BIOINSPIRED SENSORY INTEGRATION FOR ENVIRONMENT-PERCEPTION EMBEDDED SYSTEMS

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Keywords: Bioinspired Systems, MEMS, MEMSoC, Integrated Systems, Sensors, Environment Perception.

Abstract: In this work, the architecture of a system intended for bioinspired environment perception is described. Considering the technology trends and applications requirements, the properties of such a system are discussed. The system consists of four main blocks: a) A set of different integrated microsensors and microactuators with the associated signal conditioning circuits; b) A data encoding block that in its simplest form performs spike encoding of information; c) a bioinspired digital processing block that efficiently emulates a spiking neuron network; d) a monitoring and self-adaptation block that provides feedback to the sensors and actuators. In its final implementation, the full system would eventually be almost fully integrated in a CMOS integrated circuit.

1 INTRODUCTION

In the latest decades, impressive advances in Information and Communication Technologies (ICTs) have led computing and network collaboration to unsuspected limits.

The combination of continued progress in microelectronics, , Micro-Electro-Mechanical sensor and actuator Systems (MEMS), wireless communications, signal processing, power management and software engineering enables the development of small-size yet complex autonomous systems working in distributed computing networks capable of interpreting physical environment and to interact with it.

As existing state-of-the-art CMOS technology generations improve, still more computing capacity will be available. Moreover, emerging new nanotechnologies promise in an uncertain future a computing capability that would by far exceed the currently available performance. Let us review some key aspects related with computing approach and interaction with the environment.

1.1 Ubiquitous Computing

The ambitious goal of achieving a ubiquitous computing network (pervasive network computing) is the common denominator of many recent and current research efforts.

When the emphasis is on miniaturization, systems including sensing capability, processing, self-powered and communication skills are called *smart dust* (Warneke, B. et al., 2001), smart nodes or Wireless Sensor Networks (WSN) (Akyildiz I. F. et al., 2002) as Spec devices (Hill, J. et al., 2000), CCR (Hollar S. E. A., 1996), MoteTrack (Lorincz K. and Welsh M., 2006) and Intel Mote (Nachman, L. et al., 2005) among others (Wong, A. C. W. et al., 2008), (Takeuchi, T. et al., 2009), that allow to build distributed wireless sensor networks.

As a result of all the developed research activity, nowadays, several powerful wireless sensor nodes are commercially available.

1.2 Microsensors and Microactuators

Micro-Electro-Mechanical Systems (MEMS, or NEMS if their size reduces to the nanoscale) can be defined as integrated devices that combine electrical, mechanical and optical components (Senturia S. D., 2001; Gad-el-Hak M., 2001). Their size ranges from microns to millimeters and they are manufactured using processes similar to integrated circuits, but in general not compatible, that allow to selectively remove parts of the silicon wafer or add new

Madrenas J., Fernández D., Cosp J., Moreno J., Martínez-Alvarado L. and Sánchez G..
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DOI: 10.5220/0003190202600267
In *Proceedings of the International Conference on Biomedical Electronics and Devices* (BIODEVICES-2011), pages 260-267
ISBN: 978-989-8425-37-9

structural layers. MEMS can act as sensors or actuators, either individually or in arrays, to produce effects on a larger scale.

Currently, there is a large number of different MEMS. Non-comprehensive examples are pressure and displacement sensors, accelerometers, gyroscopes, cantilevers, precision instruments, manipulators, micro-relays, micromirrors, thermal, chemical, micro-fluidics, etc. Each MEMS device requires its own electronic circuitry, based on characteristic frequency, load, voltage and current levels, noise, etc. For instance, for a capacitive accelerometer the resonance frequency ranges in the order of tens of kHz, bandwidth of several kHz, under a 6 V supply. For an angular quartz sensor, the vibration is of some kHz and bandwidth over 50 Hz, with voltage over 5 V. Other kinds of MEMS require much higher frequency, such as those operating in RF. In electrostatic actuators, voltage requirements may be tens of volts or more. Therefore, treatment should be completely different for each particular case.

Besides the previous consideration, MEMS sensors and actuators characteristics variation with aging, temperature, humidity or other physical phenomena, as well as reliability, raise the need for a self-adaptive conditioning systems.

Therefore, MEMS/NEMS already offer and promise more interaction with the environment at micro/nano scale. Thus, embedded in computing nodes, reduced-size and low-power systems able to interact with the environment become feasible.

MEMS technologies are not CMOS compatible in general, so further integration is limited from this point of view. Several research efforts in developing compatible CMOS MEMS have been done in the latest years, as it will be discussed (Baltes H. et al., 2002; Brand O. et al., 2005).

1.3 Self-adaptation and Bioinspiration

Despite technology already offers powerful computing and sensing devices, artificial algorithms still are limited in the extent of environment interaction capabilities, compared with even the simpler existing living beings.

The inspiration more directly related to environment perception is the autonomous function of the human central nervous system. The human autonomous control employs motor neurons to send indirect messages to organs at a subconscious level. These messages regulate unconscious processes and variables such as temperature, breath, heartbeat or digestion, among many others. The parallel for artificial systems is a network of processors which performs the necessary operations at the right time without the need of dedicated attention, in the so-called autonomic computing paradigm (Kephart, J. O.; Chess, D. M., 2003).

Such computing paradigm changes from the conventional processing power to another one driven by data. Besides the traditional centralized storage, access to data from multiple distributed sources enable users to access to information when and where needed. The main objectives of these distributed and *autonomous* architectures are often referred to as self-* properties. Systems able to self-manage should be *self-configuring*, *self-healing*, *self-optimizing*, and *self-protecting* and exhibit *self-awareness*, *self-situation*, *self-monitoring*, and *self-adjustment* (Dobson, S. et al., 2010). Thus, the information they can provide from the physical environment they are immersed is essential for those systems.

In addition to the *autonomic computation* proposal, there are many other similar approaches, for example Organic Computing (Gudemann, M. et al. 2008) Systemic Computation (Bentley, P. J., 2007) and Æther (Soto, V. J. et al., 2009).

Due to the power and interconnect limitations, increased processor performance is nowadays coming more from the increasing computing parallelism rather than from clock frequency improvements. The nanometer-size cutting-edge VLSI devices suffer from great variability and non-ideal effects. Further, with reduced dimensions, cosmic radiation-produced soft errors start to appear also at ground level. For these reasons, very serious reliability issues arise and a holistic strategy for fault tolerance and self-repair is required.

Because of their nature, bio-inspired neural networks promise feasible solutions: they are constructed with slow and unreliable elements, they are tolerant to manufacturing defects and to noisy environments, they are robust in the presence of hardware failures, they are not programmed but they adapt and self-organize, and they interact with the real world.

Based on studies of the human cortex the fields of computer science and cognitive neuroscience have been combined from a top-down approach (Hawkins J. and Blakeslee S., 2004). It is conjectured that the resolution of complex perception problems is done by means of few layers of neurons, evenly distributed and massively parallel working further massively interconnected with direct and feedback flows of information. The ability to predict is what sets the human intelligence and it is based on recording pattern sequences, in self-associative recovery, to capture invariant representations in the organizational hierarchy (but uniform) of cognitive tasks and decision taken with Bayesian criteria.

1.4 Bioinspired Devices

In the context of sensor nodes and bio-inspired computing, in the Perplexus project (Upegui A. et al., 2007) the *ubidule* was defined as a *UBI*quitous computing mo*DULE* with high computing power (sequential control processor combined with powerful programmable logic) and networked external communication, wired or wireless, with a large number of peers. The difference with other proposed sensor nodes is that the ubidules include bioinspired mechanisms. Among several modes of operation, the ubidule can emulate massively-parallel bioinspired spiking neural networks (Madrenas J., Moreno J. M., 2009).

In its current implementation, the ubidule is a purely digital processing device and it can use only a very limited number of standard sensors with high consumption and low bandwidth, sufficient for demonstration but not for advanced applications. Thus, it would require a parallel acquisition system which allows the massive use of sensors and actuators, as well as encoding information in pre-processed data streams treatable by ubidules.

In this paper, the NESSIE (Neural and Self-adaptive Sensory Integration for Environment Perception Embedded Systems) architecture is introduced. NESSIE systems enhance the ubidule functionality by providing integrated microsensors and actuators as well as a mixed-signal information pre-processing and self-adaptation, thus enabling simple environment interaction in the initial versions, and allowing scaling to complex applications.

In Section 2, the NESSIE architecture is proposed. In the following sections, the different parts are introduced: the proposed integrated microsensors and actuators and their conditioning circuits (Section 3), the data encoding block (Section 4), the boinspired digital processing block (Section 5) and the monitoring and self-adaptation blocks (Section 6). In Section 7, a possible application is pointed out. Finally, in Section 8, conclusion and future work are detailed.

2 THE NESSIE ARCHITECTURE

As discussed in the introduction, an artificial system able to exhibit some extent of environment perception and interaction should endow sensory elements and some kind of bioinspired or biological-like information processing. Furthermore, given the complexity of biological systems, that provide an extraordinary degree of redundancy and parallelism, one of the main efforts in developing such artificial systems should consider integration as a fundamental issue. In the direction of the ultimate objective of biological system emulation, this work proposes one step of microsensors and actuators integration in the CMOS technology, as well as the full system architecture that embeds bioinspired information processing. The extrapolation of this work to future more advanced technologies would allow the development of low-power, reduced-size environment perception devices.

In Fig. 1, the block diagram of the NESSIE environment perception embedded system is shown.

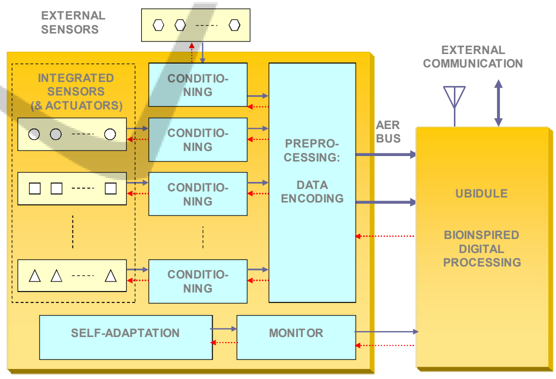

Figure 1: The NESSIE architecture.

It consists of the following elements:

- A *set of different integrated sensors* that could be either individual or arrays of them. External sensors could be provided as well when integration is not possible. Specific for each class of sensor, signal conditioning associated circuits provide the transduced information in proper electric form.
- *Data encoding block*. It is a preprocessing analog block that in its simplest form performs spike encoding of information; however, it can be extended to also perform data compression/fusion.
- *Bioinspired digital processing block*.
- *Monitoring and self-adaptation blocks*.

Whereas the ultimate goal is to integrate the whole NESSIE system in a single chip, in the present proof-of-concept, the analog blocks are integrated in different chips from the ubidule, which is purely digital. Furthermore, the present implementation of the ubidule mainly consists of a bioinspired chip and a separate microcontroller.

3 CMOS INTEGRATED SENSORS AND ACTUATORS

Nanometer-size CMOS technology currently allows to integrate very complex SoCs (System-on-Chip) in a single silicon die. Integrating microsensors or microactuators, however, is a much more challenging task, because of manufacturing process compatibility.

3.1 Transducers

A number of different CMOS-compatible sensors can be currently integrated in a CMOS-technology silicon die. Some of them are:

- *Optical integrated photodetectors*. Based on the photodiode, the CMOS photodetectors are a mature technology that allow for the implementation of linear- and 2D-array cameras in CMOS substrate. Furthermore, many conditioning circuits have been proposed that allow a logarithmic response of the sensor in order to accommodate the large dynamic range of visible light.
- *Temperature sensors*. By means of parasitic bipolar transistors, high performance temperature sensors can be implemented in CMOS (Matranga G. et al., 2002; Udrea, F. et al., 2008). Also, temperature sensors based exclusively on MOS transistors have been reported (Prakash S. B et al., 2006; Ren Y. et al., 2009).
- *Magnetic sensors*. CMOS compatible based on the Hall effect and integrated magnetic concentrators, e.g. (Randjelovic, Z. B. et al., 2002).
- *Pressure sensors.* These devices are implemented by means of standard CMOS silicon die micromachined after the CMOS processing (Zhou M. X. et al., 2004).
- *Electrostatic capacitive sensors and actuators*. Several experiments have been done to obtain CMOS-compatible electrostatic actuators. In particular, we have designed a number of structures in standard 0.35 micron CMOS technologies. Using the metal layers to build electrostatic actuators and the inter-metal silicon dioxide as sacrificial layers, membranes and cantilevers were designed. After this, the sacrificial material is selectively removed through windows opened on the passivation layer mask of the same manufacturing process by means of a wet or gas etchant (Fernández D. et al., 2010).
  In Fig. 2, an interferometer image of a membrane obtained with the indicated release process is shown.

In the present work, focus has been directed to photodetectors, temperature sensors and electrostatic MEMS.

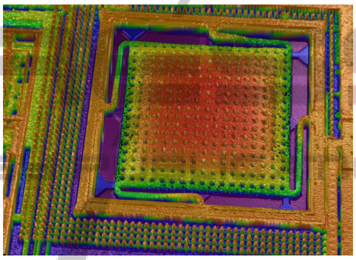

Figure 2: Standard-CMOS electrostatic membrane MEMS.

3.2 Signal Conditioning Circuits

As it is well-known, the signal conditioning circuits are very transducer-dependent. The sensed physical variable is transduced either to current, charge or voltage form and information is carried in the magnitude value or some signal property, as for instance frequency.

For the case of optical photodetectors, in order to provide broad dynamic range, logarithmic-response circuits are mostly used, this requires specific circuits developed for this purpose (Delbruck T., 2004; Guo J., Sonkusale, S., 2009; Wang C., 2010).

Concerning electrostatic MEMS sensors for accelerometers, a capacitive Wheatstone bridge output signal can be amplified by means of continuous-time voltage and classic instrumentation amplifier-based circuits, optimized by means of synchronous modulation (Lemkin, M., 1999) or switched-capacitor offset compensation (Wu J., 2004). Alternatively, the transducer information can be directly encoded in frequency by means of relaxation oscillators and a high-precision digital frequency demodulator based on counters (Michalik P. et al., 2010).

Similarly, temperature sensor conditioning can be done by means of a fully-analog or some mixed-signal (or mostly-digital) approach (Park S, 2009; Woo K, 2009).

Taking into account the steady CMOS down-scaling it seems that mixed-signal circuits operating mostly as digital devices (switches) are more likely to adapt to the limited characteristics of nanoscale transistors.

4 DATA ENCODING BLOCK

As from the sensors output signals the physical value is represented by means of a voltage or current, this block performs a translation into a form that is feasible to apply as input to a spiking neural network. The most straightforward is to encode information in the frequency domain and from there to a spiking stream, although this is not the only possibility.

For instance, a low-power spike event coding/decoding scheme for transmission of analog signals that uses a reduced number of transitions in signals with low high-frequency components has been proposed (Gouveia, L. C. et al., 2009) and could be applied as a more sophisticated encoding strategy.

Spikes are then transmitted to the bioinspired digital processing block by means of synchronous address-event representation (AER) (Sivilotti M., 1991), (Moreno, J. M. et al., 2009). In this protocol, each spike is encoded indicating a sensor label (*address*) that uniquely identifies its origin and permits routing it to the destination neuron input synapse, using the same physical communication bus for all inputs. Thus, all the spikes from the different sensors are transmitted through the same AER bus and they are connected to the spiking neural network inputs by means of a packet-switching scheme.

5 BOINSPIRED DIGITAL PROCESSING BLOCK

As indicated in the Introduction and shown in Fig. 1, the NESSIE architecture includes bioinspired processing based on spiking neural networks (SNN). The basic element is the so-called *ubidule*, that embeds a microcontroller (sequential control processor), an application-specific integrated circuit called *ubichip* (that can be either an FPGA or a custom chip) that accelerates the emulation of SNNs and external wired or wireless communication channels to be able to interact with other ubidules.

In Fig. 3, the multiprocessor ubichip architecture is shown. The ubchip architecture combines parallelism and time multiplexing in a balanced form:

- Neuron input synapses are time-multiplexed and executed by the same physical processing element (PE).
- Neurons are parallel-emulated, each one by the same PE that previously executed the algorithm corresponding to its input synapses.
- All PEs (processing Elements) operate synchronously in a SIMD (Single-Instruction Multiple-Data) scheme. The PE consists of a simple 16-bit ALU and two 8-register banks.
- The ubichip contains a 10×10 PE-array, a sequencer, an AER bus controller, a configuration unit to program the device and an interface to the microprocessor. External RAM and a Content-Addressable Memory (CAM) are also required.
- The sequencer block fetches instructions from the external SRAM memory and broadcasts them to the PE array. The SRAM is also used to store the SNN parameters, both neurons and synapses.
- The spiking neuron model assumes a pulsed binary output, with long steady times and short pulses. These output spikes are time-multiplexed and broadcasted to all neurons by means of a global AER bus. As indicated before, the same AER bus is used as input for the incoming spikes generated by the sensory encoding.
- The CAM (Content-Addressable Memory) decodes the spike address and generates an input spike to the neuron synapses being connected to that output spike.

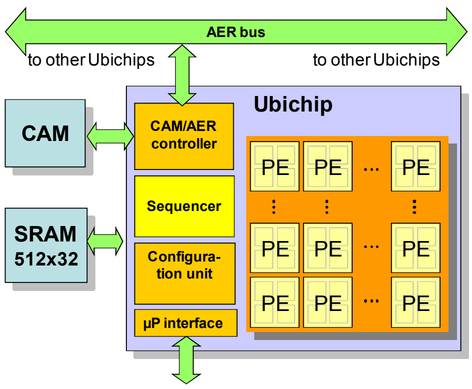

Figure 3: Multiprocessor ubichip architecture.

The digital processing block is thus able to perform bioinspired processing of the sensor information. Learning from the inputs is done by means of the previous experience, by self-adaptation of synapses. The platform is flexible enough to support multi-model implementation of SNNs (Hauptvogel M. et al., 2009).

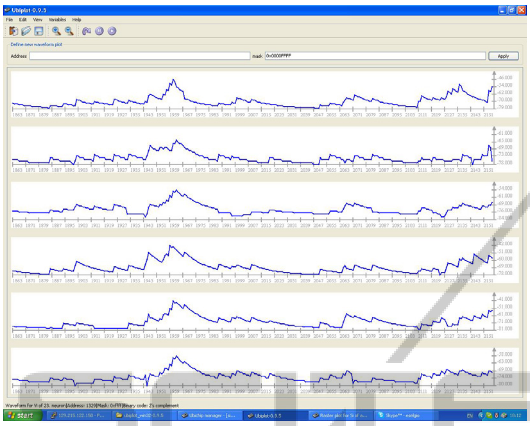

Figure 4: Example of emulated membrane potential over time of six neurons in a 6x6 neuron array.

In its current proof-of-concept implementation, a 6x6-PE array, each one emulating a neuron, has been mapped on a Xilinx Spartan xc3s5000 FPGA. Once programmed, the FPGA configuration is locally controlled by means of an Xscale PXA270 processor operating under Linux. An Ethernet connection allows sending commands from a terminal (Upegui A. et al., 2007).

Two different bioinspired spiking neural models (Iglesias J. et al. 2005, Izhikevich E. M., 2006) have been encoded in the multiprocessor using specific software development tools (Hauptvogel M. et al., 2009). The system programmability allows the implementation and parallel emulation of virtually any spiking neuron model.

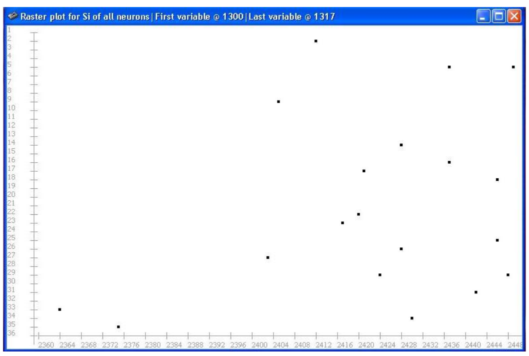

Figure 5: Example of emulated spike raster plot over time in a 6x6 neuron array.

As an example, figures 4 and 5 display, respectively, the membrane potential and spike raster plot snapshots of the 6x6 spiking neural network emulation of one of the Iglesias model.

6 MONITORING AND SELF-ADAPTATION BLOCKS

The monitor is in charge of analyzing the signal acquisition process. As a function of the outputs and also from the bioinspired digital processing block outputs, it can decide modifying the sensor distribution. For instance, activate/deactivate some of them, increasing the number or their sensitivity.

The self-adaptation block regulates the sensors signal conditioning blocks as a function of the signal output and the monitor commands.

7 CONCLUSIONS AND FUTURE WORK

Present and coming micro- and nano-technologies challenges started conditioning the way data processing and environment interaction are performed for building intelligent systems. Together with the increasing difficulty of implementing fully-deterministic systems in terms of reliability and operation and power and size constraints, conventional artificial systems show limited capability to perform environment perception tasks, at least compared with biological beings.

Taking into account these constraints, the proposed approach combines integration of electronic computing devices, sensors and actuators together with mostly-digital signal conditioning and bioinspired computation.

The mostly-digital (or mixed-signal) approach may be at the cost of individual sensor performance, but, consistently with bioinspiration and technology integration, the use of parallelism may compensate in this tradeoff.

The NESSIE architecture targets to this paradigm. It has been introduced as a proposal of new generation of artificial bioinspired systems, with capability of environment perception and interaction.

The main features of the NESSIE architecture are:

- CMOS integration of sensors and electronics, which allow reduced system size and low power consumption.

- Encoding all sensor outputs in a common spiking form.
- Bioinspired digital processing using SNN algorithms which supports learning from the sensors past experience.
- Sensor adaptation to compensate for variations and aging.

As an application example of the NESSIE architecture, a system that contains the following elements is under development:

- A linear array of 10 photodetectors with logarithmic detection circuit.
- A temperature sensor with voltage output.
- An accelerometer with frequency output.
- Conditioning circuits with spike stream for all the sensors.
- Asynchronous-to-synchronous AER bus adaptation.
- A ubidule element.
- System monitor and self-tuning circuit for linear photodetector array mismatch and sensor aging compensation.

When available, the complete system will be ready to be used in robotic applications. In this case, the robots can learn from incoming previous conditions, such as the correlation between the vibration and light conditions.

In next NESSIE system implementations, microactuators can be used for a full environment interaction, leading ultimately to MEMSoC (Micro Electro Mechanical System on Chip) devices.

ACKNOWLEDGEMENTS

This work has been partially funded by the Spanish Ministry of Science and Innovation project TEC2008-06028/TEC. Luis Martinez-Alvarado and Giovanny Sánchez hold research fellowships supported by the Catalan Department of Innovation, Universities and Companies, and the European Social Fund (ESF).

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