# Exploration of Local and Central Processing for a Wireless Camera Based Sensor Node

Khursheed Khursheed, Muhammad Imran, Mattias O'Nils, Najeem Lawal
Department of Information Technology and Media, Division of Electronics Design,
Mid Sweden University, Sweden
{khursheed.khursheed,muhammad.imran,mattias.onils,najeem.lawal}@miun.se

**Abstract. Wireless vision sensor network is an emerging field which combines image sensor, on board computation and communication links. Compared to the traditional wireless sensor networks which operate on one dimensional data, wireless vision sensor networks operate on two dimensional data which requires both higher processing power and communication bandwidth. The research focus within the field of wireless vision sensor network has been based on two different assumptions involving either sending data to the central base station without local processing or conducting all processing locally at the sensor node and transmitting only the final results. In this paper we focus on determining an optimal point for intelligence partitioning between the sensor node and the central base station and by exploring compression methods. The lifetime of the visual sensor node is predicted by evaluating the energy consumption for different levels of intelligence partitioning at the sensor node. Our results show that sending compressed images after segmentation will result in a longer life for the sensor node.**

## I. INTRODUCTION

The camera based networks for security purposes presented at an early stage in the literature included independent cameras which transmitted continuous data streams to the central base station for further processing. This required a great deal of resources such as a wired network, high energy consumption and significant amounts of storage space [2]. The technological development in image sensors, sensor networking, distributed processing, low power processing and embedded systems have paved the way for smart camera networks which have the ability to perform even the more complex jobs by using batteries, a wireless link and possessing only a limited storage facility. Such camera based networks could easily be installed in out-door areas where there is a limited power availability, where access is difficult and where it is inconvenient to modify the locations of the nodes or to frequently change the batteries. Later work in Wireless Vision Sensor Networks (WVSN) consisted of a number of smart cameras in which an individual smart camera is referred to as a sensor node. The node is built from an image sensor, local processor, storage facility and wireless transceiver [9, 12]. The WVSN is expected to work under stringent power supply conditions, on board processing capability and storage and transmission bandwidth requirements. In order to have real-time performance, the smart cameras must be able to perform processing, be able to make some subsequent intelligent decisions and then to provide successful transmission over the wireless link. The focus is on producing a system which is power aware, is able to perform the necessary on board computations, has sufficient on board storage, and is able to fulfill the energy requirements of the system and transmission bandwidth.

The energy consumption and bandwidth are major constraints in wireless vision sensor networks. A low energy requirement is of great interest as the choice of wireless for sensor network means that wiring is a difficult option. The large amount of data generated by a vision sensor node requires a great deal of energy for processing and transmission bandwidth compared to other types of sensor networks [2, 3, 5]. It is the case that on board processing and communication both influence the energy consumption and that more on board processing reduces the energy consumption due to communication and vice versa [1]. Different software and hardware approaches are proposed in order to minimize the energy consumption in wireless sensor networks [1, 4]. The majority of the work has concluded that by reducing the energy consumption due to communication this will result in less total energy consumption. A hybrid vision system is proposed in [7], which uses two kilo pixel imagers for low resolution images and one high resolution camera module for detailed object snapshots. One of the kilo pixel imagers constantly monitors objects entering the field of view and when an object is detected, the second low resolution image sensor is activated to compute the location and size of the object based on stereo vision. Subsequently, a high resolution camera is triggered so as to capture a high resolution gray or color region of interest including only the detected object. CMUcam3 [8] was presented by Carnegie Mellon University in 2007. It was the third version of CMUcam. FireFly Mosaic [9] wireless camera and consists of a wireless sensor platform FireFly [10] node together with a CMUcam3. It uses a real-time distributed image processing infrastructure together with a collision free TDMA based communication protocol. The FireFly Mosaic has the ability to handle multiple cameras performing local processing. The FireFly is a low-cost, low power sensor platform that uses a real time operating system and supports an expansion board for light, temperature and battery-voltage level sensing capabilities. SensEye[11] is a multi-tier of heterogeneous wireless nodes and cameras which aims at low power, low latency detection and low latency wake-up. In this approach low power elements are used to wake up high power elements. Resource-constraints mean that low power sensors are used to perform simple tasks while high power sensors conduct the more complex tasks.

In the literature many authors have focused on different implementation strategies for vision processing at the sensor nodes. Some authors have taken the images of the field of view, compressed the images and sent them to the base station for further processing [1]. In this case the communication cost is much higher because they have not performed any vision processing at the sensor node and are sending compressed images directly to the base station. The main processing unit at the sensor node must also be alive for the communication of these compressed raw images and hence its power must be considered. On the other hand some authors have performed all the vision processing at the sensor nodes and have merely sent the object features to the base station as the final results. In this case the communication costs are much lower but the computational costs are very high because the sensor node is performing operations for a longer time. An algorithm is required for partitioning the level of vision processing between the sensor node and the central base station, so that the overall power consumption is reduced. In our work we have addressed this intelligence partitioning between sensor nodes and the central base station. We have calculated the total energy consumption for different levels of intelligence at the sensor nodes by means of a summation of the communication and computational energy. Fig.1 shows the different levels of partitioning in our algorithm. Based on our results for the total energy consumption we have determined that the energy consumption will be at a minimum if we perform computation up to segmentation at the node, perform TIFF compression and then send the results. The dashed lines after some stages in Fig. 1 show that the results after these stages could be compressed and sent to the base station.

## II. TEST SYSTEM

The application for our work is the detection of magnetic particles in a flowing liquid. The particles are classified both by their size and number and this system is used for failure detection in machinery. The flowing liquid in the system might contain air bubbles which can be identified as objects. The removal of the bubbles can be handled in two different ways. In the pixel based method, the individual pixels of each bubble are identified and removed from the image, while in an object based method, the whole bubble is treated as a moving object, which can be identified and removed. The following are the main stages of our algorithm.

*Pre-Processing:* In this step the image is subtracted from the background. In the pixel based method, the background is initially stored and this stored background is used for the subtraction operation. In the object based method, a real time background is generated from the original image by using a low pass filter. This real time estimated background is then subtracted from the image in order to detect objects which could be magnetic particles or bubbles. All pixels having a gray scale value less than a pre-defined threshold are assigned a zero(representing black) value and all other pixels in the image are assigned the value one (representing white). A morphological operation is then performed on the segmented image in order to remove one to two pixel false objects.

*Bubble Remover:* Bubbles can be identified as moving objects, so if an object changes its location in two consecutive frames, this provides confirmation that it is a bubble. In the pixel based method, the corresponding pixels in two consecutive frames are compared and if their gray scale values are different then a zero is placed at that pixel location. In this way, the bubbles are easily identified and removed. In the object based method, the location and area of the objects are compared in two consecutive frames and if the location or area for any object has changed, this means that it is a bubble and is removed. The challenge associated with this method is that, sometimes, due to changes in the illumination, the area of the object could be decreased or increased in consecutive frames and that magnetic particles might be treated as bubbles. We have dealt with this challenge by introducing a flexibility of one to three pixel variations in the area and location of objects in consecutive frames. The bubbles in two consecutive frames definitely have a variation which exceeds three pixels because of the high speed of the oil. In the pixel based method the bubbles are removed after the morphological operations while in the object based method the bubbles are removed after classification as shown by the dotted lines in Fig. 1.

*Labeling and Classification*: Each object is assigned a unique label. Following this, the areas and locations of each object are determined. The final results are transmitted to the central base station through an IEEE 802.15.4 transceiver.

*Image Compression:* TIFF compression could be performed after stages A, B, C or D as shown in Fig. 1.

In Fig.1, images are taken from a setup of the system in which A is the image after the image has been subtracted from the background, B is the image after segmentation and C is the result after the morphological operation. In images A, B and C bubbles are visible which are removed in image E. For these images we have applied an object based bubbles remover algorithm.

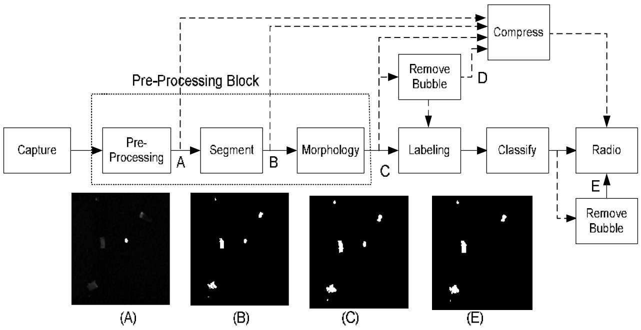


Fig.1. Algorithm flow for possible intelligence partitioning

## III. TARGET PLATFORM

The target Platform is SENTIO32 [12], a platform for wireless sensor networks developed at Mid Sweden University. It has a CC2520 RF transceiver with 2.4 GHz IEEE 802.15.4, with on-board antenna. SENTIO 32 has a high performance low power AVR32 32bit RISC MCU running at 60MHz for only 23.5mA. It has 256KB flash, 32KB SRAM, DSP instruction set and peripheral DMA channels. It has a low sleep power consumption of 60µA when only the 32 KHz clock is running. It has a support to integrate a microSD card up to 16GB and data I/O speeds up to 50Mb/s. Images are captured using the CMOS Image Sensor.

## IV. RESULTS

Table 1 shows the energy consumption of individual components in the sensor node. These energies are captured by characterizing each function separately on the SENTIO 32 platform. Table 2 shows a comparison of the energy consumption of the AVR32 for different intelligence partitioning strategies. It can be observed from Table 2 that sending the raw images (RAW_IMG) directly to the base station results in the minimum computational energy (0.835 mJ) but if we perform all image processing tasks at the sensor node and only transmit the final object features (FEATURES) to the base station, a higher computational energy is required (639.408mJ). Sending raw images implies that more data is sent over the wireless link which will contribute to the higher communication energy shown in Table 3. If only FEATURES are sent, it will contribute to a minimum communication energy (1.0179 mJ) but on board computational energy is much higher (639.408 mJ). Sending a compressed image after segmentation is the optimal solution.

If raw data (RAW_IMG) or compressed raw data (COMPRES_RAW) is sent from the sensor node, then the energy consumption is higher due to the higher communication cost as shown in Fig. 4 and Fig. 5. When each strategy is repeated, after a particular length of time it becomes visible in the life time curves of Fig. 6 that the life time of the strategy when a raw image is sent (RAW_IMG) is at a minimum, while at the other extreme, if a compressed binary image after segmentation is sent over the wireless link, this will result in a longer life time. The reason for this is that, at the COMPRESS_AF_SEG stage, the proportions in relation to the energy consumption due to the processing and communication are such that this results in the minimum energy consumption. The life time is calculated using 4 AA batteries, see Fig. 6. It can be observed in Fig.1 that when the sample period increases, the sleep energy also increases. For the analysis we have used the case in which a compressed binary image after segmentation (COMPRESS_AF_SEG) is sent over the wireless link (this strategy is chosen because it is optimal). The conclusion drawn in this case is that as the sample period is increasing, the sleep energy will dominate the other energies.

TABLE 1. ENERGY CONSUMPTION OF INDIVIDUAL COMPONENTS

| Component | I (mA) | V (v) | T (ms) | E (mJ) |
|---|---|---|---|---|
| Light | 15 | 3.3 | 1.484 | 0.0734 |
| Camera | 35 | 3.3 | 9.2857 | 1.1 |
| IEEE 802.15.4 | 40 | 3.3 | 39.78 | 5.250 |
| AVR32 | 23.5 | 3.3 | 910.83 | 72.78 |

TABLE 2. ENERGY OF AVR32 FOR DIFFERENT PROCESSING STRATEGIES

| Processing stages | No. of bytes | T_AVR(ms) | E_AVR (mJ) |
|---|---|---|---|
| RAW_IMG | 241078 | 11.01 | 0.835 |
| BINARY_AF_SEG | 30134.75 | 617.43.8 | 46.811 |
| COMPRESS_AF_SEG | 1218 | 910.838 | 69.96 |
| COMPRESS_AF_MOR | 1282 | 3244.43 | 247.088 |
| BUBBLE REMOVER | 458 | 3428.56 | 261.064 |
| FEATURES | 114 | 6009.53 | 639.408 |

TABLE 3. ENERGY OF IEEE 802.15.4 FOR DIFFERENT STRATEGIES

| Processing stages | No. of bytes | T_IEEE (ms) | E_IEEE(mJ) |
|---|---|---|---|
| RAW_IMG | 241078 | 7715.29 | 1018.419 |
| BINARY_AF_SEG | 30134.75 | 965.112 | 127.394 |
| COMPRESS_AF_SEG | 1218 | 39.78 | 5.250 |
| COMPRESS_AF_MOR | 1282 | 41.82 | 5.520 |
| BUBBLE REMOVER | 458 | 15.46 | 2.040 |
| FEATURES | 114 | 3.84 | 1.0179 |

In Table 2, E_AVR and T_AVR are the energies consumed and the time spent on the computation of the operations respectively. Similarly in table 3, the E_IEEE and T_IEEE are the energies consumed and the time spent on the communication of the results respectively.

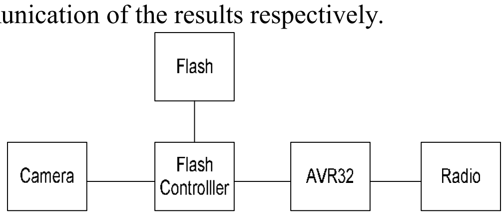


Fig.2. Individual Components of the Sensor Node

In table 3, the T_IEEE is calculated using equation 1.

$$T\_IEEE = (X + 19) \cdot 0.000032 + 0.000192 \quad (1)$$

where X is the number of bytes transmitted.

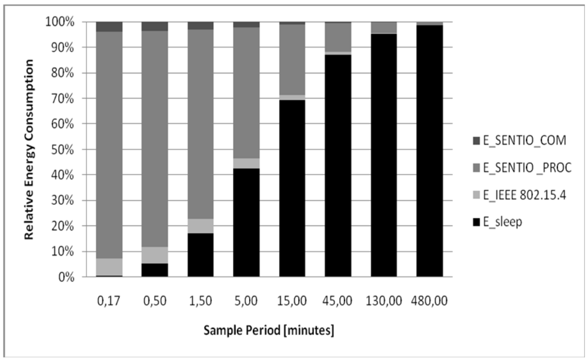


Fig.3. Energy consumption showing sleep energy dominancy

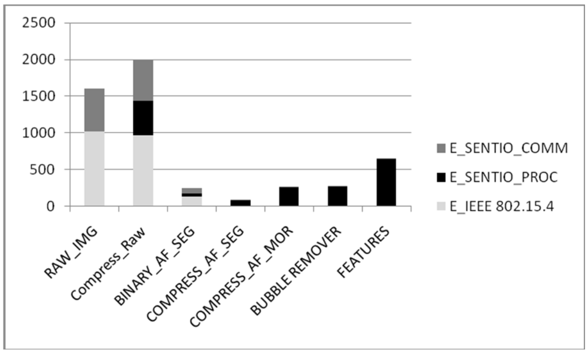


Fig.4. Absolute Energy Consumption for Each Strategy.

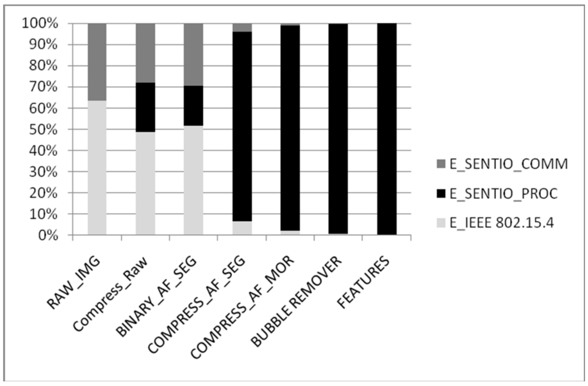


Fig.5. Relative Energy for Each Strategy.

## V. Conclusion

We have shown that partitioning between local and central computation affects the energy consumption in visual sensor nodes. When compressed data is sent after segmentation, it will result in less energy consumption and hence the sensor nodes will last longer. For a high sample frequency the main challenge of increasing the life time of the sensor node is to optimize the vision processing. When the sample period is 15 minutes, the life time of the sensor node for sending raw data is less than a year and, for the optimum case, when the local node is performing the operations of preprocessing, compression and then sending the compressed binary image to the central base station for further processing, the life time of sensor node is 4.22 years as shown in Fig. 6.

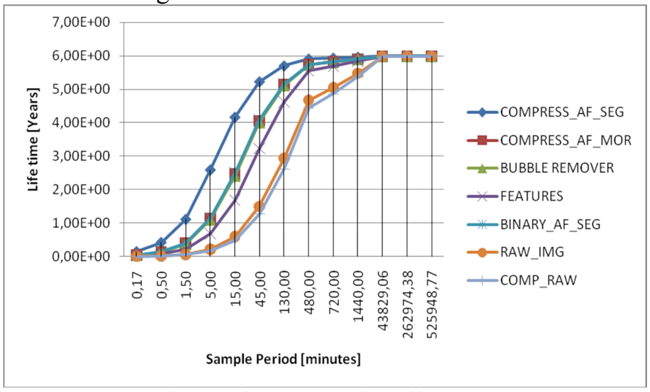


Fig.6. Life time of sensor node for different strategies.

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