A Differential Coding-Based Scheduling Framework for Wireless Multimedia Sensor Networks

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***Abstract*—In wireless multimedia sensor networks (WMSNs), visual correlation exists among multiple nearby cameras, thus leading to considerable redundancy in the collected images. This paper proposes a differential coding-based scheduling framework for efficiently gathering visually correlated images. This framework consists of two components including MinMax Degree Hub Location (MDHL) and Maximum Lifetime Scheduling (MLS). The MDHL problem aims to find the optimal locations for the multimedia processing hubs, which operate on different channels for concurrently collecting images from adjacent cameras, such that the number of channels required for frequency reuse is minimized. After associating camera sensors with proper hubs, the MLS problem targets at designing a schedule for the cameras such that the network lifetime of the cameras is maximized by letting highly correlated cameras perform differential coding on the fly. It is proven in this paper that the MDHL problem is NP-complete, and the MLS problem is NP-hard. Consequently, approximation algorithms are proposed to provide bounded performance. Since the designed algorithms only take the camera settings as inputs, they are independent of specific multimedia applications. Experiments and simulations show that the proposed differential coding-based scheduling can effectively enhance the network throughput and the energy efficiency of camera sensors.**

***Index Terms*—Differential coding, scheduling, spatial correlation, wireless multimedia sensor networks.**

I. Introduction

THE availability of hardware has fostered the development of wireless multimedia sensor networks, i.e., networks of resource-constrained wireless devices that can retrieve multimedia content such as video and audio streams, still images, and scalar sensor data from the environment [2]. WMSNs not only enhance the existing sensor network applications, but also enable new applications such as multimedia surveillance, traffic enforcement, and industrial process control. These new applications normally involve gathering a number of images from energy-constrained camera sensors, thus demanding more effective networking and image compression techniques to limit the bandwidth and energy consumption.

In a WMSN, multiple camera sensors can perceive the environment or the events of interest from different and unique viewpoints. Since camera sensors generally have large sensing radius, the spatially separated cameras can still possess overlapped field of views (FoV). These overlapped FoVs further incur a certain degree of visual correlation among multiple cameras, thus leading to unnecessary redundancy in the captured images. To remove such redundancy, camera sensors can perform inter-camera differential coding with each other by allowing one camera encodes its image conditional on the image of the other, and sends its image with a reduced coding rate. This differential coding rate depends on the degree of the correlation between the two cameras. In our recent work [4], for the first time, visual correlation among multiple cameras is explicitly measured by a function of camera settings, which are independent of image and codec types. By leveraging this unique characteristic, we propose a differential coding-based scheduling framework which addresses two fundamental problems regarding the image gathering process and provides effective solutions accordingly.

The first problem we consider is how to construct a scalable network architecture that improves spectrum utilization. In a WMSN, a multi-tier network architecture is recommended [2], in which the energy constrained camera sensors are partitioned into multiple clusters with each cluster coordinated by a multimedia processing hub, which is either a normal camera sensor or a special device equipped with higher communication and processing capabilities. Under this network architecture, the network throughput is enhanced by applying the concept of frequency reuse, which allows concurrent transmissions within multiple clusters. However, in a WMSN, the effectiveness of frequency reuse may be jeopardized by the constrained resource of camera sensors. More specifically, the number of available orthogonal channels that camera sensors can switch to is limited by their hardware specifications and the spectrum availability. On the other hand, vertex coloring theorems [9] imply that the number of orthogonal channels should exceed the maximum number of neighboring clusters in a network to guarantee that all neighboring clusters can be assigned with different channels, Therefore, to increase network throughput of a WMSN, placing hubs at proper locations that facilitate frequency reuse is of paramount importance.

After cameras are assigned to proper hubs, our second problem is how to design an image gathering schedule within each cluster so that the camera sensor's lifetime is increased. Specifically, we design a differential coding-based scheduling approach (DCS). In DCS, a camera is allowed to wake up at a certain time slot and overhear the on-going transmission of a neighboring camera. After that, it encodes its own image conditional on the previously overheard image, and sends its image with a reduced coding rate. The differential coding rate a camera can generate depends on the degree of the correlation between this camera and the one whose image it overhears.

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Thus, the design of a visual correlation-oriented schedule, which significantly reduces the differential coding rates, helps to prolong the sensor's lifetime.

To address the problems above, we formally define two optimization problems, namely, MinMax Degree Hub Location (MDHL) and Maximum Lifetime Scheduling (MLS). The MDHL problem aims to find the optimal locations to place the multimedia processing hubs such that the number of channels required for frequency reuse is minimized. By defining the degree of a hub as the number of hubs within its 2-hop neighborhood, the MDHL is defined as: find a set of hub locations such that the maximum degree of the deployed hubs is minimum and each camera is covered by at least one hub. In Section III, we prove that MDHL is NP-complete and therefore can not be solved in polynomial time unless $\mathrm{P} = \mathrm{NP}$. Consequently, an $O(\log^2(n))$ factor approximation algorithm is proposed by using linear relaxation and random rounding techniques, where n is the number of camera sensors in the network.

Given a hub and its associated cameras, the MLS problem targets at designing a schedule for the cameras such that the camera's lifetime is maximized. Assuming all cameras have equivalent initial energy, the MLS problem is defined as: find a pair of slots for each camera to transmit and overhear, respectively, such that the maximum energy consumption of the cameras is minimized. In Section V, we prove that the MLS problem is NP-hard by formulating it as an equivalent binary program. Consequently, we present a randomized approximation algorithm, which produces a solution $\leq \mathrm{OPT} + c_{\max}/e$, where OPT is the optimal result and $c_{\max}$ is the maximum energy consumed by a camera to send its image to the hub without performing differential coding and e is the exponential constant. Moreover, a joint power control and scheduling scheme is proposed to further improve the energy efficiency of the camera sensors.

This work is based on the the preliminary results in [22]. In this extended version, an extensive literature review on the resource aware solutions in WMSNs is given. An enhanced algorithm for the MDHL problem is proposed to yield a better approximation ratio than the one proposed in [22]. Along this new algorithm, the heuristic cluster member assignment algorithms are proposed and the inter-cluster connectivity is analyzed. What is more important, a new joint power control and scheduling solution is designed, which, as shown, can lead to significantly enhanced energy efficiency. Moreover, a comprehensive simulation study is performed to verify the proposed solutions and reveal the fundamental impact of network settings and camera configurations on the energy efficiency of WMSNs.

The rest of this paper is organized as follows. Section II mathematically formulates the problems. In Section III, we introduce the related work. In Section IV, we present the approximation algorithm for the MDHL problem. We address the MLS problem in Section V. The performance of the proposed algorithms is examined in Section VI. Finally, Section VII concludes this paper.

II. Related Work

Recent studies have addressed resource awareness in video sensor networks from different perspectives. The problem of object detection and tracking for battery-powered smart cameras is studied in [3], where camera sensors are put to idle states to save energy consumption. A feedback method is first proposed for detection and tracking, which provides significant savings in processing time. Then, an adaptive methodology is proposed to send the camera sensor to idle state without affecting the performance of the tracking system. The feedback method and the adaptive methodology are combined together so as to provide further savings in energy consumption. In [19], the authors study how multiple cameras should efficiently share the available wireless network resources and transmit their captured information to a central monitor. Three different types of resource allocation solutions are analyzed and compared: a centralized optimization approach, a decentralized game-theoretic approach, and a distributed greedy approach. It is shown that resource allocation solutions for multicamera wireless surveillance networks need to explicitly consider both the dynamic source characteristics and network conditions. In [6], the joint camera selection and resource allocation problem is investigated with an objective to optimally set the camera configurations to meet the coverage and QoS requirements. To solve this problem, an approximation solution based on the evolutionary algorithms is presented, which can effectively and timely yield a suboptimal solution. [25] addresses the problem of optimal selection of a set of cameras from all available cameras to maximize the network lifetime, while achieving the desired coverage performance. To attack this problem, a stochastic model is proposed to approximate the network lifetime based on the coverage geometry of cameras and data request statistics. Accordingly, based on this model, the optimal camera selection which leads to the maximum expected remaining network lifetime is derived. In [10], an analytical power-rate-distortion model is developed to capture the impact of the resource limitations of camera sensors on their rate-distortion performance. Utilizing a simpler model, the optimal power allocation solution is developed to minimize the distortion performance of the camera sensors subject to their power constraints.

In sum, the resource allocation solutions introduced above aim to enhance the energy efficiency of WMSNs, while maintaining the certain performance requirements in terms of coverage, distortion, frame rate, and so on. However, none of them exploits the inherent visual correlation among camera sensors, which, as shown in this work, has significant impact on the energy efficiency of WMSNs. What is more important, none of above solutions addresses the critical problem of how to gather the high-volume image data from resource constraint camera sensors in an efficient and collaborative manner. Such problem of scheduling the image collection from sensor nodes is related to the MAC protocol design in wireless sensor networks (WSNs). Based on the channel access policies, MAC protocols designed for WSNs could be classified into contention-based protocols and contention-free protocols. Contention-based protocols are mostly based on variants of the Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) protocol. For example, the S-MAC [23] and the T-MAC [5] protocols are in this type. These protocols alternate between sleep cycles and listen cycles to save energy in sensor networks, but energy saving is accomplished at the cost of latency and by allowing throughput degradation. Some contention-based MAC protocols also provide differentiating network services based on priority levels to satisfy QoS requirements [18]. However, there is little performance guarantee due to the random access nature of contention-based protocols. Contention-free protocols are primarily based on reservation of time slots or channels or codes. The Time Division Multiple Access (TDMA) is a representative protocol of this class, in which the cluster head or sink helps in slot assignment, querying particular sensors and maintaining time schedules. There have been extensive studies on TDMA for sensor networks due to its energy efficiency, bounded delay performance, and high throughput for high load multimedia traffic [14], [13], [17]. However, none of the exiting solutions takes the inherent inter-camera correlation into account to generate the optimal schedule that can significantly increase the network lifetime. This is partially attributed to the difficulty of efficiently and effectively predicting the correlation coefficient among camera sensors.

To enhance the throughput of WMSNs, the concept of frequency reuse is also exploited in this work, where any two neighboring processing hubs are assigned with different frequencies. The conventional frequency assignment problem aims to assign frequencies to the users or the cellular cells in such a way that the signal interference from neighboring users or cells is avoided, while the required total number of frequencies is minimized. This problem is closely related to the well studied vertex coloring problem [9], which is shown to be NP-hard. Accordingly, many centralized and distributed approximation/heuristic algorithms have been proposed [11], [12], [15]. Different from the well-known frequency assignment problem, we address an unique problem for WMSNs regarding how to find optimal locations to place the processing hubs in such a way that the upper bound of the number of the frequencies required for frequency reuse is minimized.

III. Problem Formulation

A. Correlation-Based Joint Coding and Differential Coding

To remove the redundancy among correlated camera sensors, a group of camera sensors with overlapped Field of Views (FoVs) as shown in Fig. 1 can collaboratively compress their data by joint coding and differential coding. Consider a cluster consisting of a multimedia hub with high processing capabilities and N ordinary camera sensors $\{v_1, \ldots, v_N\}$, where each camera v_i produces image X_i. We can perform *multi-camera joint coding* in the cluster: each camera sends its individual images to the hub, while the hub acts as a single encoder that takes all the collected images as inputs and perform joint coding. We denote the total coding rate of all the images by $R(X_1, \ldots, X_N)$. According to Shannon's source coding theorem, the total coding rate of all nodes within a cluster is lower bounded by the joint entropy of the observations $H(X_1, X_2, \ldots, X_N)$, given by $R(X_1, \ldots, X_N) \geq H(X_1, X_2, \ldots, X_N)$.

On the other hand, two camera sensors can also perform *inter-camera differential coding* with each other. For two images X_i and X_j observed by cameras v_i and v_j, we can compress X_i based on the prediction of X_j. We denote the resulting

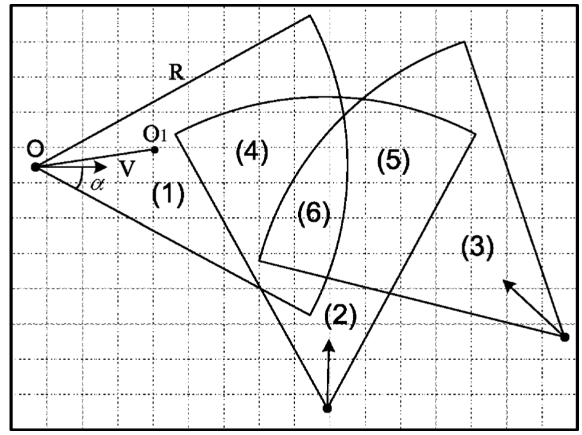

Fig. 1. Field of views of multiple cameras.

differential coding rate of X_i by $R(X_i \mid X_j)$, and $R(X_i \mid X_j)$ satisfies $R(X_i \mid X_j) \geq H(X_i \mid X_j)$, where $H(X_i \mid X_j)$ is the conditional entropy of X_i given the knowledge of X_j. The conditional entropy can be derived from joint entropy as $H(X_i \mid X_j) = H(X_i, X_j) - H(X_j)$.

Our previous results [4], [20], [21] show that the joint entropy for multiple images can be effectively estimated based on the visual correlation between cameras, and this correlation is given by a function of camera settings before the actual images are captured. Specifically, if two cameras C_j and C_k can both observe an area of interest P_i, a spatial correlation coefficient $\rho_{j,k}$ for the observations of P_i at C_j and C_k is derived as

$$\rho_{j,k} = f(O_j, \vec{V_j}, O_k, \vec{V_k}, P_i) \tag{1}$$

which indicates that $\rho_{j,k}$ is a function of the two cameras' locations (O_j, O_k) and sensing directions $(\vec{V_j}, \vec{V_k})$ as well as the location of the area of interest P_i.

B. MinMax Degree Hub Location Problem

Consider a camera network modeled by a graph $G = (V, E)$, where V is a set of cameras, i.e., $V = \{v_1, v_2, \ldots v_n\}$, and E is a set of links. A link (v_i, v_j) exists if v_i and v_j are within 1-hop range of each other.

Definition 1: The degree of a hub h, denoted by $\deg(h)$, is the total number of hubs (except h) that reside within the 2-hop range of the hub h.

To facilitate frequency reuse, the neighboring clusters must be assigned with different channels and the cameras must be able to operate on the channels of their associated clusters. Since the maximum distance between two neighboring clusters is 2-hop distance, by graph coloring theorems [9], this implies that the maximum degree of hubs should be less than the available orthogonal channels to ensure the effectiveness of frequency reuse. For this purpose, we define the MinMax Degree Hub Location Problem as follows.

Definition 2: MinMax Degree Hub Location Problem (MDHL): given a graph $G = (V, E)$ and a set of potential hub locations $F = V$, find a subset $F' \subseteq F$ such that the maximum degree of hubs, $\max_{h \in F'}(\deg(h))$, is minimum, and for all $v_i \in V$, there is at least one hub $h \in F'$ for which $(h, v_i) \in E$.

Note that by the definition above, the set of hubs F' is actually a dominating set of the WMSN so that every camera sensor is at most 1-hop away from at least one of the hubs in F'.

C. Maximum Lifetime Scheduling Problem

Given a hub and its member cameras, each hub will generate an order to schedule image collections from its members. Our task is to find the optimal schedule such that the lifetime of the member cameras is maximized.

Definition 3: The lifetime of the member cameras is the time duration when all the members of a hub keep alive.

Assume that cameras have equal initial energy. The maximization of the lifetime of the cameras in a cluster is equivalent to minimization of the maximum energy consumption of the cameras in this cluster. Let $E_{tx}(h, v_i)$ denote the energy consumed by the camera v_i to convey its image to the hub h. $E_{tx}(h, v_i)$ is a function of $\{d_{(h,v_i)}, R_{v_i}\}$, in which $d_{(h,v_i)}$ is the Euclidean distance between h and v_i and R_{v_i} is the predicted differential coding rate of v_i. Consequently, we formulate the Maximum Lifetime Scheduling Problem (MLS) as follows.

Definition 4: Maximum Lifetime Scheduling Problem (MLS): given a hub h and a set A_h of cameras assigned to h, find a schedule σ assigning a pair of slots for each cameras to transmit and overhear in such a way that the maximum energy consumption, $\max_{v_i \in A_h} E_{tx}(h, v_i)$, is minimum.

In the following sections, we prove the NP-completeness of the MDHL problem and the NP-hardness of the MLS problem. Consequently, approximation algorithms are proposed.

IV. MinMax Degree Hub Location

In this section, we first prove that MDHL is NP-complete. Next, we formulate MDHL problem as an integer program (IP). Then, we present an approximation algorithm by applying the linear relaxation and random rounding technique, which was originally studied in MAX-2SAT [8] and Covering & Packing problems [16].

A. NP-Completeness

First, the decision version of the MDHL is as follows.

Definition 5: Decision Version of MDHL: given a graph $G = (V, E)$, a set of potential hub locations $F = V$, and a positive integer k, determine if there exists a subset $F' \subseteq F$ with the maximum degree of hubs, $\max_{h \in F'}(\deg(h)) \leq k$ such that for all $v \in V$, there is at least one hub $h \in F'$ for which $(h, v) \in E$.

Theorem 1: The MDHL is NP-complete.

Proof: First, we argue that the decision version of MDHL $\in$ NP since given an instance of MDHL, a verification algorithm can efficiently check if each camera has at least one hub in its neighborhood, and if the maximum degree of hubs is k. Thus, the MDHL belongs to NP.

We now show that the Minimum Dominating Set problem (MDS) is polynomial time reducible to MDHL, i.e., MDS $\leq_P$ MDHL. An instance of MDS is given by a graph $\bar{G} = (\bar{V}, \bar{E})$, and a positive integer $k - 1$. The objective is to determine if there exists a dominating set $\overline{V'} \subseteq \bar{V}$ such that $|\overline{V'}| \leq k - 1$ and each element $v \in \bar{V}$ is a neighbor of at least one element of $\overline{V'}$.

Next, we will construct an instance of MDHL problem from an instance of MDS. We define sets V, F, E as follows: let $V = \bar{V} \bigcup \{f'\}$, where f' is a new element and f' is put into the 2-hop neighborhood S_i^2 of each node i; Let $F = V$; Let $E = \bar{E}$. Then, the instance of MDHL is given by a graph $G = (V, E)$, a set F, and a positive integer k.

We now prove that the original instance of MDS is a yes instance if and only if the MDHL instance we created is also a yes instance. First, suppose the instance of MDHL has a solution $F' \subseteq F$ with $\max_{h \in F'}(deg(h)) \leq k$. By our construction, f' is the 2-hop neighbor of every element in V and thus f' has to be added in F' to cover itself. This implies that f' is the element in F' that has the maximum degree k. Meanwhile, since $\bar{V} = V - \{f'\}$, this indicates that the instance of MDS has a dominating set $\overline{V'} \subseteq \bar{V}$ of cardinality less than $k-1$. Next, suppose that there is a dominating set $\overline{V'} \subseteq \bar{V}$ with $|\overline{V'}| \leq k - 1$ in the original MDS instance. By the similar arguments, the degree of the elements in F' is at most k in the constructed MDHL instance.

We now have shown that MDS problem can be solved by the proposed construction and an algorithm that solves MDHL. Since our construction takes polynomial time, and MDHL is NP, we can conclude that MDHL is NP-complete. ■

B. IP Formulation of MDHL

We first model the MDHL as an integer nonlinear program (INP). Consider a camera network described by a graph $G = (V, E)$ and a set of potential hub locations $F = V$. First, we define 1-hop neighborhood and 2-hop neighborhood of a camera $v_i \in V$, respectively.

Definition 6: The 1-hop neighborhood of v_i, denoted by S_i^1, is a set consisting of v_i and cameras within 1-hop range of v_i.

Definition 7: The 2-hop neighborhood of v_i, denoted by S_i^2, is a set of cameras within 2-hop range of v_i, excluding v_i.

We assign a variable x_i for each camera $v \in V$, which is allowed 0/1 values. This variable will be set to 1 iff a hub is placed at the location of v_i. Consequently, the MDHL problem can be formulated as an Integer Nonlinear Program INP_{MDHL}

$$\text{MIN} \quad y \tag{2}$$
$$\text{s.t} \quad \sum_{j: v_i \in S_j^1} x_j \geq 1, \quad \forall v_i \in V \tag{3}$$
$$\sum_{j: v_i \in S_j^2} x_i x_j \leq y, \quad \forall v_i \in V \tag{4}$$
$$x_j \in \{0, 1\}, \quad \forall v_j \in V \tag{5}$$

The objective function y is the maximum degree of all hubs $(\{v_i \,|\, x_i = 1\})$. The first constraint states that each camera $v_i \in V$ must reside within the 1-hop neighborhood of at least one hub, whereas the second constraint indicates that the degree of each hub (described in Definition 1) must be less than the maximum value. As the second constraint (4) is quadratic, the formulated integer program INP_{MDHL} is not linear. To linearize INP_{MDHL}, the quadratic constraint (4) is eliminated by applying the techniques proposed in [7]. More specifically, the product $x_i x_j$ is replaced by a new binary variable w_{ij}, on which several additional constraints are imposed. As a consequence, we can reformulate INP_{MDHL} exactly to an integer linear Program IP_{MDHL} by introducing the following linearlization constraints:

$$\sum_{j:v_i \in S_j^2} w_{ij} \leq y, \quad \forall v_i \in V \tag{6}$$

$$w_{ij} \leq x_i, w_{ij} \leq x_j, \quad \forall v_i, v_j \in V \tag{7}$$

$$w_{ij} \geq x_i + x_j - 1, \quad \forall v_i, v_j \in V \tag{8}$$

$$w_{ij} \geq 0, \quad \forall v_i, v_j \in V \tag{9}$$

and removing the quadratic constraint (4). By relaxing variables $x_i \in \{0,1\}$ to $x_i \in [0,1]$, we get the relaxed linear program LP_{MDHL} consisting of the objective function (2) along with constraints (3), (6), (7), (8), (9), and $x_i \geq 0,\ \forall v_j \in V$.

C. Randomized Approximation Algorithm

Given an instance of MDHL modeled by the integer program IP_{MDHL}, the proposed algorithm (see *Algorithm* 1) is the following: first solve the relaxed linear program LP_{MDHL} to get an optimal fractional solution, denoted by $(\mathbf{x}', y')$, where $\mathbf{x}' = \langle x'_1, x'_2, \ldots, x'_{|V|}\rangle$, and round x'_i to integers $\bar{x}_i$ by a random rounding procedure. This procedure consists of three steps: (i) first set all $\bar{x}_i$ to be 0; (ii) then let $\bar{x}_i = 1$ with probability x'_i and execute this step for $\log(\mathrm{n}) + 2$ times, where n is the number of sensor nodes in the network. Step (ii) yields an integer solution $(\bar{\mathbf{x}}, \bar{y})$, where vector $\bar{\mathbf{x}} = \langle \bar{x}_1, \bar{x}_2, \ldots, \bar{x}_{|V|}\rangle$. To ensure $(\bar{\mathbf{x}}, \bar{y})$ is a feasible solution to IP_{MDHL}, step (ii) is repeated until each camera is the neighbor of at least one hub, and the maximum degree $\bar{y}$ satisfies the condition that $\bar{y} \leq \delta\alpha^2 y'$, where δ and α are some constants given in line 6 of Algorithm 1. The last step (iii)(Line 7–12) is to further reduce the maximum hub degree by removing the possible redundant hub, which has its one hop neighbors (including itself) covered by other hubs.

Algorithm 1 Approximation Algorithm for MDHL

1: Solve LP_{MDHL}. Let $(\mathbf{x}', y')$ be the optimum solution.
2: $\bar{\mathbf{x}} \leftarrow \mathbf{0}$, $j \leftarrow 0$.
3: **while** $t \leq \log(n) + 2$ **do**
4: $\quad \bar{x}_i \leftarrow 1$ with probability $\bar{p}_i \leftarrow x'_i$, $t \leftarrow t + 1$
5: **end while**
6: **Repeat** lines 3–5 **Until** $\sum_{j:v_i \in S_j^1} \bar{x}_j \geq 1, \forall v_i \in V$ and $\bar{y} = \arg\max_{v_i \in V} \sum_{j:v_i \in S_j^2} \bar{x}_i \bar{x}_j \leq \delta\alpha^2 y'$, where $\alpha = \log(n) + 2, \delta = (1 - e^{-\alpha\theta})^{-1}$, and $\theta = \min_{x'_i \neq 0 \wedge i \leq n} x'_i$.
7: find $H = \{v_i \mid \bar{x}_i = 1\}$
8: **for** $v_i \in H$ **do**
9: $\quad$ **if** $\cap_{v_j \in S_i^1}\{\sum_{k:v_j \in S_k^1} x_k \geq 2\}$ **then**
10: $\quad\quad \bar{x}_i \leftarrow 0$
11: $\quad$ **end if**
12: **end for**
13: Return $(\bar{\mathbf{x}}, \bar{y})$

Theorem 2: Let OPT denote the optimal solution of the MDHL problem. The proposed algorithm yields a solution of $O(\log^2(n))\text{OPT}$ with high probability

Proof: Let y^* denote the optimal solution to the MDHL problem. Consider any element $v_i \in V$. Its expected degree follows

$$\begin{aligned} \mathrm{E}\left(\sum_{j:v_i \in S_j^2} \bar{x}_i \bar{x}_j\right) &= \mathrm{E}(\bar{x}_i)\mathrm{E}\left(\sum_{j:v_i \in S_j^2} \bar{x}_j\right) \\ &= \mathrm{E}(\bar{x}_i) \sum_{j:v_i \in S_j^2} \mathrm{E}(\bar{x}_j) \end{aligned} \tag{10}$$

The first equality holds because v_i is not in its own 2-hop neighborhood S_i^2 by Definition 7 and thus $\bar{x}_i$ and $\bar{x}_j$ are independent. The second equality holds because of linearity of expectation.

Applying union bound, we have the upper bound of the probability that an element becomes a hub (i.e., $\bar{x}_i = 1$) when the random rounding is done, i.e.,

$$\Pr[\bar{x}_i = 1] = \Pr\left[\bigcup_{t \leq \alpha+1} x'_i = 1 \text{ at round t}\right] \leq \alpha x'_i$$

where $\alpha = \log(n) + 2$. This implies $E(\bar{x}_i) \leq \alpha x'_i$, by which, we obtain the upper bound of the expected degree of a candidate hub v_i, (i.e., $x'_i \neq 0$)

$$\mathrm{E}\left(\sum_{j:v_i \in S_j^2} \bar{x}_i \bar{x}_j\right) \leq \alpha^2 \sum_{j:v_i \in S_j^2} x'_i x'_j \leq \alpha^2 y', \tag{11}$$

As to the lower bound of $\Pr[\bar{x}_i = 1]$, we have

$$\Pr[\bar{x}_i = 1] = 1 - (1 - x'_i)^\alpha \geq 1 - e^{-\alpha x'_i} \tag{12}$$

The inequality follows from the fact that $(1 - x) \leq e^{-x}, \forall x \in [0\ 1]$.

We are now ready to derive the probability that the degree of a hub is larger than $\delta\alpha^2 y'$. Applying Chernoff bound, it follows by (11) and (12) that

$$\begin{aligned} &\Pr\left[\sum_{j:v_i \in S_j^2} \bar{x}_i \bar{x}_j \geq \delta\lambda\alpha^2 y'\right] \\ &\quad \leq \Pr\left[\sum_{j:v_i \in S_j^2} \bar{x}_j \geq \delta\lambda\alpha^2 y'\right] \leq \left(\frac{e^{(\lambda-1)}}{\lambda^\lambda}\right)^{\delta\alpha^2 y'} \end{aligned}$$

for $\lambda > 0$, where $\delta = (1 - e^{-\alpha\theta})^{-1}$ and $\theta = \min_{x'_i \neq 0 \wedge i \leq n} x'_i$. To simplify this bound, suppose $\lambda > 2e$, then

$$\Pr\left[\sum_{j:v_i \in S_j^2} \bar{x}_i \bar{x}_j \geq \delta\lambda\alpha^2 y'\right] \leq 2^{-(\lambda-1)\delta\alpha^2 y'}.$$

For $\lambda < 2e$, we can show

$$\Pr\left[\sum_{j:v_i \in S_j^2} \bar{x}_i \bar{x}_j \geq \delta\lambda\alpha^2 y'\right] \leq e^{-\frac{(\lambda-1)^2}{4}\delta\alpha^2 y'}.$$

Thus, if $y' < 1/e^2$, then let $\lambda = 1 + (1/y') > 2e$. We get

$$\Pr\left[\sum_{j:v_i\in S_j^2} \bar{x}_i\bar{x}_j \geq \delta\lambda\alpha^2 y'\right] \leq 2^{-\alpha^2} \leq e^{-\alpha} \leq \frac{1}{4n}.$$

If $y' > 1/e^2$, letting $\lambda = 1 + \sqrt{(2/y')} < 2e$, we get

$$\Pr\left[\sum_{j:v_i\in S_j^2} \bar{x}_i\bar{x}_j \geq \delta\lambda\alpha^2 y'\right] \leq e^{-\frac{\alpha^2}{2}} \leq \frac{1}{4n}.$$

In both of the above cases, summing over all elements $v_i \in V$, we get the probability that some hub has a degree larger than $\lambda\alpha^2 y'$, i.e.,

$$\Pr[\bar{y} \geq \delta\lambda\alpha^2 y'] \leq n\frac{1}{4n} \leq \frac{1}{4}. \tag{13}$$

We next consider the probability that some element has no neighboring hub after random rounding. By the fact that $\sum_{j:v_i\in S_j^1} x'_j \geq 1$, the probability that an element $v_i \in V$ has no hub in its 1-hop neighborhood at round t can be upper bounded by

$$\begin{aligned}&\prod_{j:v_i\in S_j^1} \Pr[\bar{x}_j = 0 \text{ at round t}]\\ &\quad = \prod_{j:v_i\in S_j^1}(1 - x'_j)\\ &\quad \leq \prod_{j:v_i\in S_j^1} e^{-x'_j} = e^{-\sum_{j:v_i\in S_j^1} x'_j} \leq \frac{1}{e}.\end{aligned}$$

This implies that the probability that an element v_i has no hub in its 1-hop neighborhood after the random rounding is upper bounded by

$$\Pr\left[\bigcap_{j:v_i\in S_j^1} \bar{x}_j = 0\right] \leq e^{-(\log(n)+2)} \leq 1/4n, \tag{14}$$

By (14) and union bound, we get the probability that some element has no neighboring hub

$$\Pr[\text{some element has no neighboring hub}] \leq \frac{1}{4}. \tag{15}$$

This, combining with (13), implies that with probability at least 1/2 the Algorithm 1 yields a solution which is $\delta(\log(n)+2)^2$ times the solution of the linear program $\mathrm{LP}_{\mathrm{MDHL}}$, i.e.,

$$\Pr[\bar{y} < \delta\lambda\alpha^2 y' \wedge \text{each element has a neighboring hub}] \geq 1/2.$$

This completes the proof. Observe that both events in this bound can be verified in polynomial time. If not, we repeat the entire rounding process. The expected number of repetitions is at most 2. ■

D. Member Camera Assignment

After hubs are located, each camera needs to be assigned to a hub. Towards this, we consider two strategies: distance-aware assignment and correlation-aware assignment. The first strategy assigns each camera to its closest hub so that the transmission energy can be reduced. The second strategy assigns to each hub a group of cameras having high correlation so that higher compression gain can be achieved by letting each hub perform joint coding on the images collected from its member cameras. Specifically, this correlation-aware assignment problem can be formulated by the following nonlinear binary problem. Given a set of hubs $\mathcal{F} = \{h_i\}_{i=1}^k$, let a_{ij} be an indicator variable denoting whether camera v_j is assigned to h_i. This value is set to 1 iff v_j is assigned to h_i. Let S_i denote the set of cameras residing within the one-hop range of hub h_i. Consequently, the correlation-aware assignment aims to find associate each camera with a proper hub in such a way that the total entropy (coding rate) of the whole network is minimized, i.e.,

$$\text{MIN} \quad \sum_{h_i\in F} H\left(\bigcup_{v_j\in V} a_{ij}X_{v_j}\right) \tag{16}$$

$$\text{s.t} \quad \sum_{j:v_i\in S_j} a_{ij} = 1, \quad \forall v_j \in V\ \forall h_i \in F \tag{17}$$

$$a_{ij} \in \{0,1\}, \quad \forall v_j \in V\ \forall h_i \in F \tag{18}$$

To solve this problem, a simple heuristic algorithm can be performed, which uses the average cluster entropy as the metric to associate cameras with the hubs. Specifically, each sensor is assigned to a hub with the minimum average entropy, a ratio of the estimated joint entropy of the cameras covered a hub to the number of cameras it covers.

E. Inter-Hub Connectivity

To convey the collected images to the remote data sink, the hubs need to be interconnected by multi-hop connections. Accordingly, the hubs should maintain inter-hub connectivity by properly adjusting their transmission power. The following theorem implies that each hub only needs to adjust its transmission range to three times the 1-hop distance to achieve network connectivity, i.e.,

Claim 1: In a WMSN with the minimum node degree $\delta \geq 1$, i.e., there is no isolated node in the network, any two hubs generated by the approximation algorithm are three hops away at most.

The proof is straight forward and thus is omitted for the sake of brevity.

V. Maximum Lifetime Scheduling

By solving the member camera assignment (MSCA) problem in the previous section, each hub is associated with multiple camera sensors with high visual correlation. By effectively exploiting such correlation, in this section, we study the differential coding based scheduling strategy with an objective to maximize the lifetime of the camera sensors. Towards this, we first prove that the MLS problem is NP-hard by formulating it as an equivalent binary program. Consequently, we present a randomized approximation algorithm, which produces a solution $\leq \mathrm{OPT} + c_{\max}/e$ in expectation, where $c_{\max}$ is the maximum energy consumed by a camera to send its image to the hub without performing differential coding and e is the exponential constant. In the end, we propose the joint power control and differential coding-based scheduling to further improve the energy efficiency of the camera sensors.

A. IP Formulation for MLS

Given a hub h and a set A of cameras assigned to it. To save energy, we let the transmission range of each camera $v_i \in A$ be the distance between v_i and hub h, denoted by d_{ih}. For each camera $v_i \in A$, let N_i denote a set of cameras within v_i's transmission range, and let X_i denote the image gathered by v_i. We assign two variables x_i and y_{ji} for each camera $v_i \in A$, which are allowed 0/1 values. x_i is set to 1 iff v_i sends its image without overhearing and performing differential coding. y_{ji} is set to 1 iff v_i overhears v_j's transmission and encodes its image X_i conditional on v_j's image X_j. In particular, y_{ii} is set to 1 iff v_i does not overhear anyone's transmission. Consequently, we formulate the maximum lifetime scheduling problem as an integer program $\mathrm{IP_{MLS}}$.

$$\text{MIN} \quad z \tag{19}$$

$$\text{s.t} \quad \sum_{j:v_i \in N_j} x_j \geq 1, \quad \forall v_i \in A \tag{20}$$

$$\sum_{j:v_i \in N_j} y_{ji} = 1, \quad \forall v_i \in A \tag{21}$$

$$y_{jj} = x_j \geq y_{ji} \quad \forall v_i, v_j \in A \tag{22}$$

$$\sum_{j:v_i \in N_j} y_{ji} H(X_i \,|\, X_j) d_{ih}^2 \leq z, \quad \forall v_i \in A \tag{23}$$

$$x_j, y_{ji} \in \{0,1\}, \quad \forall v_j, v_i \in V \tag{24}$$

The objective function z is the maximum energy consumption of all cameras in A. The constraint (20) ensures that each camera has at least one camera to overhear. The constraint (21) states that each camera only overhears once. The equality of the constraint (22) indicates if v_i decides to send its image without performing differential coding, it will not overhear at all, whereas the inequality $x_j \geq y_{ji}$ states that v_j must send its image before v_i can overhear v_j's transmission. The constraint (23) ensures that the energy consumed by each camera v_i to send its compressed image of $H(X_i \,|\, X_j)$ bits over the distance d_{ih} is less than the maximum value z. Slightly different from the notation of the classic information theory, we let $H(X_i \,|\, X_i) = H(X_i)$, which means that a camera only sends its original image if it does not overhear anyone's transmission, i.e., $y_{ii} = 1$. By relaxing the binary variables $x_j, y_{ji} \in \{0,1\}$ to $x_j, y_{ji} \in [0,1]$, we get the relaxed linear problem $\mathrm{LP_{MLS}}$.

B. Approximation Algorithm for MLS

In this subsection, we propose an approximation algorithm based on the random rounding techniques, shown in Algorithm 2. More specifically, we call a camera v_i as a *broadcaster* if its variable $x_i = 1$, and as a *listener* if $x_i = 0$. The proposed algorithm works as follows (see *Algorithm* 2): initially, let all cameras $v_i \in A$ stay as listeners, after solving the linear problem $\mathrm{LP_{MLS}}$, which yields an optimal fractional solution $(\mathbf{x}', \mathbf{y}', z')$, let each camera $v_i \in A$ become a broadcaster with probability x_i'. Otherwise, the camera stays as a listener. For each listener v_i, find all broadcasters $v_j \in A$ that have nonzero y_{ji}', and if such broadcasters exist, assign the listener v_i to the broadcaster having the smallest cost $H(X_i \,|\, S_j) d_{ih}^2$, otherwise let v_i become a broadcaster itself.

Algorithm 2 Approximation Algorithm for MLS

1: Solve $\mathrm{LP_{MLS}}$. Let $(\mathbf{x}', \mathbf{y}', z')$ be the optimum solution.
2: $\bar{\mathbf{x}} \leftarrow \mathbf{0}$, $j \leftarrow 0$.
3: $\bar{x}_i \leftarrow 1$ with probability x_i', $\bar{y}_{ii} \leftarrow 1$ if $\bar{x}_i = 1$
4: For each $v_i \in A$ with $\bar{x}_i = 0$, find $O_j = \{v_i \,|\, y_{ji}' \neq 0, \bar{x}_j = 1\}$
5: **if** $O_i \neq \emptyset$ **then**
6: $\quad v_{j^*} = \arg\min_{v_j \in O_i} H(X_i \,|\, X_j) d_{ih}^2$ and $\bar{y}_{j^*i} \leftarrow 1$
7: **else**
8: $\quad \bar{x}_i \leftarrow 1$ and $\bar{y}_{ii} \leftarrow 1$
9: **end if**
10: Return $(\bar{\mathbf{x}}, \bar{\mathbf{y}}, \bar{z})$

Theorem 3: Let OPT denote the optimal solution of the MLS problem. The solution of the proposed algorithm is at most $\mathrm{OPT} + H(X) d_{\max}^2 / e$ in expectation, where $d_{\max}$ is the maximum distance between a camera and its assigned hub and e is the exponential constant.

Proof: First, by the pseudo code in *Algorithm* 2, we can verify that the proposed algorithm produces a feasible solution, that is, when the algorithm is done, every camera is either a broadcaster or a listener. To get the expected energy of a camera v_i, we establish an overhearing list L_i for v_i, which consists of i's potential broadcasters $(v_j \,|\, y_{ji}' \neq 0)$. These potential broadcasters are arranged in an increasing order of the cost $c_{ji} = H(X_i \,|\, X_j) d_{ih}^2, j = 1, 2, \ldots, l$, where l is the list length. By this way, we have

$$y_{1i}' = x_1', y_{2i}' = x_2', \ldots, y_{li}' = x_l'. \tag{25}$$

The above equalities hold because to reduce the cost of a listener, it has to listen to the broadcaster that leads to the smallest cost as possible as it can. Now, we get the probability that a camera v_i has no broadcaster in its overhearing list.

$$p_i = \prod_{j:v_j \in L_i} (1 - x_j') \leq \prod_{j:v_j \in L_i} e^{-x_j'} = e^{-\sum_{j:v_j \in L_i} x_j'}$$
$$= e^{-\sum_{j:v_i \in N_j} y_{ji}'} = \frac{1}{e}$$

The first inequality results from the inequality $(1 - x) \leq e^{-x}, \forall x \in [0,1]$. The first equality in the second line holds because of (25). The last equality follows the fact that $\sum_{j:v_i \in N_j} y_{ji}' = 1$.

According to the algorithm, if v_i is a broadcaster, an event that occurs with probability x_i', then v_i has a cost c_{ii}. Otherwise, v_i overhears the first camera in the list. If this camera is a broadcaster, an event that occurs with probability $(1 - y_{ii})' y_{1i}'$, then v_i has a cost c_{1i}. If the first camera is not a broadcaster and the second is, an event that occurs with probability $(1 - y_{ii}')(1 - y_{1i}{}')y_{2i}'$, v_i has a cost c_{2i}, and so on. If there exists no broadcasters in the list, an event that occurs with probability p_i, then v_i becomes a broadcaster and has a cost less than $c_{\max} = H(x) d_{\max}^2$. By the fact $\sum_{j:v_i \in N_j} y_{ji}' c_{ji} \leq z' \leq \mathrm{OPT}$, the expected cost of a camera has an upper bound

$$y_{ii}' c_{ii} + (1 - y_{ii}') y_{1i}' c_{1i} + \cdots + (1 - y_{ii}') y_{li}' c_{li} + p_i c_{\max}$$
$$\leq \sum_{j:v_i \in N_j} y_{ji}' c_{ji} + c_{\max}/e \leq \mathrm{OPT} + H(x) d_{\max}^2 / e.$$

which completes the proof. ■

Note that the solution of the MLS problem only defines the precedence constraints in the schedule. For example, if $y_{ji} = 1$, this only implies that v_j's transmitting slot must be ahead of v_i's, without specifying v_j's or v_i's slot location in the schedule. Thus, as long as the precedence constraints are satisfied, the cameras' transmitting slots can be arranged in any order. One of the simplest way to convert the pairwise precedences into the transmission schedule SCH_t is as follows. First, identify the broadcasters, which are the camera nodes with non-zero value x_i (or non-zero value y_{ii}) and the listeners, which are the camera nodes with zero value x_i. Next, arrange the transmission sequence SCH_b of the broadcasters in the ascending order of their IDs and so does the transmission sequence SCH_l of the listeners. Then, the transmission schedule SCH_t is equivalent to the sequence SCH_b followed by SCH_l. By constructing the transmission schedule in this manner, we can guarantee that if $y_{ij} = 1$, which means $x_i = 1$ and $x_j = 0$, then the node v_i surely transmits before the node v_j. In addition, for each listener v_j with $y_{ij} = 1$, v_j will wake up during the transmission slot of v_i and overhear v_i's transmission.

C. Joint Power Control and Scheduling

In the previous section, we assume that the transmission range of each camera is fixed, which is equal to the distance between the camera and the hub. In the section, we will study the maximum lifetime scheduling problem by allowing each sensor to adjust its transmission power. Specifically, the transmission range, the transmission slot, and the overhearing slot are jointly assigned for each member camera in such a way that the lifetime of the member cameras is maximized. Intuitively, this joint power control and scheduling strategy could lead to more energy saving since each camera has more candidates to choose for performing differential coding.

$$\text{MIN} \quad z \tag{26}$$

$$\text{s.t} \quad \sum_{j:v_i \in P_j^k} x_j^k \geq 1, \quad \forall v_i \in A \tag{27}$$

$$\sum_{k=1}^{N} x_i^k \leq 1, \quad \forall v_i \in A \tag{28}$$

$$\sum_{j:v_i \in P_j^k} y_{ji}^k = 1, \quad \forall v_i \in A \tag{29}$$

$$y_{jj}^k = x_j^k \geq y_{ji}^k, \quad \forall P_j^k \in P \ \forall v_i \in A \tag{30}$$

$$\sum_{j:v_i \in P_j^k \wedge v_i \neq v_j} y_{ji}^k H(X_i \,|\, X_j) d_{ih}^2 + \sum_{j:v_i \in P_j^k \wedge v_i = v_j} y_{jj}^k H(X_i)(r_k)^2 \leq z, \forall v_i \in A \tag{31}$$

$$x_j, y_{ji} \in \{0, 1\}, \quad \forall v_j, v_i \in V \tag{32}$$

Before formulating the maximum lifetime scheduling problem with power control (MLS_PC), we first introduce some notations. Consider a hub h and a set A of cameras assigned to it. Each camera can switch among N potential transmission ranges by properly adjusting its transmission power. We model each potential transmission range of each camera as a set of cameras residing within this range. The potential transmission ranges of all cameras constitute a collection of sets of cameras, denoted by P. Each set $P_j^k \in P$ consists of a *center camera* v_j and the cameras residing within the *radius* $r_k \leq R_{\max}$, where r_k is a potential transmission range of the center camera v_j. For each $P_j^k \in P$, we assign a binary variable x_j^k such that $x_j^k = 1$ iff P_j^k is selected and its center camera transmits its original image without overhearing and performing differential coding. For each camera v_i, we assign a binary variable y_{ji}^k, which is set to 1 iff v_i overhears the transmission of the center camera v_j of the set P_j^k. Let $H(X_j \,|\, X_i)$ denote the coding rate of encoding the image X_j from the camera v_j conditional on the image X_i from the center camera v_i of the set P_i^k. Consequently, we formulate the maximum lifetime scheduling problem with power control as an integer program $\mathrm{IP}_{\mathrm{MLS}}^{\mathrm{PC}}$.

The objective function is the maximum energy consumption of all member sensors. The first constraint (27) ensures that each camera has at least one camera to overhear. The second constraint (28) indicates that if one set with the center camera v_i is selected, no other sets with the same center camera can be selected, which guarantees that a center camera can not be equipped with multiple transmission ranges simultaneously. The third constraint (29) guarantees that each camera only overhears once. For the fourth constraint (30), the first equality says that if the center camera v_i of P_j^k becomes a broadcaster (i.e., it decides to send its image without performing differential coding), it will not overhear at all, while the second inequality indicates that a broadcaster v_j (i.e., the center camera of the set P_j^k) must transmit its image before its neighboring camera v_i can overhear this transmission. The fifth constraint (31) states the energy consumed by each camera is less than the maximum value z. Specifically, the energy consumption of a camera v_j depends on whether it is a broadcaster or not. If v_i is a listener, it only needs to send its compressed image of $H(X_i \,|\, X_j)$ bits over the distance d_{ih} between v_i and the hub h. Otherwise, if v_i is a broadcaster, it has to send its entire image of $H(X_i)$ bits over its transmission range r_k. By relaxing the binary variables $x_j, y_{ji} \in \{0, 1\}$ to $x_j, y_{ji} \in [0, 1]$, we obtain the relaxed linear problem $\mathrm{LP}_{\mathrm{MLS}}^{\mathrm{PC}}$.

To solve the $\mathrm{IP}_{\mathrm{MLS}}^{\mathrm{PC}}$ problem, we propose an approximation algorithm (See Algorithm 3), which works as follows. First, solve the linear problem $\mathrm{LP}_{\mathrm{MLS}}^{\mathrm{PC}}$, which yields an optimal fractional solution $(\mathbf{x}', \mathbf{y}', z')$. Let $(\bar{\mathbf{x}}, \bar{\mathbf{x}}, \bar{z})$ denote the integer solution. Then, select the set $P_i^k \in P$ (i.e., $\bar{x}_i^k = 1$) with probability $(x_i^k)'$. The center camera $c(P_i^k)$ of the selected set P_i^k becomes a broadcaster with the transmission range equal to the set radius r_k. The sensors which are not broadcasters become listeners. For each listener v_i, there will be two scenarios. (1) If at least one of the selected sets has the center camera with nonzero $(y_{ji}^k)'$, associate the listener v_i with the set having the smallest cost $H(X_i \,|\, X_j) d_{ih}^2$. Note that given a listener v_j, this cost only depends on the center camera v_j of the set. Therefore, multiple sets with the same center camera and different transmission ranges can lead to the same smallest cost. In this case, we select the set with the shortest transmission range. (2) If there are no selected sets having the center camera with nonzero $(y_{ji}^k)'$, let the listener v_i become a broadcaster itself. The last step of the algorithm is to check the uniqueness of the broadcasters' transmission range. Specifically, when the above procedures terminate, a broadcaster could be associated with multiple transmission ranges since it could be the center camera of multiple selected sets. In this case, we let the transmission range of the broadcaster be the one that covers all the listeners assigned to this broadcaster.

Algorithm 3 Approximation Algorithm for MLS_PC

Solve $\mathrm{LP}_{\mathrm{MSL}}^{\mathrm{PC}}$. Let $(\mathbf{x}', \mathbf{y}', z')$ be the optimum solution.
$\bar{\mathbf{x}} \leftarrow \mathbf{0}$, $\bar{\mathbf{y}} \leftarrow \mathbf{0}$, $R_{tx}(v_i) \leftarrow \emptyset$
$v_i \in \{Broadcaster, Listener\}, \forall v_i \in A$
$P \leftarrow \{P_i^k \mid \bar{x}_j^k \leftarrow 1 \text{ with probability } (\mathrm{x}_j^k)'\}$
if $\bar{x}_j^k = 1$ **then**
  $v_j \leftarrow Broadcaster, \bar{y}_{jj}^k \leftarrow 1, R_{tx}(v_i) \leftarrow R_{tx}(v_i) \cup \{r_k\}$
end if
if $v_i \neq Broadcaster$ **then**
  Find $O_i = \{P_j^k \in P \mid (y_{ji}^k)' \neq 0\}$
  if $O_i \neq \emptyset$ **then**
    $v_i \leftarrow Listener$ and $R_{tx}(v_i) \leftarrow \{d_{ih}\}$
    $E \leftarrow \arg\min_{e \in O_i} H(X_i \mid X_j) d_{ih}^2$
    $P_j^k \leftarrow \arg\min_{p_i^k \in E} r_k$ and $\bar{y}_{ji}^k \leftarrow 1$
  else
    $v_i \leftarrow Broadcaster$ and $R_{tx}(v_i) \leftarrow \{d_{ih}\}$
  end if
end if
if $|R_{tx}(v_i)| > 1$ **then**
  $R_{tx}(v_i) \leftarrow \sup\{r \in R_{tx}(v_i) \mid \|v_i - v_j\| \leq r, \forall v_i \in A \wedge \bar{y}_{ji}^k = 1\}$
end if
Return $(\bar{\mathbf{x}}, \bar{\mathbf{y}}, \bar{z})$

Theorem 4: Let OPT denote the optimal solution of the MLS_PC problem. The solution of the proposed algorithm is at most $\mathrm{OPT} + H(X) R_{\max}^2 / e$ in expectation, where $R_{\max}$ is the maximum transmission range of the camera sensor and e is the exponential constant.

The proof is similar to the one for Theorem 3. Thus, the proof is omitted here for brevity.

VI. Performance Evaluation

In this section, we evaluate the performance of the proposed image gathering schemes. First, we evaluate the effectiveness of the estimator that predicts the efficiency of differential coding between correlated cameras. Then, we study the efficiency of the proposed network deployment approach that consists of the proposed hub placement and camera assignment algorithms. In the end, we evaluate the differential coding-based scheduling algorithm in terms of energy saving.

A. Validation of the Coding Efficiency Prediction

Since the entropy-based estimator provides predicted coding efficiency for the proposed visual correlation-based schemes, we need to validate its effectiveness by comparing the estimated coding efficiency with the actual coding efficiency from practical coding experiments. Since the performance of the estimator for predicting joint coding efficiency was tested in [20] and [21], we only need to validate its capability to predict the differential coding efficiency. Suppose image X_i is coded based on the prediction of image X_j, and we can define an *estimated differential coding efficiency* as

$$\eta_H^D = 1 - \frac{H(X_i \mid X_j)}{H(X_i)} \tag{33}$$

where $H(X_i \mid X_j)$ is the theoretical coding rate of differential coding. This metric predicts the percentage of rate savings of differential coding compared to individual coding. The actual differential coding efficiency is calculated by replacing the entropy terms in (33) with the corresponding coding rates from our coding experiment.

TABLE I
Experimental Parameters

H.264 MVC			
RD optimization	on	Entropy coding	CABAC
Search range	128	Reference frames	1

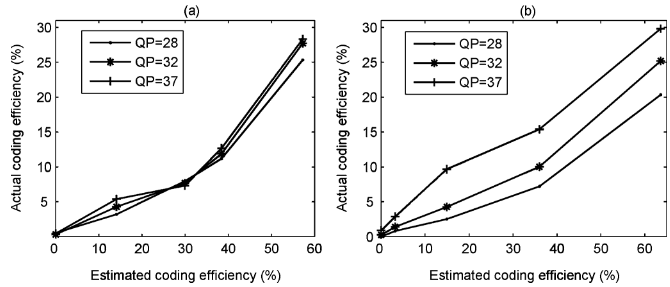

Fig. 2. Estimation of coding efficiency.

In our experiment, we deploy a number of camera nodes in a field and record each camera's FoV parameters. We deploy the cameras in two scenes, an indoor scene and an outdoor one. For each scene, we let each camera capture an image at the same time, and perform coding experiments on the observed images. For any 2 images in the same scene, we take one image as the reference frame and perform multi-view coding on the other image. The H.264 Multi-View Coding (MVC) coding standard with reference software version JMVC 2.5 [1] is used here. To test the performance of differential coding under different parameters, we set three different quantization steps ($\mathrm{QP} = 28, 32$, and 37). Other key parameters for the encoder are listed in Table I.

In this experiment, we used the same data sets and coding parameters as that in our previous paper [21]. The difference is that we considered *joint coding efficiency* in [21] and evaluate *differential coding efficiency* here, which serves as an important design metric for the proposed differential coding based scheduling algorithm. The resulting estimated coding efficiency and actual coding efficiency for the two scenes are plotted in Fig. 2. When the quantization step increases, the actual coding efficiency is slightly higher. This is because a larger quantization step allows for more distortion, in which case more bits could be potentially saved from differential coding. Comparing the results of the two scenes, there is more deviation in coding efficiency for the outdoor scene when the quantization step varies. We find that this is because the outdoor scene contains more texture information, so that the coding performance of

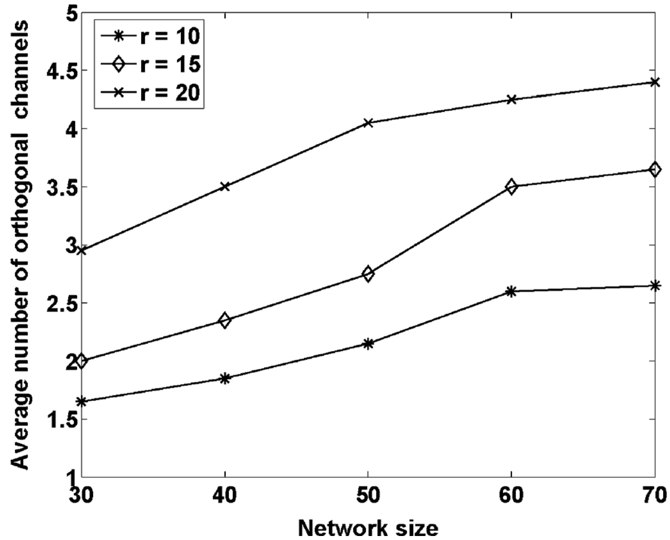

Fig. 3. Number of orthogonal channels under $\mathrm{MDHL_{AP}}$.

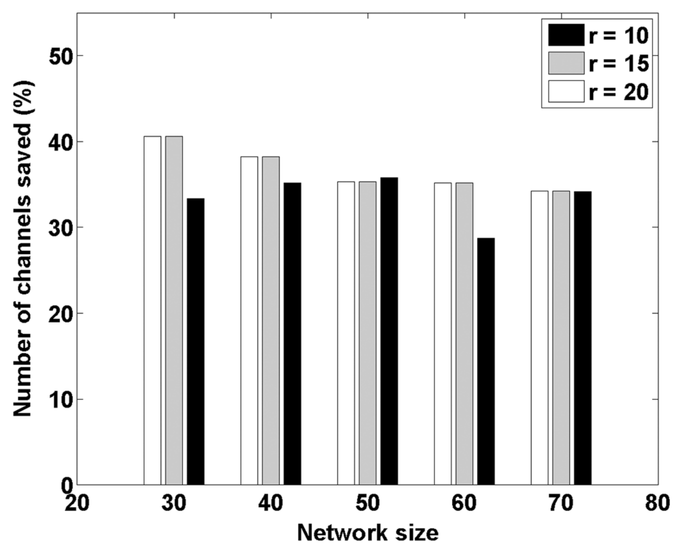

Fig. 4. Performance enhancement of $\mathrm{MDHL_{AP}}$ compared with HEED.

the outdoor scene is more sensitive to the extent of quantization. In both cases, the actual differential coding efficiency is approximately proportional to the estimated differential coding efficiency. Therefore, the proposed entropy-based estimation method can be used to predict the performance of inter-camera differential coding.

B. *Effectiveness of Hub Location Scheme*

In this section, we first evaluate the performance of the proposed algorithm for the MDHL problem. We study the required number of orthogonal channels, varying network size and transmission range. Specifically, we consider a WMSN with camera nodes uniformly deployed in a 100×100 meter region. The network size or number of deployed sensors ranges from 30 to 70 and the transmission range increases from 10 to 20 meters. Fig. 3 recodes the mean maximum hub degree of 20 topology instances. It is shown that the number of required orthogonal channels slightly increases as the network size or the transmission range increases. This is as expected since larger network size or transmission range implies a single cluster may have more neighboring clusters so that more orthogonal channels are required to enable the current transmissions of multiple clusters.

We next compare our approximation algorithm, denoted by $\mathrm{MDHL_{AP}}$, with the hybrid energy-efficient distributed clustering (HEED) protocol [24]. HEED is a well known clustering protocol that is specially designed for wireless sensor networks. HEED is a good candidate for reducing the number of orthogonal channels, since it is able to make the hubs evenly distributed across the network, which implies lower opportunity of having larger hub degree in the network. The HEED protocol consists of two phases: cluster head (hub) selection and cluster member assignment. In the first phase, sensor nodes are selected as CHs probabilistically. More specifically, each node is given an initial probability p (i.e., 0.05 in [24]) with which it becomes a CH. In the first iteration, each sensor uniformly draws a value between 0 and 1 and compares this value with the initial probability. If this value is less than p, the sensor becomes a CH and all its neighbors are covered. After this iteration, many sensors may still be uncovered since the initial probability (i.e., 0.05) is very small. Therefore, in each of the following iterations, every sensor doubles p and with this probability the uncovered sensors become new CHs. When p reaches 1, the first phase completes. In the second phase, each sensor is assigned to the closest CH as its cluster member.

In Fig. 4, we measure the number of required orthogonal channels under HEED and evaluate the percentage of channels saved by $\mathrm{MDHL_{AP}}$, compared with HEED, varying the network size n and transmission range r. Since $\mathrm{MDHL_{AP}}$ is a dedicated algorithm for minimizing the maximum hub degree, it is expected that $\mathrm{MDHL_{AP}}$ can lead to better hub placement by reducing the number of required orthogonal channels. As shown in Fig. 4, $\mathrm{MDHL_{AP}}$ requires 28%–40% percent less orthogonal channels compared with HEED. Meanwhile, we observe that $\mathrm{MDHL_{AP}}$ can maintain the comparable performance enhancement under different network size and transmission range, which indicates that $\mathrm{MDHL_{AP}}$ is less sensitive to the network settings and has good network scalability. This is as expected since by approximately solving the MDHL problem, $\mathrm{MDHL_{AP}}$ can explicitly avoid such hub placement which leads to larger hub degree and consequently more required orthogonal channels. It should be noted that although the proposed solution yields better performance than HEED protocol in terms of required orthogonal channels, HEED protocol, as a distributed heuristic algorithm, requires less computational efforts than our solution, which is a centralized approximation algorithm and involves solving the linear program.

We now evaluate performance of the two camera assignment schemes: distance-aware assignment and correlation-aware assignment. Specifically, we study the overall coding/compression efficiency under the two schemes, where the overall coding efficiency is used to predict the percentage of rate savings of joint coding and defined as follows. Consider a WMSN with N camera sensors with observations $X_1, \ldots, X_N$. Let $\mathcal{F} = \{h_i\}_{i=1}^{k}$ denote the set of hubs, where each hub i is associated with a set of member cameras, denoted by S_{h_i}. Letting $H(S_{h_i})$

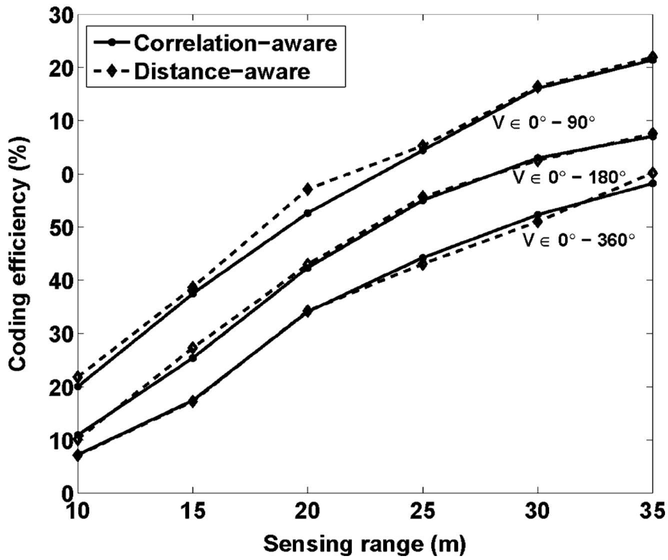

Fig. 5. Overall coding efficiency of member camera assignment schemes.

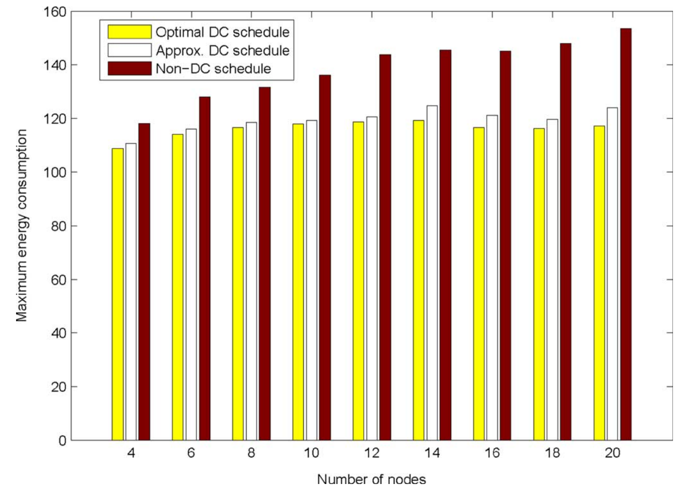

Fig. 6. Energy Consumption Under Different Cluster Sizes.

denote the joint entropy of cameras in S_{h_i}, the *overall coding efficiency* is defined as

$$\eta_H^J = 1 - \frac{\sum_{h_i \in F} H(S_{h_i})}{\sum_{j=1}^{N} H(X_j)} \tag{34}$$

where $\sum_{j=1}^{N} H(X_j)$ is the total coding rate when the cameras compress their observations individually. In Fig. 5, we evaluate the overall coding efficiency in a network of 70 nodes with transmission range $r = 20$ meters. The FoV parameters of the cameras are set as follows. The sensing directions V of the cameras are uniformly chosen among three scenarios $V \in 0°–360°$, $V \in 0°–180°$, and $V \in 0°–90°$, the sensing radius R ranges from 5 to 30 meters, and the offset angle α equals $60°$. In Fig. 5, we observe the elevation in coding efficiency of both schemes with larger sensing radius and smaller deviation in sensing directions. This observation is due to the fact that larger sensing radius or smaller deviation in sensing directions leads to higher correlation among adjacent camera nodes, implying more visual redundancy in the network. In this case, more bits can be saved by performing joint coding. It is also seen that the performance of distance-aware and correlation-aware assignment is comparable, varying different camera settings. This is attributed to the following: under the network hierarchy constructed by the $\mathrm{MDHL_{AP}}$, the hubs are evenly located across the network so that most of the camera sensors are covered by a single hub. For those sensors, the distance-aware assignment associates them to the same hubs as the correlation-aware one, which makes the two schemes yield comparable performance.

C. Energy Saving of Differential Coding-Based Scheduling

We now investigate the performance of the proposed differential coding-based scheduling scheme. We test the energy efficiency of a cluster by varying the cluster size, deployment range, as well as the FoV parameters of camera sensors.

We consider a cluster with camera nodes uniformly deployed in a 10×10 meters region. A hub is placed in the center of the region, and each camera node can communicate directly with the hub. To test the performance under different cluster sizes, we deploy 4 to 20 camera nodes within the region. The sensing directions of the cameras are uniformly chosen between $0°–360°$, while the FoV parameters of all the cameras are fixed, with the sensing radius $R = 30$ meters and the offset angle $\alpha = 60°$. For each number of camera nodes, we randomly generate 50 instances and measure the maximum energy consumption per image yielded by our proposed approximated algorithm. As benchmarks, the optimal schedules are also found by the Branch and Bound algorithm, an enumeration based technique. These two algorithms are compared to a conventional TDMA-based scheduling scheme where correlation is not exploited.

The average maximum energy consumption per image for the above schemes are shown in Fig. 6. The energy consumption in the vertical axis corresponds to the minimization term z in (19), which is measured as a relative value here. Specifically, to transmit image X_i over a distance d_i, if X_i is differentially coded based on another image X_j, the transmission energy is proportional to $H(X_i \mid X_j) \cdot d^2$ (corresponding to (23)). In our simulation, the entropy of an individual image $H(X_i)$ is set as a unit value, and $H(X_i \mid X_j)$ is estimated from our correlation model as a relative value of $H(X_i)$. We observe that the maximum energy of the approximated algorithm is comparable with the optimal solution regardless of cluster sizes. Based on the data in Fig. 6, the average maximum energy of the approximated algorithm is merely 2.75% more than that of the optimal solution. The approximated scheduling algorithm also leads to 13.68% reduction in terms of average maximum energy consumption compared with the conventional TDMA-based scheduling. This is due to the fact that the differential coding-based scheduling allows cameras to remove the redundancy between each other, thus reducing the bits sent to the hub. Moreover, for the conventional TDMA-based scheduling scheme, the average maximum energy consumption increases as the cluster size increases. In the case that no correlation is exploited, the maximum energy consumption is brought by the node that is farthest away from the hub. Therefore, when the cluster size is large, there is higher probability for a node to be placed far away from the node, so that the average maximum energy consumption is

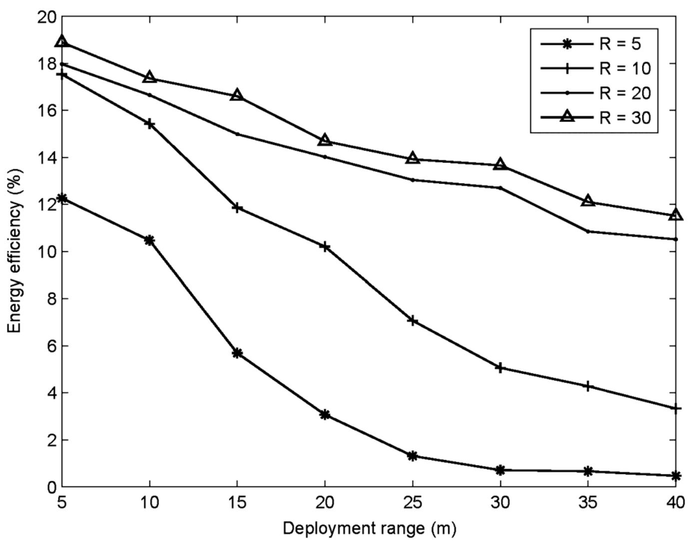

Fig. 7. Energy Efficiency Under Different Deployment Ranges and Sensing Radiuses R.

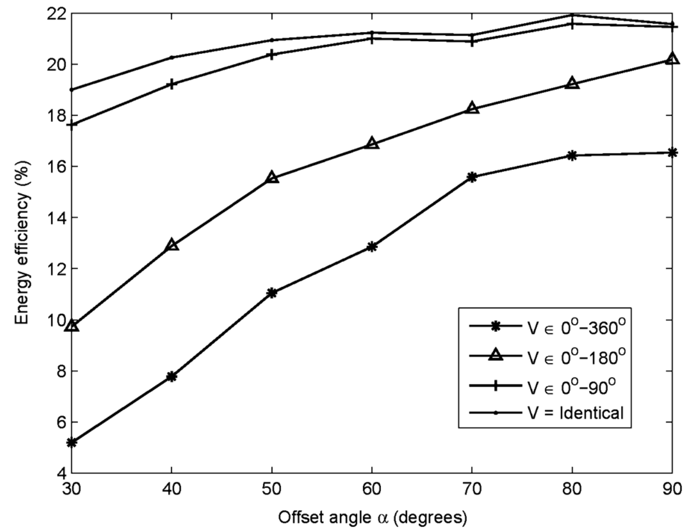

Fig. 8. Energy Efficiency Under Different Sensing Directions $\vec{V}$ and Offset Angles α.

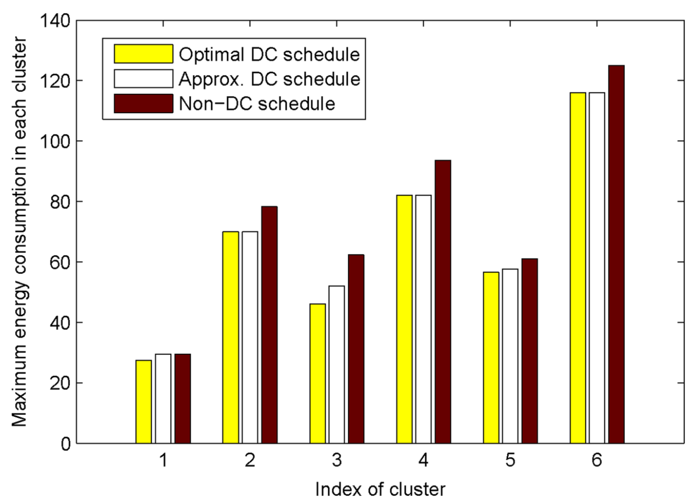

Fig. 9. Energy Consumption of Maximum Lifetime Scheduling for Clusters Resulted from MDHL.

higher. However, as the proposed scheme introduces correlation-based differential coding to reduce the maximum energy consumption, there is no obvious increase in average maximum energy consumption in the proposed algorithm when the cluster size increases.

We now study the impact of deployment range and sensing radius on the performance of the proposed scheduling algorithm. We deploy 10 camera sensors in a cluster, where the deployment range varies from 5×5 meters to 40×40 meters. We also vary the sensing radius R to 5, 10, 20, and 30 meters, respectively. Other parameters are the same as given above. Fig. 7 shows the impact of different deployment range and sensing radius on the energy efficiency, which is given by the percentage of maximum energy reduction of the approximated algorithm over the conventional TDMA-based scheduling scheme. The energy efficiency increases as the sensing radius increases, while the energy efficiency decreases as the deployment range increases. This can be attributed to the following: larger sensing radius and smaller deployment range can lead to more overlapped FoVs of the cameras and more redundancy of the observed images, so that higher energy efficiency could be achieved by differential-coding based scheduling.

The distribution of cameras' sensing directions and the offset angle of cameras' FoVs can also affect the performance of the proposed scheduling algorithm. To evaluate these factors, we fix the other parameters in the experiment. (The cluster size is set to 10 camera sensors, the deployment range is set to 10×10 meters, and the sensing radius is $R = 30$.) We then measure the average energy efficiency under changing sensing direction distributions and offset angles. The sensing directions of each camera sensor is randomly selected within a region of degrees. The deviation in the sensing directions of multiple cameras can affect the degree of correlation of the observed images. According to our previous results on correlation [4], sensors with similar sensing directions are likely to have higher degree of correlation, resulting in more potential bit saving by differential coding. This explains the results in Fig. 8, where the lowest energy efficiency is obtained when the sensing directions are selected within 0°–360°, while the best energy efficiency is achieved when all the cameras have identical sensing directions. As shown in Fig. 8, the energy efficiency is also related to the degree of the offset angle in the camera's FoV. The energy efficiency increases when the offset angle increases. Since a large offset angle leads to a wide FoV, there is greater probability that the cameras share large common area and have high correlation. The energy efficiency reaches the maximum value when the offset angle reaches 80°–90°.

Furthermore, we show the result of MLS scheduling on clusters formed by MDHL. We first run MDHL algorithm for a network of 40 nodes, where the communication range for each node is 15 meters. The MDHL algorithm selects 6 nodes as processing hubs in the network, (i.e., 6 clusters are formed), and the number of cluster member nodes are 2, 4, 5, 6, 7, and 10. We then find the MLS schedule for each cluster. Fig. 9 shows the maximum energy consumption of these 6 clusters. In average, the approximation algorithm for MLS can reduce the

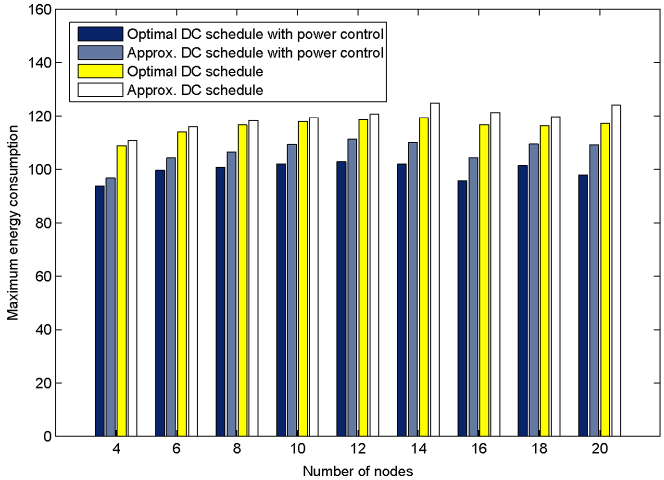

Fig. 10. Energy Consumption of Maximum Lifetime Scheduling with Power Control.

maximum energy consumption by 9% compared to the conventional TDMA-based scheduling.

We now evaluate the performance of the joint power control and maximum lifetime scheduling algorithm in Section V.C. We consider the same settings as the previous experiment: there is a cluster with camera nodes randomly deployed in a 10×10 meters region. A hub is placed in the center of the region, and each camera node can communicate directly with the hub. For different cluster sizes (4 to 20), we randomly generate 50 instances and measure the maximum energy consumption per image yielded by the optimal maximum lifetime scheduling with power control scheme (MLS_PC). The corresponding approximated solution is also found from Algorithm 4. The results are compared to our MLS scheme without power control. Fig. 10 shows the optimal and approximate solutions of MLS_PC and MLS. For MLS_PC, the approximation algorithm results in 7.28% more energy than the optimal solution. Because of power control, more candidate power levels could be utilized to minimize the maximum energy consumption in a cluster. Therefore, MLS_PC can reduce the maximum energy consumption compared to the MLS scheme. Based on the results in Fig. 10, the optimal MLS_PC scheme can reduce the maximum energy consumption by 14.34% compared to the optimal MLS, and the approximation algorithm of MLS_PC can reduce the maximum energy consumption by 10.58% compared to the approximation algorithm of MLS.

VII. Conclusion

In this paper, we address two fundamental problems involved in the process of image gathering. More specifically, the MDHL problem aims to find the optimal hub locations such that the required number of orthogonal channels for frequency reuse is minimum. To solve this problem, an $O(\log^2(n))$-factor approximation algorithm is proposed. After assigning the camera sensors to the proper hubs, a novel differential coding-based scheduling scheme is proposed with an objective to maximize the sensor's lifetime. It is proven that the proposed scheme yields a near-optimal performance, which, as shown, can be further elevated by jointly considering power control and differential-coding based scheduling. Experiments and simulations show that the proposed differential coding-based scheduling framework is effective and efficient in improving the spectrum utilization and energy efficiency in a WMSN.

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