Controlling Distributed Cooperative Systems – Robots, Fish, Energy

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Research Area

- Temporal pattern recognition/modeling
  - With hybrid systems
    (discrete-event systems & dynamical systems)

Automaton, etc.	Differential equations
Decisions / rules (Cyber World)	Law of nature (Physical World)

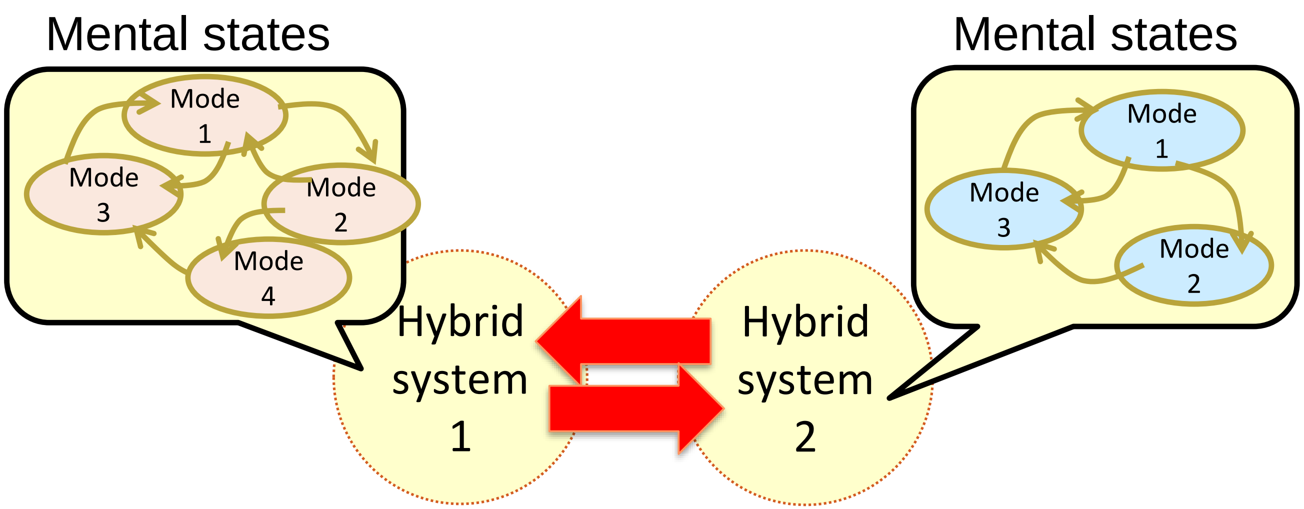
- Apply to human behavior/communication analysis
  - Face motion analysis, gaze understanding, lipreading, etc.

Research Area

- Temporal pattern recognition/modeling
  - With hybrid systems
- Apply to human behavior/communication analysis

Mathematical modeling of human interaction…

Too complicated … Decided to start from simpler “agents” (e.g., robots/software agents, animals, etc.)



Visiting Georgia Tech. (2010.6.8～2012.6.7)

- Georgia Institute of Technology (Georgia Tech, GT)
  - JSPS Postdoc fellowship
- Georgia Robotics and Intelligent Systems (GRITS)
- Prof. Magnus Egerstedt
- Research area: Control theory＋Robotics
  - Hybrid system
  - Networked control systems
  - Mobile Robots

Controlling Collective Behaviors

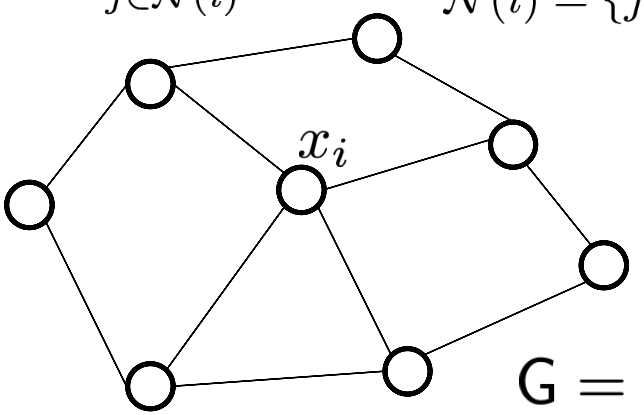
Modeling Collective Behavior

Information-exchange networks

Motion of each agent is determined by the local interaction with its neighbors

$$\dot{x}_i = \sum_{j \in \mathcal{N}(i)} f(x_i, x_j) \quad i = 1, \ldots, N$$

$$\mathcal{N}(i) = \{ j \mid (v_i, v_j) \in \mathsf{E} \}$$



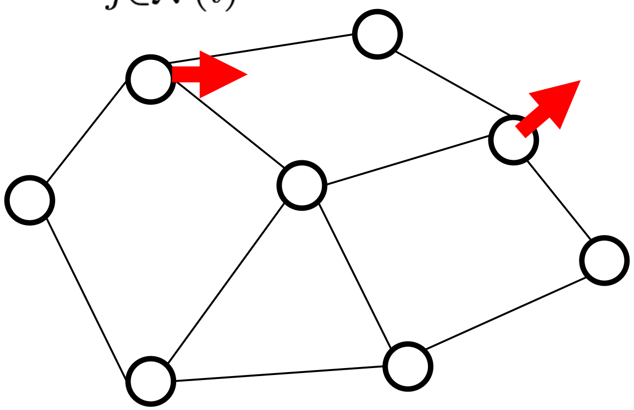
$$\mathsf{G} = (\mathsf{V}, \mathsf{E})$$

Leader-follower Networks

Inject inputs to the network

$$u$$

$$\dot{x}_i = \sum_{j \in \mathcal{N}(i)} f(x_i, x_j)$$



$$\dot{x} = \begin{bmatrix} \dot{x}_1 \\ \vdots \\ \dot{x}_N \end{bmatrix} = F(x)$$

$$u$$

Leader-follower Networks

Driving nodes propagate external inputs

Q. Which node affects the group the most?

Q. How to measure its influence?

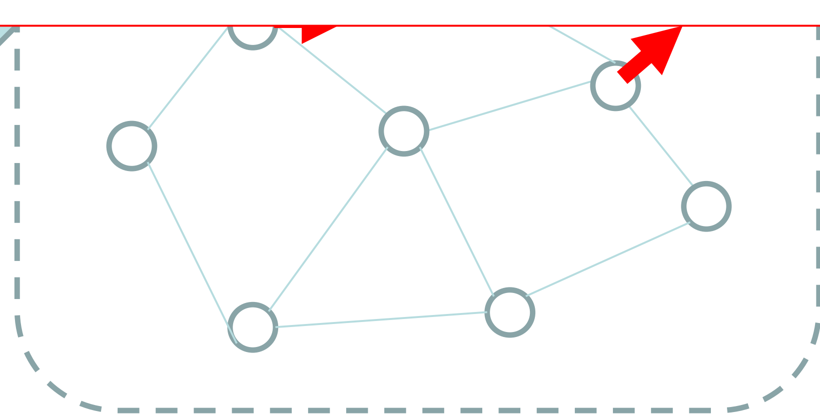
Controllability of networked systems (Rahmani,2009)

Manipulability of networked systems (Kawashima 2014)

Inject i

u

$$\dot{x} = \begin{bmatrix} \dot{x}_1 \\ \vdots \\ \dot{x}_N \end{bmatrix} = F(x)$$



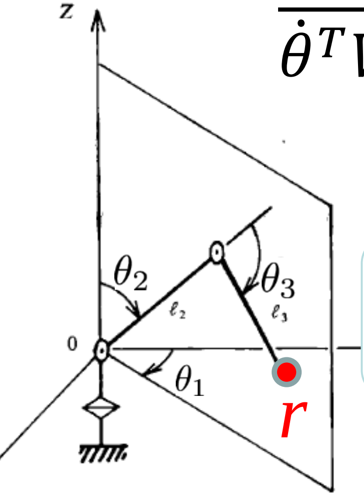
Robot-arm manipulability

[Yoshikawa 1985]

$$\frac{\dot{r}^T W_r \dot{r}}{\dot{\theta}^T W_\theta \dot{\theta}}$$

end-effector velocity

angular velocity of joints



r : states of end-effector
θ : joint angles
$W_r, W_\theta \succ 0$: weight matrices

Kinematic relation

$$r = f(\theta), \quad \dot{r} = \left.\frac{\partial f}{\partial \theta}\right|_\theta \dot{\theta}$$

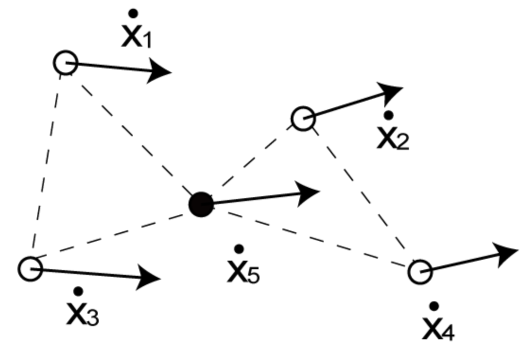
Velocity of end-effector is directly connected with the angular velocity

Leader-follower manipulability

$$m = \frac{\dot{x}_f{}^T Q_f \dot{x}_f}{\dot{x}_\ell{}^T Q_\ell \dot{x}_\ell}$$

followers' vel.

leaders' vel.



Dynamics of agents

$$\dot{x}_\ell(t) = u(t)\text{: given}$$

$$\dot{x}_f(t) = -\frac{\partial \mathcal{E}(x_f, x_\ell)}{\partial x_f}^T$$

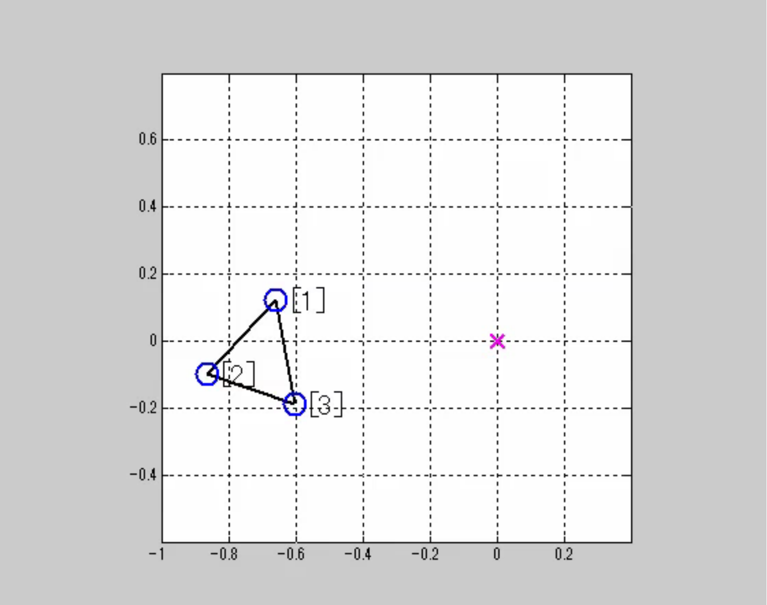
Ratio of the follower's response to the leaders' input

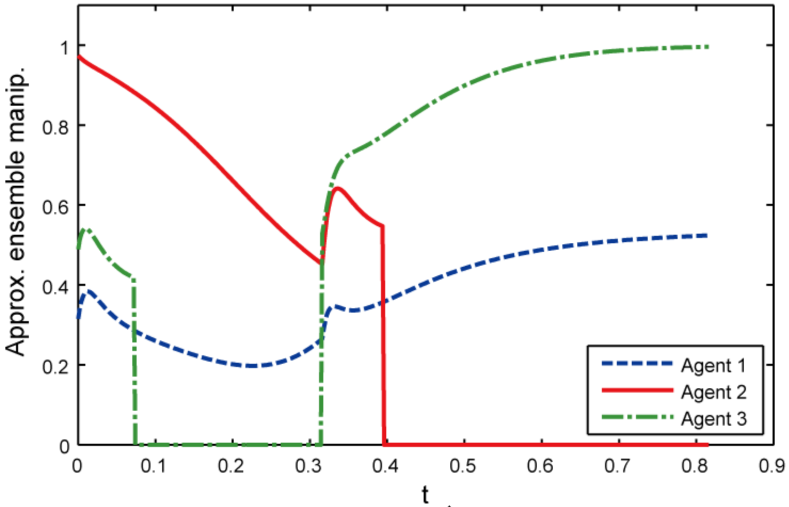
Example: online leader selection

[Kawashima+ 2012]

Online leader selection (Find most influential agents)

$$\ell(t) = \underset{i \in \mathcal{L}(t)}{\arg\max}\ \hat{m}_e(i, x(t)) \quad \text{where} \quad \mathcal{L}(t) = \{i \mid k_i(x(t)) > 0\}$$



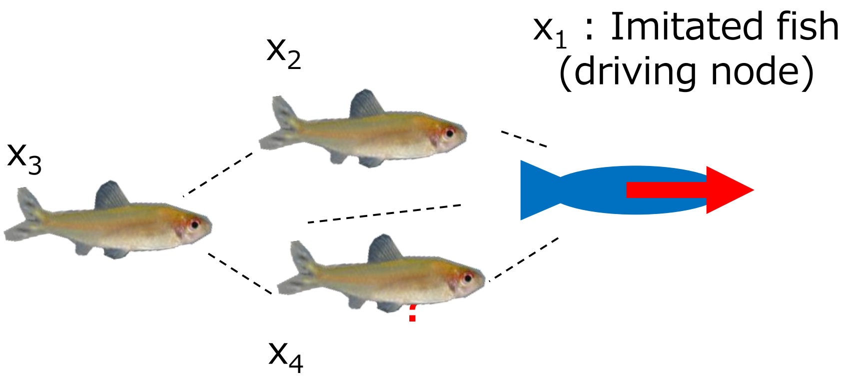


Temporal change of $\hat{m}_e$ in N=3 case

Controlling/Navigating Fish School

- To control real fish group via imitated fish (driving nodes), a precise model of fish collective behavior is required
  - We focus on a low density group

http://www.belfasttelegraph.co.uk/breakingnews/offbeat/secret-of-herding-sheep-discovered-30541127.html



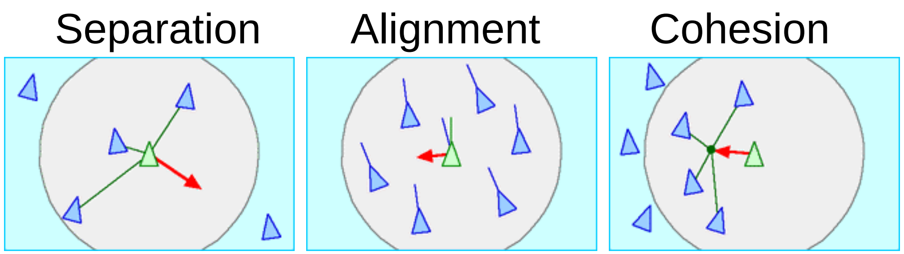
$$
\begin{cases}
\dfrac{dx_1}{dt} = \cancel{f(x_1)} \quad u \\
\dfrac{dx_2}{dt} = f(x_1, x_2, x_4) \\
\dfrac{dx_3}{dt} = f(x_1, x_2, x_3, x_4) \\
\dfrac{dx_4}{dt} = f(x_1, x_2, x_4)
\end{cases}
$$

But, what is an appropriate fish model?

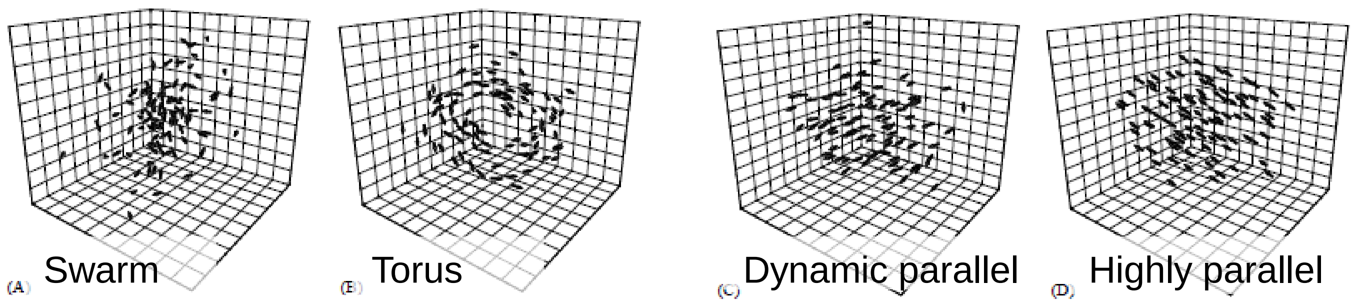
Models of Fish Collective Behavior

- Interconnected individual (differential eq.) models

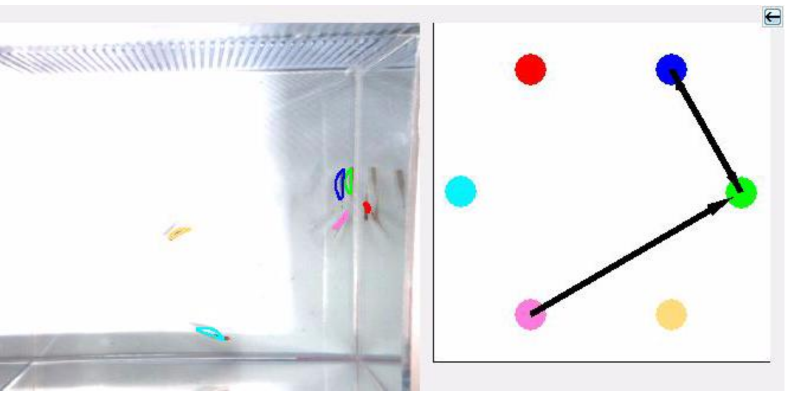
Individual behavior is determined by neighbors



[Reynolds,1987]



[Couzin+, 2002]



Too simple to predict actual fish behavior

Approach

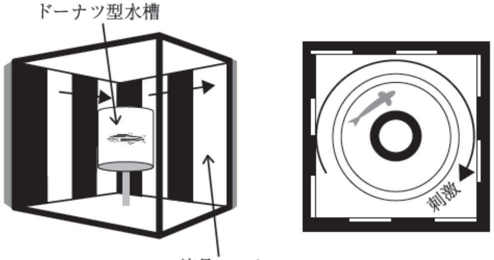
– Learn individual-level and network-level dynamics from data

Data-Driven Modeling

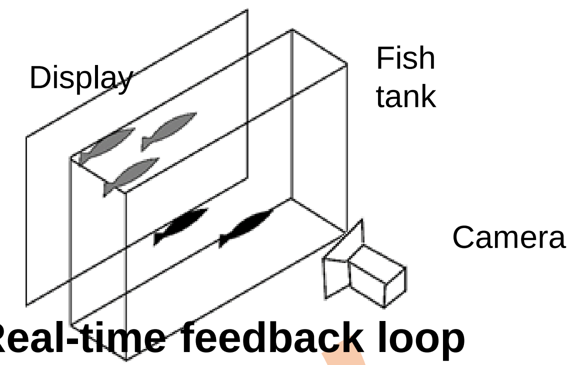
- How to obtain large dataset of trajectories including a variety of individual-level interaction?

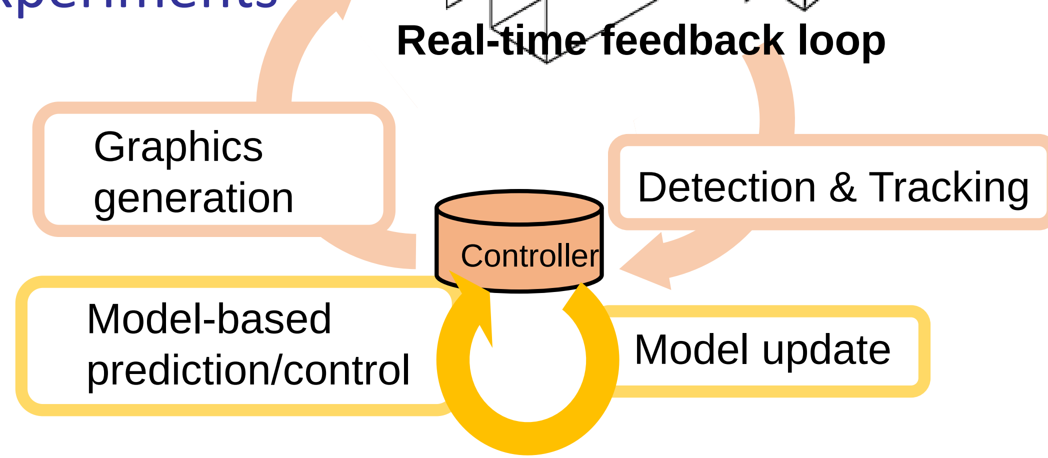
→ Use visual stimuli for <u>data collection</u> and <u>evaluation</u>

1. Vision is a major modality for fish (e.g., optomotor response)
2. System-identification framework: informative than passive observation
3. Good for long-term experiments (compared to robots)



[Ishikane et al., 2013]

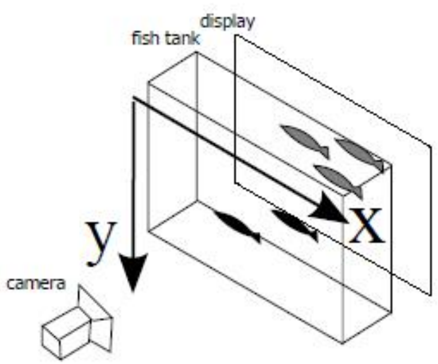


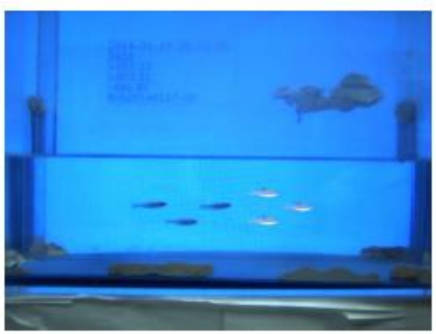


Interaction Analysis Using Visual Stimuli

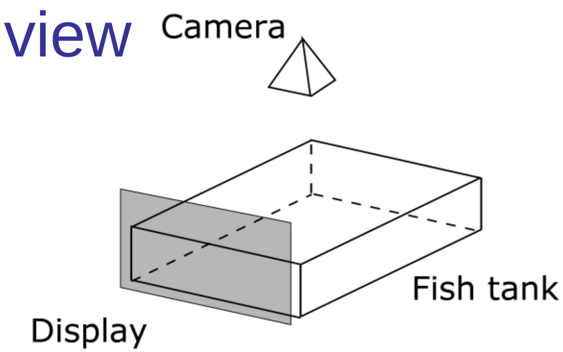
- Attractive stimuli
  - Fish-like graphics
  - Analyze real fish vs fish graphics
- Repulsive stimuli
  - Induce group-level state transition: shoaling to schooling
  - Analyze interaction among real fish

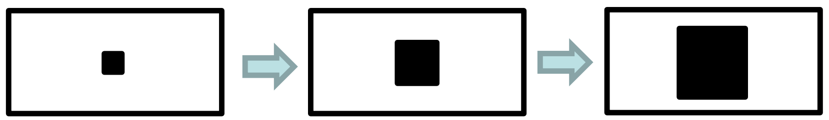
Side view





Top view

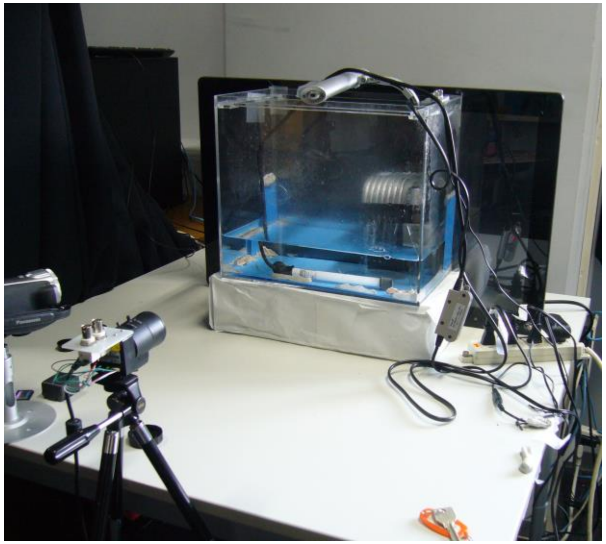


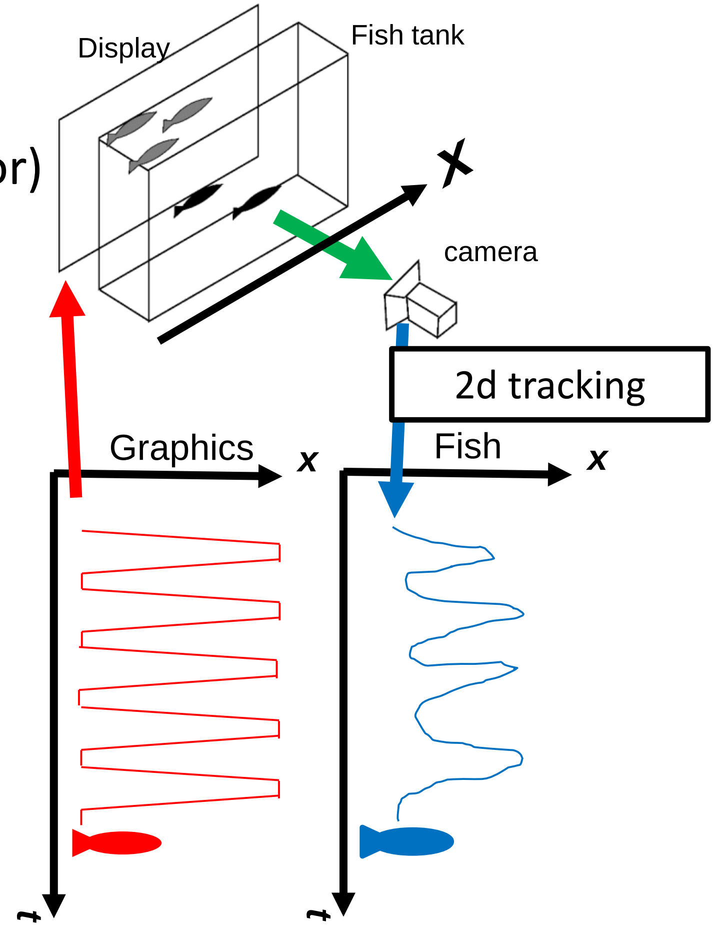


Preliminary Experiments (1)

Is fish graphics useful? (really attract live fish group)?

- Setting
  - Tank: 35cm(W) x 30(H) x 20(D)
    - Area: 20 → 5cm(D) (with a separator)
  - Side-view camera: 15fps
  - Fish: Three Rummy-nose tetra

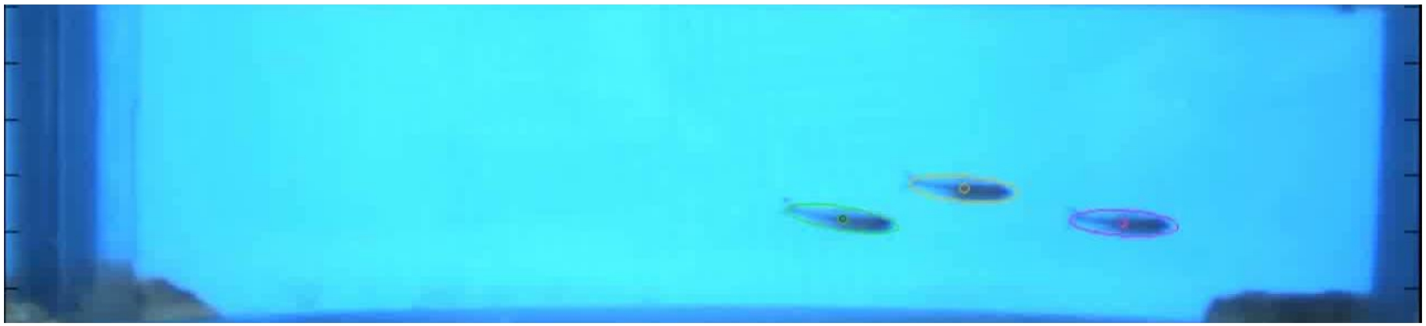


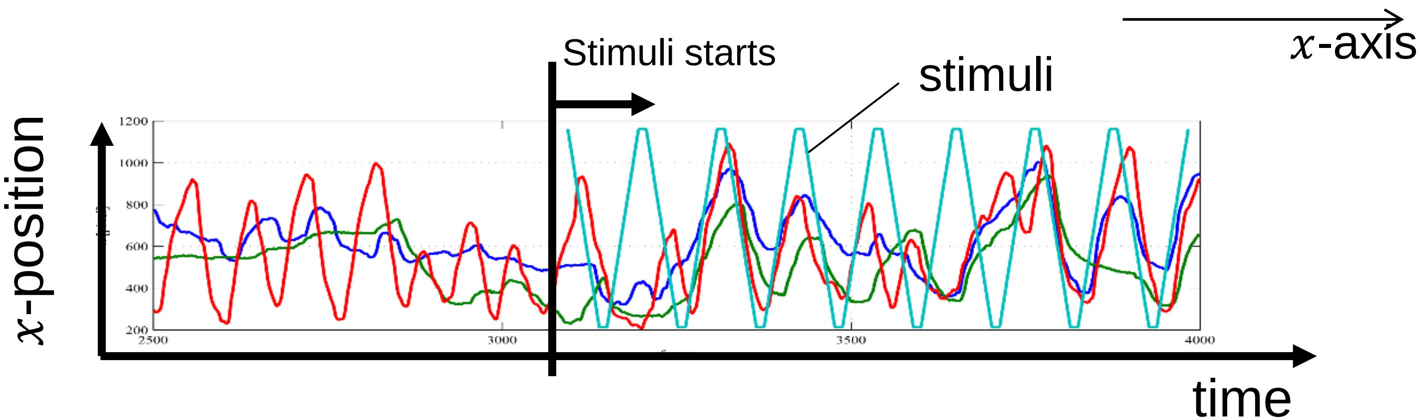


Can fish graphics attract real fish?

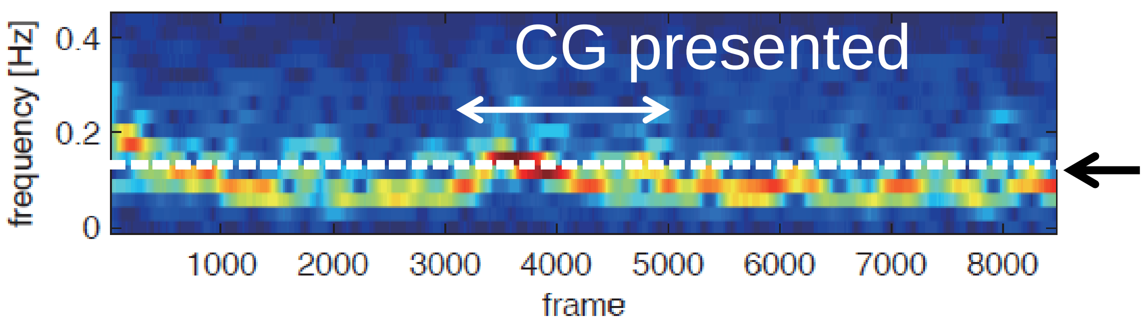
[兼近+ CVIM2014]

- Fish-like graphics (reciprocating motion in x axis)





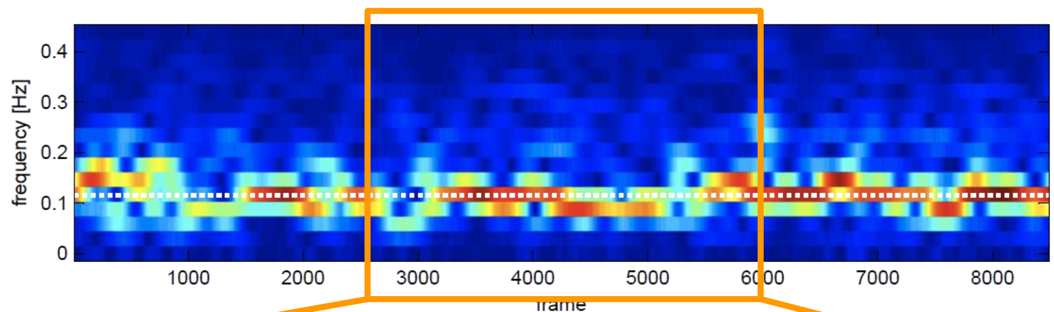
Frequency Sync.



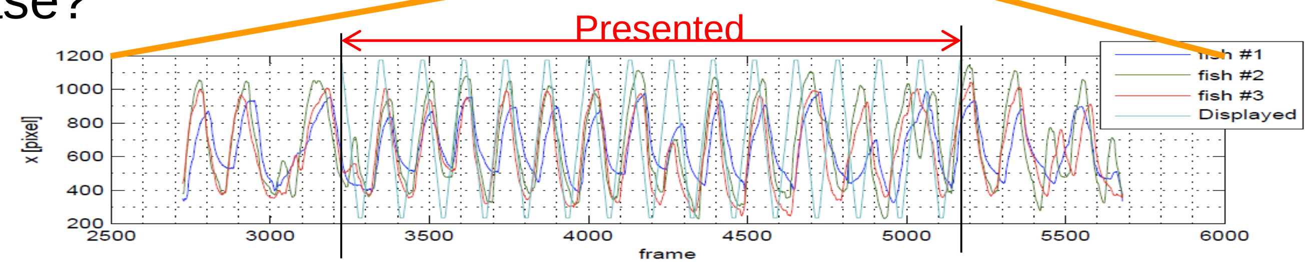
Frequency of the stimulus

Can fish graphics attract real fish?

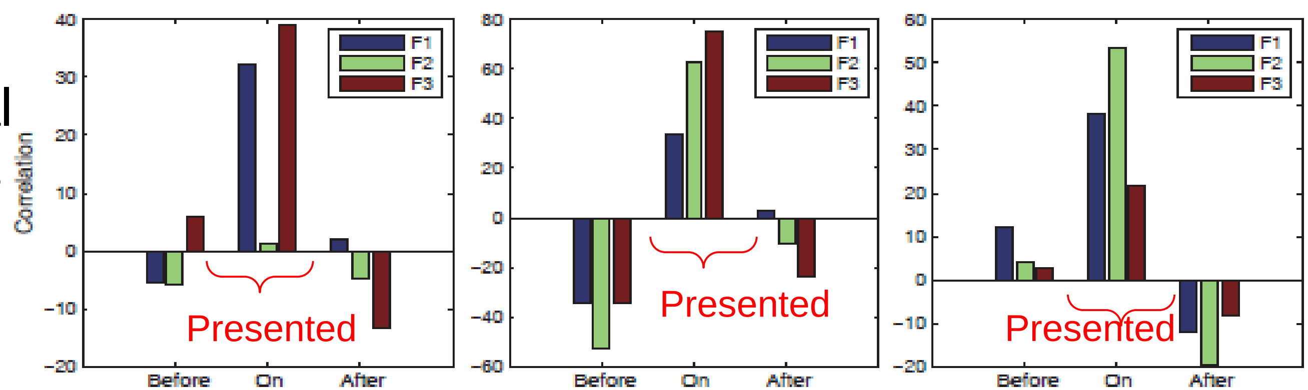
- Fish can move with similar frequency as stimuli without presenting stimuli



How about phase?



Correlation of real fish and graphics (phase sync.)

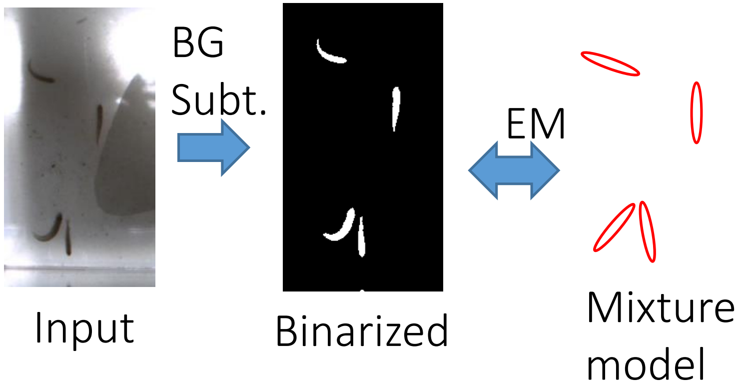


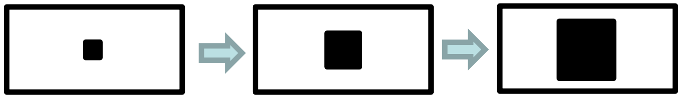
Sequence 1 Sequence 2 Sequence 3

Preliminary Experiments (2)

Can we estimate interaction network of fish group?

- Induce a group-level state transition
  - "aggregation/shoaling" to "schooling"
- Setting
  - Fish tank: 30 (W) x 30 (D) x 10 cm (H)
  - Top-view camera: 60fps / Fish: 10
- Tracking positions by a mixture model
  - Each fish is modeled as an ellipse





Example of Induced Schooling Behavior

- Induced “schooling” behavior and tracking result

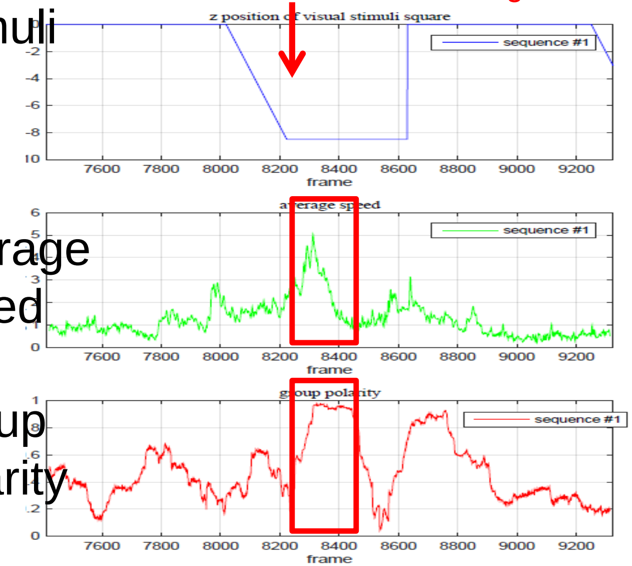
Visual stimuli→ (Display)

Maximum rectangle size

Stimuli

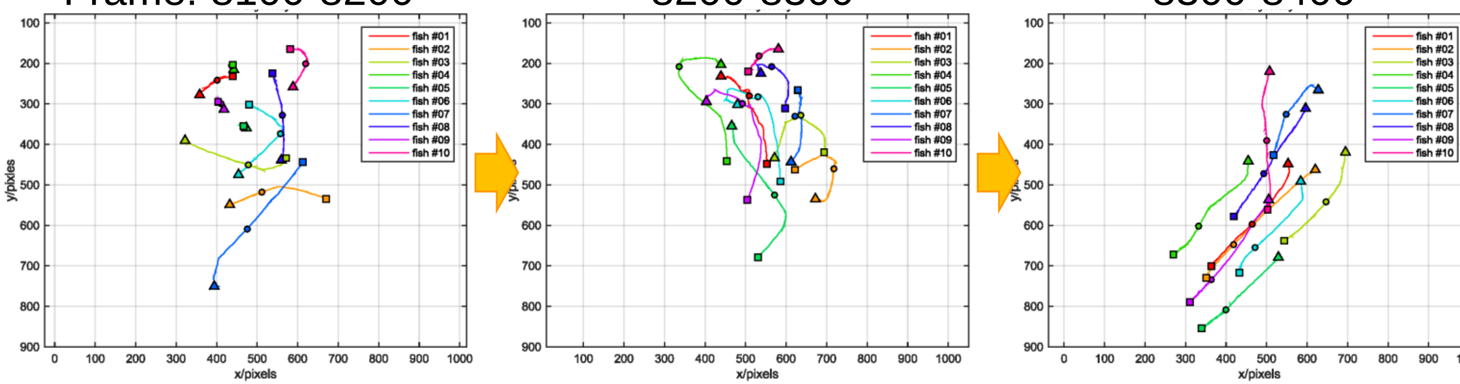
Average speed

Group polarity



Tracking result (only x,y position)

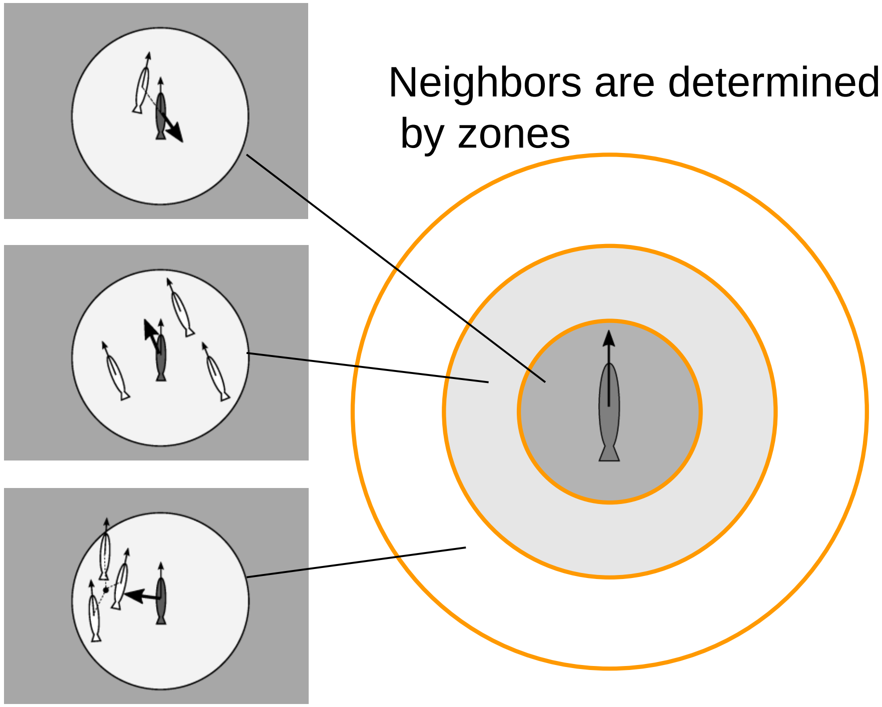
Frame: 8100-8200 8200-8300 8300-8400



Modeling Interaction

“Consensus model” is often used in existing studies
[Raynolds 1987, Couzin 2002]

- Repulsion
  - Move away from neighbors
- Orientation
  - Align with neighbors
- Attraction
  - Move toward neighbors



Position of fish j Position of fish i

$$\dot{\boldsymbol{x}}_i(t+\tau) = \sum_{j=1, j\neq i}^{N} w_{ij} \frac{\boldsymbol{x}_j(t) - \boldsymbol{x}_i(t)}{\left\|\boldsymbol{x}_j(t) - \boldsymbol{x}_i(t)\right\|}$$

Velocity of fish i

Degree of influence from fish j

Estimation of Network Topology

- Individual behavior model with autonomous term

Coordination term

Autonomous term

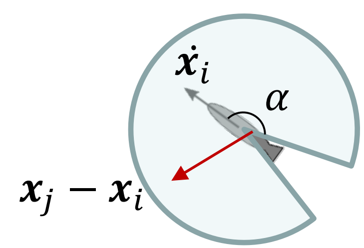
$$\dot{\boldsymbol{x}}_i(t+\tau) = \boxed{\sum_{j=1, j\neq i}^{N} w_{ij} \frac{\boldsymbol{x}_j(t) - \boldsymbol{x}_i(t)}{\left\|\boldsymbol{x}_j(t) - \boldsymbol{x}_i(t)\right\|}} + \boxed{w_{ii}(\boldsymbol{c}_i - \boldsymbol{x}_i(t))}$$

Target position

Degree of influence from fish j

Degree of moving toward fish i's own target

- Short-term ridge regression with constraints
  - Assume $w_{ij}(j \neq i), w_{ii}, \boldsymbol{c}_i$ are constant in a time window and estimate them with some constraints:
    - $w_{ij}(j \neq i), w_{ii} \geq 0$ (only "attraction")
    - $\frac{\dot{\boldsymbol{x}}_i{}^T(\boldsymbol{x}_j - \boldsymbol{x}_i)}{\|\dot{\boldsymbol{x}}_i{}^T\| \|(\boldsymbol{x}_j - \boldsymbol{x}_i)\|} \geq \cos\alpha$ (visual field)
    - $\dot{\boldsymbol{x}}_i{}^T(\boldsymbol{c}_i - \boldsymbol{x}_i) \geq 0, \boldsymbol{c}_{min} \leq \boldsymbol{c}_i \leq \boldsymbol{c}_{max}$ (target is in front & in the tank)



Estimation of Network Topology

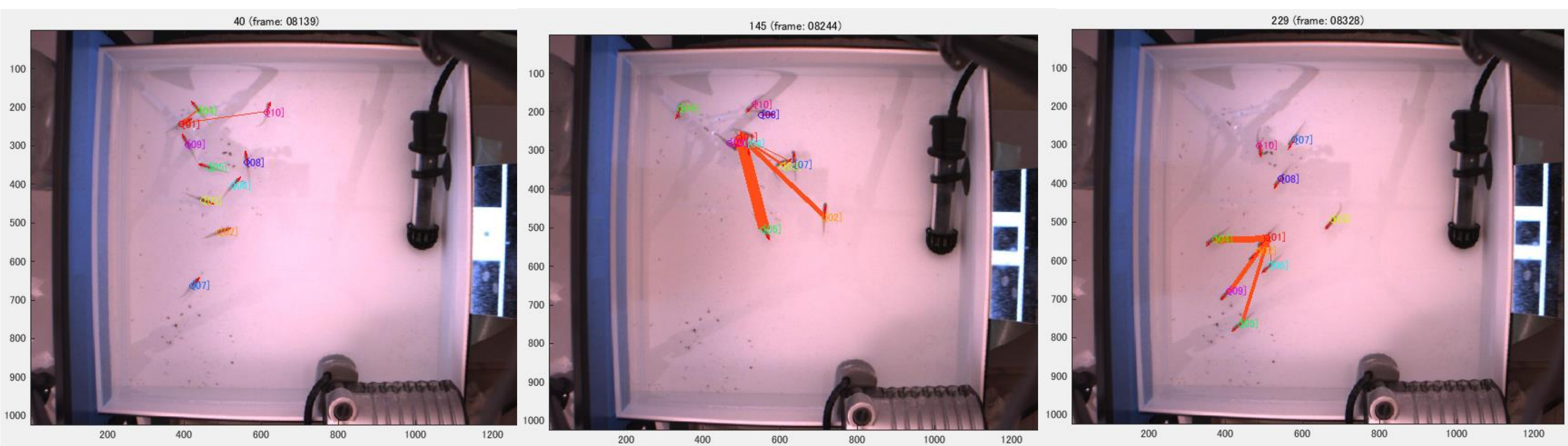
- How schooling behavior emerges?
  - Compare individuals using estimated weights $\{w_{ij}\}$

Coordination term

Autonomous term

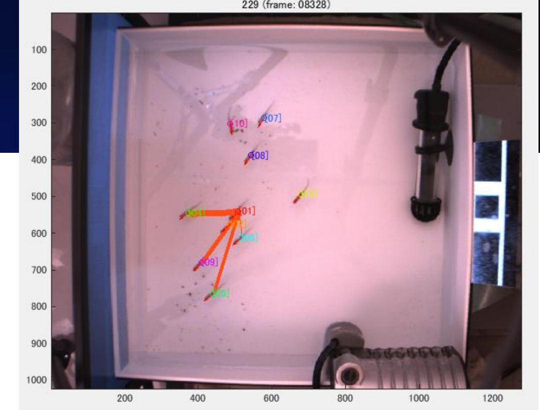
$$\dot{\boldsymbol{x}}_i(t+\tau) = \boxed{\sum_{j=1, j\neq i}^{N} w_{ij} \frac{\boldsymbol{x}_j(t) - \boldsymbol{x}_i(t)}{\left\|\boldsymbol{x}_j(t) - \boldsymbol{x}_i(t)\right\|}} + \boxed{w_{ii}(\boldsymbol{c}_i - \boldsymbol{x}_i(t))}$$

Target position



$i = 1$ (figures show weighted edges for only Fish#01)

Roles of Individuals?



- Coordinated vs. Autonomous

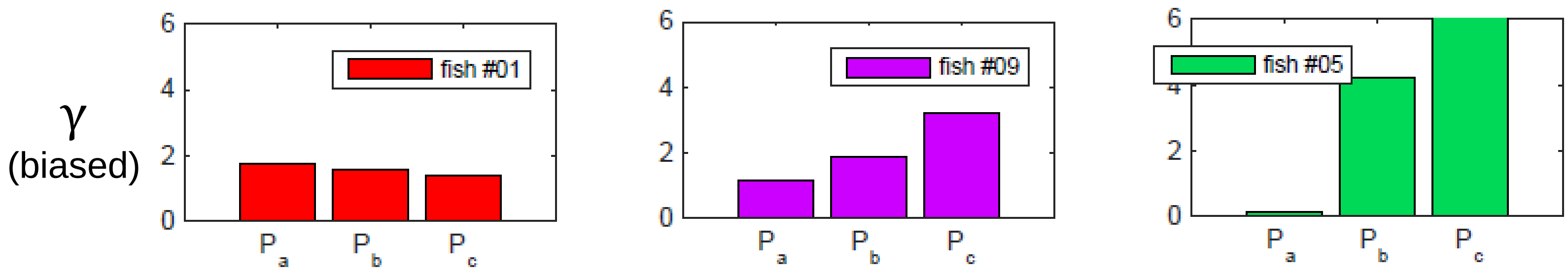
$$\gamma = \ln \frac{\boxed{\sum_{t \in P} w_{ii}(t)}}{\boxed{\sum_{t \in P} \sum_{j=1, j \neq i}^{N} w_{ij}(t)}}$$

P: time interval (part)

Coordination

Autonomous

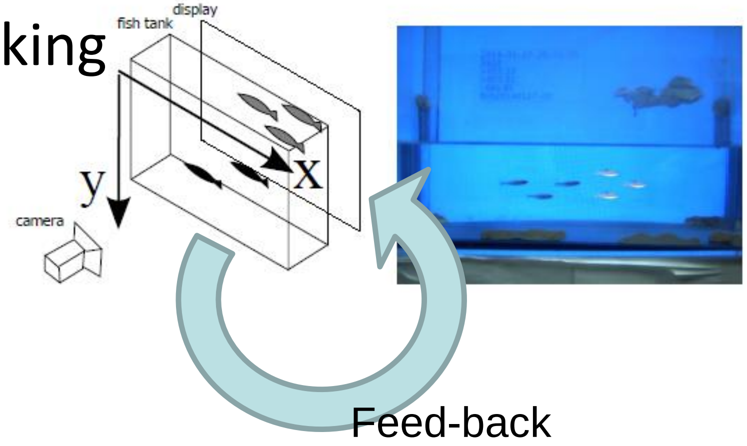
$$\dot{\boldsymbol{x}}_i = \boxed{\sum_{j=1, j \neq i}^{N} w_{ij} \frac{\boldsymbol{x}_j - \boldsymbol{x}_i}{\|\boldsymbol{x}_j - \boldsymbol{x}_i\|}} + \boxed{w_{ii}(\boldsymbol{c}_i - \boldsymbol{x}_i)}$$



Interval (frames)	Fish #1	Fish #9	Fish #5
P_a $(8100 - 8200)$	Low speed	Low speed	Auto. (w_{ii}) >> Coordination (w_{ij})
P_c $(8300 - 8400)$	Following others	Leading others	Leading others

Toward Control of Fish Group

- Introduce a framework of model estimation using visual stimuli and fish-group response
  - Design of visual stimuli + 2D tracking
    - Attractive, repulsive design
  - Estimation of interaction topology change

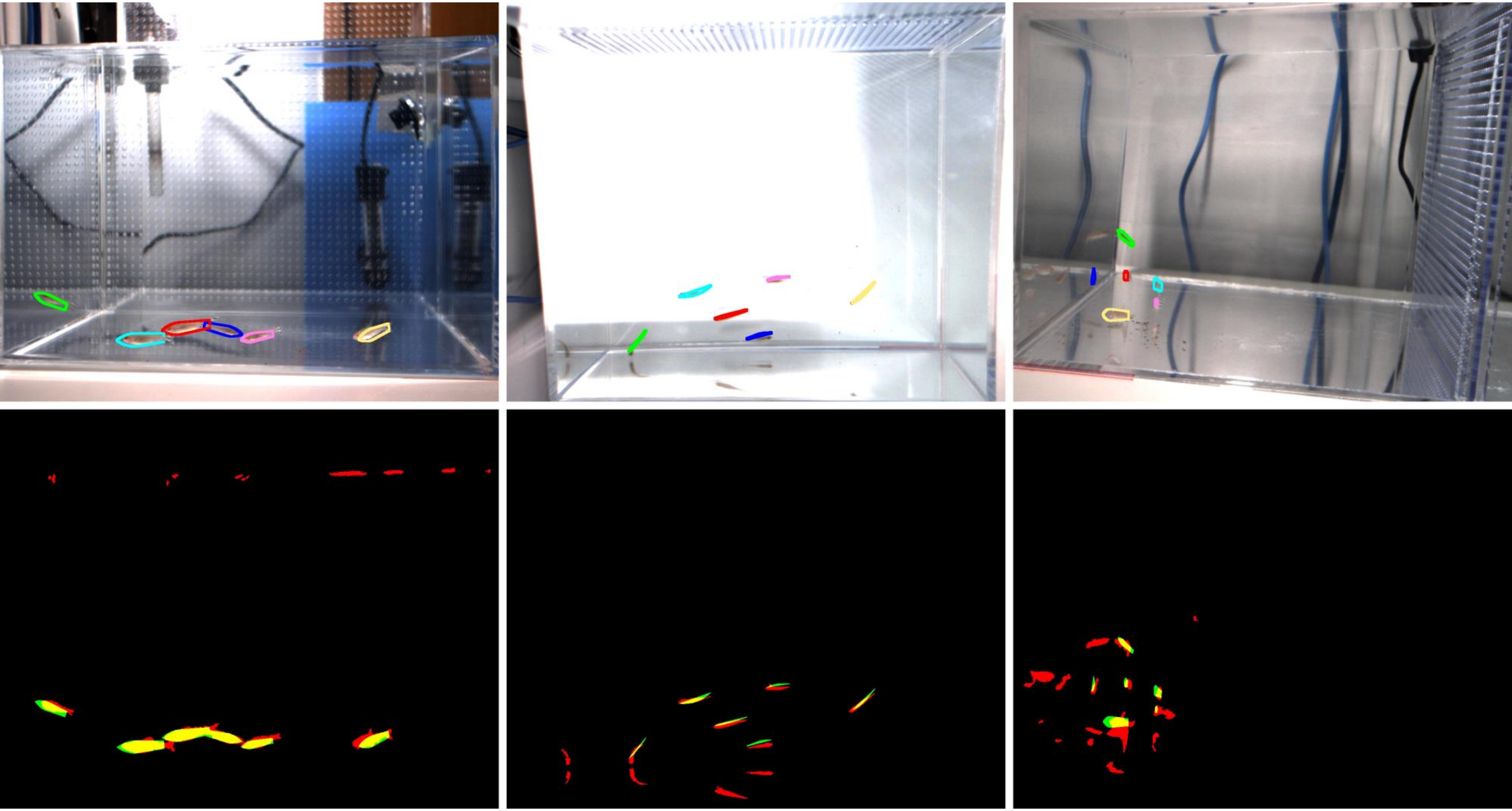


- Future work
  - Learning feed-back control of visual stimuli **reinforcement learning** and **behavior model (dynamics of w)**
  - Fish robots & 3D tracking → **Fish school navigation**

Thanks to Yu Kanechika (B4, M2 student; graduated 2014, 2016)

3D Tracking

- 2D tracking limits the area of group motion
  → 3D position & orientation (6 DOG) [Y. Zhong (M2) 2015]



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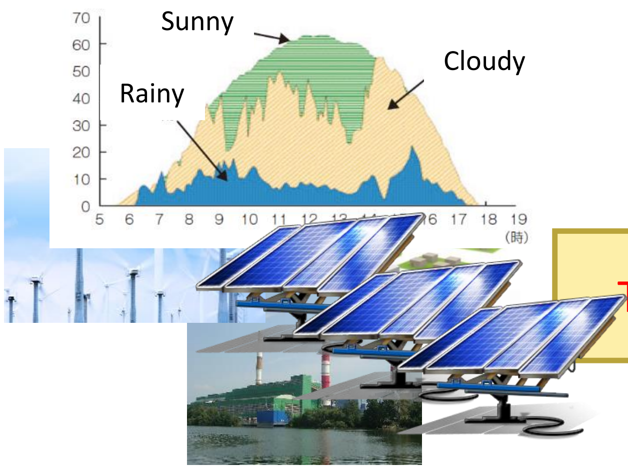
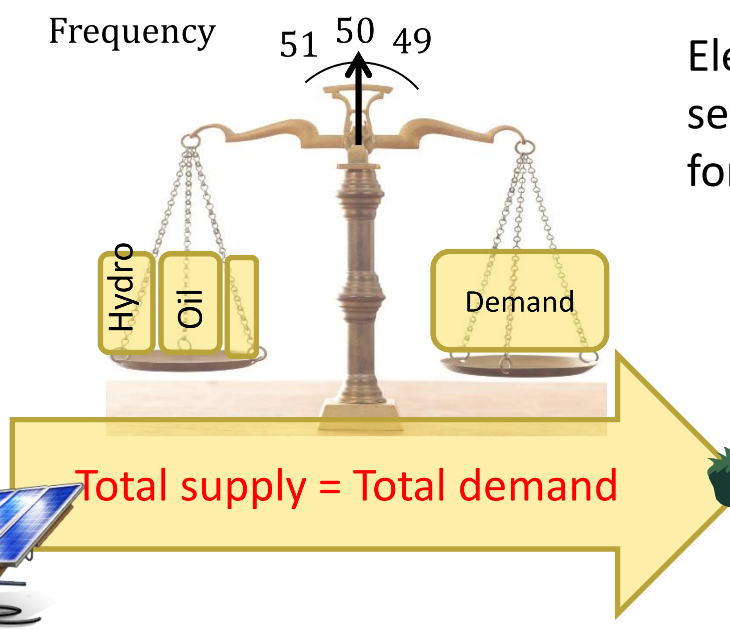
Coordinated Energy Management

Power Balancing

- Supply = Demand (+Loss) [W] should be satisfied for all time
  - If not, frequency (50/60Hz) cannot be maintained
- (In the future) Volatility of power supply & demand
  - Battery capacity is still limited (and expensive)

Solar & wind power strongly depend on weather, etc.





Electric Vehicle (EV) require several kW x several hours for daily charging

Relation between Supply and Demand

- Until now

Supply Side → Follow → Demand Side

Follows the total demand

Use electricity as much as they want

→ Many power plants are required only for peak periods (inefficient)

- Future

Supply Side ↔ Demand Side

Fluctuation of renewable energy

Become more flexible

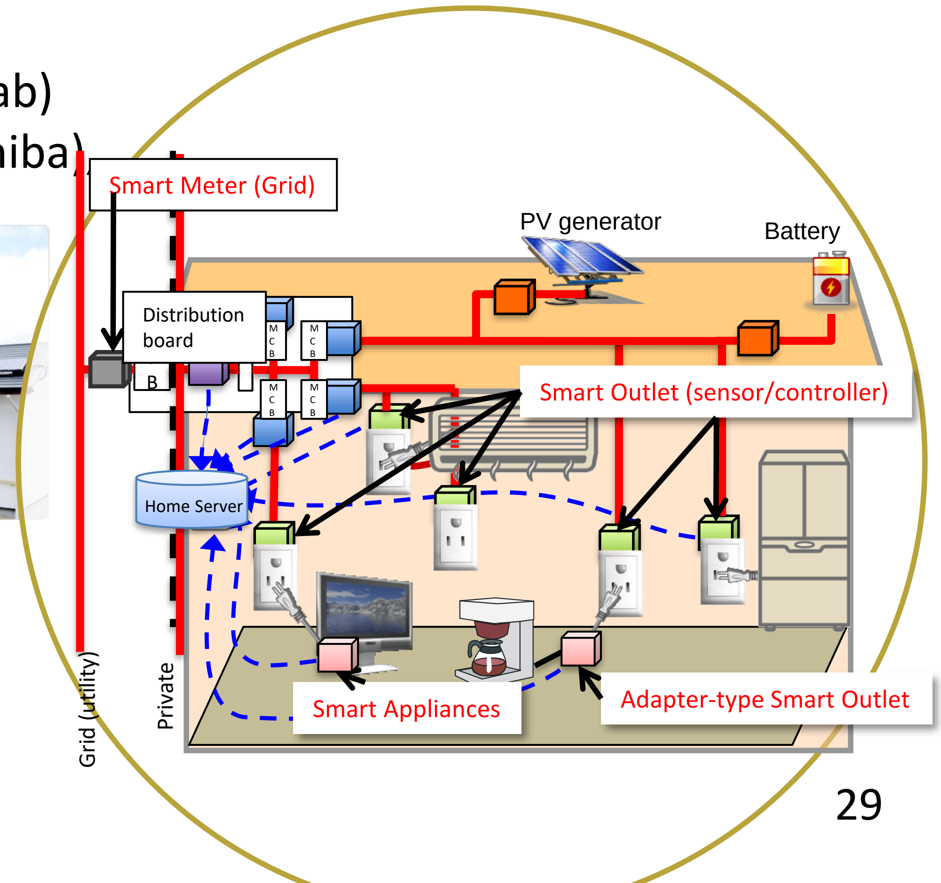
Controllers are installed to manage devices (e.g., A/C, EV) by considering supply side

Demand Side Management

End Users are going to be “Smart”

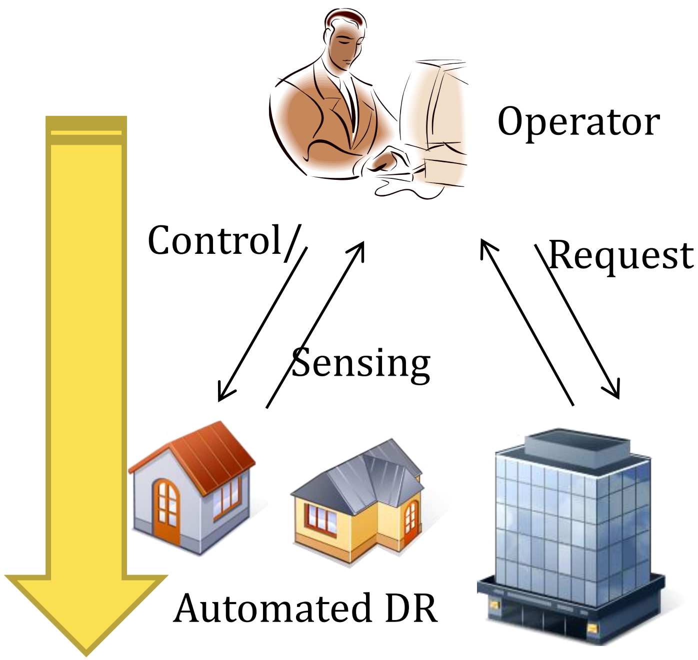
- End user: a unit of decision making for energy management
  - Household, office, factory, etc.
- Energy Management System (EMS) is installed
  - Smart meter, communication device, controller of appliances
- Prosumer: Producer + Consumer
- Autonomous (software) agents
  - Energy-on-Demand system (our lab)
  - AiSEG (Panasonic), Feminity (Toshiba)

Eco house in Kyoto
(From http://www.kyo-ecohouse.jp)

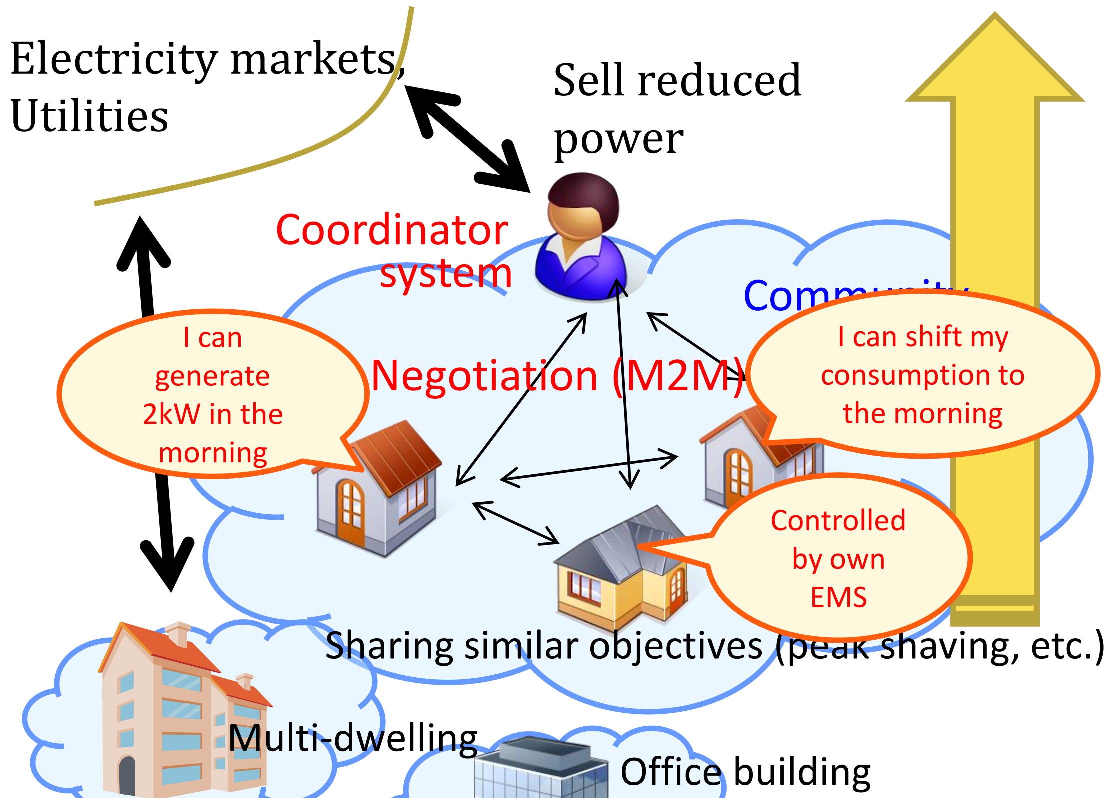


Coordination of End Users' EMS

- Demand Response



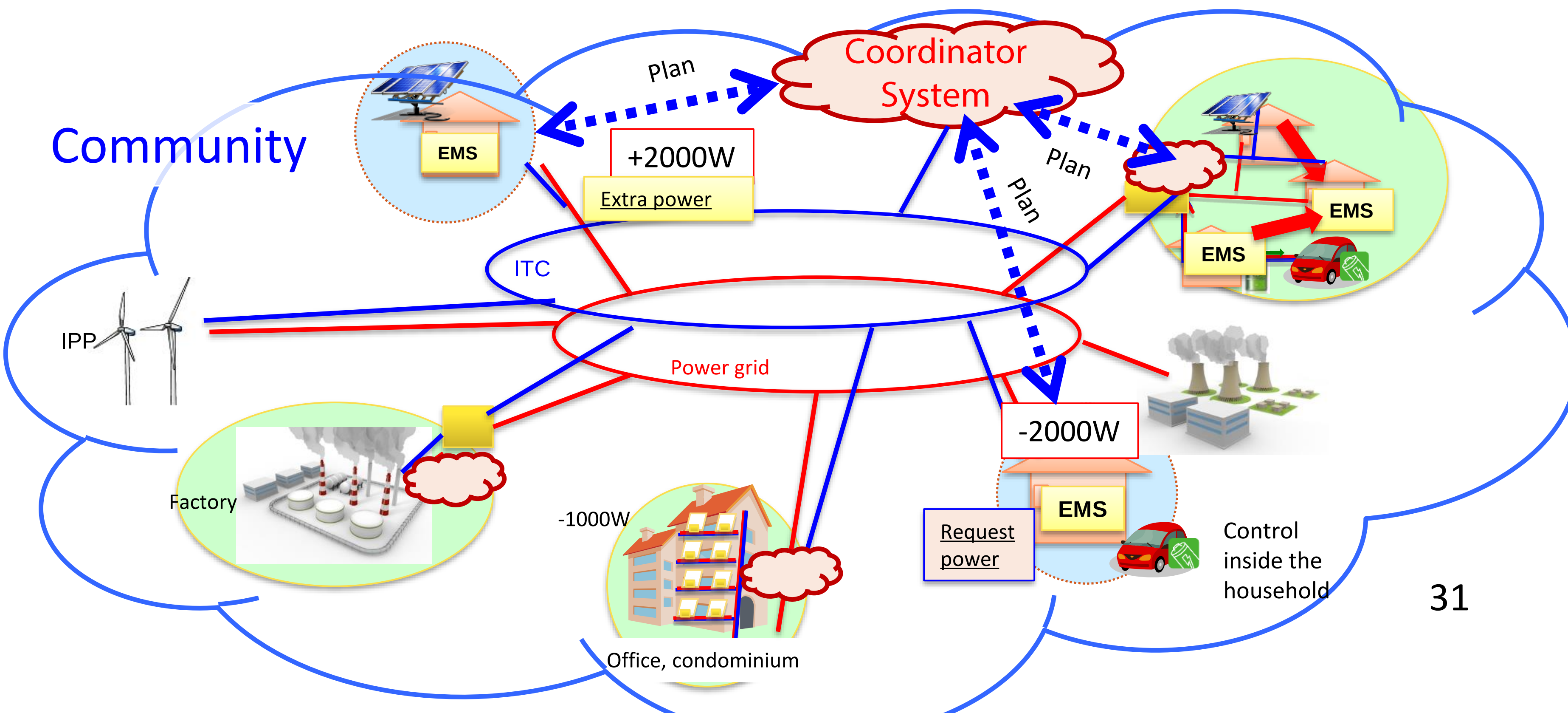
- Coordination as a community



Demand-side management "from demand side"

Community-based Coordination Scenario

- Distributed architecture
  - Each end user has own controller (EMS, software agent)
- EMS negotiate their plans via the coordinator
  1. Day-ahead scheduling (forecasting one day)
  2. Online coordination (no forecast)



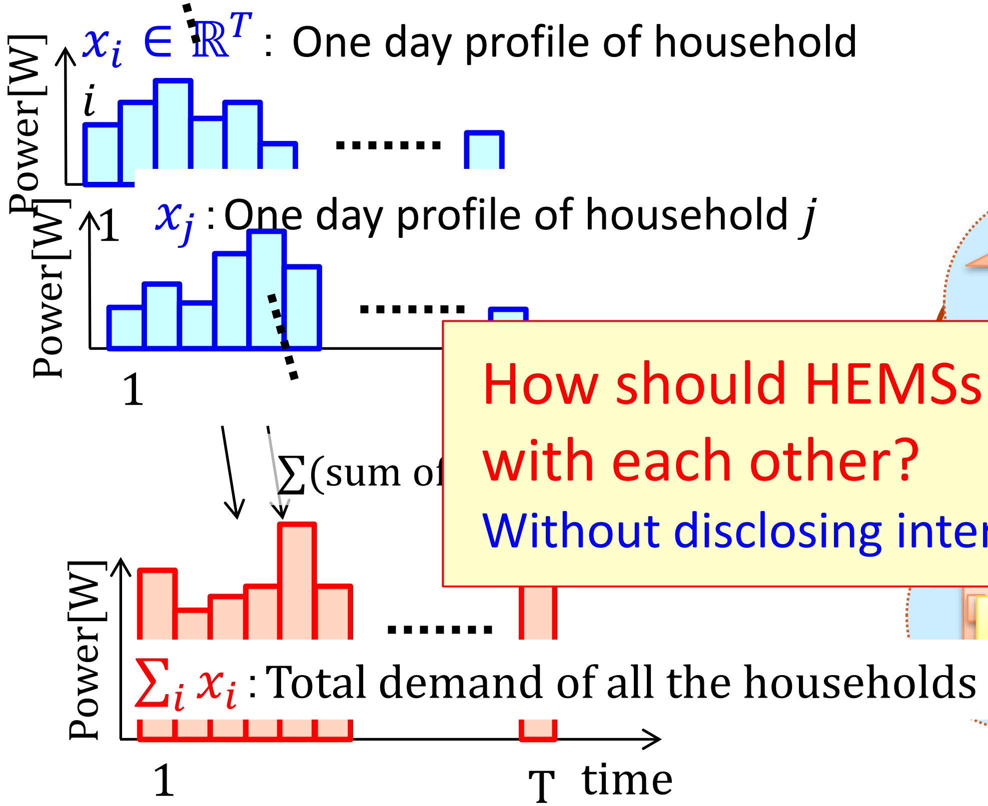
Multiple Objectives (Each Household & Group)

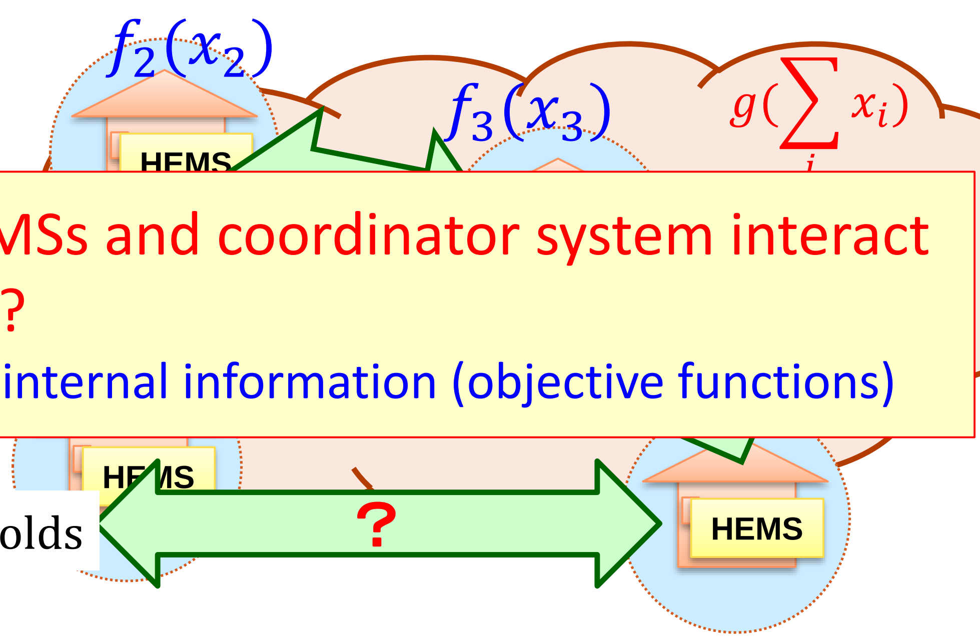
- Flatten the peak power while preserving each household's satisfaction:

$\sum_i$ Objective of household i $\quad f_i(x_i)$ Dissatisfaction (gap from normal consumption profile)

$+$Objective of the group $\quad g(\sum_i x_i)$ Penalty function for peak

→ minimize over x_i $(i = 1, \ldots, N)$





How should HEMSs and coordinator system interact with each other?

Without disclosing internal information (objective functions)

Idea1: Profile-based Distributed Optimization

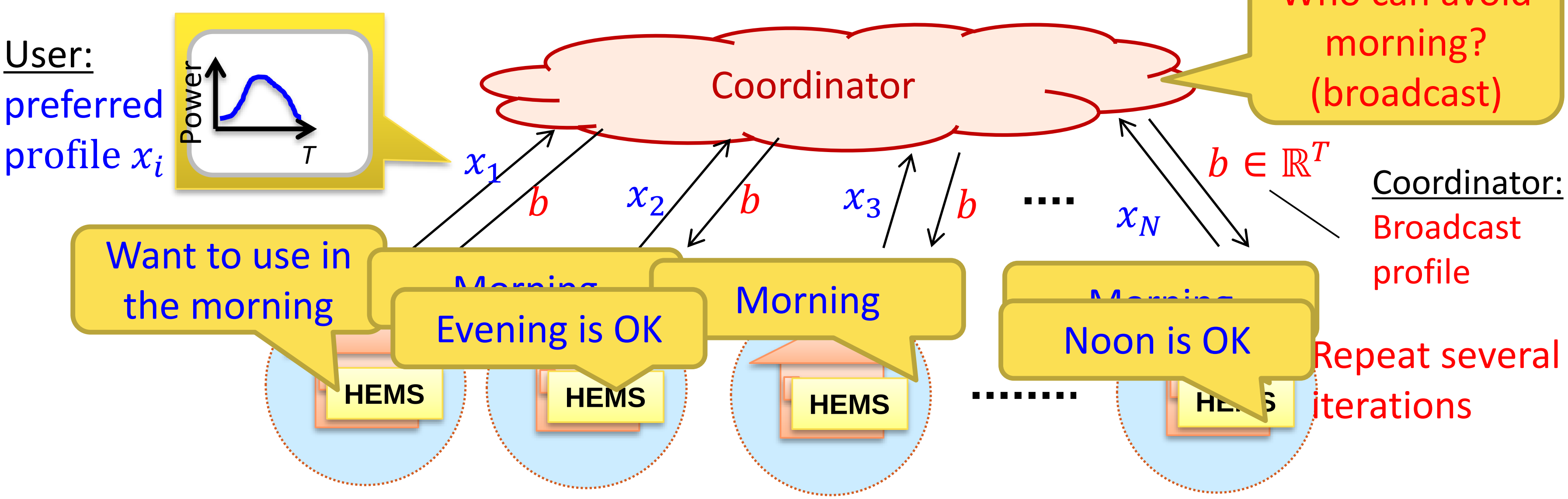
- Flatten the peak power while preserving each household's satisfaction :

$$\underset{x_1,\dots,x_N}{\text{minimize}} \quad \sum_i \boxed{f_i(x_i)} + \boxed{g\left(\sum_i x_i\right)}$$

Dissatisfaction of using x_i — Penalty function for peak

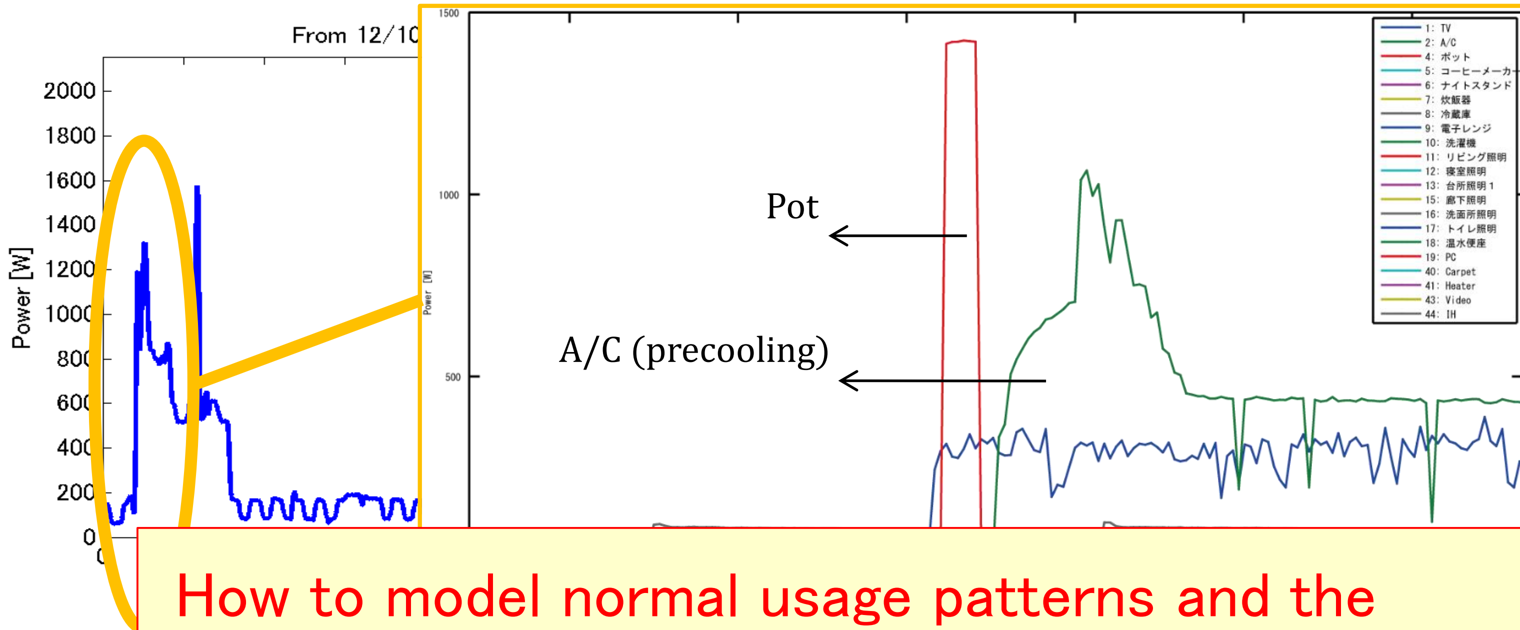
- Coordination of distributed controllers (autonomous agents)
  - Each household does not disclose their objective function f_i
  - ☺ Scalable; can integrate different types of EMS; avoid some privacy issues

Profile-based negotiation to find best plan $x_i (i = 1, \dots, N)$



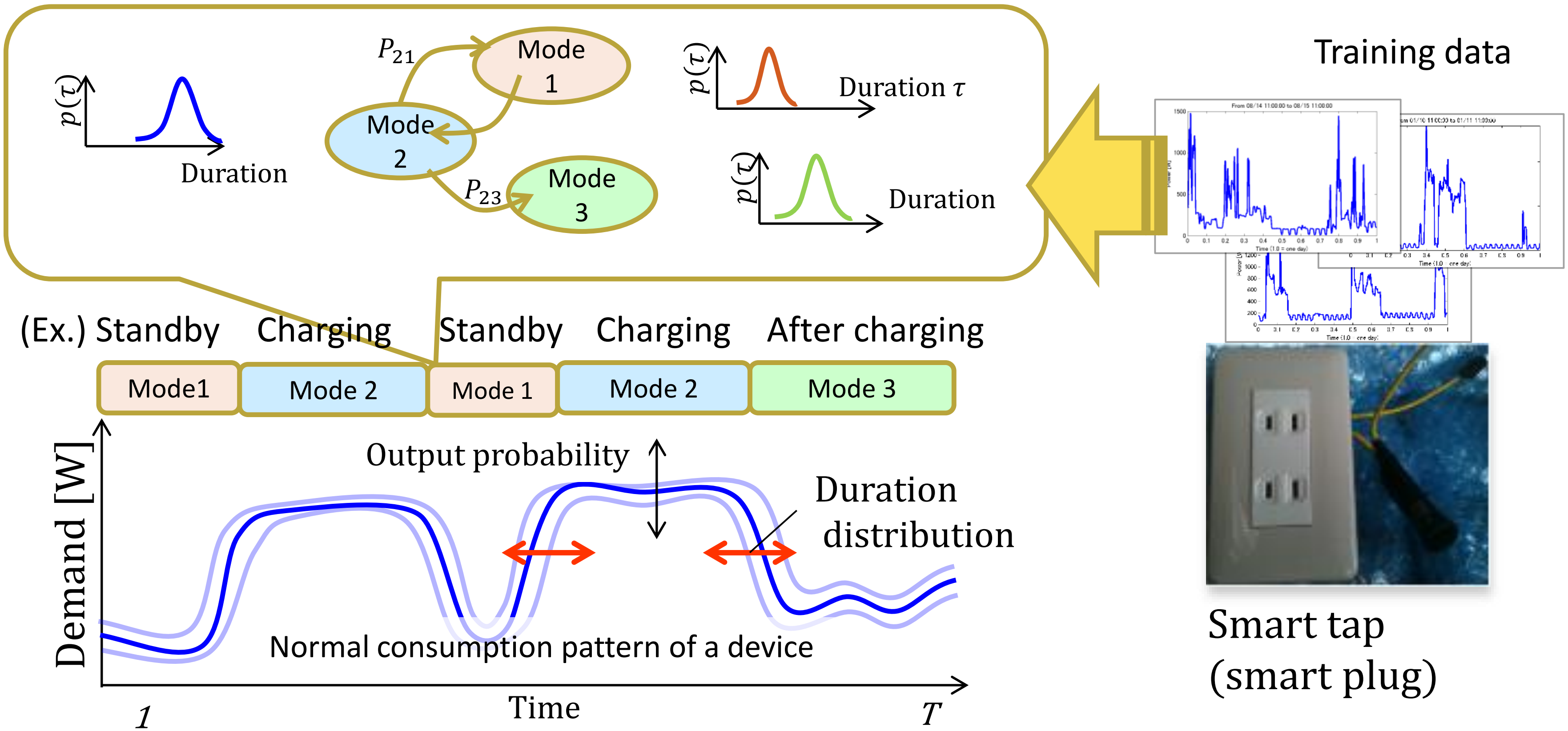
Control in a Household

- Change of device usage: time shift & power level
- We focus on time shift (scheduling) of appliance usage in a household as it has a large effect in power flattening
  - (Ex.) EV charging, A/C, dryer, dish washer, rice cooker



How to model normal usage patterns and the flexibility of changing it in each household?

Idea 2: Probabilistic Model of Usage Timing



- Hidden Semi-Markov Model (used in speech generation) [黒瀬+ 2013]
  - Can model the flexibility of time-shift (“mode switching” timing)
  - All the model parameters can be learned from daily usage data

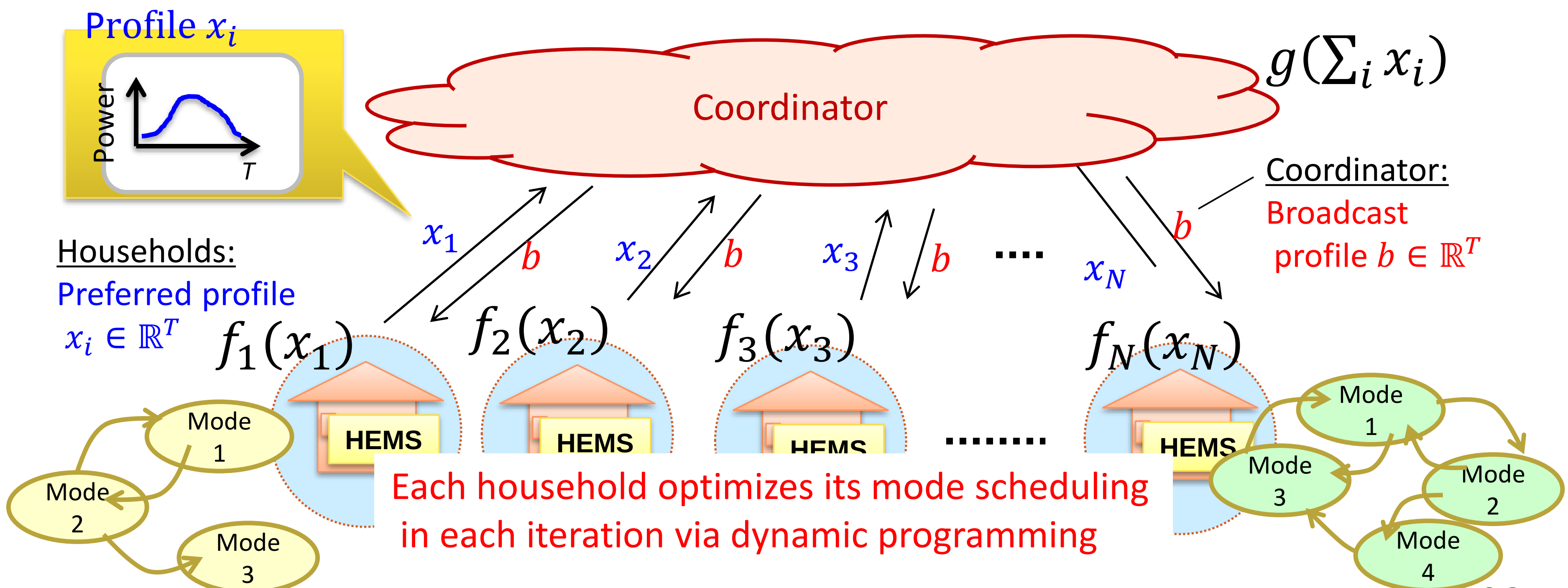
Distributed Mode Scheduling

[Kawashima, et al. *SmartGridComm2013*]

- Flatten the peak power while preserving each household's satisfaction

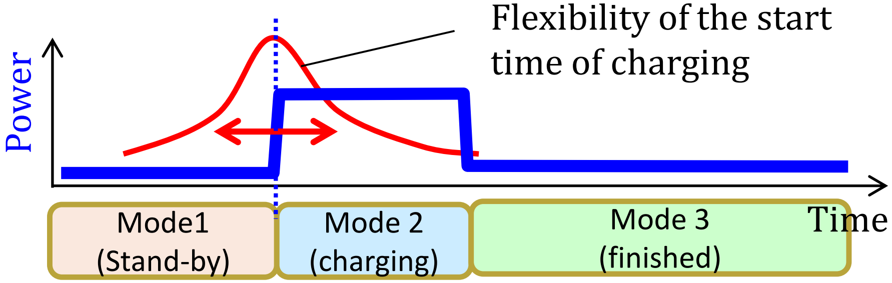
$$\underset{x_1,\dots,x_N}{\text{minimize}} \sum_i f_i(x_i) + g\left(\sum_i x_i\right)$$

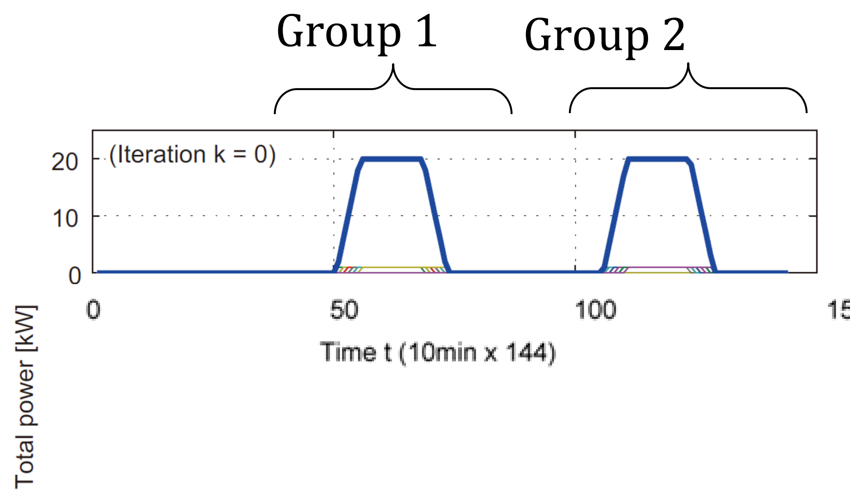
- Household need to send only their profiles
  - The coordinator do not need to know each objective function



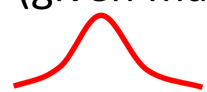
Simulation (Day-ahead Scheduling)

- PHEV charging
  - 1kW x 3hours in a day

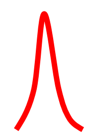




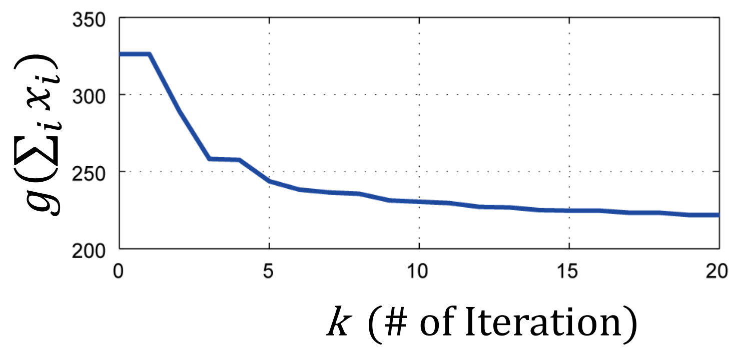
- Two groups with different flexibility (given manually)
  - Group 1 (20 households)
    - Large flexibility of changing the start time



  - Group 2 (20 households)
    - Small flexibility



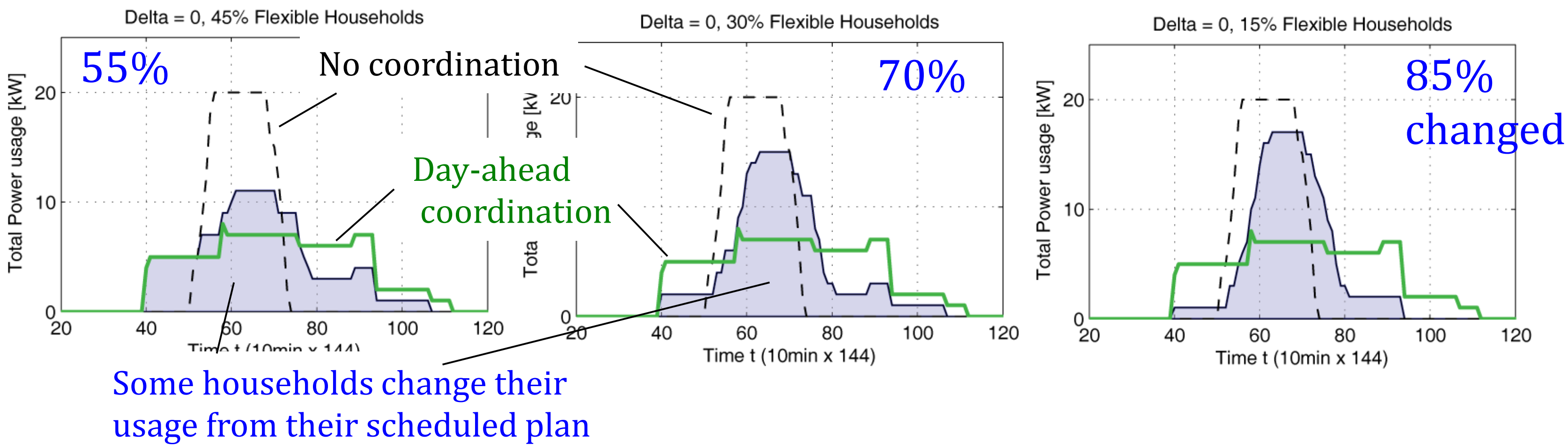
- Result
  - Almost converge with in 20 iterations
  - Realize group objective (peak shaving) while taking into account users' flexibility



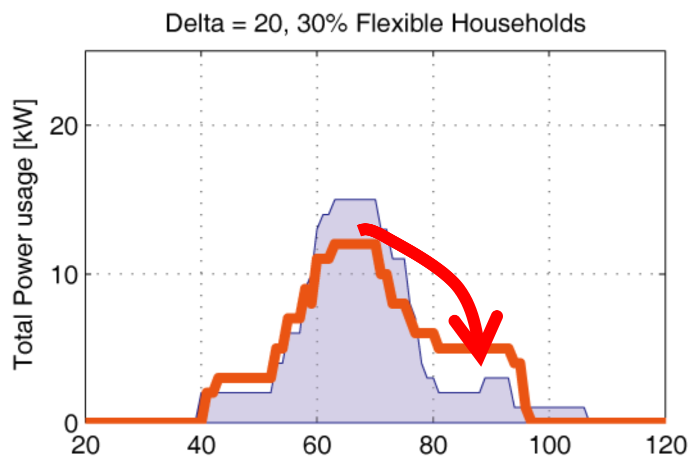
Simulation (Online Negotiation)

[Verschae+ 2014]

- Some households do not follow the schedule



- Online coordination
  - Other households compensate the changes using online negotiation via the coordinator



Summary

- Power balancing is crucial for electrical grid
  - Supply = Demand (+Loss) [W] should be satisfied for all time
  - Electricity is difficult to store (battery capacity is limited)
- In future, demand-side management will be important

→ This is essentially a multi-objective optimization
  - Users have their objective (e.g., maintain their quality of life)
  - Community has an objective (e.g., reduce the total peak)

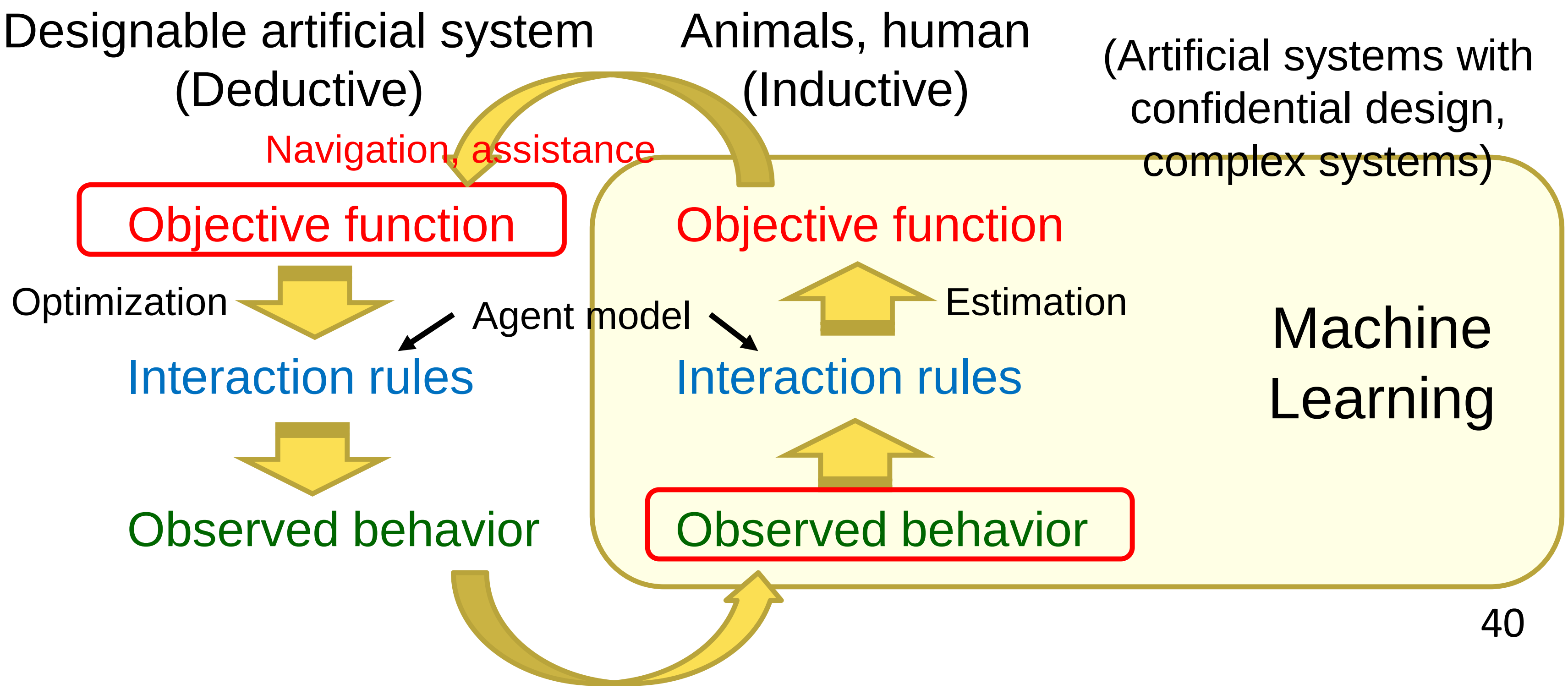
Using distributed optimization, we can decompose user-side optimization and community-level optimization.

Global optimization → Local optimizations + Communication

→ Possible to design flexible coordination

Controlling Distributed Cooperative Systems

- Controlling collective behaviors
  - Leader-follower control of mobile robots and fish school
- Designing distributed cooperative systems
  - Distributed optimization of energy management systems



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