# Value-of-Information Aware Active Task Assignment

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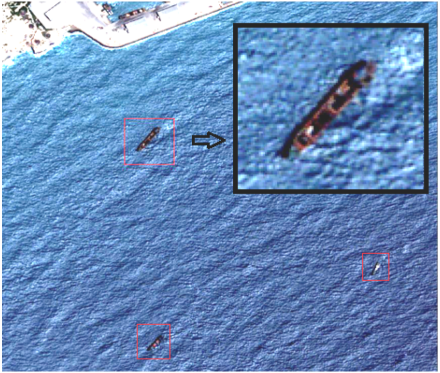
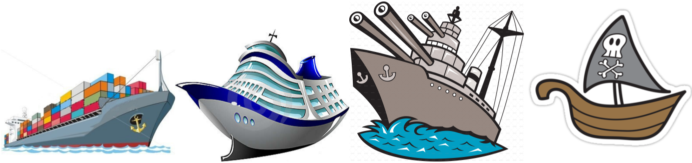
# Motivation



Multiple Targets

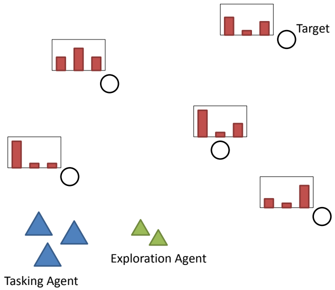
- **Mult-target, multi-vehicle System**:
  - Uncertainty in targets
  - Mission return affected by uncertainty
  - Heterogeneous vehicles, exploration & exploitation
  - System constraints, e.g. position, velocity, fuel, time



# Vechile Assignment Problems

- **Problem**: Assign heterogeneous Unmanned Vehicles (UV) to multiple targets to maximize mission score in an uncertain environment

- **Contributions:**
  - Develop algorithms that assign heterogeneous vehicles (Exploration and Tasking) simultaneously
  - Couple exploration into mission return
  - Use CBBA to incorporate system constraints
  - Develop a hardware testbed




Multi-agent Assignment

## Robust UV Planning

- Mathematical programming [1, 2]. e.g. assign task vehicles (TV) to maximize collected score

$$\max \sum_{i=1}^{N} f(C_i) x_i \quad \text{s.t.} \quad \sum_{i=1}^{N} x_i \leq n$$

  - $C_i$ is the probability distribution of target $i$'s score at time $k$
  - $x_i \in \{0, 1\}$ indicates whether a UV is assigned to do tasks at target $i$
  - $f(C)$ map probability distribution to score

- If score is deterministic & known, can use integer programming
- With uncertainty in the score, can use various metrics:
  - Expected score [3]
  - Worst case score [4]
  - Expected offset by standard deviation [2]
  - Chance constraint [5–7]

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# Uncertainty Reduction by Exploration

- Dedicate **Exploration Vehicles** (EV) exist to take observations
  $\Rightarrow$ uncertainty reduced, performance improved
- **EV assignment**: sensor management [8–12] $\Rightarrow$ **expected posterior**
  - Uncertainty propagation $p(C_i|z_i) = \dfrac{p(z_i|C_i)p(C_i)}{\int p(z_i|C_i)dp(C_i)}$
  - Uncertainty measure: $g(C_i) \Rightarrow g(C_i|z_i)$
  - $z_i$ unknown $\Rightarrow$ expected posterior score

$$\mathbb{E}_{z_i}[g(C_i|z_i)] = \int g(C_i|z_i)dp(z_i)$$

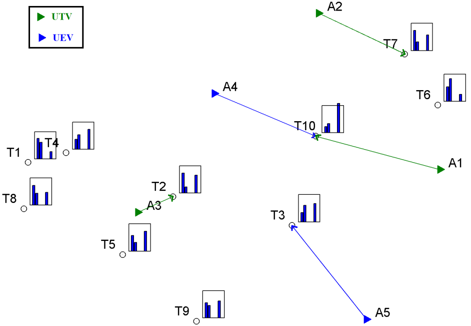
  - Assign EV based on uncertainty reduction

$$\max \sum_{i=1}^{N} (g(C_i) - g(C_i|z_i))\, y_i \quad \text{s.t.} \quad \sum_{i=1}^{N} y_i \le m$$

    - $y_i \in \{0, 1\}$ denote whether a EV is assigned to target $i$

# Assignment of Heterogeneous Vehicles [2]

- **Decoupled Assignment**
  - Assign **Tasking Vehicle** (TV) to maximize score
  - Assign **Exploration Vehicle** (EV) to maximize uncertainty reduction




Assignments of Tasking/Exploration Vehicles in a **decoupled way**

- TVs and EVs are assigned to different targets
- Exploration by EV does not necessarily help TV obtain higher score

# Value of Information based Exploration

- **Key idea: couple** exploration to task scores $\Rightarrow$ expected score

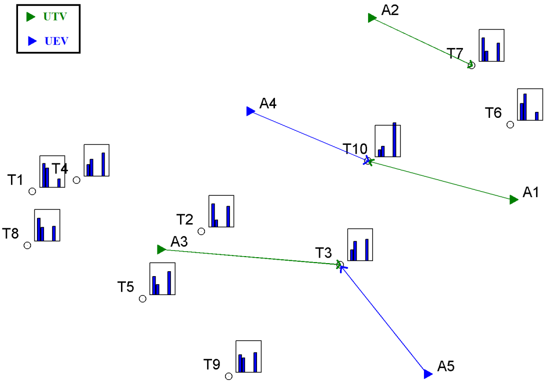
$$\mathbb{E}_{z_i}\left[f(C_i|z_i)\right] = \int f(C_i|z_i)dp(z_i)$$

- **Value of Information** based exploration
  - Exploration adds value only when a TV is also assigned to the target
- **Value of Information based Task Assignment**

$$\begin{aligned} \max \quad & \sum_{i=1}^{N} \mathbb{E}_{z_i} f(C_i|z_i)x_i y_i + f(C_i)x_i(1-y_i) \\ \text{s.t.} \quad & x_i, y_i \in \{0,1\} \\ & \sum x_i \leq n \\ & \sum y_i \leq m \end{aligned} \tag{1}$$

  - $f(C)$ map a probability distribution to a score
  - $z_i$ denote a measurement of target $i$

# VoI based Active Task Assignment




Assignments of Tasking/Exploration Vehicles in a **coupled way**

- Assignments of EVs are coupled into assignments of TVs ⇒ EVs and TVs are paired up
- EVs can always help TVs to reduce uncertainty and thus get higher score

# Consensus-Based Bundle Algorithm (CBBA)

## System dynamics and constraints

- Various features
  - e.g. Location, speed
- Cooperation put extra constraints
  - EV finish exploration before TV starts task
- Integer programming ⇒ combinational number of candidate solutions

## CBBA

- Given agents and tasks features, give agent-task assignment pairs

## Feature

- incorporate system dynamics
- decentralized
- polynomial in number of targets and vehicles

Input

| | |
|---|---|
| Agent | UV ID<br>UV location<br>speed |
| Task | task ID<br>task location<br>start time<br>duration<br>max score |

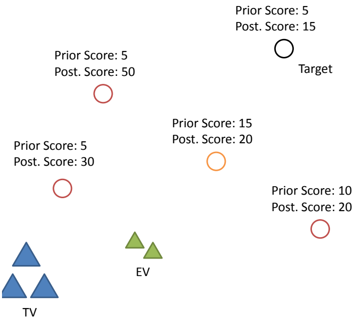
Output

| | |
|---|---|
| Assignment | UV ID<br>task ID<br>stat time |

# VoI based Coupled Planning using CBBA

**Algorithm 1** VoI Based Coupled Distributed Planning

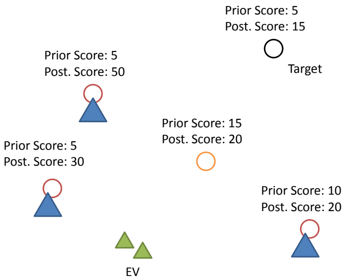
initialize candidate solution queue $Q$
**while** UTV requirement not satisfied **do**
  $\mathcal{P}$ = nextBestCandidate($Q$)
  $Q = \{Q,$ sub-candidates$(\mathcal{P})\ \}$
  call CBBA to assign UTVs
    $\mathcal{A}_T$ = CBBA$(\mathcal{P}, agents, tasks)$
  call CBBA to assign UEVs
    $\mathcal{A}_E$ = CBBA$(\mathcal{A}_T, agents, tasks)$
  check whether UTV requirement
    checkMatch$(\mathcal{A}_T, \mathcal{A}_E)$
**end while**
return $\mathcal{A}_T$, $\mathcal{A}_E$



# VoI based Coupled Planning using CBBA

**Algorithm 2** VoI Based Coupled Distributed Planning

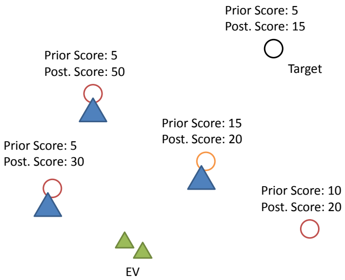
initialize candidate solution queue $Q$
**while** UTV requirement not satisfied **do**
    $\mathcal{P}$ = nextBestCandidate($Q$)
    $Q = \{Q,$ sub-candidates($\mathcal{P}$) $\}$
    call CBBA to assign UTVs
        $\mathcal{A}_T$ = CBBA($\mathcal{P}, agents, tasks$)
    call CBBA to assign UEVs
        $\mathcal{A}_E$ = CBBA($\mathcal{A}_T, agents, tasks$)
    check whether UTV requirement
        checkMatch($\mathcal{A}_T, \mathcal{A}_E$)
**end while**
return $\mathcal{A}_T$, $\mathcal{A}_E$



# VoI based Coupled Planning using CBBA

**Algorithm 3** VoI Based Coupled Distributed Planning

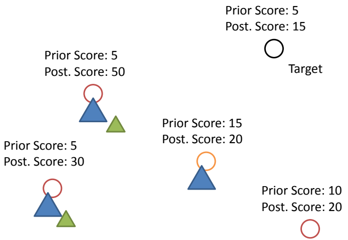
1: initialize candidate solution queue $Q$
2: **while** UTV requirement not satisfied **do**
3: $\mathcal{P}$ = nextBestCandidate($Q$)
4: $Q = \{Q,$ sub-candidates($\mathcal{P}$) $\}$
5: call CBBA to assign UTVs
6: $\mathcal{A}_T$ = CBBA($\mathcal{P}, agents, tasks$)
7: call CBBA to assign UEVs
8: $\mathcal{A}_E$ = CBBA($\mathcal{A}_T, agents, tasks$)
9: check whether UTV requirement
10: checkMatch($\mathcal{A}_T, \mathcal{A}_E$)
11: **end while**
12: return $\mathcal{A}_T$, $\mathcal{A}_E$



# VoI based Coupled Planning using CBBA

**Algorithm 4** VoI Based Coupled Distributed Planning

initialize candidate solution queue $Q$
**while** UTV requirement not satisfied **do**
    $\mathcal{P}$ = nextBestCandidate($Q$)
    $Q = \{Q,$ sub-candidates($\mathcal{P}$) $\}$
    call CBBA to assign UTVs
        $\mathcal{A}_T$ = CBBA($\mathcal{P}, agents, tasks$)
    call CBBA to assign UEVs
        $\mathcal{A}_E$ = CBBA($\mathcal{A}_T, agents, tasks$)
    check whether UTV requirement
        checkMatch($\mathcal{A}_T, \mathcal{A}_E$)
**end while**
return $\mathcal{A}_T$, $\mathcal{A}_E$

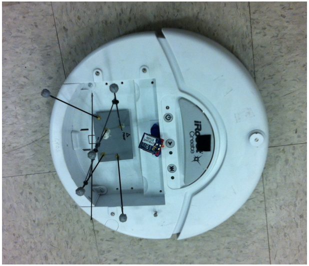


# Hardware Testbed Overview


robot system in the MIT Aerospace Control Laboratory [13]

# Vehicles

**TV**

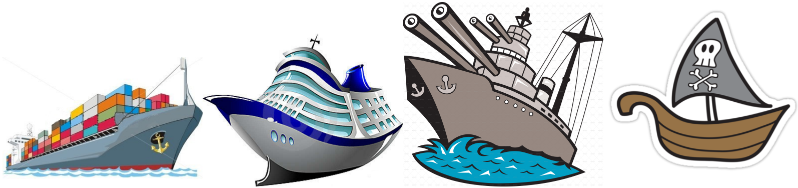


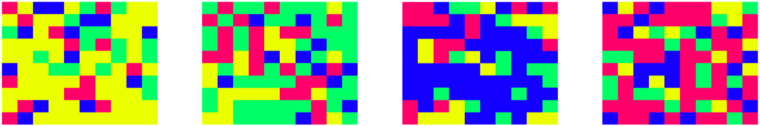

- iRobot *Create*
- Communicate with the controller computer using Xbee

**EV**

- P5512 security camera
- Tune pan/tilt/zoom to focus on different ground points
- Move from one point to another takes time, speed can be specified

# Targets

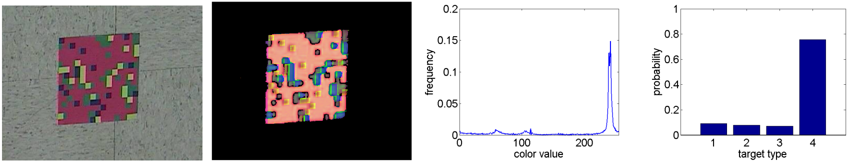




Target Uncertainty

- Colored papers glued on the floor
- Dominant color represents target classification
- Non-dominant color creates noise and uncertainty

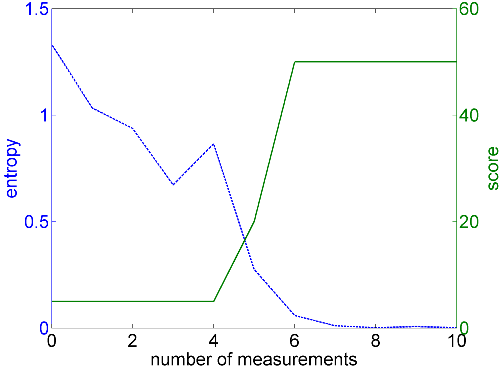
# Measurement Model




(a) camera picture (b) target hue (c) color histogram (d) class prob.

- Camera randomly reports a pixel of the camera picture as a measurement of the classification
- Probability of report 4 (yellow, green, blue, red) classifications
  - Filter background and extract hue values, figure (b)
  - Count the occurence of hue values, figure (c)
  - Map hue values into classification, figure (d)

# Effect of Measurements




- Measurement not perfect ⇒ uncertainty reduced but non-zero by one observation
- Uncertainty further reduced by more measurements
- Longer dwell time ⇒ more measurements ⇒ less uncertainty ⇒ higher score

# Execution Result

Planning Algorithm Performance Comparison

| Decoupled | | | | Coupled | | | |
|---|---|---|---|---|---|---|---|
| Target | Score | Entropy | Time(sec) | Target | Score | Entropy | Time(sec) |
| T02 | 5 | 0.6599 | 17.1 | T08 | 50 | 0.1663 | 13.1 |
| T06 | 5 | 0.6599 | 20.3 | T05 | 50 | 0.1663 | 29.9 |
| T07 | 5 | 1.0336 | 30.0 | T03 | 30 | 0.1663 | 48.3 |
| T05 | 50 | 0.1663 | 65.4 | T10 | 20 | 0.0001 | 70.4 |
| T08 | 50 | 0.1663 | 82.1 | T09 | 20 | 0.0007 | 89.0 |
| T10 | 20 | 0.1663 | 88.0 | T02 | 20 | 0.1225 | 97.2 |
| T03 | 30 | 0.0587 | 108.4 | T06 | 20 | 0.0569 | 110.8 |
| T04 | 20 | 0.0357 | 114.3 | T07 | 5 | 0.0149 | 122.4 |
| T01 | 5 | $10^{-4}$ | 123.8 | T04 | 20 | 0.0003 | 135.9 |
| T09 | 20 | $10^{-10}$ | 152.3 | T01 | 5 | 0.0003 | 142.8 |

- **Mean entropy**: **decoupled** 0.2947; **coupled** 0.0695
- **Total score**: **decoupled** 210; **coupled** 240
- **Decoupled** slowly finds the most rewarding targets
- **Coupled** approach most rewarding targets from the beginning, because it coordinates EV to take measurements first.

# Conclusion and Future Work

## ▶ Conclusion

- Based value of exploration on mission goals
- Coupled exploration into mission assignments
- Implemented VoI based coupled planning algorithm in a distributed framework using CBBA
- Developed a hardware testbed to compare the coupled and decoupled approaches

## ▶ Future Work

- Target Detection
  - number and location of targets is unknown
- Dynamics in targets
  - e.g. moving targets where uncertainty of targets may change with time
- Extend to information gathering

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