Learning Block Memories with Metric Networks

Mario Gonzalez, David Dominguez, and Francisco B. Rodriguez

Abstract—An attractor neural network on the small-world topology is studied. A learning pattern is presented to the network, then a stimulus carrying local information is applied to the neurons and the retrieval of block-like structure is investigated. A synaptic noise decreases the memory capability. The change of stability from local to global attractors is shown to depend on the long-range character of the network connectivity.

Keywords—Hebbian learning, image recognition, small world, spatial information.

I. INTRODUCTION

While it is known that the most efficient arrangement for storage and retrieval of patterns by an attractor neural network as a whole (global information) is the random network[1], connections in real brains do not appear to be fully random. The majority of connections appear to occur between nearby regions, suggesting a small-world topology[2],[3].

In this work a model of sparsely connected Hopfield-type neural networks [4],[5] on the small-world topology of Watts-Strogatz is presented[6],[7]. It is studied in deeper detail the advantages of the small-world network topology going from the one dimensional ring to the random graph[8],[9], with emphasis on networks capable of recovering global information where local stimulus is relevant or only block information is at disposal for the network. This can be successfully applied in pattern recognition, such as image recognition, or any type of pattern carrying local spatial information[10].

The response of a network to a given input stimulus leads to a particular configuration of the neural activity. Local order can emerge if the stimulus has some neighbourhood structure, and the topology of the network favors stronger connectivity with nearest neurons than between neurons in far regions. The block-like attractor is explored to study in which conditions (parameters), its dynamical behaviour favours retrieval of local spatial information.

II. THE MODEL

In order to describe the neural activity the following model is used. A pattern is presented to the network and the neurons \( \sigma_i \) are initialized in one of two states, ±1 (active/inactive). The state of a neuron \( \sigma_i \) is updated in time \( t \) through the following equation:

\[
\sigma_i^t = \text{sign} \left( \sum_i h_i^{t-1} - \theta \right), \quad h_i^t \equiv \sum_j C_{ij} \sigma_j^t
\]  

(1)

where \( h_i \) is the postsynaptic field arriving at neuron \( \sigma_i \). Here the sign function is defined as: \( \text{sign}(z) = 1 \) if \( z \geq 0 \), and \( \text{sign}(z) = -1 \) if \( z < 0 \). \( K_i \) is the number of connections of each neuron and \( W_{ij} \) represents the weights of the synapses between neurons \( i \) and \( j \). The variable \( \theta \) is the firing threshold which is considered to be zero. We use synchronous update and asymmetric weights. The synaptic couplings between neurons \( i, j \) are \( J_{ij} \equiv C_{ij} W_{ij} \), where \( C = \{ C_{ij} \in [0, 1] \} \) is the topology matrix and \( W = \{ W_{ij} \} \) are the learning weights.

The topology matrix splits in local and random links. The local links connect each neuron to its \( K_L \) nearest neighbours, in a closed ring. The random links connect each neuron to \( K_R \) others uniformly distributed along the network. Hence, the network degree is \( K = K_L + K_R \). The network topology is then characterized by two parameters: the connectivity ratio, and the randomness ratio, defined respectively by:

\[
\gamma = K/N, \quad \omega = K_R/K,
\]

(2)

where \( \omega \) plays the role of a rewiring probability in the small-world model[2].

The synaptic weights \( W_{ij} \) are given by

\[
W_{ij} = cW_{ij}^0 + (1 - c)\xi_i \xi_j
\]

(3)

The term \( W_{ij}^0 \) is randomly generated to be either +1 or −1 with equal probability, multiplied by a factor \( c \in (0, 1) \) which is the load rate, which accounts for all the previous synaptic processing, including both short-term and long-term memory of the network. The second term describes the Hebbian learning of a given pattern multiplied by \( 1 - c \). For a given \( c \), there is a competition between the learning pattern \( \xi = \{ \xi_i \} \) and the noise played by the random term. The pattern the network is learning is the picture of Lena in Figure 1 - left.

We use a mesoscopic variable \( m_i^t \) to describe the overlap between the neural activity of block \( b \) of information, and the pattern activity in this same piece of information, at time \( t \). The block – overlap restricted to the block \( b \) is:

\[
m_i^t \equiv \frac{1}{N_b} \sum_{i \in b} \xi_i \sigma_i^t,
\]

(4)

at time step \( t \). We can define averages over blocks as: \( \langle f_i \rangle_b \equiv \frac{1}{b} \sum_{i=1}^b f_i \).

The relevant order parameter are the mean overlap between the neural states and the pattern, \( m_b \), and the blocks-variance \( v_b \), given by (dropping the time index \( t \))

\[
m \equiv \langle m_b \rangle, \quad v \equiv \langle m_b^2 \rangle - \langle m_b \rangle^2.
\]

(5)

Note that \( m \) is the usual global overlap, also written as \( m \equiv \frac{1}{N} \sum_i \xi_i \sigma_i \). The standard deviation, one names block overlap is \( \delta = \sqrt{v} \). If the size of the blocks are taken \( L = 1 \), then
the \( b = N \) blocks, with \( m_1 = \pm 1 \), carry no macroscopic order. On the other hand, if there is only one block \( b = 1 \), then \( v = 0 \). However, if the size is large but \( 1 \ll L \ll N \), the blocks carry local information. We also define \( m \) as the similarity between the learned and recovered pattern, and \( \delta \) as their local similarity.

### III. RESULTS OF SIMULATION

Figure 1 - left shows the original pattern learned by the network which is the picture of Lena Söderberg, a standard test image used in digital image processing. The picture is 256 × 256 pixels, it has been binarized and properly formatted to be either ±1 by pixel. We want to study the stability and the attractor properties of a block state of the network, characterized by a spatial partition of the pattern in a correct zone and an inverted zone. The correct zone has the neuron states identical to the learned pattern, while the inverted zone has the neurons states in opposition to the pattern: each neuron positioned at the same site as the pattern is switched off, i.e. the active neurons become inactive and other way round. It is represented in Figure 1 - center.

This state has vanishing overlap with the original pattern, however one sees that it still carry information about Lena! Most of the work found in the literature about memory networks with metrics \([1],[6],[7],[8]\) are focused only on the global retrieval of a pattern, does not considering the possibility of spatially correlated states. To study the stability of the block states, one should start the network evolution precisely with the block, so that \( m^t=0 = 0 \) but \( \delta^t=0 = 1 \). Then, if the network stays at this block state, or if it goes close to it, it means that there is a block phase which is stable. However, this could be a marginal stability, with a very narrow attractor basin. To check for the size of the attractor basin, one must verify different initial conditions. For instance, the initial configuration considered here in this paper has \( m = 0, \delta = 0.2 \), which is a strongly noisy 2-blocks structure of overlaps, as can be seen in Figure 1 - right.

The network \((N = 65,536, K = 64)\) in average) starts in a noisy 2-blocks Lena, and the neural dynamics leads to a stationary state. Two cases are plotted in the Figure 2: at left, the network has \( \omega = 0.1, c = 0.74 \) at right it is \( \omega = 0.2, c = 0.8 \). One sees that the attractor for a more local topology (small \( \omega \)) and with moderate loading (not so high \( c \) rate) is the block state (Fig.2 - left). For larger number of long-range connections and higher loading, the attractor is the global state (or the negative of it, as in Fig.2 - right). The evolution in time for the network with block attractor is depicted in Figure 3. One sees that the blocks are fulfilled in the first \( t = 10 \) time steps, and it stays forever in the B phase, except for small random fluctuations. The evolution for the network with the global attractor is in Figure 4. One sees that the network quickly evolves into a global phase, with a completion of 93 percent of the learned pattern, \( m \approx 0.93 \), according to the Figure 2 - right.

In Figure 5 a phase diagram describes the regions of block (B), global (G) and stationary (Z) states. One can conclude from this figure that block activity appears for values of \( c \)
less than approximately 0.84, and for \( \omega \) not greater than 0.3. One can observe a phase transition between global and block retrieval.

The equation for the the block-activity is then \( m_l = \langle \text{sign}(\xi h) \rangle_{\Omega} \), where the average in the angular brackets are over the noise \( \Omega \). But from the Equation (6), after averaging over the \( y_i \) one gets

\[
\begin{align*}
m_l &= m + y_i \delta, \\
\delta &= \langle y_i \text{sign}(\xi h) \rangle_{\Omega, \omega},
\end{align*}
\]

The average over \( \Omega \) stands for the noise distribution.

This noise is Gaussian distributed, \( \Omega \equiv N(0, \Delta^2) \). Its variance is given by the sum of random and local terms, \( \Delta^2 = \text{Var}(\Omega) = \omega \Delta^2_l + (1 - \omega) \Delta^2_r \). Neglecting the feedback terms, it is \( \Delta^2 = K \). This approximation is valid in the limit of strongly diluted networks (\( K \ll N \)). However, for local connections, even extreme dilution do not eliminate the feedback, and \( \Delta \) needs more precise calculations, which is outside the scope of the present work.

The continuous transition from the G to the Z phase may be analysed by taking first \( \delta = 0 \) in the Equations (10), which gives \( m = \langle \text{sign}[(1 - c)Km + c\Omega] \rangle \), then expanding around \( m \sim 0 \). It gives the constant line: \( c = [1 + \sqrt{2K}]^{-1} \), which coincides with border G-Z plotted in Figure 5. The transition between B and G phases is not continuous, so no expansion is possible, but the equation: \( \delta = \langle \text{sign}[(1 - c)K(1 - \omega)\delta + \Omega] \rangle \), is similar to the previous equation for \( m \) except that it depends on \( \omega \). The finite solution \( \delta > 0 \) is stable only if \( c = [(1 - \omega) + \sqrt{2K}]^{-1} \), which fits well also with the phase diagram in Figure 5.

\[\text{V. C ONCLUSION}\]

An attractor neural network with a metrical topology, (i.e, a small-world with local and random connections) was studied in this paper. The overlap between a learning pattern and the neuron states is the usual global parameter which measures the network retrieval ability. When the connections are preferentially local, however, there are spatial correlations between neurons which allow for states retrieving blocks of a pattern. It is observed here that these block states are stable, with a large basin of attraction.

Simulations for the dynamics of the global and block overlaps are presented, and a diagram for the transitions between global, block and zero-retrieval phases is built. A theoretical set of macroscopic equations is obtained, and their fixed point solutions agree quite well with the simulation results.

The present proposal of a block-like structure of patterns, can be extrapolated to other types of topology. It could be closely related to biological brain systems, on the one hand, where different sensory blocks of patterns (arising from several cortical structures) may be independently retrieved. On the other hand blocks may represent incomplete pieces of information which can be used to codify images (as shown here) or other kind of signals (voice, fingerprints, genetic code, etc). These are subjects of future research.

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REFERENCES


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