

Green Surveillance Applications

J. Silvestre-Blanes
Universidad Politécnica de Valencia (UPV)
Instituto Tecnológico de Informatica (ITI)
Ferrandiz y Carbonell, Alcoy, 03801, Spain
jsilves@disca.upv.es

Abstract

Currently, falling prices in technologies associated with surveillance applications has led to a huge increase in their use in all types of environments, although the most common applications are monitoring of traffic and people. In surveillance applications, the majority of the algorithms and applications are based on robustness in the detection and monitoring of people, vehicles, etc., in all kind of conditions, in which power consumption is not a parameter of the system. In this work, we present the use of this technology to develop energy aware light control systems for large installations and to reduce energy consumption. Depending on the architectures and algorithms used significant power reduction is achieved.

1. Introduction

Video surveillance technology [3, 9] is a current reality widely used today in industrial, domotic and domestic environments. This is motivated by falling prices of the different elements used, mainly cameras, and the increase in camera interface possibilities (from USB and firewire to the expansion of IP cameras through Ethernet or WiFi links). Finally, the generalization and expansion of internet has facilitated telemonitoring and increased the advantages and performance of this technology. Here, Intelligent Video Surveillance (IVS) has become an important research area over recent years. The increase in processing power and the development of new algorithms enables their use and increases the range of applications of this technology.

The energy-aware considerations are analysed typically only in surveillance applications where Wireless Sensor Networks (WSN) are used with the objective of maximizing the sensor network lifetime [5, 6] while the application requirements are satisfied. However, in these papers only scheduling aspects are usually analysed without taking into account the other energy costs of the applications. Maier et al. analyse the power consumption properties in IVS [4, 8] and add this aspect in the QoS set, since it is connected to the availability of the service.

It is assumed by researchers that the algorithms used in video analysis are very demanding with respect to computer resources [4, 2], however their power consumption incidence is not usually considered. This consideration, strongly associated with execution time, is crucial today, since the sensors are constantly increasing the number of pixels to process, reaching today up to 21 Mpixels.

The objective of the system is the development of surveillance applications to save lighting energy in large installations, using COTS equipment, which means that algorithms of low energy and computing costs are needed. This type of technology can be applied as a domotic technology in industrial environments and buildings which generally have a high consumption of energy with traditional lighting systems. In this type of complex environment, control of the presence of people using computer vision can provide useful information for managing lighting systems which cannot be replaced by other systems such as photocells which are incapable of providing the correct information in a great variety of different cases, or RFID technology which has higher installation and energy cost, and also requires that tags are used by people which cannot always be guaranteed in public buildings.

2. Power Saving Applications

2.1 Energy Considerations in IVS

A usual generic architecture of an IVS is shown in fig. 1. An image is acquired through a sensor (analog, digital or intelligent cameras) in which the acquisition power consumption depends on the video acquisition properties; mainly resolution and frequency. The image has to be transmitted from sensor to processing node (except for intelligent cameras) through an analog or digital interface. Here, the image can be transmitted raw, or encoded (mainly MJPEG or MPEG4). When the frame is decoded, if necessary, the last step is processing it to get the results required. The classical video surveillance system pipeline is shown in the same figure [2]. Note that the separation between background (**BG**) and foreground (**FG**) objects is a crucial part of the algorithm, and that these are not trivial algorithms so their computational and energy cost will be important [2].

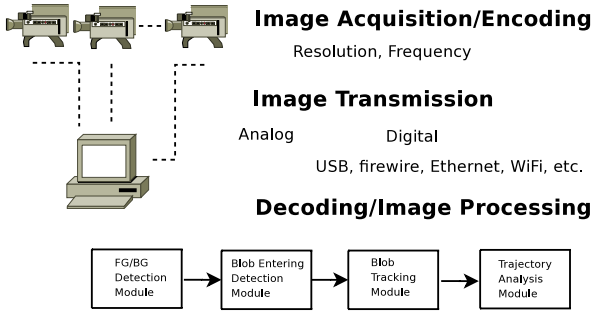


Figure 1. Architecture of a classical IVS

2.2 Problem formulation

Being n the number of sensors to control m objects, in this case lights. We denominate as e_L the energy needed by one light, and E_L the energy needed by the m lights in a system without the power-control mechanism, being $E_L = me_L$. The elements of the power-control system are the energy needed by the sensors in the system E_s , the energy needed by the processing nodes E_p , the energy needed by the light control systems E_c and the energy used by lights using the power-control mechanism as E_l . Consequently, to save energy the following must be fulfilled:

$$E_s + E_p + E_c + E_l < E_L \quad (1)$$

We denominate e_s to the energy used by one light using the save power mechanism whereas e_m and e_L are the lower and the higher energy used by the light. The mission of the IVS in this case is to control the light intensity according to need, with the objective of reducing power consumption.

The light energy used by one light i can be defined as:

$$e_s^i = r^i e_l^i + (1 - r^i) e_m^i \quad (2)$$

being r^i the ratio of time where the light i must be at maximum energy rate due to the application requirements. For simplicity, we assume that the mean r^i is the same for all lights covered by the n sensors, and they are also always of the same kind, so we can calculate E_l as:

$$E_l = \sum_{i=1}^m (r e_l + (1 - r) e_m) \quad (3)$$

Concerning E_s , it will depend on n and on the energy used by one sensor e_s including acquisition and transmission (and encoding if necessary). This will depend on the frequency f of the acquisition, so $E_s = n e_s(f)$. We have to consider that the energy consumed by the processing node will depend on the power energy needed by the algorithm to process a stream with frequency f , that is $e_p(f)$. Then $E_p = n e_p(f)$. On the other hand E_c , being e_c the energy to manage one light, then $E_c = m e_c$. Equation (1) can be expressed as:

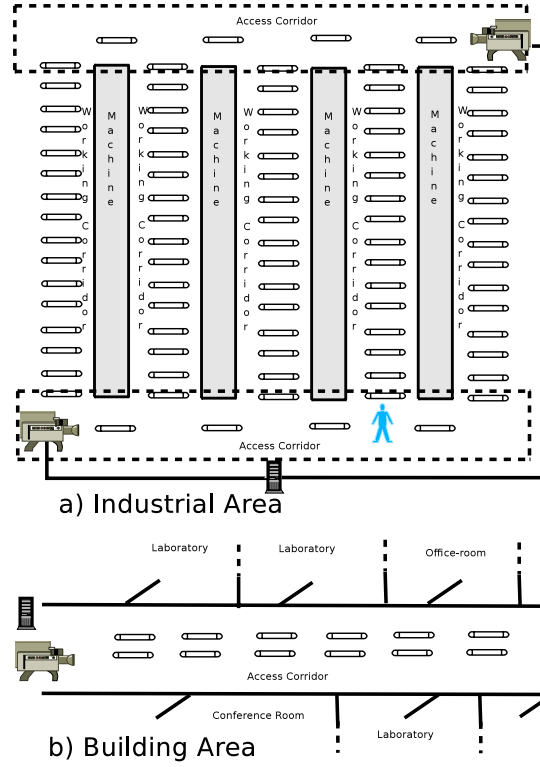


Figure 2. Examples of application

$$e_s(f) + e_p(f) < \frac{m}{n} ((1 - r) e_L + r e_m - e_c) \quad (4)$$

This equation shows that the key parameters to maximizing the power saving are r , and the relation m/n between the number of lights and the number of sensors necessary for their control. These parameters are dependent on the application and its environment, and therefore there are constants which limit the achievable power saving. Other variables which influence this are f , and the influence of this value on e_s and e_p . Moreover, f as well as n also influence the reliability of the system, limiting the maximum power saving achievable.

2.3 Numerical example

In this work, the aspect analyzed is the energy saving that this type of application can provide. In fig. 2.a we can see a plan that is very common in industrial environments, applicable with different topologies in buildings, as shown in fig. 2.b. In many public buildings there are lights on continuously, whether people are present or not, as in fig. 3. On the other hand, in industries where production is highly automated, the lights are permanently on 24 hours a day, 7 days a week. An example of this situation is shown in fig. 4. Although in the working areas there are no operatives present, as in b, c and d, the light remains on at maximum intensity (e_L). Access to the working areas has to be gained through an access corridor (see fig. 4.a),



Figure 3. Application in buildings



Figure 4. Application in Industry

in which a vision system can control the appearance and movement of people.

In the example shown in fig. 3 there are 12 lights permanently on for 18 hours per day with a consumption of $e_L = 55W$ per light. This represents in a year a consumption of 4.340 KWh. In the example shown in fig.4 there are 150 lights permanently on 24 hours a day. Assuming the same light consumption, this represents a consumption of 72.300 KWh over a year .

Using dimmable electronic ballast, the consumption of a light goes from $e'_L = 55W$ with 10 Vdc in the input, to $e_m = 6W$ with only 1 Vdc in the input. Each 0-10Vdc channel needs 0,300mW, that is, 15,12KWh, which is negligible with respect to the consumption of the light controlled by them. The parameter e_p has been measured using the *ACPI* (Advanced Configuration and Power Interface) capabilities on a laptop with ubuntu 7.10 and a Pentium M processor which can scale the frequency at 800, 1067, 1333 or 1733MHz. The system can pro-

Table 1. Power Consumption

fps	Alg. 1	Alg. 2	Alg. 3
1	16W	18W	21W
15	31W	31W	31W
time (msec.)	230	290	630

Parameters of the algorithms blobtrack:

Alg. 1: fg=FG_0S bd=BD.Simple bt=CC

Alg. 2: fg=FG_0 bd=BD.Simple bt=CC

Alg. 3: fg=FG_1 bd=bd_CC bt=MSPF btp=Kalman BTA=IOR

Table 2. CPU Freq. Scaling at 1fps

Freq (MHz)	Alg. 1	Alg. 2	Alg. 3
1733	25.5%	30.9%	69.2%
1333	0.1%	2.0%	1.3%
1067	0.0%	0.9%	0.5%
800	74.4%	66.2%	29.0%

vide the mAh consumed by the system functioning with batteries. As a video surveillance algorithm, the software tool *blobtrack* provided by opencv libraries [1] is used. This function has implemented functions for foreground/background separation, blob detection and blob tracking, and the different parameters in which the blob-track application have been launched is shown in table 1. For the first algorithm, the simplest algorithm is selected, which is a simplified version of the algorithm used in alg.2 [7]. The blob entrance and tracking algorithm is also the simplest. Algorithm 3 uses the most advanced capabilities in FG/BG discrimination and blob detection and tracking. In table 1 the time consumed by each algorithm is shown, and the e_p that their execution represents for their execution at 1 fps (since the time needed exceeds the acquisition period for 15 fps, the maximum consumption is obtained in the three cases). In table 2 the average frequency scaling performed by the procesing nodes where the algorithms are executed with sequences at 1 fps is shown. The values obtained by the tool *powertop* show a clear correlation between the CPU Frequency and the energy needed.

The difference of power dissipation for 1 and 15 fps for e_p are of 98 and 131 KWh for building and industrial scenarios. With these results, the most significant parameter in power reduction is r , since this, managed by a computer vision system, can reduce the consumption where it is necessary. In the building scenario, since m is a low value and the ratio m/n is low, the difference between the frames per seconds can be appreciated, obtaining differences in reduction of 3% (fig. 5). In the industrial scenario, the difference in frame rate becomes insignificant, as it is not significant with respect to the saving obtained in light consumption.

In fig. 6 the difference in the result between the use of 1 or 15 frames over one sequence using Algorithm 1 can be seen. Although the sequence capture at 15 fps allows

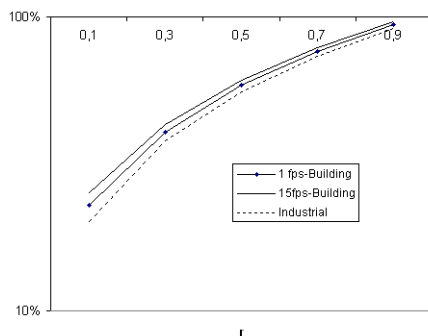


Figure 5. Power Reduction



Figure 6. Results of Algorithm 1

us to determine with precision the tracking of people, the processing at 1 fps also allows the same tracking, although with the presence of some errors.

3 Conclusions and future work

The use of surveillance technologies to reduce power consumption can give very significant result depending mainly on the r parameter, which is application dependent. The relation between the number of objects to be controlled m (light in this case), the number of sensors n and processor nodes, and the frame rate acquisition f also has some impact. Power consumption e_p is only relevant if the ratio m/n is quite low. However, the analysis of surveillance algorithms is of great interest in any case independently of m and n the application. Firstly, this reduction allows us to increase the frequency and the number of sensors to obtain better results in the application. Sec-

ondly, it also allows us to increase the number of areas covered by the same process node. Finally, given the explosion in surveillance applications, the reduction in consumption in sensors as well as in image transmission and processing nodes presents both ecological and economic advantages.

We are currently working on vision modules to obtain good performance in segmentation and tracking of the object as the objective of the system. The algorithm has to take into account the lower illumination conditions in the first blob detection, and the frequency considerations according to the blob velocity, sensors distribution, image frequency and energy considerations.

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