Spatio-Temporal Data Reduction Technique in WVSN for Smart Agriculture

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***Abstract*—Nowadays, to improve animal well-being in livestock farming applications, a wireless video sensor network (WVSN) can be deployed for surveillance and livestock monitoring to early detect injury or Asiatic hornets attacks [1]. They are composed of small embedded video and camera motes that capture video frames periodically and send them to a specific node called a sink. Sending all the captured images to the sink consumes a lot of energy on every sensor and may cause a bottleneck at the sink level. Energy consumption and bandwidth limitation are two important challenges in WVSNs because of the limited energy of nodes and the medium scarcity.**

In this work, we exploit the Spatio-temporal correlation between neighboring nodes to reduce the number of captured frames. For that purpose, Synchronization with Frame Rate Adaptation SFRA algorithm is introduced where overlapping nodes capture frames in a synchronized fashion every $N-1$ period, where N is the number of overlapping sensor nodes. The results show more than 90% data reduction, surpassing other techniques in the literature at the level of the number of sensed frames by 20% at least.

***Index Terms*—data reduction, synchronization, overlapping sensor nodes, event detection, WVSN.**

I. Introduction

Nowadays, the smart agriculture domain faces a lot of challenges for better usage of its natural resources. However, the agriculture domain includes livestock farming. Understanding the wild animals' behavior would facilitate the means of protection of cattle in places beyond man's control. For that, wireless video sensor networks (WVSNs) are deployed in a remote site to monitor livestock that is exposed to threats from wild animals like jackals in South Africa. WVSNs process in real-time and retrieve multimedia data periodically to be sent to a sink. They represent a low-cost monitoring solution and are considered an important part of the surveillance field systems, where they are taking great attention to livestock monitoring [2]. Different architectures have been studied in the literature. Figure 1 represents the general architecture of a wireless sensor network, where the nodes capture frames from videos with a given frequency (frame rate) and wirelessly send them to the sink.

In a WVSN system, limited energy resources nodes capture frames periodically. This periodic cycle leads to a lot of redundant data sent to the sink if no changes occur in the monitored zone of interest, especially when dealing with multimedia data that consumes a lot of energy. Maximization of system

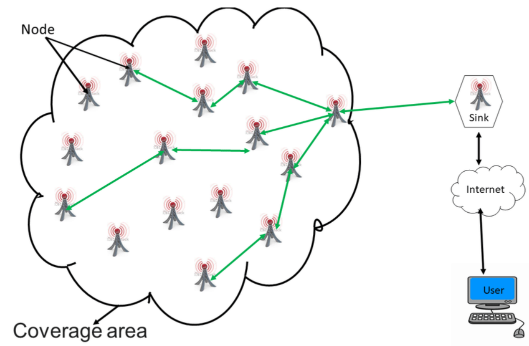

Fig. 1: General architecture of a wireless sensor network

lifetime and energy conservation is commonly recognized as a key challenge in the design and implementation of wireless video sensor networks. So, the main target is to reduce the energy consumption related to the sensing process, and the transmission phase at the sensor node level.

As an example, let us assume that a frame is captured once each second. When the shooting time is $12h/day$ and the frame size is 1920×1080, the total amount of captured frames per month is approximately 1800 GB (1.8 TB). If we capture frames from different sensor nodes, the amount of data will escalate exponentially as the number of deployed sensors increases. Moreover, network energy consumption gets highly stressed by the transmission of a huge amount of redundant and unnecessary data [3].

Therefore, a method that can minimize the amount of sensed data at the sensor-node level and transmitted data is required. Thus, to achieve data reduction on each sensor node in the overall system, there are three main phases to be studied: The sensing phase, processing techniques, and the transmission phase. The main focus of our work is to reduce redundant data between neighboring nodes.

Neighboring nodes are defined by their field of view (FoV). Overlapping FoVs in dense networks causes wasting power of the system because of redundant sensing of area [2]. Figure 2 represents three neighboring sensor-nodes that have overlapping FoV. To achieve data reduction between overlapping sensors, we proposed a Synchronization with Frame Rate Adaptation (SFRA) algorithm. The main aim of the proposed

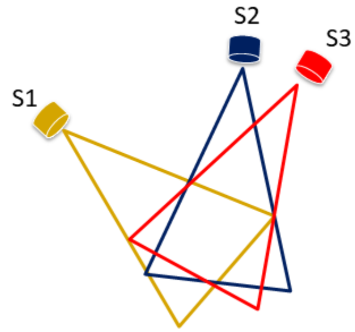

Fig. 2: Overlapping wireless video sensor nodes

synchronization method is energy conservation and prolonging network lifetime while preserving all needed information.

After having all overlapping sensor nodes detected in a stable state from the FRABID algorithm in [1] (a stable state is defined when no motion is detected), the nodes will start synchronization. Each node will capture frames in a different time slot from its overlapping nodes with the minimum frame rate.

The addition of the SFRA algorithm to other approaches presented in the literature for overlapping sensor nodes is the synchronization fashion, which reduces the number of sensed frames while still preserving almost the needed information. This method has shown more than 90% reduction of data compared to other methods. In SFRA algorithm, we are concerned with data reduction at the sensor-node level which affects proportionally energy consumption and bandwidth limitation. The remainder of this paper is structured as follows: Section 2 presents a general review of previous contributions presented in the literature. Section 3 describes the system model and presents some assumptions. Section 4 presents the main contribution about the overlapping sensor nodes, then Section 5 presents and discuss the results. Finally conclusions are drawn in Section 6 with perspective on future work.

II. Related Work

Different techniques and research work have been proposed in the literature to reduce energy consumption and data redundancy in Wireless Video Sensor Networks (WVSNs). In this section, we will browse some of these approaches while focusing on the data reduction between overlapping sensor-nodes at the application level.

Several research work for energy reduction has been proposed to decrease data redundancy: Scheduling methods [2], [4], [5], Data aggregation [6], Geometrical criteria [7]–[9], prediction techniques [10], frame rate adaptation [11]–[13].

To reduce the redundancy of captured data, the overlapping field of views (FoVs) of sensor nodes is exploited to achieve data reduction. Nodes can considerably prevent wasting power avoiding redundant sensing, processing or sending similar multimedia data. Thus, it prolongs network lifetime particularly in dense networks that are usually deployed with a high number of low power, low resolution and inexpensive multimedia nodes in random manner [2]. Several approaches tried to solve the issue of data redundancy by taking into consideration overlapping sensor-nodes. The authors in [11], [12] used geometrical conditions to detect overlapping sensors. After detecting the overlapping sensor-nodes, the authors in [11] defined a stable situation, where no motion is detected in the monitored zone. In the stable situation, the node with less residual energy will decrease its frame rate to its minimum, while the other overlapping sensor-node will continue sensing with its initial frame rate. This approach [11] outperforms the algorithm in [14] where in every period, the video shots are compared using a similarity process, and if the two shots surpasses a predefined threshold then one of the sensor-nodes will send the frame.In [15] Priyadarshini et al. investigated the overlapping method, which reduces redundancies by turning off certain cameras and activating the appropriate number of cameras based on the overlapping FOVs (field of view) of various cameras.

Based on the different approaches mentioned above, our contribution presents a synchronization method (SFRA algorithm) that achieves data reduction between overlapping sensor nodes that reduces redundancy. Before describing the approach, we introduce the general scenario and conditions needed to achieve our technique.

III. Assumptions and System Model

In our scenario, the wireless video sensor network (WVSN) is composed of two different kinds of nodes: the video sensor nodes and the sink node as shown in Fig 3. In this system model, frames are captured periodically and sent directly to the sink. At the very beginning of the sensing, the initial frame rate is set to its maximum ($FR_{max} = FR_{init}$), then after the activation of our data reduction algorithm, a new frame rate (NFR_i) is dynamically computed at every period Δt_i.

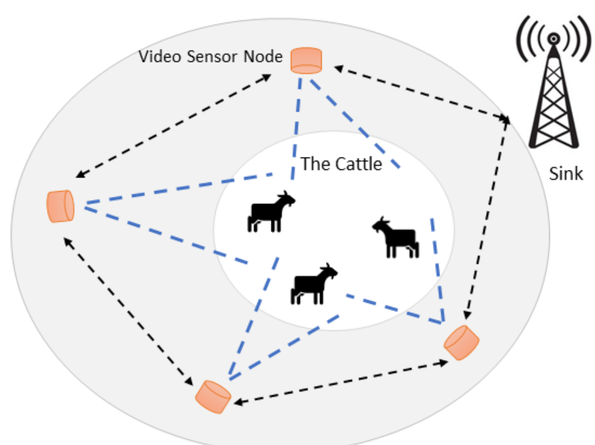

Fig. 3: System Model Architecture

We assume that a wireless video sensor network is homogeneous, where all sensors have the same storage, processing, battery power, sensing, and communication capabilities. In this system model and in a normal situation, all nodes will have the same battery power over time (since they are capturing with the same frame rate). The sensor nodes are deployed outdoors, and they are battery devices. Battery depletion has been identified as one of the primary causes of lifetime limitation of these networks [16]. Replacing them regularly is impractical in large networks or may even be impossible in hostile environments [16].

The nodes are prone to failure for any internal or external reasons or die of the battery however stop functioning. By the time, after applying any algorithm that may put some nodes into sleep mode, or power-saving mode, we will get a group of sensor nodes with different battery power percentages. Suppose nodes x, y and z are homogeneous, and node x is in power saving mode, then basically its battery lifetime will last more than y and z. These variations and variables will help in the identification of our approaches in the upcoming sections.

IV. Data Reduction in Overlapping Sensor-nodes

In previous work in [1], we were interested in reducing the amount of sensed and sent frames from each node to the sink by applying FRABID algorithm at the sensor node itself. In this algorithm, We address the energy and bandwidth reduction by reducing the number of frames first captured and then sent over the air in two steps: 1) it adapts the rate at which the frames are captured, and 2) it selects among the captured frames the pertinent to send. To furthermore reduce the data transmission, we now focus on the spatial correlation between neighboring sensor nodes to reduce the redundant sensed frames between overlapping sensor-nodes by applying a new approach based on synchronization.

Before describing the Synchronization with Frame Rate Adaptation (SFRA) approach, we introduce the video sensing model and the characteristics of every video sensor node to proceed with the SFRA algorithm.

A. Video Sensing Model

We consider a 2-D model of a video sensor node where $z = 0$ (XOY plane) and all the captured frames are compared as 2-D images not taking into account of the third dimension. A video sensor node S is represented by the Field of View (FoV) of its camera. A FoV covers only a part of the surrounding area of a video sensor. A FoV is a vector of 4-tuple S(P;R_s; $\overrightarrow{V}$;θ) where P is the position of S, R_s is its sensing range, $\overrightarrow{V}$ is the vector representing the line of sight of the camera's FoV e.g. its sensing direction, and θ is the offset angle of the FoV as shown in Figure 4.

As mentioned before, we assume that all video sensor-nodes are identical with fixed lenses providing a θ angle FoV thus same sensing range R_s , densely deployed in a random manner. Each node S_i covers a sector area in its FoV. We define U_{S_i} the set of sensors that have intersecting coverage zone (FoV).

B. The Overlapping Method and Coverage

As mentioned above, in our topology sensor nodes are deployed randomly. This may increase the spatial correlation

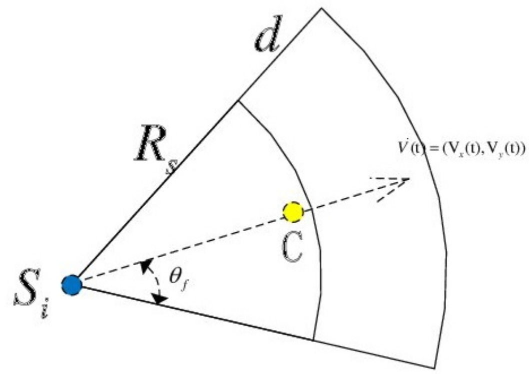

Fig. 4: Video sensor node behaviour during period Δt_i

between neighbouring sensor nodes, so the sensing range of two or more sensor-nodes may overlap (Figure 5). In such a scenario, the sensors capture typically redundant data of a given target since the same event may be captured by multiple sensors. Several approaches studied how to detect overlapping sensor-nodes [2], [11], [12], [14]. In our work we will consider that the overlapping nodes are already detected using the geometric condition method presented in [11].

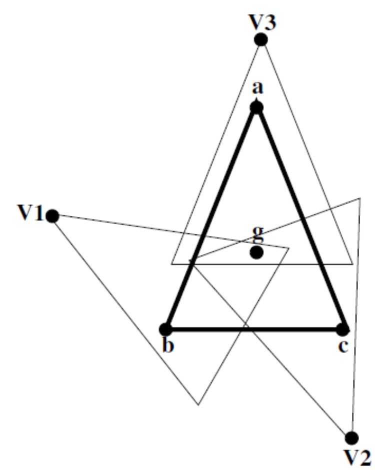

Fig. 5: FoV Coverage [4]

Suppose the video sensors S_1, S_2 and S_3 are overlapping sensor nodes with a stable state and are selected to run the synchronization with frame rate adaptation algorithm (SFRA) as explained in the next section.

C. SFRA Algorithm

The idea behind synchronization is to reduce the number of sensed frames while preserving all needed information. As mentioned earlier, synchronization phase starts when all overlapping sensor nodes (U_{s_i}) are in a stable state. Inspired from [11], a stable situation is a state where the sensor node is not capturing new information. Using the equations from [1] the sensor will compute the similarity between the captured frames. If two consecutive sensed frames are estimated as similar (no new information is represented in the second frame),

the node does not send the second frame to the coordinator. The node counts the number of consecutive similar frames, if it surpasses nb (the required number of consecutive similar frames), the state of the area of interest monitored by the node is considered as stable (situation=1).
To activate the SFRA algorithm, each node should know:

- The set of overlapping nodes (U_{s_i}) with its FoV
- The state of each node that belongs to U_{s_i}

When all overlapping nodes that belong to U_{s_i} are in a stable state (situation = 1), they will set their frame rate to its minimum (FR_{min}) and synchronize capturing frames between each other as illustrated in Figure 6.

One of the main challenges in SFRA algorithm is to guarantee that the nodes are well synchronized. We assume that the system is well synchronized, where the clock drift which is the result of the clock skew (the difference between the two clocks frequency [17]) is approximately negligible.
The capturing phenomenon will be as follows:
In each period one sensor node that belongs to U_{s_i} will be capturing frames with (FR_{min}). The other nodes will be in a sleep mode. So, each node will sense at period Δ_i then sleeps for $N-1$ periods, where N is the number of sensor nodes that belongs to U_{s_i}.

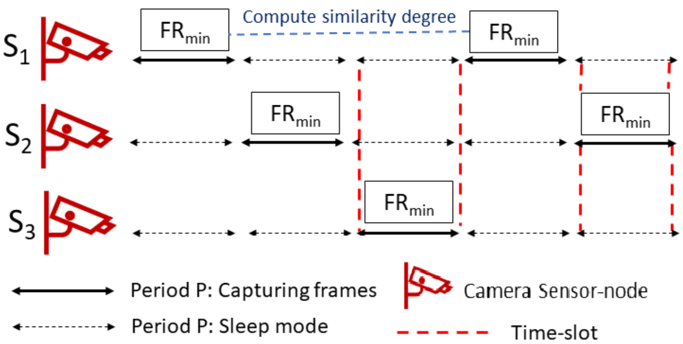

Fig. 6: Synchronization behavior

Each captured frame will be compared with the last sent frame to the sink (F_{last}), based on L1 norm. If the difference surpasses a predefined threshold th_{diff}, the sensor-node will return to its normal state with frame rate FR_{max} and will notify the other nodes that belongs to U_{s_i} to deactivate SFRA algorithm, since the new captured frame represents a new event as explained in algorithm 1.

Algorithm 1 SFRA run at node S_1

Get $situation_2$ and $situation_3$
Get F_{last} the last sent frame to the sink
Set N the number of overlapping nodes
while $situation_1 = 1$ and $situation_2 = 1$ and $situation_3 = 1$ **do**
  FR_{S_1} = 1 fps
  sleep (N - 1)
  Capture frame F_0
  Generate img_{diff} between F_0 and F_{last}
  Compute per with equation from [1]
  if $per > th_{diff}$ **then**
    Stop synchronization phase
    Set $FR_{S_1} = FR_{max}$
    Notify all overlapping nodes
    Send img_{diff} to the sink
  end if
end while

V. Results

In this section, we present the results that validate our approach and compare them to the INS algorithm in [11]. We implement the algorithms (SFRA and INS) using Python Imaging Library (PIL) that has light image processing tools. First we used the function from PIL imaging library in Python for image comparison to generate $image_{diff}$, the difference image between frames F_0 and F_1.

We made our simulations on a data-set named ToCaDa [18], contains two sets of 25 temporally synchronized videos corresponding to two scripted scenarios. 25 cameras were scattered around the university campus of Universite Paul Sabatier in Toulouse. 8 among the cameras were located in front of the building and filmed it with large overlapping fields of view as it can be seen in the figure 7. Cameras C4, C5 and C7 are selected for our simulation to test SFRA algorithm.

The initial frame rate to capture the video is set to 30 frames per second ($FR_{init} = 30$ fps) which is the maximum frame rate ($FR_{max} = FR_{init} = 30$), and the minimum frame rate is set to 1 frame per second ($FR_{min} = 1$ fps) for each camera. Each period is $\Delta_t = 1s$, and initial frame rate is equal to $FR_{init} = 30$ frames per second. The threshold to detect critical frames is set to $th_{diff} = 1.3\%$. The aim is to reduce the number of captured frames in a stable state by reducing the frame rate and applying synchronization between the overlapping nodes.

Fig. 7: Scenario

A. Data Reduction: Sensing Phase

The selected videos are capturing for 10204 periods. Table I presents the initial recorded data in a normal state of the three cameras C4, C5 and C7 when no reduction algorithm is activated, where Initial Event Detected represents the number of the frame where the intrusion is detected.
A stable state is detected at the following time intervals:
C4: 20s from 900 to 1512
C5: 20s from 900 to 1500
C7: 21s from 900 to 1540

C5 first detected the event at frame number 1500, then C4 at frame number 1512, and for C7 the event appears at period 51 at frame number 1540.
A stable state is defined after having 60 consecutive similar frames ($nb = 60$) which means 2 seconds of stability. The thresholds and all the parameters can be adapted according to the application and the QoS required.

The SFRA algorithm is activated after satisfying the conditions explained in IV-C. Synchronization starts at period 33 (frame number 990), since the first $3sec$ are dedicated to detect the stable state and exchange information needed to start synchronization. So, SFRA algorithm is tested on the three overlapping cameras (C4, C5 and C7) in the stable state from period 30 to 50. There are different ways to start the synchronization depending on the selected order for the nodes to capture frames. For that, we made different simulations taking into consideration the different order possibilities of camera sensor-nodes to achieve the synchronization phase and observe the results at different conditions.

TABLE I: Data-set Records for overlapping cameras C4,C5 and C7 before activating any algorithm

	Total Captured Frames	Initial Event Detected
Camera 4	612	1512
Camera 5	600	1500
Camera 7	640	1540

TABLE II: Scenario 1: C4,C5 and C7 respectively

	Sensed	First Frame Detected
C4	8	1531
C5	8	1561
C7	8	1591

TABLE III: Scenario 1: C5,C4 and C7 respectively

	Sensed	First Frame Detected
C4	8	1561
C5	8	1531
C7	8	1591

After activating the SFRA algorithm, the results presented in tables II, III, IV and V show a reduction of 98% of the captured frames in a stable state. The simulations show the different scenarios of capturing frames which is based on the order of cameras selected to start synchronization.

TABLE IV: Scenario 2: C7,C5 and C4 respectively

	Sensed	First Frame Detected
C4	12	1861
C5	8	1561
C7	9	1621

TABLE V: Scenario 3: C4,C7 and C5 respectively

	Sensed	First Frame Detected
C4	8	1531
C5	7	1500
C7	8	1591

Table III shows the results of the number of captured frames by the overlapping nodes, where C5 was first selected to start synchronization then C4 and C7 respectively. C5 first detected the new event at period 51 (frame number 1531). The impact of synchronization delayed the detection of the intrusion by one period at maximum for all overlapping nodes (at period 52, all the overlapping nodes will set their frame rate to FR_{max} for each period returning to their initial state). While based on the records of table IV, where the order of camera selection is C7, C5 and C4 respectively shows that C5 first detected the event at period 52, which is a delay of at most 2 periods from detecting the event on time.

Table V presents the results of the best case which is detecting the new event on time. As we can see C5 first detected the event at period 50 (frame number 1500), which is the first event captured by all the overlapping sensor nodes as shown in table I. For that, the best case will be when the synchronization technique selects C5 to be the last node to capture.

B. Comparison

SFRA algorithm is compared to the INS algorithm in [11]. In INS algorithm one out of the selected overlapping nodes that has more residual energy is selected to sense frames with FR_{max}, and the other nodes will go to transmission idle mode where the frame rate is set to its minimum ($FR_{min} = 1$ frame per second).

The simulation is done in the stable state from period 33 to period 50 on the three selected overlapping cameras C4, C5 and C7. We assume that C4 has more residual energy, so for INS algorithm, C4 will capture frames with $FR_{max} = 30$ frame per second while C5 and C7 with $FR_{min} = 1$ frame per second.

In INS we can guarantee the capture of the new event in time, while in SFRA we may miss few frames due to the impact of synchronization. The difference between those approaches in terms of data reduction is shown in Table VI. The results show that SFRA algorithm outperforms INS algorithm [11] in terms of sensing data reduction. INS achieved 65%

data reduction while SFRA 98%. So, SFRA algorithm added 33% more data reduction over INS algorithm.

TABLE VI: SFRA and INS comparison

	Initial Captured Frames	**INS**	**SFRA**
C4	510	510	8
C5	510	17	8
C7	510	17	8
Total	1530	544	24

The overall power consumption reduction cannot be specified since there are different levels to be studied like the cost of synchronization which is based on the mechanism used to achieve this aim. The cost of using GPS, type of the used hardware. Our main focus is on data reduction, which can be achieved regardless of other constraints.

VI. Conclusion

In recent times, the interest in video surveillance and environmental monitoring applications has increased. Energy conservation and maximization of system lifetime are commonly recognized as a key challenge in the design and implementation of WVSNs [2]. For this purpose, in our work, we have designed an algorithm dedicated to data reduction between overlapping nodes.

In our approach we exploit the condition of overlapping sensor nodes by proposing the SFRA algorithm. When a stable state is detected in the monitored area, the overlapping nodes will decrease their frame rate to the minimum and capture frames in a synchronized fashion. When one of the overlapping nodes captures an event, all nodes must return to their initial state with maximum frame rate. Simulations were conducted on a real data set. The results showed a reduction up to 75% in general. The selected order of nodes to achieve synchronization will even lead to a best case, where the event will be detected in time, or intrusion detection will be delayed at maximum N periods which is considered the worst case. The evaluation of the results depends on the criticality of the use case. In our scenario, missing a few critical frames is not considered a big loss, since the case is not delicate and the nature of motion is not of high speed.

For future work, we will first combine this approach to our approach on each node in [1]. Then, we will investigate the impact of the different parameters such as the convergence speed v of the new frame rate setting, the threshold value th_{diff} above which an action is taken, and the value which detects the stable state.

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