Neural Crystal
A Dynamic Recurrent Network

Frédéric D. Jordan

Commissariat à l'énergie atomique DMA/AIM
Centre de Limeil-Valenton, FRANCE

1. DESCRIPTION

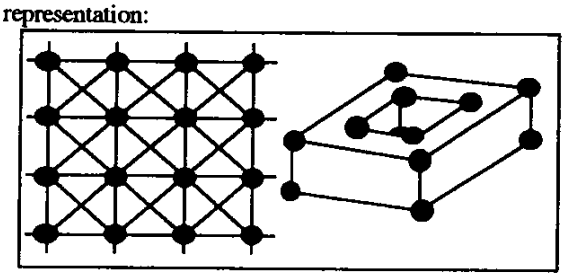
1.1. Introduction

Unlike feedforward MLP, recurrent networks have ability to work with temporal inputs and outputs. So the signal can be input directly to the network without pre-processing like time-windowing and without having direct dependency between signal duration and number of neurons.

Crystal organisation of neurons has already been proposed by a number of neurobiologists [1] [2] but less work has been done to study properties of such ANNs. An important difference with recurrent multilayered networks lies in the 8 isotropic directions of the structure: it has the same topological organisation along 8 directions. The motivation for the architecture described in this paper is then to propose a model which presents the following properties: Hardware feasibility, compact matricial formalism and temporal dynamic. So we present a mathematical formalism and four examples of application in robotic and signal recognition.

1.2. Architecture

Neurons are connected within a d-dimensional cubic structure, so each neuron is connected to its $(3^d - 1)$ neighbours. This connection pattern is repeated for all the neurons to create a d-dimensional hypercube. The number n of neurons on cube side defines a n^d sized network. The side neurons are edge to edge connected so that the structure can be visualised as a d+1 dimensional torus. Following figure shows a 2d, 4x4 sized network and its toroidal representation:



1.3. Transfer Function

Each neuron computes a weighted summation of its inputs, a low frequency filtering and a non-linear activation function (sigmoïd). The neuron has a feed-back with a w_{00} weight. So the Laplace transform of the filter is written as:

$g(p) = \frac{1}{1+\tau p}$ so in closed loop by w_{00} with low signals

$$s(p) = \frac{e(p)/(1-w_{00})}{\left(1 + \tau p/(1-w_{00})\right)}$$

The neurone stability can then be adjusted using w_{00} to obtain a time constant $\tau' = \frac{\tau}{1-w_{00}}$

1.4. Relaxation Equation

The neuron states at time t are represented by the $s_{ij}(t)$ elements of a nxn matrix S(t). Neuron inputs are represented by the $i_{ij}(t)$ elements of a nxn matrix I(t).

Weights are the elements of a nxn matrix which is composed of 3x3 matrices. Each 3x3 matrix W_{ij} represents the weights of input connections to the ij-neuron. In the particular case of a 4x4 2-dimensional network, we get:

$(\text{with } \bar{1} = -1)$

$$W = \begin{pmatrix} W_{00} & W_{01} & W_{02} & W_{03} \\ W_{10} & W_{11} & W_{12} & W_{13} \\ W_{20} & W_{21} & W_{22} & W_{23} \\ W_{30} & W_{31} & W_{32} & W_{33} \end{pmatrix} \text{ with } W_{kl} = \begin{pmatrix} w^{kl}_{\bar{1}\bar{1}} & w^{kl}_{\bar{1}0} & w^{kl}_{\bar{1}1} \\ w^{kl}_{0\bar{1}} & w^{kl}_{00} & w^{kl}_{01} \\ w^{kl}_{1\bar{1}} & w^{kl}_{10} & w^{kl}_{11} \end{pmatrix}$$

$$\text{and } S(t) = \begin{pmatrix} s_{00}(t) & s_{01}(t) & s_{02}(t) & s_{03}(t) \\ s_{10}(t) & s_{11}(t) & s_{12}(t) & s_{13}(t) \\ s_{20}(t) & s_{21}(t) & s_{22}(t) & s_{23}(t) \\ s_{30}(t) & s_{31}(t) & s_{32}(t) & s_{33}(t) \end{pmatrix}$$

With this structure there is no zero element in weight matrices. This compactness property offers a good use of the memory allocated for matrices storage.

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