Smart, Intelligent and Cogent Microsensors – Intelligence for Sensors and Sensors for Intelligence

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ABSTRACT

The paper develops a terminology to describe sensors which have been enhanced in some way by the integration of some additional processing circuitry. Several terms, current in the literature, including 'smart sensors' and 'intelligent sensors' are discussed and the ‘cogent’ sensor is introduced. This is followed by a brief review of existing and potential applications of Artificial Intelligence (AI) to microsystems, in terms of technology integration, device level performance enhancement and system level added functionality.

Keywords: sensor, smart, intelligent, cogent, MEMS, artificial intelligence

1 INTRODUCTION

The fast maturing MEMS field is presently seen as a core enabling technology both in the civil and military application domains.

A particularly buoyant sector in the MEMS industry is that of sensors. Traditionally, the main sensor requirements were in terms of metrological performance, i.e. the (most often) electrical signal produced by the sensor needed to match relatively accurately the measurand. If such basic sensor functionality was adequate several years back, this is no more the case. The use of sensors by industry has seen a gradual shift, away from large systems incorporating relatively few and expensive transducers towards the utilization of more and more sensors as components, or in subsystems. A new set of requirements was therefore generated which can potentially be met by using micromachining as a sensor fabrication technology. MEMS devices can be designed and produced to achieve: low cost, low mass and low power consumption, plug and play, digital output, enhanced reliability, sensitivity and selectivity and high accuracy, to name a few, general, desired sensor features.

Whilst some of the above requirements can be met by advances in the manufacturing techniques of the sensing element itself (to produce linear, accurate, highly sensitive and reliable sensing devices), others have to rely on efficient and clever processing of data generated by the sensing device, before such data reaches the outer world.

It is here, in the area of data processing and extraction of information, that the authors propose to clarify some commonly used terminology and introduce new terms. The definitions are supported by examples.

2 SMART, INTELLIGENT AND COGENT SENSORS

The MEMS/micro sensors field has become an interdisciplinary one, pulling together researchers from microelectronics, mechanics, physics and computer sciences. As a consequence, “borrowed” technologies, methods and terminology from the macrosystems domain began to be used in conjunction with the development of microsystems. Several terms are current in the literature, including 'smart sensors' and 'intelligent sensors'. 'Adaptive', 'distributed', 'autonomous' and other adjectives are also routinely applied to pick out the function of a particular sensor enhanced by some processing capability from the common herd of 'dumb' sensors. (Such terminology, a few years ago, was solely dedicated to macrosystems, with a much stronger meaning.)

By comparison with the usage of these terms in other fields, it would appear that the sensor community is over-selling the 'intelligence' of their products. The phrase 'intelligent sensor' often merely indicates that the sensor is integrated with a digital processor, it may say nothing about the intuitive abilities of the functionality programmed into the sensor. Given that the terms 'smart' and 'intelligent' have become somewhat confusing and meaningless with respect to sensors, we introduce a new term, the ‘cogent sensor’. In contrast to the above terminology, we define the meaning of cogent sensor by what it does, rather than what came before it or how it is constructed.

Smart sensors -The original 'smart sensors' [1] came about with the opportunity to enhance the capabilities of sensors by the integration of some signal conditioning circuitry within the sensor. According to the IEEE 1451 smart transducer interface standards (which describe a set of open, common, and network-independent communication interfaces for smart transducers), “smartness” means on-board data storage/processing capability, interfaced/integrated with the and/or digital sensor [2]. Variations of the term referred to the hardware implementation of the sensor, as follows: when a microsensor is integrated with signal processing circuits in a single package, it is referred to as an integrated sensor. A monolithic integrated sensor has the signal processing circuitry fabricated on the same chip as the sensor, while a hybrid integrated sensor has the signal processing circuit on the same hybrid substrate as the sensor chip.

'Smart' is however a term which, although used in conjunction with nearly every newly designed/produced sensor, means different things to different people. To some, it just means sensors which can communicate digitally, while to others it means sensors that have serious computing power integrated within them, to include calibration, non-linearity correction, offset elimination, failure detection, communication and decision making ability. It is important to mention that, such designs have been developed strictly for a sensor type and manufacturing technique and are, mostly, highly application oriented, so much so that, it is often difficult to assess whether it is the sensor or the application that is 'smart'.

Intelligent sensors - As the capacity of VLSI techniques increased, it became possible to integrate substantial digital or analogue processing capability onto a sensor. The term 'intelligent sensors' was often used incrementally from 'smart sensor'. Initially "intelligence" meant and served the same purposes as the electronics in a smart sensor: enhancement of the function of the sensor itself. In macrosensors, the term intelligent sensor was coined in 1992 [3]. Trade journal and popular news articles still use smart and intelligent interchangeably [4].

There are however, several examples of work here, where by using the term intelligent the authors implied the use of macro-scale intelligent techniques (i.e. artificial intelligence and most often neural networks (NN)). Such works are discussed in Section 3. It should be noted however that the nonlinear signal processing abilities of NNs were merely exploited rather than more evolved 'thinking/decision making in new situations' aspects of the technique.

Cogent sensors - What is common to the previous classes of sensors is that they provide raw data. Essentially, the readings of the original sensor are passed on, albeit linearized, temperature corrected, hysteresis corrected, packetised, network routed or re-packaged in one of many ways specific to the 'intelligent sensor' in question. What these sensors do not do is reduce the data to information, neither do they do processing to remove unneeded data and convert it to the particular form that the application requires. We term a sensor that performs the above two functions a 'cogent sensor'. Below we give some examples of existing and proposed cogent sensors and discuss some ways in which artificial intelligence techniques may be used to implement them.

3 AI FOR MEMS INTELLIGENCE

Amongst the "borrowed" macrosystems design techniques and tools, AI appears to be receiving increasing attention [5, 6] in the microsensors world. Despite the promise of application of 'intelligence', in many cases the AI techniques contribute only to a 'smart' sensor, let alone a cogent one. One exception to this is the case of virtual/software sensors, where AI techniques act on a system/array of microsensors and infer new information from multiple sensor data. Examples for each sensor category defined in Section 2 follow.

3.1 AI in smart sensors

We classify the applications below as 'smart' because no additional functionality has been added to the sensor, rather the quality of the data is enhanced by the AI techniques.

Sensor metrological performance enhancement

Optimizing analogue and digital methods for a transducer's characteristic interpolation and/or linearization is a field where constant research is being done. Different calibration methods have been applied for a variety of macro and microsensors (for example Newton, Lagrange, LMS regression and ANN). It has been found that ANN interpolation is more accurate than polynomial interpolation, especially when multivariable extrapolation or nonlinearity characteristics are under analysis. The extrapolation errors with ANNs are lower both inside and outside the calibration range. The computational load with ANN interpolation is of the same order as polynomial interpolation; however, ANN training requires more computational resources. This is not important in NN applications where training can be performed in a central host or implemented locally based on previous training weights and biases [7,8].

Sensor Data Validation

In this application of AI the 'intelligence' is applied to validate [10] or restore missing or corrupted data [11], by exploiting either physical sensor redundancy or other observable states within the sensor or the application itself. The output is still data, as opposed to information.

3.2 AI in intelligent sensor systems

In this category the system as a whole uses sensors and AI but the sensor itself is not endowed with the data to information transformation.

Multiple sensor systems – actuator control

The adventurous Silicon Active Skin project [12,13], lead by the Center for Neuromorphic Systems Engineering at Caltech, aims to integrate MEMS sensors and actuators, neural network sensory processing, and control circuits all on the same silicon substrate to form a "smart skin", capable of reducing drag on an aircraft wing. This is one of the best examples of intelligent microsystems. The system senses the shear stress, while a neural controller with feedback mechanism efficiently actuates robust micro actuators for surface stress reduction. The neural network controller is trained off-line to predict actuation using data from near-wall controlled experiments. The controller is allowed to adapt on-line, as it is included in an on-line adaptive inverse model scheme. In simulation, a 20% shear stress reduction was obtained.

3.3 AI in cogent sensors

Our category of 'cogent sensors' includes sensors integrated with the means to reduce raw data to 'information', of the type required by a specific application. Up to date, most examples of cogent sensors in the literature are of a multidimensional nature, so they are, strictly speaking cogent sensor systems. Two categories here are: the mono-type sensor systems (all sensors measure the same physical quantity) and the multi-type ones. Examples follow for each category.

At individual sensor level, cogent functions have been reported as work in progress and two examples are offered here.

Multi-type sensor systems

In some applications, the information has to be inferred from available measurements of observable quantities using a statistical model, which is referred to as a "software" or "virtual" sensor [14]. The actual measurement devices within such virtual sensors are often MEMS components. Software sensors were the first and major application of ANN to the instrumentation field and today they continue the lead in terms of number of research contributions. The innovative aspects of such works are primarily application specific and reside in the integration of various techniques in a global system allowing for prediction of the quantity of interest. Some contributions extend the role of ANN (or add on specific NN modules) to enhance the designed system with functions such as data validation, reconstruction, and analysis of uncertainties. It is not the scope here to survey the multitude of such applications. The work by Roppel et. al. is however mentioned as it is a good example of design for hardware integration of MEMS and AI. They successfully designed a low-power, portable sensor system using mixed analog and digital VLSI circuitry for on-board data pre-processing together with pulse coupled neural networks for feature extraction and also for pattern recognition [15]. The design is aimed at minimizing cost, size, weight, power and post-sensing computational burden. The sensor testbed is a 30 nodes, MEMS sensor array consisting of tin-oxide gas sensors and the target is to discriminate among 7 odors (acetone, ammonia, beer, etc.). Spatio-temporal encoding is used for pre-processing of the dynamic sensor outputs. The system provides correct identification rates of 96% for the odor data sets considered. Other good example of a gas sensing array with NN processing and a VLSI-MEMS was presented in [16].

Mono-type sensor arrays, smart sensor webs

Several researchers have noted the potential benefits of organizing/designing and exploiting large sensor systems based on the same principles as those governing both natural and artificial neural processing. This has led to the proposal that functions be distributed across a network of 'intelligent' sensors. The network itself then, collaboratively extracts information from the data field provided by the sensor network. Sensors are seen as ANN nodes and ANNs are designed to have architectures approximating those of the biological NN that performs analogous functions [17]. Such systems are part of a "third wave of computing" that could use NN to build sensors and other machines capable of the unsupervised learning exhibited by the human brain [18].

Fault detection and classification.

Over the past 10 years, neural networks have found wide application in systems that are designed to recognize fault conditions from sensor data, the derived information being whether the data is trustworthy or not [19,20]. If information of this kind is derived by a microsensor, about its own data and independent of the application of which the sensor is part of, such a microsensor would be subscribing to our "cogent" property.

The authors' work in this respect includes the development of a microsensor with such ability [21]. The fault detection function is intrinsic to the sensor functionality and provides the cogent sensor not only with the means of detecting its healthy/faulty state but also with the power of decision about its appropriateness of contributing its data to the specific application. Such a sensor can be used when two or more sensors of the same type are linked in an intelligent array. The method is based on the use of Neural Networks (NN) both for detecting faults and for classifying them. When implementing this function, use is made of the existing hardware resources in an array of intelligent sensors. The outmost merits of the method are:

-the low communication level necessary for performing the diagnosis: at any one time, only two neighboring sensors need to exchange data in order for the diagnosis decision on a particular sensor to be made;

-the real-time element – the diagnosis is performed based on a 3 steps back only history of the sensor readings;

-no a priory information is needed on the devices themselves as the sensor signatures are to be analyzed and learnt by the NN;

-the method is application independent and easily scalable.

Work is in progress to add new cogent features to the proposed sensor, apart form the diagnosis ability.

Real time monitoring

As part of the UMCP Small Smart Systems Program, a team of researchers aims at developing MEMS-VLSI single chip sensors where the smart portion of the system is a NN [22]. In the proposed designs, a fluid or gas acts within a portion etched out of the VLSI chip to activate the sensor. Upon NN processing of the sensor data, decisions are taken by the cogent sensor and feedback is produced for other components of the application (biomedical or environmental determinations for ex.)

4 CONCLUSIONS

As we have seen, the term 'intelligent' is applied to a wide variety of MEMS systems, ranging from those that have processing capability, through those that use artificial intelligence to those that, in a sense, think, sense, act and communicate. We reserve the term 'cogent' for the latter.

Cogent sensors are of great interest in a variety of industries. MEMS technology offers new ways of realizing cogent sensors by combining sensing, signal processing and actuation on a microscopic scale.

MEMS will open up a broad new array of cost-effective solutions only if they prove sufficiently reliable and their use does not pose insuperable systems design problems. The basic purpose of sensors is measurement. Achieving high metrology performance is the primary design aim, which has been achieved/solved in two ways: by technological perfection (which is inherently expensive and difficult to achieve) or by the application of structural or structural-algorithmic methods.

Relaxing the requirement for technological perfection allows designers to achieve the same performance with lower cost, design effort and on shorter time-scales. The second approach not only allows for increased measurement accuracy but also allows the extension of functional capabilities of such systems. The concept of the cogent sensor extends this principle further. What is important is not so much the quality of measurement itself, but the quality of the information derived from it. With cogent sensors the information required by the application may be available, in the form required by the application directly from the sensor or network of sensors. The information may directly reflect the sensed data or it may have been deduced and sifted by the application of degrees of 'intelligence'.

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