Analysis of Dynamics and Object Recognition Performance in Coupled Map Networks

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Abstract: Coupled logistic map lattices can perform object recognition by mapping class members to a point in a space defined by partition cell occupancies, measured at a readout time t for the entire lattice. Each map (unit) represents average spiking dynamics in mixed excitatory-inhbitory neuronal populations. Non-stationary parameters improve peak recognition rate and recognition time, suggesting one role for interaction of multiple time scales in neural oscillations. A hypothesis that recognition functions by modulating the approach to an invariant measure was rejected by examining the response to noise. Moderate correlation (r=.3) between a configuration entropy measure and recognition rate is found.

Keywords: entropy, nonlinear dynamics, object recognition

This report presents new results in ongoing study of oscillations in coupled map lattices in the recognition of three dimensional objects [1, 2, 3]. Such networks are interpreted as in the tradition of neuronal ensemble models, where each units stands for the collective behavior of a mixed pool of excitatory and inhibitory neurons, and the entire network to a regular spatial ensemble of locally connected column-like units. Previously it was shown that such systems could be trained via a genetic algorithm to map various viewpoints of paperclip objects to approximately the same distribution of at some readout time. Recognition rates of 85% were obtained with complete training on a set of 20 objects using a family of recognizer networks.

Two follow-up studies are presented here. A feature of the network is intrinsic non-stationarity in dynamical parameters uniformly applied to each cell in a nearest neighbor connected lattice. This was motivated by a particular hypothesis on the operational principle, and a possible role of interactions between slow and fast oscillations in biological systems. This conception proved an oversimplification, revealing by examining time series of the network evolution and observing that stationary parameters performed almost as well as non-stationary. Early results indicated that a small advantage in both average and peak recognition rates, as well as the number of iterations (i.e. recognition time) were obtained with non-stationarity. Here, we report on a more extensive series of 50 learning trials with each condition; these basic trends were confirmed.

Comparison of CML network Recognition: Stationary and Two Parameter Epochs

Scenario	Average Rec. rate	Maximum Rec. rate	Average Time (iterations)	Time variance	Learning Trials
Stationary	75.2	82.9	13.4	1.39	50
Two epochs	78.8	87.9	12.7	2.7	51

A second series of computational studies was undertaken based on the resulting large set of network parameters, with a goal of improved understanding of underlying network operating principles. While the network is understood from a computer science standpoint as a generalization of the dynamical recognizer framework [5], a better *physical* understanding might give insight into the variations in performance, and lead to performance improvements within the genetic algorithm learning framework, or suggest more direct adaptive learning methods.

Distance from Noise Response

During recognition, a particular network characterized by a parameter 6-tuple must achieve two goals – to map diverse views of an object to a point in the space whose axes are defined by state space intervals, and to map other objects to different points in space. Differential rates in the approach to equilibrium of the target object and other stimuli might serve the latter. The first set of measurements was formulated to test a hypothesis that networks ability to obtain a unique distribution for a particular object is predicated on an anomalous time course in an approach to statistical equilibrium.

I examined the Euclidean distance between the characteristic distribution for an object, and of the distribution created by the recognizer parameters applied to a noise initial configuration (a 300x300 matrix of states uniformly distributed in range $-1 < s < 1$). This distance was computed and averaged separately for correct and error object presentations in a given learning trial, and the ratio between distances of matching and non-matching trials was evaluated against the error rate. No significant correlations were found ($r < .1$).

Sum of Configuration Entropies

A well known measure of dynamical systems is the information dimension, closely related to Shannon entropy and the capacity dimension of a dynamical system [4]. Normally, this measure is defined for infinite times, and practically measured over a long integration window for a one dimensional system. Given the transient nature of the processing in the present system, a different but related measure is required.

The measure employed here is the sum of the Shannon information for each configuration (lattice state at iteration i, computed over partition cells in the usual manner for information dimension: H_s, the Shannon entropy of the current signature (occupancy distribution at the readout time of a recognizer) with k bins is

$$H_s = \sum_{i=1}^{k} S_i \log_2 S_i \qquad (1)$$

and the measure I designate as sum of configuration entropies is

$$H_c = \sum_{i=1}^{t} H_s \qquad (2)$$

where t is the total number of iterates, in this case over two parameter epochs.

It is conjectured that the reason for the slight performance edge of the two epoch dynamics is attributable to a higher entropy obtainable by increasing the reachable states, increasing the chance of finding dynamical trajectories leading to the common subspace from different views, and of diverting undesired configurations and partial trajectories (of distractor memories) away from the subspace corresponding to the best match.

In figure 1 below, this measure is plotted against recognition rate for a set of 16 two epoch trials, exhibiting a low-moderate positive correlation (r=0.28); individual data points are shown along with a least squares linear fit. In figure 2, the ratio of this measure for correct identification trials to error trials is plotted. In this case, the correlation is negative, again with a low-moderate correlation (r=0.33). This inverted relationship - with matching views having slightly lower entropy than error views - suggests that one error mechanism occurs when misidentified views spread out in state space during recognition dynamics; successful recognition enhanced by limited entropy for distractor objects. It is plausible to test whether this proposition holds in biological subsystems involved in coding object representations.

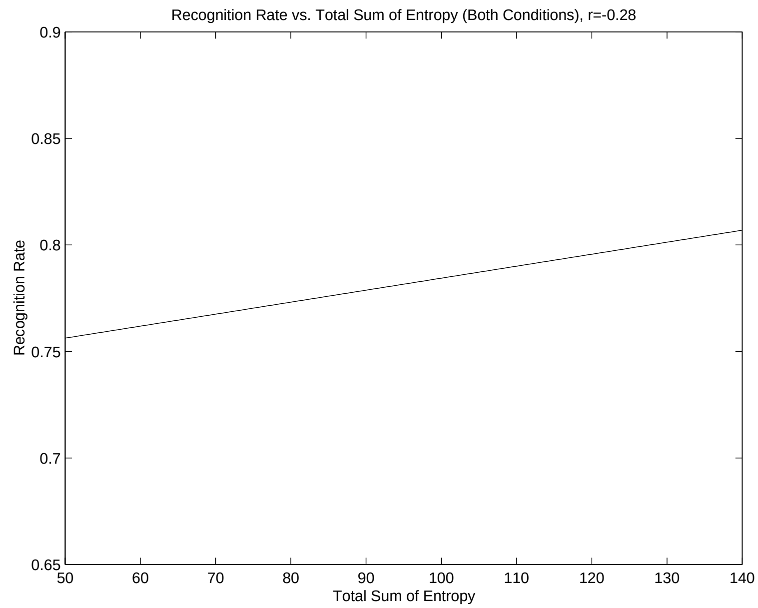

Fig 1: Total sum of point wise entropy over all iterations vs. recognition rate for 16 trials of the CML recognition system applied to 20 paperclip objects.

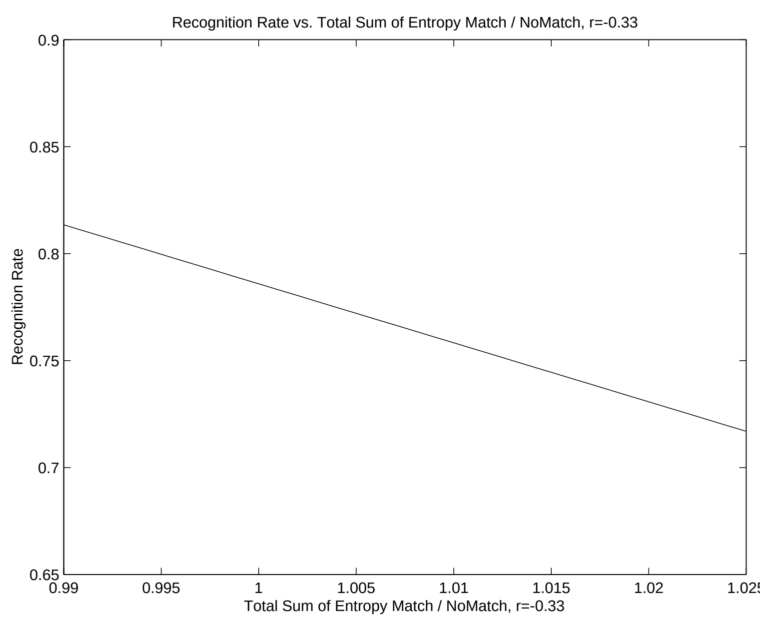

Fig 2: Ratio of Match to Non-matching sum of point wise entropy over all iterations vs. recognition rate for 16 trials of the CML recognition system applied to 20 paperclip objects.

Conclusions

After examining the recognition dynamics, the nature of the processing seems best conceived of as a parallel, distributed stochastic switching network in the state space of the recurrent spatio-temporal dynamics. The evidence of the point wise entropy measures in particular (figures 1 and 2) suggests that specific pathways through slightly lower entropy configurations are visited in successful matches, while the overall high point wise entropy is correlated with higher performance.

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