Hierarchical Collaborative Control of UVs: Stochastic Potentials, Parallel Gibbs, NMPC

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A battle field scenario

Mission

Autonomous, distributed maneuvering of a vehicle group to reach and cover a target area

Constraints

Desired inter-vehicle distance

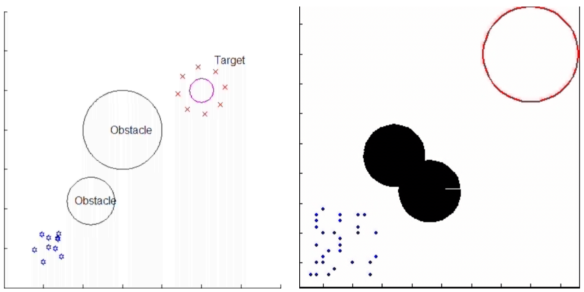
Obstacles avoidance

Threats (stationary or moving) avoidance

Requirement

Using only local or static information

Being trapped by local minima

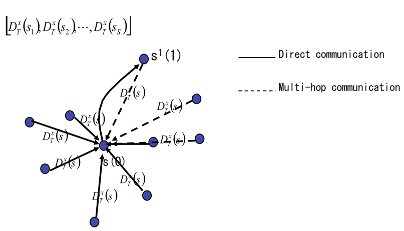


Gibbs sampler based algorithm

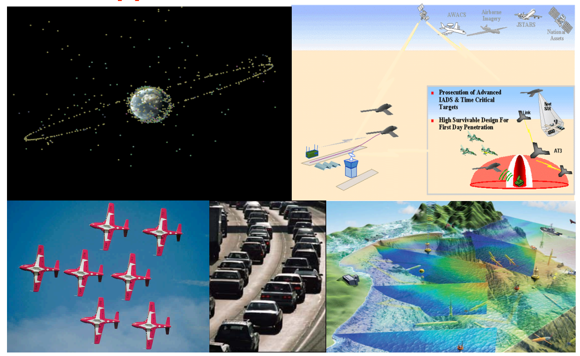
Step 1. ***Initialization.*** Pick a cooling schedule $T(n)$ and ☒. Pick arbitrary agent s(0). Let all agents calculate $D_T^x(s)$, and send to s(0). The initial ***proposal distribution*** can then be evaluated by

$$G_{T(1)}^{x(0)}(s) = \frac{D_T^x(s)}{\sum_{s'} D_{T(1)}^{x(0)}(s')} \qquad D_T^x(s) = \sum_{z\in N_m^x(s)} e^{-\frac{\Phi_s(z)-\Phi_s(x)}{T}}$$

Agent s(0) then selects an agent s¹(1) by sampling the ***proposal distribution***, and sends the vector $\left[D_T^x(s_1), D_T^x(s_2), \cdots, D_T^x(s_S)\right]$ to s¹(1)



Applications of UAV swarms



Step 2. ***Update the select agents.*** Agent $s^k(n)$ updates its location by sampling its local characteristics.

$$P(x_s = l) = \frac{e^{-\Phi(x_s = l, x_{S\setminus s})/T}}{\sum_{l'\in C_m^s} e^{-\Phi(x_s = l', x_{S\setminus s})/T}}$$

where C_m^s is the set of candidate locations node s can take.

Step 3. ***Selecting the next agent.*** The agent $s^k(n)$ thus collects and updates $D_{T(n)}^{x^k(n)}(s)$ from neighboring nodes. Let $k = k+1$. If k = ☒, let $k = 0$ and $n = n+1$. The current agent evaluates and samples new ***proposal distribution***, selects the next agent to be updated.

Step 4. If $n < N_{max}$, go to Step 2; otherwise quit.

Note: *Local move only affects the local potential evaluation of nodes within sensing range due to $R_m + R_i$ ☒ R_s. This implies agents $s^k(n)$ can update $\left[D_T^x(s_1), D_T^x(s_2), \cdots, D_T^x(s_S)\right]$ locally by communicating with "neighbor"*

Asynchronous Sampling

Synchronous Parallel Sampling

Require global clock to synchronize movement

Asynchronous Parallel Sampling

Agents move based on their own schedule

Less stringent, more flexible

Hard to analyze

Results – Methods

- Stochastic potential based approach guarantees global objective can be achieved by simple local strategies
- The parallel sampling algorithm saves running time compared with the sequential sampling algorithm
- Asynchronous sampling eliminates the need of synchronization, which further reduces the overhead
- Convergence analysis shows that under certain conditions, parallel sampling algorithm leads to desired group configuration

Hierarchical Collaborative Control Scheme

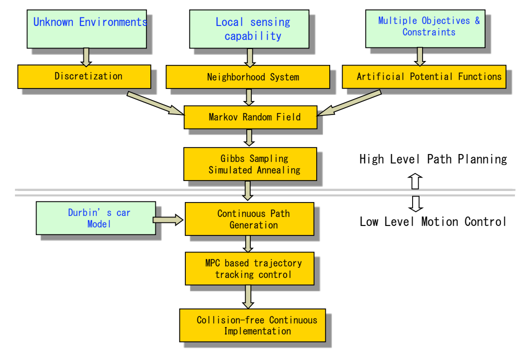
High level path planning (macro level)

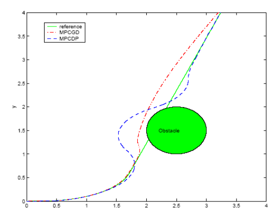
- Generate desired way-points
- Achieve group objectives
- Simplified vehicle dynamics (point mass)

Low level motion control (micro level)

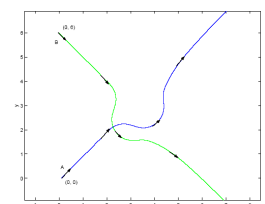
- Generate continuous trajectory
- Track follow desired trajectory
- Consider real vehicle dynamics

Collaborative Control Hierarchical Framework





Obstacle avoidance



Collision avoidance

Results-Methods

- Hierarchical framework can separate the collaborative control design into two levels:
  - Collaborative path planning for achieving collective behavior
  - Local motion control to deal with local traffic, unpaved road, actuator saturation, etc.
- NMPC base approach provide a general frame work to deal with multiple constraints and objectives
- Two numerical methods were investigated