Nikolaus Correll, Michael Friedman, Karin Krauthausen

Interview with Nikolaus Correll: Robotic Materials

MF: We would like to begin with how you perceive yourself in the field of active matter and active materials. There is a wide range of adjectives that are attached to these active materials, like ‘smart,’ ‘robotic,’ ‘autonomous,’ and so on. How would you describe the development of your research in this field? And how would you characterize robotic materials – a category that you and Richard Voyles introduced into materials science already in 2014?¹

NC: I see myself as a proponent of computation in the field of smart materials. But the word ‘smart’ is overloaded; there is also a lot of discussion about active materials. I created the term ‘robotic materials’ because I come from robotics and my research is on materials for robots. Robots are placed in the real world and must therefore respond to an often uncertain environment. Robotic materials can take an active part in this challenge since they integrate acting and reacting into the material itself [Mengüç et al. 2017]. I think a robotic material is the ultimate smart material because it actually behaves like a robot – for example, it can move, it can change its shape, and its appearance [Hughes, Heckman, and Correll 2019]. It is about a new class of metamaterials that tightly integrate sensing, actuation, computation, communication, and power routing in a periodic fashion.²

To return to the first part of the question, I am a proponent of computation and I have a training in electrical engineering, where you learn about signals, systems,

¹ For the first mention of the concept of robotic materials as a new class of materials, see: [Correll and Voyles 2014]. Since then the research field of robotic materials has become more and more important. Cf. the documentation of the workshop “Robotic Materials” (Washington, DC, April 23–24, 2018) in [Correll et al. 2018, pp. 1–16]. Apart from at Correll’s laboratory at the University of Colorado Boulder (since 2009, online: <http://correll.cs.colorado.edu/> (Accessed May 5, 2021) research is also being carried out at the new Robotic Matter Lab in Evanston, Illinois, led by Ryan Truby at Northwestern University (starting fall 2021) and the new department Robotic Materials led by Christoph Keplinger at the Max Planck Institute for Intelligent Systems in Stuttgart (also starting in 2021).

² The term ‘metamaterials’ is referring to materials that “overcome the limitations of classical composite materials” [Correll and Voyles 2014]. Since first presenting the concept of robotic materials in 2014, Correll has written on various occasions about this class of materials (together with Richard Voyles and others but also on his own). Robotic materials are defined as: “[...] an emerging class of metamaterials that tightly integrate sensing, actuation, computation, and communication. Such ‘robotic materials’ extend the class of composite materials by providing them with autonomous functionality. In particular, they enable off-loading signal processing and control into the material” [Correll 2019, abstract].

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and controllers, as well as mathematical analysis or flow diagrams. Very few people in the materials sciences would speak about programming in the way an engineer would. When they speak about programming material, they usually mean something like heating a material up and getting a phase transition and freezing it in this state. Then, when you heat it up again, the material restores itself. There is a huge disconnect when I say that I program the material because what I have in mind is to describe the response algorithmically. This is actually a continuum. What I like to use as an example is a simple feedback controller, that is, I measure something and then decide whether it has to go faster or slower. You can do this in many different ways, either purely mechanically or by using something that swells and then shuts off, acting like a valve. When there is too much of a liquid there, it will shut off the flow of liquid. That is a feedback controller. Or you could have a centrifugal governor, which is a simple flywheel mechanism like the one used to regulate the rotational speed of a steam engine. The flywheel pulls up a weight, which in turn regulates the steam. By changing the weights, you can regulate the speed at which the engine is throttled. However, I could also say I can measure it and run it through an electronic circuit, such as an operational amplifier, that implements this computation, but it would not be very variable at all. And, of course, I can really program it using computer language using a microcontroller that is connected to sensors and actuators.

One can take the human body as an inspiration, because it is carefully tuning where the signal processing happens. Does the signal processing happen in the brain or is it autonomous, like in the colon? Is it integrated in the material or is a nervous system involved?

MF: Hence, in your research, you are asking where the computation is actually taking place. I think that this is a crucial aspect of robotic materials: the program does not have to be centrally controlled. Do you see this as some sort of design shift or just a shift in how materials are actually being perceived?

NC: The people who make active materials – for example, something that exhibits phase transitions like changing color – would probably model an active material with differential equations. I can describe this same transition computationally. But irrespective of how you model it, either using equations or computation, the active material implies computation – and nevertheless it is not a computer. For me, the centrifugal governor is also about computing, even a clock is about computing. If you build a clock, you will think about gear ratios, so you actually hard wire the computation. When does it become a computer? I think the transition is very fluid. If you think about the Turing machine or, more explicitly, the universal Turing machine, this is a mathematical model for any kind of computation,³ a simple device,

3 A 1936 paper on computing by Alan M. Turing proposed an answer to the so-called *Entscheidungsproblem* (decision problem) raised in 1928 by the mathematicians David Hilbert and Wilhelm

but with it Turing was able to demonstrate the properties of computation in general. Whatever can be computed can already be computed with a Turing machine, and what is not computable with a Turing machine is not computable at all. The original Turing machine is about a central processing unit that controls all data manipulation. The universal Turing machine is even more abstract, as it is the simulation of an arbitrary Turing machine and allows a second-order observation on the machine and the input.

Hence the question is: why or when is a computation a Turing machine? If you take the NAND gates in digital electronics, you build a computer up with NAND gates in a simulator; then you have a universal Turing machine and can build the rest of the computer, that is, you can program *Tetris* to run on it (see Fig. 1).⁴

A NAND gate is a NOT–AND gate, hence a universal binary logic gate that has the property of functional completeness, which means that any Boolean function can be implemented by using a combination of NAND gates.⁵ A NAND gate can be made from two, sometimes four, transistors. Therefore, a NAND gate, and hence a universal Turing machine, can be constructed from anything that works like a transistor, for

Ackermann. Hilbert and Ackermann doubted that there could be a formal procedure (an algorithm) for deciding on the universal validity of a mathematical axiom – nevertheless they still asked for one. On the *Entscheidungsproblem*, cf. [Hilbert and Ackermann 1950 (1928), pp. 112–124]. See also [ibid., p. 112]: “From [the previous] considerations [...], there emerges the fundamental importance of determining whether or not a given formula of the predicate calculus is universally valid.” Turing was able to prove that such a formal procedure is not possible. With his model, he formalizes (among other things) mathematical procedures, that is, the calculation of numbers. And although Turing speaks of a concrete “computer and his tape” and sees the processing as a “physical system,” this computer is an abstract machine in the sense that for any computational work of a computing machine one can construct another machine that does the work of the first computing machine by observing the first machine and reading the work instructions [Turing 1937, p. 250]. See also the famous definition of computer in [ibid., p. 232]: “If an *a*utomatic-machine prints two kinds of symbols, of which the first kind (called figures) consists entirely of 0 and 1 (the others being called symbols of the second kind), then the machine will be called a computing machine.”

4 A NAND gate is a “primitive logic gate” (a logic governor) based on Boolean algebra that can be used to build other logic gates in order to get a standard set of gates that can be used to construct a computer’s processing and storage chips [Nisan and Schocken 2005, p. 7]. See also [ibid.]: “Every digital device – be it a personal computer, a cellular telephone, or a network router – is based on a set of chips designed to store and process information. Although these chips come in different shapes and forms, they are all made from the same building blocks: Elementary logic gates. The gates can be physically implemented in many different materials and fabrication technologies, but their logical behavior is consistent across all computers.” For Simon Schocken and Noam Nisan’s courses “From NAND to Tetris: Building a Modern Computer from First Principles,” which became quite famous and formed the basis of their publication, see: <https://www.nand2tetris.org/> (accessed April 10, 2021).

5 Functional completeness means that any Boolean function (hence any other logic function and even an entire processor) can be implemented by using a combination of NAND gates [Mano, Kime, and Martin 2008, pp. 81–85].

Fig. 1: A computer architecture (from physics and hardware to software). From: [Nisan, Schocken 2005, p. xvi, Fig. I.1]. © 2005 Massachusetts Institute of Technology, by permission of The MIT Press.

example, something that swells like a switch and by doing so controls the emission and flow of signals. You could also have something like a chemical process that does this kind of switching and works like a transistor. This kind of computation is complementary to morphological computing [Pfeifer and Gómez 2009], where a body's structure and morphology can contribute to control and cognition in natural or artificial systems, and the two can work together nicely.⁶ An example for this task is the artificial 'sensing skin' that you have seen in my laboratory (see Fig. 2).

Fig. 2: A soft, amorphous texture-sensitive skin mounted on the back of a Baxter robot. From: [Hughes and Correll 2015, fig. 1]. © 2015 IOP Publishing Ltd.

This computational metamaterial is for texture recognition. The idea comes from the human skin, which includes many different sensors for measuring static and dynamic information with highly varying bandwidth, like pressure, shear, temperature, and textures. To replicate such a sensing system is a challenge for engineering. We constructed a robotic material that samples and processes high-bandwidth information locally and addresses a central processing unit only when an event occurs. Our design considers the skin as an amorphous material capable of processing stimuli within the material itself. Omnidirectional microphones serve as vibration sensors, and we collocate microcontrollers with these sensors (see Fig. 3) [Hughes and Correll 2015]. If you mount this texture-sensitive skin on the back of a Baxter robot, it will augment the robot's environmental awareness when navigating through an environment and when interacting with humans in order to assist them.

⁶ See the special issue on morphological computing in *Artificial Life* 19 (1) (2013). For a review and examples, see: [Müller and Hoffmann 2017].

The sensitive skin does a discrete Fourier transform of the frequencies it feels. In other words, it puts the different frequencies into different bins. Then I can look up the height of each of these bins and, as every material would create distinct frequencies, say this is wood or this is metal.

Fig. 3: System overview over a computational metamaterial that can identify and localize textures rubbed against it. Printed circuit boards and microphones are embedded in flexible rubber and suspended on a neoprene mesh. Figure is provided by Nikolaus Correll (a similar but slightly different figure was originally published in [Correll and Voyles 2014, fig. 1]). © Nikolaus Correll.

The sensor node network does exactly what the cochlea in the human ear does. The cochlea looks like a trumpet, that is, a channel that starts out wide and gets narrower and narrower, and the sound comes in and gets reflected inside. Since the function of the frequency that comes in depends on this geometry, you have different points in this grafted channel where you have resonance. The ear puts nerve ends into this channel and in this way is able to grab the frequencies. If you have a cochlea implant then it does exactly that, but in a computer, it takes the sound, it bins the frequencies, and then it excites the nerve ends.

For me, the interesting point of the sensing skin is the computation. I actually have a little computer that implements what is known as the fast Fourier transform (FFT). We programmed this – it is an algorithm that is very well understood and available in any textbook, such as *Numerical Recipes in C* [Press et al. 1992] – or I go and actually mechanically put in a grafted channel that is made for the frequencies that I am interested in, which is in the 250,000 Hz range, and physically put sensors at the right places to get my Fourier transform. Then I put little vibration sensors at these different points and I pull it into my computer. And then my computer does not have to do all these thousands of lines of code for the FFT. Unfortunately, the frequency range of vibrations is around 10 times larger than that of the audible

spectrum, making the wavelengths ten times shorter, and therefore an appropriate mechanism to measure vibrations 10 times smaller than the cochlea, which is difficult to make. Indeed the Cochlea in the human ear has a length of 9 mm when stretched out, whereas the Pacinian corpuscle, which is responsible for detecting vibrations in the human skin has a size of only 1 mm.

So, how and where to implement computation is a complete continuum spectrum with a wide variety of available tools.

MF: What you describe seems to be an interplay between discrete and continuum computations, because the skin is only computing the sound on several occasions, but it is not taking everything into account. This raises the following question: what is the correct modeling for the local sensing of the skin? If I rub my skin here, it does not matter what happens at the same time in my foot for example.

NC: You mean what is the correct distribution of where the computation should be? I always argue that, if you have high-bandwidth information and you have many sources thereof (like the textures that you want to detect), the Pacinian corpuscle, which is one of the four major types of mechanoreceptor cell in the human skin and especially sensitive to vibrations, receives the signals.⁷ That is the resonance frequency of the Pacinian corpuscle. It is still unclear what exactly the Pacinian corpuscles are doing. What we do know is that they take the continuous signal and turn it into spikes of neurons. I argue that there must be an information reduction, because it would be a complete waste to wire this kind of bandwidth to the brain. What the information reduction actually is we do not know, but it does take place in a certain way. And the Pacinian corpuscle does not send information when it does not have any. A computer camera always sends information even when there is nothing. The sensing body works differently: if nothing happens, it does not send anything to the brain. It is like when you get used to your clothes and do not feel them anymore. This is because the cells (they are called ‘slow adapting’) adapt to the stimulus and the fast adapting cells (like the Pacinian corpuscles) give you the changes. Thus, the body has all of these things, but there is very little computation. The skin is autonomous like the retina or the colon. They all preprocess things.

MF: And what you are attempting to build in your laboratory are materials that decide by themselves, materials that are decentralized and in this sense autonomous?

NC: That is exactly what I want. As an engineer, I create hypotheses by building. At the moment, we are building a camouflage skin for robots. The inspiration for this distributed particle system comes from the octopus, because the cephalopod skin has extraordinary camouflage capabilities. Octopuses change the color of their skin

⁷ On the mechanoreceptors of the human skin and their signaling, see: [Kandel, Schwartz, and Jessell 2000, pp. 430–441].

by using small structures known as chromatophores. These devices can expose pigments of a certain color by activating an annular muscle structure.

When we read the biological and physiological literature, we were quite confused: where is the camouflage pattern generated? It is not like a display – hence, the octopus is not controlling every pixel with its brain. Rather, the pattern is locally generated and self-organized.⁸ It is a Turing pattern, a differential equation, since it is a function of some parameters [Turing 1952]; different pattern schemes can be triggered by providing only a few parameters. That is what makes the cephalopod skin autonomous. We simulated the chromatophores with a miniature robotic platform, the ‘droplets,’ which look like ping-pong balls but can change their color using a built-in light-emitting diode. They are, of course, also equipped with a color sensor in order to register colors and patterns in the environment. We used a distributed computation for the information exchange between the droplets. For collectively performing a certain pattern type, the droplet swarm then uses a discrete version of Turing’s reaction-diffusion models (see Fig. 4).

The inspiration is not only going from the animal world to engineering. I think by looking at it from an information-theoretic perspective, you can in turn generate hypotheses for the physiologists. There is a nice paper by Barbara Webb in which she wonders how constructing robots can help us to understand insects and other small animals [Webb 2020]. You have a hypothesis on how their sensory motor system works, you build a robot that way, it works, you can show that in the mechanical world this information is sufficient to realize a certain function, so maybe the animal does it in a similar way. The robotic engineering generates a new hypothesis that physiologists and biologists can then test. I think such an exchange is valuable.

KK: With their capacity for coordinated sensing, information processing, and response activity, living systems are an important inspiration for the research on robotic materials. As you said, this stunning agency of living systems is not always derived from a central processing unit such as the brain; it can also happen locally, for example in the organs and hence in the ‘material’ itself. How would you describe the relation between ‘natural’ active materials like the skin of an octopus and ‘artificial’ active materials like the robotic materials that you are working on? And as a follow-up question: with these new kinds of robotic materials, what is or will be the status of robots?

NC: A robot is very complicated to make and we do not have any autonomous robots, except vacuum cleaners, that are doing anything reasonable. Biological systems are not made from the homogenous materials that are currently used to construct robots, such as links, gears, and joints. If you want to build something, you choose your

⁸ The camouflage of the octopus is not (or not only) driven by the animal’s visual system, as this is color blind, nor is it driven solely by the brain; rather it relies on local sensing and control [Correll 2019; Li, Klingner, and Correll 2018].

Fig. 4: Distributed particle system for artificial camouflage. (A) Chromatophores in the cephalopod skin show typical self-organized patterns. CC0 Public Domain (<https://creativecommons.org/publicdomain/zero/1.0/>). (B) Artificial camouflage can be realized by selecting both a pattern (here vertical stripes) and a color scheme by finding dominant colors in the environment. Reprinted by permission from Springer Nature: [Li, Klingner, and Correll 2018, p. 1639, fig. 2]. (C) Different patterns can be realized by a fully distributed, self-organized process, here showing speckle and striped patterns. Reprinted by permission from Springer Nature: [Ibid., p. 1643, fig. 8]. (D) Implementation on a swarm of miniature robots that can only communicate locally. Reprinted by permission from Springer Nature: [Ibid., p. 1657, fig. 12].

materials based on functional requirements. You go to Home Depot and buy materials because you have a function that needs to be satisfied. If you want to construct a table you probably buy wood – you will not use stone because the way you can work with wood is different, the weight of wood is different, it is lighter yet stiff enough for your application, and it maybe even has aesthetic benefits. However, if you want to have a really complex functionality then it helps to use materials where you can off-load functionality – if you want to build a robot that can manage the inflow of information from tactile events for example, as with sensing skin. If I did this in a conventional way, then all these signals would be wired to a central processor, as to the brain. The brain would get a lot of data all the time from millions of sensors and it would have to decide all the time which data to ignore. However, if you transfer this decision to the material – for example, the human skin or the artificial sensing skin – then it provides you or the robot with that functionality, and you do not have to do anything. And, when something happens, you get a high-level piece of information which says: I got touched on my back and I should probably look. I can then compose the robotic system out of these functional components in a much simpler way. Such

modularization makes things simpler. And that is how I think about robotic materials: they are multifunctional composites with autonomous functionality.⁹

If you take any materials science textbook on advanced composite materials, it will usually end with the bone. The authors of these books celebrate the bone as a very smart material and they will probably say that you should go and design your bridge like a bone structure. However, the bone that you have in your body is much more functional than any structure that one can build. The bone regenerates, and if you load it more it will grow stronger. And it also stores energy in terms of fat that you can draw on – people eat bone marrow from animals because it is high-energy and it generates white blood cells. The bone is actually a machine with sensing capabilities, and it even does information processing in some hard-coded way, that is, with lots of cells measuring the strain and then emitting a chemical substance that creates or attracts calcium. We need to have these kinds of materials for robotics in order for it to really advance.

KK: In this respect, do robotic materials blur the distinction between device and material, and maybe even between machine and material? You mentioned the first possibility in one of your articles on robotic materials.¹⁰

NC: Robotic materials are blurring the dynamics of the system and the control algorithm. In a way, this is already happening in the centrifugal governor – and I could build a centrifugal governor that is so small that you cannot see it, but I use the same principle. That is where the blurring happens.

All these biological systems are machines. You have atoms that make molecules and these are already machines, molecular machines – or materials. These molecules make cells, and then the cells make materials such as a bone. And now I have to correct myself: the bone is not a machine; it is a material and a device. There are many devices in the body that make it a complex machine, and all of these devices are only materials. The computer is also only a material. If I gave it to you and I

9 On the necessary conditions for an engineered structure to be called a “robotic material” see [Correll 2019, p. 297]: “[A robotic material should] 1. Consist of many homogeneous elements that are arranged in either an amorphous or a grid-like fashion. 2. Integrate computation with sensing or actuation in multiple elements. 3. Function independently of its size, that is, the number of constituent elements, for example, even when cut in half or rearranged in an arbitrary shape (scalable). 4. Not lose its capabilities even if individual units fail (robust).”

10 See [Correll and Voyles 2014, footnote 1]: “Advances in polymer science, miniaturization of computing, and manufacturing techniques have enabled a new class of robotic devices that embed sensing, computation, actuation and communication at high densities. This embedding can be so tight that the distinction between device and material blurs. This new class of materials has the ability to change its physical properties such as stiffness, density, weight, shape or appearance in response to external stimuli, and is able to adapt and learn. Here, the boundary between the dynamics of the physical system and control algorithms blurs, which allows trade-offs between morphological and silicon-based computation.”

gave you all the tools to analyze it, you would never figure it out. It is like giving you a bunch of atoms and then asking you what is going on? Why is it not exploding? Why cannot you just shake the atoms out?

MF: Would you claim that the structural point of view on bones that one often finds in materials science reduces the complexity of what is actually going on?

NC: Yes, that is what the materials community is stuck in: they see the stunning properties of the octopus arm and then think about making a liquid that could alter its stiffness or its color in a similar way, but they do not appreciate that the octopus has a nervous system. If you want to build something like an octopus arm then you have to put in a nervous system. Given the continuous nature of computing, you can do this in many ways, for example with polymer electronics and a neuromorphic architecture. Or you could implement the mathematical function – I can type it into the computer and compile it into a Turing machine, and then I have a million transistors that do that. That is actually amazing.

MF: This brings me to another question: what is the relation of your research on robotic materials to nature? Are there materials that nature either cannot combine together or that nature simply does not have? And then what kinds of materials do we get? You would not call these ‘bioinspired’ would you?

NC: You get supranatural materials. For instance, wireless communication is supranatural. If I build a gripper that has all the tactile information that you have as a human, but which can also see its environment and even the 3D geometry of any object, then with this robotic material I actually get supranatural grasping and manipulation abilities.

MF: I will explain why I asked the question. You mentioned Barbara Webb, a professor of biorobotics at the University of Edinburgh. She argues that bioinspiration works in two ways: robotics can learn from biology a lot about smart materials and biology can learn from robotics about how to understand animal physiology and behavior.¹¹ The question that came to my mind was: why should this be an argument for robotics? Why cannot we just build robots that function better than earlier devices?

NC: The question is: does building robots contribute to anything or are we just wasting public money? Webb argues for people like me who build cockroach-like robots. She says that this is actually an efficient way to generate hypotheses and advance

¹¹ See [Webb 2020, p. 244]: “It is an engineer’s dream to build a robot as competent as an insect at locomotion, directed action, navigation and survival in complex conditions. But as well as studying insects to improve robotics, in parallel, robot implementations have played a useful role in evaluating mechanistic explanations of insect behavior, testing hypotheses by embedding them in real world machines.”

our understanding of natural systems. I ask myself the same question: what can we contribute to biology? We build these swarm droplets that can form camouflage patterns, we show that they can recognize their environment and then decide what camouflage pattern to perform in a fully distributed way. This is not what the octopus does when exhibiting camouflage, because the octopus does it in the brain. It has a semantic understanding of its surroundings, which means that it knows that it is in a cave or near food or in a kitchen, and then it decides what to do, and this is high-level reasoning. Our swarm works differently. However, I still think we can contribute to biology – for instance when the famous octopus researcher Benny Hochner wonders how the octopus can control millions of tactile and chemical sensory cells (activators) distributed all over the body, arms, and suckers [Hochner 2012].¹² In neurobiology, one tries to understand how the central nervous system can work as a controller and coordinate sensory feedback and motor commands (see Fig. 5). This is not so far away from robotics.

So how do I know what to do with hundreds of activators? The robotics people have written down all the equations which are very complicated and very difficult to compute. Then how can the octopus compute the huge amount of sensory information? The biologists do not know. I was thinking about a similar problem when building a multisegment shape-changing material that consists of variable-stiffness elements. Each was equipped with a networked computing element, and I wanted a simple way of computing it. I asked myself: what happens if I only change one of the cells in this robotic material? In my laboratory, we then tried to get closer to that and found a distributed algorithm for calculating the inverse kinematic solution for the resulting *N*-body system [McEvoy and Correll 2018]. We also developed a communication model based on a central element collecting information from its neighborhood (see Fig. 6).

The way the algorithm works is to compute how a single piece of the arm would need to change so that the tip would get closer to its goal. We are doing this for every piece from the beginning to the end of the arm, and then start over, until the arm reaches its desired end point. That is, the computation literally travels along the arm in wave-like patterns. And then I read that the octopus's nervous system activation pattern actually has something like this [Gutfreund et al. 1996; Gutfreund et al. 1998; McEvoy and Correll 2018]. Does it work exactly like that? We do not know, but we have provided an explanation that is actually feasible given what else we know about the octopus nervous system. In general, we roboticists feel that neurobiology is extremely important in helping us to see where robotic material should go.¹³ Because

¹² Hochner is referring to the concept of ‘embodied organization,’ which is important for roboticists. According to Hochner the term “implies the dynamic interplay of information and physical processes between four components comprising the embodied creature: the controller, the mechanical system, the sensory system and the task-environment [...]” [Hochner 2012, p. R887]. On ‘embodiment’ see also: [Pfeifer, Lungarella, and Iida 2007].

¹³ For a review, see: [Webb 2017].

Fig. 5: Scheme of embodied organization in a living system. From: [Pfeifer, Lungarella, and Iida 2007, p. 1089, fig. 1]. Reprinted with permission from AAAS.

neurobiologists study the nervous system and how the animal is built. If I did not know that two-thirds of the neurons are in the octopus's arms, I do not think I would be so excited about pushing to make materials that way.

MF: Your research includes a lot of mathematical modeling, and you model in very different ways, for example with partial differential equations or with probabilistic methods. How do you actually combine this mathematical modeling with robots?

NC: Yes, the modeling and implementation is very difficult. Take, for instance, the two-bridge experiment with Argentine ants that Jean-Louis Deneubourg, a professor at the Université libre de Bruxelles, did. In order to understand when and how the transition from unorganized exploring to organized pathfinding happens in the ant colony, the researchers installed a diamond-shaped bridge; hence, a bridge that allows two different paths, between the ant's nest and a source of food. Initially

Fig. 6: Communication model of a robotic material beam with shape-changing properties. From: [McEvoy and Correll 2018, fig. 5]. © 2018, Mary Ann Liebert, Inc.

choosing between both paths at random, the ants quickly converge onto the shortest path.¹⁴ At its heart, this can be modeled by a nonlinear system with an attractor for the mathematical equivalent of the shortest path [Deneubourg et al. 1990].¹⁵ Obviously, nonspatial differential equations can describe very well the number of ants on each bridge.

In a similar experiment, we let a swarm of cockroaches choose between two shelters in a circular arena [Halloy et al. 2007]. Here, the same equations as with the bridge experiment are used to model the number of cockroaches underneath each shelter. But that assumes that I have a uniform distribution and that the animals' behavior is so simple that they end up in a Brownian motion and are creating this uniformity. Now the animals' behavior is actually not that simple because the cockroaches like to wall-follow, running in circles around the arena instead of congregating under the shelters. Hence, I have to think whether to put in a third equation that models the number of insects that wall-follow. Or I start modeling it in a spatial way so that I have a partial differential equation that describes the distribution over

¹⁴ The researchers modeled the ant behavior with a Monte Carlo simulation.

¹⁵ For the thermodynamic view on instabilities in reaction-diffusion systems (far-from-equilibrium systems) and the role of attractors, see: [Prigogine and Stengers 1984, pp. 146–153].

space. What is needed is spatial computing or amorphous computing.¹⁶ In our research, we actually found a couple of problems which do require that.

In my thesis at the École polytechnique fédérale de Lausanne in 2007, I had a jet turbine inspection case study with a swarm of robots [Correll and Martinoli 2009]. The swarm should inspect the turbine blades by going around them (Fig. 7). You can model this and uniformly distribute the robots. Basically, you draw random blades and put the robots in and see how long they take for this task. That is the simplest model. We also built more complex models, but when we tested them in experiments they did not match. Hence, you have to take into account the actual geometry of this environment. The robots were programmed to hit the blades at some point and then always do a right turn and go around, then go around one more time, and once they detected the tip they should leave. With this, we wanted to make sure that the swarm covers the entire turbine. Now if the robots always leave in the direction of the tip you get a very obvious distribution that is highly skewed to this result [Prorok, Correll, and Martinoli 2011]. Whereas when you release them in a uniform way, the chance that this blade is covered is much lower.

The problem is that you are locked into certain mathematics and you can only make it more versatile by simulating the system in a physical environment. You have to simulate every individual robot and how it moves. We also had robot simulators, and we would see that the swarm behaves the same, because the robots would also leave. The simulator is like a 3D computer game. We can use the computer game as a predictor. And the hope with this ‘multilevel modeling,’ as my advisor Alcherio Martinoli called it, is always that you have many layers of abstraction, and in the end, you get this one equation that is the takeout.

When you do research on ant behavior, it is similar: you have to write down the differential equation, but you also have to think about the geometry of the environment. At the end of the day, you have to model every single aspect including the ant’s emotional state and if it is hungry or not hungry. It is a Pandora’s box of problems. I got a little bit away from this because the models are so limiting. However, I

16 On spatial computing as a manipulation of referents to real objects and spaces, see: [Greenword 2003]. For the first manifesto on amorphous computing, see [Abelson et al. 1996, n.p.]: “A colony of cells cooperate to form a multicellular organism under the direction of a genetic program shared by the members of the colony. A swarm of bees cooperates to construct a hive. Humans group together to build towns, cities, and nations. These examples raise fundamental questions for the organization of computing systems:

- How do we obtain coherent behavior from the cooperation of large numbers of unreliable parts that are interconnected in unknown, irregular, and time-varying ways?
- What are the methods for instructing myriads of programmable entities to cooperate to achieve particular goals?”

The authors of the manifesto refer to [Prigogine and Stenger 1984] and [Turing 1952]. For an introduction with examples, mathematical tools for computing, and programming styles, see: [Stark 2013].

Fig. 7: Simulation of swarm robots on an inspection tour between the blades of a turbine. From: [Correll and Martinoli 2009, p. 110, fig. 10]. © 2009, IEEE.

often use the Gillespie algorithm, a variant of the Monte Carlo method [Gillespie 1976]. With that, you basically just simulate and see what happens in your complex system. But I have to admit that I prefer actually to build stuff [Correll et al. 2022].

KK: That brings me to our last question: how do you see the relation between fundamental research and engineering (or applied science), especially in the field of active matter?

NC: There has always been a tension between science and engineering, which actually exists less now because the engineers try to be hypothesis driven too. The design loop is to identify a problem and then think about solutions and then carry out tests. So the engineers actually do the same thing as the scientists, but they are goal oriented. I think it is called teleological research science.

My research on robotic materials is sometimes misunderstood, as one might think we are only putting things together without a more fundamental approach. I can say that I am doing fundamental algorithms – not the mathematics of nonlinearity and dynamics but fundamental algorithms. I am trying to prove that I can build anything mechatronic by putting together smart particles like the droplets, akin to cells in biology. However, it is not possible to build everything with such an approach. You can just build the subset that biology does. You cannot build an animal that is the size of the Eiffel Tower. It does not exist in nature because of some physical limitations.

I think today's materials are so interdisciplinary that they require integration and the integration is by default engineering (vs. science). In my view, what we need to have is an academic center for the science of the integration of materials – preferably materials that integrate sensing, actuation, and communication. It would change the world completely to make active materials the way I want them to be. One has to pull it off.

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Nikolaus Correll is an associate professor in the Computer Science Department at the University of Colorado Boulder and the director of the Interdisciplinary Research Theme “Multi-Functional Materials” at the College of Engineering and Applied Science. Nikolaus obtained his PhD in computer science from the École polytechnique fédérale de Lausanne (EPFL) in 2007, working with Alcherio Martinoli, and a diploma in electrical engineering from the Eidgenössische Technische Hochschule Zürich in 2003, with stints at the Technical University of Munich, Lunds Tekniska Högskola, and Caltech. From 2007 to 2009, he was a postdoc at the Massachusetts Institute of Technology, working with Daniela Rus. His research interests are materials that integrate sensing, actuation, computation, and communication, for which he coined the term ‘robotic materials,’ with particular emphasis on applications in robotics, including smart skins that can camouflage and sense touch, tactile sensing, shape changing materials, robotic muscles, as well as grasping and manipulation. Nikolaus’s research has been awarded with an NSF CAREER Award, a NASA Early Career Faculty Fellowship, the Provost Achievement Award, and multiple Best Paper Awards at international conferences.