On-site forest fire smoke detection by low-power autonomous vision sensor

Jorge Fernández-Berni
Ricardo Carmona-Galán
Luis Carranza-González
Institute of Microelectronics of Seville (IMSE-CNM-CSIC), Avda. Américo Vespucio s/n Seville (Spain), berni@imse-cnm.csic.es
Alberto Cano-Rojas
Dpto. Informática y Analísis Numérico (Universidad de Córdoba), Campus de Rabanales (edificio Einstein) Córdoba (Spain), i52caroa@uco.es
Juan Francisco Martínez-Carmona
Andalusian Fire-Fighting Service (INFOCA), Avda. Manuel Siurot 50 Seville (Spain), juanfrancisco.martinez.ext@juntadeandalucia.es
Ángel Rodríguez-Vázquez
Institute of Microelectronics of Seville (IMSE-CNM-CSIC, U. Sevilla), Avda. Américo Vespucio s/n Seville (Spain), angel@imse-cnm.csic.es
Sergio Morillas-Castillo
AnaFocus – Innovaciones Microelectrónicas S.L., Avda. Isaac Newton 4 Seville (Spain), sergio.morillas@anafocus.com

---

Abstract

[Early detection plays a crucial role to prevent forest fires from spreading. Wireless vision sensor networks deployed throughout high-risk areas can perform fine-grained surveillance and thereby very early detection and precise location of forest fires. One of the fundamental requirements that need to be met at the network nodes is reliable low-power on-site image processing. It greatly simplifies the communication infrastructure of the network as only alarm signals instead of complete images are transmitted, anticipating thus a very competitive cost. As a first approximation to fulfill such a requirement, this paper reports the results achieved from field tests carried out in collaboration with the Andalusian Fire-Fighting Service (INFOCA). Two controlled burns of forest debris were realized (www.youtube.com/user/vmoteProject). Smoke was successfully detected on-site by the EyeRIS^{TM} v1.2, a general-purpose autonomous vision system, built by AnaFocus Ltd., in which a vision algorithm was programmed. No false alarm was triggered despite the significant motion other than smoke present in the scene. Finally, as a further step, we describe the preliminary laboratory results obtained from a prototype vision chip which implements, at very low energy cost, some image processing primitives oriented to environmental monitoring.]

Keywords: [forest fires, monitoring systems, wireless sensor networks, automatic early detection, artificial vision, autonomous sensors, vision algorithms]

1. Introduction

Early detection and precise location are two crucial points when it comes to prevent forest fires from spreading. The reason is that stopping the spread of a forest fire beyond 15 minutes following ignition is very difficult in most cases (INSA, 2000). Thus, the intervention of fire fighting resources becomes much more efficient if an alarm signal is delivered within such a time interval containing the geographical coordinates of the fire.

Wireless Sensor Networks, WSN (Pottie, 2000; Akyildiz et al., 2002) constitute one of the most promising technologies to achieve, at low cost, the necessary spatio-temporal resolution in the surveillance grid which permits to trigger fire alarms with the aforementioned characteristics. In these networks, a set of low-power low-cost nodes endowed with different possibilities of sensing is deployed throughout a region of interest. Processing and communication capabilities are also enabled on each sensor node. Currently, the monitoring systems based on WSN are oriented to predict rather than detect forest fires (Yu et al., 2005; Chaczko, 2005; Doolin, 2005; Son et al., 2006; Hefeeda, 2007). It is due to the sensing modules available, restricted to scalar measurements like humidity, temperature or barometric pressure (http://www.xbow.com). These systems therefore determine the probability of a fire starting according to observations of the environmental conditions coming from the sensors.

This paper addresses a further step into the possibilities of monitoring systems based on WSN: the incorporation of vision into the sensing nodes. It will permit not only to make predictions on the grounds of environmental conditions but really to detect a forest fire by visual inspection. The main drawback of implementing vision capabilities into low-power nodes is the energy consumption associated to the processing of the multidimensional data flow encoding a sequence of images. It is therefore necessary to adopt strategies which maintain this consumption within reasonable limits, keeping in mind that a major objective of the system is to prolong the autonomy of the sensors as much as possible. In our case, such strategies can be summarised into two fundamental issues: a simple but reliable vision algorithm, already described in (Fernández-Berni et al., 2008), and power-efficient vision hardware. A feasible way of achieving very high energy efficiency in the hardware implementation of visual processing is trying to exploit the physics of transistors for doing the computations. All in all, we report in this paper the results of carrying out on-site smoke detection from controlled burns of forest debris emulating the beginning of a real fire. We use the EyeRIS™ v1.2, a general-purpose autonomous vision system built by AnaFocus Ltd. (http://www.anafocus.com), as the vision node in which the vision algorithm is programmed. The hardware implementation of this vision system follows the design principles previously mentioned. Smoke was successfully detected without false alarms. Finally, we describe the preliminary results obtained in the laboratory from a prototype vision chip whose design, oriented to environmental monitoring, has been greatly inspired by the feedback extracted from these field tests.

2. Autonomous vision system

The vision system chosen to carry out on-site smoke detection is the EyeRIS™ v1.2, a programmable CMOS smart camera with QCIF resolution (176×144 px). Its characteristics makes it rather suitable for an initial approximation to the problem. First of all, its compactness and low power consumption --- it can be powered by a single 9V commercial battery for around 2 hours --- allow for an easy arrangement of field tests. Secondly, an application development kit is provided with the system, permitting thus a fast implementation of standalone applications. Finally, its operation is inspired in natural vision systems, whose front-end device, the retina, does not only acquire but also pre-processes the visual information (Roska, 2001). The EyeRIS™ system emulates this scheme by moving part of the image processing to the focal plane. In this way, early vision tasks, which are uniformly applied to all the pixels, are concurrently performed with the image acquisition in the analog domain. The outcome of this focal-plane processing is a simplified representation of the scene comprising features such as object locations, shapes, edges etc. It is such a simplified representation what is then post-processed by a digital RISC processor in order to make the final decision. The functional diagram of the vision system is depicted in Fig.1.

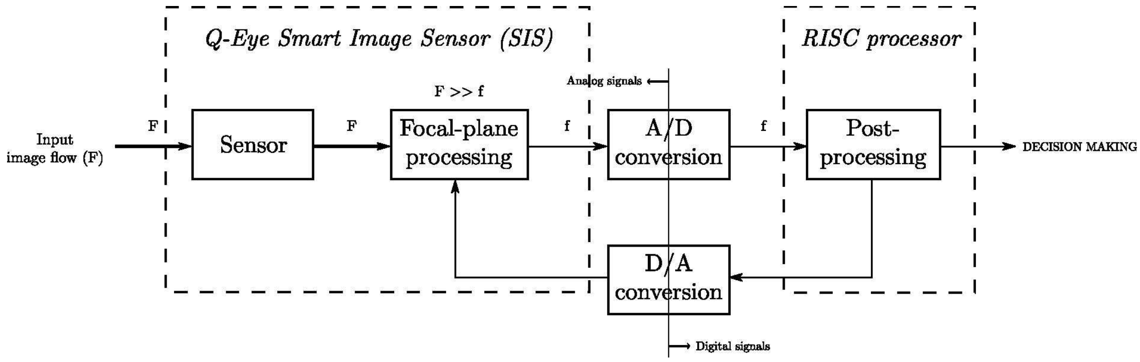

Fig.1: Functional diagram of the EyeRIS™ vision system.

Several advantages can be pointed out about this emulation of natural vision systems. Firstly, the bottleneck associated to the serialization of the vast amount of raw image data in a conventional Imager-Memory-DSP architecture along with the repeated accesses to memory to operate over each and every pixel are removed. This permits to alleviate the processing load over the digital processor what in turn permits to decrease its clock frequency, reducing thus the power consumption (Govil et al., 1995). In the meantime, the early vision tasks performed at the focal plane are very efficiently realized in the analog domain, taking into account that only moderate accuracy is necessary at this point of the processing scheme (Martin et al., 1998). No extra energy is spent here in obtaining a digital representation of the data. Furthermore, the physics of transistors can be exploited in order to reach maximum efficiency in the operation. All these aspects lead to the conclusion that artificial vision systems implementing processing architectures similar to that of Fig.1 are the adequate choice for applications where compactness, cost, power consumption and operation speed define major targets. That is, such systems are especially suited to incorporate vision to wireless sensor networks.

3. Vision algorithm

The vision algorithm programmed into the EyeRIS™ system was described in Fernández-Berni et al. (2008). It tries to capture the spatio-temporal dynamics of the forest fire smoke by analysing a simplified representation of the scene. Such a representation divides the scene into portions, or bins, whose value is the average of their corresponding pixels. From this representation, some candidate bins to contain smoke are extracted. These candidate bins are in turn analysed in order to track their clustering ratio, growth rate and propagation speed during two different stages: a detection phase and a confirmation phase. If all the conditions eventually fulfilled, an alarm is triggered. The corresponding flowchart is depicted in Fig.2. There are two subtle aspects of this flowchart which are worth to be carefully considered. First of all, the value of $N(t)$, which denotes the number of candidate bins along time, is replaced by 0 whenever a dynamics other than smoke is detected. It is necessary to dismiss false candidate bins when the condition about the growth rate:

$$N(t) - N(t - T_C) \leq G_{MAX} \qquad \{t \in [t_0, t_F]\} \tag{1}$$

is checked for the next image of the flow. Secondly, let us analyse how the flowchart represents the condition about the duration of the detection phase:

$$t_D - t_0 \leq T_{D_{MAX}} \tag{2}$$

where t_D establishes the end of the detection phase and the beginning of the confirmation phase, t_0 determines the time instant at which the first candidate bins were detected and $T_{D_{MAX}}$ represents the maximum time interval within which smoke must appear once the first candidate bins were detected. Consider the conditional decision in the flowchart $t - t_0 \leq T_{D_{MAX}}$. If it is fulfilled, the possible value of t_D at that time instant, $t_D = t$, satisfies Eq.(2). Therefore, the algorithm must continue checking conditions over that frame as all the conditions established to detect smoke could be eventually fulfilled. However, if the conditional decision $t - t_0 \leq T_{D_{MAX}}$ is not satisfied, the possible assignment $t_D = t$ at that time instant does not meet Eq.(2). At this point, the value of t_D must be checked. A value of -1 means that Eq.(2) will never be fulfilled by the dynamics detected as no value was previously set for t_D. On the contrary, a value other than -1 does imply that a value for t_D was previously assigned which satisfied Eq.(2). In this case, the algorithm must also continue checking conditions over that frame as, again, all the conditions established to detect smoke could be eventually met.

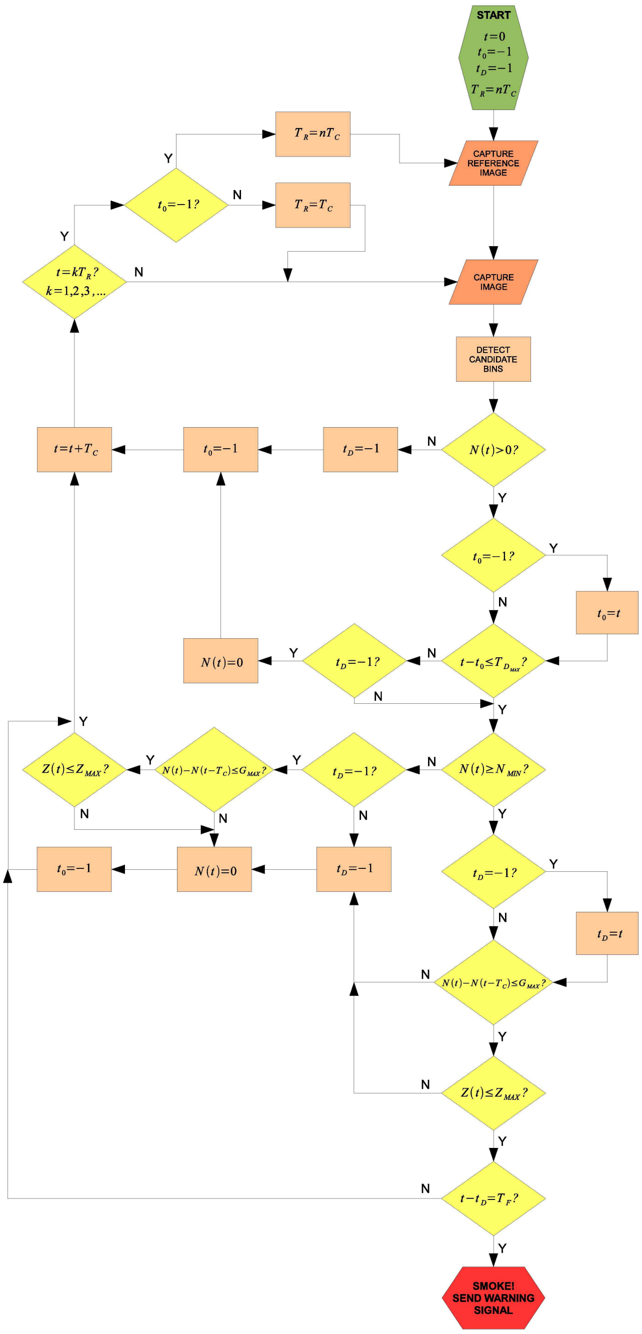

Fig.2: Flowchart of the algorithm.

4. Results of the field tests

Once the vision algorithm was programmed into the EyeRIS^{TM} system, it was tested in the laboratory. To this end, some of the video recordings containing smoke sequences reported in Fernández-Berni et al. (2008) were displayed on a computer screen towards which the EyeRIS^{TM} was focused. In this way, we made sure that the evolution of the algorithm when analysing a flow of images similar to that of the field tests could be supervised in real time from a PC connected to the EyeRIS^{TM}. This real-time supervision was very useful to detect minor problems during the field tests. Besides, it also permitted to store the resulting images from the processing in a PC.

The field tests were realized in the public estate “Las Navas-El Berrocal”, located in the province of Seville (37.85N, 6.04W). Two controlled burns of forest debris like those of Fig.3 were overseen by personnel of the Andalusian Fire-Fighting Service (INFOCA). The EyeRIS^{TM} was placed on top of a three-meter high pole powered by a commercial 9V battery connected to a DC-to-DC converter in order to supply it 5V. A camcorder was also placed on top of the pole in order to record the sequences with the same perspective than the EyeRIS^{TM}. The arrangement of both the EyeRIS^{TM} system and the camcorder can be seen in Fig.4. The pole was situated around 50 meters far from the forest debris. Besides this, another camcorder on a tripod was situated at different positions around the burns to record them from different perspectives. All the sequences can be found and downloaded in http://www.imse-cnm.csic.es/vmote.

Fig.3: Forest debris burnt during the field tests

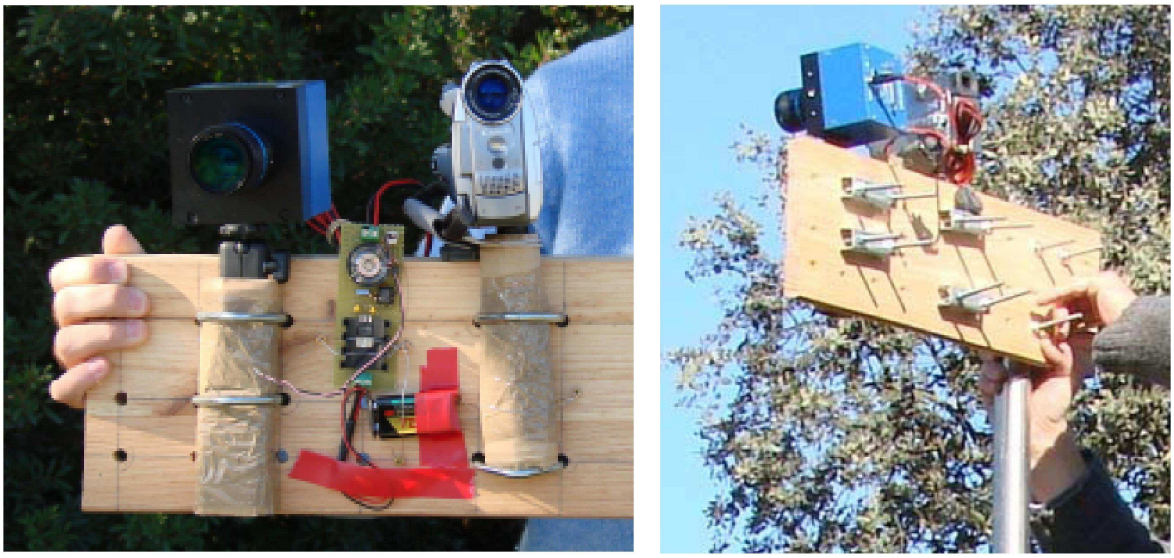

Fig.4: Arrangement of the EyeRIS^{TM} system (left at both photos) and the commercial carmcorder (right at both photos) during the field tests.

Smoke was detected without false alarms in both burns. For the first one, the alarm was triggered at 2min 50sec from ignition whereas for the second one the alarm was delivered at 57sec. Some consecutive frames captured by the EyeRIS^{TM} during the first burn along with their corresponding candidate bins are represented in Fig.5. The evolution of the number of candidate bins, $N(t)$, and the number of 8-connected regions of candidate bins, $Z(t)$, is depicted in Fig.6 for both burns. The most remarkable aspect about the results is the ability of the algorithm to filter motion other than smoke. In fact, it can be seen from the image sequences extracted from the EyeRIS^{TM} (http://www.imse-cnm.csic.es/vmote) that two main sources of false alarms like the motion of tree leaves due to wind and the motion of people across the scene are mostly filtered. Thus, the alarms are undoubtedly triggered by the smoke rising from the burns.

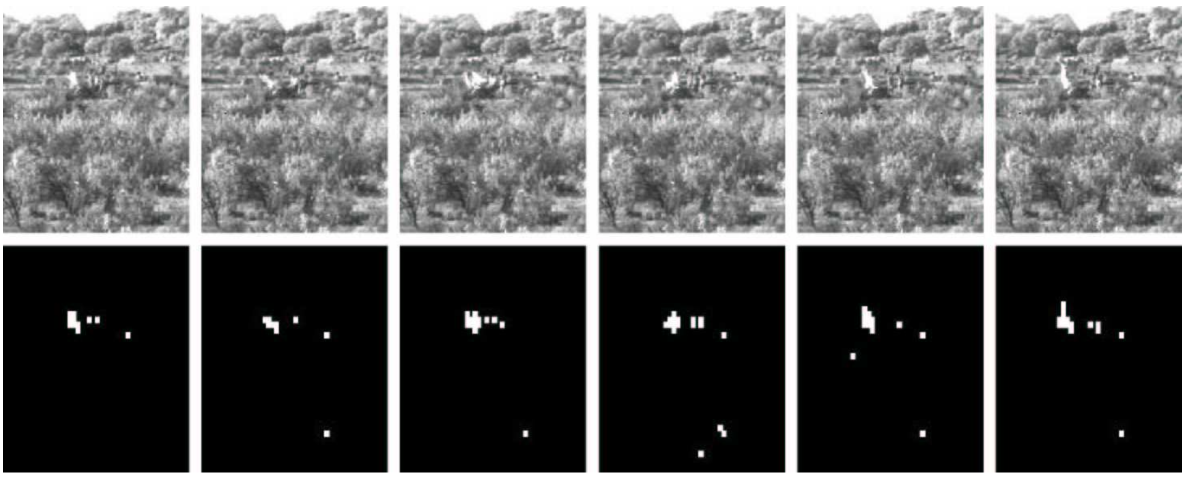

Fig.5: Consecutive frames captured by the EyeRIS^{TM} (first row) and their corresponding candidate bins (second row) during the first controlled burn.

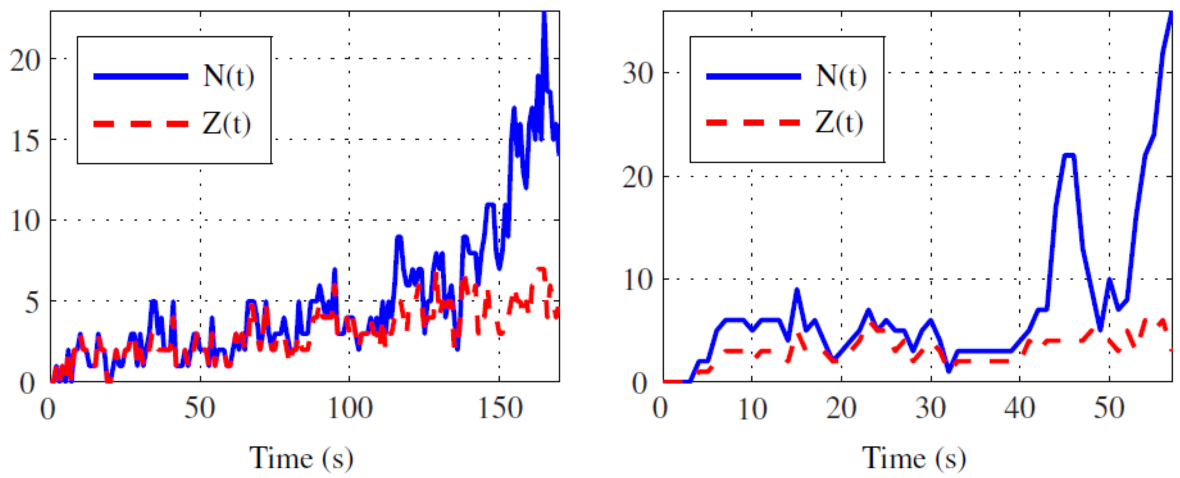

Fig.6: Evolution of $N(t)$ and $Z(t)$ for the first and second burn respectively.

5. Prototype chip oriented to environmental monitoring

As previously mentioned, the EyeRIS™ is a general-purpose vision system. It implicitly means that a great deal of image processing primitives are available in order to be able to implement any kind of vision algorithm. This in turn implies an important cost in terms of compactness and power consumption when compared to an application-specific vision system. And unfortunately compactness and power consumption are precisely two key points at the nodes of WSN. Under these circumstances, the design of a prototype vision chip was addressed. The objective of the design was to achieve, at very low energy cost, the physical implementation of only a subset of image processing primitives by following a processing scheme similar to that of Fig.1. In order to not restrict ourselves to the application of forest fire detection, the subset of primitives chosen are oriented to environmental monitoring, a more general application which can take enormous advantage of the characteristics of WSN. The resulting vision chip, with the same resolution as the EyeRIS™, 176×144 px, is showed in Fig.7. It carries out image sensing, focal-plane processing running concurrently with the sensing, and analog-to-digital conversion. In this way, the chip can output from full-resolution digital images to different simplified representations of the scene which can be reprogrammed in real time according to the result of their processing. As an example of the image processing capabilities of the chip, three different images read out from it are depicted in Fig.8. The first one corresponds to the full-resolution representation of the scene when the chip focusing a screen which displays one of the sequences recorded during the field tests. The second one represents the same scene after applying the binning demanded by the algorithm. It has been represented with the same resolution as the first image for the sake of clarity. However, bear in mind that a digital processor only needs one pixel out of every bin in order to extract the candidate bins. Finally, the third image also represents the same scene but after applying a process of “foveatization”, that is, keep full-resolution only at that regions of the scene which result interesting while the rest of the scene is represented in a progressive coarser way as getting farther from the region of interest. The point is that these simplified representations of the scene are achieved at a energy cost from 10 to 50 times smaller than that of the focal-plane processing performed by the EyeRIS™.

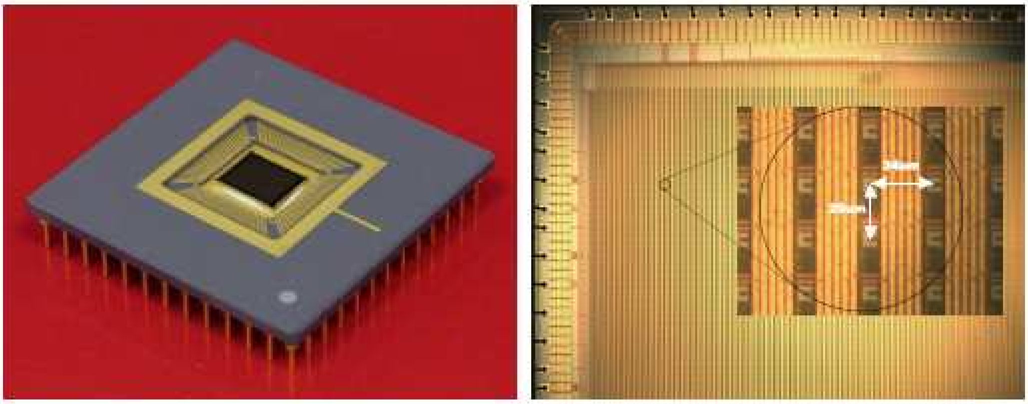

Fig. 7: Packaged vision chip (left) and microphotograph of part of the focal plane with a close-up of the photosensors (right).

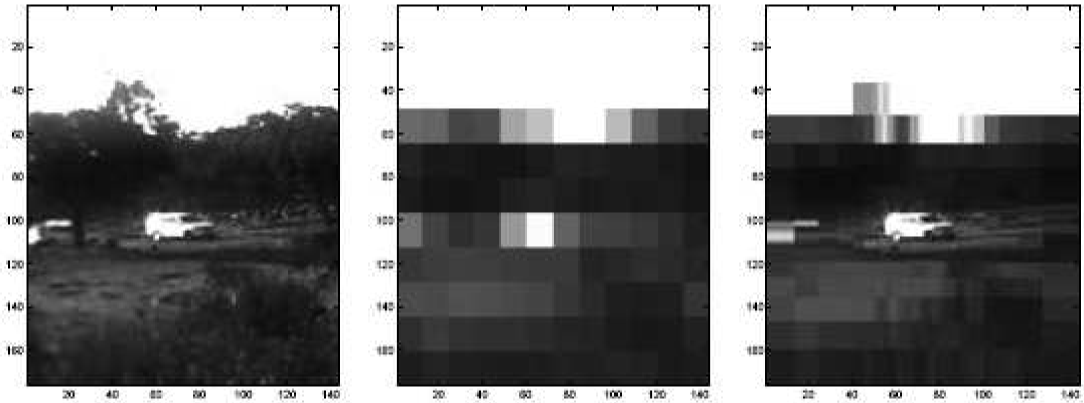

Fig. 8: Example of the image processing capabilities of the prototype chip: full-resolution image (left), binning (center) and foveatization (right).

6. Conclusions

The incorporation of vision into the nodes of wireless sensor networks means a remarkable further step in the possibilities of these networks concerning real-time forest fire detection. We demonstrate in this paper through real field tests that this incorporation is possible by means of smart vision sensors with reduced power consumption and high image processing reliability. In order to keep advancing on the reduction of the power consumption associated to the image processing, a prototype chip has been manufactured which delivers simplified representations of the scene at a energy cost which is from 10 to 50 times smaller than that of the vision system used for the field tests. Future work is intended to achieve on-site smoke detection from this chip connected to a commercial wireless sensor network node, transmitting thus an alarm signal to a remote location.

Acknowledgments

The authors would like to thank Mr. Manuel Larios of INFOCA for the organization of the controlled burns. This work is funded by CICE/JA and MICINN (Spain) through projects 2006-TIC-2352 and TEC2009-11812 respectively.

References

Akyildiz, I., Su, W., Sankarasubramaniam, Y. & Cayirci, E., A survey on sensor networks. IEEE Communications Magazine, 40(8), pp. 102–114, 2002.

Chaczko, Z. & Ahmad, F., Wireless sensor network based system for fire endangered areas. Third Int. Conf. on Information Technology and Applications (ICITA'05), Sidney, Australia, pp. 477–484, 2005.

Doolin, D. & Sitar, N., Wireless sensors for wildfire monitoring. SPIE Symposium on Smart Structures and Materials, San Diego, USA, pp. 477–484, 2005.

Fernández-Berni, J., Carmona-Galán, R. & Carranza-González, L., A vision-based monitoring system for very early automatic detection of forest fires. Forest Fires 2008: I Int. Conf. on Forest Fires (Wessex Institute), Toledo, Spain, pp. 161–170, 2008.

Govil, K., Chan, E. & H., W., Comparing algorithms for dynamic speed-setting of a low-power CPU. I Int. Conf. on Mobile Computing and Networking, San Diego, USA, pp. 13–25, 1995.

Hefeeda, M., Forest fire modelling and early detection using wireless sensor networks. Technical report, School of Computing Science, Simon Fraser University, 2007.

INSA, FUEGO instrument design, prototype, construction and validation. Technical report, INSA Ingeniería y Servicios Aeroespaciales, 2000.

Martin, D., Lee, H. & Masaki, I., A mixed-signal array processor with early vision applications. IEEE Journal of Solid-State Circuits, 33(3), pp. 497–502, 1998.

Pottie, G. & Kaiser, W., Wireless integrated network sensors. Communication of the ACM, 43(5), pp. 51–58, 2000.

Roska, B. & Werblin, F., Vertical interactions across ten parallel, stacked representations in the mammalian retina. Nature, 410, pp. 583–587, 2001.

Son, B., Her, Y. & Kim, J., A design and implementation of forest-fires surveillance system based on wireless sensor networks for south korea mountains. Int J. of Computer Science and Network Security, 6(9), pp. 124–130, 2006.

Yu, L., Wang, N. & Meng, X., Real-time forest fire detection with wireless sensor networks. Int. Conf. On Wireless Communications, Networking and Mobile Computing (WiMob'05), Montreal, Canada, pp. 1214–1217, 2005.