Towards situational awareness and task allocation in mixed networks

Center Kickoff Meeting
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Background

DoD funding since 2001:

(i) formal models of robotic networks

(ii) deployment algorithms
ground vehicles in nonconvex urban environments

(iii) rendezvous/formation control algorithm

(iv) task allocation: dynamic, nonholonomic aspects

(v) boundary estimation

(vi) pursuit-evasion

Outline

(i) introduction to decision making in mixed networks

(ii) distributed signal processing/detection for situational awareness

(iii) distributed coordination/task allocation algorithms for command and control

(iv) workplan

Network with mixed assets

Broad objectives

(i) situational awareness from heterogeneous sources

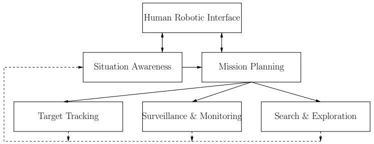
(ii) scalable & efficient command and control

Technical objectives

- process and aggregate large amount of data from mixed agents
  - (i) distributed detection & signal processing and information theory
  - (ii) human cognition
- task allocation with mixed agents
  - (i) cooperative control and distributed algorithms
  - (ii) human behavior

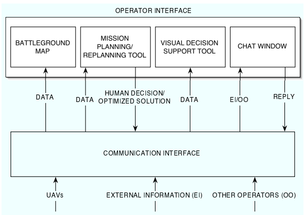
decision dynamics in mixed networks

Architectures



Human Robotic Interface

- high-level mission tasking
- rules of engagement
- constraints



Topic #1: detection for situational awareness

(i) Sequential decision making and human cognition

Bogacz, Brown, Moehlis, Holmes, and Cohen. Physics of optimal decision making *Psychological Review*, 2006

(ii) Decentralized sequential decision making with central data fusion, team theory

Varshney, *Distributed Detection and Data Fusion*, 1996

Tsitsiklis, "Decentralized detection," Advances in Statistical Signal Processing, 1993

(iii) Distributed Bayesian inference

Pearl 1988

Kreidl and Willsky, *An efficient message passing for decentralized detection*, 2007

Olfati-Saber, Franco, Frazzoli, Shamma *Belief consensus and distributed hypothesis testing*, 2006

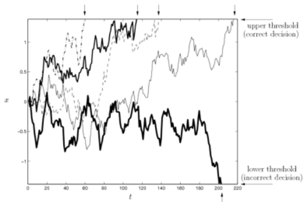
(iv) Distributed computing with faulty nodes

Pasqualetti, Bicchi and Bullo *Distributed intrusion detection for secure consensus computations*, 2007

Distributed decision making in noisy environments

Optimal speed/accuracy detection

(i) evidence integrated over time
(ii) threshold-based decision
(iii) free response vs interrogation paradigm
(iv) multiple alternative version
(v) drift-diffusion models of human decision making



Distributed hypothesis testing

Bayesian inference

$$p(h_\gamma|\{z_i\}) = \frac{p(h_\gamma)}{p(\{z_i\})}\prod_{i=1}^{n} p(z_i|h_\gamma)$$

Belief consensus algorithm

$$\pi_i(0) = p(z_i|h_\gamma)$$

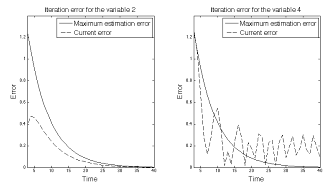
$$\pi_i(\ell+1) = \sqrt[1+d(i)]{\pi_i(\ell)\prod_{j\in N_i}\pi_j(\ell)}$$

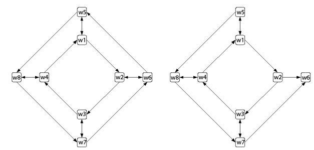
$$\pi_i(\ell) \to \prod_{i=1}^{n} p(z_i|h_\gamma)$$

Detection with faulty noisy communication

(i) evidence integrated via averaging
(ii) failures: absent, constant or malicious communication
(iii) trust management: handle and isolate outliers

(i) Faulty behavior quantified through "unknown input observability"
(ii) At each node, filters estimate amount of unknown distortion at neighboring nodes
(iii) At each node, threshold-based detection and isolation algorithm





joint work with: F. Pasqualetti, A. Bicchi

Topic #1: detection for situational awareness

Literature:

(i) Sequential decision making and human cognition

(ii) Decentralized sequential decision making with central data fusion, team theory

(iii) Distributed Bayesian inference

Objective: Unified theory of decision making among mixed nodes

(i) model human decision making as DD

(ii) distributed speed/accuracy tradeoffs

(iii) detection in mixed networks

(iv) trust management

Topic #2: task allocation

(i) distributed assignment via auction algorithms

Bertsekas and Castañón, 1991 — Castañón and Wu, 2003

(ii) evolution-based global optimization

Pongpunwattana, Rysdyk, Vagners, and Rathbun, 2003

(iii) assignment via numerical optimization, MILP

Richards and How, 2005 — Earl and D'Andrea, 2005 — Schumacher et al, 2003-present

(iv) geometry/graph theory algorithmic approaches

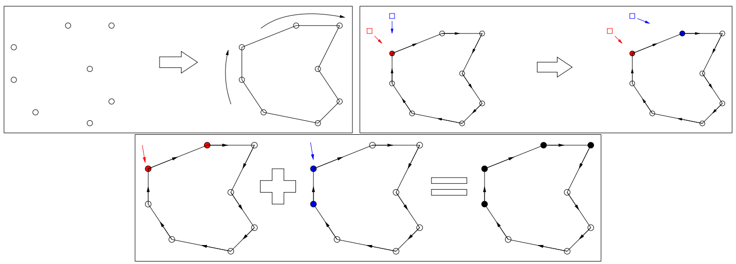
Frazzoli and Bullo, *Decentralized algorithms for vehicle routing* 2004

Smith and Bullo, *Target assignment for robotic networks*, 2007

Savla, Frazzoli and Bullo, *TSP for Dubins vehicle*, 2005-2007

Task allocation: target assignment

Assumptions: n agents know n targets
bounded: communication range, speed, message length



Results:

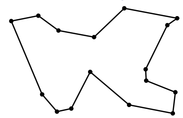
(i) completion time $\Theta(\sqrt{n}\ell(n))$ in sparse environments: $\ell(n) \approx \sqrt{n}$

(ii) robust to: agent arrival, comm delays and asynchronicity

joint work with: S. Smith

Task allocation: TSP with bounded curvature

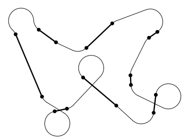
Euclidean TSP (ETSP)



- NP-hard
- effective heuristics available
- length($ETSP$) of order $\sqrt{n}$
  (Supowit et. al. '83)

Dubins TSP (DTSP)

Given a set of points find the shortest tour with bounded curvature

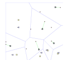


- not a finite dimensional problem
- no prior algorithms or results
- for stochastically uniformly generated targets
  length($DTSP$) of order $n^{2/3}$!

joint work with: K. Savla, E. Frazzoli

Task allocation: dynamic scenarios

Objective: Given agents $(p_1, \dots, p_n)$ moving in environment Q
service targets in environment



Model:

- targets arise randomly in space/time
- vehicle know of targets arrivals
- low and high traffic scenarios

Results:

(i) bounds on achievable performance
(ii) algorithms with asymptotic optimality
(iii) capacity vs delay tradeoffs

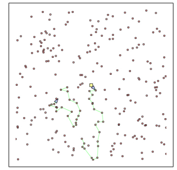
joint work with: M. Pavone, E. Frazzoli

Coverage + TSP algorithm, I

Name: (Single Vehicle) Receding-horizon TSP

For $\eta \in (0, 1]$, single agent performs:
1: while no targets, move to center
2: while targets waiting
  (i) compute optimal TSP tour through all targets
  (ii) service the η-fraction of tour with maximal number of targets

Asymptotically constant-factor optimal in light and high traffic

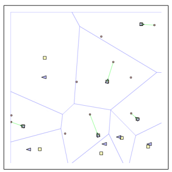


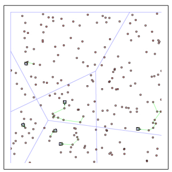
Coverage + TSP algorithm, II

Name: Receding-horizon TSP

For $\eta \in (0, 1]$, agent i performs:
1: compute own dominance region V_i
2: apply Single-Vehicle RH-TSP policy on V_i

Asymptotically constant-factor optimal in light and high traffic





Workplan

(i) **Human cognition and behavior modeled as drift-diffusion**
- nominal, adverse and time-varying conditions

(ii) **Process and aggregate large amount of data in mixed networks**
- integrate human cognition in network-wide data fusion
- network of decision makers modelled as DD

(iii) **Task allocation in mixed networks**
- human decision making + receding-horizon combinatorial problems
- task-specific geometric intuition on how to integrate human collaboration

(iv) **Optimal human-automation partition and interaction**
competency comparison — human versus automata
- more credible nodes in networked decisions (trust management)
- slower (excellent performance at low frequency, poor at high frequency)
- independent mobility (controlled mobility)

Human-aided detection/localization/tracking

Scenario

(i) mixed nodes = humans and robots with different characteristics

(ii) detection failure and false alarm

(iii) distributed sensing/information = cognition

(iv) mobility and sensor selection = attention control

Varying degrees of human involvement

(i) supervision scenario: 1 human, n vehicles, random $\#$ of targets

(ii) cooperation scenario: multiple humans, multiple vehicles

Conclusions

(i) architectures

(ii) situational awareness:
distributed stochastic detection + human cognition
detection theory in mixed networks

(iii) command and control:
distributed task allocation + human behavior

(iv) workplan: human-aided detection/localization