Intelligent Systems Research

Curators: **Joachim Spatz & Stefan Schaal**[1]
Max Planck Institute for Intelligent Systems

Intelligent systems are systems that can perceive, create action, and learn in an autonomous fashion, i.e., without external supervisory intervention for an extended amount of time. Figure 1 depicts a generic control diagram for such systems. There is a system to be controlled, i.e., the "control system" which lives in a particular, potentially stochastic, environment. Both the control system and the environment have some form of dynamics, for instance Newtonian dynamics for a simple particle that may live in a fluid, modeled by Navier-Stokes equations. The controller is supposed to create some form of actuator commands that make the control system accomplish a desired behavior. The controller receives noisy signals from some sensors, processes these signal to

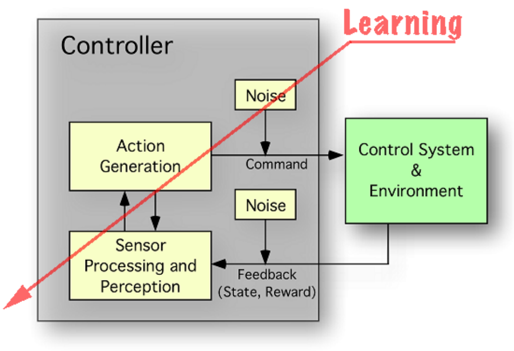

Figure 1: Generic diagram of a perception-action-learning system

form a more task relevant percept, and generates some actuator commands from this information to be sent, possibly via noisy channels, to the control system. In order to adapt to novel situations, the controller may need to have a learning component that can improve performance on the desired behavior.

The abstract diagram in Figure 1 applies partly to synthetic and biological systems. Nature has provided us with a plethora of examples of intelligent systems. On a large or macroscopic scale, human and non-human animals are part of our daily experience. On a smaller length scale, we may admire the almost infinite number of different insects, which, despite rather small nervous systems, still fulfill our definition of intelligent systems with unparalleled excellence. But we can even further reduce the length scale to the micro of even nanometer domain, where bacteria or cells are examples of systems that adhere to the abstract control diagram of Figure 1.

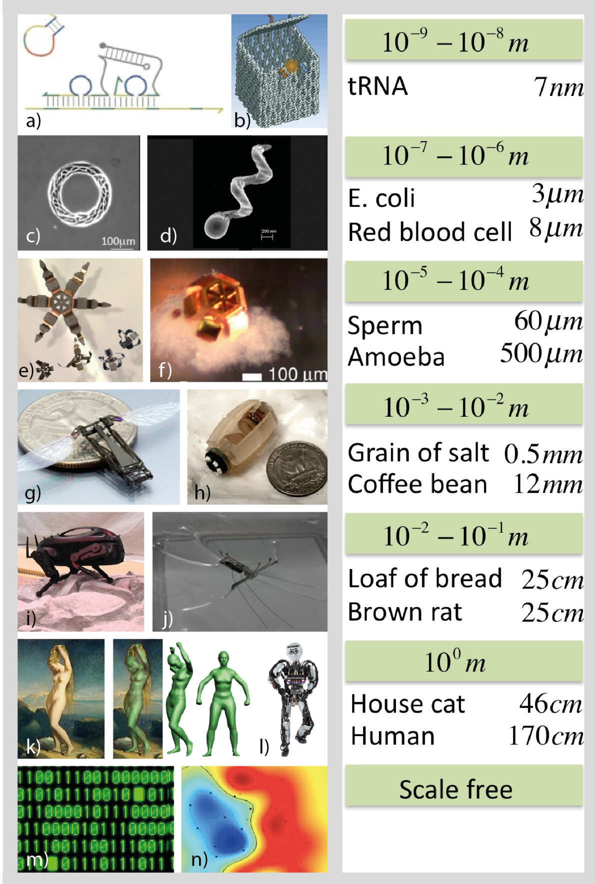

Figure 2: Research on intelligent systems at many length scales, from the nanometer to the meter scale, also including scale-free or theoretical work. The right column provides the relevant length scale and examples from biology for this scale. The left column shows synthetic systems from a) DNA walkers [1] or b) DNA self-assembly into 3D geometric structures [2], c) Prokaryotic cells forming a swarm guided by material properties [3], d) a corkscrew design that could help nanobots tunnel through viscous fluid [4], e) and f) chemically actuated micro grippers [5], g) micro-robotic insects [6], h) a micro-robotic capsule endoscope [7], i) a small robot dog that learned to autonomously walk over rough terrain [8], j) an insect-like water-striding robot [9], k) a perceptual system estimating body shape and pose from paintings using shading [10], l) an advanced humanoid robot [11], m) and n) scale free computing and machine learning [12].

Figure 2 depicts a variety of systems and research topics in intelligent systems at different length scales. Each system has to realize some form of perception-action-learning cycle, but when traversing the length scales, the relevant physics for the control system and the environment change, as does the hardware that is capable of sensing, actuation, and computing. Understanding intelligent systems at each of these length scales, and, moreover, understanding the commonalities and differences in sensing, actuation, and computing as scales change is one of the key scientific challenges of research in intelligent systems. Studying realizations of intelligent systems in biology and what principles are required to synthesize such systems in artificial, biological, or even bio-hybrid hardware is one of the grand challenges for the 21st century.

[1] We gratefully acknowledge the contributions of Michael Black, Bernhard Schölkopf, and Metin Sitti in this perspective.

1 How Length Scales Affect Physics, Sensing, Actuation, and Computing

As a guideline for some of our following discussions, it is useful to characterize how the physics change when length scales change, and what this implies for sensing, actuation, and computing in intelligent systems.

1.1 Gravity vs. Friction and Surface Tension

On the macroscopic level, e.g., the size of dogs, humans, or elephants, inertial forces are dominant. Or, in simple words, on this level, we are dominated by mass and gravity. Viscous forces are negligible in comparison to inertial forces. Since about 150 years ago, the Reynolds-number (Re) is used as a measure to characterize this effect: it is defined as the ratio of inertial forces to viscous forces (Re= inertial force/viscous force) acting on a system in motion. Macroscopic systems are in a domain where Re>>1.

When shrinking the size of a control system to the level of insects, several interesting changes take place. First of all, gravity and mass become less important, characterized by Re~1. For instance, falling from a 10-meter high roof is disastrous for a human, but does not matter at all for a beetle, as the forces of the air during falling break down the fall of the beetle significantly. With this little mass, forces like surface tension become suddenly quite significant relative to gravitational forces. Thus, with the right kind of hydrophobic (water-repellant) leg material, some insects can actually walk on water. The ratio of inertial forces to surface tension forces is often characterized by the Weber-number (We=internal forces/surface tension forces), where We<1 for all water walking insects [13], and We>>1 for humans, such that humans have no chance to walk on water.

Going to the micro or nano scale, Re<<1, such that fluid dynamics and thermal effects play suddenly the most significant role, as described in more detail below.

1.2 Determinism vs. Stochasticity

Stochastic events, e.g., caused by thermal effects such as Brownian motion in fluid mechanics, have no significant impact on macroscopic systems, i.e., the actuation of the system easily overcomes stochastic events in the environment. But it is dominant, largely unexplored nor constructively used for the control of small-scale systems' perception-action cycles. In fluid dynamics, the Péclet-number is used to measure such effects. Formally, the Péclet-number is defined as the ratio of transport caused by convection to transport by Brownian motion (Pe = convective transport/transport by Brownian motion). We apply this concept to intelligent systems, and Pe>>1 would characterize macroscopic systems, which are largely deterministic in their behaviors. At small length scales, Pe < 1 means that transport is influenced by Brownian motion, in other words, small-scale objects are randomly jostled by colliding water molecules around them. The effect of everything being shaken around continuously requires new design principles for control at small scales, e.g., stochastic control of large swarms of systems, and opens also new opportunities for the design of intelligent systems.

1.3 Mechatronics vs. Material Science

Realizing synthetic macroscopic systems, we have a fair amount of space to design sensors and actuators. This domain is typically addressed by mechatronics research, where design principles revolve around mechanical systems, new materials and fabrication methods (e.g., composite materials and 3D printing), electrical effects, magnetic effects, optical effects, etc. Sensors and actuators remain fairly big, and so far, are far away from what nature realized with biological materials in terms of energy efficiency, density of sensors, and mechanical properties of actuators.

Fabricating synthetic systems on a millimeter scale is not the domain of traditional mechatronics anymore, but requires special fabrication processes (e.g., laser micro-machining followed by folding processes, photolithography, and 3D printing) and novel materials. Sensors and actuators for a millimeter size system quickly become sub-millimeter components and start to require special principles, fabrication techniques, and materials.

Sensing in micro and nano systems can be accomplished by chemical reactions, optics, magnetism, etc. The conversion of sensed information into commands to the actuation system is now a direct, reflex-like connection, not unlike what was suggested more than 30 years ago by Braitenberg for some simple robotic systems [14].

1.4 In Silico or Not

Information processing in macroscopic systems typically happens in the domain of tens of milliseconds for reflexes up to several seconds for more cognitive processes. Silicon-based computing hardware is well suited to for these requirements and the space available in macroscopic systems. For more cognitive processes, researchers have begun to investigate "computing in the cloud" [15], e.g., to use vast networks of databases and servers to recognize complex scenes and plan intricate behaviors.

There is not much space left for computers in millimeter size intelligent systems, which limit all of the on-board system components severely in respects of size, performance, lifetime, and weight. Still, this is a domain where silicon-based computing could work, but the luxury of massive deliberative computing as in macro-scale system is gone. Moreover, millimeter systems often act on very fast time scales, e.g., the domain of a few milliseconds. Not surprising, small scale animals are mostly dominated by reflexes and rather stereotypic behaviors that can be realized by smaller nervous systems at very high speed [16]. In synthetic insects, computing is currently kept mostly outside of the system and routed to an external standard digital computer.

Information processing on the nano scale is beyond our current silicon-based computing paradigm,

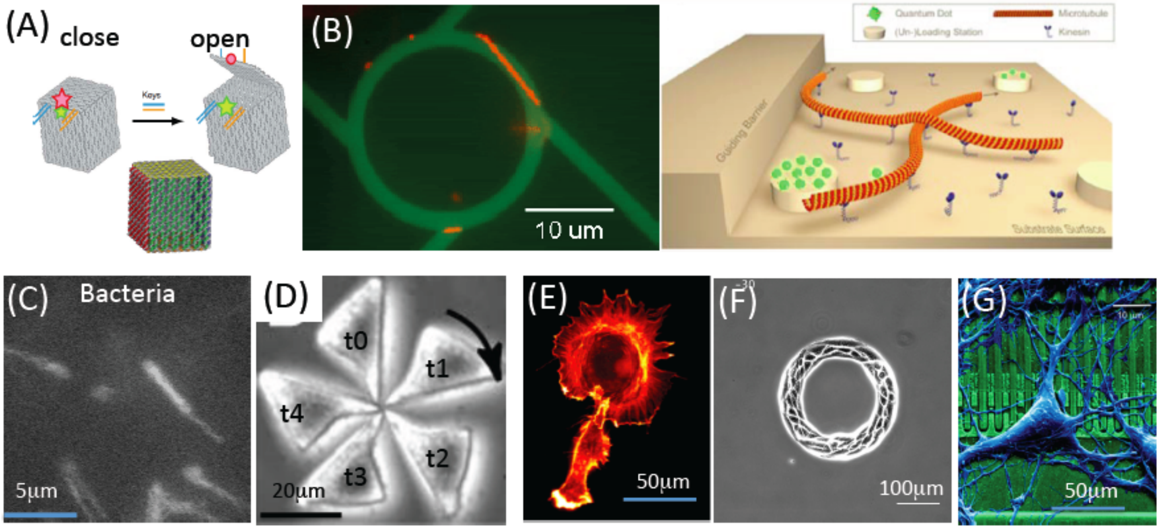

Figure 3**:** Natural models of small-scale machines: (A) DNA can be programmed to self-assemble into defined structures, such as containers. By playing with the programmable affinities of DNA these containers can be opened and closed on demand [2]. (B) Molecular motors such as Kinesin and Myosin are nature's smallest motors. They convert chemical energy (ATP) into mechanical energy through structural changes in the motor protein. Concepts for using such motors in biotechnical applications exist (example from the MPI for Molecular Cell Biology and the University of Dresden) [17]. (C) Bacteria can swim either individually or collectively in water, also called swarming. The attachment of flagellated bacteria to a solid surface promotes a synergistic, collective swarming behavior involving thousands of bacteria, which results in the coordinated translation and rotation of the surface [18]. (E) Prokaryotic cells from the immune system, such as dendritic and antigene presenting cells, form synapses defined by molecular specificity and arrangement for communicating information from one cell to another. (F) Prokaryotic cells can also form swarms. The cells within the swarm form a collective, exhibiting coordinated, synergistic behavior (E and F are examples from the MPI for Intelligent Systems) [3]. (G) Neurons in networks synchronize in order to provide a coherent output (example from the MPI for Biochemistry) [19].

and becomes a domain of chemical reactions, electro-static forces, and other inter-molecular forces. Combining the fundamental understanding of physics and chemistry with our modern thinking in information theory is one of the novel challenges in intelligent systems research.

2 Research Perspectives on Different Scales

In the following, we will illustrate some of the current research areas in intelligent systems on different length scales with on-going state-of-the-art research.

2.1 Intelligent Micro and Nano Systems – The Scale of Living Bacteria and Cells

Natural machines often possess superior properties and behavior especially at small-scales. Natural systems at small scales operate in complex environments not despite of, but often because they operate in fluctuating and noisy environments. One of the advantages is that they consist of soft components, which allows them to adapt and makes them tolerant to errors. Usually, complex natural systems consist of a large number of elementary units, whose behavior is strongly influenced by thermal fluctuations. Even though these units only interact with a few neighbors, this is sufficient for collective phenomena to emerge, including a statistically controlled macroscopic output that no longer appears random. Examples of nature's small-scale machines are shown in Figure 3B-G – these serve as stimulating examples for which there is currently yet no means of fabrication and which one would like to be able to build synthetic counterparts. In contrast, man-made machines are in general much larger in scale, consist of rigid materials, operate by silicon-based computing, and their navigation and control are often deterministic in character.

Especially fascinating are the highly specialized abilities of micro-organisms like prokaryotic cells, e.g. bacteria, as well as eukaryotic (plant and animal) cells. Bacteria were the first form of life on earth and are both simpler and smaller than eukaryotic cells. Evolution has created a huge diversity of eukaryotic cells, which are sufficiently functional and adaptive to create complex organs like the brain or the immune system.

Yet, even bacteria possess remarkable functionality that has stirred the interest of natural scientists, computer scientists and engineers alike. Their research interest is twofold: (i) to understand and (ii) to synthesize objects that at least partially possess the functionality of living bacteria or even eukaryotic cells. While it has been possible to gather large amounts of detailed information on living systems throughout the last decades, the synthesis of cell-like systems remains a vision for the future.

2.1.1 *Why are scientists and engineers fascinated by bacteria and to synthesize their analogs?*

Size: Bacteria are very small – about a micrometer in length. This is a length scale that human fabrication techniques of today cannot easily master. Such length scales are better approached by self-organiza-

HIGHLIGHT BOX

From nanocomponents to nanopropellers

Researchers at the Max Planck Institute for Intelligent Systems in Stuttgart have developed a 3D fabrication method that combines shadow deposition with nanoscale patterning to grow nanostructures from a wide choice of materials and with controlled complex three-dimensional shapes. Tuning the mechanical, optical, and electromagnetic properties of a material requires simultaneous control over its composition and shape. Achieving this at the nanoscale is challenging, because surface-energy minimization generally causes small structures to be highly symmetric. In an hour the researchers can for instance cover an entire wafer with a hundred billion gold nanohelices that have two turns and an overall length of only 90nm, see Figure 4a [4]. Depending on the size of the seed pattern, the method allows for the growth of structures with a critical dimension between 20nm to several microns. The researchers were able to develop colloidal screw-propellers (Figure 4b) that resemble artificial flagella. These screw-propellers can be magnetized and moved through fluids with micron-level precision (Figure 4c) [20].

tion of molecules and proteins guided by distinct molecular recognition sites. This is the reason why bacteria can only exist if they are made of sufficiently soft materials that provide sufficient chemical and mechanical flexibility.

Autonomous behavior: Within their micrometer-sized body, bacteria pack machinery that enables them to be autonomous. They can generate energy, move, sense, and process information for making decisions on how to adapt their behavior - all within a dynamically changing environment.

Collective intelligence: Bacteria use their machinery to move individually or team up with other bacteria in order to mount collectively coordinated responses to challenging environments. They can establish communities of high morphological and functional complexity, that frequently flourish in the face of fluctuating environments - a property which is referred to as swarming.

Decision-making: Bacterial decisions are non-silicon based and rely on biochemically-governed networks. Bacteria learn by gathering feedback information from their environment. This information is used to modify their inner biochemical networks for decision-making or to change the chemical specificity of molecules through changing their structure and/or chemical building units. The use of a feedback mechanism enables cells to adjust their behavior in a complex environment. Such intelligent learning remains unmatched in synthetic systems and its development is perhaps one of the greatest future challenges.

2.1.2 *What is required to develop bacterial equivalents in a synthetic world - towards small-scale synthetic machinery*

The important functional length scale of bacteria is the nano and micro scale; therefore, this scale is the right one for intervening in these biological environments. This imposes significant consequences on the fabrication and operation of small-scale machines that could serve as functional equivalents of bacteria. Necessary steps include, on the one hand, the development of fundamentally new materials with nano scale dimensions, fabrication concepts for them and strategies for how to assemble and apply them. On the other hand, new approaches to solving problems concerning control (e.g. locomotion, navigation, sensing, communication) and on-board powering principles at such a small-scale must be explored. Obviously, actuation of synthetic micro and nano systems entirely leaves the domain of mechatronics. Power could be provided to the system from external fields, like magnetic fields [20], from chemical reactions, or, following the idea of bio-hybrid systems, from harvesting energy from living cells in the vicinity [21]. For steering systems to a desired goal, methods including chemical and magnetic gradients, material properties of the environment, or atom force microscopy have been employed. Some researchers also employed bacteria to adhere to a synthetic body and to coordinate these cells in external gradients to push the object forward [22].

Interesting physics and chemistry emerges at very small length scales and is used by nature's models. While macroscopic objects operate at Re ≥ 1, small-scale objects with a size of around one mi-

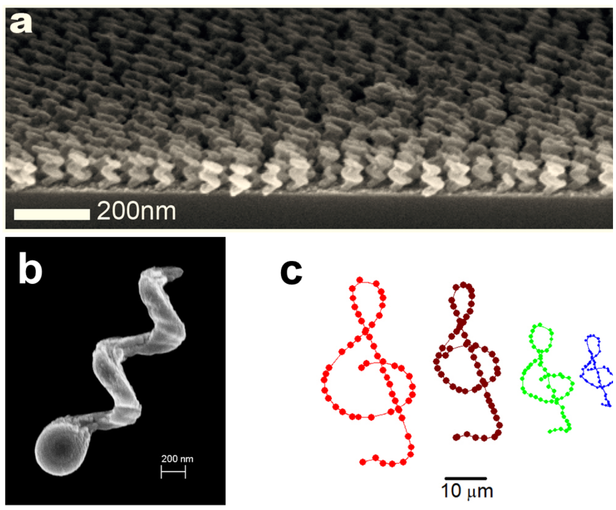

Figure 4: Artificial flagella and their navigational control: (a) mass fabrication of the world's smallest synthetic screws, (b) close-up image of a single microscrew for propulsion-type locomotion in liquid, (c) trajectories of nanoswimmers directionally controlled by external magnetic fields.[7,8]

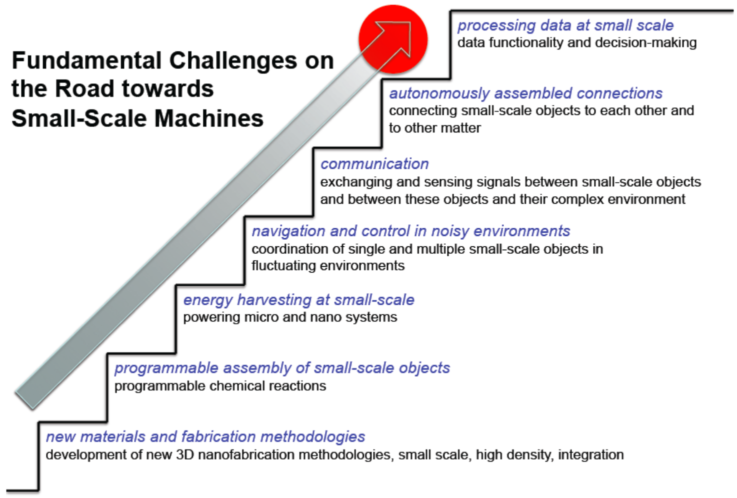

Figure 5: Road map for challenging fundamental questions towards small-scale intelligent systems.

crometer reach Re values << 1 and introduces drastic fluidic changes. Because viscosity dominates at small length scales, water at the nanoscale "feels" like syrup or honey to the micro-organism. For this reason, bacterial locomotion is very different from how larger living systems swim. To be able to move, bacteria have had to develop innovative means for moving forward - they literally "screw" themselves through the liquid. The obvious approach to small-scale synthetic locomotion is the creation of nature-mimicking lookalikes, in other words, the development of screw-shaped swimmers at the micrometer length scale – the scale of bacteria. The groups of Fischer at the MPI for Intelligent Systems and Nelson at the ETHZ successfully mastered this challenge only lately. On a ten-micrometer-scale [23], i.e., larger than the size of a single bacterium, Nelson et al. demonstrated the successful movement and external navigation of small-scale objects. The group of Fischer was the first to realize the smallest synthetic swimmers that are equivalent in size to a bacterium (see Highlight Box).

At small length scales the Péclet-number Pe < 1 means that transport is influenced by Brownian motion. In this context, the group of Bechinger at the MPI for Intelligent Systems developed self-propelled microshuttles for the pickup and transport of cargos. One of the potential applications of microswimmers is their use as shuttles, which are able to pick up and deliver small objects (cargo). Self-propelled swimmers, as the name suggests, obviate the need for external guiding fields to direct their motion. This is an important advantage, as the use of external guiding fields would limit the simultaneous operation of large numbers of swimmers. These swimmers can be fabricated in large quantities by photolithography and their propulsion is realized by a light-induced local de-mixing of a binary solvent close to its critical point [24,25].

The need for theoretical support for such investigations is ever increasing. For example, studies at the MPI for Intelligent Systems on catalytically active colloids moving as particles self-propelled by diffusiophoresis have successfully addressed the following issues [26]: (i) influence of confinement on the speed of self-propelled particles, (ii) influence of particle shape on the speed, (iii) cargo-controlled direction of motion, (iv) trajectories of complex active particle carrier-inert cargo composites. Future efforts are devoted to providing a microscopic understanding of the engine driving self-propelled particles in terms of statistical physics.

2.1.3 *Conclusion and Outlook*

The goal of developing novel small-scale synthetic machines and functional equivalents of nature's autonomous intelligent systems opens up new avenues of research reflected in the studies described above. Especially biology, biophysics, chemistry, and soft matter researchers have been at the forefront of exploring the behavior of the smallest living units in the past few years. Based on the large amount of accumulated knowledge, a roadmap for the synthesis and fabrication of small-scale machines that can nearly achieve the functionality of living cells can be developed. Research to successfully develop innovative solutions for the challenging fundamental questions of small-scale machine development proceeds step-by-step as shown in Figure 5.

While individual aspects of this list are being realized, their integration remains a scientific and engineering challenge. To address the system aspect will require input from numerous different disciplines including natural, engineering and computer sciences. It is important to understand nature's cells and systems, to learn from it and to eventually match or even overcome its functionality with these synthetic counterparts. The path towards this goal will discover fundamentally interesting science and engineering applications such as in the biomedical field or the synthesis of new material classes. For example, today we do not have synthetic materials, which can heal themselves such as in the case of natural tissue.

2.2 Intelligent Micro and Milli Systems – The Scale of Insects

Intelligent systems at the millimeter scale occupy an interesting domain. While their system components are limited in size, performance, lifetime, and weight, they usually move very fast, quite faster than big scale systems, which have to work against significant inertial forces, and quite faster than microscopic systems, which are largely at mercy of the relatively slow fluid and thermal dynamics of their environments. Millimeter systems are still largely deterministic in their behavior, such that sophisticated control of individual systems is reasonable – for instance, a fly has the ability of intricate flying maneuvers with high precision navigation, obstacle avoidance, and targeted landing. Nevertheless, such complex sensing and control has to be realized by very tiny nervous systems instead a voluminous

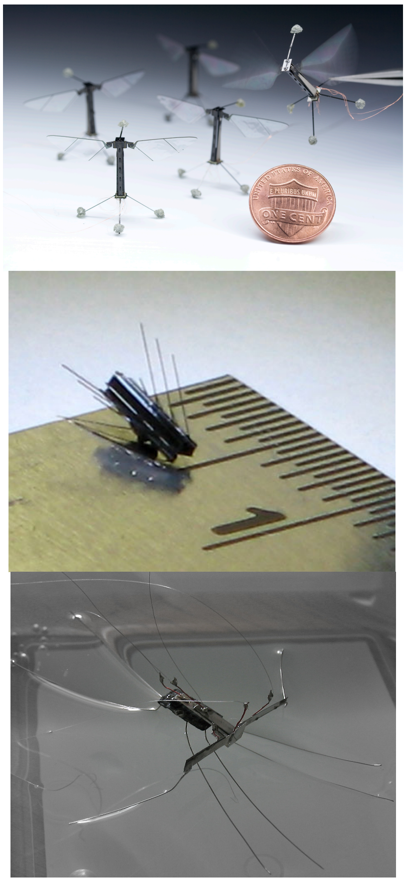

Figure 6: Some examples of insect-inspired micro robots: a) RoboBees flying insect robots [6], b) a tiny robot able to crawl through a person's veins [27], c) a water strider robot [9]

brain — realizing such agility even on a normal silicon computer has not been achieved.

It is only recently, that insect like robots have been synthesized [21] by using new fabrication methods and advanced materials -- Figure 6 shows several examples of such systems. Besides the fabrication process, there are several key challenges to overcome to realize intelligent micro robots. First, insufficient on-board power capacity is a significant obstacle, as current battery technology would not provide more than a few minutes of energy. Novel on-board powering, remote powering, energy efficient locomotion and computing, and energy harvesting methods are required to achieve long-duration operations for millimeter scale systems. Next, on-board actuation methods require new principles such as on-board actuators using piezoelectric, shape memory based, thermal, electrostatic/capacitive or magnetic actuation principles, and remote actuation using magnetic or electric fields and laser beams, as electric motors at this length scale become entirely inefficient. Finally, understanding how to provide onboard computing and appropriate algorithms for the amazing motor skills that systems at this scale need to have in rather complex environments of Re~1 is currently beyond reach. Using tiny physical filters and processors integrated to sensors, actuators and mechanical structures for fast and compact computing could be one of the approaches to create sufficient on-board computing for control of complex millimeter scale systems.

2.3 Intelligent Macro Systems – The Helpers of Tomorrow

When moving to the full scale of humans and animals in their daily environments, one of the greatest challenges is that systems require a lot of versatility and generalized abilities to act in the macro scale world. A simple stimulus-response mechanism for several specialized behaviors is insufficient in order to survive and succeed in behaviors. Sensors like the human eye or cameras can extract vast amounts information from their input signals, but also require massive parallel and intricate computations to accomplish these processes robustly. Actuation and control needs to protect relatively heavy bodies against collisions, but also accomplish fine manipulation for an unforeseeably large set of different objects. Learning and adaption appears the only way to handle these complex environments, and what humans and animals can learn robustly surpasses any synthetic system to date. Inserted into an infrastructure built for humans, the hope is that macro scale intelligent system can at some point fill in, where we have too few humans to do the job, from obvious disaster and space exploration scenarios, to assisting in care giving and independent living in a world with an unproportionally large fraction of older people.

The key topics of intelligent systems, i.e., perception, action, and learning have been addressed in isolation with growing success in the last two decades. For instance, computer vision has made major progress in the recognition of objects [28], action recognition [29], visual attention [30], and many other areas [31]. Machine learning has created algorithms that are remarkably successful in a broad range of domains, like Support Vector Machines [12], Gaussian Process Regression [32], Deep Learning [33] to name just a few. And robotics has created marvelous novel systems, as shown in Figure 7. But in order to achieve robust intelligent systems, a lot is still missing. While visual perception has progressed significantly, is has been largely developed in the domain of databases that have been compiled in the past. However, the normal world of an intelligent system is a continuous stream of sensory data in ever varying conditions, e.g., light variations, color variations, blur from weather conditions, etc. Robust perception under these conditions remains very hard. While we often think of visual perception as the dominant modality, touch perception, acoustic perception, and olfactory perception are equally important components that need to be fused and that significantly contribute to a truly robust perception system.

As a next component, perception needs action, and action needs perception: some motor acts are solely for the purpose to improve the confidence in a percept, and perception needs to be goal directed to subserve the behavioral aims. This kind of active perception has been explored in the past in the context of moving eyes, but needs to be revisited in

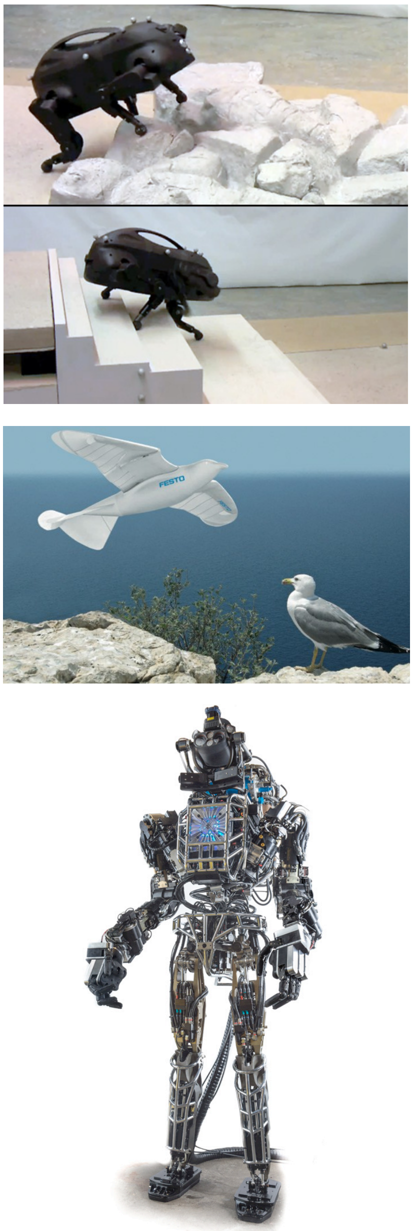

Figure 7: Some example of advanced robotics research from the past years: a) the Little Dog robot can autonomously navigate a variety of terrains that is has never seen before [8], b) the Festo robot bird demonstrates unprecedented elegance in a flapping wing robot [35], c) the Boston Dynamics Atlas robot that is supposed to help in disaster scenarios in the future.

terms of mobile robots with multiple perceptual modalities [34] and addressing the complete loop of perception, action, and learning.

Learning in autonomous robot system remains a research topic in its infancy. Various machine learning techniques have been carried over to the domain of moving and perceiving systems in feasibility studies, but essentially no robotic systems runs learning as a standard routine. Various issues can be held responsible. Intelligent systems need to create their own data to learn from, i.e., they need to explore new ideas and then exploit the gathered information for improved performance. This issue is tricky, as it is easy to create useless data that never leads to useful performance, and it is a time consuming process with high risks of doing something seriously wrong or damaging. Robots can accumulate massive data in such processes, but we have hardly any robust algorithms that can process this data and ensure safe improvements in real-time, a topic that has been studied in the field of adaptive control [36]. And, importantly, learning includes to learn when to stop learning, e.g., when the data received is contaminated by a stumble, or, generally speaking, by outliers – a research branch denoted as meta-learning[37].

But even on the mechatronics side, a lot remains to be done. Actuators of macro scale systems are heavy, energy inefficient, and have usually inferior mechanical properties in comparison to the muscle-based actuation of most macro-scale animals. Creating a power-autonomous robot can work with the best batteries for about 30-60 minutes at the cost of a rather heavy system. What we need is light-weight robots that are compliant to external perturbations and can achieve the speeds and accelerations of movement as in animals – we are very far away from this. Novel fabrication methods like 3D printing and working with composite materials could help in the near future. But the true solution might need to combine the nano-fabrication level with macro-scale robots, i.e., to create molecular motors that can actuate muscle-like systems that can create the performance needed in large scale intelligent systems.

3 Conclusions

Intelligent systems that can autonomous perceive, act, and learn are a formidable research challenge for this century. We outlined which ingredients matter for intelligent systems at different length scales, and how this leads to a variety of research programs. Initially, understanding differences and commonalities of intelligent systems at these scales is one of the key research goals. Ultimately, however, understanding how the nano-level can give rise to micro and macro level systems would be the ultimate dream of synthesizing artificial intelligent systems.

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