Advances in Weightless Neural Systems

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Abstract. Random Access Memory (RAM) nodes can play the role of artificial neurons that are addressed by Boolean inputs and produce Boolean outputs. The *weightless* neural network (WNN) approach has an implicit inspiration in the decoding process observed in the dendritic trees of biological neurons. An overview on recent advances in weightless neural systems is presented here. Theoretical aspects, such as the VC dimension of WNNs, architectural extensions, such as the Bleaching mechanism, and novel quantum WNN models, are discussed. A set of recent successful applications and cognitive explorations are also summarized here.

1 From *n*-tuples to artificial consciousness

It has been 55 years since Bledsoe and Browning [20] introduced the *n*-tuple classifier, a binary digital pattern recognition mechanism. The pioneering work of Aleksander on RAM-based artificial neurons [1] carried forward Bledsoe and Browning's work and paved the path of weightless neural networks: from the introduction of WiSARD (Wilkes, Stonham and Aleksander Recognition Device) [2][3], the first artificial neural network machine to be patented and commercially produced, into the 90's, when new probabilistic models and architectures, such as PLNs, GRAMs and GNUs, were introduced and explored [4][5][6][7][8][9]. A natural drift into cognitive and conscious architectures followed, due to the work of Aleksander and colleagues [10][11][12][13][14][15]. A brief but more detailed history of weightless neural systems can be found in [16].

While Braga proposed a geometrical and statistical framework to model the state space of pattern distribution in the *n*-dimensional Boolean space [22], Bradshaw introduced the use of statistical learning theory tools in the analysis of the *n*-tuple classifier and related weightless neural models [23]. Interestingly, Bradshaw found out that the VC dimension of the *n*-tuple classifier suggests much poorer generalization capabilities than found in practice, which also motivated the production of the effective VC dimension for this weightless model [24][25]. The high VC dimension of the *n*-tuple classifier looks underexplored since saturation of RAM nodes contents often happens if a relatively small *n* value is chosen, i.e., when the size of the training set is large enough to allow for writing 1's in most of the RAM nodes positions. The introduction of the *bleaching* mechanism [40][56] was possible via extending RAM nodes from one-bit positions to counters able to register the number of times a particular RAM position was accessed during the training phase. This extension follows early probabilistic weightless models, such as PLNs and GRAMs, where RAM positions can also hold values different from 0's and 1's that are interpreted as firing probabilities. In the next section, bleaching is explained together with how it is related with “mental” images [26][55] produced by the DRASiW model [48][81].

Section 3 summarizes how quantum computing [66] can be regarded as the mathematical quantisation of (classical) Boolean logic computing. Truth values (bits) are regarded as an orthonormal basis (cbits) of a two dimensional complex vector space where an arbitrary vector is called qubits, multiple bits are tensor products of cbits and Boolean operators are realised as unitary matrix. A RAM-based neural network, a universal Boolean realiser, is then trivially quantised into a q-RAM-based neural network [67][68][69]. Section 4 concludes this paper.

2 “Mental” images and Bleaching

DRASiW is an extension to the WiSARD model provided with the ability of producing pattern examples, or prototypes, derived from learned categories [26] [48][81]. RAM-discriminators are modified in what their memory locations may hold and, correspondingly, in their training algorithm. Similarly to PLN nodes, introduced by Aleksander [4], such change allows one to store m-bit words in memory locations, and such can be exploited in the generation of **“mental” images** of learned pattern categories, i.e., to be able to produce prototypes [56].

It is possible that some of the “mental” images produced by DRASiW are contour-saturated images, predominantly composed by dark grey/black pixels. In such a scenario, WiSARD’s discriminators generate ambiguous responses, i.e., draws between true and false winner responses. This is due to the saturation that (i) is quickly reached for a training set with a relevant number of class examples and (ii) occurs in an inverted order of the size of RAM neurons: smaller RAM neurons get saturated (most RAM positions written) sooner as the number of patterns used in the training phase increases.

By taking advantage of DRASiW’s prototype generation capability, one can avoid ambiguous discriminator responses. Consider the introduction of an integer variable threshold b, $b \geq 1$, over all RAM neurons contents at all discriminators. At the start of a pattern test, $b = 1$ and, if one observes a draw between discriminator responses, b is incremented and the discriminators outputs are re-calculated taking into account only RAM neuron contents above b. A straightforward convergence policy, called **bleaching**, is to have b incremented until just one of the discriminators producing a winner response. Notice that this process is directly related to the way pattern examples are produced from “mental” images in the DRASiW internal retina. Furthermore, based on the “mental” image threshold idea to generate a prototype, it was shown in [56] that, by re-evaluating the set of RAM-discriminator responses upon the detection of a draw, higher rates of correct classification could be obtained.

The improvement of WiSARD’s learning mechanism has allowed us to successfully implement new applications of weightless system in those domains that would not have been tackled without the changes introduced [30][32][35][36][37][40] [44].

The most interesting and recent application of the conjunct use of both mental images and bleaching is a WiSARD-based approach for non-rigid deformable object tracking [54]. The proposed approach allows deploying an on–line training on the texture and shape features of the object, to adapt in real–time to changes, and to partially cope with occlusions. In Figure 1 sketches of the WiSARD tracking results are reported.

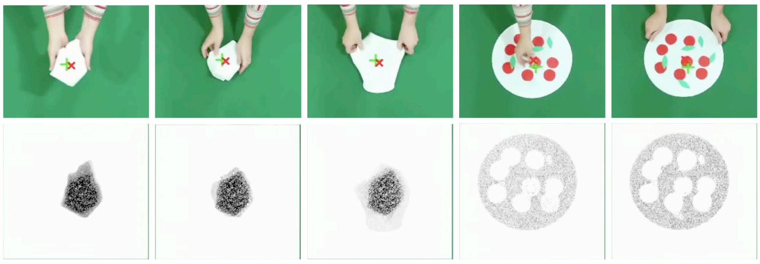

Fig. 1: Tracking and "mental" image adaptation during pizza making process

3 Quantum Weightless Models

The mathematical quantisation of the Boolean logic is an embedding of the classical bits $\mathbf{B} = \{0,1\}$, the field of integers modulus 2, in a convenient Hilbert space. A natural way of doing this is to represent them as an orthonormal basis of a Complex Hilbert space. Linear combinations of the basis span the whole space whose elements, called states, are said to be in superposition. Any basis can be used but in Quantum Computing it is customary to use the canonical one as column vectors: $|0\rangle = [1 \quad 0]^T$ and $|1\rangle = [0 \quad 1]^T$. In this context these basis elements are called the computational-basis states. A general state of the system, a vector $|\varphi\rangle = [\alpha \quad \beta]^T$, can be written as: $|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle$, where α, β are complex numbers, called *probability amplitudes* when constrained by the normalisation condition: $|\alpha|^2 + |\beta|^2 = 1$. This is the model of one *qubit*. Multiple qubits are obtained via tensor products. A common notation for tensor on the basis: $|i\rangle \otimes |j\rangle = |i\rangle|j\rangle = |ij\rangle$, where $i, j \in \{0,1\}$. The values stored in a PLN Node 0, 1 and u are, respectively, represented by the qubits $|0\rangle, |1\rangle$ and $\mathbf{H}|0\rangle$, where $\mathbf{H}$ is the Hadarmard matrix defined as $\mathbf{H}|0\rangle = 1/\sqrt{2}(|0\rangle + |1\rangle)$ and $\mathbf{H}|1\rangle = 1/\sqrt{2}(|0\rangle - |1\rangle)$. The probabilistic output generator of the PLN are represented as measurement of the corresponding qubit. There is an obvious relationship between outputs of a PLN and that of a q-PLN that associates i to $|i\rangle$, where i = 0, 1 and u to $\mathbf{H}|0\rangle$, resulting 0 or 1 with probability ½. The random properties of the PLN are guaranteed to be implemented by measurement of $\mathbf{H}|0\rangle$ from the quantum mechanics principles (see e.g. Section 2.2 and Chapter 8 of [66] for a lengthier discussion). Another useful unitary matrix is the quantum not: $\mathbf{X}|0\rangle = |1\rangle$ and $\mathbf{X}|1\rangle = |0\rangle$. A quantum weightless neural networks is simply [67][68]: $N = \sum_{x \in \mathbf{B}^n} A_x |\alpha_x\rangle\langle x|$ where $\mathbf{B}^n$ can be seen as the set n-bits strings, has a very interesting interpretation which relates it to a a sort of generalised look up table or

RAM memory: the action of N on a basis element $|x\rangle$ returns $A_x|\alpha_x\rangle$ which can be interpreted as the content of the memory location addressed by x (or $|x\rangle$), where A_x is an arbitrary unitary matrix for each x and $|\alpha_x\rangle$ is an m-qubit. In the case of a q-PLN, each A_x is one of the unitary matrices **I**, **X** or **H** and $|\alpha_x\rangle = 0.$ Whilst for the q-MPLN, each A_x is of the form: $A_p|0\rangle = \sqrt{1-p}|0\rangle + \sqrt{p}|1\rangle$ and $A_p|1\rangle = \sqrt{p}|0\rangle - \sqrt{1-p}|1\rangle$ and $|\alpha_x\rangle = 0,$ where p is real number in the interval [0, 1]. This view of WNN is a novelty in [69]. Learning is to change the matrices A_x. This can be achieved by using controlling qubits (selectors). We refer the reader to [77][78][79] for further details on learning. This model is of sufficient generality as of being universal for quantum computation [80] and even more [69].

4 Final remarks

Recent applications based on the WiSARD n-tuple classifier showed competitive and/or matched state-of-art, but with training being performed orders of magnitude faster. Credit analysis [18], data stream clustering [35][36], indoor positioning [37], language POS-tagging [38], target tracking [46][54][64], face recognition [59], and recognition of HIV-1 subtypes [82] are among the problems tackled. Most of these applications made use of the *bleaching* [40][56] and other content write-frequency-based (e.g., [5]) disambiguating mechanisms.

The exploration of "mental images" in the WiSARD model in different problems such as rule extraction and tracking of shape-shifting targets constitute ongoing research work. On the cognitive perspective, where awareness remains as the mainstream interest, one should notice that research would be much harder if it couldn't count with the agility of weightless neural systems. On the other hand, quantum extensions of the Boolean neuron [67][68] are also a natural and promising way to search for a much more powerful [69] neural computational paradigm.

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