Sensor Scheduling and Energy Allocation For Lifetime Maximization in User-Centric Visual Sensor Networks

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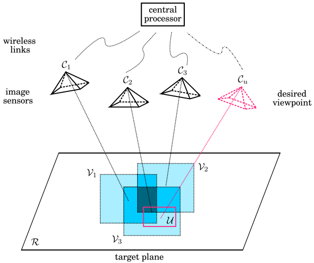
December 4, 2008

Outline

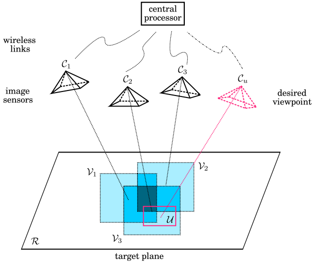
User-Centric VSN

- $\mathcal{R}$ monitored by cameras $\{\mathcal{C}\}_{i=1}^{N}$.
- $\mathcal{C}_i$ covers a sub-region $\mathcal{V}_i$
- cameras only communicate with CP.
- CP receives sequence of user request for $\mathcal{U}$,
  - select camera to provide data,
  - synthesize $\tilde{\mathcal{U}}$
- Lifetime: the duration a certain percentage (e.g. 90%) of $\mathcal{R}$ is covered by at least one camera



Camera Scheduling and Energy Allocation

Questions to ask



Camera Scheduling and Energy Allocation

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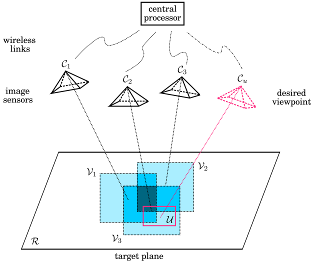
- A formulation of the network lifetime



Camera Scheduling and Energy Allocation

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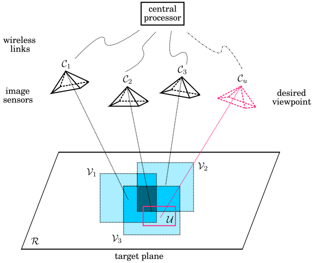
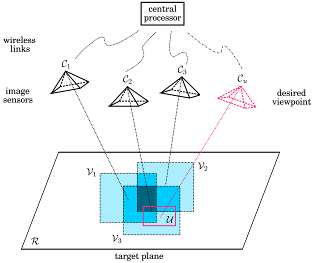
- A formulation of the network lifetime
- Given a desired view,
  - multiple cameras contain the data
  - how to select a camera to provide the data



Camera Scheduling and Energy Allocation

Questions to ask

- A formulation of the network lifetime
- Given a desired view,
    - multiple cameras contain the data
    - how to select a camera to provide the data
- Given total available energy w_t
    - how to allocation w_t among cameras



Outline

Notations

- divide $\mathcal{R}$ into M_r blocks: $\{\mathcal{R}_j, j \in [M_r]\}$
- coverage matrix: $\mathbf{B}^r \in \mathbb{R}^{N \times M_r}$, where

$$\mathbf{B}^r_{i,j} \stackrel{\text{def}}{=} \mathbf{I}(\mathcal{R}_j \subseteq \mathcal{V}_i),$$

  if region $\mathcal{R}_j$ covered by camera $\mathcal{C}_i$, $\mathbf{B}^r_{i,j} = 1$, otherwise 0.

- $\mathcal{U}$: M_u blocks $\{\mathcal{U}_j, j \in [M_u]\}$
- $\mathbf{B}^u \in \mathbb{R}^{N \times M_u}$, where

$$\mathbf{B}^u_{i,j} \stackrel{\text{def}}{=} \mathbf{I}(\mathcal{U}_j \subseteq \mathcal{V}_i) \qquad (1)$$

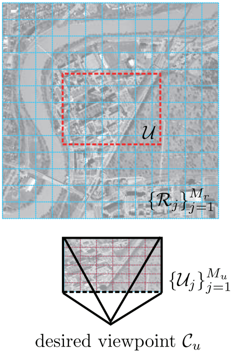


Figure: The discretization of the target plane $\mathcal{R}$ and desired view $\mathcal{U}$.

Notations

- p_j: probability that $\mathcal{R}_j$ is requested by the user, $\sum_{j=1}^{M_r}(p_j) = 1$.

$$\mathbf{p} = [p_1 \ p_2 \ \ldots \ p_{M_r}]^T$$

- w_j^t: energy of camera $\mathcal{C}_j$ at time t.

$$\mathbf{w}^t = [w_1^t \ w_2^t \ \ldots \ w_{M_r}^t]^T$$

- $L(\mathbf{p}, \mathbf{w}^t, \mathbf{B}^r)$: the network lifetime
- $\mathrm{E}[L(\mathbf{p}, \mathbf{w}^t, \mathbf{B}^r)]$: the expected network lifetime

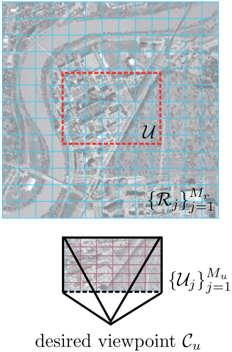
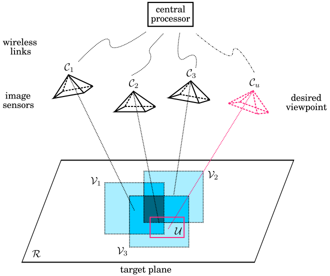


FIGURE: The discretization of the target plane $\mathcal{R}$ and desired view $\mathcal{U}$.

Camera Scheduling Strategy

- At time t, if $\mathcal{C}_s$ is selected, $\mathbf{w}^t$ updated as $\mathbf{w}_s^{t+1}$.
- optimal camera selection strategy: maximize $\mathrm{E}[L(\mathbf{p}, \mathbf{w}_s^{t+1}, \mathbf{B}^r)]$.



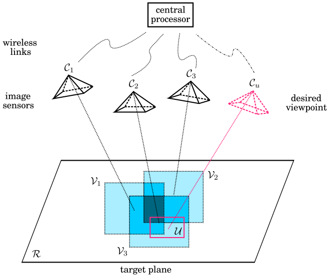
Camera Scheduling Strategy

- coverage energy:the sum of the energies of all the cameras that cover $\mathcal{R}_j$.

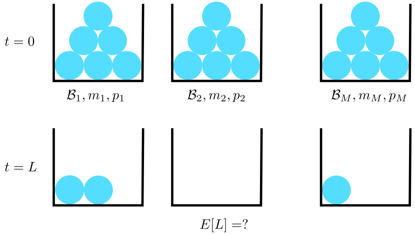
$$\mathbf{m}_s^{t+1} = \mathbf{B}^r \mathbf{w}_s^{t+1},$$

  the j^{th} entry $m_{j,s}^{t+1}$ represents the coverage energy of $\mathcal{R}_j$
- approximate: $L(\mathbf{m}_s^{t+1}, \mathbf{p})$
- the optimal camera scheduling strategy at time t:

$$s^t = \underset{i \in \lambda^u(j)}{\operatorname{argmax}} \mathrm{E}[L(\mathbf{m}_i^{t+1}, \mathbf{p})]$$



Abstraction



- box $\mathcal{B}_i$ contains m_i balls, $i \in [M]$
- at each request, a ball is taken from $\mathcal{B}_i$ with probability p_i.
- After L requests, one of these boxes first become empty

characterization of

$$\mathsf{E}[L(\mathbf{m}, \mathbf{p})]$$

Exact Solution for $M = 2$

Proposition 1

For $M = 2$, the p.m.f of L can be written as:

$$\begin{aligned} \Pr(L = l) &= \mathbf{I}(m_1 \leq l \leq (m_1 + m_2 - 1))\alpha(l - m_1; m_1, p) \\ &\quad + \mathbf{I}(m_2 \leq l \leq (m_1 + m_2 - 1))\alpha(l - m_2; m_2, 1 - p) \end{aligned}$$

where $\alpha(k; \tau, b)$ represents the p.m.f of a negative binomial distribution [M.Hilbe, 2007] ,

$$\alpha(k; \tau, b) = \binom{k + \tau - 1}{k} b^{\tau} (1 - b)^{k}$$

Exact Solution for $M = 2$

Proposition 1 (cont'd)

the expectation of L can be obtained as

$$E[L] = \beta(l - m_1, m_1, p) + \beta(l - m_2, m_2, 1 - p)$$

where

$$\beta(k; j, b) = \frac{jF_\alpha(k; j, b) - (k+1)\alpha(k+1; j, b)}{b} \tag{1}$$

and $F_\alpha(k; j, b) \stackrel{\text{def}}{=} \sum_{i=0}^{k} \alpha(k; j, b)$

Recursive Calculate of L for $M > 2$

consider a sequence of M experiments

- in the k^{th} experiment $k (2 \leq k \leq M)$ only the first k boxes $\{\mathcal{B}_i\}_{i=1}^{k}$ are utilized
- a ball requested from the i^{th} box with normalized probability $p_i' = \frac{p_i}{\sum_{i=1}^{k} p_i}$.
- let L_k denote the number of requests after which one of the boxes $\{\mathcal{B}_i\}_{i=1}^{k}$ first becomes empty, then immediately we see $L = L_M$
- recursively calculate the p.m.f of $L_k (2 \leq k \leq M)$ from the p.m.f of L_{k-1}.

Exact Solution for General Case $M > 2$

Proposition 2:

$$\begin{aligned}\Pr(L_k = l) \quad &= \quad \mathbf{1}(m_1 \leq l \leq \pi(k)) \sum_{j=0}^{m_k-1} \binom{l-1}{j} (p'_k)^j (1-p'_k)^{l-j} \Pr(L_{k-1} = l-j) \\ &+\mathbf{1}(m_k \leq l \leq \pi(k)) \binom{l-1}{l-m_k} (p'_k)^{m_k} (1-p'_k)^{l-m_k} \Pr(L_{k-1} > (l-m_k))\end{aligned}$$

where

$$\pi(k) \stackrel{\text{def}}{=} (\sum_{j=1}^{k} m_j - k + 1).$$

- p.m.f of $L_2, L_3, \ldots, L_{M-1}$ are calculated in sequence to obtain L_M
- direct evaluation: $E[L_k] = \sum_{l=m_1}^{\pi(k)} l \Pr(L_k = l)$
- computationally prohibitive as k increases
- need for approximation

Approximate Evaluation of $E[L]$

Proposition 3

The expectation of L can be obtained as

$$E[L] = \sum_{l=m_1}^{\pi(M)} \Omega_M(\mathbf{m}-\mathbf{1}; l-1, \mathbf{p}) + (m_1 - 1)\Omega_M(\mathbf{m}-\mathbf{1}; m_1 - 1, \mathbf{p})$$

where $\Omega_M(\cdot)$ represents the c.d.f of a multinomial distribution.

- efficient approximation for $\Omega_M(\cdot)$ exists [Levin, 1981]
- allows approximation of $E[L]$ without calculating $\Pr(L = l)$

Experimental Evaluation

	Exact	Approx	Simulation
$m = 5$	13.55	13.59	13.33
$m = 10$	30.65	30.54	30.42
$m = 20$	66.59	66.29	66.86
$m = 30$	103.47	103.04	102.91

- Three boxes contain $(m, m, 2m)$ balls, $\mathbf{p} = [0.25, 0.25, 0.5]$
- *Exact:* the exact lifetime
- *Approx:* approximate lifetime using Proposition 3
- *Simulation:* average lifetime from 200 Monte Carlo simulations.

further approximation ?

Asymptotic approximation of $E(L)$

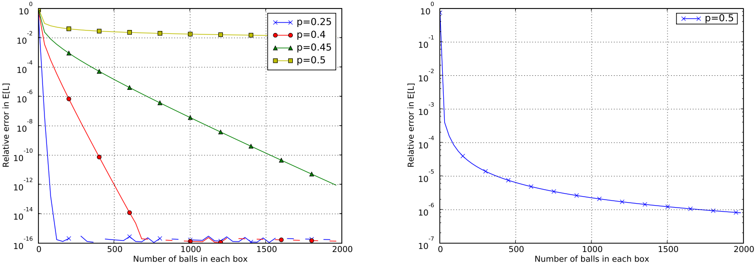
Proposition 4:

When $M = 2$ and m_1, m_2 are sufficiently large,

$$\mathrm{E}[L] \approx \begin{cases} \min\left(\frac{m_1}{p}, \frac{m_2}{1-p}\right) & \text{if } \frac{m_1}{p} \neq \frac{m_2}{1-p} \\ \frac{m_1}{p} - \frac{(m_1+1)\mathcal{N}(m_1+1; m_1, p)}{p} - \frac{(m_2+1)\mathcal{N}(m_2+1; m_2, 1-p)}{1-p} & \text{if } \frac{m_1}{p} = \frac{m_2}{1-p} \end{cases}$$

the approximation error reduces at an exponential rate

Experimental Evaluation



(a) (b)

- $\mathcal{B}_1, \mathcal{B}_2$ contain balls $m_1 = m_2$, $\mathbf{p} = [p, 1-p]$,
- Abscissa: the value of m_1, m_2, ordinate: relative error
- (a): simple approximation: $\min(\frac{m_1}{p}, \frac{m_2}{1-p})$
- (b): refined approximation for the case $\frac{m_1}{p} = \frac{m_2}{1-p}$

Asymptotic Approximation for $M > 2$

$$E[L(\mathbf{m}, \mathbf{p})] \approx \min(\frac{m_1}{p_1}, \frac{m_2}{p_2}, \ldots, \frac{m_M}{p_M})$$

- asymptotic approximation
- *hot-spot* exist: the difference between the two smallest values in $\{\frac{m_i}{p_i}\}_{i=1}^{N}$ is not negligible
- very easy to calculate

Recap

- formulation of the expected network lifetime of a user-centric VSN
- exact solution for $M = 2$,
- exact solution for $M > 2$: recursive approach
- efficient approximation of $E[L]$, $M > 2$
- asymptotic analysis for $E[L]$

Next, camera scheduling and energy allocation schemes

Outline

Camera Scheduling Strategy

When block $\mathcal{U}_j$ is requested:

$$s = \operatorname*{argmax}_{i \in \lambda^u(j)} \{\min(\frac{m_{i,1}}{p_1}, \frac{m_{i,2}}{p_2}, \ldots, \frac{m_{i,M_r}}{p_{M_r}})\} \qquad (2)$$

interpretation: maximize the normalized energy of the *hot-spot* block in the monitored plane.

if the hot-spot block doesn't belong to $\lambda^u(j)$,

$$s = \operatorname*{argmax}_{i \in \lambda^u(j)} \{\min(\frac{m_{i,k}}{p_k}, k \in \kappa^r(i))\}$$

$\kappa^r(i)$ denotes the set of blocks in the monitored region $\mathcal{R}$ covered by camera $\mathcal{C}_i$

Camera Scheduling Strategy

- stochastically optimal for lifetime-maximization
- user interactions are explicitly modeled
- very intuitive interpretation
- computational efficient

Outline

Energy Allocation Strategy

the expected lifetime can be given by

$$E[L(\mathbf{m}, \mathbf{p})] \approx \min\left(\frac{m_1}{p_1}, \frac{m_2}{p_2}, \ldots, \frac{m_N}{p_N}\right),$$

Optimized energy allocation strategy is a max-min optimization,

$$\begin{aligned} \max_{\mathbf{w}} \ \min_{i} \{f_i\}_{i=1}^{N} \\ s.t. \sum_{i=1}^{N} w_i = w_t \\ \mathbf{f} = \mathbf{P}\mathbf{B}^r\mathbf{w} \\ w_i \geq 0 \end{aligned} \tag{3}$$

where $f_i \stackrel{\text{def}}{=} \frac{m_i}{p_i}$ for $i = 1, 2, \ldots, N$ and $\mathbf{f} = [f_1, f_2, \ldots, f_N]$, $\mathbf{P}$ is the diagonal matrix formed by the vector $[\frac{1}{p_1}, \frac{1}{p_2}, \ldots, \frac{1}{p_N}]$.

Linear Programming Formulation

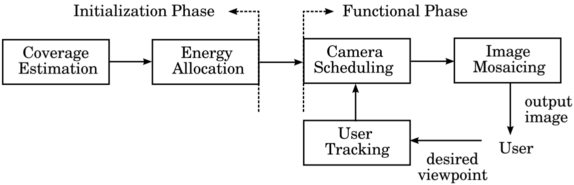
introduce a new variable t,

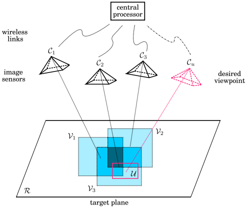
$$
\begin{aligned}
&\min_{\mathbf{w}} t \qquad (4)\\
&s.t. \sum_{i=1}^{N} w_i = w_t \\
&\quad \mathbf{f} = \mathbf{PBw} \\
&\quad f_i \leq t, w_i \geq 0, \text{ for } i = 1, 2, \ldots, N
\end{aligned}
$$

- efficient optimization in polynomial time

Outline

System Setup





- plane-based camera calibration
- image mosaicing

Image Mosaicing

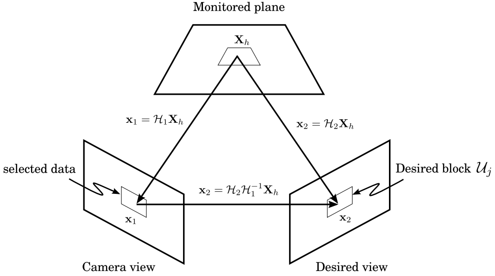


Figure: image coordinate of $\mathbf{X}_h$ in the second (desired) view $\mathbf{x}_2$ can be obtained from $\mathbf{x}_1$ through the homography.

- $\mathbf{x} \sim \mathcal{H}\mathbf{X}_h$
- $\mathcal{H}_1^{-1}\mathbf{x}_1 = \mathbf{X}_h = \mathcal{H}_2^{-1}\mathbf{x}_2$, $\mathbf{x}_1 = \mathcal{H}_1\mathcal{H}_2^{-1}\mathbf{x}_2$

Simulation Setup

- target plane $\mathcal{R}$: size $4m \times 3m$
- N cameras placed randomly within a $4m \times 3m$ field, $3m$ from $\mathcal{R}$
- Users' viewpoints: a Markov random walk on a 16×16 grid
- cameras and users' views point toward $\mathcal{R}$, random rotation within ± 0.1 radian along each of the three axes.
- all images of 200×200 (in pixel units)
- $M_u = 100$,
- bilinear interpolation.
- for camera scheduling: focal length $f = 218.75$, $N = 36$
- results averages over 100 simulations.

Simulation: Camera Scheduling

three schemes compared

- OptCOV: proposed scheme
- MinANG: most similar viewing direction
- CovCOST: a heuristic defining a coverage cost [Yu et al., 2007]

$$\xi_i = \sum_{j \in \lambda^r(i)} \frac{1}{m_j}$$

Simulation: Camera Scheduling

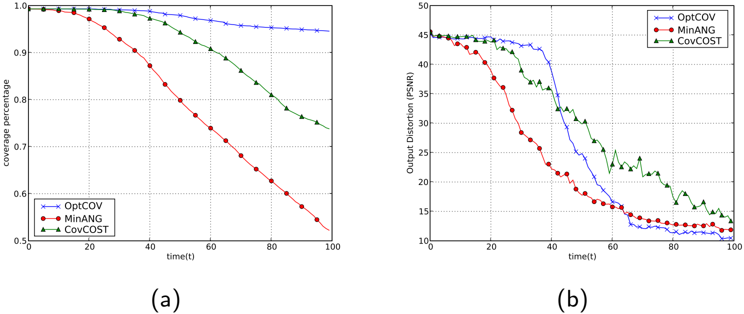


Figure: Simulation results. (a): comparison of percentage coverage (b): comparison of distortion in output image.

- OptCOV significantly prolongs network lifetime

Snapshots of rendered images

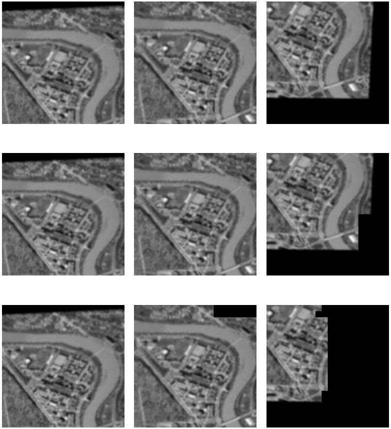


Figure: Snapshots of images rendered in the simulation. *Top row:* Mosaiced image using OptCOV at the $20^{th}, 27^{th}, and 54^{th}$ user request. The desired views are fully covered. *Middle:* Using CovCOST, minor part of the desired view is not covered, denoted by black area in the mosaiced image. (d) Using MinANG, significant fraction of the desired view is not covered.

Simulation: Energy Allocation

three energy allocation schemes compared:

- uniform allocation: UniForm
- using LP: LinOpt
- using max-min optimization: MaxMin

Simulation: Energy Allocation

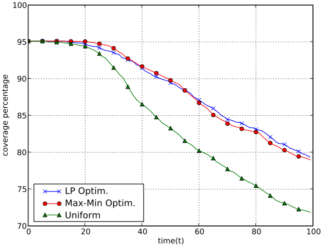


Figure: Comparison of coverage from different energy allocation schemes.

- Optimized energy allocation significantly prolongs network lifetime
- LP optimization: 2.3 sec, Min-Max optimization: 157.2 sec, Pentium IV 3.0G CPU, 1M memory, implemented in Matlab^{TM}

Outline

Summary

- stochastic formulation of the expected network lifetime
  - coverage/lifetime of a VSN differs from traditional WSN
  - user interaction
- abstraction of expected network lifetime
  - exact and approximate solutions: computational expensive
  - asymptotic analysis
- lifetime-maximizing camera scheduling
  - hot-spot of the network
- lifetime-maximizing energy allocation
  - LP formulation

Remarks

- simplicity
    - well known: binomial/multinomial
    - known: negative binomial/multinomial
    - proposed: bounded negative binomial/multinomial
        - exact, approximate, asymptotic behaviors

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  - other VSN applications: coverage information $\mathbf{B}^r, \mathbf{B}^u$ by suitable discretization (e.g in $3D$ domain).
  - e.g. task (storage, bandwidth) allocation among networked computing servers,
  - sensor deployment problem: much larger parameter space, location, rotation

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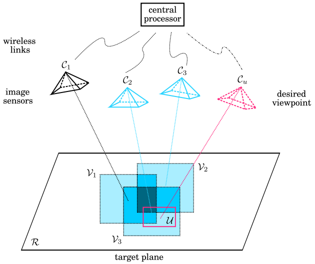
  - e.g. task (storage, bandwidth) allocation among networked computing servers,
  - sensor deployment problem: much larger parameter space, location, rotation
- sub-optimality
  - neglected the dependency of each block being requested
  - mitigation: parameters updated afresh at each request

Ongoing work

- collaborative transmission between two sensors
- wyner-ziv coding techniques
  - certain robustness to calibration error
  - certain tolerance to non-planar scenes
  - complexity: a fraction of JPEG compression



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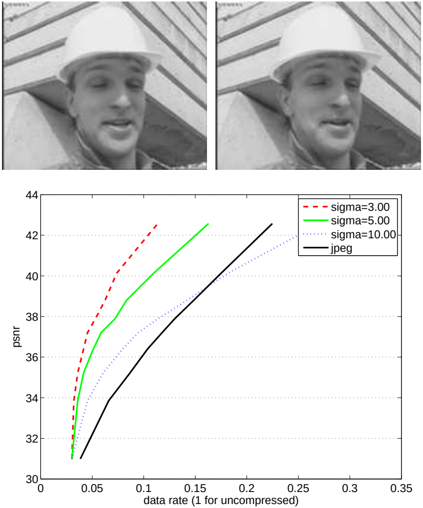

Figure: Wyner-Ziv image compression v.s. JPEG.

Reference

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Joseph M.Hilbe. *Negative Binomial Regression*. Cambridge University Press, 2007.

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