*INNS World Congress on Neural Networks, 1996, 1305-1309.*
*Lawrence Erlbaum Associates, Inc., Publishers*

# Solving the Transverse Patterning Problem by Learning Context Present: A Special Role for Input Codes.

William B Levy, Xiangbao Wu, Joanna M. Tyrcha
Department of Neurological Surgery
University of Virginia Health Sciences Center
Charlottesville, Virginia 22908 USA
wbl@virginia.edu, xw3f@virginia.edu, joan@sans.kth.se

**Abstract** Rats require a hippocampus to solve the transverse patterning problem, and a simple model of the hippocampus is found to solve the transverse patterning problem. Two procedures are necessary to produce this result. First, a learning paradigm called progressive learning, is required. Progressive learning is also needed by behaving rats and humans for successful performance. Second, a coding of inputs which repeats the different inputs, and thus increases the statistical dependence of the simple coding of this problem, is necessary. It is found that repetitive presentation of the same patterns in a sequence facilitates the formation of local context neuronal firings. We believe such patterns of neuronal firings are critical to the functions of this hippocampal model and hypothesize that they are analogous to place cells found in behaving animals.

An important function of the hippocampus is to learn and help the rest of the brain use context (e.g. Hirsh 1974; Kesner & Hardy 1983). A very simple, biologically motivated model of the hippocampus (Levy 1989; Minai & Levy 1993; Levy 1994) demonstrably encodes and uses context. For example, there is the disambiguation problem (Minai et al. 1994; Levy et al. 1995; Wu et al., in press). The disambiguation problem is a sequence completion problem in which two sequences, with a central and common subsequence, are learned. Because the neuronal codings move in time, the only way to decide between the two possible correct paths for sequence completion is for the network to produce context dependent codes of the shared subsequence. To make a useful code and the correct choice, there must be memory for events earlier in the sequence. The ability of our model to solve this problem is interesting because there are no elements in the network that have a temporal memory extending more than one time step. One time step is not far enough back in the past to solve the disambiguation problem that the network is tested on. That is, the neurons themselves are McCulloch-Pitts neurons with no capacitance, so these neurons forget their current state from time step to time step. The associative modification rule is only minimally time spanning. Thus, we conclude that there must be a special coding that provides the memory needed for past patterns of the test sequence. It is this code for the past that must be the basis for the correct decision when transitioning out of the shared subsequence (see, e.g., Wu & Levy, WCNN96 submitted).

We hypothesize that this special coding is mediated by the existence of cell firing patterns that are, individually, called a local context unit. By looking at the neuronal firing patterns in simple sequence completion problems, we note that neurons go from firing in a somewhat random fashion before learning to a very specific pattern of firing after learning. After learning, such neurons are, individually, able to detect, or recognize, small subsequences within the larger sequence. Moreover, we note that such local context firings are, in some sense, randomly positioned within a sequence. Thus, we hypothesize that it is the interaction of such temporally local patterns of firing that allow the network to solve problems that require context from the past.

## *Configural Learning and the Problem of Transverse Patterning.*

Recently, Alvarado and Rudy (1995) have demonstrated that the hippocampus is necessary for a configural learning problem called transverse patterning. In configural learning, the meaning of an input that is a configuration of multiple stimuli is determined by the configuration itself. That is, whether a particular stimulus implies one response or another depends upon the context supplied by the other stimuli that are simultaneously present. In comparison to the disambiguation problem that uses context based on the past, the configural problem of transverse patterning must use context based on the present.

Consider three atomic stimuli A, B, and C. Then let these stimuli be presented as pairs including (AB), (BC), and (AC). Then reinforce behavior in the following manner: when the pair is (AB), then A is the correct answer; when the pair is (BC), then B is the correct answer; and when the pair is (CA), C is the correct answer. Thus, in this configural learning problem, each individual stimulus is equally rewarded and punished, and the only way to solve such a problem is to consider the stimulus complex. In this sense the transverse patterning problem requires a system that can learn and use the context provided by the configuration of stimuli themselves: meaning comes by virtue of the context that is built from the combination of stimuli.

Because our hippocampal model solves disambiguation problems by learning and using context, we thought it possible that the transverse patterning problem could also be solved by our model of the hippocampus. Moreover, the hippocampal dependency of this task requires that our model solve this problem if the model is to remain a valid hypothesis.

We turned the configural learning problem into a very simple sequence because our hippocampal model is a sequence learning system. The first pattern in the sequence is the configured stimulus such as we have just described above (e.g., BC). The second pattern in the sequence is a randomly selected motor response that represents a response that chooses one of the two atomic stimuli (e.g., response b chooses B), and the third pattern in the sequence would be either the positive or negative reinforcement as appropriate (e.g., reward = +). The system is tested as suggested by the method of goal finding (Levy et al. 1995; Wu & Levy, WCNN96 submission). That is, the desired outcome (reward = +) is turned on along with a test configuration of paired stimuli.

*The Network.*

The hippocampal model is essentially a model of region CA3. The input layer corresponds to a combination of the entorhinal cortex and dentate gyrus. To make the system's operation as transparent as possible, decoding is performed by similarity comparisons rather than a CA1-subiculum-entorhinal decoding system. The CA3 model is a sparsely (10%) interconnected feedback network of 512 neurons where all direct connections are excitatory and the network elements are McCulloch-Pitts neurons. Inhibition is of the divisive form, but the system is not purely competitive because of a slight delay. Synaptic modification is a postsynaptic rule that includes both potentiation and depression aspects (Levy & Steward 1979; Levy 1982). More details about this network can be found in Wu and Levy (WCNN96 submitted), Wu et al. (in press) and Levy & Wu (in press).

**Results.** We found that this model of the hippocampus could not learn the transverse patterning problem when transverse patterning is coded as described above and when each input just activated neurons orthogonal to all other inputs and patterns. However, when we repeated inputs so that instead of giving the input AB, then the response "a", then +, we gave inputs AB, AB, AB, response "a", response "a", response "a", followed by + + +, then the network was able to correctly perform the transverse patterning problem, with one proviso.

A particular result discovered by Alvarado & Rudy (1992) explains why the transverse patterning problem has been found to be extremely difficult, in that results between labs are contradictory on the learnability of this problem. That is, when learning trials using all stimuli pairs are totally intermixed, then even college sophomores, as well as fourth graders, as well as rats, appear largely incapable of discovering the correct solution to the transverse patterning problem. However, when a special learning paradigm called, progressive learning, is used, then humans and rats are able to learn and solve the transverse patterning problem. This is exactly the same observation for our network. Thus, there is something very special about the progressive learning paradigm. The progressive learning paradigm is reminiscent of the interleaved learning discussed by McClelland et al. (1995). In the progressive learning paradigm, first the correct response to AB is learned; then learning trials for BC occur intermixed with further AB trials; finally, the third pair, CA, is added into the mix of learning trials. Thus, the progression is from learning one pair, to learning two pairs, to learning all three pairs. It appears that our model reproduces this requirement for progressive learning as

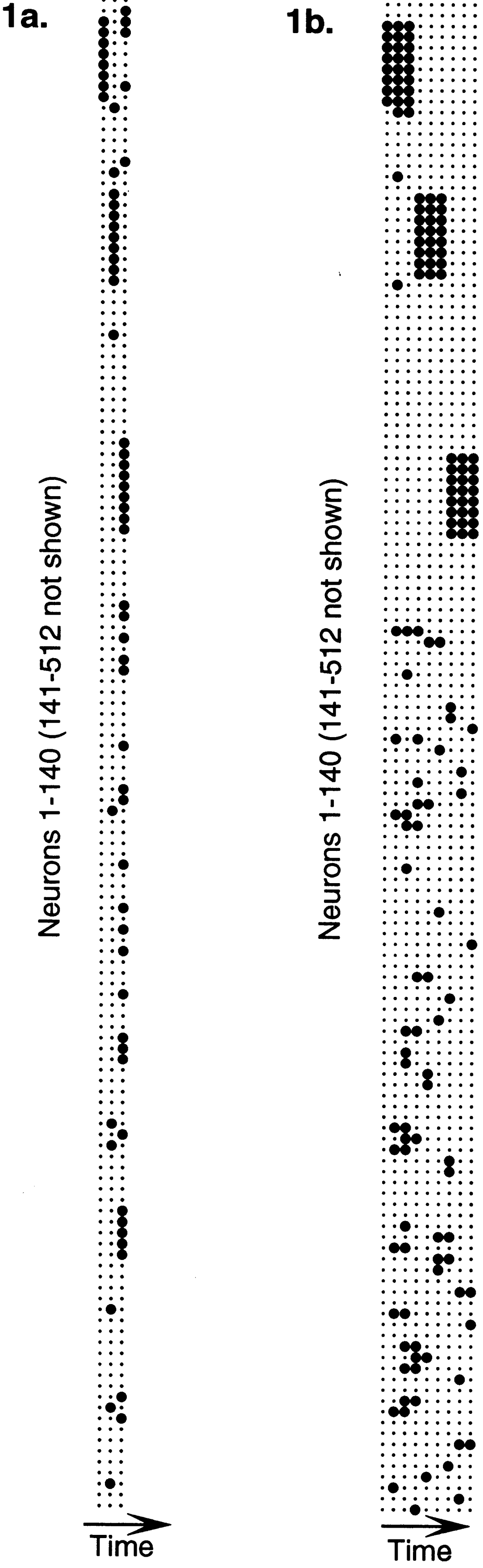

Figure 1. CA3 activities at the end of training for two types of inputs. The simple orthogonal input sequence of 1a does not produce local context neurons while the same input sequence "stuttered", in 1b, produces local context neural firings. The two sequences of neural firing illustrated here are for a sequence that is part of the configural learning problem. Here we illustrate an AB trial (A = neurons 3-6, B = 7-10, the response of choice A is represented by neurons 19-26, and the + reinforcement given for this correct response is represented by externally activating neurons 43-50). All other neuronal firings are driven by recurrent connections. In 1b, the externally driven inputs are repeated three times while in 1a just a single pattern of each is given. As a result, in 1b, some of the recurrently driven neurons fire repetitively and selectively in time. Such repetitive firing can be asynchronous relative to all the externally driven input patterns. Note also that these local context neurons overlap with one another so that they can efficiently pass their information on from one time step to another. Only 140 neurons of the 512 are illustrated due to space limitations. Neuron 1 is at the top of the page, neuron 140 is at the bottom.

opposed to just randomized learning, and it is our opinion that such a paradigm prevents overwriting in such a way that the system can develop what we call local context neurons. We return now to consider the importance of the input code for controlling the development of local context neurons.

### *Local Context Neurons.*

We have previously discussed the formation of local context neurons in our hippocampal model (e.g., Levy & Wu, in press). Presumably, these neurons are an analogy of place cells that have been discovered in hippocampus (O'Keefe & Nadel 1978). Like place cells, local context neurons fire in response to places in a sequence. In fact, the harder examples of sequence prediction (e.g., disambiguation) are successfully resolved by the network by virtue of such neurons, which are essentially selective subsequence recognition devices. That is, a particular neuron will not fire for a long period of time, will fire in response to a particular portion of a sequence and then not fire anymore throughout the sequence.

In the past, we have used inputs in sequences that were not always orthogonal and would often be overlapping, one pattern to the next, as an analogy to the time varying inputs a rat would experience as it moved in a slowly varying path. Occasionally we did throw in an orthogonal pattern followed by another slowly changing sequence of patterns as if the rat had gone through a door or made a turn into an alley, i.e., the world would occasionally change abruptly and then go back to slowly changing. Now, in studying the transverse patterning problem the network sees inputs that are only sequences made up of orthogonal patterns. Apparently, without capacitive elements and with the narrow time span of synaptic associative modification of this study, such orthogonal sequences do not allow the formation of local context neurons. Because the network with such inputs fails in the transverse patterning problem and because we have seen the network fail under similar circumstances in the disambiguation problem, we hypothesize that local context neurons are critical to all the context problems.

Without a slowly shifting input sequence, it appears that the "preprocessing" technique of repeating inputs will produce the necessary firing patterns. Figure 1a shows a portion of a CA3 network responding to a simple orthogonal input after learning. Figure 1b shows the response to the three-fold "stuttered" version of this input. Note the local context cell firing patterns of some neurons not driven by the external inputs in Fig. 1b.

### *Sequence Completion and Local Context Firing with Stuttered Inputs.*

In general we find that orthogonal input sequences do not promote local context firing patterns unless the patterns are repeated. We have systematically investigated this type of preprocessing and quantified the average length of local context neuron firing and the amount of "stuttering" of the input sequence. In fact, there is a tendency for the network to produce local context neuron firing that slightly exceeds the amount of stuttering of the input sequence. We believe it is this situation that accounts for the appropriate performance by the network in the transverse patterning problem.

We studied the effect of repeating inputs directly on simple sequence completions. For example, we compared CA3 codes for the sequences abcd and the sequence aaaabbbbccccdddd. With an activity level of 15%, for instance, such a four-fold stuttering gives an average context neuron firing a time span of between seven and eight. Such stuttering of the input and creation of context neurons is not without its problems. Sometimes stuttering reduces the sequence length memory capacity when we scale count the number of different patterns. For example, at 7.5% activity and a quadrupling of inputs, sequence length capacity goes down by about 25%.

**Discussion.** The technique of preprocessing an input by repetitively presenting it to the network is an example of increasing the statistical dependency, or increasing the redundancy of coding, that leads to improved performance. We have previously observed and discussed (Levy & Adelsberger-Mangan 1995) that — and in contrast to a prevalent theme of neural computing concerning the importance of lowering statistical dependency, a theme which we support in general — there are certain, very clear situations where statistical dependency should be retained or even increased in order to improve a computation made by another network further down the line. Here we have another example where added redundancy helps a neural computation.

**Acknowledgments.** This work was supported by NIH MH48161, MH00622, and EPRI RP8030-08, and Pittsburgh Supercomputing Center Grant #1 P41 RR06009 from the NIH National Center for Research Resources to WBL, and by the Department of Neurosurgery, Dr. John A. Jane, Chairman. The authors also thank Dr. A. Lansner of the SANS Research Group, Department of Numerical Analysis and Computing Science, Royal Institute of Technology, Stockholm, Sweden for his graciousness and generosity in allowing us access to the SANS computing facilities.

**References.**

Alvarado, M.C. & Rudy, J. W. Some properties of configural learning: An investigation of the transverse-patterning problem. J. Exp. Psychol.:Animal Behav. Processes 18, 1992, 145-153.

Alvarado, M. C. & Rudy, J. W. Rats with damage to the hippocampal-formation are impaired on the transverse-patterning problem but not on elemental discriminations. Behav. Neurosci. 109, 1995, 204-211.

Hirsh, R. The hippocampus and contextual retrieval of information from memory. Behav. Biol. 12, 1974, 421-444.

Kesner, R. P. & Hardy, J. D. Long-term memory for contextual attributes: Dissociation of amygdala and hippocampus. Behav. Brain Res. 8, 1983, 139-149.

Levy, W. B Associative encoding at synapses. Proceedings of the Fourth Annual Conference of Cognitive Science Society, 1982, 135-136.

Levy, W. B A computational approach to hippocampal function. In: Computational Models of Learning in Simple Neural Systems. (R. D. Hawkins and G. H. Bower, Eds.), New York: Academic Press, pp. 243-305, 1989.

Levy, W. B Unification of hippocampal function via computational considerations. INNS World Congress on Neural Networks, 1994, IV-661-666.

Levy, W. B & Adelsberger-Mangan, D. M. Is statistical independence a proper goal for neural network preprocessors? INNS World Congress on Neural Networks, 1995, I-527-531.

Levy, W. B & Steward, O. Synapses as associative memory elements in the hippocampal formation. Brain Res. 175, 1979, 233-245.

Levy, W B & Wu, X. B. The relationship of local context codes to sequence length memory capacity. Network, 7, 1996, 371-384.

Levy, W. B, Wu, X. & Baxter R. A. Unification of hippocampal function via computational/encoding considerations. In: Proceedings of the Third Workshop: Neural Networks: from Biology to High Energy Physics. International J. of Neural Sys. Supplement, 1995, 71-80.

McClelland, J. L., McNaughton, B. L. & O'Reilly, R. C. Why there are complementary learning systems in the hippocampus and neocortex: Insights from the successes and failures of connectionist models of learning and memory. Psychol. Rev. 102, 1995, 419-457.

Minai, A. A. and Levy, W. B Sequence learning in a single trial. INNS World Congress on Neural Networks, 1993, II-505-508.

Minai, A. A., Barrows, G. L., and Levy, W. B Disambiguation of pattern sequences with recurrent networks. INNS World Congress on Neural Networks, 1994, IV-176-181.

O'Keefe, J & Nadel, L. The Hippocampus as a Cognitive Map. Oxford: Oxford Univ. Press, 1978.

Wu, X., Baxter, R. A. & Levy, W Context codes and the effect of noisy learning on a simplified hippocampal CA3 model. Biol. Cybern., 74, 1996, 159-165.

Wu, X. & Levy W. B, Goal Finding in a Simple, Biologically Inspired Neural Network. INNS World Congress on Neural Networks, 1996, 1279-1282.