Bandwidth-Effective Design of a Satellite-Based Hybrid Wireless Sensor Network for Mobile Target Detection and Tracking

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***Abstract*—Wireless sensor networks (WSNs) have the potential to assist advanced target tracking applications. The major challenge related to the design of such networks is to cope with the energy and computational limitations that characterize sensor nodes. To address this problem, we propose a hybrid architecture that integrates two sensor categories. The first performs basic detection and tracking functions while the second supports complex tasks such as imaging and broadband communication via a satellite network. Moreover, we develop a technique that allows vision sensors adapting the rate of the exchanged data according to the target activity in the monitored zone. Finally, a tracking approach taking into consideration the error on local sensor position measurements is presented.**

***Index Terms*—Energy-effective design, hybrid wireless sensor networks (WSNs), mobile target tracking, satellite backbone, vision sensors.**

I. Introduction

SENSOR networks are dense wireless networks of heterogeneous nodes collecting, forwarding, and analyzing environmental data. A large proportion of emerging sensor technology applications, such as target detection, recognition, and tracking, require the support of image sensing capabilities [1], [2]. For instance, consider a military wireless sensor network (WSN) deployed in the battlefield, once an intruder target is detected, high resolution images, and even video sequences, may be needed to explore several details about the intrusion. This encompasses the use of large image and video repositories as well as broadband links to support the storage and transmission of high-resolution multimedia data. The major problem that one should think of when designing such applications is that typical sensor nodes are characterized by hardware (i.e., processing, memory), energy, and power limitations. To better handle high quality image and video streams, we propose, in this paper, to enhance the sensor network with a satellite backbone.

This paper extends the WHOMoVeS sensor network, which has been previously devised by the authors, by addressing novel issues such as image sensing, satellite access, and multimedia communication [3]. We consider two categories of sensor nodes: detection sensors and vision sensors. The first is used to detect and track mobile targets within the monitored area while the second provides refined details about the nature of the target and the intrusion strategy. A satellite-based network assists this detection infrastructure by providing a reliable and broadband communication infrastructure. Using this approach, data gathered at distributed battlefields can be forwarded towards an analysis center where the collected information is appropriate. Furthermore, a coding technique is developed in order to adapt the size of the multimedia content to the satellite transmission and storage requirements. Effectively, the size of high-resolution multimedia stream grows according to the quality of the data. Moreover, image and video processing becomes computationally complex when high quality is required. Hence, we propose an efficient coding scheme that allows tuning the rate of the transmitted images according to the target activity in the monitored zone. For this purpose, we adapt the well-known embedded zero-tree wavelet (EZW) coding algorithm with minor modification by introducing spatial information about target activity. In other terms, the transmitted image will include different regions that have different resolutions, depending on their proximity to the intruder target(s). Finally, an approach to enhance the precision of target tracking based on information filtering is described. The idea is to take into consideration the error made on sensor location measurement so that the target position can be estimated with more accuracy.

The rest of this paper is organized as follows. Section II describes the wireless hybrid optimal mobile vehicle sensing (WHOMoVeS) infrastructure and reviews the major results that have been established. Section III details the architectural issues related to a satellite-based design of a hybrid WSN for target detection and tracking. Section IV proposes an image coding algorithm based on EZW and introduces spatial information about the mobile target location in the compression process. A target tracking technique relying on information filtering is presented in Section V. Section VI describes and analyzes the performance of the proposed techniques in a simulation environment. Section VII concludes this paper.

II. Previous Work

To use WSNs in sensitive applications, the measurement quality as well as the transmission rate and availability should meet several requirements. In fact, in such contexts, error occurrences should be minimized. In the currently available products, sensor nodes can range from small motes to image sensors equipped with long-range radio interfaces. As the use of sophisticated sensing and communication technologies in

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large areas turns out to be expensive, the deployed sensor nodes should present variety in size, processing, energy resources, and communication techniques. Therefore, new approaches involving hybrid WSNs are emerging.

Hybrid WSNs have two major properties, namely, the broadband backbone and the multimodal sensing. These features are the result of integrating different categories of sensors within a single application, allow advanced (i.e., intelligent, high-resolution) data gathering, processing, and archiving. The main advantage is to ensure processing and energy savings for resource-impoverished sensors.

In [3], Hambdi *et al.* introduced a hybrid WSN model called WHOMoVeS. The proposed architecture exhibits two fundamental advantages, which are as follows.

- *Multimodal Sensing:* The use of multiple sensing technologies enhances the analysis of the gathered data. For instance, images are more appropriate for visual control of the monitored area while electromagnetic and acoustic sensing provide efficient detection and tracking alternatives.
- *Broadband Communication:* The ability of delivering reliably large volume of high quality data is strongly needed in a hybrid WSN. However, tiny motes do not allow transmitting huge volumes of data that are gathered by sophisticated sensors. To overcome this limitation, multiple technologies such as IEEE 802.16 and possibly UWB can be used for this purpose.

WHOMoVeS is composed of two layers: the *core layer* and the *sensing layer*. The core layer includes N_c sensors, denoted by $\{c_1, \ldots, c_{N_c}\}$, which are equipped with powerful sensing and transmission capabilities. The sensing layer consists of N_s miniature devices, also referred to as elementary sensors denoted by $\{s_1, \ldots, s_{N_s}\}$, whose role is limited to the detection of hostile presence.

The major issue that has been addressed in [3] is to develop an optimal node placement strategy. In our case, since the sensors are randomly scattered, the major challenge is to determine the sensor density (i.e., number of sensors per unit of surface). We assume that N_s sensors $s_1, \ldots, s_{N_s}$ are randomly deployed in the monitored area with a density ρ_s. We assume that a sensor is characterized by a sensing range R_s^s and a communication range R_s^c. We also suppose that all the elementary sensor nodes are binary, meaning that they detect one bit of information indicating whether the Euclidian distance between the sensor and the target is lower than R_s^s or not. The authors proved in [3] that the minimal sensor density ensuring that a randomly located target is detected by k sensors equals $\rho_s^{\min} = k/\pi(R_s^s + R_t)^2$, where R_t is the radius of the target. Moreover, it has been demonstrated that if sensors s_i make a distance ϵ during a time interval $\Delta\theta$ according to uniformly distributed random directions δ_i (on $[0, 2\pi]$), and if k^θ denotes an integer such that A is (k^θ, R_t)-covered at instant θ, then the variation of k^θ according to time is expressed by

$$k^{\theta+\Delta\theta} = \left\lfloor \frac{k^\theta}{\pi R_0^2} \Upsilon(\epsilon) \right\rfloor \tag{1}$$

where $\lfloor . \rfloor$ denotes the floor operator, $\Upsilon(\epsilon) = [(\pi(R_0 - \epsilon)^2) + \pi(R_0^2 - (R_0 - \epsilon)^2) I_1(\epsilon) + \pi((R_0 + \epsilon)^2 - R_0^2) I_2(\epsilon)]$, $R_0 = R_t + R_s^s$, $I_1(\epsilon) = \int_{R_0-\epsilon}^{R_0} \int_0^{2\pi} (2\pi - \arccos((R_0^2 - r^2 - \epsilon^2)/2r\epsilon)) dr d\alpha$, $I_2(\epsilon) = 2\pi - \int_{R_0}^{R_0+\epsilon} \int_0^{2\pi} \arccos((r^2 + \epsilon^2 - R_0^2)/2r\epsilon) dr d\alpha$. Moreover, the function $\phi(\theta) = k^\theta$ is the root of the differential equation (in χ)

$$\chi'(\theta) = \frac{\delta\Gamma}{\delta(y)}(\theta, 0)\chi(\theta)$$

where $\delta\Gamma/\delta(y)$ denotes the derivative of $\Gamma(.,.)$ with respect to its second variable and $\Gamma(\theta, \Delta\theta) = \Upsilon(\epsilon)$.

In the following section, we present a satellite-based architecture that implements the WHOMoVeS approach. Broadband multimedia data transmission is performed through satellite links in order to support advanced acoustic-based and image-based target tracking.

III. Satellite-Based Backbone for Mobile Vehicle Tracking and Recognition

Tracking based on acoustic and electromagnetic sensors may not provide adequate information regarding intruding vehicles. More details related to the vehicle itself, onboard personals and/or armament, might also be interesting to gather. To achieve this need, imaging sensors can be used in conjunction with the sensing layer nodes, by being embedded in the core layer nodes. Nevertheless, the use of image sensors cannot be uncontrolled because they have a high sensing cost and they generate a huge volume of data. In fact, these factors limit their massive and continuous activation. The volume of generated data not only poses a heavy burden from the data delivery perspective but might also flood the useful image frames with a huge amount of frames of non-interesting scenes. Moreover, the considerable power consumption of image sensors may reduce the network lifetime, even though vision sensors are supposed to have much less energy constraints than simple sensors. Henceforth, imaging should be triggered by the tracking results of the sensing-layer devices, which use traditional tracking algorithms. From an architectural point of view, image sensors should be integrated within uninhabited aerial vehicles (UAVs). Using this approach, only the image scenes that exhibit a substantial interest, from the military strategy perspective, are sensed in more details. Fig. 1 depicts an overview of the proposed hybrid sensor network architecture. The reader can notice that this architecture defines three major components: ground sensors, aerial sensors, and the satellite backbone.

A ground sensor is assumed to perform three types of operations: 1) collecting information about presumably malicious objects; 2) generating real-time events related to the detected targets and transmitting the events towards the closest core sensor; and 3) relaying the events generated by other sensors to the core sensors.

At the aerial sensors' layer, nodes are able to acquire and exchange voluminous high-resolution data related to the events detected by the low-level sensors. On the one hand, this layer interfaces a satellite communication backbone allowing to spread data collected by elementary sensors on a wide area. On the other hand, it has enhanced sensing features permitting to refine the information gathered at the low level. Therefore, the major functionalities that should be supported by core sensors are: 1) acquiring high-resolution data about the detected events (i.e.,

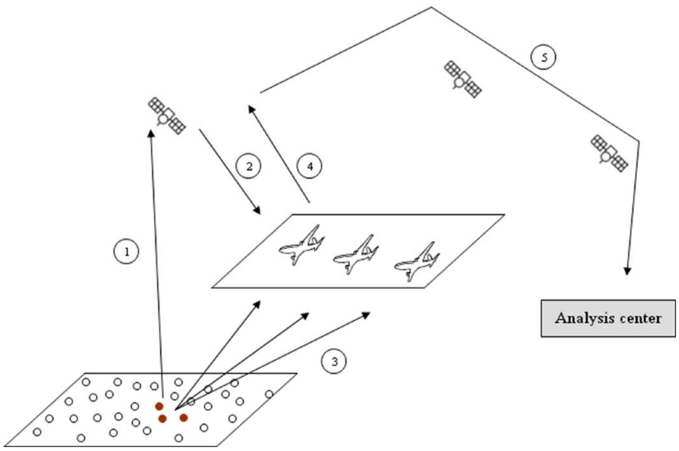


Fig. 1. Architecture of the proposed satellite-based communication backbone.

image or video data); 2) forwarding voluminous data-packets via a broadband infrastructure; 3) analyzing the events generated by low-level sensors in order to minimize erroneous decisions; and 4) communicating hostile presence to the adjacent core sensors so that they activate low-level sensors.

The process of acquiring and analyzing data related to mobile targets in the battlefield includes five steps as illustrated in Fig. 1. These steps are briefly described in the following.

1) Ground sensors detect the presence of a hostile target in the monitored field and store the events in memory. The satellite periodically contacts sensor nodes to download updates about target presence.
2) Satellite contacts the UAVs to acquire image data about the scene where the intrusion has been detected.
3) UAVs gather image data through the embedded imaging sensors.
4) UAVs establish connections with the satellite communication backbone in order to transmit high-quality multimedia data about the battlefield.
5) Images related to multiple intrusion events are forwarded through the broadband satellite backbone to the analysis center where advanced tracking functionalities are carried out.

Clearly, the focal component of the proposed architecture is the satellite backbone. Supporting the transmission of high-resolution multimedia data requires the use of new technologies in the satellite system. In fact, the current satellite system architectures are generally responder satellites. This basically means that the satellite reflects the uplink signal on the downlink frequency. Introducing processing technologies in the satellite allows demodulating the uplink signal and remodulates it to constitute the downlink signal. One major future generation satellite system that has been designed in the military context is the transformational satellite (TSAT) system, which is a composite of space-based assets of the National Aeronautics and Space Administration (NASA), the U.S. Department of Defense (DoD) and the Intelligence Community (IC). TSAT system is conceived as a constellation of five satellites, placed in geostationary orbit, that constitute a space-based high-bandwidth communication backbone to allow terrestrial units to access optical and radar imagery from UAVs and satellites in real time. This backbone provides broadband, reliable, worldwide, and secure transmission of various data. The satellite components of the TSAT system will incorporate RF and laser communication links to meet requirements for high data rate protected communications. The TSAT resources support RF data rates up to 45 Mb/s and laser communication user data rates into the 10–100-Gb/s range.

The previous description of the TSAT system illustrates the important capabilities of the next-generation satellite systems. Such satellite systems constitute one fundamental component, on which the WHOMoVeS tracking network is built.

IV. Bandwidth-Efficient Multimedia Coding

A. Embedded Zerotree Image Coding

The EZW encoder is based on progressive encoding to compress an image into a bit stream with increasing accuracy. This means that when more bits are added to the stream, the decoded image will contain more detail. The basic idea is to use the dependency between the wavelet coefficients across different scales to efficiently encode large parts of the image which are below a threshold that is updated at each iteration of the algorithm. The EZW scheme therefore includes a main loop, which is repeated for values of the threshold that are halved at the end of each iteration. The threshold is used to calculate a significance map of significant and insignificant wavelet coefficients. Zerotrees are used to represent the significance map in an efficient way. The main steps of the EZW coding scheme are given in the following.

- *Initialization:* Set the threshold T to the smallest power of 2 that is greater than $\max_{(i,j)}(|c_{i,j}|/2)$, where $c_{i,j}$ are the wavelet coefficients.
- *Significance Map Coding:* Scan all the coefficients in a predefined way and output a symbol when $|c_{i,j}| > T$. When the decoder inputs this symbol, it sets $c_{i,j} = \pm 1.5$ T.
- *Refinement:* Refine each significant coefficient by sending one more bit of its binary representation. When the decoder receives this, it increments the current coefficient value by ± 0.25 T.
- Set $T = 0.5$ T, and go to step 2 if more iterations are needed (i.e., $T > 1$).

A wavelet coefficient $c_{i,j}$ is considered insignificant with respect to the current threshold T if $|c_{i,j}| \leq T$. The zero-tree data structure is based on the following well-known experimental result. If a wavelet coefficient at a coarse scale (i.e., high in the image pyramid) is insignificant with respect to a given threshold T, then all of the coefficients of the same orientation in the same spatial location at finer scales (i.e., located lower in the pyramid) are very likely to be insignificant with respect to T. In each iteration, all the coefficients are scanned in the order shown in Fig. 2. This guarantees that when a node is visited, all its parents will already have been scanned. The scan starts at the lowest frequency (i.e., subband LL_n), continues with subbands HL_n, LH_n, and HH_n, and drops to level $n-1$, where it scans HL_{n-1}, LH_{n-1}, and HH_{n-1}. Each subband is fully scanned before the algorithm proceeds to the next subband.

Each coefficient visited in the scan is classified as a zero-tree root (ZTR), an isolated zero (IZ), positive significant (POS), or negative significant (NEG). A ZTR is a coefficient that is insignificant and all its descendants (in the same spatial orientation tree) are also insignificant. Such a coefficient becomes the

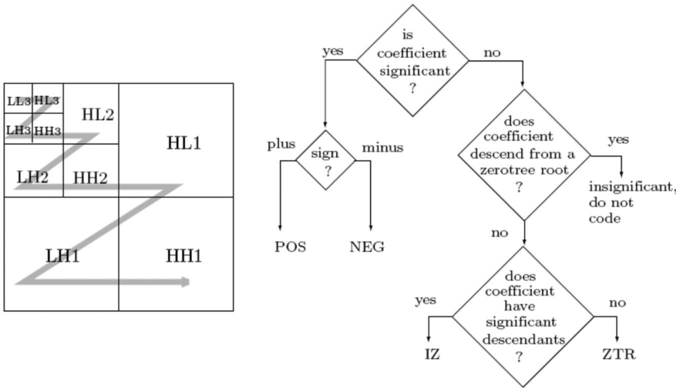


Fig. 2. EZW encoding scheme.

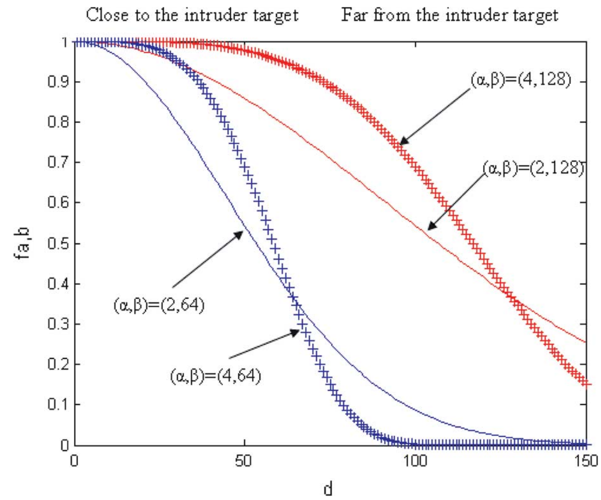


Fig. 3. Behavior of the function $f_{\alpha,\beta}(.)$ according to the distance d from the coefficient to the closest target.

root of a zerotree. It is encoded with a special symbol (denoted by ZTR), and the important point is that its descendants do not have to be encoded in the current iteration. When the decoder inputs a ZTR symbol, it assigns a zero value to the coefficients and to all its descendants in the spatial orientation tree. Their values get improved (refined) in subsequent iterations. An IZ is a coefficient that is insignificant but has some significant descendants. Such a coefficient is encoded with the special IZ symbol. The other two classes are coefficients that are significant and are positive or negative. The flowchart of Fig. 2 illustrates this classification. Notice that a coefficient is classified into one of five classes, but the fifth class (a zero-tree node) is not encoded.

Coefficients in the lowest pyramid level do not have any children, so they cannot be the roots of zerotrees. Thus, they are classified into IZ, positive significant, or negative significant. The zerotree can be viewed as a structure that helps find insignificance. Two lists are used by the encoder (and also by the decoder) in the scanning process. The dominant list contains the coordinates of the coefficients that have not been found to be significant. They are stored in the order scan, by pyramid levels, and within each level by subbands. The subordinate list contains the magnitudes (not coordinates) of the coefficients that have been found to be significant. Each list is scanned once per iteration.

B. Adapting the EZW Algorithm to WSN Multimodal Tracking

EZW coding can be seen as a prioritization of wavelet coefficients according to their magnitudes. The coder first transmits the coefficients packets starting by those with the highest magnitudes then continues with the next lower priority, and so on. In this paper, we enhance this prioritization protocol by including information about the spatial target position in the priority allocation process. The objective is to encode wavelet coefficients that correspond to a mobile target's neighborhood in the first passes so that more details about the nature and the activity of the target are provided at the received level.

To this end, we modify the EZW coefficient prioritization protocol so that pixels belonging to the target neighborhood are delivered with a resolution that exceeds a minimum threshold, and the quality of the coefficients that are far from the scene of interest do not exceed a maximal threshold. This guarantees that the pixels that do not have a substantial interest, from the tracking point of view, and consume only a limited rate of the available transmission bandwidth. Moreover, it is preferable that the minimum threshold decays faster than the maximum threshold. This allows controlling the bit-rate spent for the low priority regions and reaching a high-quality in the first iterations of the algorithm for the high priority regions. To fulfil this requirement, we use the function expressed by

$$f_{\alpha,\beta}(c_{i,j}) = \exp\left(\frac{-\sqrt{(i-i_t)^2+(j-j_t)^2}}{\beta}\right)^{\alpha} \tag{2}$$

where $c_{i,j}$ is the wavelet coefficient located at (i,j), (i_t,j_t) is the location of the closest target to (i,j), α is the concavity factor, and β is the stretching factor.

This function can be used to control the decay of the coefficient threshold according to the spatial location of the coded coefficient. The idea is to weight the EZW threshold by $f_{\alpha,\beta}(.)$. Fig. 3 illustrates the behavior of this function according to the distance d from the coefficient to the closest target for different values of α and β. The reader can notice that the decay of the function towards infinity is suitable for coefficients that are close to the target because the threshold rapidly decreases, which results in enhancing the quality of the image in the region of interest. On the opposite, the evolution of the function near zero is convenient to encode coefficients that do not belong to the neighborhood of detected targets. In this range, the function does not substantially decrease and only the coefficients with small magnitude will therefore be transmitted.

The bitstream corresponding to the coded wavelet coefficients is obtained according to the following steps:

1) define $T_{\max} = 2^{\lfloor \log_2(\max(c_{i,j}))\rfloor}$ and $\delta_0 = (\beta/2)\log(T_{\max})^{1/\alpha}$;
2) initialize $\delta_{\min} = 0$, and $\delta_{\max} = \delta_0$;
3) scan all the wavelet coefficients $c_{i,j}$ in the same order as the EZW algorithm:
   - if the distance between $c_{i,j}$ and the closest target exceeds $\delta_{\min}$, then transmit the $c_{i,j}$-related quadtree conforming to the EZW algorithm with threshold $f_{\alpha,\beta}(\delta_{\min})T_{\max}$;
   - if the distance between $c_{i,j}$ and the closest target is less than $\delta_{\max}$, then transmit the $c_{i,j}$-related quadtree

conforming to the EZW algorithm with threshold $f_{\alpha,\beta}(\delta_{\max})T_{\max}$.

4) update $\delta_{\min} := \delta_{\min}(1 + (1/\lfloor\log_2(\max(c_{i,j}))\rfloor))$ and $\delta_{\max} := \delta_{\max}(1 + (1/\lfloor\log_2(\max(c_{i,j}))\rfloor))$.

This process ensures that the decoder will provide sufficient details about the intruder's target in the first iterations. This constitutes the first advantage with respect to the traditional EZW scheme in which a coarse version of the image is provided in the first passes without taking into consideration the proximity of the coefficient to the target. At the end of the decoding process, the image regions where intruder targets have been detected by ground sensors will be exactly reconstructed while other regions will be reconstructed in a lossy manner. The second feature of the proposed approach is that it preserves the efficiency of image-based tracking approaches [7], [8] while reducing their complexity. In fact, the details related to insignificant (from the target tracking perspective) coefficients are not transmitted.

V. Enhanced Target Tracking

For a target tracking sensor network, the tracking scheme should be composed of two components. The first component is the method that determines the current location of the target. It involves localization as well as the tracing of the path that the moving target takes. The second component involves algorithms and network protocols that enable collaborative information processing among multiple sensor nodes.

A. Assessing Localization Uncertainty

Existing localization approaches [9]–[11] do not integrate the uncertainty related to sensor position when assessing a self-organizing sensor network. In the following, we demonstrate that the detection efficiency of the sensor network increases according to the average number of sensors per target. According to this result, we propose a sensor deployment algorithm that allows defining sensor positions according to the application requirements. The parameter k can effectively change according to the nature of the observed target in the sense that it should be decreased when the target size increases. Let $\overrightarrow{t}$ and $\overrightarrow{m}$ be two vectors representing the target position and the measured features, respectively. If the target is covered by k sensors, the angle α_i corresponding to the sensor i has the following expression:

$$\alpha_i = \tan^{-1}\frac{y_i - y}{x_i - x} \tag{3}$$

where $\overrightarrow{t} = (x, y)$ and $\overrightarrow{s_i} = (x_i, y_i)$ denote the position of the mobile target and sensor i, respectively. The position $\overrightarrow{t}$ is therefore computed according to these angles. The uncertainty characterizing this positioning system can be assessed by studying the variations related to the function g defined as follows:

$$\overrightarrow{m} = (\alpha_1, \ldots, \alpha_k) = g(\overrightarrow{t}). \tag{4}$$

For instance, when $k = 4$, we can consider the determinant of the Jacobian matrix $J(g)$ defined by

$$|J(g)| = \frac{\begin{vmatrix} -\sin(\alpha_1) & \cos(\alpha_1) & \sin(\alpha_1) & 0 \\ -\sin(\alpha_2) & \cos(\alpha_2) & 0 & \cos(\alpha_1)) \\ -\sin(\alpha_3) & \cos(\alpha_3) & 0 & 0 \\ -\sin(\alpha_4) & \cos(\alpha_4) & 0 & 0 \end{vmatrix}}{\begin{vmatrix} \beta_1 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 \\ 0 & 0 & \beta_3 & 0 \\ 0 & 0 & 0 & \beta_4 \end{vmatrix}} \tag{5}$$

where $\beta_i = \cos(\alpha_i)(x_i - x) + \sin(\alpha_i)(y_i - y)$. Clearly, computing this Jacobian allows estimating the target position according to the uncertainty related to sensors' positions.

The second source of uncertainty is that low-level sensors also act as relaying nodes towards core sensors. In other terms, every time the alert message crosses a router, an error is added to the target position. The position $\overrightarrow{t} = (x_t, y_t)$ of the mobile target is perceived by the sensor s_3 as

$$\begin{cases} x_t = x_{s_1} + r_t \cos(\tau_t) \\ y_t = y_{s_1} + r_t \sin(\tau_t) \end{cases} \tag{6}$$

where τ_t is the angle defined between the target and the sensor s.

If ν denotes the uncertainty related to the s_3 position, then the uncertainty of the information gathered by s_1 and sent to s_2 is expressed by

$$U(s_1, s_2, t) = \int\int_D \phi(x, y)dxdy \tag{7}$$

where $\phi(x_{s_1}, y_{s_1}) = (x + r_t\cos(\tau_t), y_{s_1} + r_t \sin(\tau_t))$ and $D = \{(x, y) : (x - x_s)^2 + (y - y_s)^2 \leq R^2\}$.

B. Predicting Target Position

If $\overrightarrow{t^\theta}$ is a vector representing target position at time θ and $\overrightarrow{m^\theta}$ is a vector representing the measured features at time θ, our method would rely on solving an equation system

$$\overrightarrow{m^\theta} = h(\overrightarrow{t^\theta}, \overrightarrow{s^\theta}) \tag{8}$$

where $\overrightarrow{s^\theta}$ represents the sensors' position at time θ. Henceforth, this model allows a more precise error control with regard to the previous approaches where the position $\overrightarrow{t}$ is obtained through the resolution of a system $\overrightarrow{m^\theta} = g(\overrightarrow{t^\theta})$.

Moreover, since the analytical expression of $h(.,.)$ is difficult to find, we propose to refine the information about the position of a mobile target at instant θ [obtained by solving (9)] by considering its position at the previous observation instants. This permits to: 1) build a motion model for the tracked targets and

2) enhance the position estimate efficiency because former positions may convey some information that is not included in the monitored metrics. To this end, we propose to extend the joint probabilistic data association filters (JPDAFs) [12], that have been previously used in robotics applications [13] to the case of WSN. The state vector X_θ models the coordinates and the velocity of the mobile target

$$X_{\theta+\Delta\theta} = \begin{pmatrix} I_{2,2} & \Delta\theta I_{2,2} \\ 0_{M_2} & I_{2,2} \end{pmatrix} X_\theta + \begin{pmatrix} \frac{\Delta\theta^2}{2} I_{2,2} \\ \Delta\theta I_{2,2} \end{pmatrix} \epsilon_1^\theta \tag{9}$$

where $I_{2,2}$ and 0_{M_2} are the identity matrix and the zero matrix in dimension 2, respectively, and ϵ_θ represents the error process due to the uncertainty on $\overrightarrow{s^\theta}$.

We also assume that measurements $\widetilde{t^\theta}$ are available according to the stochastic process

$$Y_\theta = \arctan\left(\frac{x_t^\theta - \widetilde{x^\theta}_t}{y_t^\theta - \widetilde{y^\theta}_t}\right) + \epsilon_2^\theta \tag{10}$$

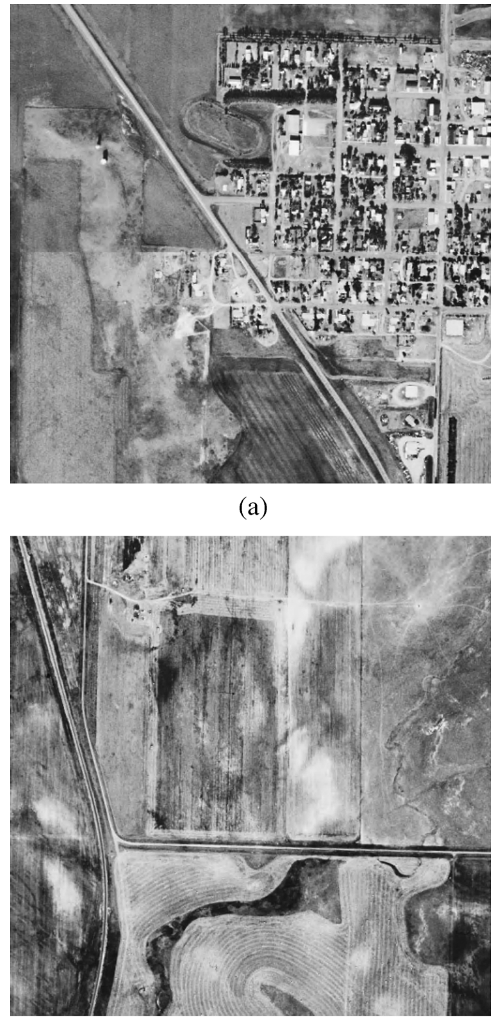
where ϵ_2^θ is a zero-mean Gaussian error independent of ϵ_2^θ.

Under these assumptions, particle filtering allows to compute an estimate $\overrightarrow{t'^\theta}$ of $\overrightarrow{t^\theta}$ such that the covariance matrix, containing the coefficients γ_θ^i, can be controlled according to

$$M = \sum^{N_i=1} \gamma_\theta^i \left(s_\theta^i - t'^\theta\right)\left(s_\theta^i - t'^\theta\right)^T. \tag{11}$$

VI. Performance Evaluation

In this section, we assess the efficiency of the image coding and target tracking techniques proposed in the foregoing sections. Real aerial image data have been used in this context.



(a)

(b)

Fig. 4. "Adams" images. (a) "Adams1" image. (b) "Adams2" image.

A. Description of the Test Images

Four test images ("Adams1," "Adams2," "Zurich," and "Vivid") have been used to simulate the image coding and target tracking techniques that have been proposed in this paper. Brief descriptions of these images are given in the following.

1) *"Adams1" and "Adams2":* These are two 512 × 512-size aerial images acquired in North Dakota in the frame of the USA National Agriculture Imagery Program (NAIP). NAIP acquires digital ortho-imagery during the agricultural growing seasons in the continental U.S. A primary goal of the NAIP program is to enable availability of ortho-imagery within one year of acquisition. NAIP provides two main products: 1) meter ground sample distance (GSD) ortho-imagery rectified to a horizontal accuracy of within $+/-5$ m of reference digital ortho-quarter quads (DOQQs) from the National Digital Ortho Program (NDOP) and 2) meter GSD ortho-imagery rectified to within $+/-10$ m of reference DOQQs. The tiling format of NAIP imagery is based on a $3.75' \times 3.75'$ quarter quadrangle with a 300-m buffer on all four sides. NAIP quarter quads are formatted to the UTM coordinate system using NAD83. NAIP imagery may contain as much as 10% cloud cover per tile.
2) *"Zurich" (Institute of Geodesy and Photogrammetry, ETH Zurich):* This image belongs to a test data set prepared for use in the project Automation of Digital Terrain Model Generation and Man-Made Object Extraction from Aerial Images (AMOBE II) being conducted at ETH Zurich between the photogrammetric (IGP) and computer vision (IKT) groups. "Zurich" is a 3737 × 3393-size image covering an area nearby the center of Zurich (Switzerland) and the ETH Hoenggerberg. The Zurich Hoengg data set is based on aerial photography collected over Zurich in 1995. The data is based on a 2 × 2 image block collected for the Surveying Office of the City of Zurich at an average image scale of ca. 1:5000. It consists of two models from two neighboring strips flown directly over Hoengg.
3) *"Vivid":* This sequence composed of 2571 images is part of the VIVID tracking evaluation dataset (available at http://www.vividevaluation.ri.cmu.edu/main.html). This dataset was developed to promote sharing and evaluation of algorithms that track objects through video sequences. The images used in this paper are from data collected

Fig. 5. “Zurich” image.

‘Vivid’ frame 200. ‘Vivid’ frame 300

Fig. 6. Sample frames from the “Vivid” dataset.

at Eglin during DARPA VIVID program. Vehicles loop around on a runway, then drive straight. It represents several military vehicles looping around on a runway, then driving straight. The vehicle being tracked, which looks very similar to another vehicles it passes, then speeds up and passes others.

Figs. 4–6 depict samples of the aforementioned image dataset.

B. Assessing the Efficiency of the Enhanced EZW Scheme

To evaluate the performance of the proposed EZW encoder, we performed both traditional and modified EZW schemes on the test images presented in the previous subsection. Figs. 7 and 8 illustrate the result of the application of the traditional and modified EZW, respectively, on the “Adams2” image. It is visually noticeable that the traditional EZW scheme produces an embedded image stream such that the quality of the whole scene is improved at each iteration. However, the proposed algorithm exhibits an important difference, in terms of visual quality, between the neighborhood of the target, which is located in this case at pixel (100,96) (right top corner of the image), and the rest of the image. The resolution in the former region is rapidly enhanced while no substantial improvements are remarked in the latter region.

Fig. 9 shows the performance of the modified EZW coding scheme in terms of compression rate (i.e., number of bits in the original image over number of bits in the coded image). The results show that the traditional EZW outperforms the modified algorithm only for the two first iterations, where the quality of the EZW image is not acceptable for target tracking. For the remaining iterations, the modified EZW gives much better results than the traditional one. This confirms the hypothesis that enhancing the resolution in the regions of interest and controlling the bit rate in regions where no intrusions occur allows to significantly enhance the performance of the progressive coding scheme.

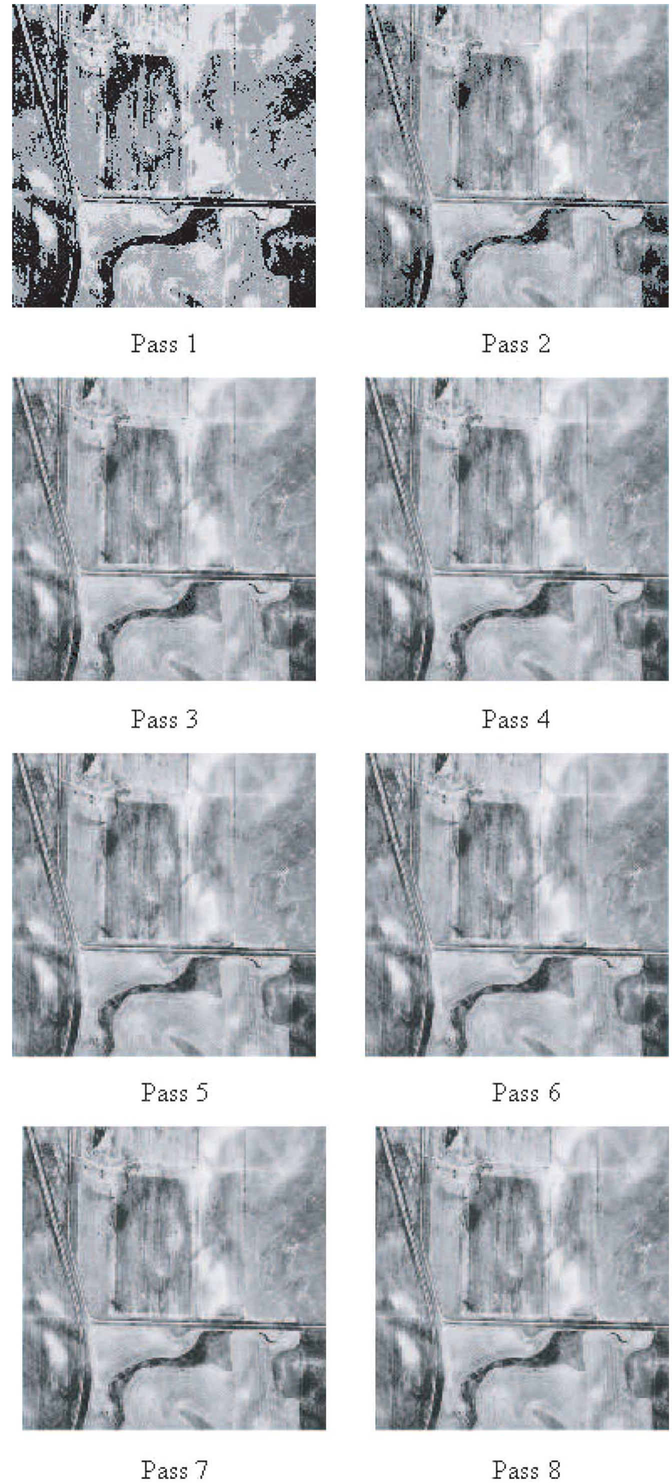


Fig. 7. Image sequence resulting from the application of the EZW encoding scheme to “Adams2” image.

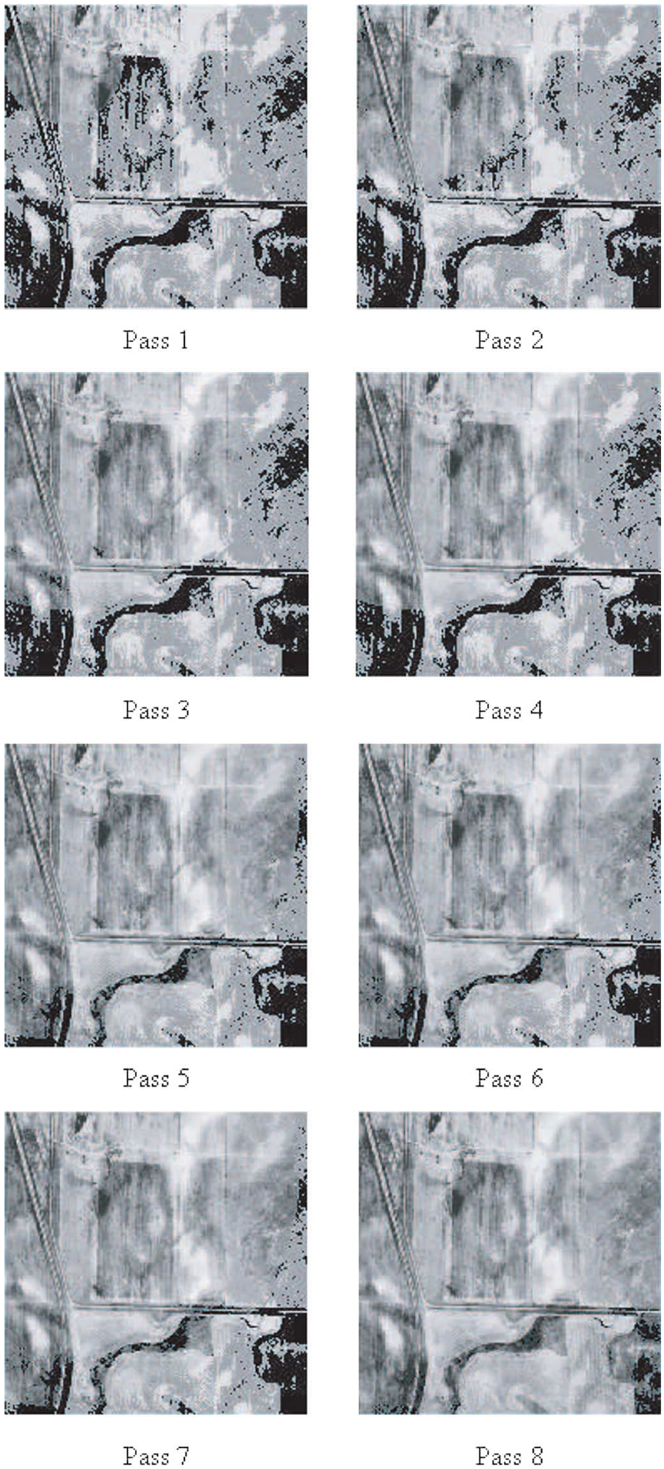


Fig. 8. Image sequence resulting from the application of the modified EZW encoding scheme to “Adams2” image.

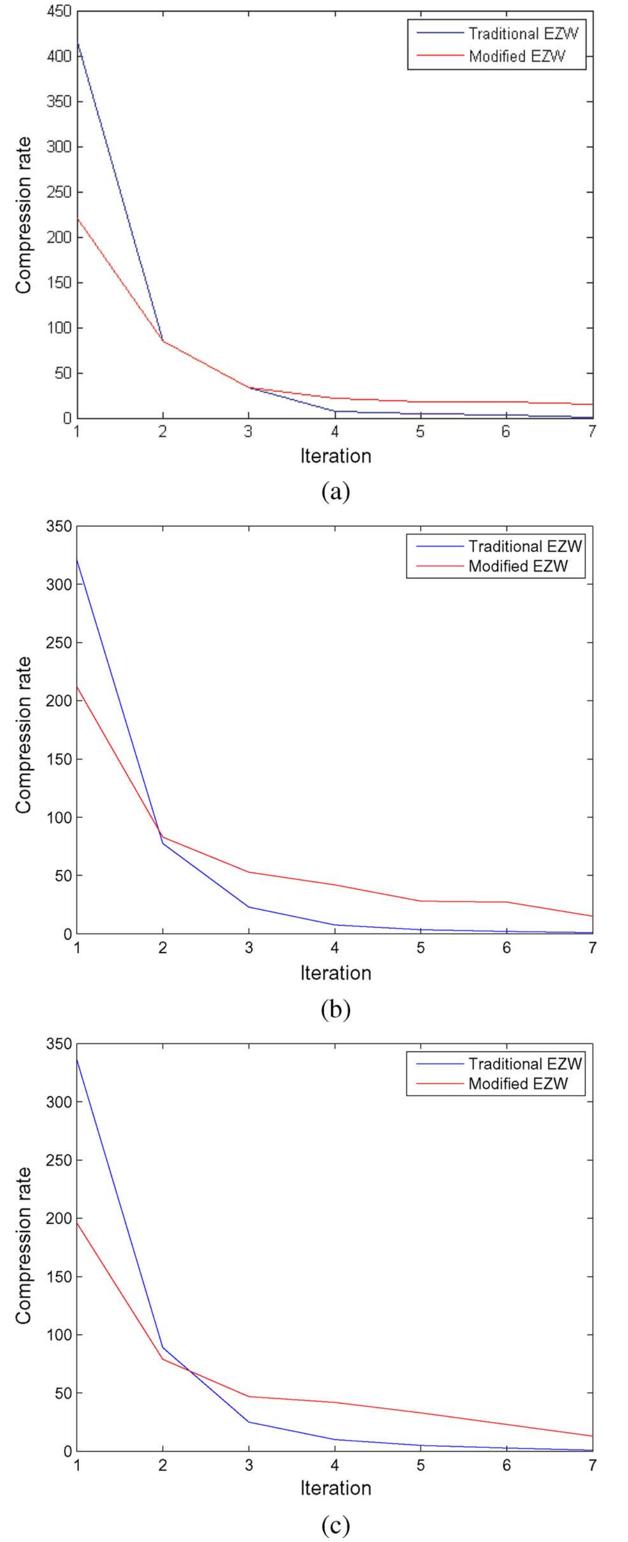


Fig. 9. Performance of the modified EZW algorithm on the test images. (a) EZW performance for “Adams1” image. (b) EZW performance for “Adams1” image. (c) EZW performance for “Zurich” image.

VII. Conclusion

In this paper, we presented a hybrid WSN architecture based on acoustic and electromagnetic sensors, imaging sensors, and a satellite communication backbone. This architecture allows multimodal sensing in the sense that the position of target can be identified using ground sensors while fine details about it can be acquired using aerial vision sensors. A progressive image coding protocol adapted to the WSN context has been presented. Unlike the available coding scheme, the proposed EZW algorithm provides high-resolution data for the regions where intrusion(s) have been detected and low-resolution data for the remaining regions. This has been shown to allow: 1) saving bandwidth and storage resources at the satellite level and 2) reduce the complexity of the image-based tracking approaches. Finally, a tracking technique taking into consideration the uncertainty on sensor node positions has been proposed. It has been analytically shown that it outperforms the existing approaches that consider only the errors made by the measurement system itself (i.e., the sensing framework).

In future works, the results presented in this paper can be improved by considering more sophisticated prioritization strategies to enhance the performance of the progressive encoder. Furthermore, a multimodal sensing technique is being developed based on both ground and aerial sensor measurements.

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