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Correlation-Aware QoS Routing for Wireless Video Sensor Networks

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***Abstract*—The spatial correlation among the images retrived from distributed video sensors leads to considerable data redundancy, thus resulting in significant performance degradation in energy efficiency and QoS satisfaction. In this paper, a correlation-aware QoS routing algorithm (CAQR) is proposed to efficiently deliver visual information under QoS constraints by exploiting the correlation among video sensors. Firstly, a correlation-aware differential coding scheme is designed to reduce the amount of traffic generated by correlated video sensors. Then, a correlation-aware load balancing scheme is proposed to prevent network congestion by spliting the correlated flows that cannot be reduced to different paths. Finally, these correlation-aware schemes are integrated into an optimization QoS routing framework with an objective to minimize energy consumption subject to QoS constraints. Simulation results show that the proposed algorithm achieves efficient delivery of visual information under QoS constraints in wireless video sensor networks.**

I. Introduction

Recent advancements in imaging hardware and wireless communications have fostered the use of video sensors in wireless sensor networks. With the ability of providing enriched observations of the environment, video sensors can enhance a lot of sensor network applications such as environmental monitoring, traffic enforcement, and remote health care. Most of these aplications require that visual information be delivered under predefined quality of service (QoS) constraints. This is a challenging task because sensors are constrained in battery and processing capabilities, while the delivery of visual information is a resource-intensive task.

Many recent works have been proposed for providing QoS support at different layers of the communication stack, including QoS routing algorithms [1][2], QoS MAC protocols [3], and cross-layer QoS solutions [4]. These works, however, only try to meet the QoS requirments by properly regulating the network traffic, while the total amount of data injected by the original sources can not be reduced. Thus, the existing QoS-oriented approaches are still resource-demanding for wireless video sensor networks, in which large amounts of images are generated and relayed by energy-constrained sensors.

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To encounter this problem, collaborative multimedia in-network processing [5] is suggested to reduce the traffic volume by allowing sensor nodes to filter out uninteresting events locally or coordinate with each other to aggregate correlated data. However, multimedia in-network processing is usually considered as a separate problem from the underlying QoS communication protocols. The joint compression/aggregation and routing approach [6] has been shown to enhance energy efficiency for sensor networks that deal with scalar data. As the processing of visual information is different from that of scalar data, and QoS support is required for the delivery of visual information, this approach cannot be directly applied to wireless video sensor networks.

In wireless video sensor networks, there exists correlation among the observations at video sensors with overlapped FoVs [7]. In this paper, we exploit such correlation and propose a correlation-aware QoS routing algorithm (CAQR) for video sensor networks. Firstly, a correlation-aware inter-node differential coding scheme is developed to reduce the amount of traffic injected into the network. Then, a correlation-aware load balancing scheme is proposed to prevent network congestion by spliting the correlated flows that cannot be reduced to different paths. By integrating the correlation-aware operations, an optimization QoS routing framework is proposed with an objective to minimize energy consumption under delay and reliability constraints.

The remainder of this paper is organized as follows. In Section II, we study the spatial correlation characteristics of visual information. In Section III, we introduce the correlation-aware QoS routing algorithm. Performance evaluation is given in Section IV, followed by the conclusions in Section V.

II. Spatial Correlation for Visual Information

In this section, we study the correlation characteristics of visual information, and discuss about how to use correlation in the design of multimedia in-network processing.

A. Correlation of Visual Information in Sensor Networks

A video sensor can only observe the objects within its field of view (FoV). As shown in Fig. 1(a), the FoV is determined by four parameters: the location (P), the sensing radius (R), the sensing direction ($\vec{V}$), and the offset angle (α). The sensing process of a video sensor is characterized by 3-D to 2-D projection, for which the key parameter is the focal length (f). Both the FoV parameters and the focal length could be estimated through calibration methods for distributed camera networks [8].

To simplify the problem, we consider the case when all the video sensors in a network are homogeneous, i.e., they have the same focal lengths (f), sensing radiuses (R), and offset angles (α). For two arbitrary video sensors V_A and V_B with FoVs F_A and F_B, suppose at a same time, their observed images are X_A and X_B, respectively. The images X_A and X_B are correlated if F_A and F_B are overlapped with each other. To quantify the correlation between two video sensors, we introduce two metrics as follows.

1) Overlapped Ratio of FoVs: The overlapped ratio of FoVs for sensors V_A and V_B, denoted by r_{AB}, is defined as

$$r_{AB} = \frac{S(F_{AB})}{S(F_A)} \tag{1}$$

where $S(F_{AB})$ ($F_{AB} = F_A \bigcap F_B$) is the overlapped area of F_A and F_B (as shown in Fig. 1(b)), and $S(F_A)$ is the area of F_A. If r_{AB} is large, large portions of the two observed images are correlated, which also indicates that the two sensors are likely to observe the same event concurrently.

2) Differential Coding Efficiency: We consider the two correlated images (X_A and X_B) from V_A and V_B in the above example. If each node compresses its image independently, we denote the resulting coding rates by $R(X_A)$ and $R(X_B)$, respectively. Since X_A and X_B are correlated, we can compress X_A using X_B as its prediction. Suppose the rate of X_A becomes $R(X_A|X_B)$ after this differential coding step. We define a *differential coding efficiency* as the percentage of rate saved through differential coding, which is given by

$$\eta = 1 - \frac{R(X_A|X_B)}{R(X_A)}. \tag{2}$$

As entropy is the lower bound for coding rate, an estimation of the differential coding efficiency can be obtained from the entropies of the image sources. Similarly, an *estimated differential coding efficiency* can be defined as

$$\eta_H = 1 - \frac{H(X_A|X_B)}{H(X_A)} = \frac{I(X_A;X_B)}{H(X_A)} \tag{3}$$

where $I(A;B)$ is the mutual information between X_A and X_B. If we assume that $H(X_A) = H(X_B)$, it can be found from our previous work [7][9] that η_H is proportional to the overlapped FoV ratio (r_{AB}) and the correlation coefficient (ρ_{AB}) [7][9]. The differential coding efficiency η_H will be high when both r_{AB} and ρ_{AB} are large.

B. Video in-network processing

Due to the huge size of raw visual information, images and video sequences are compressed prior to transmission. There exist several standards for image and video coding, such as JPEG/JPEG 2000 and H.26x/MPEG. These coding techniques can be classified into intra coding that removes the redundancy within an image, and inter coding (or differential coding) that reduces the redundancy between images. If a single snapshot image is to be reported to the sink, it is intra coded. As for a sequence of video frames, the coded stream usually consists of periodical intra coded reference (I) frames and inter coded frames between the intra frames. Inter coding has much higher coding efficiency than intra coding, resulting in smaller sizes of inter frames. For example, from the traces in [10], we find that the average size of intra frames is more than 5 times larger than that of inter frames.

In a network of correlated video sensors, nodes can cooperate with each other and remove the redundancy among their observations. Specifically, we can perform differential coding on the intra (I) frames between correlated sensors. Since video sensors that are out of the communication ranges of each other can still observe a common scene [11], (i.e., they are correlated as shown in Fig. 1(b)), the differential coding of correlated sensors could be integrated in network layer operations.

Based on the discussions above, flows generated by video sensors could also be classified into two categories:

1) *Intra flows*: flows of intra coded video frames. The amount of traffic for an intra flow might be further reduced by differential coding with correlated sensors.
2) *Inter flows*: flows of inter coded video frames, for which the amount of traffic can hardly be further reduced.

III. Correlation-Aware QoS Routing

In this section, we introduce a correlation-aware QoS routing algorithm (CAQR) for wireless video sensor networks.

A. Correlation Groups Construction

As video sensors are correlated when they have overlapped FoVs, we introduce a preprocessing step to cluster sensors with large overlapped FoV ratios into groups. Let each sensor report its focal length and FoV parameters to the sink. After receiving these parameters, the sink calculates the ratio of overlapped FoVs (1) between any two sensors. Using this ratio as a metric for clustering, we can apply various clustering algorithms[12], such as K-Means and hierarchical clustering, to cluster the sensors into correlation groups. The sink then assigns a group ID (G_{id}) for each group and broadcasts the results. Each video sensor will be notified its group ID and the sensing parameters of other sensors in the same group. Video sensors that are clustered into the same correlation group are likely to report the same event concurrently, moreover, they are likely to have high differential coding gains. In the following discussion, we will perform correlation-aware operations among the sensors that belong to the same correlation groups.

B. Routing with correlation-aware differential coding

Since the amount of traffic for intra flows could be further reduced through differential coding between correlated sensors, we introduce a correlation-aware inter-node differential coding scheme for the routing of intra flows. As shown in the example in Fig. 2, if video sensor V_A needs to find a route for

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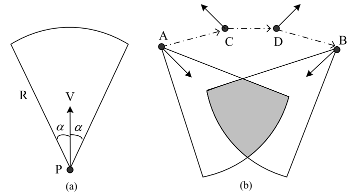

Fig. 1. (a) FoV (b) Overlapped FoVs.

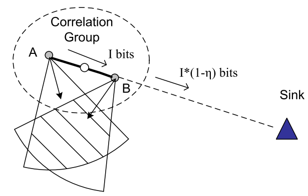

Fig. 2. Correlation-aware differential coding.

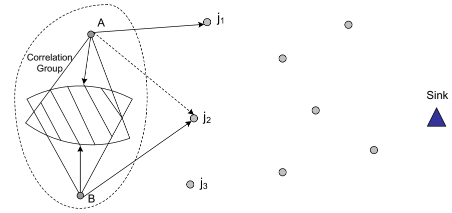

Fig. 3. Correlation-aware load balancing.

its intra frame X_A to the sink, it could find another candidate sensor in the same group that is closer to the sink to perform differential coding. Suppose video sensor V_B is in the same group as V_A and it is closer to the sink than V_A ($d_B < d_A$). From our correlation model, the differential coding efficiency (η) between V_A and V_B can be obtained as shown in (3). If the size of the compressed intra frame at V_A is I_A, the saved bits from differential coding can be estimated as $I_A \cdot \eta$. We introduce an energy gain to evaluate the potential energy efficiency of differential coding as follows:

$$G_E = \frac{\hat{N}_B \cdot I_A \cdot \eta \cdot E_0}{E_{proc}\{I_A\}}. \tag{4}$$

The numerator in (4) stands for the benefit brought by differential coding. It is the total communication energy for transmitting the saved bits from node V_B to the sink. Thus, it is given as a function of the number of saved bits ($I_A \cdot \eta$), the estimated number of hops from node V_B to the sink ($\hat{N}_B$), as well as the energy consumption for transmitting and receiving a single bit per hop (E_0). And E_0 is given by

$$E_0 = 2 \cdot E_{elec} + \epsilon_{amp} \cdot d_{hop}^{\alpha} \tag{5}$$

where E_{elec} is the energy consumption of transceiver circuitry per bit, ϵ_{amp} is a constant for communication energy, α is the path loss exponent, and d_{hop} is the average one-hop distance.

The denominator in (4) is the processing energy needed for performing differential coding, including the decoding of X_A and the differential coding of X_A based on the prediction of the frame X_B at node V_B. The energy for processing is related to video frame size and video processing hardware.

For the routing of intra flows, each video sensor will evaluate the energy gain of differential coding with its downstream nodes in the same correlation group. And the node with the maximum gain will be selected to perform differential coding. For example, if video sensor V_A has chosen V_B as the node for differential coding, it sends a request message to V_B, and V_B will send back a reply message. In this way, V_B becomes an intermediate destination for the intra frames from V_A: the intra frames from V_A will be routed to V_B first; V_B will further compress the frame and then forward it to the sink, for which the detailed routing process will be explained in Section III-D.

C. Routing with load balancing for correlated video sensors

The differential coding scheme can reduce the amount of traffic in the network if sensors have high differential coding gains. If flows from the same correlation group cannot be further compressed, the presence of traffic congestion becomes evident in that sensors from the same correlation group tend to report the same event and generate traffic concurrently. To solve this problem, we introduce a correlation-aware load balancing operation. The basic idea is to split these flows to different paths/nodes, so that the probability of network congestion could be reduced. As shown in Fig. 3, two sensors in a correlation group, V_A and V_B share large overlapped FoVs, however, the differential coding gain is low according to our correlation model. As they are likely to generate large amounts of traffic concurrently, we can try to split the video flows from the two sensors to different paths. This operation is incorporated in the proposed algorithm as described below.

D. Correlation-aware QoS routing algorithm

We now introduce an integrated QoS routing algorithm for the delivery of visual information. Suppose a node i needs to forward a video flow to the destination N, where N could be either the sink or an intermediate node for differential coding. The next hop node is selected from its neighbors that are closer to the sink ($\mathcal{F}_i$) according to the the following rules.

$$\begin{aligned}
Given: &\quad i, N, \mathcal{F}_i, V_{id}, G_{id} \\
Find: &\quad j^*, R_{ij}^C \\
Minimize: &\quad C_j \cdot E_0 \cdot \tfrac{L}{R_{ij}^C} && (6)\\
Subject\ to: &\quad \tfrac{L}{R \cdot R_{ij}^C} + \overline{t_{ij}^q} \le T_{ij} && (7)\\
&\quad \tfrac{\gamma}{1-\gamma}(\Delta t_{ij}^q)^2 \le (T_{ij} - \tfrac{L}{R \cdot R_{ij}^C} - \overline{t_{ij}^q})^2 && (8)\\
&\quad pr_{ij} \ge PR_{ij} && (9)
\end{aligned}$$

In this problem, the locally optimal next hop j^* is the node that results in the minimum weighted energy consumption under local delay and reliability requirements.

1) Local delay requirements: We use a geographic based mechanism in the routing algorithm. Suppose a video flow v at node i needs to be delivered to the destination N within time T_{iN}. The local delay constraint, T_{ij}, is given as

$$T_{ij} = (\frac{d_{iN} - d_{jN}}{d_{iN}}) \cdot T_{iN} \tag{10}$$

where d_{iN} is the distance from node i to the destination, and d_{jN} is the distance from node j to the destination.

For supporting bandwidth-demanding and real-time image and video communications, we consider a contention-free MAC in our context. The delay of a hop consists of transmission delay and queueing delay, which is given in the left part of (7). The average queueing delay from node i to node j, $\overline{t^q_{ij}}$, can be estimated from the traffic load at node j. And the transmission delay is calculated from the packet length L, the transmission rate R, and the channel coding rate R^C_{ij}.

To probabilistically guarantee the delay, we add a constraint of delay variance. It is derived from the following condition:

$$P(t^{tran}_{ij} + \overline{t^q_{ij}} \leq T_{ij}) \geq \gamma \tag{11}$$

where γ is the required probability that the packet is delivered within deadline. Based on this condition, and using the Chebyshev's inequality, we can derive the delay variance constraint in (8), where Δt^q_{ij} is the estimated delay variance of this hop.

2) Local reliability requirements: We define packet delivery ratio (PR) as the percentage of packets successfully delivered to the destination. If we require that each hop on a route should provide the same level of reliability, the required packet delivery ratio from node i to node j, PR_{ij}, is estimated as

$$PR_{ij} = PR^{1/\hat{N}_{ij}} \tag{12}$$

where PR is the required packet delivery ratio, and $\hat{N}_{ij}$ is the estimated number of hops from i to the destination if j is selected as its next hop. PR is determined by the required probability of a video frame being successfully decoded (P_D), which is given by video applications.

We incorporate a *dynamic channel coding* scheme in the QoS routing algorithm to adapt to varying channel conditions. Apart from selecting the next hop for transmission, the routing algorithm also selects a proper channel coding rate. The channel coding rate for link i to j, R^C_{ij}, is chosen from a set of predefined coding rates $\{R_0, \ldots, R_N\}$ based on the detected link SINR and the required packet delivery ratio.

3) Energy minimization with correlation-aware load balancing: The minimization term in (6) is a weighted energy consumption function. The energy consumption for transmitting and receiving a packet of L bits data and header with channel coding rate R^C_{ij} is given by $E_0 \cdot L/R^C_{ij}$, where E_0 is calculated by (5). While the weight term, c_j, is a cost function designed for correlation-aware load balancing. The goal of correlation-aware load balancing is to split flows from the same correlation group that cannot be further compressed to different paths. To achieve this, the routing decision for a flow takes its source node into account, in addition, each node stores a list of source node IDs and the corresponding group IDs of the flows that it has forwarded in the recent period.

Suppose node i needs to find a route for a flow that is generated by node V_{id}, which belongs to the correlation group G_{id}. And it's candidate next hop, node j, has a list of source nodes of the flows that it has routed recently, including a list of these source nodes' IDs ($\mathcal{L}\{V_{id}\}$) as well as their group IDs ($\mathcal{L}\{G_{id}\}$). Node j periodically exchanges this list with its neighbors, and so node i is aware of it. For the current flow to be forwarded, node i checks if j has routed flows from other nodes in the same correlation group, if this is the case, the cost c_j is set to a relatively large value, if not, c_j is set to 1. In this way, for flows from the same correlation groups that cannot be further compressed, we can penalize the case that they share the same forwarding node (e.g., node j_2 in Fig. 3), thereby reducing the possibility of congestion.

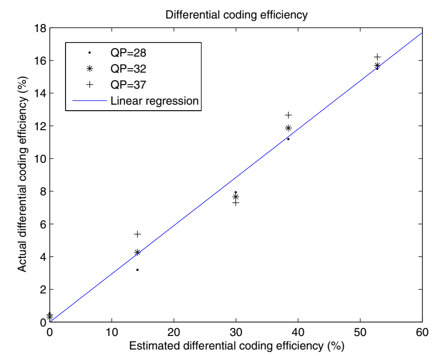

Fig. 4. Estimation of differential coding efficiency.

TABLE I
PARAMETERS

Offset angle	60	Deadline	1 s
Sensing radius	30	P_D	0.8
Intra period	2	DT	0.75
Transmission rate	500kbps	E_{proc}	0.5 mJ
Image size	176×144	Cost (c_j)	5

IV. Performance Evaluation

In this section, we first evaluate the validity of the estimated differential coding efficiency in (3), and then study the networking performance of the proposed routing algorithm.

We deploy two cameras in a field, record their FoV parameters, and let them capture images of the scene. The estimated coding efficiency in (3) is calculated from the FoV parameters of the cameras, while the actual coding efficiency in (2) is obtained by performing differential coding between the two images using the H.264 coding algorithms. We vary the positions and sensing directions of the two cameras and obtained five groups of images with different correlation levels. For each group of images, we perform differential coding under three quantization steps. As shown in the results in Fig. 4, the actual coding efficiency (η) is approximately proportional to the estimated coding efficiency (η_H), therefore, an estimation of η can be given as

$$\eta = k \cdot \eta_H \tag{13}$$

where k is a ratio that reflects the performance of specific video encoders. From the points in Fig. 4, we find that $k = 0.3$ using linear regression. This linear relationship between the predictions and the coding results validates the applicability of the entropy-based coding efficiency prediction method.

The performance of the proposed correlation-aware QoS routing algorithm is evaluated using a distributed network simulator in Java. In a field of 100m ×100m, 49 video sensors are deployed in a grid structure, and a sink node is placed in a corner of the field. The sensing directions of these sensors

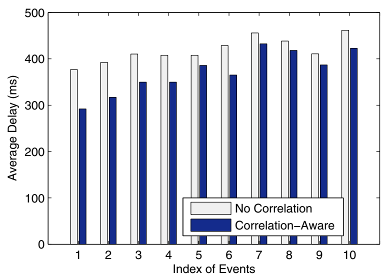

Fig. 5. Average delay.

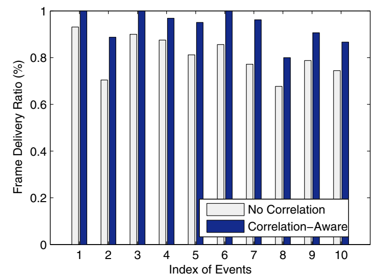

Fig. 6. Frame delivery ratio.

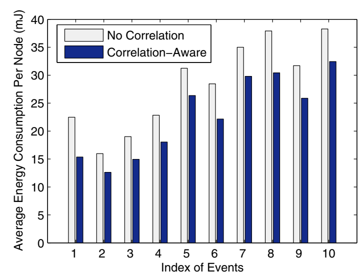

Fig. 7. Average energy consumption per node.

are uniformly chosen so as to ensure full coverage of the field. From the sensing parameters in Table I, the correlation metrics for these sensors are obtained as shown in Section II. The size of a video frame is set based on the video traces in [10]. For correlation-aware coding, we use the actual coding efficiency obtained from (13) to predict the size reduction of a frame.

The traffic of these video sensors are generated based on the features of video surveillance and monitoring applications. Specifically, we place a target in the field and let it move around according to the Random Waypoint Mobility model. A video sensor is triggered to capture an image when it detects the target in its FoV. By launching the target from 10 different locations, different network traffic scenarios can be generated. Under each scenario, we test the performance of the proposed algorithm. Crucial simulation parameters are listed in Table I.

The proposed correlation-aware QoS algorithm is compared with the corresponding QoS routing algorithm without correlation-aware operations. Three performance metrics are considered: average delay, percentage of successfully decoded image frames at the sink, and average energy consumption per node. Fig. 5 shows the average delay performance for different events. The deadline is set to 1 second, and we only consider the delays of the packets that are received within the deadline. The correlation-aware operations can effectively reduce the amount of traffic in the network. Therefore, it is seen in Fig. 5 that correlation-aware routing results in less average delay.

As for the quality of received visual information, we count the number of received packets within the deadline for each reported frame. If the percentage of received packets of a frame is above a frame decodable threshold (DT), we deem that this frame is successfully received and decoded at the sink. The percentage of successfully decoded video frames for both algorithms are shown in Fig. 6. For the 10 traffic scenarios, the proposed algorithm improves the frame decodable ratio by 12% on average. In particular, we have measured that events with indices from 6 to 10 generate relatively larger amounts of video frames, and the gains of the proposed algorithm for these scenarios are significant. This result indicates that, when the traffic load is heavy, it is crucial to exploit correlation to reduce the redundancy in the network. Fig. 7 shows the average energy consumption for each sensor node. It is evident that the proposed algorithm consumes less energy because it reduces the number of transmitted bits from the original sources in the network.

V. Conclusion

We have proposed a correlation-aware QoS routing algorithm for wireless video sensor networks. Based on the correlation characteristics of visual information, we introduce a correlation-aware differential coding scheme and a correlation-aware load balancing mechanism. These correlation-aware operations are then integrated in a distributed QoS routing component. Evaluation results show that, by integrating correlation-aware operations in the routing process, the proposed algorithm achieves efficient delivery of visual information in wireless video sensor networks.

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