Human-Multirobot Interaction in Cooperative Perception-based Search and Rescue Missions

MC-IEF Project TRaVERSE: TowaRds Very large scalE human-Robot SynErgy

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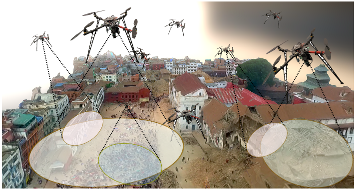
Human Perception, Cognition and Action
Max Planck Institute for Biological Cybernetics

TRaVERSE: TowaRds Very large scalE human-Robot SynErgy

Large-Scale Human-Multirobot Collaborative Task

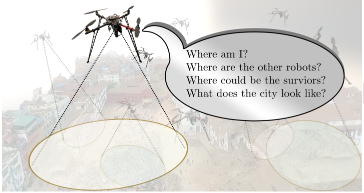


Cooperative Perception in Multirobot Systems

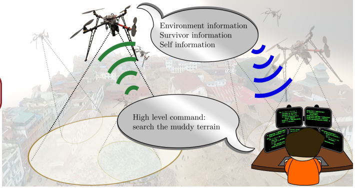
Autonomy & System Factors

Human Factors

Human-Multirobot Interaction



Maximize Task Efficiency



Multirobot Cooperative Perception

- Cooperative Perception: what does it encompass?
  - Self pose
  - Teammate poses
  - Poses of dynamic targets/objects
  - Map of the environment

Multirobot Cooperative Perception

- Cooperative Perception: what does it encompass?
  - Self pose
  - Teammate poses
  - Poses of dynamic targets/objects
  - Map of the environment
- Cooperative Perception: why do we want this?
  - Increase the accuracy and precision of the local estimates.
  - Improve robustness to individual sensor failures.
  - Increased coverage area.
  - Improves coordination when performing teamwork!

Multirobot Cooperative Perception

- **A Scalable Approach to Multirobot Cooperative Localization and Object Tracking Based on Particle Filters.** *Aamir Ahmad and Pedro Lima*, IEEE Transactions on Robotics (T-RO), (Accepted as Regular), **2017**
- **Moving-horizon nonlinear least squares-based multirobot cooperative perception.** *Aamir Ahmad, Heinrich H. Bülthoff*, Robotics and Autonomous Systems (RAS) Journal, Vol 83, pp. 275–286, **2016**.
- **Formation Control Driven by Cooperative Object Tracking.** *Pedro Lima, Aamir Ahmad, André Dias, A. G. S. Conceição, Antnio Paulo Moreira, Eduardo Silva, Luís Almeida , Luís Oliveira, Tiago P. Nascimento*, Robotics and Autonomous Systems (RAS) Journal, Vol 63 Issue 1, pp. 68–79, **2015**.

Human-Multirobot Interaction

Large-Scale Human-Multirobot Collaborative Task

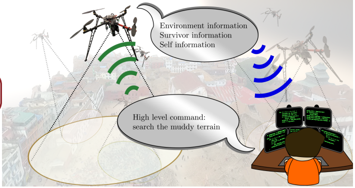
Cooperative Perception in Multirobot Systems

Autonomy & System Factors →

← Human Factors

Human-Multirobot Interaction

Maximize Task Efficiency



Why human in the loop?

- Why human-operators-in-the-loop for control of multi-UAV systems?
  - Significantly improve mission success rates [1].
  - Allow humans to be in control of life-critical decisions [2].

Why human in the loop?

- Why human-operators-in-the-loop for control of multi-UAV systems?
    - Significantly improve mission success rates [1].
    - Allow humans to be in control of life-critical decisions [2].
- Control schemes involving human-multirobot interaction (H-MRI) impose several challenges:
    - human operators' cognitive workload [3] [4].
    - optimal task allocation [5] under various system constraints.

H-MRI in the context of CP

- No comprehensive study for H-MRI in SAR missions in the context of CP.
  - CP significantly affects low-level autonomy of the robots.
  - Consequently, can potentially affect high-level shared autonomy between humans and robots.

Goal of this Work and Novel Contributions

Goal: To investigate the role of various system and human factors on SAR mission success when the involved robots also perform CP.

Novelties:

- A systematic H-MRI experiment design,
- a detailed statistical analysis on how system and human factors affect search mission success in a CP scenario, and
- a fully open-source and ready-to-use ROS-based software to replicate and extend these H-MRI experiments.

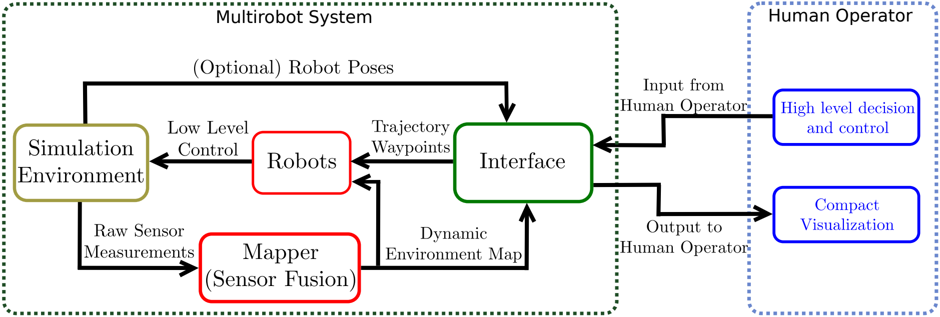
Assumptions

- A single human operator is in charge of controlling multiple UAVs in a search mission.
- The actual survivor classification task in the search mission lies with the human operator.
- The mission involves only UAVs (and no ground-based robots).

Factors

- System Factors:
  - Degree of High-level Autonomy
    - *Individually controlled (IC):*
    - *Formation controlled (FC):*
    - *Not controlled (NC):*
  - Number of Robots.
- Human factors:
  - Operator's skills and experience with strategy-based computer games.
  - Operator's Gender.

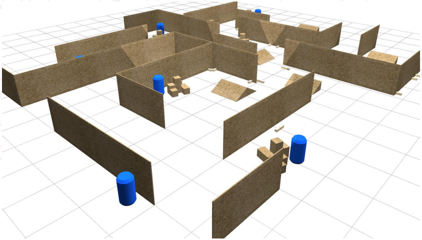
Design of the Human-Multirobot Interaction (H-MRI) Study



Overall System Architecture for the Study (ROS-based)

H-MRI System Component: Environment

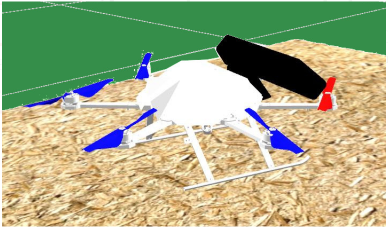
- Simulation Environment guarantees repeatability:
  - Built in Gazebo (ROS-compatible).
  - Adheres to NIST[1] standards for response robots.
  - Complex yet repeatable!



[1]U.S. National Institute of Standards and Technology

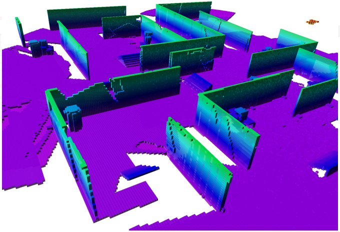
H-MRI System Components: Robots

- Robots:
  - 6-rotor UAV (Model: AscTec Firefly).
  - On-board RGB-D sensor.
  - Controllable in position (setting way-points).
  - Obstacle avoidance (potential field).



H-MRI System Components: Cooperative Perception

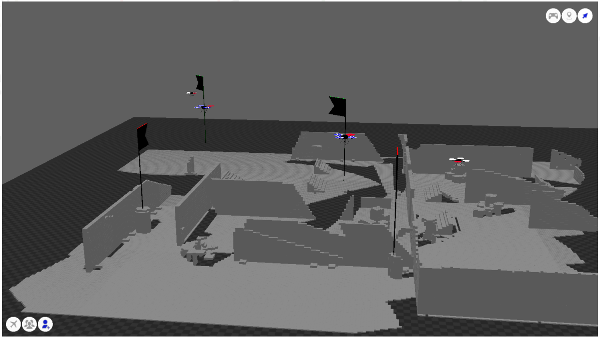
- Sensor Fusion for Cooperative Perception:
  - Baseline ‘optimal’ CP method.
  - Cooperative centralized Mapper.
  - Using only depth measurements from all robots.
  - Builds an octomap.
  - Global robot poses known from gazebo.



H-MRI System Components: Interface

Interface (built using Blender):

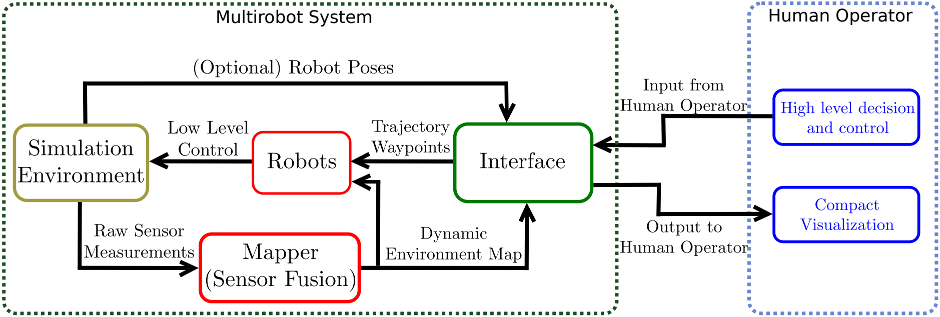
- Rendering at high frame rate.
- Two-way interfacing to command the robots.



H-MRI System Components: High-level Decision and Control.

- Controlling the robot:
  - *Individually controlled (IC):*: Way points for each robot can be set individually.
  - *Formation controlled (IC):*: Way points for the robot-team formation can be set.
  - *Not controlled (IC):*: Human operator has no control.
- Deciding on a survivor: Operator classifies and marks a survivor in the interface.

Design of the Human-Multirobot Interaction (H-MRI) Study



Overall System Architecture for the Study (ROS-based)

H-MRI Experiment Design Terms (NIST Terminology)

- Factors:
  - Number of Robots in the team (2 or 5).
  - High level control (IC, FC or NC).
- Design:
  - A set of 18 trials.
  - 6 pairs of crossed factors.
  - 3 trials for each pair of crossed factors.
  - Each trial associated to a randomly selected NIST map.
- Balanced Design:
  - Each crossed factor combination – a treatment.
  - Each treatment – same number of observations (all participants).

H-MRI Experiment Design Terms (NIST terminology)

- Randomization:
  - Randomized sequence of trials.
- Replication (with sufficient variability in setup):
  - 3 trials for each pair of crossed factors.
  - Randomized Map association for each treatment.
- Responses:
  - Marked survivor rate (efficiency $= \frac{\text{survivors found}}{\text{total survivors}}$).
- Ethics:
  - Participant handling (anonymity).
  - Consent form and hourly payments.
  - Thanks to the excellent participant database software!

Experiment Illustration

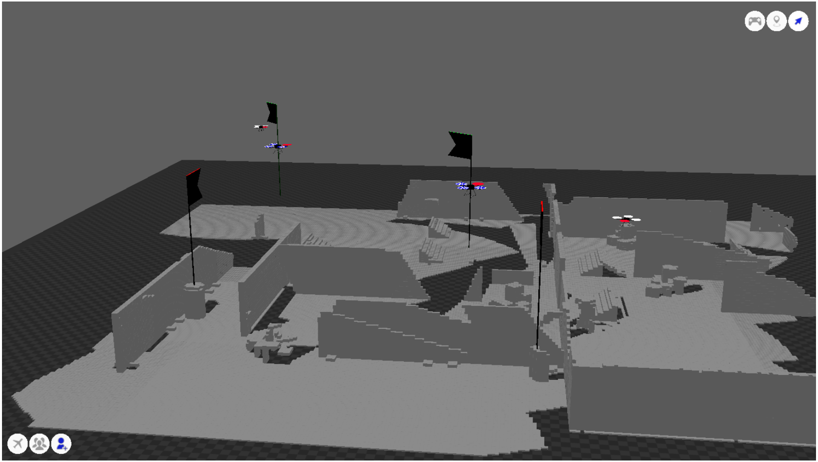
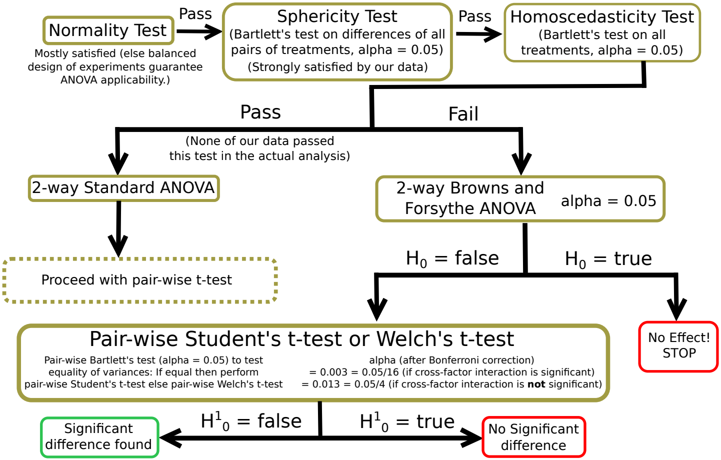


Figure: *Illustration of the simulated world, interface and controls.*

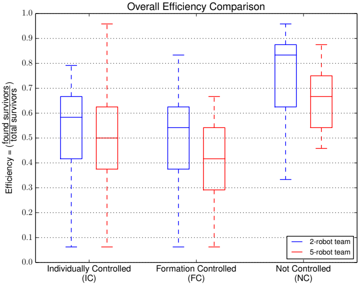
H-MRI Experiments and Results (NIST Terminology)

- Preliminaries:
  - 35 participants performed the role of human operator.
  - A total of 105 hours ($\sim$3 hours/participant) of experiments.
  - 6 participants excluded (3 pre-experiment trials & 3 unusable).
  - Data from 29 remaining participants was analyzed.
    1. Responses (Efficiency)
    2. Age and Gender
    3. 7-point Likert scale-based questionnaire: Gaming experience (how often) and self-assessed gaming expertise.

Analysis Scheme



Overall Comparison (Over all 29 Participants)



Box plot comparison chart.

Stat → / Effect ↓	S_{sq}	df	F	p-val	eta_{sq}
Robot	1.8e-01	1	5.5	2.1e-02	2.4e-02
Control	1.9e+00	2	28.1	4.3e-11	2.4e-01
Rob:Con	1.9e-02	2	0.3	7.5e-01	2.5e-03
Residual	5.6e+00	151.4			

Two-way Browns and Forsythe ANOVA.

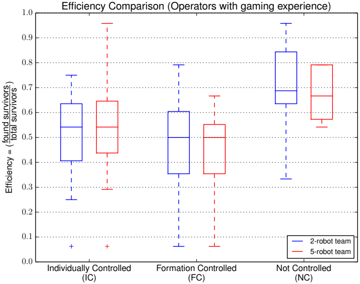
Effect	2-IC	2-FC	2-NC	5-IC	5-FC	5-NC
2-IC		5.4e-01	4.0e-07	3.6e-01		
2-FC	6.2e-01		3.4e-06		3.3e-03	
2-NC	-6.6e+00	-5.8e+00				9.4e-02
5-IC	9.3e-01				1.5e-02	1.4e-04
5-FC		3.2e+00		2.6e+00		2.0e-08
5-NC			1.7e+00	-4.2e+00	-6.7e+00	

Pair-wise t-test. Lower triangle (F-values). Upper triangle (p-values).

Overall Comparison: Main Inferences

- Number of robots make small but significant difference in the overall performance.
- Clearly the mode of control affects the performance.
- There is no crossed-factor effect.
- Operators clearly perform better in the Not Controlled (NC) mode compared to the other two modes.
- However, no significant improvement w.r.t. the number of robots within the NC mode.
- No significant difference between IC and FC modes.
- Significant drop in efficiency from 2-FC to 5-FC: increasing number of robots detrimental?

Comparison over 12 participants with above-average gaming experience



Box plot comparison chart.

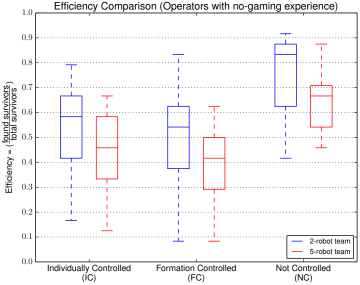
Stat → / Effect ↓	S_{sq}	df	F	p-val	eta_{sq}
Robot	2.7e-03	1	0.1	8.0e-01	7.9e-04
Control	6.9e-01	2	8.6	5.5e-04	2.1e-01
Rob:Con	1.5e-02	2	0.2	8.3e-01	4.4e-03
Residual	2.6e+00	57.4			

Two-way Browns and Forsythe ANOVA.

Effect	2-IC	2-FC	2-NC	5-IC	5-FC	5-NC
2-IC		5.6e-01	4.3e-03			
2-FC	5.9e-01		3.5e-03			
2-NC	-3.6e+00	-3.7e+00				
5-IC					5.2e-02	7.4e-02
5-FC				2.2e+00		3.9e-04
5-NC				-1.9e+00	-5.0e+00	

Pair-wise t-test. Lower triangle (F-values). Upper triangle (p-values).

omparison over 17 participants with below-average gaming experience



Box plot comparison chart.

Stat → Effect ↓	S_{sq}	df	F	p-val	eta_{sq}
Robot	2.6e-01	1	9.0	3.6e-03	6.2e-02
Control	1.2e+00	2	20.2	6.4e-08	2.8e-01
Rob:Con	6.7e-03	2	0.1	8.9e-01	1.6e-03
Residual	2.8e+00	87.0			

Two-way Browns and Forsythe ANOVA.

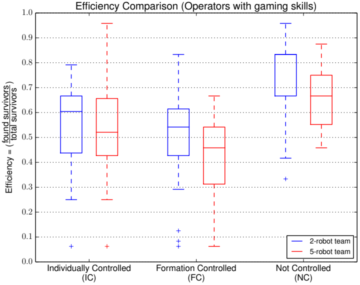
Effect	2-IC	2-FC	2-NC	5-IC	5-FC	5-NC
2-IC		7.4e-01	4.4e-05	1.2e-01		
2-FC	3.4e-01		5.4e-04		3.4e-03	
2-NC	-5.5e+00	-4.3e+00				6.8e-02
5-IC	1.6e+00				1.4e-01	1.3e-04
5-FC		3.4e+00		1.5e+00		7.7e-07
5-NC			1.9e+00	-5.0e+00	-7.8e+00	

Pair-wise t-test. Lower triangle (F-values). Upper triangle (p-values).

Gaming experience: Inferences

- Number of robots makes no difference for people with gaming experience.
- Type of control makes a small difference for experienced people and a large difference for non-experienced.
- No significant difference between 5-IC and 5-NC mode: gamers tend to maximize exploration.
- Some evidence that gamers are better than non-gamers in IC and FC modes, but this needs further study.

Comparison over 22 participants with above-average gaming skills



Box plot comparison chart.

Stat → / Effect ↓	S_{sq}	df	F	p-val	eta_{sq}
Robot	1.4e-01	1	4.2	4.2e-02	2.4e-02
Control	1.4e+00	2	21.2	1.4e-08	2.4e-01
Rob:Con	2.4e-02	2	0.4	6.9e-01	4.3e-03
Residual	4.0e+00	114.1			

Two-way Browns and Forsythe ANOVA.

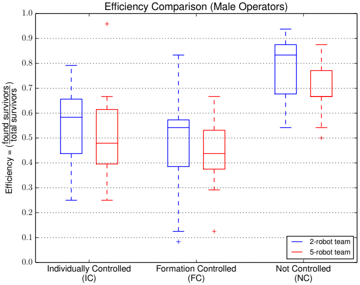
Effect	2-IC	2-FC	2-NC	5-IC	5-FC	5-NC
2-IC		3.0e-01	7.6e-06	5.5e-01		
2-FC	1.1e+00		5.9e-05		1.7e-02	
2-NC	-5.9e+00	-5.0e+00				8.7e-02
5-IC	6.1e-01				1.4e-03	5.4e-03
5-FC		2.6e+00		3.7e+00		2.1e-08
5-NC			1.8e+00	-3.0e+00	-8.7e+00	

Pair-wise t-test. Lower triangle (F-values). Upper triangle (p-values).

Gaming skills: Inferences

- Sub-set of participants with gaming skills different from that of gamers: overestimation of personal skills!
- Performance significantly poor in IC mode compared to NC mode, irrespective of the number of robots.
- Overestimation of personal skill is the highly likely cause of this.
- More robust experiment needed here!

Comparison over 14 male participants



Box plot comparison chart.

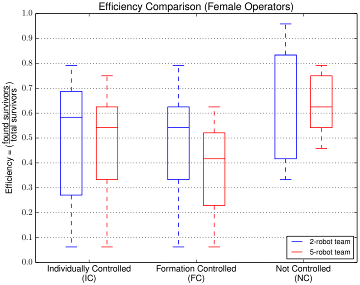
Stat → Effect ↓	S_{sq}	df	F	p-val	eta_{sq}
Robot	1.0e-01	1	4.0	5.0e-02	3.2e-02
Control	1.1e+00	2	21.1	1.1e-07	3.4e-01
Rob:Con	7.0e-03	2	0.1	8.7e-01	2.2e-03
Residual	1.9e+00	61.4			

Two-way Browns and Forsythe ANOVA.

Effect	2-IC	2-FC	2-NC	5-IC	5-FC	5-NC
2-IC		3.1e-01	4.7e-04			
2-FC	1.1e+00		5.4e-04			
2-NC	-4.6e+00	-4.1e+00				
5-IC					3.0e-02	1.7e-03
5-FC				2.4e+00		6.8e-06
5-NC				-3.9e+00	-7.2e+00	

Pair-wise t-test. Lower triangle (F-values). Upper triangle (p-values).

Comparison over 15 female participants



Box plot comparison chart.

Stat → / Effect ↓	S_{sq}	df	F	p-val	eta_{sq}
Robot	8.1e-02	1	2.0	1.6e-01	1.9e-02
Control	8.2e-01	2	10.0	1.4e-04	1.9e-01
Rob:Con	3.1e-02	2	0.4	6.9e-01	7.0e-03
Residual	3.4e+00	73.9			

Two-way Browns and Forsythe ANOVA.

Effect	2-IC	2-FC	2-NC	5-IC	5-FC	5-NC
2-IC		9.3e-01	4.7e-04			
2-FC	-9.5e-02		4.9e-03			
2-NC	-4.5e+00	-3.3e+00				
5-IC					1.3e-01	1.3e-02
5-FC				1.6e+00		1.7e-04
5-NC				-2.7e+00	-4.5e+00	

Pair-wise t-test. Lower triangle (F-values). Upper triangle (p-values).

Gender: Inferences

- For male participants type of control significantly affects efficiency.
- Increase in number of robots marginally deteriorates efficiency for male participants.
- (Not grounded on significance test results) Female participants seem to show greater variance in efficiency than males.
- (Not grounded on significance test results) Males seemed to have outperformed females because the set of males included mostly gamers!

Conclusions I

- Collaborative task performed much better when robots are fully autonomous in performing exploration and the human operators only searching for survivors.
- If human operators also control the robots in terms of planning the search way-points, performance drops significantly unless they possess good gaming experience.
- Slight benefit in increasing the number of robots when performing the collaborative task assuming a single human operator is responsible for
  - controlling all the robots, and
  - the actual survivor search and classification task.

Conclusions II

- Increasing the number of robots, in a scenario where the robots together maintain certain formations, becomes detrimental to exploration as it rapidly increases the computational overhead.
- For a small number of robots there is no significant difference in the collaborative task efficiency between an individually controlled multirobot team or a formation controlled team.

Recommendations and Future work

- It might be beneficial to split a large number of robots into several small-size teams
- A small set of such teams should be assigned to a separate human operator
- Operator must be responsible for the search and classification task only in a specific region.
- Operator training would obviously help.
- Combination of IC and FC modes?
- Other search strategies that might affect or improve NC case?

Thank you all for attending my talk and
for your kind attention!

Questions?

References I

- M. L. Cummings, J. P. How, A. Whitten, and O. Toupet, "The impact of human-automation collaboration in decentralized multiple unmanned vehicle control," *Proceedings of the IEEE*, vol. 100, pp. 660–671, March 2012.

- C. C. Murray and W. Park, "Incorporating human factor considerations in unmanned aerial vehicle routing," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 43, pp. 860–874, July 2013.

- J. Moore, R. Ivie, T. Gledhill, E. Mercer, and M. Goodrich, "Modeling human workload in unmanned aerial systems," in *AAAI Spring Symposium Series: Formal Verification and Modeling in Human-Machine Systems*, pp. 44–49, Citeseer, 2014.

- L. Bertuccelli, N. Beckers, and M. Cummings, *Developing operator models for UAV search scheduling*.

  American Institute of Aeronautics and Astronautics (AIAA), 2010.

References II

M. S. Malvankar-Mehta and S. S. Mehta, "Optimal task allocation in multi-human multi-robot interaction," *Optimization Letters*, vol. 9, no. 8, pp. 1787–1803, 2015.