Is Artificial Neural Network Intelligent?

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Abstract

This article is written for the purpose of breaking the ice in the round table discussion of this conference – The International Conference on Neural Network and Artificial Intelligence. Thus the topic of this article is, "What is intelligence?" when we talk about artificial intelligence in general, and artificial neural network in particular. In the history of the field of artificial intelligence, we have had many arguments claiming that artificial intelligence was not yet intelligent enough, or would not be possible to be intelligent even in the future. We take a brief look at such arguments in the history, and then try a speculation concerning if a machine intelligence is as flexible as human intelligence or not. Two experiments of path-finding with spiking neurons from this point of view are shown following a further consideration on a role of consciousness for a machine to be intelligent.

1 Introduction

> *In the 'Star Trek' prequel, Spock's father tells him, "You will always be a child of two worlds," urging him not to keep such a tight vise on his emotions. And Spandexy Old Spock, known as Spock Prime, tells his younger self: "Put aside logic. Do what feels right." – by Maureen Dowd, from her article in the New York Times on 10th May 2009.*

Once my friend, who worked with a world famous electric company as an engineer, told me, "It's amateurish," when I admired a food in a Chinese restaurant telling him, "It's really wonderful that they cook every time in a slightly different way whenever I order the same one, and every time it's delicious." He told me, "Real professional should cook exactly the same way every time."

McClelland, one of the authors of the seminal book *'Parallel Distributed Processing'* (Rumelhart and McClelland, 1986),[1] who had started the book by asking, *"Why are people smarter than machines?"* asked more than two decades later, *"Is it still true that people are smarter than machines? And if so: Why?"* in his recent paper entitled *'Is a machine realization of truly human-like intelligence achievable?'* (McClelland 2009).

Quite pessimistic. However, as far as its application to industry is concerned, the state of the art of machine intelligence reaches an impressive level nowadays. But what is *human-like intelligence*?

Assume, for example, we are in a foreign country where we are not so conversant in its native language, and assume we ask, "Pardon?" to show we have failed to understand what they were telling us. Then intelligent people might try to change the expression with using easier words so that we understand this time, while others, perhaps not so intelligent, would repeat the same expression, probably a little louder.

Or, what if your canary stops singing? There are legendary three different strategies for this in Japan: (i) *Wait until she sings again*; (ii) *Do something so that she sings again*; and (iii) *Kill her if she doesn't sing any more.* A good suggestion to be intelligent, however, might be *"Be always flexible. Don't stick to one strategy even if you encounter a similar event as you met before."*

The title of this conference includes *"Artificial Intelligence and Neural Network,"* expecting an establishment of artificial intelligence by means of neural

[1] The book introduced the connectionist model of cognition using neural networks. Also known as 'PDP' from its abbreviation.

network. In fact, we have had lots of successful reports proudly declaring like, “We have designed an intelligent machine.” Then question arises. What is intelligence?

Some of what they call an intelligent machine may indeed perform the given task much more efficiently, effectively, or precisely than human. However, we human are not usually very efficient, effective nor precise, but rather spontaneous, flexible, unpredictable, or even erroneous sometime.

What we expect when we address a *human-like intelligence* is, somewhat of a different behavior than the one as we behaved before, not exactly the same one, even when we come across a same situation again.

Assume a neural network that has a fixed configuration of synaptic strengths. It will repeat exactly the same action whenever it comes across the same situation as the one in which the neural network learned the action. However may it be a very sophisticated one, could we call it an intelligent behavior? This is the main topic of this article.

Before we proceed into this topic, let’s take a brief look at what happened in the history of artificial intelligence community.

2 What is intelligence?

> *As when Dreyfus asks "How can a determinate process give rise to experienced indeterminacy?" (Phenomenology) one could equally well ask: "How can small neural activity give rise to experienced largeness or blueness or anger?" and so reject neurology as well as Artificial Intelligence. - from MIT Artificial Intelligence Memo. No. 154. by Seymour Papert.*

Is Artificial Intelligence intelligent?

In fact, the topic is not a new at all. As long ago as the 1960’s, in an early days when the research area of artificial intelligence just started to attract people’s interests, Hubert Dreyfus (1964) posed a harsh criticism in his paper *'Alchemy and Artificial Intelligence.'*

What then was the reaction of artificial intelligence community? Seymore Papert, one of the founders of the field of artificial intelligence, rebuffed Dreyfus’ claim in his article *'The Artificial Intelligence of Hubert L. Dreyfus: A budget of Fallacies.'* (Papert 1968).[2]

Papert started the dispute by writing, *“In December 1965 a paper by Hubert Dreyfus revived the old game of generating curious arguments for and against Artificial Intelligence.”* Papert continued to write his motivation as, *“What does affect me is that so many people praise his papers because they like his conclusions, and show no concern for the quality of his arguments.”*

The other founders of the field of artificial intelligence, such as Herbert Simon and Alan Newell, also strongly rebuffed. McCorduck (2004) described well about this rivalry between the two parties in her book *'Mind as machine: a history of cognitive science.'* Edward Feigenbaum said in the interview by McCorduck, *“What does he offer us? Phenomenology! That ball of fluff. That cotton candy!”* Or others ignored like Marvin Minsky who said, *“They misunderstand, and should be ignored.”* [3] See (Crevier 1993, p. 143).

When Dreyfus expanded *'Alchemy and Artificial Intelligence'* and published as a book titled *'What Computers Can’t Do?'* (Dreyfus 1972), no one from the artificial intelligence community responded any more. Nevertheless, Dreyfus kept his criticism. The 3rd edition of the book was published by changing the title to *'What Computers still Can’t Do: a critique of artificial reason'* (Dreyfus 1992).[4]

McCorduck (2004) quoted Papert as saying (p. 230), *“... all social sciences are, for Dreyfus, as wrong-headed as AI. This is not an attitude widely held in universities.”* And then McCorduck posed a question, *“If Dreyfus is so wrong-headed, why haven’t the artificial intelligence people made more effort to contradict him?”*

Though it would be hard to know what computers can and what computers can’t do, or to judge which side had well predicted the future at that time, Brooks (1991) who was then with Artificial Intelligence Lab at Massachusetts Institute of Technology as Dreyfus did too, wrote, *“Artificial intelligence started as a field whose goal was to replicate*

[2] Also available at http://dspace.mit.edu/bitstream/handle/1721.1/6084/AIM-154.pdf?sequence=2, with a stump 'Draft – Not for distribution.' on it.

[3] Who are they? One is Dreyfus and others seem to be also critiques from philosophy such as Searle whom we will mention later.

[4] Also available at http://www.rand.org/pubs/papers/2006/P3244.pdf.

human level intelligence in a machine. Early hopes diminished as the magnitude and difficulty of that goal was appreciated. ... No one talks about replicating the full gamut of human intelligence any more."

We also have another claim by John Searle (1980) that even if a system passes the Turing test, still the system cannot be described as thinking, by his famous thought-experiment called *'Chinese Room.'* We will skip this philosophical topic since we now are running out of space.

Can computer play chess?

Yet another hot topic in the history of developing artificial intelligence is, chess playing computer.

Again a crappy event of acrimonious slander to Dreyfus by Papert. Dreyfus wrote, *"In fact, in its few recorded games, the Newell, Shaw, Simon program played poor but legal chess, and in its last official bout (October 1960) was beaten in 35 moves by a ten-yea-old novice."* (Dreyfus 1960).[5] Later, without his intention, the expression was appeared in 'The New Yorker' January 11, 1966 edition as an article in 'The Talk of the Town.' It was to cause a sensation as to what's going on in computer world, and the article was concluded with the phrase, *"We don't care what the machine is going to do."* [6]

Then, one day Papert arranged a chess match between Dreyfus and a computer chess program.[7] McCorduck (2004, p. 231) quoted Papert as saying, *"I organized the famous chess match. That was beautiful."* McCorduck (2004) went on to write, *"The results of the game were printed in the bulletin of the Special Interest Group in Artificial Intelligence, the Association for Computing Machinery,*

> *'A ten-year-old can beat the machine' – Dreyfus: But the machine can beat Dreyfus."*

Aside from this tiny event in the history, much more sensational news was, the first real chess match in the history between a human world champion and a computer, which was held in 1996. That is, the then world champion Garry Kasparov vs. IBM's Deep Blue. In a six-game match Deep Blue won one game, tied two and lost three. The next year, Deep Blue defeated Kasparov also in a six-game match. Kasparov had won the 1st game, lost the 2nd, tied 3rd, 4th and 5th, then lost the 6th.

Nowadays, however, everyone knows the Deep Blue did not employ an intuitive skill of a human grandmaster but instead, relied on a brute force to evaluate billions of future positions. Is it intelligent employing a brute computing power to search for all the possibilities to select the optimal one? Most people do not think in that way these days.

Is intelligence for a perfect performance?

Dreyfus (1965) wrote *"... a little intelligence is not intelligence at all but stupidity. Any program that does just one thing well is at best more like an idiot savant than like an intelligent man."*

As already suggested, we object this assertion by Dreyfus, more or less. Brooks (1991) wrote, *"It is clear that their domain of expertise is somewhat more limited, and that their designers were careful to pick a well circumscribed domain in which to work. Likewise it is unfair to claim that an elephant has no intelligence worth studying just because it does not play chess."*

In this article, however, our aim is not *"revealing the secrets of the holy grail of artificial intelligence,"* as Brooks (1990) put it, or we don't expect artificial intelligence to be as efficient or perfect as human, but focus on its flexibility, spontaneity, or unpredictability. Frosini (2009) wrote *"... contradiction can be seen as a virtue rather than as a defect. Furthermore, the constant presence of inconsistencies in our thoughts leads us to the following natural question: is contradiction accidental or is it the necessary companion of intelligence?"*

Is neural network intelligent?

What will be necessary in order for us to be able to expect a different action of the agents every time whenever the agents come across an identical situation? Any neural network with a set of fixed synaptic weight values would never behave in that way. So, why don't we try to make an agent learn during its action? In other words, let's make it by modifying those synaptic weights while the agent acts.

Floreano et al. (2000) reported their interesting experiment in which their mobile robot, who is controlled its movement by a neural network, navigates

[5] Also see the 3rd edition of his book *'What computers still can't do'* (Dreyfus 1992, p. 83).

[6] Nothing to do with the topic of chess, but also a sarcastic description regarding machine translation at that time can be read in this same article. That is, *"Machine translated 'Time flies like an arrow,' in Russian into 'Time flies enjoy eating arrows,' in English," which we doubt if it was a true story.*

[7] Program called MacHack designed by Richard Greenblatt.

properly in the given environment by modifying the synaptic weights of its own neural network during navigation. The modification was based on a set of four Hebbian and Hebbian-like rules with each of the rules being specified by a number of parameters. Each of the connection weights determines which rule with which parameters to modify itself during its navigation. Starting with a random configuration of the weights, a population search eventually converges an optimal configuration. Later, Stanley (2003) united these four rules into one equation with two parameters. Recently, Durr (2008) proposed a more general equation of learning, to which we will go back later a little more in detail.

The experiments above were made using McCulloch & Pitts neurons with a sigmoid function, that is, states of neurons are represented by continuous values.

Later Floreano (2006) performed a similar experiment using spiking neurons. The implementation was somehow cleverly tricky as follows. He exploited a fully connected neurons of spike response model[8] with additional sensory neurons. The network consists of excitatory and inhibitory neurons with outgoing synaptic weight all being either 1 or -1 depending on its pre-synaptic neuron, i.e., excitatory or inhibitory, which is genetically prespecified. Then a genetic algorithm determines just which connections to be pruned. Though it worked amazingly well, it was not an implementation of modifying weight during action.

Now we want to modify weights of spiking neural network during a run. One possible option for that is, as Di Paolo (2002) suggested, an application of above mentioned more general learning rule proposed by Durr (2002) to a spiking neuron network using the equation:

$$\dot{w}_{ij} = \eta_{ij}(A^0_{ij} + A^1_{ij} z_i + A^2_{ij} z_j + A^3_{ij} z_i z_j),$$

where η_{ij} is learning ratio and z_i is firing rate of neuron i. We can search for the optimal parameter set of η, A^0, A^1, A^2, and A^3 for each of the connections by an evolutionary algorithm.

In the next section, we use a neural network with spiking neurons with *spike-timing-dependent-plasticity*, or *STDP* – a counterpart of Hebbian learning for the McCulloch & Pitts neurons.

[8]which is the simplest model of spiking neuron according to Izhikevich (2004).

3 A path-finding problem

Path-finding or path-integration is not a simple toy problem. Since the theoretical suggestion of the role of Hippocampus as a spatial map of a free moving rat (O'Keefe 1976), or empirical discovery of a role of place cell firing for a sensory control (O'Keefe and Conway 1978), lots of meaningful researches to reveal brain mechanisms concerning the function of hippocampus have been made. See (McNaughton et al. 2008) and (Poucet 2004) and references therein.

We consider possibilities of applying two neural network models to a seemingly the simplest problem ever, to see whether the resultant behaviors of the agent are intelligent or not. The problem is the shortest path-finding in a virtual world where we have no obstacles such as wall, corridor, or dangerous river, as Stolle et al. (2002) once made the agents explore in it, for a different purpose though.

Ironically, such an empty environment is not as easy to be explored as imagined. In fact, in many applications of path-finding, obstacles sometimes are not obstacle but implicit guides to the goal.

Anyway, our benchmark is to find a shortest path in the Cartesian coordinate from (0,0) to (m, n) without no obstacle in between. Assuming now a gridworld to make calculation simple, the number of paths with minimum Manhattan distance from (0,0) to (m, n) is

$$\sum_{i=0}^{m+n} {}_mC_i \times {}_nC_{m+n-i}.$$

So, we have a infinitely large number of such routes of the identical minimum Manhattan distance for a large enough m and n. The question could be, "Can the agent be flexible to follow a different shortest path whenever it tries anew?"

Here, for a change, let me try a little different scenario. As it might be easily pointed out that we have only unique shortest path, say, from $(0, 0)$ to $(m, 0)$. And we change the question to, "Nevertheless the agent takes its route spontaneously?" It implies if the agent follows its feeling rather than pursuing the optimal efficiency.

In the following two subsections we speculate two models of spiking neurons which are already published in the literature to solve the other more complicated problem.

3.1 Recurrent neural network with evolved spike timing dependent plasticity

To control a robot, Di Paolo (2002) used a recurrent neural network composed of conductance-based integrate-and-fire model of spiking neurons. See, e.g., (Gerstner et al. 2002). Let's summarize the method. Membrane voltage of each neurons $v(t)$ evolves with time as:

$$\tau_m \dot{v} = V_{rest} - v + g_{ex}(t)(E_{ex} - v) + g_{in}(t)(E_{in} - v),$$

where τ_m is the membrane time constant, V_{rest} is the rest potential, E_{ex} and E_{in} are reversal potentials, and g_{ex} and g_{in} are conductance, with suffix 'ex' and 'in' being meant excitatory and inhibitory, respectively.

When no income spike exists conductance decay exponentially as:

$$\tau_{ex}\dot{g}_{ex} = -g_{ex}; \quad \tau_{in}\dot{g}_{in} = -g_{in}.$$

If a spike arrives to neuron j from an excitatory presynaptic neuron i, then g_{ex} of neuron j is increased by the current value of the synaptic weight $w_{ij}(t)$. That is,

$$g_{ex} = g_{ex} + w_{ij}(t).$$

If the incoming spike is from inhibitory pre-synaptic neuron, then

$$g_{in} = g_{in} + w_{ij}(t).$$

The Poisson spike trains coming from the two sensors are fed into specific two neurons in the recurrent neural network. Florian (2004) who also exploited this model explained the reason as follows.

"Each sensor of activation s drives two input spiking neurons, one being fed with activation s and the other with activation $1-s$. Thus, both the activation of the sensor and its reciprocal was fed to the network, ... The reason of this duplication of the sensory signal in the spiking neural network is twofold. First, this allows the network to be active even in the absence of sensory input. For example, if the agent is in a position where nothing activates its sensors (there is no object in its visual range, no tactile contact etc.), there must be however some activity in the neural network, in order for the effectors to be activated and the agent to orientate to stimuli. Second, this mechanism implies that the total input of the network is approximately constant in time (the number of spikes that are fed to the network by the input)."

Spike timing dependent plasticity

To simply put, spike timing dependent plasticity is an algorithm to potentiate (strengthen) synapses when post-synaptic spike immediately follows presynaptic spike, and to depress (weaken) the synapse if the order of these two spikes is opposite. To be more specific,

$$\Delta w = \begin{cases} A^+ \exp(-\Delta t/\tau^+) & \text{if } \Delta t > 0 \\ -A^- \exp(-\Delta t/\tau^-) & \text{if } \Delta t < 0 \end{cases}$$

where Δt is a time from pre-synaptic firing to postsynaptic firing.

To perform this implicitly, Di Paolo changed synaptic weights by means of two recording function per synapse $P^-(t)$ and $P^+(t)$ following (Song et al. 2000). He clearly describes:

"Every time a spike arrives at the synapse the corresponding $P^+(t)$ is incremented by A^+, and every time the post-synaptic neuron fires the corresponding $P^-(t)$ is decremented by A^-. Otherwise, these functions decay exponentially with time constant τ^- and τ^+ respectively. P^- is used to decrease the synaptic strength every time the pre-synaptic neuron fires: $w_{ij} \to w_{ij} - w_{max}P^-(t)$. Analogously, P^+ is used to decrease the synaptic strength every time the pre-synaptic neuron fires: $w_{ij} \to w_{ij} - w_{max}P^+(t)$."

Then with those four parameters for each of synapses being a chromosome, the optimal values of these parameters from one synapse to the next in the whole network are searched for by a genetic algorithm. Fitness is simply the Euclidean distance between the point the agent reaches after pre-specified time and the point of destination, in our problem in this paper.

3.2 Feedforward neural network with reward-modulated spike timing dependent plasticity

Next of our speculation is following the model by Florian (2005) – a neural network made up of *stochastic leaky-integrate-and-fire neurons*. Membrane potential $v_i(t)$ of neuron i at time t evolves in discrete time δt according to:

$$v_i(t) = v_i(t-\delta t)\exp(-\delta t/\tau_i) + \sum_j w_{ij}(t-\delta t) f_j(t-\delta t),$$

where τ_i is a time constant of neuron i, w_{ij} is synaptic weight value from neuron j to neuron i, and

$f_j(t) = 1$ if neuron j fires at time t otherwise 0.

The neuron i fires stochastically with probability $\delta t/\tau_\sigma \exp(\beta_\sigma(v_i - \theta_i))$ if the value is less than 1, otherwise 1.

If the neuron fires, then the membrane potential is reset to a rest-potential V_{rest}.

We experiment here, among others, with a feed-forward architecture with two sensor neurons, input layer with 4 neurons, hidden layer with 8 neurons, output layer with 2 neurons. All neurons from one layer to the next layer are fully connected. At the beginning of a run, the synaptic weights were initialized with random values from -1 to 1 except for those from the sensor neurons which take a value from 0 to 1 at random.

Since we have no obstacle, the activation of the sensor neurons takes a random value between 0 and 1. The sensor neurons fire Poisson spike trains, proportional to the activation, with a firing rate $r = 200$ Hz. The probability of emitting one spike during δt, is $r\delta t$.

The motor activations $a_i(t)$ $(i = 1, 2)$ of the output neurons evolve according to the following equation with time constant $\tau_e = 2$ sec.

$$a_i(t) = a_i(t - \delta t)\exp(-\delta t/\tau_e) \\ +(1 - \exp(-1/\nu_e\tau_e))f_i(t).$$

The factor of $f_i(t)$ is to normalize the activation to 1 when the neuron fires regularly with frequency ν_e = 25 Hz. One output neuron's activity determines the distance d, the amount the agent moves at time t, and the other output neuron's activity determines the direction θ toward which the agent should move, that is, $\theta = 2\pi a_i(t)$ from the direction of the x-axis. Then agent moves with its increment being $\delta x = d\cos\theta$ and $\delta y = d\sin\theta$. Note that the world is no more discrete grid-world.

Florian's learning formula of the synaptic weight values is a sort of reinforcement learning. See, e.g., (Baxter et al. 1999). Weights are modified as:

$$w_{ij}(t + \delta t) = w_{ij}(t) + \gamma r(t + \delta t)\zeta_{ij}(t),$$

where $r(t)$ is reward at time step t and γ is *discount rate* by which eventual reward is estimated as

$$r(t) + \gamma r(t + \delta t) + \gamma^2 r(t + 2\delta t) + \gamma^3 r(t + 3\delta t) + \cdots.$$

Dynamics of ζ_{ij} is given by:

$$\zeta_{ij}(t) = P^+_{ij}(t)f_i(t) + P^-_{ij}(t)f_j(t),$$

and $P^\pm_{ij}$ are:

$$P^+_{ij}(t) = P^+_{ij}(t - \delta t)\exp(-\delta t/\tau_+) + A_+ f_j(t)$$

$$P^-_{ij}(t) = P^-_{ij}(t - \delta t)\exp(-\delta t/\tau_-) + A_- f_i(t)$$

where $\tau_\pm$ and $A_\pm$ are constant parameters.

In our problem of finding a shortest path, reward $r(t)$ could be an inverse of distance to the goal from the position of agent at time t. The closer to the goal, the larger the reward.

3.3 Simple heuristics

Are we happy with the above two experiments?

We can make an agent explore by a walk with a heuristic with an occasional random derail controlled by a random number. As shown in Figure 1, a walk starting at (0,0) with the goal being $(N, 0)$ might be able to look like a spontaneous path more or less, and we can see a different spontaneity from run to run. Clearly, however, it is not a result of an intelligent action.

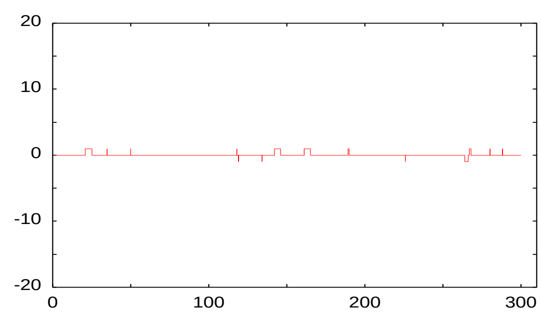

Figure 1: An example of a path starting from (0,0) to the goal (300,0) by a random walk incorporated with a heuristic strategy. Heuristic says, "Go strait to the goal," in this particular case out of the general case of (0,0) to (m,n), but agent is still allowed to derail from time to time by a random number.

This might be an example of *"a very simple algorithm can sometimes obtain the same results as the holistic, intuitive human mind,"* as Papert (1965) put it.

Thus far, *'an always different reaction in a similar situation'* is a necessary condition at the best but not sufficient for the neural network to be intelligent.

4 Consciousness

Science has always tried to eliminate the subjective from its description of the world. But what if subjectivity itself is its subject? – from "A Universe of consciousness: How Matter becomes imagination" – by Gerald M. Edelman and Giulio Tononi.

Now we see that spontaneity, flexibility, or unpredictability are not sufficient to be a human-like intelligence. What we should take into account next is, these properties should be made at least *consciously.*

What is conscious then?

In their paper *'Science of the conscious Mind,'* Ascoli et. al (2008) wrote: *"We need to design mathematically sound metrics reflecting definite aspects and elements of our subjective experiences, and a corresponding system of quantitative measures. Important phenomenological experience may be tied to individuals (consciousness of beauty, responsibility etc.), rather than to concrete objects whose features could be explained by the pattern-recognition properties of neural networks."*

The authors continues: *"The idea of semantic space, defined as the set of all possible meanings that words can express, may be formalized with the notion of cognitive mapping. Cognitive maps index representations by their context, such as spatial location, and are employed by mammals for path-finding and navigation,"* citing (Samsonovich et. al 2005) as an example of such path-finding navigation of rodent using spatial location by hippocampus.

Izhikevich (2006) also defined consciousness as *attention to memory.*

Now we try our navigation problem using memory function in the brain.

4.1 Navigation by hippocampus

Following Muller et al. (1996), we speculate here a navigation using a cognitive map created in a recurrent connections of CA3 pyramidal cells as place cells with functions of long-term potentiation modeled by spiking neurons.

This model is based on the finding by O'Keefe and Dostrovsky (1971) that firings of hippocampal neurons in freely moving rats is location specific, that is, they fire rapidly only when the rat is in a specific location. Hence, such neurons are now called *place cells*, and these neurons are pyramidal cells of the CA3 and CA1 regions of the hippocampus.

Here assumption is, mapping information, or equivalently, distance relation of the points in the environment, is represented as the strength of long-term potentiation modifiable Hebbian synapses. In other words, the mapping information is stored in the strength of the connection, specifically here, in the strengths of CA3 to CA3 synapses of their recurrent connection. So, a short interval between pre- and post-synaptic spikes is expected to cause an increased synaptic strength.

Since each cell is a place cell, any path in the graph corresponds to a path in 2-D space.

Then the question is, "The optimal paths in neural space are optimal too in geometrical 2-D space of surroundings?"

What Muller (1996) proposed is, strength of a synapse is determined according to a decreasing function of the distance between two points the two neuron represent. As such, the longer the distance in 2-D space, the weaker the strength between the corresponding two neurons. That is, synaptic strength should decrease with distance between two points.

Now let me summarize Muller's experiment. First, a recurrent network should be constructed to represent a cognitive map as follows. (i) Create n place cells; (ii) Connect each cell to p other cells such that at least one route exists from any cell to any other cell; (iii) Each cell is randomly assigned a location in 2-D space represented by pixels; (iv) All the synapses are given a strength according to the distance between the corresponding two locations in 2-D space using a decreasing function of distance.

Then a path in the 2-D space is found as follows: (i) Specify the start and goal points in the 2-D space; (ii) Starting at the neuron corresponding to the start point in the 2-D space, select a series of synaptic connections which eventually lead to the neuron corresponding to the goal point in the 2-D space such that the sum of strengths of these synapses is maximized; (iii) Then the route in the recurrent network is translated into a path in the 2-D space by listing the points corresponding to the neurons in the route obtained in the recurrent network.

4.2 Is navigation by hippocampus intelligent?

Back in 1997, in their graduate-level seminar home page at the University of Illinois at Urbana-Champaign,[9] Joe Sullivan exemplified animals' intelligent navigation in their familiar surroundings. Let's name a few: *Merriam's kangaroo rat can learn the distribution of food patches around its nest in three evenings of foraging; Marmoset monkeys reliably relocate food sites and do not revisit a place where food was already eaten on that foraging trip; and Black-capped chickadees hide insects and seeds in numerous, widely spread caches in trees over its home range.*

It might not sound like an intelligent behavior, but as already quoted Brooks (1990), an elephant could be intelligent even if it cannot play chess.

5 Belief, desire and intention

The belief-desire-intention (BDI) model is a well studied computational model to construct multi agent system, originally developed by Bratman (1967). Or we might even add '*emotion*' to the three properties, as Pereira et al. (2005) proposed a model of emotional BDI agents. Though since this topic is beyond the scope of this article and we will not go into further detail, *belief, desire*, and/or *intention* could be other condition for machine intelligence to approach closer to human-like intelligence.

6 Concluding remarks

> *Thus, the only question which can reasonably be discussed at present is not whether robots can fall in love, or whether if they did we would say they were conscious but rather to what extent a digital computer can be programmed to exhibit the sort of simple intelligent behavior." – from "Alchemy and Artificial Intelligence" by Hubert L. Dreyfus.*

A real human-like intelligent behavior of an artificial neural network does not seem to be strongly required in industry world. What about, however, a robot pet? We find lots of commercial-based products of those robot pets these days. For instance, a toy robot dog AIBO produced by SONY.

It splendidly learns the environment of the owner. It acts differently in a different situation according to how it learned these situations. However, it acts exactly in the same way if it comes across the same situation it has already learned. Although AIBO can play a role of a wonderful pet, this *identical-action-in-identical-situation* would lose the owner's interest, sooner or later.

On the other hand, McClelland (2009), as we already cited in the Introduction, concluded his paper by writing, *"It may well be, then, that over the next decade, the butterfly will finally emerge from the chrysalis, and truly parallel computing will take flight."* So let's be optimistic.

Now, to conclude this article, let me propose also a very simple looking but a little more sophisticated benchmark of path-finding problem, as a challenge.

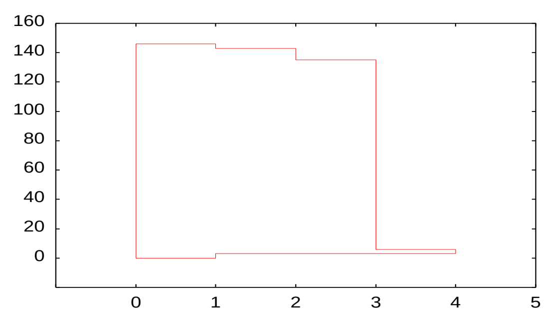

Figure 2: An example of a loop created by an agent who had started at the base located at (0,0) with a limited amount of fuels of 300 units which is supposed to be consumed one unit to move from one grid to the next. This example is not by an intelligent machine technique but a random walk with a heuristic. Can you guess what sort of heuristic is it?

We might call it '*Mars Land-rover Problem.*' The problem is as follows: A robot starts at home at (0,0) with a limited amount of fuels to move the field. The mission is to explore along a maximum loop that never crosses, and should return home before the robot exhausts all the fuels it filled at the start. See Figure 2. Can we design a robot such that it navigates flexibly enough to take a different route from run to run, using a memory which stored during previous runs, with some conscious intention, hopefully with belief and some sort of desire?

[9] The page 'Topics in Neuroethology' is still available at http://nelson.beckman.illinois.edu/courses/neuroethol/models/spatial_learning/spatial_learning.html

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