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Soure and Transmission Control for Wireless Visual Sensor Networks with Compressive Sensing and Energy Harvesting

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Abstract

The lifetime of the emerging Wireless visual sensor network (WVSN) is seriously dependent on the energy shored in the battery of its sensor nodes as well as the compression and resource allocation scheme. In this paper, the energy harvesting technology was adopted to provide almost perpetual operation of the WVSN and compressed-sensing-based encoding was used to decrease the power consumption of acquiring visual information at the front-end sensors. A Dynamic Source and Transmission Control Algorithm (DSTCA) was proposed to jointly determine source rate, source energy consumption, and the allocation of transmission energy and available bandwidth under energy harvesting and queue stability constraints. A virtual energy queue was introduced to control the resource allocation and the measurement rate in each time slot. The algorithm can guarantee the stability of the visual data queues in all sensors and achieve near-optimal performance. The distributed implementation of the proposed algorithm was discussed and the achievable performance theorem was also given.

Keywords*: wireless visual sensor network, energy harvesting, compressive sensing, power*

1. Introduction

With the availability of inexpensive visual sensors such as CMOS cameras as well as the needs of continuous monitoring of events over wide areas, wireless visual sensor networks (WVSNs) are emerging [1-3]. Visual sensors in a WVSN are typically comprised of camera module, microprocessor unit and radio module, and can cover larger fields of view, extract visual information about the scene and transmit it through wireless links to the sink of the WVSN for further processing [4-5]. An exemplary WVSN is shown in Figure 1. WVSNs are is able to enhance the traditional sensor networks with content-enriched information and thus have found applications in many fields such as surveillance and ambient Intelligence.

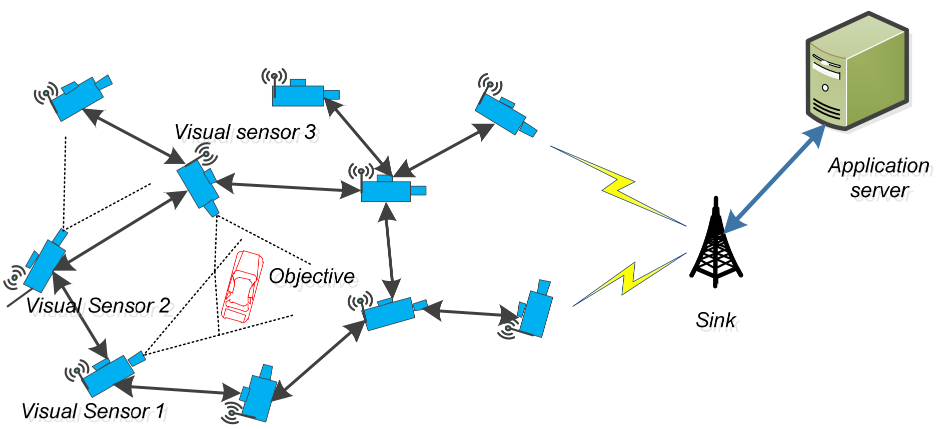

Figure 1. An example of wireless visual sensor networks

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Visual information (which is usually presented in the form of a sequence of images or a video) acquisition and transmission is challenging due to error-prone wireless link, limited resource and low computational capacity. Compression of visual information based on traditional video encoders (such as H.264 [6]) is not suitable for WVSNs due to high coding complexity. On the other hand, compressive sensing (CS) paradigm [7-8] is adopted to reduce the cost of encoding video frames/blocks, which is identified as sparse in a certain transform domain. Distributed CS-based [9-11] video encoder can compress each frame independently while jointly recover a group of frames at the sink by exploits their correlation.

The lifetime of a WVSN is limited by the initial energy stored at the battery-powered sensors. With ambient energy harvesting technologies [12-14], WVSNs can survive perpetually. The challenging in the operation of energy harvesting network is that the amount of energy harvested during each time slot is variable, which makes it difficult to maintain an optimal and stable transmission policy.

In this paper, we aim to investigate the optimal dynamic control of a WVSN with energy harvesting and using compressive-sensing-based visual information acquisition scheme. The problem of minimizing the sum time-average distortion of visual information for all sensors under the constraints of the stability of all the data queues and resource allocaton on wireless links is formulated. We design a virtual energy queue scheme to indicate the state of the energy harvested and used by the sensors. A Dynamic Source and Transmission Control Algorithm (DSTCA) that determines source rates and resource allocation based on the virtual queues is proposed. We also dicuss and analyze the implementation of the DSTCA in pratical deployment of a WVSN and the time-average performance that can be achieved by the proposed algorithm.

2. System Model

We consider a single-hop WVSN, in which the visual sensor nodes are observing some event, compressing the visual information independently and transmitting to a sink node in the uplinks.

2.1. Distortion and Power Consumption Model for the Visual Sensor

The visual information is sensed and encoded into video using compressive sensing paradigm, which can exploit both the spatial redundancy within each frames and temporal redundancy between adjacent fames. The pattern of the group of pictures (GoP) is IPP…PIPP…, as shown in Figure 2, where I frames are coded individually using compressed sensing, while P frames are coded by taking CS operation on the deference vector with respect to the latest I frame.

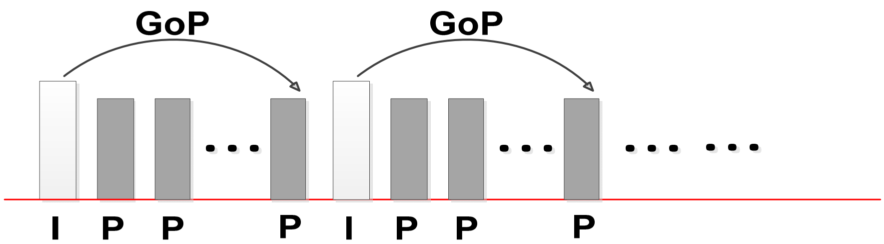

Figure 2. Group of pictures in the sensed visual information

Assume that an I frame of the video is presented by $\mathbf{x} \in R^N$. $\mathbf{x}$ can be measured through a $M \times N$ ($M < N$) linear operator Ψ, i.e., $\mathbf{y} = \Psi \mathbf{x}$, $\mathbf{y} \in R^N$. A sparse representation v of X in some transformed domain using a $N \times N$ transform matrix Ω is $x = \Omega \boldsymbol{v}$, and thus the measurement vector $\mathbf{y} = \Psi \Omega \mathbf{v}$. We can recover $\mathbf{v}$ using a convex optimization problem as follow [8].

$$\begin{aligned} &\text{Maximize } \|\mathbf{v}\|_1 \\ &\text{Subject to } \|\mathbf{y}\text{-}\Psi\Omega\mathbf{v}\|_2 < \varepsilon \end{aligned} \tag{1}$$

P frame is coded by first taking the deference as $\mathbf{dx} = \mathbf{x}_I - \mathbf{x}_P$, where $\mathbf{x}_I$ is the latest I frame and then coding $\mathbf{dx}$ with CS. Due to temporal correlation, $\mathbf{dx}$ is much sparse than $\mathbf{x}_p$ and can be measured with less measurements. $\mathbf{dx}$ can also be recovered by (1). Using the above CS-based paradigm and following the similar results from [15], the source distortion D_m of the received video from visual sensor m due to compression can be model as

$$D_m = D_m^0 + \theta_m / (r_m - R_m^0), \quad D_m^0 > 0, \quad R_{\max} > r_m > R_m^0 \tag{2}$$

where r_m is the CS measurement rate of sensor m. D_m^0 , θ_m and R_m^0 are determined by the video characteristics. In addition, we also consider the power consumption in the compression and sensing in each sensor, which is modeled as linear function of measurement rate at r_m as

$$P_m^s(r_m) = \beta_m r_m \tag{3}$$

where β_n is the constant coefficient for sensor m.

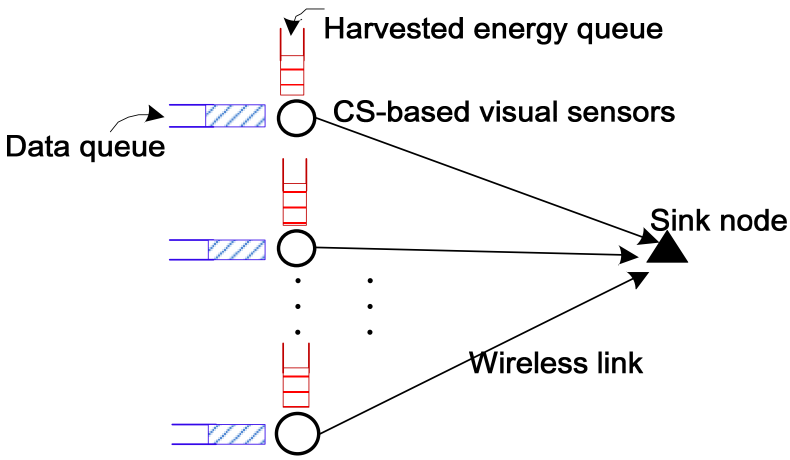

Figure 3. System Model

2.2. Transmission Model

The system model of the considered WVSN is showed in Figure 3. There exist N visual sensor nodes and one sink nodes in the networks. Thus there are N wireless uplinks. Define rate vector as $\mathbf{R} = [r_1, \ldots, r_N]^T$ We consider a time-slotted system and the interval of a slot is equal to the duration of a GoP, which is assumed to be T. At every time slot $t = 1, 2, \cdots$, each node spends power $p_n(t) < P_{\max}$ to its uplink for data transmission. The total bandwidth is W , and the bandwidth allocated to sensor n in slot t is $w_n(t)$, and thus

$$\sum_{n=1}^{N} w_n(t) = W \tag{4}$$

Denote the channel state at time t as $S(t) = \{s_n(t)\}$. The transmission rate $f_n(t)$ of sensor n depends on the allocated bandwidth and power as well as the channel state, i.e., $f_n(t) = C_n(w_n(t), p_n(t), s_n(t))$.

Define $Q_n(t)$ as the backlog of the visual data queue at sensor n for time slot t, and each $Q_n(t)$ evolves as follow,

$$Q_n(t+1) = \max(Q_n(t) - T \times f_n(t), 0) + T \times r_n(t) \tag{5}$$

2.3. Energy Harvesting Model

Every sensor in the WVSN is assumed to be powered by energy harvesting and equipped with a rechargeable battery of a maximum storage $E_{\max}$. The available energy at sensor n in time slot t is $E_n(t) \le E_{\max}$. The total energy consumption due to transmission and compression for the sensor node n must satisfy the following constraint

$$p_n(t) + P_n^s(r_n(t)) \le \frac{E(t)}{T} \tag{6}$$

We denote $B_n(t)$ as the amount of energy harvested by sensor n in time slot t. The energy harvested in the slot t can be used in the next slot, and thus the energy queue at the sensor n evolves as follow,

$$E_n(t+1) = \min(E_n(t) - T(p_n(t) + P_n^s(r_n(t))) + B_n(t), E_{\max}) \tag{7}$$

2.4. Problem Formulation

The system objective is to minimize the sum average distortion of visual information for all sensors while guarantee the stability of all the visual data queues, and thus the optimization problem is

$$\begin{aligned} &\text{Minimize } \sum_{n=1}^{N} \bar{D}_n \\ &\text{Subject to } \ (4), (6) \\ &\qquad \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{i=1}^{N} \mathrm{E}[Q_n(t)] < \infty \qquad (8) \end{aligned} \tag{9}$$

where $\bar{D}_n = \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathrm{E}[D_n(t)]$, and the constraints in (8) are the conditions under which the data queues are stable. The solution of (9) are index policies, $\{\pi(t) : t = 1, 2, \cdots\}$, and $\pi(t) = (\boldsymbol{R}(t), \boldsymbol{P}(t), \boldsymbol{W}(t))$.

3. Proposed Control Policy

3.1. Introduction of the Energy Virtual Queues

To deal with finite capacity of the battery and avoid battery discharge as far as possible, in spirit of [16-17], we introduce virtual queues $Y(t) = E_{\max} - E(t)$, which evolve as

$$Y_n(t+1) = Y_n(t) - B_n(t) + T(p_n(t) + P_n^s(r_n(t))), \quad \forall 0 \le n \le N \tag{10}$$

3.2. Dynamic Source and Transmission Control Algorithm (DSTCA)

The algorithm consists of three components: source control (measurement rate and compression power control), transmission control (power and bandwidth allocation) and queue update. Solution in each slot only depends on the instantaneous values of the system state. The procedure of the proposed Dynamic Source and Transmission Control Algorithm (DSTCA) is described as follow,

Step 1. (**Source control**) Choose the measurement rate for time slot t, $\mathbf{R}(t) = [r_1, \ldots, r_N]^T$, to be the optimal solution of the following problem:

$$\underset{r_1,\ \ldots,\ r_N}{\text{Minimize}} \sum_{n=1}^{N} [KD(r_n) + Q_n(t)r_n + Y_n(t)P_n^s(r_n)]$$
$$\text{Subject to } R_{\max} > r_n > R_m^0,\ \forall n \tag{11}$$

where K is a system parameter to control the tradeoff between optimality and average length of the visual data queues (i.e., transmission delay).

Step 2. (**Transmission control**) Choose the transmission power and bandwidth for all sensors at the time slot t to be the optimal solution of the following problem: $f_n(t)$

$$\underset{P,W}{\text{Maximize}} \sum_{n=1}^{N} [Q_n(t)C_n(w_n, p_n, s_n(t)) - Y_n(t)p_n]$$
$$\text{Subject to } p_n(t) < P_{\max} \text{ and } (9) \tag{12}$$

Step 3. (**Queue update**) Visual data queues and virtual energy queues are updated according to (5) and (10), respectively.

Remark 1: Problem (11) can be decomposed into N measurement rate control problem, each of which can be implemented and solved in the corresponding visual sensor. We can get the solution for each source as $r_n = \min(R_n^0 + \sqrt{\theta_n / (Q_n(t) + Y_n(t))}, R_{\max})$ and compression power can be obtained according to (3).

Remark 2: Solution to (12) depends on the used transmission policy which determines the capacity function $C_n(w_n, p_n, s_n(t))$. In our system model assumption, $C_n(w_n, p_n, s_n(t))$ is a convex function of variables w_n and p_n. Thus, (12) is a convex optimization problem with linear constraints and can be solved efficiently in the sink with the information of the queues from all the sensors.

4. Implementation and Performance Analysis

4.1. Implementation of the DSTCA

DSTCA is a cross-layer control algorithm and can be implemented in the distribued manner. As shown in Figure 4, the source control corresponds to the application layer problem and can be decomposed into N subproblems that can be solved in each source visual sensor independently as follow

$$\underset{r_n}{\text{Minimize}}\ KD(r_n) + Q_n(t)r_n + Y_n(t)P_n^s(r_n)$$
$$\text{Subject to } R_{\max} > r_n > R_m^0 \tag{13}$$

Each source sensor n have individual requirements by the application layer, i.e., $R_{\max} > r_n > R_m^0$.

Transmission control corresponds to the MAC layer problem, which should be implemented in the Sink node (or BS) of the WVSN. In this case, each sensor node should send its (virtual) queue informaton to the Sink node, which is responsible for detecting the channel state, $s_n(t)$, of each link, solving problem (12) centrally and and then send back the resulting resource allocation policy in the time slot t.

It can reduce the computational power consumption of sensor nodes to allow the complex resource allocation problem solved in the powerful Sink node, and it can significantly reduce the power of transmitting signalings to distribute the easy source rate control problem in the individual sensor.

4.2. The Achievable Performance of the DSTCA

We have the following theorem with regard to the performance of the proposed algorithm.

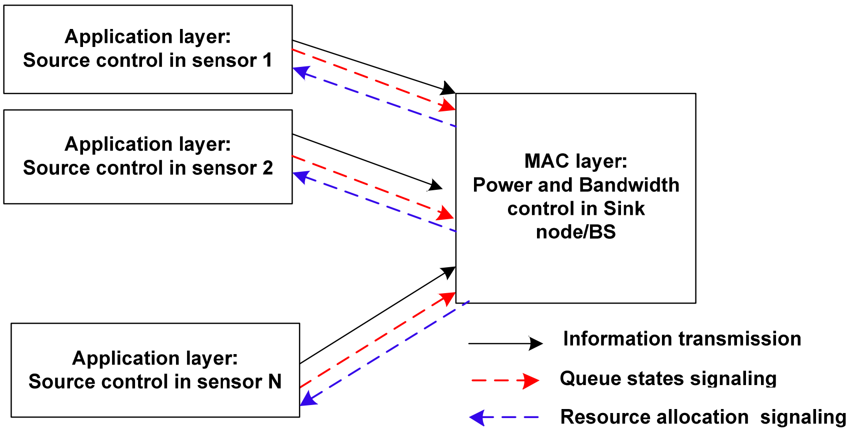

Figure 4. Implementation of the DSTCA in WVSN

Theorem 1: Applying the proposed **DSTCA** to a compressiv-seing-based WVSN with energy-harvesting sensors, for sufficient large $E_{\max}$, we have:

1) the visual data queue in each sensor are stable, i.e.,

$$\limsup_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathrm{E}[\mathrm{Q}_n(t)]<\infty ,$$

2) the maximum legth of the queues is a linear function of K (i.e., $\mathrm{Q}_n(t)\propto K$);

3) the total time average distortion achieved by the algorithm satisfies

$$\sum_{n=1}^{N}\bar{D}_n\le\sum_{n=1}^{N}\bar{D}_n^*+A/K ,$$

where $\bar{D}_n^*$ is the optimal total time average distortion of the problem (9) , and A is a constant value related to the system constants (N , $R_{\max}$, $E_{\max}$, $P_{\max}$, and α_n).

Remark 3: In a pratical energy harvesting devices, sufficient large $E_{\max}$ is the common case. As stated in Theorem 1, when we increase the value of K, the performance achieved will be closer to the optimality, while the visual data queue (and thus the transmission delay) would becomes larger. **Theorem 1** can be proved by using the Lyapunov drift method in [17].

5. Conclusion

Compressive-sensing-based encoding scheme and energy harvesting technology ware adopted in the wireless visual sensor networks. *A Dynamic Source and Transmission Control Algorithm (DSTCA) was* proposed to jointly assign source measurement rate, energy in both compressive-sensing-based video acquisition and data transmission, as well as bandwidth for each uplink. *DSTCA* is a cross-layer optimization algorithm. To achieve the near-optimal performance under energy harvesting and stability constraints, a virtual energy queue was introduced to indicate the state to both application layer and MAC layer. *DSTCA can be implemented in a distributed manner*The time-average performance that can be achieved by the proposed algorithm was also obtained.

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