# OPTIMAL IMAGE TRANSMISSION OVER VISUAL SENSOR NETWORKS

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## ABSTRACT

In this paper, we propose a methodology for optimal image transmission over a VSNs (Visual Sensor Networks) via cross-layer optimization. Toward this goal, we control the compression ratio of a captured image and network parameters such as source rate, flow rate and routing path. In particular, since this scheme is based on distributed optimization, we can avoid energy concentration in a specific node such as CH (Cluster Head) which increases the network lifetime. In the simulation, we demonstrate the network adaptation procedure over a randomly deployed VSNs and evaluate the quality of the transmitted image using the SSIM (Structural Similarity) index.

## 1. INTRODUCTION

Recently, the availability of inexpensive CMOS cameras has led to the development of VSNs for industrial applications such as environmental monitoring and ad-hoc surveillance [1] [2]. In order to maximize the image quality with a limited budget of bit-rate over VSNs, it is necessary to develop network control and image compression techniques that operate as functions of the residual energy in the manner of distributed computation.

For energy efficient transmission in VSN, most of papers [8] [9] [10] [11] [12] concentrated on temporal and spatial correlation by means of the background subtraction and non-overlapping transmission among FoVs (Field of Views). On the other hand, a few of them [8] [12] considered only transmit energy for the optimization of the peer-to-peer network without use of processing and receive energies.

In this paper, we propose a methodology for optimal transmission of captured images over the network from the perspective of network optimization by controlling the major system parameters including the compression ratio (quantization ratio), the source rate, the flow rate and the routing path.

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## 2. PROBLEM DESCRIPTION

For simplicity, only intra-frame (I-frame) coding of H.264/AVC is assumed. We use the CMU cam as the camera sensor node and the CC2420 as the radio module in [2]. In addition, the parameters related to power consumption and latency are arranged in Table 1. To describe each network node, let $V$ be the set of nodes (or vertices) and $E$ be the set of directed links (or edges) in a directed graph that describes the network deployment.

For each time slot, we determine an optimal active duration through scheduling for the synchronous MAC protocol. During the active time period, each camera sensor node captures the scene, compresses the image, receives the traffic from neighboring nodes and transmits the aggregated images through the routing path.

The main objective is to maximize the image quality transmitted over VSNs by controlling the quantization rate through the network optimization based on the residual energy. When the average SSIM index [3] [4] is employed as the image quality metric, the objective function is represented as

$$(\vartheta_i^\tau)^* \quad = \quad \arg\max \sum_{i \in V} \overline{\mathrm{SSIM}}(D_{s,i}^\tau, \vartheta_i^\tau) \qquad (1)$$

where $D_{s,i}^\tau$ is the image captured at node $i$ at time $\tau$ and $\vartheta_i^\tau$ is the compression ratio. The optimal solution could be obtained by taking the differential of the objective function. However, it is difficult to get a closed-form equation [4].

Here, we utilize the log utility function known for proportional fairness [5] by

$$\sum_{i \in V} \log(\ g_i^\tau\ ) \qquad \text{where} \quad g_i^\tau = \vartheta_i D_{s,i}, \qquad (2)$$

where $g_i^\tau$ is the maximum available source rate of node $i$ at time $\tau$ which controls the compression ratio ($\vartheta_i$) of the image $D_{s,i}$. Using (2), it is possible to maintain the fairness of the image quality over the network while satisfying the following conditions.

Flow Conservation with Image Compression : The outgoing rate is the result of the image compression.

$$\sum_{j \in I(i)} f_{(j,i)}^\tau + g_i^\tau = \sum_{j \in O(i)} f_{(i,j)}^\tau\ , \ \ i,j \in V,\ (i,j) \in E$$

where $O(i)$ and $I(i)$ are sets of neighboring nodes of node $i$ for outgoing $f^{\tau}_{(i,j)}$ and incoming $f^{\tau}_{(j,i)}$ traffics. Thus, each link between node $i$ and one of the nodes in $O(i)$ or $I(i)$ should be covered under coverage $R_{tx}$ with a maximum transmit power.

Rate Bound : the incoming and outgoing rates of node $i$ are bounded by the achievable energy $E_{r,i}$. If we consider the transmit, receive and capturing energies, we can set the boundary for the incoming and outgoing rates of node $i$,

$$P_{cap}\cdot t_{cap} + \frac{P_{rx}}{R}\sum_{j\in I(i)} f^{\tau}_{(j,i)} + \frac{P_{tx}}{R}\sum_{j\in O(i)} f^{\tau}_{(i,j)} \le \frac{E_{r,i}}{T} - c$$
$$\longrightarrow \sum_{j\in O(i)} f^{\tau}_{(i,j)} + \gamma\sum_{j\in I(i)} f^{\tau}_{(j,i)} \le \rho^{\tau}_i \qquad (3)$$

where $T$ is the expected life time represented by the number of time slots, $c = P_{sp}t_{sp} + P_{wake}t_{wake}$, $\gamma = \left(\frac{P_{rx}}{P_{tx}}\right)$ and $\rho^{\tau}_i = \frac{R(\frac{E_{r,i}}{T} - c - P_{cap}\cdot t_{cap})}{P_{tx}}$.

In addition, the power and latency used in Eq.(3) are arranged in Table 1.

**Table 1**. Parameter Definition

| Parameter | Meaning | value |
|---|---|---|
| $P_{tx}$ | transmit power | 35 mW |
| $P_{rx}$ | receive power | 38 mW |
| $P_{cap}$ | capturing power | 1165 mW |
| $t_{cap}$ | capturing latency | 132 mS |
| $P_{sp}$ | sleep power | 30 $\mu$ W |
| $t_{sp}$ | sleep latency | $\approx$ 1 time slot |
| $P_{wake}$ | wake-up power | 33 mW |
| $t_{wake}$ | wake-up latency | 0.2 mS |
| $R$ | data rate | 240 Kbps |

## 3. OPTIMIZATION SOLUTION

The problem of maximizing the utility of each camera sensor node can be formulated

$$\max_{F,G}\sum_{i\in V}\log(\ g^{\tau}_i\ ) \qquad (4)$$

$$\text{subject to} \sum_{j\in I(i)} f^{\tau}_{(j,i)} + g^{\tau}_i = \sum_{j\in O(i)} f^{\tau}_{(i,j)}\ ,$$
$$\sum_{j\in O(i)} f^{\tau}_{(i,j)} + \gamma\sum_{j\in I(i)} f^{\tau}_{(j,i)} \le \rho^{\tau}_i,$$
$$g^{\tau}_i,\ f^{\tau}_{(i,j)},\ f^{\tau}_{(j,i)} \ge 0,\ \ i,j\in V,$$
$$f^{\tau}_{(i,j)}\in F,\ \ g^{\tau}_i\in G.$$

where $F$ and $G$ are vector expressions of the link flow and source rates at time $\tau$. The dual problem expressed in (4) is, unfortunately, not strictly concave relative to $F$. To overcome this difficulty, an approximation in [7] is used, whereby a regularization term is added: $\epsilon\sum_{(i,j)\in V}(f^{\tau}_{(i,j)})^2$.

Defining Lagrange multiplier vectors $\overline{\lambda}$, $\overline{\mu}$ = $[\lambda_i]$ and $[\mu_i]$, the Lagrangian function in (4) can be written

$$L(F,G,\overline{\lambda},\overline{\mu}) = \sum_{i\in V}\log(\ g^{\tau}_i\ ) - \epsilon\sum_{(i,j)\in E}(f^{\tau}_{(i,j)})^2$$
$$-\sum_{i\in V}\lambda_i\left[\sum_{j\in I(i)} f^{\tau}_{(j,i)} - \sum_{j\in O(i)} f^{\tau}_{(i,j)} + g^{\tau}_i\right]$$
$$-\sum_{i\in V}\mu_i\left[\sum_{j\in O(i)} f^{\tau}_{(i,j)} + \gamma\sum_{j\in I(i)} f^{\tau}_{(j,i)} - \rho^{\tau}_i\right].$$

.

Then the dual problem becomes

$$\begin{array}{ll} \min & D(\overline{\lambda},\overline{\mu}) \\ \text{subject to} & \overline{\mu}\succeq 0 \end{array}$$

where $\succeq$ denotes the component-wise inequality and the objective function can be expressed

$$D(\overline{\lambda},\overline{\mu}) = \max_{F,G} L(F,G,\overline{\lambda},\overline{\mu}).$$

Using the subgradient method, we construct the following four steps towards finding the solution of the Lagrange dual problem:

- Step 1: Initialization - Start with any point $\lambda_i(1)$, $\mu_i(1)$ as real-positive values, where $\lambda_i(1)$ and $\mu_i(1)$ are the initial values of $\lambda_i(k)$ and $\mu_i(k)$ in the iteration. Choose an infinite sequence of positive step-size values $\{\alpha_k\}^{\infty}_{k=1}$ and $\{\beta_k\}^{\infty}_{k=1}$ for $\lambda_i$ and $\mu_i$. Set $k = 1$.
- Step 2: Supergradient - Find optimal solutions ($F$, $G$) such that

$$F,G = \arg\max_{F,G}\left\{\sum_{i\in V}\log(\ g^{\tau}_i\ ) - \epsilon\sum_{(i,j)\in E}(f^{\tau}_{(i,j)})^2 - \sum_{i\in V}\lambda_i(1)\nu_i(F,G) - \sum_{i\in V}\mu_i(1)\omega_i(F)\right\},$$

where $\nu_i(F,G) = \sum_{j\in I(i)} f^{\tau}_{(j,i)} - \sum_{j\in O(i)} f^{\tau}_{(i,j)} + g^{\tau}_i$,

$$\omega_i(F) = \sum_{j\in O(i)} f^{\tau}_{(i,j)} + \gamma\sum_{j\in I(i)} f^{\tau}_{(j,i)} - \rho^{\tau}_i.$$

Since $G$ and $F$ are also optimal solutions of transport and network layers, update them via

$$g^{\tau *}_i(k) = \left[\frac{1}{\lambda_i(k)}\right]^+,$$

$$f^{\tau *}_{(i,j)}(k) = \left[\frac{\lambda_j(k) - \lambda_i(k) + \mu_i(k) + \gamma\cdot\mu_j(k)}{-2\epsilon}\right]^+.$$

Set $\nu_i := \nu_i(F,G)$ and $\omega_i := \omega_i(F)$.

- Step 3: Step-size - Compute the step-sizes $\alpha_k$ and $\beta_k$ from the step-size series.

- Step 4: Update the iteration - Set

$$\lambda_i(k+1) \leftarrow \left[ \lambda_i(k) + \alpha_k \frac{\nu_i}{\|\nu_i\|} \right],$$

$$\mu_i(k+1) \leftarrow \left[ \mu_i(k) + \beta_k \frac{\omega_i}{\|\omega_i\|} \right]^+, \quad k \leftarrow k+1.$$

  If $\|\nu_i\| \leq \delta^{th}$ and $\|\omega_i\| \leq \delta^{th}$, where $\delta^{th}$ is a small stopping threshold, stop the searching procedure and obtain the optimal solutions $F$ and $G$. Otherwise, go to Step 2.

In addition, we omit the proof that $\nu_i(F, G)$ and $\omega_i(F)$ are the supergradients for the dual Lagrangian problem in Step 2, because it is a well known result.

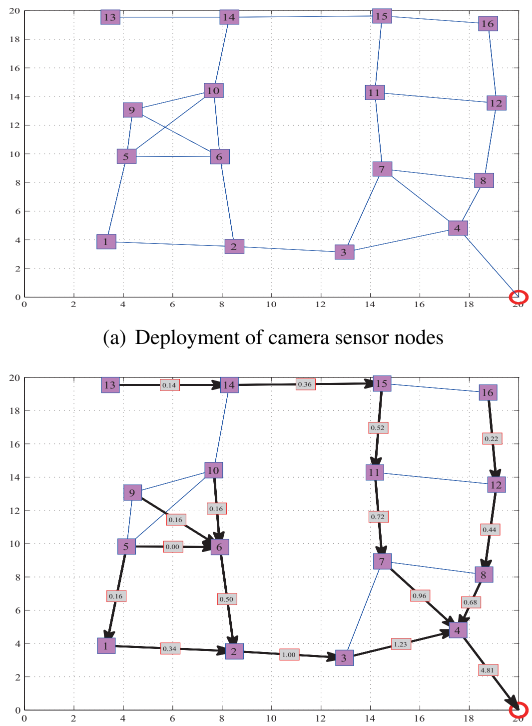
## 4. SIMULATION RESULTS

For the simulation, we utilize 16 camera sensor nodes deployed over a parking area of 20m $\times$ 20m for surveillance as shown in Fig. 1(a). In addition, each link between two nodes is configured by using the maximum power as the transmit power of each node in Fig. 1(a). When the time duration of each slot is set to 60 sec and the available energy at time $\tau$ is $\frac{E^{\tau}_{r,i}}{T} = 300$ mJ, $\rho^{\tau}_i$ is equal to $7.68 \cdot R$. The image size captured at each node is $255 \times 176$ and about 100 K bits.

Fig. 1(b) shows the routing path and the flow rates optimized by the proposed solution. The generated traffic at each node flows to the sink node via the CH of node 4 so that the flow rate between the CH and the sink node becomes a bottleneck of determining the rate of each node. The flow rate of each node is determined after sharing the bottle-neck rate of $\rho^{\tau}_i = 7.68 \cdot R$ between node 4 and the sink. Usually, the flow rate is usually much lower than the bottle-neck rate. In particular, since node 4 is the most important node as the CH for the transmission of all traffic in the VSNs, the overall performance relies on the transmit flow of node 4. From Fig. 2(b), the source rate of node 4 is largest compared to other nodes based on the principle of the proportional fairness.

Figs. 2(a) and 2(b) show the convergence of the flow and source rates using the subgradient algorithm and less than 100 iterations. Actually, an approximate solution can be obtained in 50 iterations. By distributing the energy consumption into the overall nodes, an efficient energy distribution can be achieved.

Finally, when each node transmits their captured image based on the source rate written in Fig. 2(b), the received images at the sink are represented by SSIM scores in Fig. 3.



(a) Deployment of camera sensor nodes

(b) Optimal routing and flow rates

**Fig. 1**. Deployment of a VSNs on a parking lot and the optimal routing paths

## 5. CONCLUSION

We proposed a methodology for optimal image transmission over VSNs via cross-layer optimization. In particular, the optimal compression ratio should be determined using the optimal source rate and the flow rate over the available energy. To determine the network parameters, we employ a distributed optimization scheme to distribute the network energy to each node efficiently, which makes a contribution to the improvement of the network lifetime. For the simulation, the SSIM index and intra-frame H.264/AVC coding are utilized. In addition, the CMU cam nodes equipped with CC2420 radio module were employed. From the simulation results, it can be seen that the CH node which delivers the network traffic to the sink node becomes the bottleneck of the overall system performance. In addition, the CH has the largest source rate according to the principle of proportional fairness.

## 6. REFERENCES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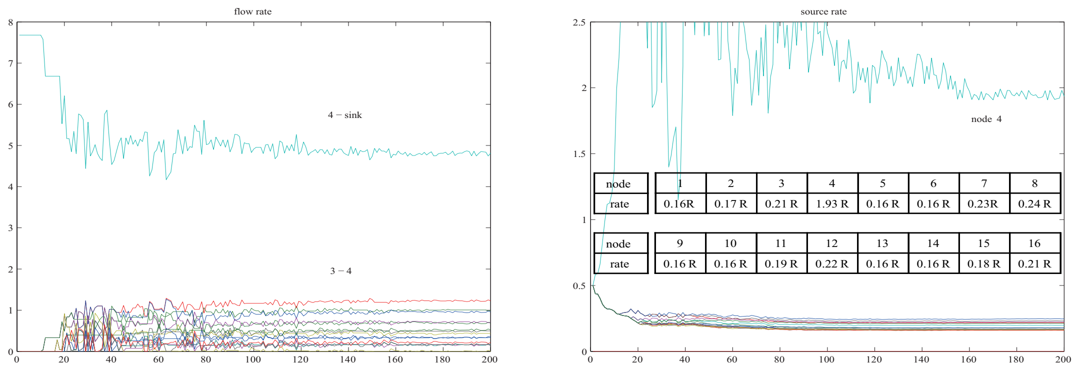
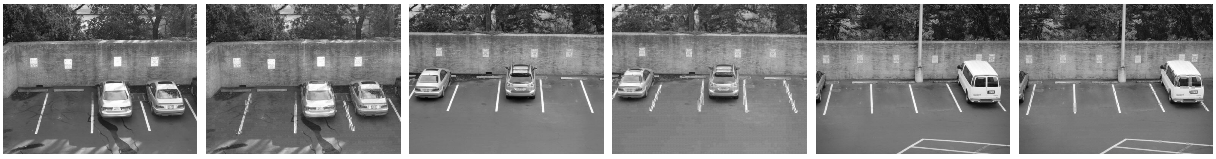



(a) The convergence of the flow rate at each link

(b) The convergence of the source rate at each node

**Fig. 2**. Parameters determined using the distributed optimization



(a) Original image at node 2

(b) Transmitted image (SSIM = 0.6788)

(c) Original image at node 3

(d) Transmitted image (SSIM = 0.6660)

(e) Original image at node 4

(f) Transmitted image (SSIM = 0.8274)

**Fig. 3**. Original and compressed images at nodes 2, 3, 4

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