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Synchronization opponent systems: attractor basin transient statistics as a population code for object representation

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Abstract

A network of recurrent logistic units with local, orientation-sensitive coupling is used to study the transformation of spatial forms in a computational framework called synchronization opponent cooperative action networks. Evolutionary search finds dynamics for which curves, rank-ordered by a generating parameter, are transformed to produce a similarity space with dimensions defined by partitions of the phase space. The network also recognizes objects by normalizing several views of 3-D objects to a characteristic distribution. A spatio-temporal population code where both active and quiet units convey information is proposed, with the phase space interpreted as ensemble average frequency of coupled populations. © 2001 Published by Elsevier Science B.V.

Keywords: Synchronization; Binding; Coupled map lattice; Similarity space; Intra-temporal cortex

1. Introduction

The nature of shape representation and fundamental principles of neural coding beyond early visual cortex remains controversial. Recent work in psychophysics [22] suggests that view-based representations with interpolation are used in human vision, in contrast to object-centered, view invariant representations. Related to any theory of representation is the neural code supporting it. Models of coding and computation at the level of objects and feature integration historically fall into two basic categories: *local coding* and *population-level coding*, with *sparse population-level coding* taking an intermediate position between these extremes. Evidence for population level coding is

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1 accumulating [10], even in primary visual cortex where local coding has been the
2 working hypothesis for many years [14]. I propose a form of population coding over
3 a network of oscillating groups, exploiting regular alternation between epochs of
4 loosely coupled chaotic dynamics and more strongly coupled chaotic dynamics across
5 a regularly connected, orientation-sensitive array of recurrent units. These alternating
6 dynamical stages are designated synchronization opponent cooperative action
7 (SOCA) network. Attractor *convergence time distributions* from local pattern config-
8 urations leading to *partial synchronization* have been found to support population
9 coding of a metric representation space for parametric forms, and to support recogni-
10 tion of objects rotated in depth [6]. In this paper, the emphasis will be on formulating
11 a neural code with such dynamics, rather than on details of learning or performance of
12 the network. A brief discussion of the network and competing accounts of object
13 recognition is included, with some proposed experiments to falsify or confirm the
14 theory.

15 The relevant population dynamics which carry the code (and must be observed for
16 at least a brief window) are aperiodic oscillation patterns over the entire network,
17 rather than individual units or small groups used in sparse coding. In this sense, the
18 dynamics is similar to the proposed encoding of olfactory memories by Freeman and
19 colleagues [9]. The model proposed here differs in that *particular temporal intervals of*
20 *increased synchronization* in an ongoing switching between opposing dynamical ep-
21 ochs, rather than chaotic attractors, is the carrier of information. The epochs of
22 desynchronization and synchronization with particular parameters are designated in
23 this network as *attractor frames*. To form a representation space, the oscillation
24 patterns converge to a characteristic instantaneous distribution over the population
25 during the synchronization interval. The distribution is uniquely determined for
26 a particular category (family of shapes) by a learning procedure. The present model
27 hypothesizes that *feature integration* or *binding* occurs for objects by complex, spatio-
28 temporal interactions in ensemble frequencies of locally connected non-linear oscil-
29 lators, as a strongly synchronized initial stimulus spreads over a limited region from
30 contours extracted in early visual areas. Thus two roles are established for increased
31 synchrony. Early visual areas must present briefly synchronized edge extractions to
32 higher levels; these form representation spaces based on local image statistics of the
33 contours. The higher level areas exhibit transient periods of synchronization as both
34 signatures of this computation and as the carrier in a population code. Jaeger [12] has
35 also recently advocated that such epochs of phase space contraction in non-stationary
36 systems be considered as symbols or representational elements, in contrast to chaotic
37 attractors in stationary systems.

39 2. Simulation methods and results

40 To explore the possibilities of computation and representation of similarity spaces,
41 two families of experiments were performed with highly schematized networks. The
42 first set sought to discover whether the SOCA network could discover parameters for
43 which the resulting distributions formed a metric representation of parametric curves.
44
45

1 Such curves were chosen so that similarity can be unambiguously defined, in contrast
2 to the general space of all possible input configurations. A second set demonstrated
3 that the stimulus invariance problem could be solved for 3-D objects by finding
4 parameters for which the final distribution is roughly equivalent for the same object
5 seen from different viewpoints.

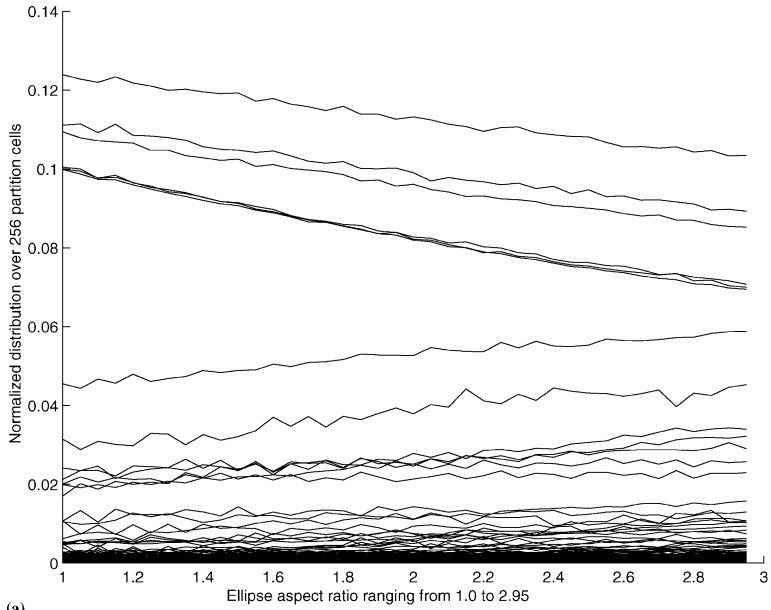
6 In simulations, a network of recurrent logistic units is given several views of
7 a parametric curve as an initial condition (see Appendix A for the network equations).
8 Each view is a binary image; an edge in this image is interpreted biologically as
9 (momentarily) strongly synchronized active units adjacent to background rate units.
10 The distribution of states (interpreted as ensemble average frequency in a local
11 oscillating group) after 6–16 iterations of the network is a vector which acts as a point
12 in a representation space, just as output units in radial basis function networks
13 support a representation space [8]. Euclidean distances between these vectors are
14 used as a similarity metric between the forms. Evolutionary search finds network
15 parameters which produce a near-linear correspondence between the state distribu-
16 tions and the parameter-determined similarity of the form provided as initial condi-
17 tion to the model. Parameters are time varying; typical solutions reached are a regime
18 of coupled chaos followed by stronger coupling, with the second stage resulting in
19 contraction of the phase space (sharpening the distribution).

20 Typically 2–6 distribution components with more than 4% of the units are present,
21 with the remaining states (ensemble frequencies) occupied at low levels and evolving
22 irregularly with respect to the parametric form changes. In the object recognition task,
23 explicit limits on synchronization (a maximum of 15% of the population in any one
24 partition cell) during learning proved effective in solving the problem. The resulting
25 broad distribution suggests that studies which fail to find synchronization in infero-
26 temporal (IT) cortex with a limited sample of neurons do not rule out this coding
27 strategy [23].

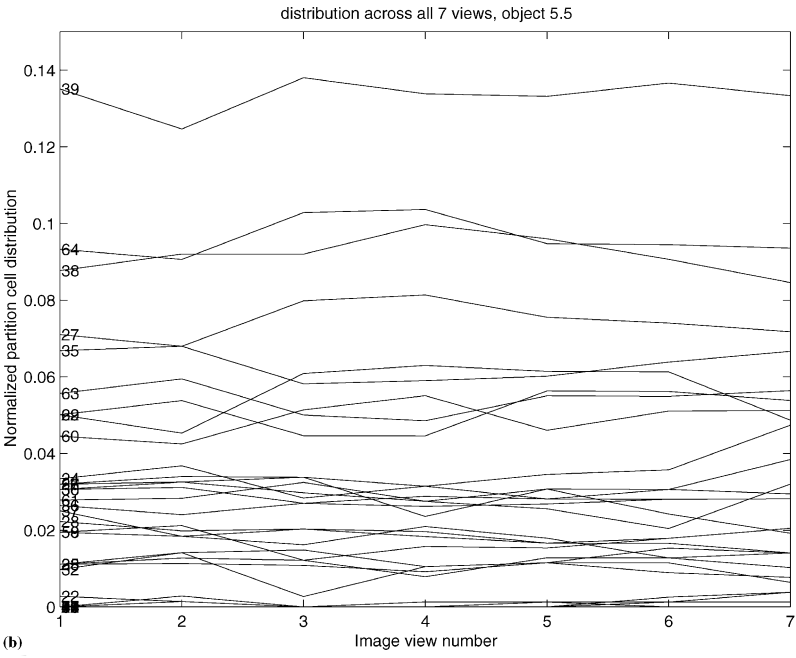
28 It should be stressed that synchronization as discussed here (and elsewhere in the
29 emerging literature on chaotic synchronization) refers to synchronization of many
30 units through coupling. This is in contrast to typical usage in neuron spike studies,
31 where synchronization refers to in-phase oscillations or firing. The first sense con-
32 sidered here is general enough to cover both cases. If the state variable is interpreted as
33 spike train phase offsets, relative to a stimulus locked reference, the resulting states are
34 readily interpreted as phase synchrony. Such interpretation would require a different
35 micro-circuit justification of the use of coupled chaotic ensembles, since existing work
36 referenced here uses state variables of spike rates or pulse density (Fig. 1).

37 The mapping of forms to overall network state distributions can also normalize
38 views to the same distribution and interpolate between training views, as can feed-
39 forward radial basis function (RBF) ensemble networks proposed for view interpola-
40 tion [8]. Initial results on a recognition task are comparable to reported implementa-
41 tions of RBF models (both better than 80%) when similar numbers of views are used.
42 In contrast to RBF and recent feature histogram models [17], here it is assumed that
43 spatio-temporal patterns in networks of spike time sensitive units are the key compu-
44 tation and coding mechanism. In RBF models, broad tuning allows the summed,
45 weighted output of multiple units with different center peaks and widths to interpolate

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(a)



(b)

1 views for a given family of objects. The present network similarly exploits the statistics
 2 of pattern dependent attractor convergence times in units with identical parameters
 3 and coupling strengths for a given category. As the initial binary distribution evolves
 4 due to orientation-sensitive diffusive connections, diverse pathways through attractor
 5 basins allow the network to interpolate a wide range of shape transformations after
 6 finding a good fitness in the network parameter space. As in the RBF network, each
 7 family of shapes requires a unique classifier. One notable difference in these models
 8 concerns the observed variability of reaction times for different objects [16].
 9 Feed-forward models provide no direct explanation for such variability; the
 10 SOCA model produces classifiers with a wide range of iteration times (Appendix A).
 11 This is suggestive, but a more biologically realistic dynamics for comparing
 12 the incoming dynamical states with a stored representation is needed before claiming
 13 that the SOCA network provides a convincing explanation for variable reaction
 14 times.

17 3. Discussion

19 Reviewing lesion studies indicates that certainly infero-temporal cortex [19] and
 20 possibly ventral medial frontal cortex [2] are key sites in object recognition. The
 21 majority of recent experimental investigations and models assume a local rate code
 22 [15,3,21]. The theory here is partially motivated by neuron recording data showing
 23 the spiking response of IT cortex cells to be complex, time varying signals over an
 24 active background [20], and to observations of multiple-cell recordings in primary
 25 visual cortex and demonstrating systematic fluctuations in correlation over time [1].
 26 Both of these groups argue for the significance of temporal patterns in spike trains, in
 27 contrast to classical local or feature detector coding, where frequency is maximized for
 28 an optimal stimulus.

29 The ultimate *memory* code supporting the perceptual dynamics rests on micro-
 30 circuit parameters, such as excitatory–inhibitory ratios in local populations and
 31 lateral connections corresponding, respectively, to the *bifurcation* and *coupling* dy-
 32 namical parameters in this model of large scale dynamics. Many studies demonstrate
 33 that network or population level oscillatory dynamics of the type exhibited by the
 34 logistic units are possible [5,4]. Note that the term oscillations as used here (and
 35 generally in non-linear dynamics) simply means that a time series evolves non-
 36 monotonically; thus both periodic and chaotic behavior are oscillatory, though

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 40 Fig. 1. (a) Fraction of units in 256 partition cells at sampled after 14 iterations with winning SOCA
 41 parameter set for a family of ellipses as the major to minor axis aspect ratio ranges from 1.0 to 3.0. The set of
 42 points for each view is essentially a histogram turned on its side. The smooth parallel evolution of the lines
 43 indicates the network creates a representation space, with each ellipse represented as a point on a hypercube
 44 whose dimensions correspond to partition cells. (b) Fraction of units in 64 partition cells at sampling time
 45 with parameter set found to perform normalization for seven views of object 5.5 in the Tarr paperclip image
 set. The numbers above each line indicates which partition cell (bin) is drawn. Mean values of each bin
 across all trained views are used for matching in the object recognition task.

1 a chaotic time series might conventionally be regarded as a stochastic signal rather
2 than an oscillation.

3 Single unit or pair-wise unit spike rate measurements are unlikely to directly reveal
4 this code, since they may reflect an ensemble level frequency (pulse density) code only
5 indirectly and statistically.

6 The observed correlation of single neuron firing rates with a particular stimulus is
7 not incompatible with population coding; it may simply indicate that a particular
8 localized region (corresponding to a particular classifier parameter set in the present
9 model) has some columns which are on average excited by a stimulus, while others are
10 inhibited. Gochin et al. [11] found that five stimuli could be inferred from a histogram
11 of excited and inhibited responses of 40–50 cells in monkey IT cortex. These results
12 suggest an ensemble interpretation in terms of histograms of numbers of excited and
13 suppressed units without regard to location. (They use temporal integration, rather
14 than instantaneous statistics as in the present model.) Studies of modulations in
15 correlation and effective connectivity as pioneered by Aertsen et al. [1], if performed
16 in IT cortex along with procedures of Gochin et al., could reveal whether the best
17 histogram predictions are obtained in intervals of increased correlation for many
18 pairs, as the present theory of computation and coding would predict. RBF networks
19 would predict no relationship between the highly correlated epochs and best histo-
20 gram prediction. The issue is confused by doubts over whether sub-regions of IT
21 represent the locus of a feed-forward representation network or an area of comparison
22 of incoming dynamics with memory representation by unknown processes (possibly
23 involving synchronization dynamics). In tasks with a visual memory component (the
24 monkey must release a bar when a match to the target is shown after several
25 distractors), it has been shown that neuronal responses are *decreased* substantially
26 from their optimal stimulus when a stimulus matching the target is shown [18].
27

29 4. Conclusion

31 The correlation or *dynamical cell assembly* hypothesis proposed by Fuji and
32 colleagues [10] attempts to reconcile and extend a variety of theoretical and experi-
33 mental data related to oscillations, temporal modulations of individual units, and
34 multi-channel unit correlations. Their proposed population code is at the level of
35 dynamic states rather than a population of broadly tuned detectors. The SOCA model
36 suggests a different interpretation for such oscillations and their role; it uses dynamics
37 alternating between loosely coupled (desynchronizing) chaotic *attractor frames* and
38 a second *opponent* stage or frame which partially synchronizes transient trajectories.
39 During the synchronization frame, the spike frequency distribution sharpens, exhibi-
40 ting peaks with time as more units approach the characteristic distribution of units
41 operating in that attractor frame with random initial conditions. Surprisingly, this
42 distribution can be approached in only a few iterations for fully chaotic systems [7]
43 from an ensemble of random initial conditions. The random initial condition must be
44 approximated by the first desynchronization stage. The adaptive search process must
45 therefore find a dynamics which maximizes entropy from all local configurations in

1 the family of initial condition implied by the shape family. The exact dynamics of the
 2 second stage varies from highly coupled fully chaotic local dynamics, to more loosely
 3 coupled networks but with the local bifurcation below the transition to chaos. By
 4 partially synchronizing *transient trajectories*, it is stressed that no attractors are
 5 reached in the processing dynamics, in contrast to attractor recurrent networks. Since
 6 the dynamics are terminated in this highly schematic model, the readout and storage
 7 of states *functions* much like an attractor network. In a biological system operating on
 8 these principles, an ongoing modulation between two such stages would be expected,
 9 with correspondingly more complex modes of readout, long term memory formation,
 10 and use of the encoding in visual search tasks. Exploring such dynamics and formulat-
 11 ing a more biologically plausible learning rule are the next logical steps in this
 12 research program.

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 19 for suggestions.

21 Appendix A. Equations used in the dynamical evolution of patterns

23 The short range coupled logistic map [13] is used here; the actual implementation is
 24 divided into two steps; first a diffusion step is applied

$$27 \quad S_d(x, y) = (1 - c)S_t(x, y) \\ 29 \quad + \frac{c}{4}[S_t(x, y + 1) + S_t(x, y - 1) + S_t(x + 1, y) + S_t(x - 1, y)],$$

31 where S_d is the intermediate diffusion array, t is the current time step, x, y are the
 32 spatial indices of the pixel array S at the center of the diffusion neighborhood, S is the
 33 state variable at each pixel of the array restricted to the range $[-1.0-1.0]$, and c is
 34 the coupling constant restricted to the range $[0.0-1.0]$. The scaling term $1 - c$ is
 35 a squashing function preventing the sum of the surround from exceeding the state
 36 bounds; in micro-circuit parameters it is perhaps interpreted as a gain control limiting
 37 the instantaneous influence of a highly active neighborhood.

The second computational unit applied in each time step is the logistic map

$$39 \quad S_{t+1}(x, y) = 1 - bS_d(x, y)^2,$$

41 where S , t , x , and y are as above and where b is the bifurcation parameter, restricted
 42 to the range $[0.0 < b < 2.0]$. Initial and intermediate states S are restricted to the
 43 range $[-1.0 < S < 1.0]$.

44 Each stage or attractor frame consists of a triple $\{b, c, s\}$, where s is number of
 45 iterations in the stage. Two such frames are applied in turn. During evolutionary

1 search for the parameter sets, the first stage is constrained to 2–6 iterations, the second
 3 constrained to 2–9 stages. The total iterations required to create the representation
 space ranges from 6 to 14 iterations, with a mean of 11.3 on the 39 objects in the
 Tarr paperclip⁺ geon set.

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