Cooperative Environmental Monitoring for PTZ Camera Networks:
Payoff-based Game Theoretic Learning Approach

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Outline

- Introduction
- Problem Setting
- Formulation a Potential Game
- Experiment
- Schedule

Introduction

Environmental monitoring

Large-scale persistent environmental monitoring has become crucial due to recent serious natural disasters.

Earthquake Flood Landslide

Camera/visual sensor network

A network consisting of spatially distributed smart cameras

Earthquake Flood Landslide

Objective

Monitoring the environmental change by PTZ camera network

Practical Work

Objective

Monitoring the environmental change by PTZ camera network

Control Approach

Game Theoretic Control: Potential Game[2]

Advantages : Robustness for environmental change ϕ
Scalability
Adaptability in real time

Component[3]
- Utility Design
- Learning Design: PIPIP[1]

Practical Work
- Utility Design (based on [4])
- Experiment and Analysis

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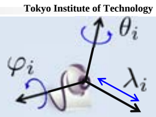
Problem Setting

player $\mathcal{C} = \{c_1, \cdots, c_n\}$

action $a_i = (\theta_i, \varphi_i, \lambda_i) \in \mathcal{A}_i$ (Pan Tilt Zoom)

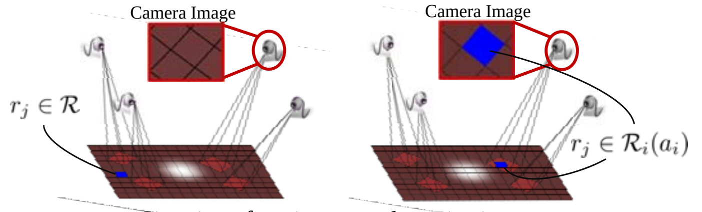


constrained action set

$\bar{\mathcal{A}}_i(a_i) = \{a_i + (5b_1, 5b_2, 2b_3) \in \mathcal{A}_i | b_1, b_2, b_3 \in \{-1, 0, 1\}\}$

resource $\mathcal{R} = \{r_1, \cdots, r_m\}$

visible resources from camera c_i with a_i $\mathcal{R}_i(a_i) \in \mathcal{R}$



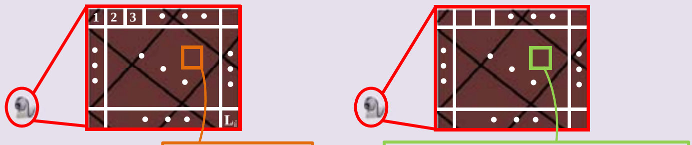
Situation of environmental monitoring

Problem Setting

$\mathcal{C}=\{c_1,\cdots,c_n\}$ $a_i=(\theta_i,\varphi_i,\lambda_i)\in\mathcal{A}_i$ $\mathcal{R}=\{r_1,\cdots,r_m\}$

Information got from the camera image

$l\in\mathcal{L}_i:=\{1,\cdots,L_i\}$ $y_{i,l}\in\{0,\cdots,255\}$

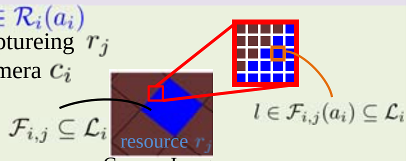


pixel $l\in\mathcal{L}_i$ Image value $y_{i,l}\in\{0,\cdots,255\}$

Information about resource $r_j\in\mathcal{R}_i(a_i)$

$\mathcal{F}_{i,j}\subseteq\mathcal{L}_i$ the set of pixels captureing r_j in the image of camera c_i

$\mathcal{Y}_{i,j}(a_i)=\{y_{i,l}\}_{l\in\mathcal{F}_{i,j}(a_i)}$



Camera Image

Problem Setting (Environmental change)

$\mathcal{C}=\{c_1,\cdots,c_n\}$, $a_i=(\theta_i,\varphi_i,\lambda_i)\in\mathcal{A}_i$, $\mathcal{R}=\{r_1,\cdots,r_m\}$

$l\in\mathcal{L}_i:=\{1,\cdots,L_i\}$, $y_{i,l}\in\{0,\cdots,255\}$

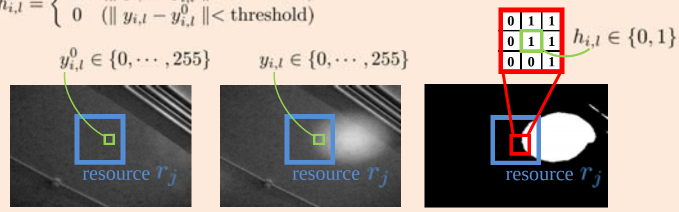
$\mathcal{F}_{i,j}\subseteq\mathcal{L}_i$ the set of pixels capturing r_j

Information of environmental change about resource $r_j\in\mathcal{R}_i(a_i)$

$\mathcal{Y}^0_{i,j}(a_i)=\{y^0_{i,l}\}_{l\in\mathcal{F}_{i,j}(a_i)}$, $\mathcal{Y}_{i,j}(a_i)=\{y_{i,l}\}_{l\in\mathcal{F}_{i,j}(a_i)}$

$$h_{i,l}=\begin{cases}1 & (\|y_{i,l}-y^0_{i,l}\|\geq \text{threshold})\\ 0 & (\|y_{i,l}-y^0_{i,l}\|<\text{threshold})\end{cases}$$

$y^0_{i,l}\in\{0,\cdots,255\}$ $y_{i,l}\in\{0,\cdots,255\}$ $h_{i,l}\in\{0,1\}$



Initialized Image Current Image Difference Image

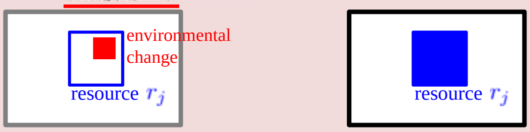
Problem Setting(Cost Function)

$\mathcal{F}_{i,j}\subseteq\mathcal{L}_i$ the set of pixels capturing r_j, $h_{i,l}=\begin{cases}1 & (\|y_{i,l}-y^0_{i,l}\|\geq\text{threshold})\\ 0 & (\|y_{i,l}-y^0_{i,l}\|<\text{threshold})\end{cases}$

Cost function

$$W_{i,j}(a_i)=\begin{cases}I^{\rm info}_{i,j}(a_i)I^{\rm qual}_{i,j}(a_i) & (I^{\rm info}_{i,j}(a_i)I^{\rm qual}_{i,j}(a_i)>\alpha)\\ \alpha & (I^{\rm info}_{i,j}(a_i)I^{\rm qual}_{i,j}(a_i)\leq\alpha)\end{cases}$$

$I^{\rm info}_{i,j}(a_i)=\left(\sum_{l\in\mathcal{F}_{i,j}(a_i)}h_{i,l}\right)/|\mathcal{F}_{i,j}(a_i)|$ $I^{\rm qual}_{i,j}(a_i)=|\mathcal{F}_{i,j}(a_i)|/L_i$



Camera Image Camera Image

Welfare $W_j(a)=\max_{c_i\in\mathcal{C}_j(a)}W_{i,j}(a_i)$

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Problem Setting (Potential Game)

Cost function

$$W_{i,j}(a_i)=\begin{cases}I^{\rm info}_{i,j}(a_i)I^{\rm qual}_{i,j}(a_i) & (I^{\rm info}_{i,j}(a_i)I^{\rm qual}_{i,j}(a_i)>\alpha)\\ \alpha & (I^{\rm info}_{i,j}(a_i)I^{\rm qual}_{i,j}(a_i)\leq\alpha)\end{cases}$$

Welfare $W_j(a)=\max_{c_i\in\mathcal{C}_j(a)}W_{i,j}(a_i)$

Utility $U_i(a)=\sum_{r_j\in\mathcal{R}_i(a_i)}W_j(a)-W_{j,-i}(a)$

Global Objective $W(a)=\sum_{r_j\in\mathcal{R}}W_j(a)$

U_i, W satisfy the following equation

$U_i(a'_i,a_{-i})-U_i(a_i,a_{-i})=W(a'_i,a_{-i})-W(a_i,a_{-i})$ $\forall i,a_i,a'_i,a_{-i}$

➡ a game $G=(\mathcal{C},\mathcal{A},\{U_i\}_{i\in\mathcal{C}},W)$ compose a potential game

Learning Algorithm PIPIP

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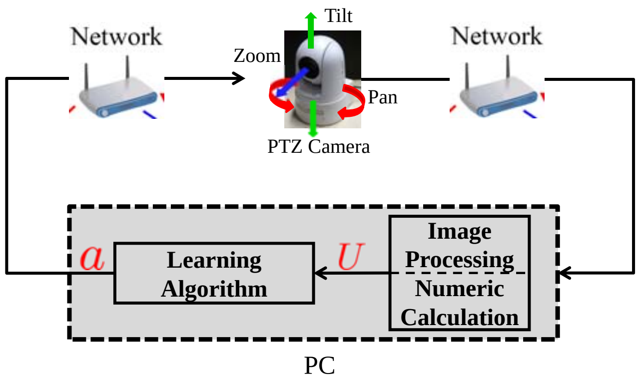
- Problem Setting
- Formulation a Potential Game
- **Experiment**
- Schedule

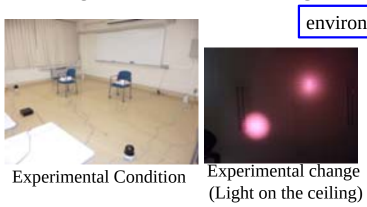
Experimental System

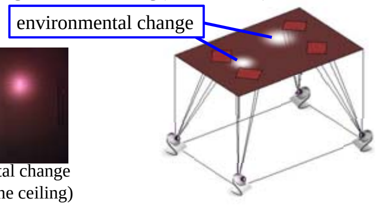


Experimental Setting

Experimental Condition

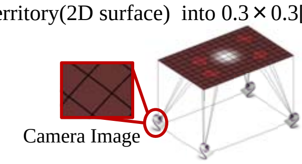
Monitoring the environmental change on the ceiling(2D surface)





Resources arrangement

divide the monitoring territory(2D surface) into 0.3×0.3[m2] areas.



Experimental Setting

Experimental problem setting

$\mathcal{C} = \{c_1, c_2, c_3, c_4\}$, $a_i = (\theta_i, \varphi_i, \lambda_i) \in \mathcal{A}_i$

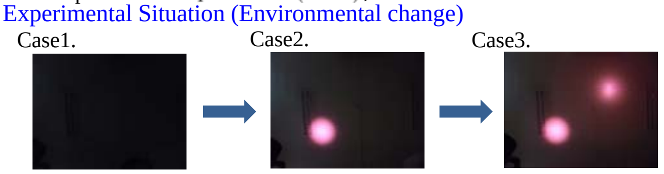
$\bar{\mathcal{A}}_i(a_i) = \{a_i + (5b_1, 5b_2, 2b_3) \in \mathcal{A}_i | b_1, b_2, b_3 \in \{-1, 0, 1\}\}$

$\mathcal{R} = \{r_1, \cdots, r_{150}\}$

$$W_{i,j}(a_i) = \begin{cases} I^{\rm info}_{i,j}(a_i) I^{\rm qual}_{i,j}(a_i) & (I^{\rm info}_{i,j}(a_i) I^{\rm qual}_{i,j}(a_i) > 0.05) \\ 0.05 & (I^{\rm info}_{i,j}(a_i) I^{\rm qual}_{i,j}(a_i) \le 0.05, r_j \text{ is visible perfectly}) \\ 0 & (I^{\rm info}_{i,j}(a_i) I^{\rm qual}_{i,j}(a_i) \le 0.05, r_j \text{ isn't visible perfectly}) \end{cases}$$

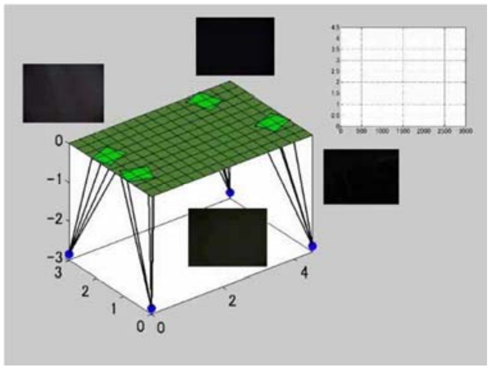
PIPIP parameter : $\text{eps} = 0.05$ (const), $\kappa = 0.3$

Experimental Situation (Environmental change)

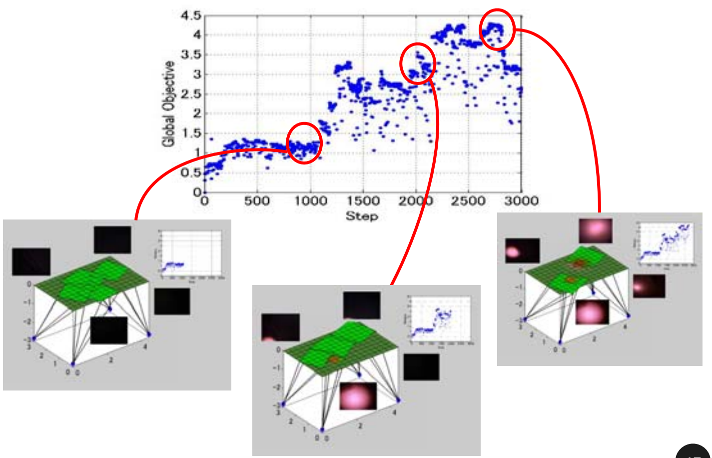


0 light (No environmental change) 1 light 2 light

Experimental Result



Experimental Analysis



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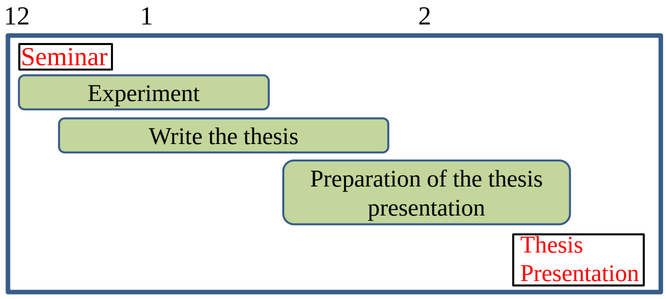
Schedule



Experiment

- Try similar experiment again
- Change the Experiment situation (ex. the light number)
- Experiment with another Learning Algorithm (Simple Experimentation with Irrational Decisions)

Reference

[1] T. Goto, T. Hatanaka and M. Fujita, “Payoff-based Inhomogeneous Partially Irrational Play for Potential Game Theoretic Cooperative Control: Convergence Analysis,” *Proc. of the 2012 American Control Conference*, pp. 2380-2387, 2012.

[2] J. R. Marden, G. Arslan and J. S. Shamma, “Cooperative Control and Potential Games,” *IEEE Trans. on Systems, Man and Cybernetics*, Vol. 39, No. 6, pp. 1393-1407, 2009.

[3] R. Gopalakrishnan, J. R. Marden and A. Wierman, “An Architectural View of Game Theoretic Control,” *Proc. of ACM Hotmetrics: Third Workshop on Hot Topics in Measurement and Modeling of Computer Systems*, 2010.

[4] J. R. Marden and A. Wierman, “Distributed Welfare Games,” *Operations Research*, sumbitted, 2008.

Appendix

Learning Algorithm (PIPIP)

Initialization: Action a is chosen randomly from $\mathcal{A}$

Set $a_i^1 \leftarrow a_i, a_i^2 \leftarrow a_i, U_i^1 \leftarrow U_i(a), U_i(a)_i^2 \leftarrow U_i(a), \Delta_i \leftarrow 0$ for all $i \in \mathcal{V}$ and $t \leftarrow 2$

Step 1: Update ε.

Step 2: If $U_i^1 > U_i^2$ or $U_i^1 = U_i^2 > 0$, then set

$$a_i^{tmp} \leftarrow \begin{cases} \mathrm{rnd}(\mathcal{C}_i(a_i^1)\backslash\{a_i^1\}), & \text{w.p. } \varepsilon \\ a_i^1, & \text{w.p. } 1-\varepsilon \end{cases}$$

If $U_i^1 = U_i^2 = 0$, then set

$$a_i^{tmp} \leftarrow \begin{cases} \mathrm{rnd}(\mathcal{C}_i(a_i^1)\backslash\{a_i^1\}), & \text{w.p. } \alpha\varepsilon \\ a_i^1, & \text{w.p. } 1-\alpha\varepsilon \end{cases}$$

Otherwise, set

$$a_i^{tmp} \leftarrow \begin{cases} \mathrm{rnd}(\mathcal{C}_i(a_i^1)\backslash\{a_i^1\}), & \text{w.p. } \varepsilon \\ a_i^1, & \text{w.p. } (1-\varepsilon)(\kappa\varepsilon^{\Delta_i}) \\ a_i^2, & \text{w.p. } (1-\varepsilon)(1-\kappa\varepsilon^{\Delta_i}) \end{cases}$$

Step 3: Execute the selected action a_i^{tmp}.

Step 4: Receive $U_i^{tmp}{}_i(a^{tmp})$.

Step 5: Set $a_i^2 \leftarrow a_i^1, a_i^1 \leftarrow a_i^{tmp}, U_i^2 \leftarrow U_i^1, U_i^1 \leftarrow U_i^{tmp}$ and $\Delta_i \leftarrow U_i^2 - U_i^1$.

Step 6: $t+1$ and go to Step 1 .

Problem Setting

$\mathcal{R} = \{r_1, \cdots, r_m\}$ resources

$\mathcal{R}_i(a_i) \in \mathcal{R}$ visible resources from camera c_i with a_i

Information got from camera image

$l = \{1, \cdots, L_i\} \in \mathcal{L}_i$ the pixel number in the image of camera c_i

$y_{i,l} \in \{0, \cdots, 255\}$ the visual measurements(raw data)about camera c_i

Information about resource $r_j \in \mathcal{R}_i(a_i)$

$\mathcal{F}_{i,j}(a_i)$ the set of pixels captureing r_j in the image of camera c_i

$\mathcal{Y}_{i,j}^0(a_i) = \{y_{i,l}^0\}_{l \in \mathcal{F}_{i,j}(a_i)}$ stored initial visual information about $r_j \in \mathcal{R}_i(a_i)$

$\mathcal{Y}_{i,j}(a_i) = \{y_{i,l}\}_{l \in \mathcal{F}_{i,j}(a_i)}$ the visual information about $r_j \in \mathcal{R}_i(a_i)$

$h_{i,l} = \begin{cases} 1 & (\| y_{i,l} - y_{i,l}^0 \| \geq \text{threshold}) \\ 0 & (\| y_{i,l} - y_{i,l}^0 \| < \text{threshold}) \end{cases}$ the information of environmental change