Fabrication and Programming of Large Physically Evolving Networks

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Physically Evolving Networks (PENs) were first proposed by Alan Turing in his 1948 paper "Intelligent Machines" [1]. PENs capture some important features of the information processing of biological neural systems, such as mimicking animal and human error patterns, and implement massively parallel, non-algorithmic processes, where the sequence and concurrency of operations is determined at run time. PEN simulations on conventional digital computers have been successfully used for speech recognition, image analysis, and adaptive control. PEN implementations on computers with von Neumann architecture are slow compared with other algorithms, which are optimized for the sequential processing of explicit instructions. In the following, we discuss hardware implementations of PENs. Would it be possible to fabricate a PEN of the size of a human brain with a billion times more neurons? And if so, how could such a PEN be programmed or trained?

Metal particles in oil are a potential PEN hardware implementation. The metal particles form wires if a voltage is applied and a current starts to flow [2]. Figure 1 shows that these wire networks often form ramified structures like the branches of a tree. Therefore, they are called arbortrons [3].

Arbortrons are not perfect conductors, because there tend to be small gaps between the particles, but if they are used as electrical conductors their conductivity increases [4]. This behavior is similar to the neural plasticity of human neurons introduced by Hebb [5]. Human neurons strengthen and become more conductive if they are used frequently and weaken or decay if they are unused. Unused arbortrons are decaying as well, i.e., their particles separate and drift away.

Unused arbortrons repair only if the applied current exceeds a threshold, because of static friction and gravity. For that reason, they tend to have a high resistance for small current and become good conductors if the current exceeds a threshold. Therefore, arbortrons are nonlinear conductors with a threshold.

Neural plasticity and conductance with thresholds are the key features of PENs. Therefore, arbortrons may be considered hardware implementations of PENs.

Hardware implementations of PENs may have some features which exceed biological neural nets. Human axons and dendrites in the central nervous systems system are about 1 μm thick, whereas nanoparticle arbortrons have a diameter of a few nanometers. Because nanoparticle arbortrons are a factor of 1000 thinner, $1000 \times 1000 \times 1000 = 1$ billion nanoparticle arbortrons occupy the same volume as one human neuron. A PEN hardware implementation of the size of a human head with nanoparticle arbortrons could theoretically have a billion times more neurons than the human brain. The power consumption of such a large PEN is probably less than

DOI 10.1002/cplx.20378
Published online 27 April 2011 in Wiley Online Library (wileyonlinelibrary.com)

FIGURE 1

Steel spheres (diameter 1 mm) in a 1 mm horizontal layer of castor oil agglomerate and form arbortrons under the influence of an electric field. There are two input electrodes (black) and one output electrode (red). The right input electrode is activated. When the particles are close but do not touch, there is arcing between them.

the power consumption of human brain (~20 W), because nanoparticle arbortrons are better conductors than human neurons.

Training a large PEN would be a challenge. It takes about 20 years to train human brains before they become productive. Therefore, one might conclude that it might take 20 billion years to train a large PEN with a billion times more neurons. However, on human neurons pulses travel with a speed of 1 m/s to 100 m/s, whereas electrical pulses travel along arbortrons with at the speed of light (0.3 billion m/s). Because the pulse speed is roughly a factor of a billion larger, it might be possible to train a large PEN within a couple of dozen years.

But how can a large PEN be trained? How could it learn to recognize speech or act like a word processor? Experiments with small arbortron PENs suggest that they form patterns which minimize their resistance, i.e., learn to extract energy from complex environments. For instance, the system depicted in Figure 1 forms wires to the electrodes. If the location of the electrodes is changed then the wires disintegrate and new wires form and connect the electrode at the new location. If an electrode is never charged, no wires connect to it. Recent experiments suggest that arbortron PENs can learn to play simple computer games, such as Tetris.

Initially, the arbortron PEN is random. The current configuration of the game activates the corresponding input electrode. In response to the activated input electrode, the arbortron output electrodes trigger a move in the game. If the move is "incorrect" the input electrode is turned off immediately. If the move is "correct" then the input current continues for a certain period of time, which strengthens the arbortron branch which produced the "correct" move. The extra current can be considered as an energy reward for the arbortron network.

This experiment offers some insights into how a large PEN could be trained by a human or a complex environment: with energy rewards. If the PEN hardware implementation responds "correctly," it is rewarded a small amount of energy. In summary, training a large PEN is not like programming a digital computer, it is more like training a pet: If its behavior matches the expectations it is rewarded with a treat. The treat is energy.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the support for this work by Defense Advanced Research Projects Agency (DARPA) Physical Intelligence subcontract (HRL9060-000706).

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DOI 10.1002/cplx