the above robotic nervous system architecture to determine their individual tolerance (sensitivity) on the optimal number of neural path action potentials. The capability for accuracy in action potential transmission from this combined software and hardware capability, also improves the coordination required in the weight lifting function of the robotic arm, involving robotic fingers.

The values of the optimal number of action potentials and respective delays for the path from the brain to the fingers or legs will be stored in the three dimensional (i, j, k) entries of the cubic software structure closely replicating the cubic structure determined by Mountcastle[27] for the cerebral cortex (Figure 6). A similar cubic structure for the cerebellum will be developed for the cerebellum entries (Figure 7). These delay entries[45,53] are computed from the following equation: (The individual delay component values are generated from Moore probabilistic automata (MPA) models.)

$$[D_{ij}]_p = [\sum_{g=1}^{\alpha} (D_{ij})_g + \sum_{c=1}^{\varepsilon} (D_{ij})_c + \sum_{k=2}^{\alpha} (D_{ij})_k] \qquad (1)$$

where,

$(D_{ij})_p$ = total path p delay
$(D_{ij})_g$ = soma delay + processing delay
$(D_{ij})_k$ = accumulative cell body delay
α = number of levels of nodes in path
ε = number of stages of channels in path.

Utilizing the cubic structure, the condition in time where each cortex in the cerebral cortex or each lobe in the cerebellar cortex utilizes the same neuron type path, can be illustrated in the software by collapsing the cube to a two-dimensional square or rectangle. The complete brain software cubic entities will be linked together as illustrated in Figure 2. This structure can be visualized as the horizontal stacking of the sections of the brain and other CNS components in a neural path, in their order of occurence. This will enable accurate simulation of the influence of incoming information at the neuron cell level, relating distribution and location, as well as the number of synapses on the dendritic tree and cell soma which sample columnar arrays of axons.

Plasticity

Plasticity in the CNS is the capability of sections of the

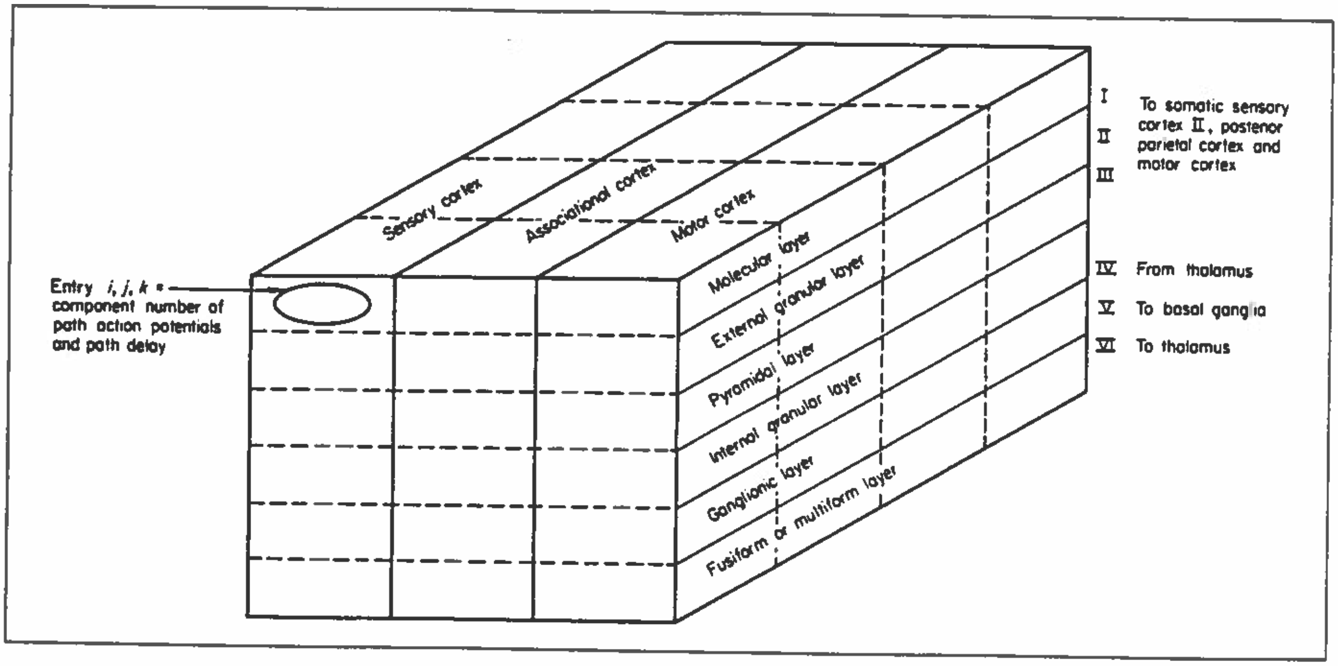

Figure 6. Organization of the robotic brain cerebral cortex software structure

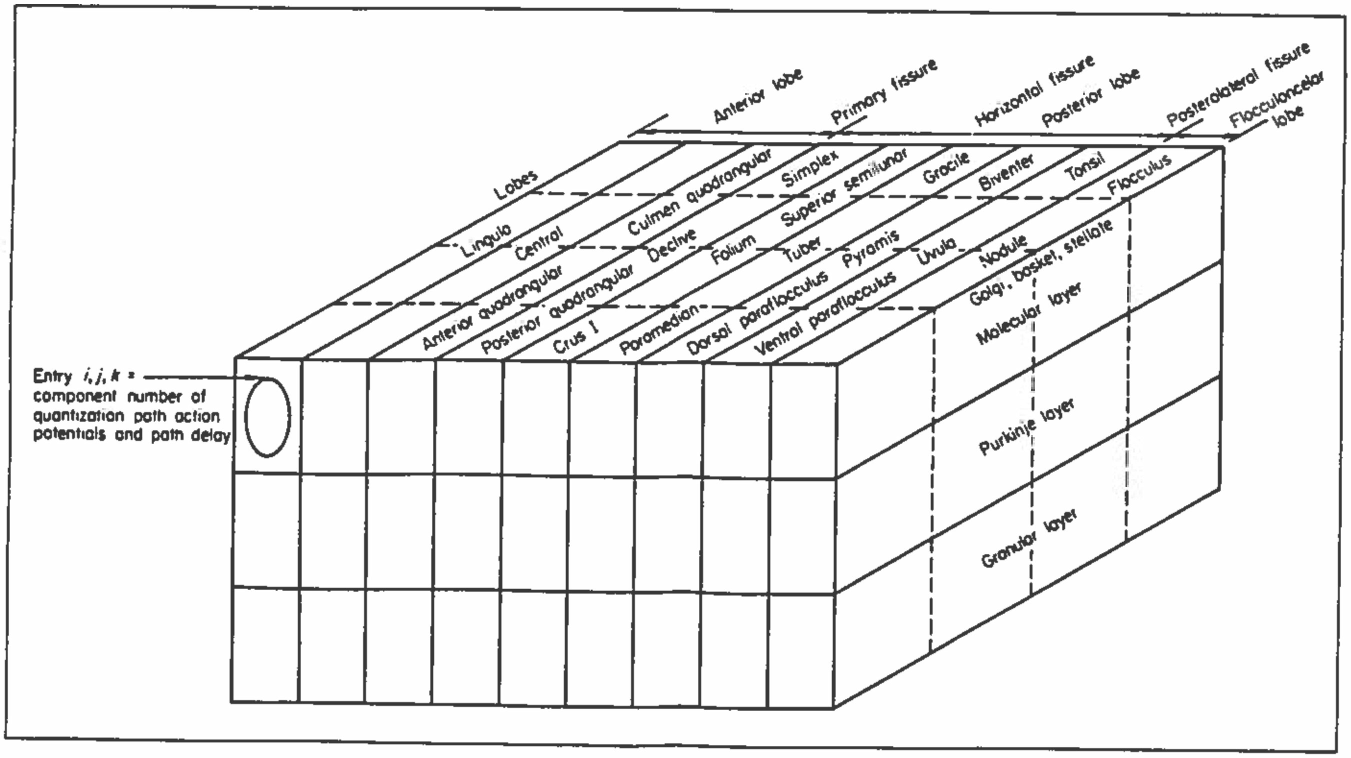

Figure 7. Software organization of the robotic brain cerebellar cortex

neural circuitry to learn from a change in their interrelationships. This ability of human neural tissue to change its response to stimulation occurs because of its past activation record.

Neural cells located in the area of the brain following the visual cortex will demonstrate plasticity, because their location will be modelled as the learning automata. Plasticity can occur in the granule, basket, Purkinjie or Golgi cells of the cerebellar cortex based on an increase or decrease in the horizontal quantization interval in the software and the correlated hardware parameters. A larger number of action potentials may or may not increase the capability of the neural cell in the learning automaton to learn. These learning potential amplitude and capability measures will be developed from the upper and lower quantization bound theory of the optimal number of action potentials.

ROBOTIC NERVOUS SYSTEM HARDWARE THEORY AND IMPLEMENTATION: INTERCONNECTING PATH AND FUNCTION CONTROL AUTOMATA

Microcircuits with signal processing capabilities of biological nervous systems[2,13,14,34,40–44], circuits for motion control[57], and neural control of vision microprocessors[2] are developed and analysed in this section. MOS (metal oxide silicon) circuits are ideal for the basic modelling of the implementation of the quantization and plasticity properties. These devices will implement the central nervous system with low power and less energy with the same computer power as required by higher energy sources. These properties will allow construction of these devices mimicking the central nervous system in large numbers via the use of VLSI (very large scale integrated-circuit) technology.

Linking of computer and circuit quantization

The form of horizontal (time) quantization[50] of the optimal number of action potentials from the theory described in the previous section, results in an amplitude representing a specific functional path in the central nervous system. The functional path will be between the visual cortex in the brain circuitry and the fingers in the hand, since our objective is accuracy in the coordination of the connection and synchronization of the robotic computer vision and limb extremities. (i.e. hand and finger manual dexterity). To formalize this theory, the following parameters are introduced to describe the horizontal and vertical quantization.

- n_π = number of action potentials in a discrete time interval π of an amplitude representative of a specific functional path in the nervous system.
- $(\overline{n-m})_\pi$, $(\underline{n-m})_\pi$ = the respective upper bound and lower bound optimal action potentials during time interval π.
- $P_f = (p_1, \ldots, p_\delta)$ δ action potential amplitudes ϵf and $f = 1, \ldots, \rho$ functions where each member amplitude can be equal during a time π.
- h = horizontal quantization interval, width of each action potential during time interval $\pi = \delta h$, where δ is the number of h in each π.
- PMC = peak measurement complexity = $k\gamma$, where k is the upper or lower bound constant ($\bar{k}$ of $\underline{k}$), and γ is the multiple of common quantization width along π on the t axis.
- PMA = peak measurement accuracy for a specific width (time interval) π. Time width multiple γ and PMC of action potential pulses in π, are defined with reference to the constant k.

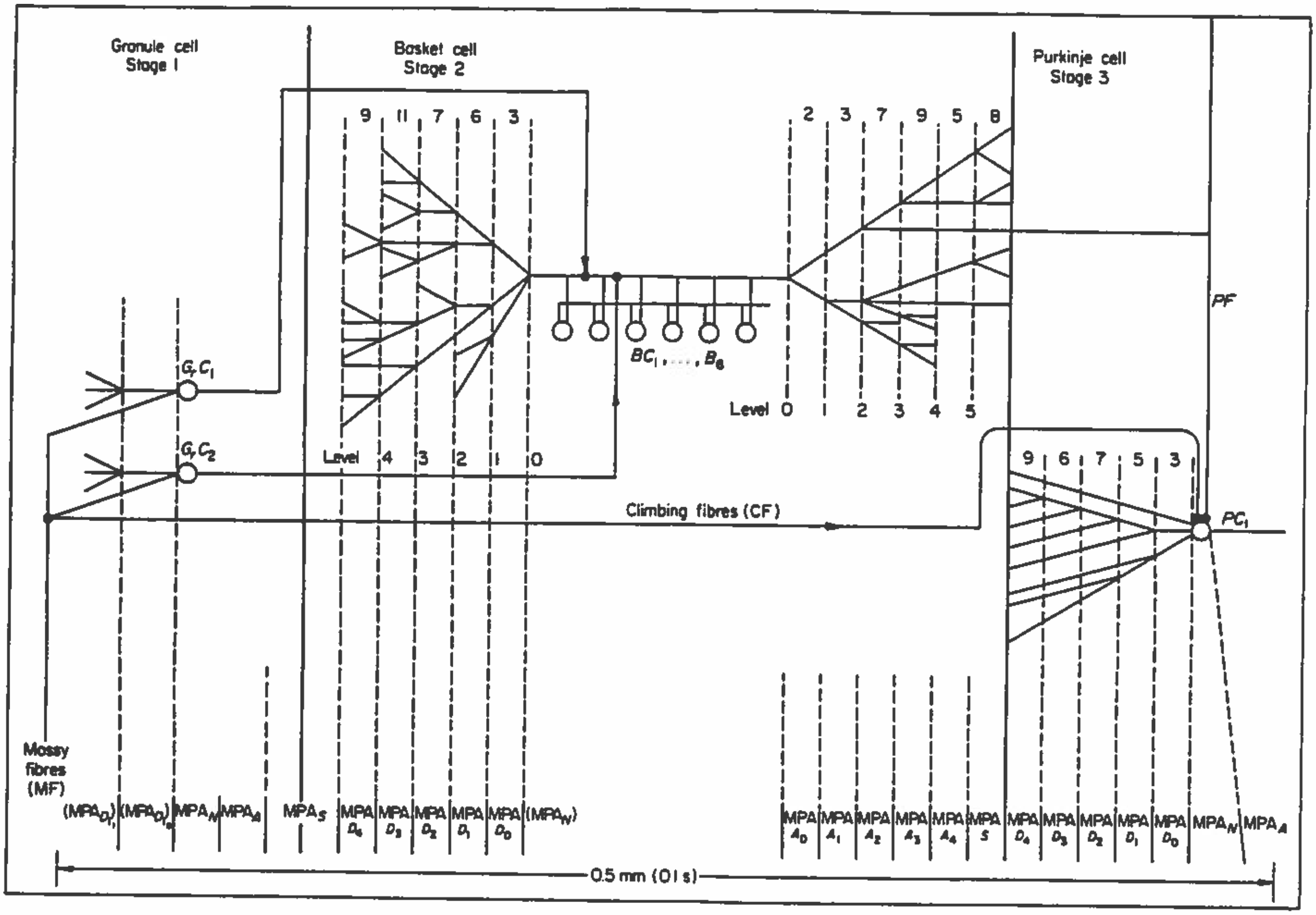

Figure 8. Mathematical and computer networking topological circuit details for robotic cerebellar cortex

The MOS circuits can also be used to model retinal processing[2]. The following three topics are considered for the linking of this circuit and computer quantization theory:

- the achievement of action potential type pulse firing rate control (horizontal quantization) by input characteristics[40], i.e. control of δ and the $(n-m)$ bounds,
- use of an adjustable threshold for horizontal (p_i) or vertical (δ) quantization and adaptation (horizontal quantization) for pulse production. The robotic nervous system proposed is composed of multiple combining points[41], i.e. control of h,
- the switching in, via MOS switches, of subsystems for specific pulse processing[43], i.e. adaptation and plasticity based on Turing's concepts of morphogenesis.

Figure 8 illustrates the mathematical and computer networking topological circuit details for the neural type system of a robotic cerebellar cortex with reference to the delay equation (1).

Sensors

Touch information in the human nervous system depends on the number of action potentials transmitted per unit time interval, i.e. the frequency of action potentials (not their size) and the number of neurons activated. This fact implies the theoretical connection between the quantization theory and the sensor circuitry. The cerebral cortex software model shown in Figure 6 will enable conscious awareness of temperature changes in these robotic finger sensors as in the human conscious awareness, enabling a robotic voluntary response. Also, stretch sensors (strain transducers) can be used to initiate action potentials in the nervous system. Highly sensitive pressure sensors[12,37-39] and high resolution, high accuracy, low power, miniaturized direct angle to digital code converters are proposed for investigation and implementation within this robotic system. Hybridization of the hand sensing system will be a first step to miniaturization of the sensing and sensor–nervous system interface device. The proposed robotic system will include interfacing the robot's nervous system with two types of sensors:

- *touch sensors,*
- angular and translatory position sensors.

In the early phases of development, relatively low spatial resolution sensors will be used to evaluate the characteristics and properties required for interfacing the sensors with the neuristors and to evaluate the quality of information transmission. Higher spatial resolution sensors will then be developed and incorporated in experimental systems.

ROBOTIC COMPONENT NETWORKING SIMULATION PARAMETERS

Returning to the evaluation of the cost function, the technical aspects of robotization[52] developed here are simulated, requiring consideration of the following parameters to determine the system capability and thus enabling elimination of dangerous tasks in hostile environments, productivity, human personnel reductions, computer networks connected by gateways to mechanical vision and sensing functions. The constraint of the quantization theory determination of the number of action potentials per neural type circuit, also determines the number of parallel position level neural circuits for each sensing path. Therefore, the software and hardware work load is specified here by the number of action potentials (computation of alternate path signal possibilities) for the following components:

- SN = number of sensory neuron circuits,
- NM = number of motor neuron circuits,
- IN = number of interneuron circuits,
- CAC = number of cerebral cortex software circuits,
- CEC = number of cerebellar cortex software circuits,
- VC = number of visual cortex software circuits,
- V = number of visual (retinal) devices,
- S = number of hand and finger sensor devices,
- I_{V-VC} = number of interface circuits — retinal to visual cortex,
- I_{CNS-S} = number of interface circuits — nervous system to hand and finger sensors.

Using these parameters, the return from robotization for a specific capability can be approximated, but not precisely evaluated, far into the future.

ACKNOWLEDGEMENTS

The authors would like to thank Dr C C Li and Dr Z Meiksin for their suggestions for the interconnection of the robotic circuit, visual and sensory system hardware to the robotic central nervous system.

REFERENCES

1 **Albus, J S** *Brains, Behaviour and Robotics,* McGraw Hill (1982)

2 **Ajmera, R C, Kohli, C K and Newcomb, R W** 'Retinal-Type Neuristor Sections' *Proceedings of Southeastcon* (1980) pp 267–268

3 **Balci, O and Sargent, R G** 'A Methodology for Cost-Risk Analysis in the Statistical Validation of Simulation Models' *Communications of the ACM* Vol 24, No 11 (April 1981)

4 **Behuniak, J A** 'Economic Analysis of Robot Applications' *MS79–777*, pp 1–7

5 **Bialas, W F** 'A Bound for the *Error of* the Normal Approximation for the Distribution *of* the Sample Quantile' *Master's* Thesis (June 1974)

6 **Bialas, W F and Weiss, L** 'Bounds for the Error in an Approximation to the Distribution of Continuous Random Vectors with Bounded Supports' *Communications In Statistics* Vol 10 No 1 (1981) pp 67–76

7 **Bowdon, E K and Barr, W J** 'Cost Effective Priority Assignment in Network Computers' *Proceeding ,Of Fall Joint Computer Conference* (1972) pp 775–763

8 **Calo, S and Schwartz, S** 'Bounds and Bounding Functions for a Stationary GI/G/1 Queue' *Proceedings of 13th Annual Allerton Conference on Circuit and System Theory* (October 1975)

9 **Cattermole, K W** 'Graph Theory and the Telecommunications Network' *The Institute of Mathematics and Its Applications* (May 1975)

10 **Cattermole, K W** *Principles of pulse code modulation* Iliffe, London (1970)

11 **Ciborra, C and Romano, P** 'Economic Evaluation of Industrial Robots, A Proposal' *Proceedings Of 8th International Symposium On Industrial Robots* (1978)

12 **Del Vecchio, R M and Meiksin, Z H** 'The Effect of Substrate Radiation Damage on the Stability of Discontinuous Films' *Thin Solid Films* Vol 61 (1979) pp 59–64

13 **Dimopoulos, N and Newcomb, R W** 'Modelling Networks of Morshita Neurons With Application to the Cerebellum' *Proceedings of International Conference on Cybernetics and Society* (October 8–10, 1979)

14 **Dimopoulos, N and Newcomb, R W** 'Stability Properties of a Class of Large Scale Neural Networks' *Proceedings of IEEE International Symposium on Circuits and Systems* (April 28–30, 1980) pp 528–530

15 **Dolezal, J** 'Hierarchical Solution Concept for Decision Problems with Several Objectives' *Problems of Control and Information Theory* Vol 9, No 5 (1980) pp 339–345

16 **Eccles, J C** 'The Cerebellum as a Computer: Patterns in Space and Time' *J. Physiol.* (1973) 229 : 1–32

17 **Eccles, J C, Ito and Szentagothai, M J** 'The Cerebellum as a Neuronal Machine' New York, Springer (1967)

18 **Eccles, J C** *The Understanding Of The Brain* McGraw-Hill (1973)

19 **Friesen, W O and Stent, G S** 'Neural Circuits for Generating Rhythm Movements' *Annual Review of Biophysics and Bioengineering* **Mullins, L J (Ed.)**, Vol 7 (1978) pp 37–61

20 **Gersho, A** 'Quantization' *IEEE Communicating Society Magazine* (September 1977) pp 16–29

21 **Gonzalez, M J and Jordan, B W** 'A Framework for the Quantitative Evaluation of Distributed Computer Systems' *IEEE Trans. On Computers* Vol C-29, No 12 (December 1980)

22 **Hillis, W D** 'A High-Resolution Imaging Touch Sensor' *The International Journal of Robotics Research* Vol 1, No 2 (Summer 1982)

23 **Hubel, D H and Wiesel, T N** 'Brain Mechanisms of Vision' *Scientific American* Vol 1, No 3 (September 1979) pp 150–162

24 **Hughes, G F** 'Number of Pattern Classifier Design Samples per Class' *IEEE Transactions on Information Theory* (September 1979) pp 615–618

25 **Hughes, G F** 'On the Mean Accuracy of Statistical Pattern Recognizers' *IEEE Transactions on Information Theory* Vol IT-14, No 1 (January 1968) pp 55–63

26 **Kanal, L and Chandrasekaran, B** 'On Dimensionality and Sample Size in Statistical Pattern Classification' *Proceedings 1968 National Electronics Conference* pp 2–7

27 **Kandel, E R and Schwartz, J H** *Principles of Neural Science* Elsevier, North-Holland (1981)

28 **Keeney, M** 'Concepts of Independence in Multiattribute Utility Theory' pp 62–71

29 **Kleinrock, L** 'Analytic and Simulation Methods in Computer Network Design' *Proceedings of AFIPS 1970 Spring Joint Computer Conference* Vol 36 (1970) pp 569–579

30 **Kleinrock, L** *Queueing Systems Volume 2: Computer Applications* John Wiley Interscience (1976)

31 **Kekre, H B and Saxena, C L** 'Finite Buffer Behaviour with Poisson Arrivals and Random Server Interruptions *IEEE Transactions on Communications* Vol COM-26, No 4 (April 1978)

32 **Klein, C A and Wahawisan, W** 'Use of a Multiprocessor for Control of a Robotic System' *The International Journal of Robotic* Research Vol 1, No 2 (Summer 1982)

33 **Kleinrock, L** *Queueing Systems, Vol 1: Theory; Vol 2: Computer Applications* John Wiley & Sons (1976)

34 **Kohli, C K, Ajmera, R C, Kiruthi, G and Newcomb, R W** 'Hysteretic System for Neural-Type Circuits' *Proceedings of the IEEE* Vol 69, No 2 (February 1981) pp 285–287

35 **King, J L and Schrems, E L** 'Cost-Benefit Analysis in Information Systems Development and Operation' *Computing Surveys* Vol 10, No 1 (March 1978)

36 **Li, C C and Fu, K S** 'Machine-Assisted Pattern Classification in Medicine and Biology' *Annual Review Biophysics and Bioengineering* Vol 9 (1980) pp 393–436

37 **Meiksin, Z H** 'The Validity of Mathematical Models for the Strain Coefficient of Resistance of Thin Films' *Thin Films* Vol 1 (1970) pp 241–244

38 **Meiksin, Z H and Hudzinski, R A** 'A Theoretical Study of the Effect of Elastic Strain on the Electrical Resistance of Thin Metal Films' *J. Appl. Phys.* Vol 38 (1967) pp 4490–4494

39 **Meiksin, Z H, Stolinski, E J, Kuo, H B, Mirchandani, P A and Shah, K J** 'A Study of Stable Thin Film Pressure and Strain Transducer Materials' *Thin Solid Films* Vol 12 (1972) pp 85–88

40 **Newcomb, R W** 'MOS Neuristor Lines' *Constructive Approaches to Mathematical Models* **Coffman and Fix (Eds)**, Academic Press, Inc. (1979) pp 87–111

41 **Newcomb, R W** 'Neural-Type Microsystems-Circuit Status' *Proceedings of IEEE International Symposium on Circuits and Systems* (April 27–29, 1981) pp 97–100

42 **Newcomb, R W** 'Neural-Type Microsystems: Some Circuits and Considerations' *Proceedings of ICCC '80* **Guy Rabbat, N B (Ed.)** (October 1980) pp 1072–1074

43 **Newcomb, R W** 'Chaotic Behaviour and Turing-Smale Systems' NSF Grant ECS 81-05507

44 **Newcomb, R W** 'Semistate Design Theory: Binary and Swept Hysteresis' *Microsystems Laboratory Report* University of Maryland (1981)

45 **Niznik, C A** 'A Dynamic Congestion Table Algorithm for Computer Communication Networks' submitted to *IEEE Transactions on Computers* 2/82

46 **Niznik, C A** 'An Information Theoretic Approximation for Modelling Computer Network Nodel Queueing Delay: A Congestion Measure' *Proceedings of INFO II*, Patras, Greece (July, 1979)

47 **Niznik, C A** 'A Min–Max Algorithm for Computer Network Capacity Assignment' *Proceedings of ICC '80* Presented, Seattle, Washington (June 1980) pp 23.5.1–23.5.5

48 **Niznik, C A** 'A Probabilistic Algorithm for Dendrite Database Retrieval and Analysis' *Fourteenth Hawaii International Conference on System Science Proceedings* Vol 3 (January 1981)

49 **Niznik, C A** 'A Probabilistic Model for Neural Path Delay Prediction' *Proceedings of International Congress on Applied Systems Research and Cybernetics* Acapulco, Mexico (December, 1980)

50 **Niznik, C A** 'A Quantization Approximation For Modelling Computer Network Nodal Queueing Delay' *IEEE Transactions On Computers* (March :1983)

51 **Niznik, C A** 'Cost-Benefit Analysis For Local Integrated Facsimile/Data/Voice Packet Communication Network' *IEEE Transactions On Communication* Vol COM-30, No 1 (January 1982)

52 **Niznik, C A** 'State Of The Art Cost Analysis For Computer Networks' submitted to *IEEE Communication Society Magazine* 9/82

53 **Niznik, C A** 'The Neural Path Probabilistic Delay Model' to appear 6/83 *IEEE Transactions On Systems, Man and Cybernetics* Special Issue on Sensory and Neural Information Processing

54 **Rawson, E G and Metcalfe, R M** 'Fibernet: Multimode Optical Fibers for Local Computer Networks' *IEEE Transactions on Communications* Vol COM-26, No 7 (July, 1973)

55 **Rohrer, H** 'A Supervised Network Of Adaptive Automata For Pattern Recognition' *Gefördert von der Fraunhofer Gesellschaft*, Kontrakt Nr. T/0230/12340/11061, Band 8, Nummer 8, Erlangen (December 1975)

56 **Schwartz, M** *Computer-Communication Network Design and Analysis* Prentice-Hall, Inc., Englewood Cliffs, N.J., USA (1977)

57 **Sharma, B K** 'A Simulation of the Neurophysiological Mechanisms Operating During Mammalian Stepping' PhD Dissertation (under R Newcomb) University of Maryland (March 1973)

58 **Stein, R B, Leung, K V, Mangeron, D and Oguztiörelli, M N** 'Improved Neuronal Models for Studying Neural Networks' *Kybernetik*, 15 (1974) pp 1–9

59 **Stein, R B, Leung, K V, Oguztiörelli, M N and Williams, D W** 'Properties of Small Neural Networks' Springer-Verlag *Kybernetik*, 14 (1974) pp 223–230

60 **Zadeb, N** 'On Building Minimum Cost Communication Networks' *Networks* Vol 3 (1973) pp 315–331

61 **Zeevi, Y Y and Kronauer, R E** 'Signal Processing in Visual Systems and Its Relevance to Pattern Recognition' in *Signal Analysis and Pattern Recognition in Biomedical Engineering* **Inbar, C F (Ed.)** John Wiley & Sons, Inc., New York (1975) pp 261–275

computer communications

Editor Tom Twigg

Subeditor Angela Jamieson

Managing Editor Amanda Harper

vol 6 no 2 april 1983