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Battery charge saving in wireless image sensors for remote metering

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Abstract

The paper presents a methodology to reduce the energy consumption of visual sensor node in wireless sensor networks. This methodology, based on a balancing between processing and transmission tasks, can be applied in all those situations where subjective image based measurements are required. Considering that in a sensor node, the transmission task is the most energy consumption, the proposed method tries to find the best compression rate able to give a significant reduction of transmission time, returning adequate and objective image quality and compression time. Some results are presented applying the proposed methodology to a case study: the use of wireless visual sensors to the remote metering of water counters

Keywords: wireless sensor network, sensor node, power consumption, vision sensing

1 Introduction

Recent advances in micro-electronic hardware technologies have allowed the realization of low-cost, low-power, multifunctional sensor devices to satisfy the growing necessity of physical quantity measurements in a greater and greater number of applications. In a number of cases these devices do not work alone but within a network of hundreds of sensor nodes spread across a geographical area. These nodes must communicate among themselves to establish a sensing network that anytime provides access to information collected anywhere, to allow processing and analysis in a hierarchical smart environment. The mean utility of sensor networks is that they do not require particular infrastructure and human control; they automatically sense, compute and actuate into the physical environments thus allowing several applications [1]. Important steps in the communication technology have made possible the realization of wireless networks. The advantages of wireless connection in sensor networks are easy to understand: they give higher flexibility in the sensor placement and allow sensor output to be measured from everywhere both in opened and closed space. Further, they allow measurements on moving objects, and minimize human intervention in hostile and unattended environments. Finally, suitable sink nodes allow wireless network to be connected to any other network using wide-area wireless links.

A topic of great interest in realizing wireless sensors is the energy management. Energy is typically more limited in sensor networks than in other wireless networks since the choice of a wireless connection for a sensor means that it is difficult to reach it with any wiring, and it is not convenient to remove it frequently to change or recharge batteries. As a consequence the necessity of realizing power aware wireless sensor nodes often drives the choices during both hardware and software strategy design.

Two tasks significantly influence the energy consumption of sensor nodes: communication and processing. The two are strictly related: only increasing the on board computational burden the energy consumption due to communication to the control node can be reduced, and viceversa. This means that the balancing between local and central data processing becomes a crucial step along the way to the sensor node energy saving.

Many contributions can be found in the scientific and technical literature dealing with the energy saving problem in the wireless sensor networks, and either hardware or software solutions are proposed [2]-[5]. In the most of them is demonstrated that the goal of minimizing the total energy consumption can be reached through a reduction of the communication burden, since it requires more power (energy/time) than the computational one [6].

This solution is immediately applicable to objective measurements where: (a) the dynamic of the physical quantity to be acquired is low and synthetic values (i.e. mean, standard deviation, rms, peak, etc...) are required by the application; (b) the required transmission rate is close to the hardware limits and the signal can be pre-processed without loosing information. An example can be the monitoring of temperature, pressure, humidity, level or other physical quantities characterized by a limited dynamic range. The acquired signal samples can be on-board pre-processed thus reducing the total amount of data to be transmitted without loosing the required information or reducing the throughput.

In an always growing number of applications wireless networks include also image-based (visual) sensors. They can be successfully applied in many areas where the appropriate conditions for the introduction of the visual measurements arise [7]. Due to the great amount of data, the byte transfer rate required by the application is often close to the hardware limits and this represents a further incentive to on board image pre-processing.

In a significant number of applications the images acquired by sensors must be transmitted to a human operator, either to gather information that cannot be extracted automatically (subjective measurements), or for safety, or for legal problems. Then, in order to reduce the transmission burden the images must be on board compressed. But this solution to the energy saving problem looks like being less immediate than the aforementioned cases because: (i) the image compression requires computational power comparable to transmission one; (ii) the image compression could reduce the readability of information. If possible, the problem becomes more complex in the case of a dense multi-hop visual wireless sensor network. In fact in this case the energy needed for communication decreases as well as the distance between nodes, while the energy required by the computational part increases. Many authors are involved in this research field and many solutions have been presented in the technical literature. The most of them start from a numerical model of the wireless network to propose possible solutions. Two huge factors introduce great limitations to this approach: subjective measurements are not compatible with theoretical and consolidated solutions proposed by the information theory science regarding the limits for the compression and transmission rates; the real behavior of a wireless sensor network may be strongly different from the modeled one.

In a previous paper the authors, starting from their experiences about wireless connections [8]-[9], instrument interfacing [10], and image based measurements [11], have described design and realization of a low cost battery supplied visual sensor featured with BT interface. Hardware and software solutions were thought to reduce at minimum power consumption even granting the necessary bandwidth to support image transfers. The sensor can be easily inserted in a BT piconet network as a node particularly suitable for measurement applications in the field of energy, gas or water counters remote metering.

Dealing with this sensor node, the authors in this paper tackle the problem of searching for the best compromise between the compression rate and the transmission time to minimize the energy consumption. Some results are presented applying a suitable methodology to the particular case study: the use of wireless visual sensors to the remote metering of water counters. The sensor node was suitable designed to be installed to cover the front panel of traditional counters and to be remote inquired by a human operator to upload a photo of the panel, without accessing the installation site. The sensor is supposed to be inquired twice each month and the batteries should be changed with a frequency as lower as possible than once each year.

2 A wireless visual sensor node for remote metering

The wireless sensor network covers a 300m radius area with a Bluetooth *piconet*. In its full configuration a controller, the *piconet* master, can interface with up to 256 sensing devices, acting as slaves, but no more than 7 can be active at the same time. The master BT module is hosted by a handheld HP Pocket PC device and the controller software is written in LabView 7.1 language. Since the Pocket PC can be recharged periodically (each day) no hardware and/or software optimizations oriented to energy saving were thought for it.

The architecture of a single sensor node [8] is based on five modules: processing unit, memory, sensing hardware, transceiver and battery power.

Heart of the sensor node is the processing unit. It is composed by a Microchip PIC16LF877 low power micro-controller. The microcontroller device can operate in low power consumption mode (*sleep mode*); in sleep mode the normal I/O processor activities are stopped and the maximum current required by the device is less then 0,1 uA at 3.3V.

The memory module is constituted by a 256 kB FIFO flash RAM device. The FIFO architecture has been chosen to reduce at minimum both the digital I/O pins used in the communication with the micro-controller and the addressing time.

The sensing module is a 384x288 pixels gray scale digital camera with dimensional pixel resolution of 11 x 11 um and an intensity resolution of 256 gray levels. At 5V it adsorbs less than 20 mA in the active state (@50 fps) and less than 100 μA in standby.

The Transceiver consists of: (a) a BT master/slave transmission module and (b) a radio frequency (RF) module. (a) The BT transmission module is a class 1 power (300 m) device and adsorbs about 326mW at 3.3V during the connection phase. (b) The RF module is a low cost micro amps RF receiver. The module range is up to 1km and the current consumption is about 30μA at 3.3V.

The battery package is composed by two high capacitance batteries sets. The former, by the way of two high efficiency step-down circuits, supplies PIC μC and camera (5V), while the latter supplies the transceiver and the memory modules (3,3 V). A photo of the realized sensor node is reported in figure 1.

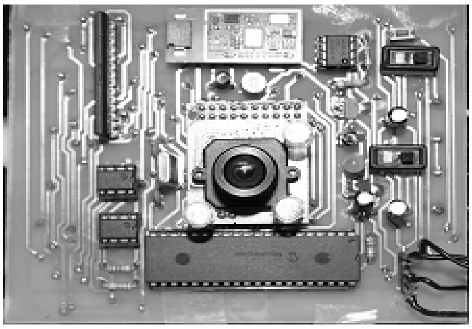

Figure 1: Photo of the visual sensor node.

Table 1: Summary of the power budgeting in the hour operating cycle

Operating state	Required Time [mS]	Required current [mA]	Charge Current * Time (Amp*Sec)
Standby	3564535	0,0301	0,107
Sensing	2035	46,030	0,093
Processing	0	26,030	0,000
Connection	19207	80,430	1,545
Communication	14223	70,030	0,996
Total	3600000	N/A	2,742

Only the microcontroller must be always powered up, all the other parts can be turned off when the sensor is not inquired. To this aim some output pins of the microcontroller were configured to enable the voltage regulator outputs.

Particular considerations require the presence of both the RF and the BT wireless modules. Also if the presence of two wireless modules could appear an useless redundancy, the RF module is indispensable because the BT module has a considerable power consumption (about 30mA) also in the standby mode and this does not match with the requirements of reduction of the overall power consumption to allow long term duration of the sensor node battery package. For this reason the author idea was to turn off the BT module during the time was not used and turn it on only when required. To make this, a second RF device, consuming only 30 µA, is always powered up and generates interrupts to wake up the microcontroller when an image acquisition has to be performed.

The sensor node operating passes through five states: (i) standby, (ii) sensing, (iii) processing, (iv) connection, and (v) communication.

(i) In standby the microcontroller is held in *sleep mode* while all the other peripherals are turned off. The arrival of a wake-up command, from the host controller device, activates the microcontroller that passes in the normal state. The current consumption in this state is about 0.031 mA, and the time the sensor remains in this state depends on the user.

(ii) During the sensing phase the counter panel image is acquired and stored in memory. The devices working are the microcontroller, the sensing hardware and FIFO memory. The overall procedure takes about 2 s, and the current consumption is about 46,03 mA.

(iii) In this state the microcontroller operates in run mode and the FIFO memory is powered up. At the moment no image processing is performed. The state current consumption is 26,03 mA.

(iv) In this state the sensor node strats the connection with the host device. The microcontroller operates in run mode, the powered up devices are the BT module and the FIFO memory. The BT inquiry and connection phases spend about 19 sec with a current consumption of about 80,43 mA.

(v) In the communication state the microcontroller is in run mode, the BT device and the FIFO memory are powered up. The maximum available transmission rate is 115200 bps while the total current consumption is 70,03 mA. If no compression or other image processing is performed the total amount of data to be transmitted is 108KB with transmission time of about 14 s.

Considering a one hour long operating cycle and one reading per cycle, the total energy consumption is reported in table 1; the following considerations can be made:

- the connection state is the highest energy consuming, while the standby state is the lowest;
- the processing state requires less energy than the communication one;
- the sensing and connection times depend only on the hardware;
- the processing and communication times depend from the user’s software choices.

It is clear that in order to reduce the sensor node energy consumption in a working cycle a solution can be a reduction of the communication time through a suitable image processing. Typically this goal is reached by image compression algorithms, which reduce the number of bytes to be transmitted with a wanted compression rate. Of course, the higher the compression rate the higher the processing time and the lower the quality of the decompressed image.

In the following, the problem of the right choice of compression algorithm and compression rate is tackled dealing with an application involving visual sensor nodes and image based measurements.

3 Choosing the compression algorithm and compression rate

The problems arisen in the previous section can be summarized in this question: how to find the compression algorithm and the compression rate that minimize the overall sensor node energy consumption

Figure 2: Example of image representing metering on a water counter.

keeping an acceptable image quality? A compressed image can be considered of good quality if good measurements can be still made after decompression. This depends on the particular measurement application, since the minimum required quality changes with the application.

In figure 2 a typical acquired image is reported which deals with the specific application of remote counter metering. In these application the minimum quality level must still allow that the counter digits and serial number can be read after the compression-decompression process. Due to the aforementioned considerations the way to an answer to the former question passes through the following steps:

a) finding an objective index to evaluate the image quality after decompression;
b) estimating a quality index threshold representing the minimum quality level;
c) estimating the max image compression ratio which does not allow to overcome the threshold for a set of well known compression algorithms;
d) measuring the image processing (compression) time required by each compression algorithm;
e) estimating the redistribution of the burden between transmission and processing states;
f) choosing the compression algorithm and rate that reduce at minimum the total charge current time in a working cycle.

In the following subsections, the authors starting from their experiences in quantization and transmission theory [12] try to describe these steps in detail.

3.1 Finding an objective image quality index

A number of indexes have been proposed in literature which measure the picture quality degradation introduced by digital coding algorithms. They are usually divided into subjective and objective classes. Subjective methods as defined in the ITU-R BT 500 are very expensive and time-consuming [12], neither can they provide constructive information on the nature of the distortions or how to devise better digital video coding algorithms/systems. The simplest and most widely used full-reference objective quality metric is the mean squared error (MSE), computed by averaging the squared intensity differences of distorted and reference image pixels, along with the related quantity of peak signal-to-noise ratio (PSNR). These are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization. But they are not very well matched to perceived visual quality because it is based on pixel to pixel difference calculation and disregards the viewing condition and the characteristics of human perception [13], [14]. Natural image signals are highly structured: their pixels exhibit strong dependencies, especially when they are spatially proximate, and these dependencies carry important information about the structure of the objects in the visual scene. The fundamental principle of the structural approach is that the human visual system is highly adapted to extract structural information (the structures of the objects) from the visual scene, and therefore a measurement of structural similarity (or distortion) should provide a good approximation of perceptual image quality. For these reasons other algorithms able to find a more direct way to compare the structures of the reference and the distorted signals have been proposed in literature. It has been shown that a very simple algorithm based on structural similarity provides surprisingly good image quality prediction performance for a wide variety of image distortions. Among the other the following algorithms seem to be the most promising: Mean Squared Moran Error (MSME), SSIM, CW-SSIM [15]-[18].

The MSME index, based on the *I* model Moran statistics, measures the sharpness from a local area. Its advantages are: (1) measuring the sharpness of image that is strongly related to image quality; (2) providing a regional measurement which is relatively unaffected by the spatial displacement between two images; (3) measuring the structural distortion and not pixel variation. The MSME error rises from zero, absence of errors, to higher values.

The structural similarity (SSIM) index is a specific implementation from the perspective of image formation. The SSIM implementation is very simple with a low computational complexity. Like the Moran statistics, it is highly sensitive to translation, scaling and rotation of images. CW-SSIM method appears as an evolution of the SSIM index. It provides an image similarity measurement that is simultaneously insensitive to luminance change, contrast change, and small translation, scaling and rotation of images. Both SSIM and CW-SSIM go from one, maximum quality, to zero, absence of quality. In order to choose the suitable index, a reference image was produced where 35 different characters having the same dimension and structure of those reported in figure 2 are contained. Then a 58 image test set was obtained through some image transformations that keep invariant the character structure of the reference image. In particular: little rotations of maximum 5 degrees clockwise and counterclockwise, little translations of maximum 5 pixels in the left, right and diagonal direction, a little scale factors zoom in and zoom out were performed. Concerning the results reported in table 2, some considerations have to be made: (i) the CW-SSIM and the SSIM represent quality indexes while the MSME and MSE represent error index, (ii) even though the MME index show a very low error, its relative standard uncertainty is higher then the CW-SSIM and SSIM indexes, (iii) the MSME has assumed little variations also in case of very important image manipulation; held into account its range [-inf, +inf] it has shown little sensitivity. For these reasons and considering the Std Dev values for each index, the CW-SSIM can be chosen.

3.2 Choosing the threshold

Once the better image quality index has been chosen, the further step concerns with the definition of a suitable threshold related to the application required image quality level. As above said, in remote metering applications the decompressed image must still allow the counter digits and serial number to be read. In modern remote metering systems the measurement reading is often entrusted to suitable software modules, able to reconstruct the measurement information starting from an optical character recognition (OCR) procedure. Then, a received compressed image can be considered good enough if the OCR software is able to detect these digits correctly. For this reason a common OCR software as the “Omnipage pro 14.0” provided by Scansoft was adopted. The same image test set used in the previous section was corrupted with growing Gaussian, speckle, and salt and pepper noises until the OCR software was not able to recover the image information exactly. Then the CWSSIM image quality index value was estimated. The obtained value was 0,680 and hereinafter was considered as the minimum acceptable quality level of the acquired image.

3.3 Choosing the compression algorithm

Although the information theory science well describes the problem related to the use of compression algorithms to optimize the channel bandwidth occupation, and the maximum theoretical rates have been found for the different applications, the proposed problem can be considered rather different respect to the usual ones.

In this case, the authors tries to find a compression algorithm that: (i) gives the maximum compression rate preserving a given image quality, (ii) requires a computational burden allowing the implementation on a microcontroller device, and (iii) grants a significant reduction of the working cycle charge current time.

Compression algorithms are divided in two categories: lossless and “lossy”. “Lossy” methods are widespread because they offer greater compression factors than “lossless” ones, even if image quality is, of course, reduced.

Table 2: Performance of the selected image quality indexes on the realized image test set.

Index	Mean	Std Dev
CW SSIM	0.928	0.040
SSIM	0.705	0.088
MSME	-0.347	0.182
MSE	5250	2021

Table 3: Performance of the selected compression algorithms

Algorithm	CW- SSIM	Rate [bpp]	Processing Time [ms]
JPEG2000	0.760	0.20	1521
SS	0.690	0.50	15
DCT	0.720	0.26	188
SPIHT	0.700	0.18	937
JPEG	0.750	0.30	547

To this second class belong coding algorithms as the hybrid MC/DPCM/DCT [12], JPEG, EZW, and so on. These algorithms, may introduce visible distortions which have been well classified in the ANSI standard and in papers present in literature [19]-[21].

The experiments were conducted only on lossy algorithms as follows:

a) the more used algorithms were selected, in particular the well known JPEG2000, SS, DCT, SPIHT and JPEG;
b) for each algorithm the compression rate was increased until the quality index value of the decompressed image was lower than the fixed threshold;
c) the processing time were estimated on a PC based architecture in a Matlab 7.0 environment.

Table 3 reports the obtained results. It can be noted that the SPIHT algorithm gives the best compression rate, while the SS exhibits the minimum execution time. However, the SS algorithm seems to assure the best compromise between compression rate and processing time. In order to validate these results these algorithms should have been implemented on the proposed microcontroller hardware in order to estimate processing and communication times.

For sake of simplicity only the SS algorithm was implemented obtaining a processing time of 5010 ms and a communication time of 900 ms. The scaling factor between the PC based and the microcontroller based time execution was 334. The estimated results are reported in table 4 that reports, for each algorithm, the communication and processing times together with their current consumptions.

Analyzing the charge current times, it is evident that the SS algorithm can be considered the best solution for the considered application. The other compression algorithms require a total charge higher than the absence of compression. Moreover, the SS algorithm

Table 4: Performances of the proposed compression algorithm applying the execution time scaling factor.

	Communication	Processing
Required Current [mA]	70.030	26.030

Algorithm	Commun. Time [ms]	Process. Time [ms]	Charge-Cur*Time [A*S]
JPEG2000	366	519841	13,56
SS	900	5010	0,19
DCT	473	62792	1,67
SPIHT	331	186706	4,88
JPEG	544	82498	2,19

Table 5: Summary of the new power budgeting in the one hour cycle after image processing.

Operating state	Required Time [ms]	Required current [mA]	Charge Current Time [A*s]
Standby	35671758	0,0301	0,107
Sensing	2035	46,030	0,093
Processing	5010	26,030	0,130
Connection	19207	80,430	1,545
Communication	900	70,030	0.0630
Total	3600000	N/A	1,939

has the simplest implementation and doesn't require any floating point calculus. This means that the processing time of the other algorithms has to be even considered underestimated.

It is worth underlining that this solution has to be considered the best only for this particular application. If the application and/or the hardware change, the suggested procedure must be repeated.

4 Estimation of the overall energy consumption reduction

Considering the same operating cycle reported in section 2, the new power budgeting, after the SS compression, was then estimated. The obtained results are reported in table 5.

Considering the total charge current time reported in table 1 it can be noted that the energy reduction, due to the presence of image compression, is about 29%. Taking into account that the battery package was composed of a set of Duracell AA batteries, characterized by a capacitance of 2700 Ah, the sensor node lifetime passes from 147 to 209 days. Another important remark concerns with the time required to perform an image acquisition and communication that passes from 35465 ms to 28242 ms thus allowing an about 20% of throughput improvement.

5 Concluding remarks

The paper presented a software methodology to reduce the energy consumption in visual sensor nodes inserted in wireless networks. The method was based on the balancing between the computational and transmission phase in the sensor operating cycle. The obtained results have shown that, for the proposed architecture, the overall sensor charge current time can be reduced of about 30% without loosing information. Future developments will concern with the application of these technique in the case of collaborative visual wireless sensor.

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