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RATE BASED CROSS LAYER OPTIMIZATIONS FOR IMAGE DELIVERY IN WIRELESS SENSOR NETWORKS

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A number of growing sensor applications such as target tracking and health monitoring motivate rate-based image transmissions in the Wireless Sensor Network (WSN). In this paper, we propose a cross layer based optimal approach for image sensors to decide transmission patterns based on a Rate-Oriented Routing scheme, which achieves both high energy efficiencies and longer network lifetime. In this approach, a group of image sensors transmit the images through appropriate rate-based routing paths under the user requirements. The simulation results show that the proposed image transmission scheme can achieve considerable gains in terms of the WSN energy efficiency and network lifetime extension.

Keywords: Cross Layer, Network Lifetime, Wireless Sensor Network

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1 Introduction

In Wireless Sensor Networks (WSN), image sensors can provide visual information and support applications in numerous areas such as field monitoring and surveillance. These applications may require image sensor array to conduct collaborative image transmissions under limited sensor resource constraints. For example, in environmental monitoring cases, vast and inaccessible field area could be visually monitored by correlated image sensors for early detection of unusual events. Another example is military reconnaissance, where high quality images can be acquired through image sensors in WSN to improve the field perceptibility and make accurate estimation about menace.

However, the large amount of image data loads in WSN are the bottlenecks of network transmission. These burdensome image data transmissions in WSN can significantly degrade the network performance and network lifetime due to the limited power in the sensor nodes [1]-[2]. Although a comprehensive joint image compression in the sensor array has reduced the inter-redundancies for the images, it would require the simultaneous availability of image data from multiple sensors, involving high communication overheads for comprehensive data exchange. Recently, both cooperative methods [3]-[5] and predictive methods [6]-[7] are explored in utilizing sensor correlation. These approaches either involves high inter-sensor communication overheads or require the prior information of the sensor deployment. Further, how to utilize the sensor correlation model for efficient image transmissions should not only be determined by source image sensors themselves, the network parameters such as the routing pattern has to be included in this study. In this paper, we propose an effective approach where the data redundancy among correlated image sensors can be considerably reduced in a simple approach. The communication overhead for data exchange is relatively small to exploit the correlations in the proposed approach.This paper is an extensive effort to deepen and enhance our previous related works published in [8].

2 The Optimization Model for Image Transmissions

In this section, we formalize an optimal transmission model with given corresponding routing paths and deployed sensors with the corresponding energy on each sensor. For simplicity yet without loosing generality, we listed two assumptions: Each image sensor sends non-overlapping region and possibly part of overlapping regions shared with other image sensors within its field of view**;** The union of non-overlap regions and overlap regions equals the whole area of view for all correlated image sensors. For example, F1, F2 and F3 are three images taken by three image sensors, respectively. Each image can be separated into Overlap (O) regions and Non-Overlap (NO) region. Each image sensor will transmit its NO region and part of O regions to base station via single-hop or multi-hop path. To save communication energy, it would be important for each source sensor to send its own NO region and not to send the portion of O region that has already been sent by another source sensor who shares this portion of O region.

For example, there are three pictures F1, F2 and F3 captured by three sensors. Each picture can be denoted as a combination of NO and O regions. O2 and O3 are image regions overlapped by all three pictures. F1=NO1+O1+O2, F2=NO2+O1+O2+O3, and F3=NO3+O2+O3. With such region pattern and transmission diversity for different image regions on multiple paths, we try to look for an optimal solution to achieve higher energy efficiency and better load balancing under the requirement for image transmission quality, i.e., image distortion requirement. Let S be a set of nodes from image sensor groups that can perform cooperative measurements on the target, and N be the total number of nodes in S. The meanings of other symbols used in the paper are shown in Table 1. We also denote by E_i,$\{i = 1, 2, ...N\}$ the sensors' residual energy with i as the sensor index. Each NO region is labelled by NO_i, and O region is labelled by O_j, $\{j = 1, 2, ...M)$.The meaning of symbols are refereed to table 1. M is the number of overlap regions in the interest scene. We use $x_{i,j}$

Table 1. Equation Symbols Reference

Symbol	Definition
E_i	Remaining Energy of sensor i
t_i	Lifetime of sensor i
C_i	Energy Consumption cost per bit of sensor i
NO_i	Non-Overlap area of sensor i
O_j	Overlap area of region j
G_i	Source Rate of Image Sensor i
$CostP_i$	Energy cost on route path of image sensor i
$e_j^T(i)$	Transmit energy consumption per bit of node j of route path of image sensor i
$e_j^R(i)$	Receive energy consumption per bit of node j of route path of image sensor i

to denote the fraction of the overlap region O_j that is to be sent by sensor i; therefore, the i^{th} sensor's lifetime can be expressed as

$$t_i = \frac{E_i}{(NO_i + \sum\limits_{j=1}^{M} x_{i,j} \cdot O_j) \cdot C_i} \tag{1}$$

where C_i is the energy consumption per unit when the i^{th} sensor sends image to the next-hop node, In the network model, the lifetime of all correlated image sensors should be balanced at the same time to maximize the network lifetime, and be load-balanced to avoid losing the sensing coverage. Therefore, we have

$$\sum_{i=1}^{N} (t_i - \overline{t}) < \sigma \tag{2}$$

σ is a threshold with small value.$CostP_i$ denotes the average energy consumption per bit when sensor i sends image data to the base station via a specific routing path, which is the sum of all energy costs on the route. Each image sensor has a corresponding path transmission cost $C_i\{i = 1, 2, ...N\}$ associated with it. Let $e_j^T(i)$ be the transmission energy cost on a hop from node j to $j + 1$ on a specific path for sensor node i. $e_j^R(i)$ is the receive energy cost on hop j to $j + 1$, and $e_j^{retr}(i)$ is the energy cost for the collision and retransmission. Thus,

$$CostP_i = \sum_{j=1}^{HopCount} \left(e_j^T(i) + e_j^R(i) + e_j^{retr}(i) \right) \tag{3}$$

The transmission energy on hop j to $j+1$ is directly related to the transmission rate expressed in Equation (4). m is constant parameter, α relates to channel condition, which determined by BER requirements. $d_{j,j+1}$ denotes the distance between node j and $j + 1$. $R_j(i)$ is the transmission data rate on hop j to $j + 1$ on route path of image sensor i.

$$\begin{aligned} e_j^T(i) &= \alpha \cdot (R_j(i))^m \cdot d_{j,j+1}(i)^2 \\ e_j^R(i) &= \beta \cdot \frac{1}{R(i)} \end{aligned} \tag{4}$$

The receive energy of hop j to $j + 1$ is also related to the transmission rate and can be expressed in Equation (4) with β as a constant parameter. So the energy consumption for sensor i to transmit its image to the sink node can be expressed as the following:

$$\begin{aligned} E^{Path}(i) &= (NO_i + \sum_{j=1}^{M} x_{i,j} \cdot O_j) \cdot CostP_i \\ E_{total} &= \sum_{i=1}^{N} E^{Path}(i) \end{aligned} \tag{5}$$

E_{total} is the total energy consumption. We follow the convention to use the MSE parameter to measure the image quality distortion To form a performance metric for the overall image sensor transmissions, a possible approach is to use the Minkowski summation:

$$\overline{D^o} = \left\{ \frac{1}{N} \sum_{i=1}^{N} (\overline{D_i^o})^b \right\}^{\frac{1}{b}}, \quad \overline{D^{No}} = \left\{ \frac{1}{N} \sum_{n=1}^{N} (\overline{D_i^{No}})^b \right\}^{\frac{1}{b}} \tag{6}$$

where N is the number of correlated image sensors. $\overline{D_n^o}$ is the expected average Non-overlap region distortion,and $\overline{D^o}$ is the expected average overlap region distortion. Thus the optimal transmission problem can be expressed to find an optimal set$\{x_{i,j}\}$ such that

$$\{x_{i,j}^{opt}\} = \arg\min_{x_{i,j}} \{E_{total}\} \tag{7}$$

subject to (2). The image sensor captures image at frequency f (Per Frame/second). So each image sensor has a source rate

$$G_i = (NO_i + \sum_{j=1}^{M} x_{i,j} \cdot O_j) \cdot f \tag{8}$$

On the multi-hop route path for node i, due to buffer limitation, the constraint expressed in (9) also has to be satisfied.

$$\min(R_j(i)) \geq G_i \tag{9}$$

In order to utilize the route path diversity in sending NO/O regions to the sink, a special link and physical layer design would be very important to achieve energy efficiency, longer life time and required image quality. We use $R_{u,v}$ to denote the transmission rate between node u and v , and $P_{u,v}$ to denote the packet error probability between node u and v. $Delay_{u,v}$ denotes the minimum delay between nodes u and v, which is a sum of processing, transmission and propagation delays, and varying queuing delay. To achieve good reconstructed image quality, there is a function F that determines the average image region distortion $\overline{D_i^O}$(O region) and $\overline{D_i^{NO}}$ (NO region) at the sink node based on the link parameters including transmission rate, packet error probability, and minimum delay between nodes.

$$\begin{aligned} \overline{D_l^O} &= F(R_{u,v}, P_{u,v}, Delay_{u,v}), \quad \forall\, u,v \in Path(i) \\ \overline{D_l^{NO}} &= F(R_{u,v}, P_{u,v}, Delay_{u,v}), \quad \forall\, u,v \in Path(i) \end{aligned} \tag{10}$$

where $Path(i)$ is denoted as an individual multi-hop routing path for image sensor i, u, v are the end nodes of each hop on the $Path(i)$. The probability of packet error for L size packet transmission in $Path(i)$ can be expressed in (11).

$$\begin{aligned} P(L) &= 1 - \prod_{j=1}^{HopCount} (1 - P_{j,j+1}(l)) \\ &= 1 - \prod_{j=1}^{HopCount} [(1 - BER_{j,j+1})^L] \end{aligned} \tag{11}$$

where $P_{j,j+1}(l)$ is the packet error probability at the j^{th} hop link on routing path l , which can be calculated by BER value at each hop in (11) . Different BER requirements at the link layer affect packet error probability on the routing path, and hence the image distortion level. The link transmission rate $R_{u,v}$ in (10) can be adjusted by using AMC technique, and dynamic power control can offer lower BER on the wireless link. There is a relationship between the power, transmission rate, and BER in (12) with the QAM modulation scheme analyzed in [10].

$$Ps^{M-QAM} = \frac{1}{3} \cdot Rs \cdot b \cdot (b^2 - 1) \cdot \left[erfc^{-1} \left(\frac{1}{2} \cdot \left(1 - \frac{1}{b} \right)^{-1} \cdot BER \right) \right]^2 \cdot \frac{N_0}{A} \qquad (12)$$

In (12), Ps^{M-QAM} is the transmission power of the transmission node. When modulation scheme is determined, symbol rate Rs and constellation size b are also determined accordingly. Desirable BER is a system parameter, pre-defined by the system. Gaussian noise power intensity is a system constant value. Channel attenuation with antenna gain A can be calculated from lower layer. The detail descriptions in (12) can be referred to [10]-[11].

3 The Proposed Image Transmission Design

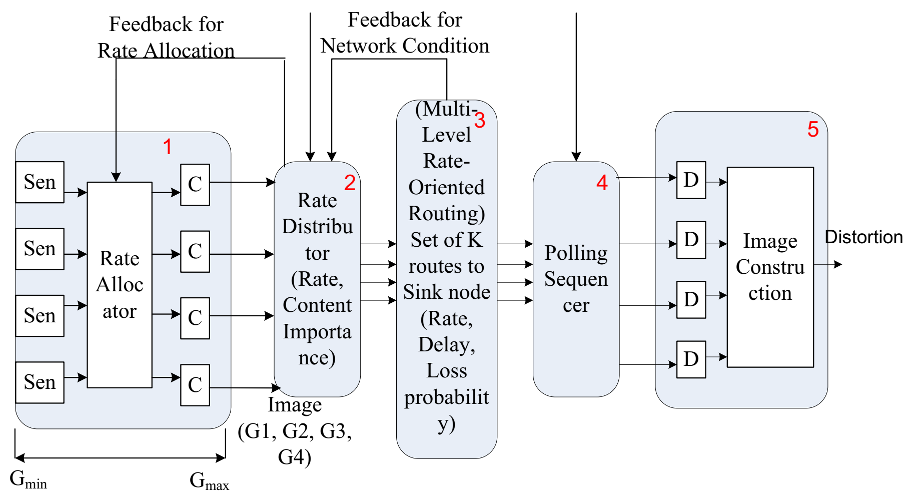

Fig. 1. Architecture design for image transmission utilizing both region and path diversities

With consideration of the diversities of both regions and multiple routing paths, we design an effective framework of image transmissions in multi-rate WSN as shown in Figure 1. In Figure 1, Component 1 allocates an appropriate source rate to each image sensor by allowing it to transmit different portion of O regions at different rates with BER requirements. In Component 2, "Rate Distributor" is to select appropriate routing paths for image transmissions with respect to source rates of sensors and image region importance. In Component 3, multiple routing paths are discovered by *Rate oriented Routing* (RR) component. We have proposed the details of RR scheme in [11]. Also, the transmission diversity on multiple paths is implemented in Component 3 by setting different network and link parameters such as transmission rate, BER, delay bounds and transmission power. However, packets received at the sink might be out of sequence due to multiple path transmissions, and multiple paths compete for the common medium at sink node due to their convergence there. Therefore, an effective polling sequencer in this bottleneck area is needed to relieve the collision and out of sequence problem. Polling Sequencer in Component 4 is specially designed for this purpose. After packets are received at the sink, they have to be decoded to reconstruct the whole image with the required image distortion, which is described in Component 5. In Figure 1, $(G_1, G_2, G_3, G_4)$is a rate vector that includes the individual source rates of image sensors, and the value of source rate of each image sensor is within the range of $(G_{\min},\, G_{\max})$.

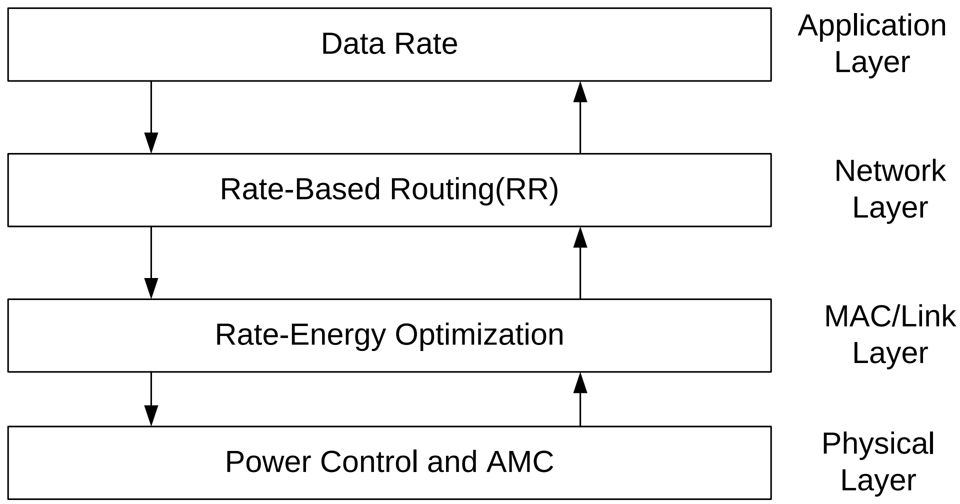

Fig. 2. Network layer Protocol architecture

As shown in Figure 2, the network architecture includes data rate assignment at the application layer, which is decided by the optimal distribution ratios. Once the source data rate has been determined, RR routing scheme can be utilized to find appropriate route path for each sensor. At the each hop, the energy is optimized based on the rate and channel condition. At physical layer, the power and AMC are adopted to achieve the energy efficiency. On each routing path, given data requirement at each link, at MAC-PHY layer, there is a transmission rate optimization to achieve minimal energy consumption at the link layer. MAC layer matches the data rate requirement with a lookup table, which maps data rates to modulation schemes. The modulation scheme together with the channel attenuation and the desirable BER are guided into the Transmission Power Controller (TPC). The TPC then sets the proper transmission power and control the radio module accordingly. Once these settings are complete, data transmission in physical layer will start with the corresponding modulation scheme, transmission rate and scaled transmission power.Based on our previous work in multi-rate WSN platforms [10], a PHY-MAC layer energy-efficient module is utilized with a handshaking mechanism. Therefore, it is very important to find an optimal distribution that allocates the appropriate data rate, so the total network energy efficiency can be achieved. In addition by setting different BER requirements at links of multiple routing paths, we can form multiple level error robust paths to implement the image transmission diversity. The different BER requirements at each wireless link can be achieved by using AMC and PC techniques.

3.1 RR Component

In this section, we propose an approximate method called RR routing scheme to form multiple node-disjoint routing paths. RR achieves longer network life time not only by associating lower transmission rate with the nodes having less residual power energy, but also exploit the multiple node-disjoint route path to accomplish load balancing. The basic idea is to separate the sensors between the source sensor group and the sink node into multiple levels according to their distance to the sink. Sensors at each level will be assigned with data rates according to their residual energy. The detail study of rate assignment is referred to our paper [11]. After a sensor determines its rate according to the residual energy level, it will choose the next hop node in the next level based on its rate. Sensors always choose the next hop node that has the same rate assignment. If some nodes at the same level have been assigned the same rate, a probability-based selection scheme will be applied. This routing selection scheme guarantees that each individual source node in the source group can find node-disjoint path while satisfying their rate constraints.

3.2 Rate-Based Polling Sequencer Component.

In RR, multiple paths still converge at the same sink node and compete for the common medium. An effective medium access in this bottleneck area is needed to replace the general inefficient sender-initiated medium contention mechanism. We design a rate-based polling sequencer, which allows sink node to dynamically schedule packet-receiving sequences from multiple paths. This polling sequencer avoids blind channel contentions and eliminates unnecessary channel access delays. It can also alleviate the out-of-sequence problem by sequentially assigning channel access priorities among multiple paths. The polling sequencer is designed based on the RTS/CTS mechanism. The sink grants its one-hop neighbors different medium access priorities according to *their transmission rate*. The neighbors of sink can be divided into two classes: rate-oriented path neighbor and non-relay neighbor. Multiple rate-oriented path neighbors always have higher priority than non-relay neighbors. Within rate-oriented path neighbors, the medium access priorities are dynamically assigned by the sink node based on the assigned transmission rate of its neighbor node. Whenever the sink receives an RTS, it assigns a new priority number to the RTS sender and adjusts the priority levels of other neighbors. The priority assignment is recorded in its lookup table. The priority number is assigned for channel access in the next data transmission period. In response to RTS, the sink sends out CTS packets that include priority update information. By checking every CTS received from the sink, the neighbors of the sink can know their priority assignment and control medium access accordingly in the next data transmission period.

3.3 Rate Distributor and Allocator

The rate distributor and allocator run inside each of the sensors, which are shown as Figure 3. In Figure 3, it describes the functionality of the rate distributor and rate allocator. The rate allocator and rate distributor are implemented inside each sensor. The optimal distribution ratio are informed by the base station, any overlap change detections are also monitored by the rate allocator. Each sensor will raise a flag to the overlap detection unit.When the overlapping detection unit find the number of flag has exceeded the pre-set threshold, it will automatically report to the rate allocator. The rate distributor will optimize the transmission

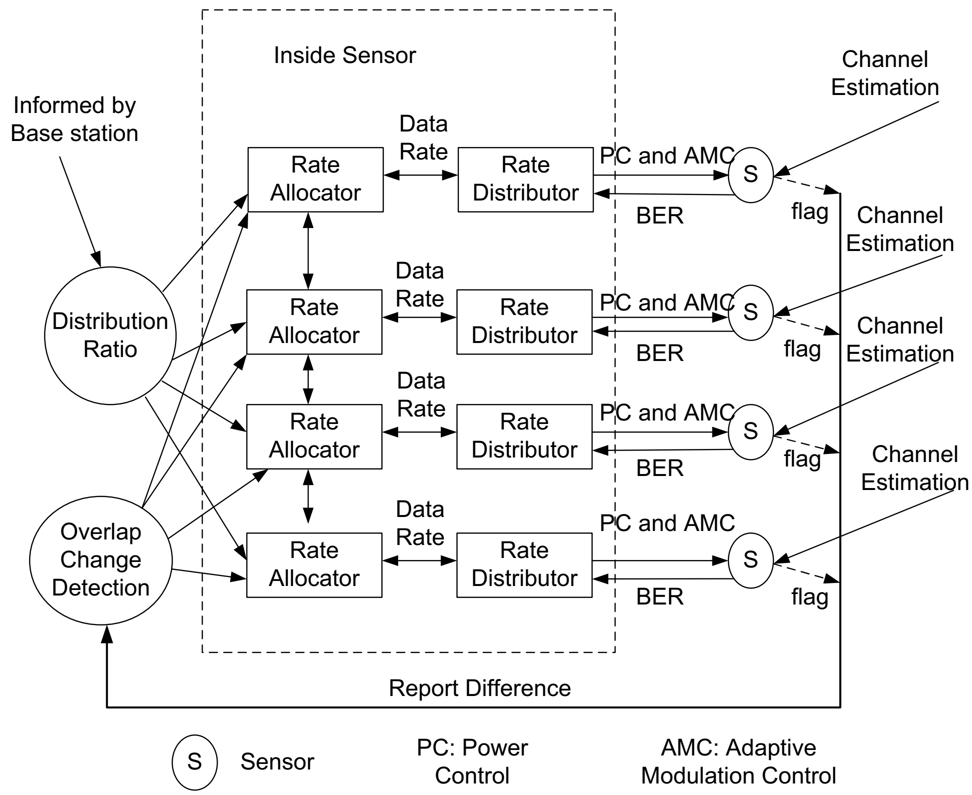

Fig. 3. Rate Distributor and Allocator

rate based on the data rate requirement from rate allocator and channel status indicated by BER. Once the optimal transmission rate are determined, the rate distributor will notify the physical layer to change corresponding modulation scheme and control power. These two components are implemented in distributed way with very small message exchange.

3.4 Overlap Image Pattern Detection and Route Update

The overlapping image region among correlated sensors can be identified by image shaping matching algorithm as described in [21]. The shape matching algorithm is operated on a very small number of the feature point, hence the computational complexity can be greatly reduced. This determination process has to be performed at the base station due to its complex image processing. However, this kind of identification may also be conducted offline when image sensor is deterministically pre-deployed with fixed image sensor angles and locations. In terms of random deployment, the identification procedure needs to be executed only at the start-up phase. Therefore, the system overhead of overlapping region pattern detection that is accomplished on the base station site with large amount resources is insignificant compared to the benefit of reduced transmission load in WSN. Even when some overlapping regions have been adjusted due to user requirements or environment changes after a period of time, a detection updating strategy can also be provided. In this updating strategy, any obvious change in the view of each image sensor beyond a threshold can be signaled as detection pattern change, which should be informed to the sink node for new overlapping image region identification. The procedure is described as follows: at the deployment phase,the base station has the basic knowledge of region distribution patterns for image sensors by learning; Base station collects the initial energy status for each sensor, and creates energy status profile. It applies the algorithm described in the previous section to calculate the routing and implement the optimal route path based on the topology information;The base station estimates the residual energy based on the image blocks it received, updates the residual energy profile for each sensor at base station. Since the route update only includes the optimized parameters and rate assignment, so the overheads are small in term of energy gains.

4 Simulation Results

Genetic Algorithm (GA) method [12]-[13] proves to be a powerful optimization technique, which is analogous to the natural genetic process in biology. To solve the optimization problem formalized in the previous sections, we design a specific GA, whose steps are described as follows.

$$F = \frac{E_{\max}^{total} - E_{\min}^{total}}{E_{c}^{total} - E_{\min}^{total}}$$

where E_c^{total} is the total energy consumption in the current generation calculated by Equation (9). Once the network topology and energy status of each node has been determined, multiple route paths could be determined by RR algorithm. Based on these determined route paths, the above designed genetic algorithm can be applied to solve this constrained optimization problem. In our algorithm, only a part of unknown x_{ij} will be coded into genes, and others will be accordingly bound by those constraint equations elaborated in section 2. This reduces the complexity of computation. Table 2 gives the overlap and Non-overlap region distribution pattern in the simulation.

Table 2. Overlap and Non-Overlap distribution pattern

$NO1$	$O1$	$NO2$	$O2$	$NO3$	$O3$
4197	2177	2798	1451	2798	2908

Our simulation is based on three correlated image sensors with both single-hop and multi-hop scenarios. In single hop scenario, three image sensors directly send image to the sink. In the multi-hop scenario, there are fifteen random relay sensor nodes deployed between image sensors and the sink node. The latter is a typical scenario in the image sensor network, i.e., there are a small number of sensors which sense the target view while others play a relay role in the WSN. Table 3 gives the optimization results for the single hop scenario. The column of GEN indicates how many generations the designed genetic algorithm takes to obtain the optimization results.

Table 4 shows optimization results for multi hop scenario. The column of GEN indicates how many generations the designed genetic algorithm spends.

Table 3. Optimization results on single hop scenario using the genetic algorithm

f	x_{11}	x_{21}	x_{12}	x_{22}	Gen
1	0.263	0.135	0.414	0.310	9
2	0.156	0.156	0.292	0.332	17
4	0.397	0.088	0.071	0.294	8
6	0.270	0.453	0.324	0.152	9
8	0.196	0.201	0.232	0.410	9
10	0.290	0.238	0.383	0.147	12

Table 4. Optimization results with RR and Multi-hop

f	x_{11}	x_{21}	x_{12}	x_{22}	Gen
1	0.011	0.300	0.020	0.393	10
2	0.003	0.356	0.030	0.343	18
4	0.003	0.360	0.026	0.062	17
6	0.007	0.310	0.041	0.271	11
8	0.016	0.317	0.087	0.221	10
10	0.001	0.325	0.011	0.319	30

From Table 4 and Table 3, we have found the optimal results had been changed with different values of f, i.e., the source image data rates at the source sensors. The optimal results of $x_{11}, x_{21}, x_{12}, \quad x_{22}$ are approached quickly by the genetic algorithm, and other parameters can then be determined by these optimal values according to the equation constrains elaborated in section 2.

We have conducted computer simulations in order to evaluate the performance of the proposed algorithm.The result is shown in Figure 4,5 and 6. In Figure 4, for a single hop scenario, we compare three approaches together:the preset 1/3 distribution ratio set scenario; optimal distribution ratio set scenario; single hop without collaboration scenario. The simulation shows that the proposed optimal approach spends less energy consumption than both non-collaborative approach and non-optimal set (preset 1/3). It achieves almost 3 times energy savings more than the Non-collaborative approach. We also found when the sampling frequency increases (i.e., the source rate increases), optimal set achieves more and more energy savings than the non-optimal set. The same performance is shown in Figure 5 by comparing Minimum Hop (MH) routing and Minimum Total Energy(MTE) routing based methods in the multi-hop scenario with the proposed optimal RR approach. In Figure 5, RR with optimal set spends less energy consumption than both MH and MTE with either preset 1/3 distribution ratio or the Non-collaborative approaches. This performance improvement becomes more obvious, up to 21% compared with MH and 30% compared with MTE in the simulation when the source rates of image sensors increase.

Figure 6 shows that the RR scheme with the optimal set based on genetic algorithm also extends the network lifetime significantly by a factor up to 4.7 than both MTE and MH at 1/3 preset distribution ratio. It is obvious that Non-collaborative approaches without the consideration of the correlation of images are not energy efficient in Figure 6. The network lifetime in Non-Collaborative approaches are reduced quickly, and the network energy resources have been wasted due to redundant transmissions. However, the proposed optimal scheme has

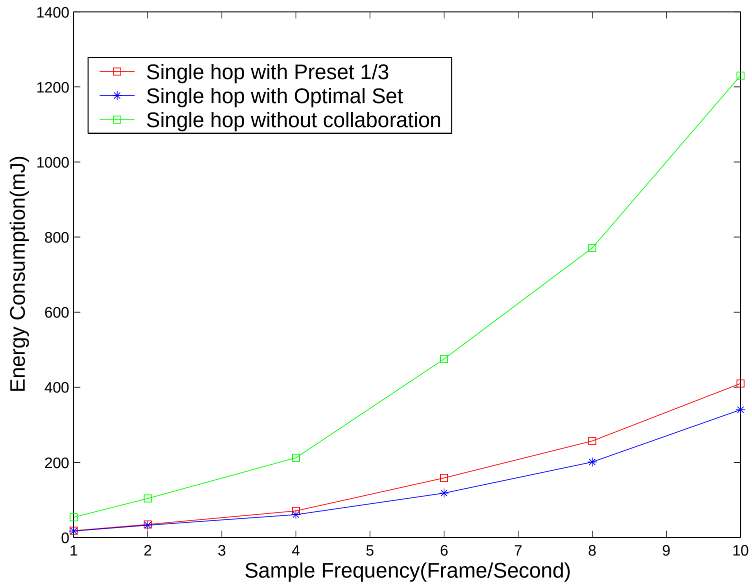

Fig. 4. Energy Consumption Vs Sampling Frequency

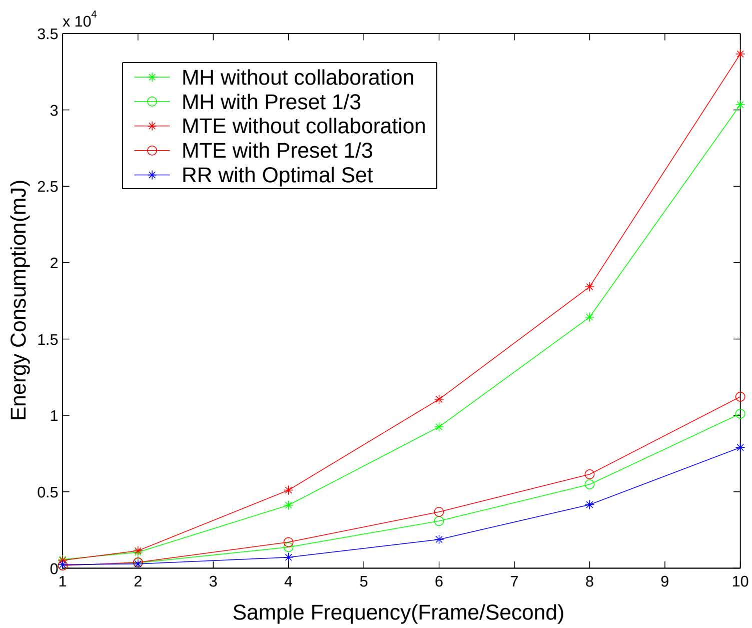

Fig. 5. Energy Consumption Vs Sampling Frequency

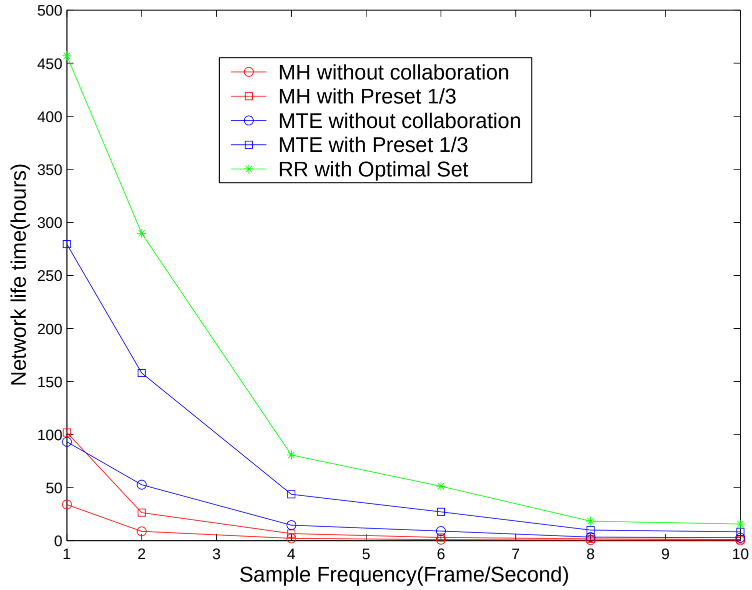

Fig. 6. Network Lifetime Vs Sampling Frequency

extended the network life time in large scale. There are two reasons for that: one is that the proposed RR with optimal set takes advantages of the correlations and importance of image regions; the other is that RR utilizes the higher residual energy nodes, and balances the node energy consumption in WSN.

5 Conclusion

In this paper, we investigated how each correlated image sensor within WSN can optimally transmit images to base station,and how images can be sent through our RR scheme. We found that the effective pattern of image transmissions is not only determined by the network resource of each image sensor itself, but also is related to the whole network routing protocol design. Based on the overlapping scenario, we formed a network optimization problem for energy efficient image transmission. The optimization problem was solved effectively by Genetic Algorithm approach. The simulation results have shown that our algorithm and procedures achieve considerable energy efficiency gains in wireless image sensor networks.

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