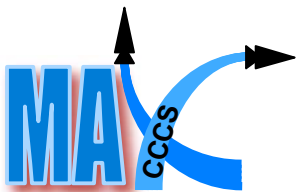




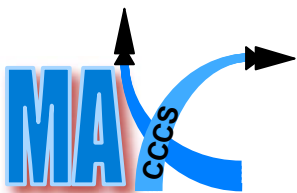
# TEAM PERFORMANCE OF UNMANNED VEHICLES WITH DIVERSE CAPABILITIES

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# Introduction

- Applications of Unmanned Vehicles
  - Intelligence
  - Surveillance and Reconnaissance
  - Search
  - Vehicle Tracking
  - Area Patrolling



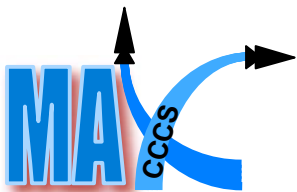
# Teams Of Unmanned Vehicles

- No Free Lunch Theorem
  - Over all search and optimization problems, all agents perform equally well, when no prior knowledge is available to exploit
  - Does not extend to teams of unmanned vehicles
- Problem Statement
  - Build an effective heterogeneous team of unmanned vehicles to search an unknown environment, without any prior knowledge of the search space.



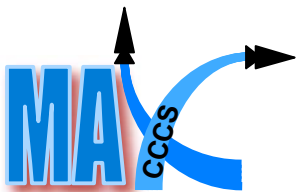
# Past Research

- Focused on
  - Multi-vehicle cooperation of predetermined (homogeneous) platoons
  - Communication among heterogeneous teams
  - Building heterogeneous teams to exploit some knowledge of the field (teams with specialized agents).
  - Classified heterogeneous and homogeneous depending on if all the agents were the same or alike



# Diversity among Heterogeneous Teams

- Past research failed to:
  - Examine the affects of diversity among heterogeneous teams
    - Varying agents on a team
    - No formal qualitative measurement of diversity



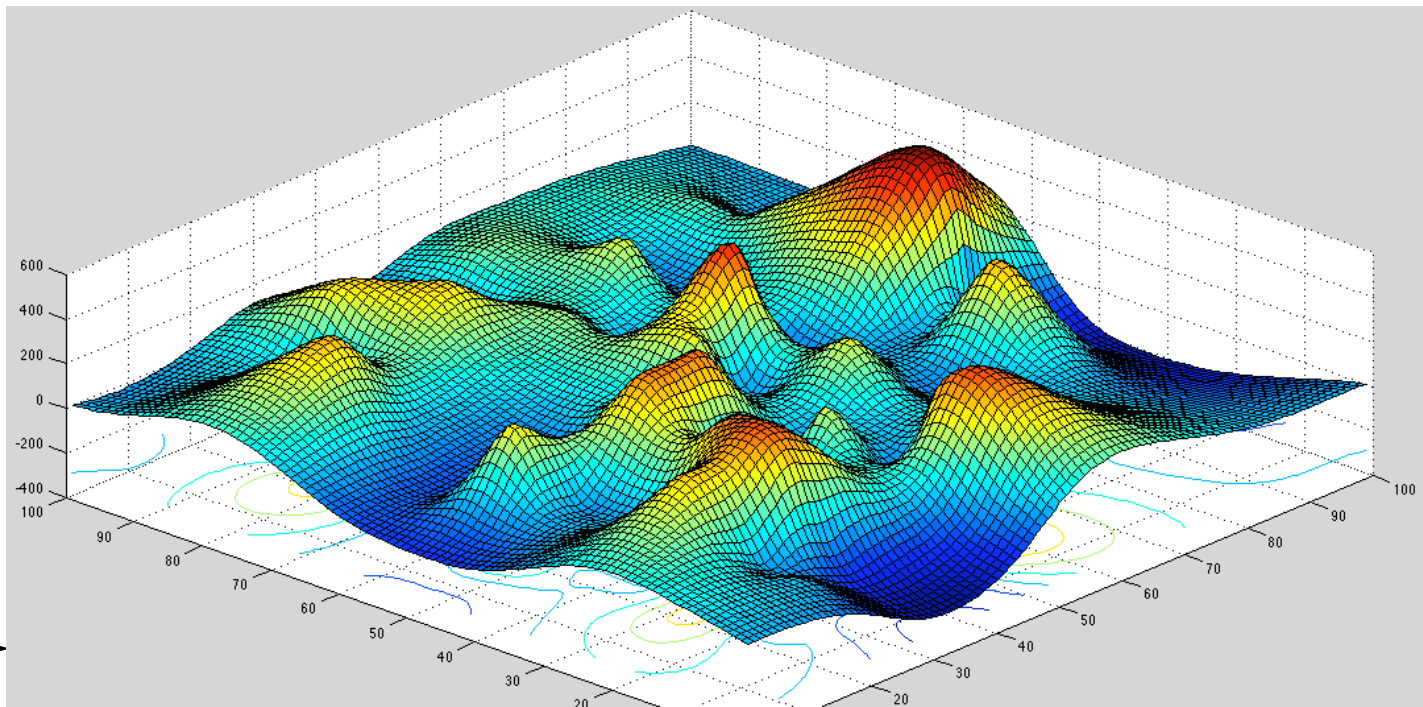
# Effects of Diversity

- Influences from Social Science (Scott Page)
  - Mathematical Proof & Computational Experiment
    - Diverse teams on average outperform the best suited team
      - Assumptions
        - 1) A problem is inherently difficult (no single agent can always find the optimum)
        - 2) There is a great enough diversity among the agents, (when one agent gets stuck, there is always another agent that can find an improvement)
        - 3) The performance of the best agent is unique



# Computational Experiment

- Team Search Mission
  - Random Team (presumably more diverse) vs. Best Team
  - Function optimization (differentiable  $F$ ),  $F : X \times Y \rightarrow Z$ ;  $X, Y, Z \in \mathbb{R}$
  - $Z$ - target value





# Steepest Ascent Method

- Characteristics
  - Function gradient, and gradient constant dependent
  - Converges relatively fast to local extrema for optimal gradient constants
  - Poor convergence for large and small gradient constants
- Example
  - An autonomous underwater vehicle equipped with sensors that measure water temperature and follows the gradient to find the position with the highest temperature

$$\Phi_k = \left\{ k \mid x_{n+1} = \frac{\partial F}{\partial x} + x_n, y_{n+1} = \frac{\partial F}{\partial y} + y_n \right\}$$

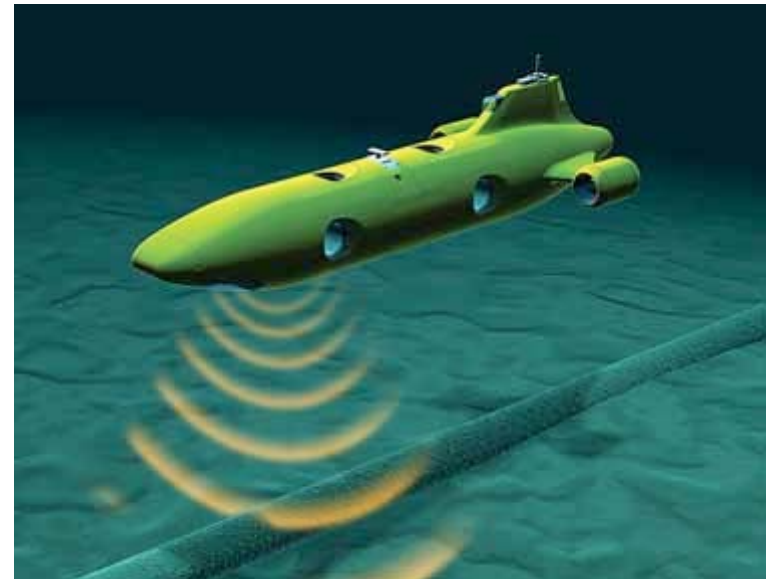
(1)

$\Phi_k$  = heuristic

$k$  = gradient constant

$\frac{\partial F}{\partial x}, \frac{\partial F}{\partial y}$  = gradient

$x_n, y_n$  = coordinates





# Step Search Algorithm

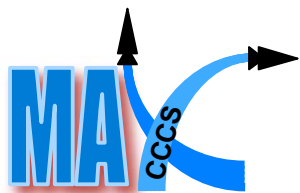
- Characteristics
  - Independent of gradient
  - Looks along a radius only in the front of its position
- Example
  - A UAV equipped with cameras as sensors that can see in front of its position

$$(2) \quad \Theta_s = \{s > 0 \mid x_{n+1} = s + x_n, y_{n+1} = s + y_n\}$$

$\Theta_s$  = heuristic

$s$  = step search constant

$x_n, y_n$  = coordinates



# Expected Performance

- Expected performance value
  - Unity probability distribution of initial conditions
    - Individual agents were allowed to start at every initial condition and apply their heuristic to traverse the search space until  $F(x_{n+1}, y_{n+1}) < F(x_n, y_n)$
  - The higher the expected performance value the better the agent is presumed to be

$$(3) \quad E[F; \psi, v] = \frac{1}{n^2} \cdot \sum_{x_i=1}^n \sum_{y_i=1}^n F[\psi(x_i, y_i)]$$

$\psi$  = heuristic

$v$  = probability distribution of initial condition

$x_i, y_i$  = initial condition

$F[\psi(x_i, y_i)]$  = expected performance



# Diversity

- Diversity is defined as the standard deviation of the step constant or gradient constant for the members on the team

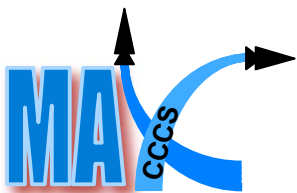
$$(4) \quad \delta = \sqrt{\frac{1}{n} \sum_{i=1}^n (c_i - \bar{c})^2}$$

$\delta$  = diversity

$n$  = number of agents on a team

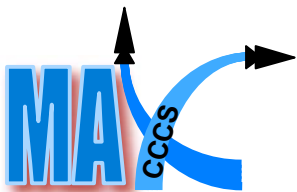
$c = s$  (step constant) for step search

$c = k$  (gradient constant) for steepest ascent method



# Computational Experiment

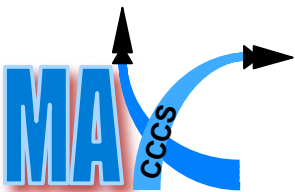
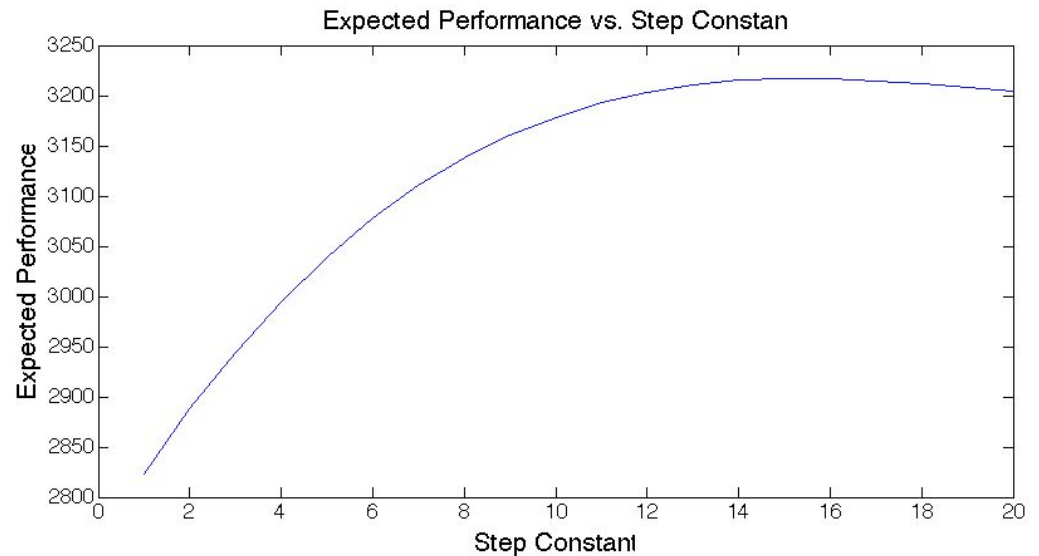
- Teams of 5
  - 5 best agents (highest expectance performance) vs. 5 random agents
  - Teams worked sequentially, the following agent started at the optimal point of the previous agent
  - Each agent attempted to optimize function 3 times
- Results are shown for
  - 5000 initial conditions per a functions/ per team
  - 2000 optimization functions



# Step Search Results

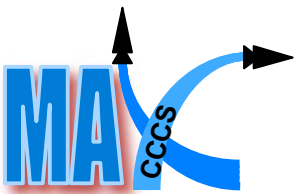
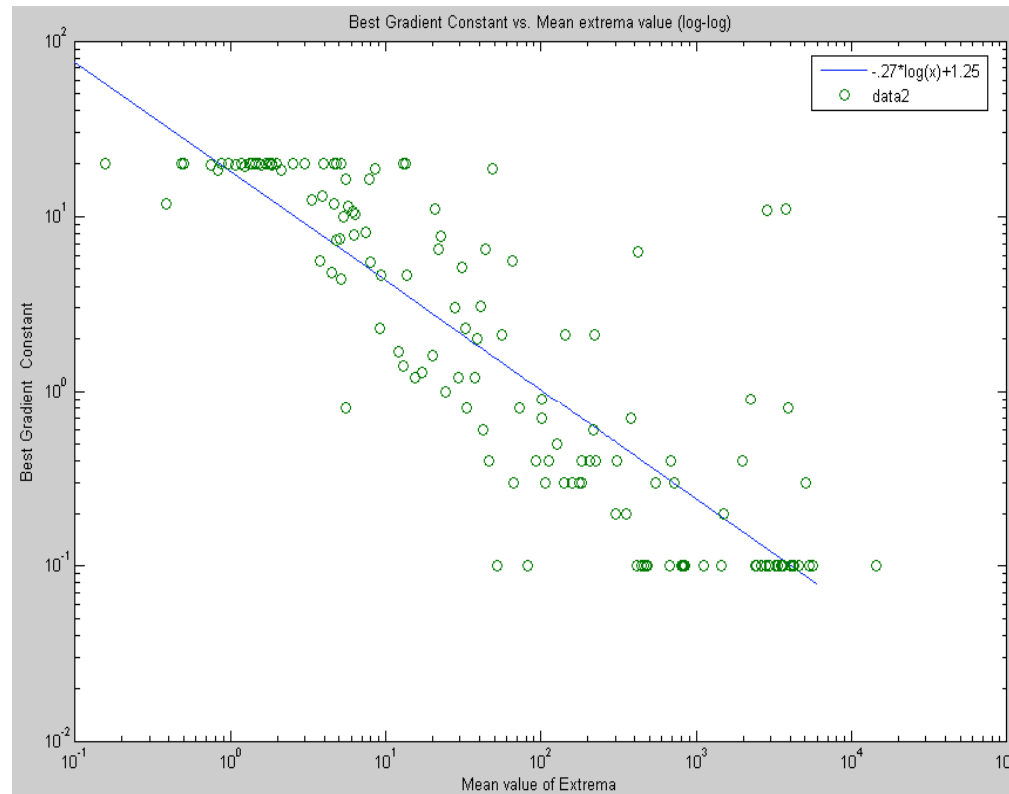
- Random team outperformed the best team by 9%
- Random team expected performance is 6% lower than the best team
- Random team outperformed its expected value by 16%
  - Greater ability to become unstuck on local minimums
- Best team outperformed its expected value by 3%

	Best Team	Random Team
Average Maximum	$6.3 \times 10^3$	
Average Expected Value	$3.3 \times 10^3$	$3.1 \times 10^3$
Average Diversity	2.9 (29%)	5.7 (57%)
Average Performance	$3.4 \times 10^3$	$3.7 \times 10^3$



# Optimal Gradient Constant

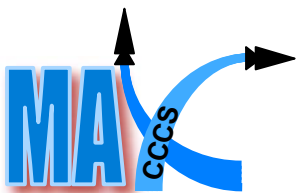
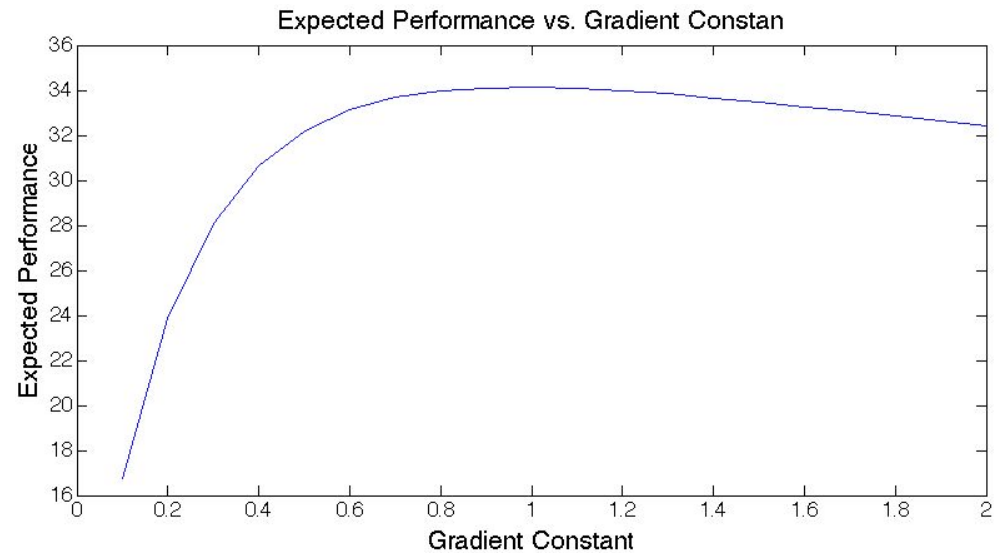
- Optimal Gradient Constant vs. Mean Extrema
  - Find range of optimal gradient constants



# Steepest Ascent Results

- Random team outperformed the best team by 3%
- Random team expected performance is 12% lower than the best team
- Random team outperformed its expected value by 19%
  - Greater ability to become unstuck on local minimums
- Best team outperformed its expected value by 6%

	Best Team	Random Team
Average Maximum	64.3	
Average Expected Value	36.0	31.8
Average Diversity	.16 (16%)	.53 (56%)
Average Performance	38.2	39.3

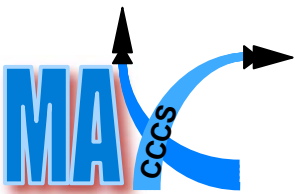
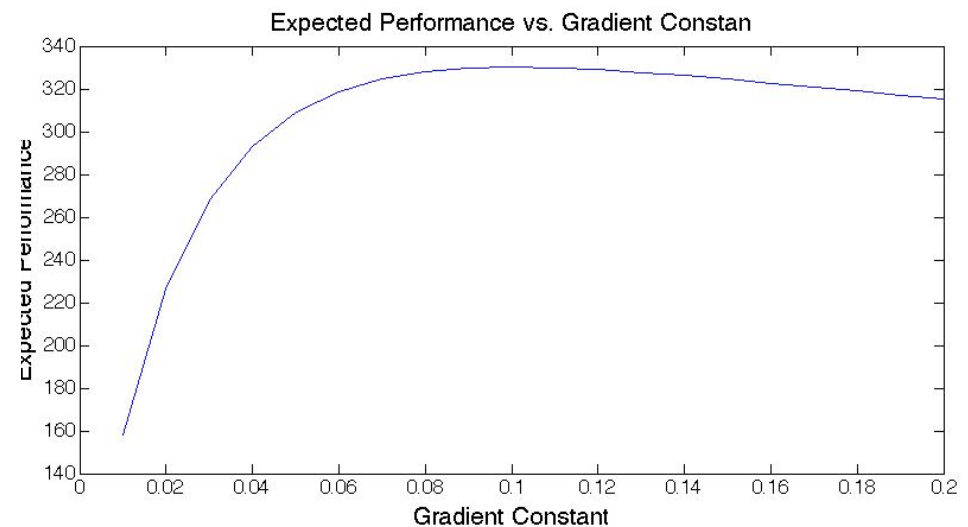




# Steepest Ascent Results

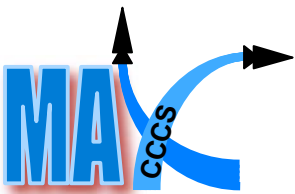
- Random team outperformed the best team by 3%
- Random team expected performance is 14% lower than the best team
- Random team outperformed its expected value by 24%
  - Greater ability to become unstuck on local minimums
- Best team outperformed its expected value by 6%

	Best Team	Random Team
Average Maximum	625.4	
Average Expected Value	347.7	304.9
Average Diversity	.016 (16%)	.053 (53%)
Average Performance	368.4	379.5



# Conclusion

- Diverse teams of UAV on average outperform the best-suited, with the goal being to search an unknown field for the highest value target.



# Publications

- Submitted: ASME Dynamic Systems and Control Conference (DSCC)-2008

