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# Introducing AI into MEMS can lead us to brain-computer interfaces and super-human intelligence

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Viewpoint

# Introducing AI into MEMS can lead us to brain-computer interfaces and super-human intelligence

David Sanders

David Sanders is a Reader in Systems & Knowledge Engineering based in the Faculty of Technology, University of Portsmouth, UK.

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Last year I spoke about the progress being made in machine intelligence[1] and with sensors and networks of sensors[2]. Earlier this year (in this journal) I spoke about ambient-intelligence, rapid-prototyping and the role of humans in the factories of the future[3]. I addressed new applications and technologies such as merging machines with human beings, micro-electromechanics, electro-mechanical systems that can be personalized, smarter than human intelligence and swarms of smart sensors. Although the research to get us to all that will include human-machine interfaces, sensors, Artificial Intelligence (AI) and Ambient Intelligence (AmI), there is one technology above all others that has the potential to get us there fast… and that is the creation and development of intelligent micro-electromechanical machines (MEMS).

The potential of very small machines was appreciated long before the technology existed to actually make them. For example, the Nobel Laureate (Feynman) considered the ability to manipulate matter on an atomic scale[4] and he concluded his 1959 talk with two challenges: first for anyone to build a tiny motor and second for anyone to write the information from a book page onto a surface 1/25,000 smaller. He offered prizes of $1000 for each[4]. The prize for the motor was won quickly using conventional tools but it was much later in 1985 when Tom Newman successfully reduced the first paragraph of “*A Tale of Two Cities*” and collected the second $1000 prize[5].

MEMS only became practical once they could be fabricated using modified semiconductor fabrication technologies such as moulding and plating, wet and dry etching and electro-discharge machining. MEMS are made up of components between 1 to 100 micrometres in size and MEMS devices are smaller than a millimetre long. They usually consist of a central microprocessor and other components that can interact with the outside world such as micro-sensors[6]. At these sizes, the customary classical physics (that we are all used to) do not always hold true. Because of the much larger surface areas compared to volumes, surface effects such as electrostatics can dominate effects such as inertia or thermal mass. For example gravity becomes less important and instead Van der Waals attraction and surface tension can become more important.

MEMS devices will use less energy, space and time, and we will come to expect more and more output for less cost. Sensors and networks of sensors are already transforming manufacturing and assembly by scrutinizing our industrial environment and sometimes feeding into control systems to improve our processes. Individual sensors have tended to obtain data and then to transform that data into electrical signals to feed higher level systems[2]. The development of such sensors has been driven by needs to reduce size and cost while increasing performance and MEMS could revolutionize the sensor markets by providing very small and very reliable devices at very little cost.

Until recently… sensors tended to be simple, unintelligent, connected directly into control systems, and static (or at best moved from place to place by separate transportation systems)… but all that is changing. Wireless networks are becoming more and more common and some smaller sensors are becoming mobile so that networks of sensors can work in mobile teams (or swarms)[2]. They can deploy and locate themselves around a factory or a machine to efficiently sample (and sometimes then control). Sensors are becoming “Smart Sensors” that can pre-process their own data to improve quality and reduce communications. These sensors become really smart when integral processing results in an adaptive sensing system that can react to external conditions and still provide useful measurements in harsh manufacturing and assembly conditions. Our future may be set to change through a combination of: smart mobile industrial sensors with enough energy to change themselves within their environment (for example, to move themselves around); effective wireless communication; automatic ranging; remote calibration; advances in microprocessors; new algorithms; and reduced costs in some key areas[2].

Increasing processing power within individual industrial sensors is improving the performance of sensor arrays and allowing for more accurate sensing of some phenomena that have traditionally required a large amount of off-line signal processing, such as image processing, sensor integration and gas sensor arrays[2]. As the information from numbers of sensor arrays becomes larger (and therefore more complicated) then this leads to a need for systems to model and then convey the information in a simple way (and sometimes in real time) to human beings. These electronic sensor systems and their components are sometimes exposed to harsh environmental conditions and some new industrial sensors could be especially robust in harsh conditions. For example, some MEMS-sensors appear to be able to withstand very high humidity, pressure and temperature and these sensors-on-a-chip are potentially low cost [2].

Meanwhile, AI systems have been improving for a decade[1,3,7] and AmI for assembly and manufacturing has been developing slowly[3,8,9]. They promise to bring improvements in flexibility, reconfigurability and reliability. Machine Intelligence combines a wide variety of advanced technologies to give machines an ability to learn, adapt, make decisions and display new behaviours[1,3]. This is achieved using technologies such as neural networks[10-14], expert systems[15-18], self-organizing maps[2,19], fuzzy logic[3,20] and genetic algorithms[1,21] and that machine intelligence technology has been developed through its application to many areas, such as: assembly[3,13,22,23], building modelling[3, 24,25], computer vision[13,26-30], environmental engineering[2,31-35], human–computer interaction[12,14,36-38], internet use[39,40], powered-wheelchair assistance[41-44], maintenance and inspection[45,46], medical systems[37,41,47], robotic manipulation[11,18,48,49], robotic programming[18, 50-55] and sensing[2,7,28,58-60].

Our machines are exceeding human performance in more and more tasks (from guiding objects to assembling other machines) and some developments in machine intelligence are already being introduced into new manufacturing methods such as rapid-manufacture[3] and the manufacture of composites[61-63]. If they can be effectively introduced into MEMS devices and into the manufacture of MEMS devices then machines can be made to merge with us more intimately and we should be able to combine our brain power with computer capacity to create a powerful artificial intelligence. It is difficult to see the boundaries to what may be possible then and some scientists are predicting a period when the pace of technological change will be so fast and far-reaching that our lives will be irreversibly altered[1]. At that point we may need a different type of engineer[64, 65].

There are some interference problems that might become critical for wireless communications between MEMS and they can also be limited by antenna size, power and bandwidth, and that is all being explored by some radio engineers. MEMS will need the ability to cope with technology or communication failures and large scale deployments and large amounts of data will need new computer science algorithms. The computer scientists are investigating some of that. The big future problems for MEMS may include constraints on resources such as energy, memory, computational speed and bandwidth. These limitations really push research towards distributed energy-efficiency. It is that potential need for smaller and more energy efficient sensors that can operate autonomously in harsh industrial conditions that will drive research towards more robust and fault tolerant MEMS that can automatically compensate for variables such as temperature.

For the immediate and medium term future, useful advances will come from research into: human-machine interfaces, sensors, AI, AmI, modelling, and improving MEMS manufacturing and design techniques. In the longer term, understanding the properties of MEMS materials and then creating more capable and intelligent MEMS machines will lead to direct brain-computer interfaces that will allow us to communicate our ideas directly to machines (and to other human members of virtual teams) and that may change our world beyond recognition.

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