Brain Mimicry: The Ultimate Challenge

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ABSTRACT
From the automobile to the computer, the light bulb to the micro-chip, the emergency of new technology has been the story of human development over the past 150 years. Technology has become a part of our lives. The issue of decide if this part is or not good for life is a controversial one. But in many aspects or we can say in every aspects contribution technology has made to modern life has been really positive and effective. The key technology in many of today's novel applications is Artificial Intelligence (AI), ranging from banking systems that detect attempted credit card fraud, to telephone systems that understand speech, to software systems that notice when you're having problems and offer appropriate advice, to the medical technology which improved the quality of human lives. These technologies would not exist today without the sustained federal support of fundamental AI research over the past three decades.

In this paper, we have covered the one of the advance research of AI i.e. ARTIFICIAL BRAIN (A-Brain) which is also called the reverse engineering of the brain. In recent years, half a dozen major research groups have simulated or constructed sizeable networks of artificial neurons, with the ultimate goal to emulate the entire human brain. While the outputs of the simulations demonstrate some features of biological neural networks, it is not even clear how to prove that artificial neural network behavior is identical in any way to biological behavior. However, enough progress has been made to draw some conclusions and make comparisons between the leading projects. Some approaches are more scalable, some are more practical with current technologies, and some are more accurate in their emulation of biological neurons. In this paper, we will discuss some challenges and predictions about the future prospects of brain emulation or the A-Brain.

Keywords: Mimic artificial brain, neuron, intelligence, emulation.

1. INTRODUCTION
For decades, some of engineering’s best minds have focused their thinking skills on how to create thinking machines computers capable of emulating human intelligence. While some of thinking machines have mastered specific narrow skills — playing chess, for instance — general-purpose artificial intelligence (AI) has remained elusive. Part of the problem, some experts now believe, is that artificial brains have been designed without much attention to real ones. Pioneers of artificial intelligence approached thinking the way that aeronautical engineers approached flying without much learning from birds. It has turned out, though, that the secrets about how living brains work may offer the best guide to engineering the artificial variety. Discovering those secrets by reverse-engineering the brain promises enormous opportunities for reproducing intelligence. Reverse-engineering the brain is one of the Grand Challenges posed by the United States National Academy of Engineering [1].

Reverse-engineering the brain is being pursued in different way. The objective is not necessarily to build a grand simulation — the real objective is to understand the principle of operation of the brain. The design of the brain is in the genome. The human genome has three billion base pairs or six billion bits, which is about 800 million bytes before compression. Eliminating redundancies and applying loss-less compression, that information can be compressed into about 50 million bytes. About half of that is the brain, which comes down to 25 million bytes, or a million lines of code.

Over the past 50 years, advances in technology have successively and phenomenally increased our ability to emulate neural networks with speed and accuracy. At the same time, and particularly over the past 20 years, our understanding of neurons in the brain has increased substantially, with imaging and micropores contributing significantly to our understanding of neural physiology. These advances in both technology and neuroscience make possible the projects, aimed at modeling large numbers of interconnected neurons. Today it is feasible to emulate small but non-trivial portions of the brain, for example thousands of neurons in the visual cortex. But even a perfect simulation of the human brain or cortex won’t do anything unless it is infused with knowledge and trained.

2. HOW WILL WE BUILD A-BRAIN?
There's an ongoing debate among neuroscientists, cognitive scientists, and even philosophers as to whether or not we could ever construct or reverse engineer the human brain. Some suggest it's not possible, others argue about the best way to do it, and still others have already begun working on it.

Regardless, it's fair to say that ongoing breakthroughs in brain science are steadily paving the way to the day when an artificial brain can be constructed from scratch. And if we assume that cognitive functionalism holds true as a theory — the idea that our brains are a kind of computer — there are two very promising approaches worth pursuing. Interestingly, the two approaches come from two relatively different disciplines: cognitive science and neuroscience. One side wants to build a brain with code, while the other wants to recreate all the brain's important functions by emulating it on a computer. It's anyone's guess at this point in time as to who will succeed and get there first, if either of them. Before we take a deeper look into these two approaches, however, it's worth reviewing what the researcher Alan Turing had to say about brains.

2.1 The Church-Turing Hypothesis
Given that scientists are looking to model the human brain in digital substrate (i.e. a computer), they have to work in accordance to a rather fundamental assumption: computational functionalism. This goes back to the Church-Turing thesis which states that a Turing machine can emulate any other Turing machine.[2] Essentially, this means that every physically computable function can be computed by a Turing machine. And if brain activity is regarded as a function that is physically computed by brains, then it should be possible to compute it on a Turing machine, namely a computer.

So, if you believe that there's something mystical or vital about human cognition you're probably not going to put too much credence into these two approaches. Or, if you believe that there's something inherently unique about intelligence that can't be translated into the digital realm, you've got your work cut out for you to explain what that is exactly — keeping in mind that any informational process is computational, including those brought about by electrical and chemical reactions. Minds are what brains do, so it's not too implausible to suggest that minds are what computers can do, too.

2.2 Rules-based artificial intelligence
One very promising strategy for building brains is the rules-based approach. The basic idea is that scientists don't need to mimic the human brain in its entirety. Instead, they just have to figure out how the "software" parts of the brain work; they need to figure out the algorithms of intelligence and the ways that they're intricately intertwined. Consequently, it's this approach that excites the cognitive scientists. Some computer theorists insist that the rules-based approach will get us to the brain-making finish line first. Ben Goertzel is one such theorist. His basic argument is that other approaches over-complicate and muddle the issue. He likens the approach to building airplanes: we didn't have to reverse engineer the bird to learn how to fly.

Essentially, cognitive scientists like Goertzel are confident that the hard-coding of artificial general intelligence (AGI) is a more elegant and direct approach. It'll simply be a matter of identifying and developing the requisite algorithms sufficient for the emergence of the traits they're looking for in an AGI. They define intelligence in this context as the ability to detect patterns in the world, including in it. To that end, Goertz and other AI theorists have highlighted the importance of developing effective learning algorithms. A new mind comes into the world as a blank slate, they argue, and it spends years learning, developing, and evolving. Intelligence is subject to both genetic and epigenetic factors, and just as importantly, environmental factors. It is unreasonable, say the cognitive scientists, to presume that a brain could suddenly emerge and be full of intelligence and wisdom without any actual experience.

This is why Goertzel is working to create a "baby-like" artificial intelligence first, and then raise and train this AI baby in a simulated or virtual world such as Second Life to produce a more powerful intelligence. A fundamental assumption is that knowledge can be represented in a network whose nodes and links carry "probabilistic truth values" as well as "attention values," with the attention values resembling the weights in a neural network. There are a number of algorithms that need to be developed in order to make the whole neural system work, argues Goertzel, the central one being a probabilistic inference engine and a custom version of evolutionary programming. Once these algorithms and associations are established, it's just a matter of teaching the AI what it needs to know.

2.3 Whole brain emulation
Neuroscientists aren't entirely convinced by the rules-based approach. They feel that something is being left out of the equation, literally. Instead, they argue that researchers should be inspired by an actual working model: our brains. Indeed, whole brain emulation (WBE), the idea of reverse engineering the human brain, makes both intuitive and practical sense. Unlike the rules-based approach, WBE works off a tried-and-true working model; neuroscientists do not have to re-invent
the wheel. Natural selection, through excruciatingly tedious trial-and-error, created the human brain — and all without a preconceived design. They say there’s no reason to believe that we can’t model this structure ourselves. If the brain could come about through autonomous processes, argue neuroscientists, and then it can most certainly come about through the diligent work of intelligent researchers. [3]

When talking about WBE it’s important to distinguish between emulation and simulation. Emulation refers to a 1-to-1 model where all relevant properties of a system exist. This doesn’t mean re-creating the human brain in exactly the same way as it resides inside our skulls. Rather, it implies the re-creation of all its properties in an alternative substrate, namely a computer system. Moreover, emulation is not simulation. Neuroscientists are not looking to give the appearance of human-equivalent cognition. A simulation implies that not all properties of a model are present. Again, it’s a complete 1:1 emulation that they’re after.

A number of critics point out that we’ll never completely emulate the human brain on account of the chaos and complexity inherent in such a system. Others disagree. As researchers from Oxford University have pointed out, we will not need to understand the whole system in order to emulate it. What’s required is a functional understanding of all necessary low-level information about the brain and knowledge of the local update rules that change brain states from moment to moment. What is meant by low-level at this point is an open question, but it likely won’t involve a molecule-by-molecule understanding of cognition. And as Ray Kurzweil has revealed, the brain contains masterful arrays of redundancy; it’s not as complicated as we currently think. In order to gain this "low-level functional understanding" of the human brain, neuroscientists will need to employ a series of interdisciplinary approaches (most of which are currently underway). Specifically, they’re going to require advances in:

Computer science: The hardware component has to be vastly improved. Scientists are going to need machines with the processing power required to host a human brain. They’re also going to need to improve the software component so that they can create algorithmic correlates to specific brain function.

Microscopy and scanning technologies: Scientists need to better study and map the brain at the physical level. Brain slicing techniques will allow them to visibly study cognitive action down to the molecular scale. Specific areas of inquiry will include molecular studies of individual neurons, the scanning of neural connection patterns, determining the function of neural clusters, and so on.

Neurosciences: Researchers need more impactful advances in the neurosciences so that they can better understand the modular aspects of cognition and start mapping the neural correlates of consciousness (what is currently a very grey area).

Genetics: Scientists need to get better at reading our DNA for clues about how the brain is constructed. It's generally agreed that our DNA will not tell us how to build a fully functional brain, but it will tell us how to start the process of brain-building from scratch.

Essentially, WBE requires three main capabilities: (1) the ability to physically scan brains in order to acquire the necessary information, (2) the ability to interpret the scanned data to build a software model, and (3) the ability to simulate this very large model. WBE may be the right approach, but it's not going to be easy. Nor is it going to be quick. This will be a multi-disciplinary endeavor that will require decades of data collection and the use of technologies that don't yet exist. And importantly, success won't come about all at once. This will be an incremental process in which individual developments will provide the foundation for overcoming the next conceptual hurdle.

2.4 Time-frames

Inevitably the question as to "when" crops up. Unfortunately, we are still quite a ways off. Kurzweil's prediction of emulating the brain by 2030 seems uncomfortably short — that's only 18 years away. Moreover, his analogies to the human genome project are unsatisfying. This is a project of much greater magnitude, not to mention that we're still likely heading down some blind alleys. Similarly, Goertzel's prediction of success via the rules-based approach within the next decade or two seems overly optimistic — though arguably not impossible given his "learning AI" approach.

A more likely scenario would see us code or emulate the human brain in about 50 to 75 years, possibly 100. That said, this is an exceptionally difficult thing to predict given the crudeness of the neurosciences on the one hand, and the rate of accelerating change on the other. The year 2050 is a kind of black hole when it comes to predictions.

Lastly, it's worth noting that, given the capacity to recreate a human brain in digital substrate, we won't be too far off from creating considerably greater-than-human intelligence. Computer theorist Eliezer Yudkowsky claimed that, because of the brain's particular
architecture, we may be able to accelerate its processing speed by a factor of a million relatively easily. Consequently, predictions as to when we may achieve greater-than-human machine intelligence will likely coincide with the advent of a fully emulated human brain.

3. MOTIVATION FOR BUILDING A-BRAINS

The human brain is one of the most complex processors we know. It still far exceeds computers in pattern recognition and creative decision making. As digital processing power increases, we’ll likely have the means to simulate the physical structure of the brain, but will there be mechanisms we haven’t anticipated? Will we really understand how the brain stores memories in its neural connectivity? When we make a simulation of the brain, will we simply copy an individual’s neuron pattern – is that even possible? – and if we don’t will the simulation be an accurate replication of a mind? Is the hardware of the brain (the neuron connections) actually the software as well, or is there an OS we just haven’t found yet? All of these questions stand in the way to creating an artificial brain.

Three motivations are frequently cited for brain simulation:

1. Researchers hope to gain a better understanding of how the brain works (and malfunctions) by creating simulations. A model can provide insight at all levels, from the biochemistry and neurochemical behavior of individual cells to the behavior of networks of neurons in the cortex and other parts of the brain.

2. Some researchers feel progress in artificial intelligence over the past 50 years has been insufficient to lead to intelligent behavior. Ideas from simulations of neural networks may yield new ideas to develop intelligent behavior in computers, for example through massive parallelism. Neural networks are already being used for applications such as computer vision and speech understanding, and many algorithmic approaches are bio-inspired, but their biological basis is, for the most part, simplified from the more-detailed models used by neuroscientists. Autonomous vehicles and other robotic applications are likely targets for such brain-like systems.

3. For the most part, computers still use the same basic architecture envisioned by John von Neumann in 1945. Hardware architectures based on the massive parallelism and adaptability of the brain may yield new computer architectures and micro-architectures that can be applied to problems currently intractable with conventional computing and networking architectures.

4. PROJECTS WORKING ON A-BRAIN

Many projects around the world have aimed at emulating neural networks.2 In this paper we only consider projects intended to scale to millions of neurons, and projects that have fabricated and tested their designs, at least on a small scale, with currently available technologies. Given this scope, although there are innovative, successful projects with more limited scope, due to space and time limitations, we elected to focus on six projects in this paper that have the most ambitious scope and the most demonstrable results:

1. The SpiNNaker [4] project at Manchester University in the U.K.,
3. The C2S2 SyNAPSE [6, 7] project at IBM Research in California,
4. The FACETS [8] project at Heidelberg University in Germany,
5. The Neurogrid [9] project at Stanford University in California, and

In the following subsections we look at each of these projects in more detail. In the last subsection, we discuss a few related projects, with a focus on emerging technologies.

4.1 SpiNNaker

The SpiNNaker project at Manchester University is based on fabricating many small CPUs on a chip, the cores communicating through a network on-chip and through a network between chips. The principal investigator, Steve Furber, was a co-designer of the ARM 32-bit RISC microprocessor, and a simplified ARM 968 processor is used for the CPUs on the SpiNNaker chips. Each CPU is designed to simulate about 1,000 neurons, communicating spike events to other CPUs through packets on the network. The SpiNNaker chip is designed to include

- 18 low-power ARM CPUs, each with about 100KB of local RAM used to store its programming and data,
- 128MB of RAM shared by all 18 CPUs through a DMA controller, used to store synaptic weights and other information, and
• An on-chip network and packet router that connects the 18 CPUs and also connects to 6 adjacent SpiNNaker chips, to reach other CPUs. The routing of packets in SpiNNaker is carefully designed to balance complexity and bandwidth. AER packets are used, as with most of the other projects described here. Routing tables stored in a content-addressable memory tell the router which packets must be routed to which CPUs, whether off-chip or on-chip. The SpiNNaker chips are connected to adjacent SpiNNaker chips in a 2-dimensional toroid mesh network; each chip has 6 network ports, connected to adjacent chips. The router need not know the eventual destination(s) of a packet, it only needs to know which port(s) to send it to.

Routing tables are built and maintained by a separate (programmable) background process responsible for connectivity, plasticity, and learning [13]. SpiNNaker is initially using a simple algorithm for neurons based on Eugene Izhikevich’s point neuron model [14]. For the purposes of this paper, we analyze SpiNNaker based on that model, although their software-based architecture could support a variety of more sophisticated neural models. Their point neuron algorithm is programmed into the local memory of each of the SpiNNaker CPUs. Post-synaptic weights for synapses are stored in the SpiNNaker chip’s shared memory; the algorithm fetches the corresponding weight into local CPU memory whenever a spike arrives at one of its “synapses,” and recomputes neuron action potentials at 1ms simulation intervals, based on Izhikevich’s equations. 16-bit fixed-point 10 arithmetic is used for most of the computation, to avoid the need for a floating-point unit and to reduce computation and space costs. Because spike delivery time in SpiNNaker is designed to be faster than a biological brain (assuming the network and routing delays are adequately controlled), SpiNNaker allows a delay of up to 15ms to be inserted in delivery of AER packets, in order to simulate longer axons. The goal is to allow the globally asynchronous, locally synchronous design to operate similarly to a biological brain possessing the same neural network. The maximum number of SpiNNaker chips supported by the packet-address structure is 216 (65,000 chips). About a billion neurons could be simulated in this configuration, if the physical chip placement, network, and other constraints do not limit scalability. The group has done some limited simulations to determine when the network and CPUs become saturated [15]. We will further discuss scalability in the last section. Work continues on the SpiNNaker project. It is expected that a full 65,000-chip configuration with 18-CPU chips will be built some time in 2012.

4.2 Blue Brain
The Blue Brain Project at EPFL in Switzerland uses an IBM Blue Gene supercomputer with 8,000 CPUs to simulate neurons and STDP in software. Henry Markram at EPFL’s Brain Mind Institute is the principal investigator. The Blue Brain group constructed a 10,000 neuron model of a neocortical column from the somatosensory cortex of a 2-week-old rat, and simulated it on the Blue Gene supercomputer. The simulation ran about ten times slower than biological neurons. The modeled cortical column is about .5mm in diameter and about 2.5mm in height. The model is not a map of real connections in any particular rat; the connections are randomly derived based on the percentage connectivity of neurons of different types in different layers of rat cortical columns. However, the model does attempt to account for the 3D morphology of the neurons and cortical column, using about 1 billion triangular compartments for the mesh of 10,000 neurons. A multi-processor adaptation of the NEURON simulation software [16] was run at this fine grain using Hodgkin-Huxley equations, resulting in gigabytes of data for each compartment, and presumably a high level of bio-realism. Timing, e.g. propagation delays along the simulated compartments of an axon, are incorporated into the simulation. Synaptic learning algorithms are also introduced, to provide plasticity. A visual representation of parts of the cortical column can be displayed for the simulation, allowing researchers to focus on particular parts or phases of the simulation in more detail. The Blue Brain project is unusual in its goal to simulate the ion channels and processes of neurons at this fine-grain compartmental level. Had the project simply used a “point neuron” model integrating incoming spikes, the simulation could have delivered orders of magnitude higher performance, but Markram opted for a higher level of bio-realism.

4.3 C2S2
Dharmendra Modha’s Cognitive Computing Group at IBM Alamaden Research Lab received funding in 2008 from DARPA’s SyNAPSE initiative with their proposal “Cognitive Computing via Synaptronics and Supercomputing (C2S2).” Modha has in turn funded professors from 5 universities (Cornell, Columbia, Stanford, Wisconsin Madison, and UC Merced) as part of their project, bringing in expertise in neuroscience, psychology, VLSI and nanotechnology. We will refer to Modha’s project as “C2S2”. Modha’s team studied data on biological brains to work toward a “connectome” database of neural connectivity [17], using experimental data from diffusion tensor imaging (DTI) and other techniques. They created a massively parallel cortical simulator called C2, which was initially used at the scale...
of a rat cortex, and more recently at the scale of a cat Cortex, running on IBM’s Dawn Blue Gene/P supercomputer, with 147,456 CPUs and 144TB of main memory. In the latter case C2 simulated 1.6B cortical neurons and 9 trillion synapses, using experimentally measured thalamo-cortical connectivity. The simulations incorporated STDP and controlled axon delays. The C2 simulation used a much simpler model of neurons than the Blue Brain, with single-compartment spiking Iszhikevich-type neurons. As with the Blue Brain, the connectome used did not match the actual connectome of any particular biological brain: it is an approximation based on the tools currently available. However, Modha points out that much can be learned even with these approximations. He reported oscillations in neural firing patterns seen over large areas of the simulated cortex at the alpha and gamma frequencies seen in mammal brains, and groups of neurons exhibited populationspecific response latencies matching those in the human cortex.

More recently, Modha has published papers on new “cognitive computing chips” [18], suggesting that IBM research will now turn to hardware for brain emulation. The prototype chip emulates 256 neurons, using a crossbar connecting 1024 input axons to the 256 neurons with weighted synapses at the junctions. Variations of the chip have been built with 1-bit and 4-bit synapse weights stored in SRAM. Another was built with low leakage to reduce power consumption. Cross-chip spikes are conveyed asynchronously via AER networking, while the chips themselves operate separately. Synapses are simulated using the Izhikevich leaky integrate-and-fire model. The results are identical to the same equations simulated in software, but all 256 neurons on the chip update their membrane voltage in parallel, at 1ms intervals. The details of the AER networking are not specified, so it is not possible to speculate on how that will scale at this time.

4.4 FACETS and BrainscaleS
The FACETS project (Fast Analog Computing with Emergent Transient States) is a consortium of 15 groups in 7 European countries, led by professors Johannes Schemmel and Karlheinz Meier of the Electronic Visions lab at the University of Heidelberg. In their early work, the “Spikey” neuromorphic ASIC chip was developed. A Spikey chip hosts a total of 128K synapses; it could simulate, for example, 8 neurons with 16K inputs, or 512 neurons with 256 inputs. The goal was to simulate analog neuron waveforms analogous to biological neurons on the same input. The Spikey neurons communicate with each other digitally, although the neuron circuit is analog. Digital action potentials are routed to synapse drivers, that convert them to voltage pulses that, in turn, control synaptic conductance. The synapse drivers also implement STDP; synaptic weight storage is implemented as static RAM. Synaptic conductance is modulated by an exponential onset and decay. Whenever an analog neuron circuit reaches an action potential, digital monitoring logic generates a spike event with the event time and the address of the spiking neuron. This event is transmitted on a network to multiple destination neurons that need not be on the same Spikey chip. About 1/3 of the Spikey chip is digital control logic that implements the digital communication between neurons. 16 Spikey chips can be operated on a custom backplane that implements high-speed digital communication between the chips with a fixed and guaranteed latency. The Spikey chip outputs, inputs, circuit parameters, and neuron interconnections can be monitored and controlled from software running on a host computer. Selected neurons can then be stimulated with experimental spikes, and neuron outputs can be recorded. More recently, the FACETS researchers developed the HICANN (High Input Count Analog Neural Network) chip and “wafer scale integration” to achieve higher connectivity between simulated neurons. HICANN bears some resemblance to Spikey in that neural emulation is analog, with digital circuits for communication and STDP. However, there are a number of differences. Instead of placing each HICANN chip in a separate package as with Spikey, the entire multi-chip wafer is enclosed in a single sealed package with horizontal and vertical “Layer 1” channels that connect the HICANN chips within and between reticles on a wafer. A total of 352 HICANN chips can be interconnected on the multi-chip wafer, producing 180,000 neurons with a total of 40 million synapses.

Synapses are implemented with groups of DenMem (Dendrite Membrane) circuits. A hybrid analog/digital solution is used for the synapses, and a hybrid of address-encoding and separate signal lines is used for communication. Each DenMem can receive as many as 224 pre-synaptic inputs based on a 6-bit address sent via a Layer 1 channel. The synaptic weight is represented in a 4-bit SRAM with a 4-bit DAC. The post-synaptic signal is encoded as a current pulse proportional to the synaptic weight, and can be excitatory or inhibitory. Neuron circuits integrate the DenMem signals. A digital control circuit implements STDP based on temporal correlation between pre- and post- synaptic signals, updating the synaptic weight. A packet-based “Layer 2” routing protocol is used to communicate between wafers, using pads on the HICANN chips that connect them to the PCB. Layer 2 channels provide 176GB/sec from the
wafer to PCB, allowing 44 billion events/second to be communicated between wafers. The Layer 2 wafer-to-wafer channels are handled by FGPA and OTS switches on the PCB with 1-10 Gbit Ethernet links. The HICANN chips implement an adaptive exponential integrator and fire (AdExp) model of neurons. This model is somewhat more sophisticated than the standard integrator and fire model used in SpiNNaker, but less sophisticated (and less computational expensive) than Blue Brain’s multi-compartmental Hodgkin-Huxley-based model. The FACETS group is now investigating more sophisticated models.

The FACETS neural networks are described in PyNN, a simulator-independent language maintained by neuralensemble.org. PyNN is Python-based and includes operations to create populations of neurons, set their parameter values, inject current, and record spike times. PyNN can be run on a simulator such as NEURON, or can be used on the FACETS host computer to initialize and control the chips. In addition, a neuralensemble.org framework called NeuroTools has been developed to assist in the execution of experiments, and the storage and analysis of results. In recent work [19], software has been developed to automatically translate a PyNN design into a hardware implementation in several stages, optimizing the physical placement of the neural components and connections on HICANN chips. A follow-on to the FACETS project, BrainscaleS [20], was started in 2011. To date, only high-level directions have been published on BrainscaleS. Two key goals of BrainscaleS are in-vivo recording of biological neural networks and the construction of synthesized cortical networks with similar behavior. The focus is on perceptual systems. The BrainScaleS project is establishing close links with the Blue Brain project and with Brain-i-Nets [21], a consortium producing a set of learning rules based on synaptic plasticity and network reorganization.

4.5 Neurogrid
The Neurogrid project at Kwabena Boahen’s “Brains in Silicon” lab at Stanford University uses programmable analog “neurocore” chips. Each 12x14 mm2 CMOS chip can emulate over 65,000 neurons, and 16 chips are assembled on a circuit board to emulate over a million neurons. The system is built and functional. Neurogrid uses a two-level simulation model for neurons, in contrast to the point neuron model used in SpiNNaker, and in contrast to the thousands of compartments used in Blue Brain’s simulation. Neurogrid uses this approach as a compromise to provide reasonable accuracy without excessive complexity. A quadratic integrate-and-fire model is used for the somatic compartment. Dendritic compartments are modeled with up to four Hodgkin-Huxley channels. Back-propagation of spikes from somatic to dendritic compartments is supported.

Neurogrid uses local analog wiring to minimize the need for digitization for on-chip communication. Spikes rather than voltage levels are propagated to destination synapses.

To simplify circuitry, a single synapse circuit models a neuron’s entire synapse population of a particular type, and each of these circuits must be one of four different types. The synapse circuit computes the net postsynaptic conductance for that entire population from the input spikes received. Although this approach limits the ability to model varying synaptic strength, and it does not model synaptic plasticity, it greatly reduces circuit complexity and size. Like SpiNNaker, Neurogrid uses an AER packet network to communicate between-chip spikes. Unlike SpiNNaker’s grid organization, Neurogrid’s chips are interconnected in a binary tree with links supporting about 80M spikes/second (this is a change from earlier work [18] in which Boahen used a grid network). Routing information is stored in RAM in each router. This AER-based networking is referred to as “softwire” connections. To reduce communication overhead, a single inter-chip spike can target multiple neurons on the destination chip. The postsynaptic input triggered in a target neuron can be propagated to neighboring neurons with a programmable space-constant decay. This requires only nearest-neighbor connections: the synaptic potentials superimpose on a single resistive network to produce the net input delivered to each neuron. A single cross-chip spike can thus reach a hundred neurons. This is analogous to cortical axons that travel for some distance and then connect to a number of neurons in local patch arbors in another cortical column.

Unlike FACETS, which is designed to run orders of magnitude faster than biological neurons, the Neurogrid neuron array is designed to run in real-time. This means that a single AER link can easily service all of the cross-chip spikes for 65,000 neurons. Furthermore, the on-chip analog connections can easily service their bandwidth, and it seems likely that the binary routing tree connecting the 16 Neurogrid chips on a circuit board can easily support a million neurons. Thus, the only potential bottleneck for Neurogrid might be in routing between multiple boards in the future. Like FACETS, the neurocore chips are programmable. Each neurocore models the ionchannel behavior and synaptic connectivity of a particular neuron cell type or cortical layer. The Neurogrid neuron circuit consists of about 300 transistors modeling the components of the cell, with a total of 61 graded and 18 binary programmable
parameters. Synapses can be excitatory, inhibitory, or shunting. The Neurogrid group has demonstrated that their neurons can emulate a wide range of behaviors.

The Neurogrid team has encouraged others to build on their work, teaching courses training students to build neural networks on their framework, and making their silicon compiler available to allow others to design neuromorphic systems for fabrication. The descriptions are written in Python.

4.6 IFAT and NeuroDyn
Like the Neurogrid and FACETS projects, Gert Cauwenberghs and colleagues at the Institute for Neural Computation (INC) at the University of California at San Diego chose to use analog neuromorphic circuit chips to model neurons. They have produced two different chips, IFAT and NeuroDyn, with different goals. The initial IFAT (Integrate and Fire Array Transceiver) chip, prototyped in 2004, could emulate 2400 simple neurons. A separate microcontroller on the same circuit board used analog-digital converters and an AER lookup table to deliver spikes to the IFAT chips based on a global “clock cycle.” The INC group applied the IFAT chips to various applications, including Laplacian filters to isolate vertical edges on images, and spatiotemporal filters to process a spike train from an artificial retina, constructing velocity-selective cells similar to those found in the medial-temporal cortex in the human brain, demonstrating brain processing. The latest version of the IFAT chip emulates 65,000 neurons. The new system, called HiAER-IFAT (Hierarchical AER IFAT), uses a tree of routers for delivery of AER events [22]. The tree is built using Xilinx Spartan-6 FPGAs connecting to the IFAT chips at the leaves. HiAER-IFAT has been demonstrated with 250,000 neurons. Like SpiNNaker, all of the connectivity information is held in RAM in the routing tables of the intermediate nodes, in this case the non-leaf nodes of a hierarchy. Unlike SpiNNaker, the maximum number of routing “hops” is logarithmic in the number of neurons. However, it is possible that the HiAER-IFAT routers in the highest level of the hierarchy could become overloaded if there is insufficient locality of reference.

The INC group has also designed a “NeuroDyn” chip, which is the most sophisticated of all of the neuromorphic chips discussed in this paper, in terms of bio-realism and neuron emulation. Their neuron emulation supports 384 parameters in 24 channel variables for a complex Hodgkin-Huxley model. This level of emulation is important, for example, in examining the effects of neuromodulators, neurotoxins, and neurodegenerative diseases on ion channel kinetics. However, NeuroDyn is not designed for large-scale brain emulation: each chip emulates only 4 neurons and 12 synapses.

In contrast to IFAT and all the other projects that generate discrete spike events to be delivered by AER or other means, NeuroDyn emulates neural and synaptic dynamics on a continuous basis. Matlab software on a workstation can monitor and control each neuron’s membrane potential and channel variables, and can adjust the 384 NeuroDyn emulation parameters to tune to any desired neuron behavior. The parameters are stored on chip in digital registers. Experiments analogous to patch-clamping biological neurons can be performed on NeuroDyn neurons through the software.

5. SCOPE/APPLICATIONS
Already, some applications using artificial intelligence have benefited from simulations based on brain reverse-engineering. Examples include AI algorithms used in speech recognition and in machine vision systems in automated factories. More advanced AI software should in the future be able to guide devices that can enter the body to perform medical diagnoses and treatments. Of potentially even greater impact on human health and well-being is the use of new AI insights for repairing broken brains. Damage from injury or disease to the hippocampus, a brain structure important for learning and memory, can disrupt the proper electrical signaling between nerve cells that is needed for forming and recalling memories. With knowledge of the proper signaling patterns in healthy brains, engineers have begun to design computer chips that mimic the brain’s own communication skills. Such chips could be useful in cases where healthy brain tissue is starved for information because of the barrier imposed by damaged tissue. In principle, signals from the healthy tissue could be recorded by an implantable chip, which would then generate new signals to bypass the damage. Such an electronic alternate signaling route could help restore normal memory skills to an impaired brain that otherwise could not form them.

“Neural prostheses” have already been put to use in the form of cochlear implants to treat hearing loss and stimulating electrodes to treat Parkinson’s disease [23]. Progress has also been made in developing “artificial retinas,” light-sensitive chips that could help restore vision. Even more ambitious programs are underway for systems to control artificial limbs. Engineers envision computerized implants capable of receiving the signals from thousands of the brain’s nerve cells and then wirelessly transmitting that information to an interface device that would decode the brain’s intentions. The
interface could then send signals to an artificial limb, or even directly to nerves and muscles, giving directions for implementing the desired movements.

Other research has explored, with some success, implants that could literally read the thoughts of immobilized patients and signal an external computer, giving people unable to speak or even move a way to communicate with the outside world.

6. CHALLENGES
In spite of the progress in many brain emulation efforts, there are major challenges that must still be addressed:

• **Neural complexity**: In cortical neurons, synapses themselves vary widely, with ligand-gated and voltage-gated channels, receptive to a variety of transmitters [24]. Action potentials arriving at the synapses create post-synaptic potentials on the dendritic arbor that combine in a number of ways. Complex dendritic computations affect the probability and frequency of neural firing. These computations include linear, sublinear, and superlinear additions along with generation of dendritic spikes, and inhibitory computations that shunt internal cell voltage to resting potentials or decrease the potential, essentially subtracting voltage. Furthermore, some neuroscientists show evidence that the location of each synapse in the dendritic arbor is an important component of the dendritic computation [25], essential to their neural behavior, and there is growing consensus among neuroscientists that aspects of dendritic computation contribute significantly to cortical functioning. Further, some propagation of potentials and other signaling is in the reverse direction, affecting first-order neural behavior (for example, see the reset mechanism affecting dendritic spiking plasticity) [26, 27]. The extent of the detailed modeling of dendritic computations and spiking necessary for brain emulation is an open question.

• **Scale**: A massive system is required to emulate the brain: none of the projects we discuss have come close to this scale at present. The largest supercomputers and computer clusters today have thousands of processors, while the human cortex has tens of billions of neurons and a quadrillion synapses. We are a long way from cortex scale, even if one computer processor could emulate thousands of neurons, and, as we will see, it is unclear whether that emulation would be sufficiently accurate.

• **Interconnectivity**: Emulation of the cortex in hardware represents a massive “wiring” problem. Each synapse represents a distinct input to a neuron, and each postsynaptic neuron shares synapses with an average of 10,000 (and as many as 100,000) other presynaptic neurons. Similarly, the axon emerging from each neuronal cell body fans out to an average of 10,000 destinations. Thus each neuron has, on average, 10,000 inputs and 10,000 outputs. If the connections were mostly local, the wiring would not be so complicated; however, recent research by Bassett et al [28] derives a Rent exponent for the biological brain that could be used to compute the quantity of connections emerging from a volume of brain tissue. Early indications are that this Rent exponent is sufficiently large (many distal connections) so as to cause connectivity problems with conventional CMOS electronics.

• **Plasticity**: It is generally accepted that an emulated brain with static neural connections and neural behavior would not produce intelligence. Synapses must be “plastic”: the strength of the excitatory or inhibitory connection must change with learning, and neurons must also be able to create new synapses and hence new connections during the learning process. Research on the mechanisms by which neurons learn, make and break connections, and possess memory is ongoing, with hypotheses and supporting data appearing frequently. These studies have led to a basic understanding of synaptic and structural plasticity. In the last decade, attention has been given to the role of glial cells in neural behavior, glial cells being much more numerous in the brain than neurons. The role of astrocytes, a type of glial cell, in learning and memory is being actively investigated [29] and neuromorphic circuits constructed [30].

• **Power consumption**: A final, indirect problem is the power consumed by a brain emulation with 50 billion neurons and 500 trillion connections, and the dissipation of the associated heat generated. The human brain evolved to use very little power, an estimated 25 watts. We do not have computing technology anywhere near this power efficiency, although nanotechnology and ultra-low power design offer promise.

We will examine how each major project addresses these challenges. Although the brain emulation field is in its infancy, progress has been made in a very short time.

7. FUTURE ASPECTS
A big step forwarded in the project that aims to make thinking chips. The next step is to demonstrate brain like visual perception, decision making, planning, and navigation in virtual environments” by mimicking how the brain interfaces with sensory organs and with muscles. IBM is also working separately on nanomaterials that could enable the construction of brain like chips. In the final phase, it plans to build a system of
100 such chips simulating 100 million neurons and 1 trillion synapses.

DARPA is not the only organization working toward brainlike cognitive systems. The best-known brain project under way in Europe is Blue Brain, at Ecole Polytechnique Fédérale de Lausanne. And the European Union has also lavished 6.7 million (US$9.3 million) on a project that will build an artificial mouse brain. The Chinese government, according to a Wall Street Journal report earlier this year, is spending $1.5 million to develop robots whose artificial brains are driven by microcircuits that evolve, learn, and adapt to real-world situations. And in the United States, the National Science Foundation has funded a three-year study at the University of Southern California’s electrical engineering department to develop a synthetic cortex, which will contain carbon-based (as opposed to silicon) nanometer-scale artificial neurons.

The Robokoneko was a proposed robot kitten (robot + Japanese ko for "child" + neko for "cat") that was intended to have a remote computer brain containing "neural net" modules that could evolve their intelligence based on experience and prearranged rules. The purpose of the kitten robot was to demonstrate the feasibility of computers that operate as human brains do, building knowledge and taking immediate action based on the newly acquired knowledge. Hugo de Garis, one of the lead researchers on a project that is now apparently defunct, suggested that within several decades, artificial intelligence better than the intelligence of humans would be able to evolve into new artificial intellects that would transcend human understanding. As a first step or "proof of concept" toward an artificial brain with 40 million neurons, de Garis and fellow researchers planned to build a life-size kitten robot with 32,000 neural nets. Although some of its brain (analogous to that of humans for reflex actions) would be built into the body, the "thinking" part of the brain would reside in a computer that was connected remotely, probably by wireless communication. The computer version of animal brain neurons was referred to as a small complex of electronic storage known as "3-D cellular automata." These modules could be loaded with data (rules and facts) very quickly using field-programmable gate array (FPGA)-based special hardware known as a CAM (cellular automata)-Brain Machine (CBM). Once available, the CBM would be able to use a "genetic" algorithm (or different algorithms) to "build a brain" (load the computer’s memory) in about one second.

The proposed robot kitten itself would have eyes that contained video cameras, ears containing microphones, a speech generator, and numerous sensors on its body. It would be able to perform a number of kitten-like movements. A proposed first step was to simulate the kitten with 3-D software. Knowledge Revolution's Working Model 3-D was proposed as the 3-D product. Although not the first computer-driven robot to be developed, the robot kitten was to be the first robot driven by a computer with a neural net architecture.

8. CONCLUSIONS

The Artificial Brain, howsoever crazy or deep-rooted in fiction it may sound is indeed an inspirational theme. Success or failure, whatever may the end results are, but it is sure that any research of the brain will only force us into accepting the presence of the one who is able to do so. A system that may be able to think for itself, feel emotions that may vary from happiness to sadness, love to anger and maybe even sensuality is indeed a technology that seems light years away, but it wouldn’t be wrong if we believe, that if we start today, the lesser the number of light years to its realization. Apart from the sheer fantasy of a system that can reflect, understand and respond, this advanced technology may help us in understanding and even provide solutions for people suffering from ailments that impair parts of the brain. Just like the vast skies and oceans have been conquered, in the same way, it could be possible that we may actually unlock the mysteries of the mind. It's exciting to think of all the possibilities that could open up from this discovery. Answers to mental retardation and brain abnormalities can be solved at earlier stages. Diseases like Alzheimer’s and Parkinson’s that rid a person of his dignity could be eradicated totally. The list is endless, everything from brain disorders to the truths about the mysteries of dreams could be found out. Pragmatism is no longer the issue as far as science is concerned. So, an Artificial Brain is not at all matter for just science fiction magazines, it could be real and the Blue Brain Project is a sure and steady step towards it.

REFERENCES
