Psychophysical Tests Reveal that Evolved Artificial Brains Perceive Time like Humans

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Abstract

Computational neuroscience attempts to build models of the brain that break cognition into basic elements. Here we study time perception in artificial brains, evolved over thousands of generations to judge the duration of tones, and compare the evolved brains' behavioral characteristics to human subjects performing the same task. We observe substantial similarities in psychometric properties in human subjects and digital brains with very similar perception artifacts, but also see differences due to different selective pressures during training or evolution. Our findings suggests that digital experimentation using brains evolved within a computer can advance computational cognitive neuroscience by discovering new cognitive mechanisms and heuristics.

The birth of the field of Artificial Intelligence Research is usually traced back to the Dartmouth Conference of 1956 (Moor, 2006), but its roots can be traced further back to the Cybernetics movement initiated by Norbert Wiener 1948, which focused on functional elements of intelligence (such as time-series prediction and filtering). The cornerstone of AI is perhaps the realization that logical calculus can be implemented using neuron-like computational elements, due to McCullough and Pitts (1943). Modern computational neuroscience continues to focus on how neurons contribute to higher functions, but these efforts fail to address how groups of neurons contribute to task-solving as a whole (Kriegeskorte and Douglas, 2018). In order to achieve such insights, it is necessary to instantiate artificial brains within agents that actively solve a cognitive task.

Here we study one such example: using Darwinian evolution to create brains that can perform a standard psychophysical task: to judge the duration of an oddball tone within the context of a background of periodic tones. This so-called "oddball paradigm" (see Fig. 1) is a staple of cognitive psychology, and is used to assess how we perceive time (Matthews and Meck, 2016). For this experiment, subjects are asked to listen to a periodic sequence of tones within which an oddball (identified by an elevated pitch) is embedded. The subject must determine whether the (variable) oddball tone is *shorter or longer* than the fixed-duration standard, by pressing one of two levers.

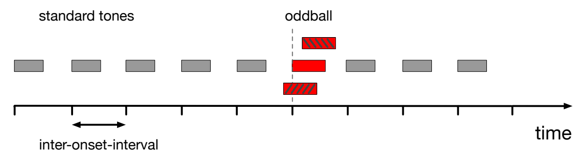

Figure 1: Oddball paradigm experiment. Standard tomes are in grey while the embedded oddball tone is in red. Both length and onset of the oddball are variable. The time between onsets of the standard tone is the "inter-onset-interval" (IOI).

In one particular version of this experiment, investigators sought to test theories of attentional entrainment (how a rhythmic series of tones might modulate our attention to the beginning or end of the tone) by modifying the onset of the oddball tone with respect to the rhythm, but without informing the subject about this manipulation (McAuley and Fromboluti, 2014). They found that when the oddball tone was delayed, subjects misjudged the tone to be longer than it was, as measured by the "Duration Distortion Factor" (DDF) (see Fig. 4b). In turn, when the oddball tone occurred earlier than expected, it was judged to be shorter than it actually was. We set out to repeat this experiment by evolving Markov Brains (Hintze et al., 2017) to perform this task. Markov Brains are a type of artificial neural network in which neurons are binary variables (firing or quiescent), and connected to other such neurons via binary logic (either deterministic or probabilistic). In this respect, Markov Brains are much more similar to the original construction of McCullough and Pitts 1943 than to the standard ANNs used today. In this approach to brain design, the connectivity between neurons and the type of logic that connects them is determined by a genome that evolves. As a consequence, the resulting networks are sparse and have no discernible structure (except for an input layer and an output layer).

For these experiments (Tehrani-Saleh et al., 2020) we are able to vary tone length and IOI to a much larger extent compared with human subjects. Using a unit tone length corresponding to 50msec per unit, we evolved Markov Brains with IOIs ranging from 10 to 25 (with a standard tone length about half the IOI) and all possible tone lengths in between the IOI for the oddball. After 2,000 generations of evolution

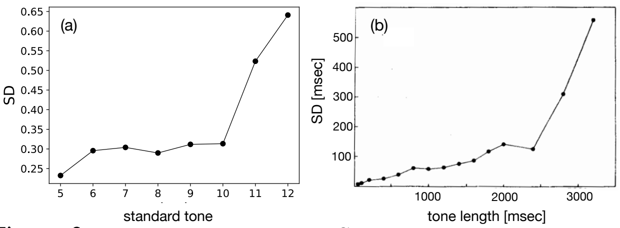

Figure 2: (a) Standard deviation SD of the psychometric density function vs. standard tone duration, for tones between 5 and 12 (from (Tehrani-Saleh et al., 2020)). (b) Standard deviation of the psychometric density function vs. standard tone duration for human subject T.W. in (Getty, 1975).

(in 50 replicates) all evolved brains are able to judge on-time oddballs (for all IOIs) with high accuracy.

We first tested whether our evolved brains conform to standard psychometric laws (Macmillan and Creelman, 2005). According to Weber's Law (Fechner, 1860), the accuracy of a tone length estimation will depend on the duration of the tone itself. In particular, the law stipulates that the discrimination threshold (the "just noticeable difference" JND of a stimulus, defined as the minimum *perceivable* change in the stimulus) should be proportional to the magnitude of the initial stimulus. The standard deviation of the psychometric density function $S(T)$ (the fraction of "long" answers, as a function of the oddball length T) is just such a measure of discrimination thresholds, shown in Fig. 2(a). Indeed, we observe that the evolved Markov Brains respond according to Weber's Law, as the standard deviation SD of $S(T)$ changes with the standard tone roughly linearly, which is similar to what is observed with human subjects, shown in Fig. 2(b).

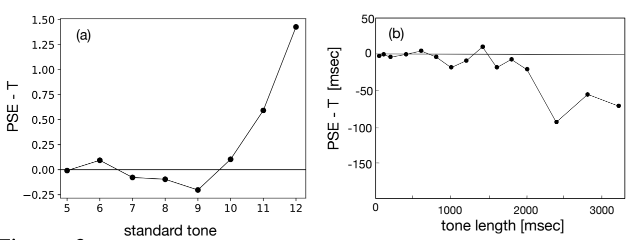

Figure 3: (a) Constant error (point of subjective equality minus standard tone duration, PSE - T) vs. standard tone in Markov brains averaged over 50 replicas. (b) Constant errors vs. standard tone duration of one of the human subjects (D.G.) from (Getty, 1975).

Fig. 3(a) shows the difference between the point of subjective equality PSE (the oddball duration that the subject perceives to be equal to the standard tone) and the actual tone length T across tone lengths in this digital experiment (again averaged over 50 brains). Fig. 3(b) shows this error for a human subject (Getty, 1975). While there is a perception bias (the difference in PSE and the standard tone, known as constant error CE) in both humans and Markov brains, these errors occur in opposite directions: CEs start to increase for longer standard tones in Markov Brains whereas CEs begin to decrease for longer tones in human subjects.

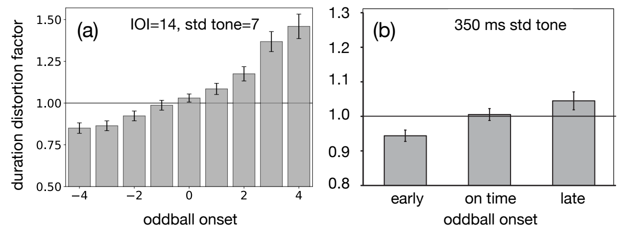

Figure 4: (a) Duration Distortion Factor (DDF) for Markov Brains, showing early and late oddball tones for a stanard tone length of 7 units and and inter-onset-interval (IOI) of 14. (b) DDF in human trials with an IOI of 700ms and a standard tone of 350ms, from McAuley and Fromboluti (2014). In "early" trials, the oddball tone arrives 231ms earlier (231ms later in "late" trials). If a unit of Markov time equals 50ms, an advance/delay of 4 units in (a) is comparable to the early and late ones in (b).

Similar results were obtained by (Jones and McAuley, 2005) where the human bias in PSE tends toward the mean of the standard tone duration range. While the origin of this difference between digital and human brains cannot be established with certainty, we surmise that past experience, in particular the difference in feedback about the performance in the two cases is to blame: in the studies by Getty (1975) and by Jones and McAuley (2005), subjects did not receive feeback on how well they judged the tone, while the evolutionary process provides such a feeback implicitly.

We then tested how these brains judge the length of tones that arrive early or late with respect to the background rhythm, a scenario that these brains had never encountered during evolution. Just as observed with the human subjects (McAuley and Fromboluti, 2014), the digital brains misjudge the length of these tones (see Fig. 4), with the error more pronounced the more off-rhythm the oddball is (Tehrani-Saleh et al., 2020).

Here we have demonstrated that digital evolution can create artificial brains that perform a cognitive task at a level similar to that achieved by human subjects, while being subjected to the same perception artifacts (illusions about the length of out-of-rhythm tones) as humans. At the same time, differences in prior experience also lead to differences in the response. Because digital brains can be examined with perfect precision, the mechanisms behind the observed perceptual biases can be determined without relying on inference, to discover new theories of cognitive processing. For example, in (Tehrani-Saleh et al., 2020) we determined that the distortion in duration perception is due to brains only paying attention to the most informative parts of the signal (in this case, the endpoint), suggesting a new theory of attention.

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