The Brain in Silicon: History, and Skepticism

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The first suggestion to design computers borrowing hints from the brain come from Alan Turing [15] who envisioned a machine based on distributed interconnected elements, called *B-type unorganized machine*. It befell even before the first general-purpose electronic computers were up and running, and his report remained unminded for decades. On the contrary, an earlier paper by McCulloch and Pitts [9] suggesting that neurons work akin logical ports, had a tremendous impact on the newborn field of Artificial Intelligence. Leveraging on this concept Marvin M.L. Minsky (1954) designed *Snark*, the first neural computer, assembling 40 "neurons" with tubes, motors, and clutches. It had no influence on the contemporary progress of digital general-purpose computers. Later on, Minsky himself was one of the most authoritative voice in begetting dismissal of artificial neural research as a whole [11]

In the 80's artificial neural networks become a hot field of research, thanks to efficient algorithms [13], and although applications were typically running in software, the interest for building brain-like hardware raised again. The European action ESPRIT om the 90's promoted the development of neural hardware with the research projects ANNIE, PYGMALION, GALATEA and SPRINT, the Japanese made neuromorphic hardware a key component of their 6th generation computing, and in the US funding in the subject was provided by DARPA, ONR and NFS [14]. At mid 90's about twenty neuromorphic hardware were commercialized, from Siemens' SYNAPSE-1, Philips' L-Neuro, to Adaptive Solutions' CNAPS, Intel's ETANN and Hitachi's MY-NEUPOWER [6]. All solutions met a negligible market interest and disappeared shortly.

At the beginning of this century a new wave of efforts towards neuron-like hardware mounted, in part driven by the large worldwide enterprise of brain reverse-engineering, in projects like Blue Brain Project in US and Human Brain Project in Europe. While the dominant approach in these projects has been the emulation of neurons in software, new neural hardware is under development too, thanks to projects like FACETs, Neurogrid, and NeuroDyn [12].

In order to get a grasp of the motivations for such a periodic impulse toward brain in silicon, it is instructive to compare three overviews of neural hardware and forecast for the future, spaced each one a decade apart [1, 4, 5]. It is impressive the similarity that they share, in finding an unsatisfactory current impact of neural hardware but expressing the confidence on the potential, in the long run, of this approach. Heemskerk in 1995 diagnosed the poor spread of neurocomputers because "Neurocomputer building is expensive in terms of development time and resources, and little is known about the real commercial prospects for working implementations [...] Another reason for not actually building neurocomputers might lie in the fact that the number and variety of (novel) neural network paradigms is still increasing rapidly.", yet his prognosis is quite optimistic "If progress advances as rapidly as it has in the past, this implies that neurocomputer performances will increase by about two orders of magnitude [...] This would offer good opportunities". Ten years later Dias et.al confirmed the same scenario of scarce acceptance of neural hardware, and professed a similar optimism: "These might be the reasons for the slow development of the ANN hardware market in the last years, but the authors believe that this situation will change in the near future with the appearance of new hardware solutions". Today Hasler and Marr nurture an even larger enthusiasm: "A primary goal since the early days of neuromorphic hardware research has been to build large-scale systems, although only recently have enough technological breakthroughs been made to allow such visions to be possible."

It is noteworthy the difference between the neurocomputer project and the AI enterprise, which is grounded on the famous *multiple-realizibility* thesis [3]: cognition is characterized as computations independent on their physical implementation. Why, instead, the mechanisms that cause computational power in a biophysical system like the brain would cause in completely different systems efficient computation in executing generic (including non cognitive) algorithms? In the words of Lande [7] "One possible answer [to CPU design problems] is to look into what life has invented along half a billion years of evolution [...] Numerous principles found in the brain can provide inspiration to circuit and system designers". But this argument is flawed on several counts.

First, the mechanisms implemented by biological evolution are carved on the specific constraints of the organic system, thus, it is unlikely that they may be of any use in semiconductor devices. Only the computational level, and possibly the algorithmic level, might be medium-independent, certainly not the implementation level. Let us take for example the radial structure of the cortex, and its plasticity, two important constituents of the highest computational power in the brain. Even in the new era of threedimensional semiconductors, which could accommodate for the density of a nervous system massive connection pool, would not suffice as ground to device the layered structure including the growth of a dendritic tree, which has no foreseeable equivalent in artificial systems. Second, for the adaptation in silicon of the brain circuital mechanism to be ventured, it would first be necessary to know it. After 40 years, the search for the *canonical neural circuit* [2], the core circuitry that explains the computational power of the cortex, is still open, and according to some scholars [8] far from being solved.

We are agnostic concerning the future of neurocomputers, our point is that the justification put forward for its realizibility is scientifically flawed, and it may be the cause of the scarce success met so far.

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