Swarms of microscopic agents self-assemble into complex bodies

Bruce MacLennan[1]

Nature produces living bodies of magnificent beauty and complexity, which are not the work of an external artist, but of a self-organized dance of a vast number of microscopic cells communicating and coordinating with each other. We can learn the dance scores from nature and use them to control massive swarms of microscopic artificial agents to assemble complex structures organized at many hierarchical levels, from the nanoscale up to the macroscale. Simulations demonstrate the application of these ideas in artificial intelligence and artificial life.

The Problem

As Richard Feynman said, "there is plenty of room at the bottom,"[2] and we are discovering ways to organize matter and processes at the microscopic scale — and even at the nanoscale — that have macroscopic effects that are relevant to technology, medicine, and art. But to date, nanotechnology has been limited to the creation of simple structures with a relatively small number of components, or to structures with a large number of components with either a highly regular or a random organization. For many purposes, however, we need to be able to create complex structures hierarchically organized at many spatial scales from the microscopic to the macroscopic. Consider these examples.

The contemporary, most successful approaches to artificial intelligence are inspired by the brain; they strive to model massive neural networks at a level of abstraction that preserves their information processing capabilities while omitting irrelevant biological detail. Research in cognitive neuroscience and artificial neural networks has revealed that much of the flexible, context-sensitive information processing of our brains depends on large numbers of massively interconnected neurons (9×10^{10} neurons in a human brain, with perhaps 10^{15} connections). Moreover, these neurons are not arranged and interconnected in either a regular or a random pattern; there are complex organizations both within individual brain regions and among the regions. All this within a volume of 1100 to 1300 cm^3, and consuming about 20W of power. If we want to achieve human-scale artificial intelligence, it is reasonable to suppose that we may need to construct artificial brains similarly organized from the microscale to the macroscale (Fig. 1).

Continuing the example of artificial intelligence, we now understand much better the importance of embodiment as a foundation for intelligence.[3] Brains have evolved to control physical bodies in their physical environments, although, of course, we also use them for abstract thought and contemplation. Nevertheless, control of our mechanically complex bodies by means of rich sensorimotor feedback provides the foundation from which language and abstract thought can emerge. Large numbers of sensory neurons embedded in our muscles, joints, and skin provide rich, high-dimensional input that allows our (quite slow) neurons to coordinate complex behavior in real time. Future robots with physical competence comparable to that of animals will be facilitated by similarly complex artificial sense organs, skin, and muscles (actuators). Although macroscopic in size, they will be complex structures of many microscopic parts. For example, the human eye has approximately 100 million retinal cells, which preprocess the visual image in real time, reducing its dimension so that it can be transmitted on about one million optic nerve fibers. It is not unreasonable to suppose that an artificial eye, with similar visual acuity and information processing capacity to ours, will have similar complexity. Such robotic devices will have important

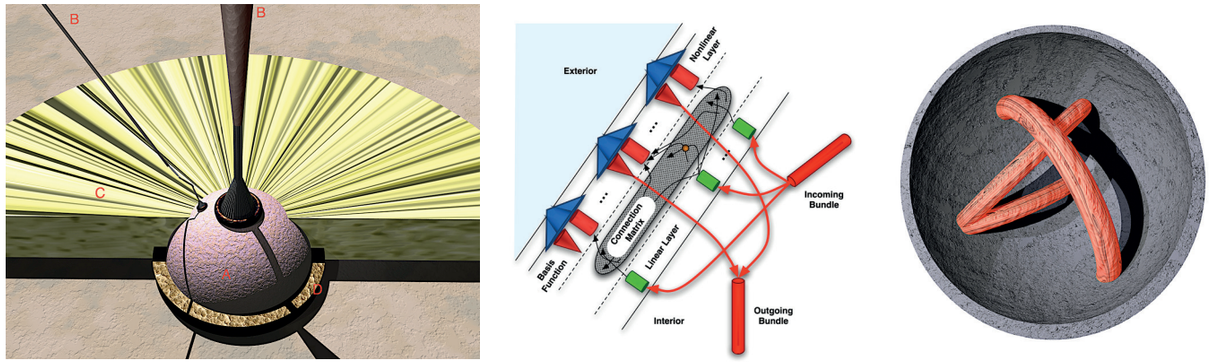

Fig. 1. Depictions of large-scale neurocomputer.[4] To left, external connections to artificial cortex. In center, computational microstructure of artificial cortex. To right, example of three massive fiber bundles connecting functional regions of cortex.

applications in medicine, such as prosthetic limbs and sense organs. Surely, we would like prosthetic eyes with the sensitivity and acuity of natural eyes, and prosthetic hands with the dexterity and sense of touch of natural hands, but these require vast numbers of components to be assembled in precise ways.

Artificial Morphogenesis

Assembling many millions of components into complex systems, structured from the nanoscale up through the macroscale, might seem impossible, but developmental processes in embryos prove that it is possible. An embryo develops from a single cell, which divides repeatedly producing an exponentially growing cell mass. These cells differentiate and orchestrate a complex dance that assembles the tissues, organs, and limbs of a complete organism (3.7×10^{13} cells in a human adult). A foetus may comprise a trillion cells, which have self-organized into innumerable structures at many spatial scales spanning five orders of magnitude. In this robust process, cells migrate, following chemical waystations to distant destinations, signaling each other to coordinate their movement and trigger context-sensitive differentiation into hundreds of cell types. Masses of cells flow viscously, forming intricately structured tissues that stretch, fold, and grow. This is our inspiration.

Artificial morphogenesis applies the principles of embryological morphogenesis to coordinating very large numbers of simple agents to assemble complex hierarchical structures.[5] It may be considered one approach to *morphogenetic engineering*, which applies principles of morphogenesis to the creation of form.[6] In artificial morphogenesis, very large numbers of microscopic agents cooperate to assemble themselves and inanimate microscopic components into a desired structure (Fig. 2). Under some conditions, they can disassemble such a structure in order to reassemble it into a new form.

The agents, which may be wholly artificial or produced by synthetic biology, have relatively simple capabilities for motion, signaling, and information processing and control. Agents need to be able to signal their immediate neighbors, but also more distant agents in order to coordinate their behavior. Cells in a developing embryo accomplish this by emitting chemical morphogens, which diffuse in the intercellular environment and can be detected by other cells. Likewise, in artificial morphogenesis, agents communicate by chemical and other signals. Agents also need to be able to move, either through a fluid medium or as a viscoelastic mass. This movement is accomplished by a variety of simple mechanical mechanisms. Finally, the behavior of agents is governed by relatively simple, primarily analog control mechanisms.

Progress in microrobotics is ongoing, and we anticipate that there will soon be sub-millimeter-scale autonomous robots with the capabilities required for artificial morphogenesis. Another attractive option is to use the techniques of synthetic biology to modify microorganisms

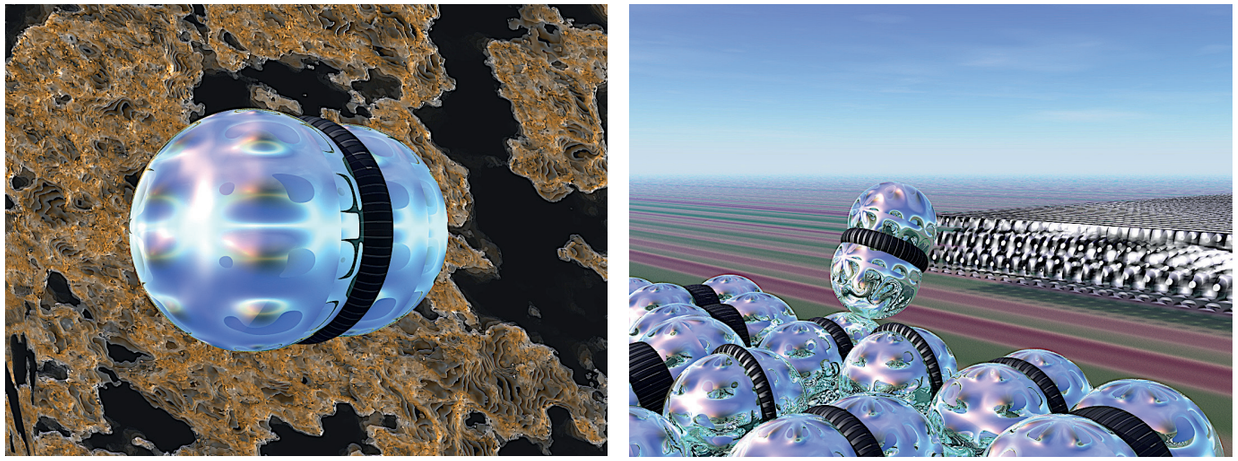

Fig. 2. Artistic depiction of microrobots.
To the left, a single microrobot attached to a surface. To the right, a swarm of microrobots assembling into a layer of an artificial tissue.

to implement the required agents. Genetic regulatory circuits are essentially analog control mechanisms, and they can be modified to implement the behavior required of a morphogenetic agent. Another advantage of biological agents is that they can reproduce, thus eliminating the need to manufacture artificial agents in large numbers.

Agents move in coordinated masses and differentiate under the influence of signaling substances that diffuse in the environment. Since our goal is to have very large numbers of very small agents moving *en masse*, we describe morphogenetic processes by partial differential equations (PDEs), which treats the agent mass as a continuous fluid or tissue. Embryologists often use PDEs for the same reason, and we can use their equations in artificial morphogenesis. Mathematically, we treat our agents as infinitesimal particles moving under the influence of forces and morphogen concentrations. This approach helps to ensure that our algorithms scale up to very large numbers of very small agents, but also keeps them largely scale-invariant, that is, independent of the exact size of the agents relative to the macroscopic object being constructed.

Examples

Since the required microscopic agents are not yet available, we test our morphogenetic algorithms through simulation.[7]

Our first example (Fig. 3) shows how an indefinite but very large number of agents can be coordinated to lay down neural fiber bundles between selected regions of an artificial brain.[8] In this morphogenetic algorithm the bundles are grown one at a time. A massive swarm of agents (equal in number to the number of nerve fibers in the bundle) is injected at the origin region, and they follow the gradient of a morphogen diffusing from the destination region, depositing fiber material as they go. Once a bundle has been created, its material absorbs the attractant, and this causes agents to steer around already created bundles, avoiding collisions. Moreover we can allow fiber bundles to split to go around obstacles when that is required.

Our second example (Fig. 4) shows how natural morphogenetic processes —in this case spinal segmentation — can be used for both similar and different applications in artificial morphogenesis, in this case, assembling an insect-like robot body frame.[9] The example exploits the idea that in morphogenesis, patterns in time can create patterns in space. In this case we use the clock-and-wavefront model of spinal segmentation, which was first proposed in 1976 but finally confirmed in 2008.[10] We use this process to assemble the spine of a robot, which is similar to its function in vertebrate development, but we also use it to assemble segmented legs, which develop differently in

nature. Thus we are using a natural process both for a purpose that it served in nature (spinal segmentation) and also for a purpose it does not serve in nature (leg segmentation). The number and lengths of the segments are parameters that we can control in each case.

In brief, morphogenesis proceeds as follows. Agents are recruited to assemble between the spine and the tail bud, which is moved rightward. Both the tail bud and completed spinal segments produce morphogens which diffuse into the undifferentiated spinal region. Periodically (and this is the temporal patterning), a pacemaker in the tail bud produces a pulse of a third morphogen, which is propagated through the tissue toward the head. As it passes through a region of relatively low concentrations of the first two morphogens, it leads to differentiation of a new spinal segment. The length of the segments is determined by the ratio of the growth rate and the pacemaker frequency; the number of segments is controlled by the product of pacemaker frequency and the growth time. This same process is used to grow segmented legs on the spinal segments.

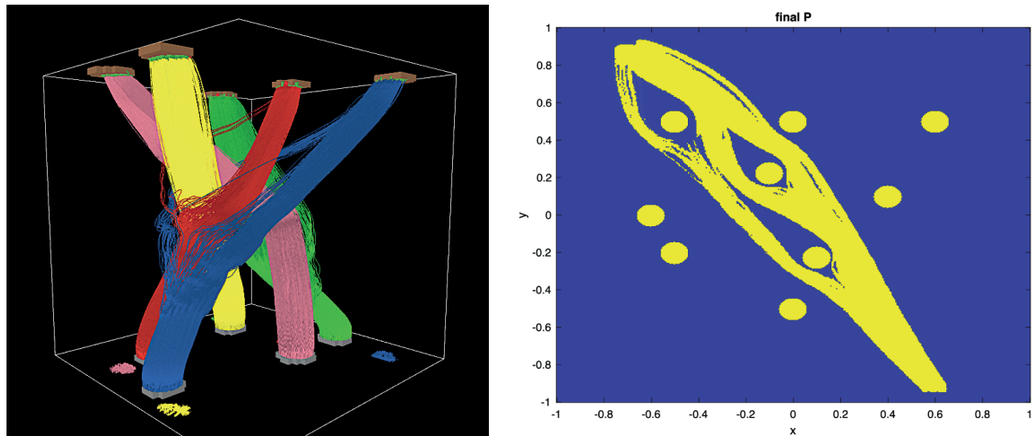

Fig. 3. To the left, simulation of swarms of 5000 agents depositing neural fiber bundles between randomly chosen origins and destinations. To the right, simulation of massive swarm of agents creating paths around obstacles from lower right to upper left.

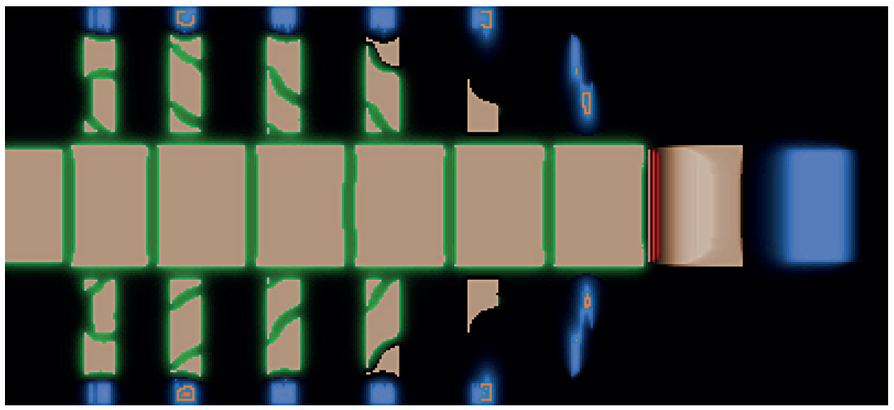

Fig. 4. Simulation of assembly of insect-like robot body frame using clock-and-wavefront process. Head end to left, tail end to right. Red color denotes wave of segmentation morphogen propagating to left, which has just passed through and differentiated the right-most tan segment. Similar processes are simultaneously assembling and differentiating leg segments.

Conclusions

Morphogenetic processes in nature can be imitated and adapted to control massive swarms of microscopic agents to assemble complex, hierarchically structured systems. Describing these processes by partial differential equations describing masses of infinitesimal particles helps to ensure that they scale up to very large numbers of microscopic agents, which is what will be required for the self-assembly of very complex structures, organized from the microscale up to the macroscale. In this way, we may hope to produce artifacts of a similar sophistication to those in nature.

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[2] R. P. Feynman, "There's plenty of room at the bottom," *Engineering and Science 23*, 1960, 22-36. https://resolver.caltech.edu/CaltechES:23.5.1960Bottom

[3] See, for example, A. Clark, *Being There: Putting Brain, Body, and World Together Again*, Cambridge, MIT Press, 1997, and G. Lakoff, M. Johnson, *Philosophy in the Flesh: The Embodied Mind and its Challenge to Western Thought*, New York, Basic Books, 1999.

[4] B. J. MacLennan, "The U-machine: A model of generalized computation," *International Journal of Unconventional Computing 6*, 2010, 265-283.

[5] On artificial morphogenesis, see for example B. J. MacLennan, "Morphogenesis as a model for nano communication," *Nano Communication Networks 1*, 2010, 199-208, and B. J. MacLennan, "The morphogenetic path to programmable matter," *Proceedings of the IEEE 103*, 2015, 1226-1232.

[6] On morphogenetic engineering, see for example R. Doursat, H. Sayama, O. Michel, "A review of morphogenetic engineering," *Natural Computing 12*, 2013, 517-535, and H. Oh, A. R. Shirazi, C. Sun, Y. Jin, "Bio-inspired self-organising multi-robot pattern formation: A review," *Robotics and Autonomous Systems 91*, 2017, 83-100.

[7] B. J. MacLennan, A. C. McBride, "Swarm intelligence for morphogenetic engineering," in A. Schumann (ed.), *Swarm Intelligence: From Social Bacteria to Human Beings*, Boca Raton, Taylor & Francis / CRC, 2020, 9-54.

[8] B. J. MacLennan, "A morphogenetic program for path formation by continuous flocking," *International Journal of Unconventional Computing 14*, 2019, 91-119.

[9] B. J. MacLennan, "Coordinating swarms of microscopic agents to assemble complex structures," in Y. Tan (ed.), *Swarm Intelligence, Vol. 1: Principles, Current Algorithms and Methods*, PBCE 119, Institution of Engineering and Technology, 2018, Chap. 20, 583-612.

[10] J. Cooke, E. C. Zeeman, "A clock and wavefront model for control of the number of repeated structures during animal morphogenesis," *Journal of Theoretical Biology 58*, 1976, 455-476. M.-L. Dequéant, O. Pourquié, "Segmental patterning of the vertebrate embryonic axis," *Nature Reviews Genetics 9*, 2008, 370-382.

Exploring chaos with analog computers

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This article shows how chaotic systems and their behaviour can be explored using analog computers instead of the now prevalent digital approach.

Many natural systems, even very simple ones such as a damped pendulum with an external driving force exhibit chaotic behaviour. One of the main characteristics of such systems is their extreme sensitivity to changes in initial conditions, something often called the "Butterfly Effect." Although these systems are fully deterministic and thus can be described mathematically in closed form, which implies that their future behaviour is completely determined by their past and thus their initial conditions, they are nonetheless not predictable. The term "chaos" was characterised by Edward Norton Lorenz, one of the founders of modern chaos theory, as follows: "*Chaos: When the present determines the future, but the approximate present does not approximately determine the future.*"[2] Interestingly, Lorenz did his groundbreaking work on a tiny digital computer, a Royal McBee LGP-30[3] which is only marginally suited for exploring chaotic systems at best.

To introduce the idea of an analog computer, a short recapitulation of the basic operation of a stored-program digital computer might help: A modern digital computer (typically) has a fixed internal structure, *i.e.* there are one or more arithmetic logic units (ALU), there is a central memory system (nowadays supplemented by a hierarchy of cache memory subsystems to speed things up), and there is a central control unit in addition to a number of input/output channels, *etc.* All of this is controlled by means of a stream of instructions, an "algorithm," stored in memory. At every moment such a machine executes one or more instructions from memory and may decide which instruction to read and process in the next step based on the result of prior instructions executed. So the execution of a program on such a digital computer is basically strictly sequential. (There are, of course, parallel digital computers but exploring this parallelism and achieving a high degree of parallelism is typically at least difficult and most problems won't scale well with this respect.)

In contrast to this, an analog computer has no fixed internal structure, it even has no memory at all and is not programmed by a sequence of instruction to be executed. At its heart an analog computer consists of a number of computing elements, each of which implements a basic operation such as summation, integration, multiplication, *etc.* Values are typically represented in a (basically) continuous form as voltages or currents and not as sequences of bits. (There are, indeed, "digital analog computers," so-called "Digital Differential Analysers," DDAs for short, but these are outside the scope of this article.) Programming an analog computer means to devise a scheme by which the various computing elements are interconnected in order to form a "model," an "analogue" for the problem to be solved.

Although analog computers have been largely forgotten for the last decades due to the low price and ubiquity of stored program digital computers, they have some advantages over their digital rivals, most notably they are extremely energy efficient (in most modern applications for analog computers this high degree of energy efficiency will be the main driver for their application), they interface well to our analog world, and they are inherently interactive. This interactivity is one of the key advantages when it comes to the study of dynamic systems in general and chaotic systems in special, where a researcher can easily change some parameters and "see" the effect in realtime on some output device such as an oscilloscope.[4]

Figure 1 shows a modern analog computer, an Analog Paradigm Model-1 in its basic configuration. The top chassis contains (among