Inferential Reasoning for Heterogeneous Multi-Agent Mission

Sagir M. Yusuf, Chris Baber

***Abstract*—**We describe issues bedeviling the coordination of heterogeneous (different sensors carrying agents) multi-agent missions such as belief conflict, situation reasoning, etc. We applied Bayesian and agents' presumptions inferential reasoning to solve the outlined issues with the heterogeneous multi-agent belief variation and situational-base reasoning. Bayesian Belief Network (BBN) was used in modeling the agents' belief conflict due to sensor variations. Simulation experiments were designed, and cases from agents' missions were used in training the BBN using gradient descent and expectation-maximization algorithms. The output network is a well-trained BBN for making inferences for both agents and human experts. We claim that the Bayesian learning algorithm prediction capacity improves by the number of training data and argue that it enhances multi-agents robustness and solve agents' sensor conflicts.

***Keywords*—**Distributed constraint optimization problem, multi-agent system, multi-robot coordination, autonomous system, swarm intelligence.

I. INTRODUCTION

HETEROGENEOUS multi-agent missions consist of a combination of different types of agents, with different capacities, sensor profiles, endurance, and roles tasked together to perform an assigned task. The heterogeneous multi-agent mission is more robust and scalable due to the task distribution base on specialization. For example, a team of heterogeneous robots conducting rescue missions may comprise different types of aerial and grounds robots. Some of the agents can be digging, searching, extinguishing a fire, etc. based on their capacities [1], [2]. Despite the precious advantage of heterogeneous multi-agent missions, challenges arise in task distribution and scheduling (i.e., who does what task and why? based on the current environmental situation) [3]-[5], information fusion [2], [6]-[8], inter-agent belief conflicts [8], communication burden [9], [10], scalability, and localization [5], [11], [12]. The issue severity varies by the architecture of multi-agent coordination used, which could be centralized or decentralized. In centralized coordination, the agents are connected to a central station which is responsible for managing all the outlined issues. In decentralized coordination, agents act independently and solely relied on their sensor information for making decisions.

The issue of task distribution involves the optimal assignment of the task to agents in order to minimize costs. Therefore redundant task allocation may increase resource consumption and mission inefficiency. The data fusion problem is the challenge that occurred in merging different data from different agents to make an optimal decision [9], [13], [14]. The belief conflict exists when agents are using different sensors to detect a target — for instance, a team of agents carrying thermal, infrared, and visual sensors to detect fire outbreaks. Agents using visual sensors (camera) may detect a yellowish object and start a false alarm while other agents could argue that it is a false alarm. In contrast, inferential reasoning involves the use of the available data to make predictions, estimations, and conclusion on other variables by making the available data as the evidence for the derived forecasts [1], [15]-[17], for example, using previous cases to predict the occurrence of future variables. In this paper, we are going to apply the concept inferential reasoning to heterogeneous multi-agent belief variation using inferential reasoning.

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II. BACKGROUND

A. Inferential Reasoning

Inferential reasoning involves the act of utilizing little data to make predictions, estimations, and conclusions with a high degree of accuracy [16], [17]. Bayesian inference is the well-known statistical approach of making inferences (prediction) using conditional probabilities in (1) [18]:

$$P(X_i(t)|Y(t)) = \frac{P(X_i(t))*P(Y(t)|X_i(t))}{\sum_i^n P(X_i(t))*P(Y(t)|X_i(t))} \quad (1)$$

where $X_1(t)$, $X_2(t)$, $X_3(t)$, ..., $X_n(t)$ is the set of mutually exclusive events at a given time. BBN provides the graphical representation of the variables (as nodes) and their causal relationships. It comprises of an acyclic graph and a conditional probability table for making decisions. The acyclic graph G(V, E) where V represents the nodes containing state S = $\{s_1, s_2, s_3, s_4, \ldots, s_n\}$ $\forall$ $s_i \epsilon V$. E is the set of directed edges showing relationships between nodes hierarchy. A directed links from node A (parent) to node B (child) shows a causal relationship between the nodes (from A to B). The conditional probability table provides a list of cases and their outcomes. Fig. 1 shows an example of a BBN for updating agents' belief on the presence of fire using heat sensors.

BBN in Fig. 1 shows that flame and hotspot cause smoke and raise in temperature, flames cause hotspot. If there is a high temperature, the agents believe that there is a fire and it raises an alarm. The conditional probability table provides the set of conditions for checking fire present. For example, Table I shows an example of a conditional probability table for the node start alarm.

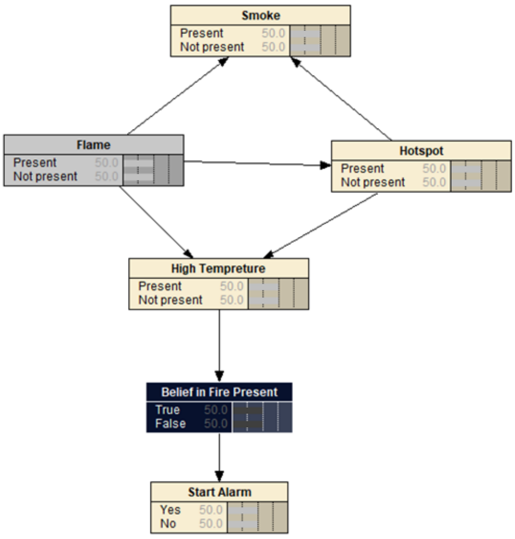

Fig. 1 BBN for Fire Detection

TABLE I
EXAMPLE OF CONDITIONAL PROBABILITY TABLE (CPT) FOR STARTING AN ALARM

Belief in Fire	Alarm
True	Yes
False	No

In every BBN, each node has its CPT, and experts or agents (based on learning) can provide the probabilities of the states during missions. Predictions can be made using (1). Cases can be recorded and using a set of algorithms to train the network using previously gathered data. For example, in search and rescue missions, previous operations data can be used in training the network. The most popular training algorithms are gradient descent, expectation-maximization, and counting algorithms [19]. Gradient descent and expectation-maximization provide an iterative approach in finding optimal predictions using missing or uncertain findings. Counting algorithms is only applicable during BBN diagnosis and deal with only known and specific data [19].

Agents can also make an inference from self-presumption based on the known parameters of other co-agents in a mission. For instance, in a multi-agent search and rescue mission, if an agent sees its co-partner loitering over a place, it can perceive that there is an exciting object (based on the in-built knowledge) in that location and therefore act cognitively to support that agent. These collaborative behaviours enhance the agents' efficiency and minimize resource consumption [20]-[23].

Definition. Multi-agents' self-presumption inferential reasoning can be defined as the tuple I = (A, α, λ, β). A = $\{a_1, a_2, a_3, ..., a_n\}$, $a_i \epsilon A$, a_i is the set of agents in multi-agent mission. α is the set of parameters known by each agent in the mission. λ is the set of actions corresponding to the parameters. β is an function for mapping parameters with the set of actions ($\beta: \lambda \setminus \alpha \rightarrow A$).

B. Heterogeneous Multi-Agent Coordination

Coordination of multi-agents involves planning, reasoning, and decision strategies to maintain the formation, planned paths, task distribution, and self-organization of the agents [24]. It also involves task allocation among robots, information merging, collision avoidance, collaborative behaviours enhancement, pathfinding, and navigation control [25]-[30]. Managing a team of agents can be achieved broadly in two ways. These are centralized or decentralized (distributed) approaches [31]. Centralize coordination allows the use of a central server to control the coordination problem. In a decentralized approach, agents act independently [32]. Heterogeneous multi-agent coordination involves the reasoning activities to control different types of agents with different sensor profiles, endurance, and roles effectively. Mostly, heterogeneous multi-agent missions provide a robust solution to the various multi-agent missions such as search and rescue, surveillance missions, etc. It allows an effective task distribution by categorizing agent based on their area of specialty. It comes with various issues such as conflicts in belief variation due to sensor differences and so on. For example, tasking a team agents (e.g., Quadrotors UAVs, fixed wings UAVs, legged robot, and wheel robot) to conduct forest fire monitoring, the agents with the thermal sensor may have a different belief with the other agent. This belief variation can affect the outcome of the mission. Positive affection allows the agent to detect false alarm. Challenge also arises in making a decision and agents' sensor data prioritization. Table II summarizes some of the challenges in handling heterogeneous multi-agent missions.

TABLE II
SUMMARY OF ISSUES IN HETEROGENEOUS MULTI-AGENT COORDINATION

Challenge	Causes	Effects
Belief variation	Different sensor profile, sensor fault, and uncertainty during data collection	Robust task allocation and central decision making [8]
Data fusion	Time-varying data acquisition	Poor decision making and communication burdens [9], [13]
Connectivity	Centralized coordination or information merging [33], [34]	Communications cost and unreliability in communication link.
Task allocation	Division of labour among agents	Effective and non-redundant task allocation [5]

In this paper, we pay attention to the application of distributed BBN in belief variation of heterogeneous multi-agent missions. We also itemize some challenges and applications of inter-gent belief conflict.

III. RELATED WORK

Different challenges of heterogeneous multi-agent missions were addressed in the literature, such as the challenges of task allocation were addressed in [5], [35], [36], communication burden [10], [35], collaborative behaviours [37], [38], Bayesian reasoning [8], [18], [39] etc.

Bayesian reasoning was applied to solve various issues in a heterogeneous multi-agent mission. In [9] is modelled multi-agent data fusion tasks using BBN. Each agent represents a node in the network, and agents are arranged in hierarchical order (Distributed Perception Network). Protocols were assigned for interpreting information using Markov boundaries (i.e., agents' self-presumption inference). The Markov boundary of each node comprises of its children, parents, and parents of children. Separate rules were used in interpreting messages from different Markov boundaries. The rule-based approach reduces the communication burden during data fusion. In [8] we described how Bayesian reasoning and learning can be merged with published-subscribe strategy to solve inter-agent sensor data conflicts. In order to allow situational reasoning, we used a priority-based strategy. Multi-agent sensor data fusion using machine learning novelty detection algorithms were described in [40]. They monitored a polymer industries section using different sensors and applying neural networks, support vector machine, K-nearest neighbours algorithms to detect and filter out novelty (data conflicts) before merging the information. Reference [41] describes a confirmation-based approach for heterogeneous multi-agent belief evaluation in forest fire lookout mission. Different agents carrying different sensors were tasked with the mission. When an agent detects the target, other agents have to confirm in order to evaluate and filter out the real detections and false detections.

In [16] the authors described a logical crime evidence assembling using BBN. The conflict between facts is resolved by adjusting and prioritizing node's probabilities to make optimal decisions. The priority came from the belief in the data saliency. Reference [17] shows a process of applying Bayesian inference to logical implications where the causality relationship can be posed as logical propositions. In the above mentioned literature, Bayesian inferential reasoning provides a suitable way of making appropriate estimations, concluding, and resolving conflicts from the little data at hand under severe constraints and uncertainty. This paper wants to show how inferential reasoning (both Bayesian inference and self-presumption) can be applied in resolving heterogeneous agents' belief variations.

Our approach modelled the issues of multi-agent belief variation due to sensor differences and applied Bayesian and agents' self-presumption to agents' prediction and learning behaviours. This approach will allow mission tracking and prediction using Bayesian learning. For instance, agents' mission data will be used for the BBN training. The learned BBN can be used by the agents to predict what will happen in the mission with some high degree of accuracy.

IV. Experimental Results

We set patrol missions for a team of heterogeneous Unmanned Aerial Vehicles (UAVs) conducting forest fire lookout on Aerospace Multi-agent Simulation Environment (AMASE) [42]. The patrol waypoint follows the levy distribution of (2). It is an animal-inspired exploration approach that gives a well-diverse waypoint for multi-agents searching [43]-[45].

$$P(\lambda) = \frac{1}{\pi}\int_0^{\infty} \cos(\lambda t).e^{-t\lambda^c} \quad 0<c\leq 2 \qquad (2)$$

where λ is the step size, and c is the constant value, t is the time since the last generated waypoint. The agents are of different capacities and sensor profile. Fig. 2 describes one of the scenes from our experiment.

Fig. 2 Team of Heterogeneous Agents Conducting

Fig. 2 describes a team of fixed-wing and multi-rotor UAVs conducting fire lookouts tasks. We assume that the fixed-wing UAVs are carrying visual sensors due to their endurance capacities. Their BBN, together with state probabilities, are shown in Fig. 3. The multi-rotor UAVs are carrying heat sensors due to their maneuverability. We design the agents BBN for visual and heat sensors on Netica [19], as shown in Figs. 1 and 3. In order to have an effective sensor conflict modelling, the yellowish shapes labeled 'A' and 'B' represent real and fake fire. The fake fire will be confusing one of the agents, for example, agent using camera sensor will be confused by a dried yellow grass.

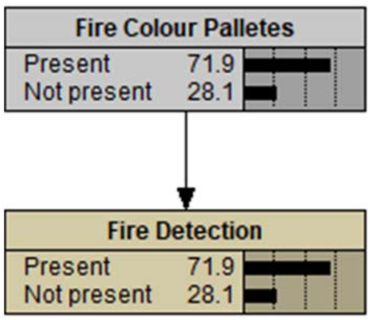

Fig. 3 BBN for Agent using Visual Sensors

We assume that the agents have instant access to their BBN and update the probabilities. The forest fire wardens or agents at a base station can detect belief variation and set plans for confirmation by other agents. The recorded conflict can be used to train the networks to detect and abandon belief conflict. Fig. 4 describes the operation cycle.

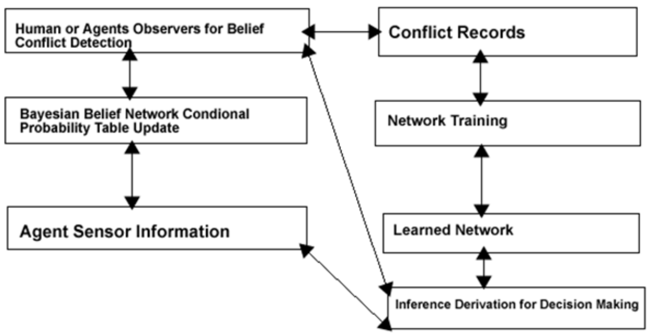

Fig. 4 Multi-agent Belief Conflict Monitoring

TABLE III
AGENTS' BELIEF CONFLICT REPORT SHEET

Event_ID	Agent	Time	Location
0	UAV1	T1	L2
1	UAV4	T2	L6
2	UAV1	T7	L7
3	UAV1	T2	L8
4	UAV4	T5	L9
5	UAV4	T4	L7
6	UAV4	T10	L8
7	UAV1	T3	L5
8	UAV1	T1	L6

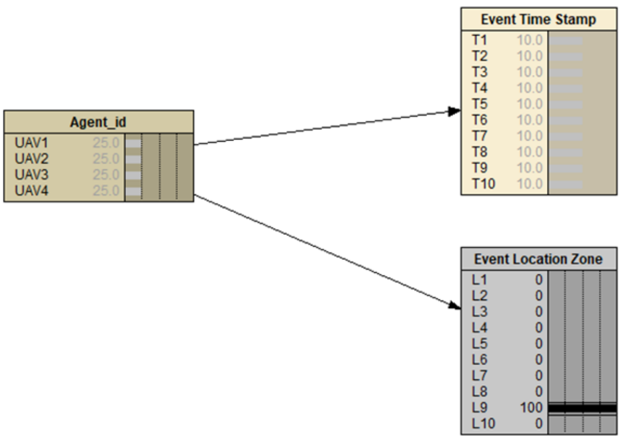

Fig. 5 Agents' Belief Conflict Recording and Training BBN.

From Fig. 4, the agents will be updating their BBN based on the sensor data. Agents and/or humans monitoring the missions can detect beliefs conflict and send other agents for the missions' updates as well as record the event on for BBN training purposes (Fig. 5). All conflict recorded by the agents or humans from the UAVs can be monitored and used for the BBN training using gradient descent [46], or expectation maximization [47] algorithms. The outcome of these algorithms is another BBN with predictions capacity which can be used for decision making and prediction purposes by the agents. Table III describes the sample of the reports recording sheet. $T_1,...,T_n$ and $L_1,...,Ln$ represent the time and location range respectively (e.g. 02:15-03:15, 14^0E-18^0E).

We train the network in Fig. 5 using the belief variation conflict (detected by the fixed-wing UAVs in Fig. 2) using the expectation-maximization algorithm [47]. During the expectation-maximization training, we monitor the location node prediction error, which is directly proportional to the sample number network (Fig. 6). The output learned BBN will be used in making predictions against near future event for the occurrence of sensor conflict (based on experience) and how it occurs given the BBN current conditions.

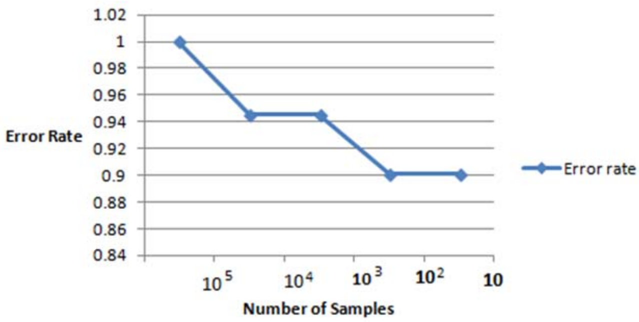

Fig. 6 Number of Sample versus Error Rate

Fig. 6 describes graph of the number of samples versus the error rate of the prediction. The error rate is the measure of the number of times the learned network predicted a wrong entry [19]. It ranges from 0 zero to 1, with 0 being the best. The result shows that the network perfection grows up (lower error rate) by the increase in the number of samples. If it followed random distribution as in Fig. 6, average data could be used in training the network (i.e., it does not need much data). The learned network can be applied in diagnosing agents' mission failures, agent's and co-agent's future actions as such optimizing the mission cost, and may serve as estimation measure for other optimization algorithms.

V. CONCLUSION

In this paper, we describe the issues bedeviling heterogeneous multi-agents missions. Our attention goes to inter-agents belief conflict due to sensor differences. We also describe inferential reasoning using Bayesian inference and agents' self-presumption. Our experiment uses a team of different agents in conducting wildfire monitoring. Agent belief variations were tracked and used to train the BBN. The results show that the higher the available cases, the higher the perfection of the trained network. We also describe how this can be applied in detecting beliefs conflict using Bayesian learning algorithms (expectation-maximization and gradient descent). Although result came as expected, our approach gives the first step in predicting and tracking sensor conflict and multi-agent mission using Bayesian reasoning. In the future, we are looking at sufficient conflict resolution, BBN merging, and learned network error rate behaviours with big data.

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REFERENCES

[1] S. Yusuf and C. Baber, "Handling Uncertainties in Distributed Constraint Optimization Problems using Bayesian Inferential Reasoning - ICAART 2020." http://www.insticc.org/node/TechnicalProgram/icaart/presentationDetails/91571 (accessed Feb. 26, 2020).

[2] S. M. Yusuf and C. Baber, "Human-agents Interactions in Multi-Agent Systems: A Case Study of Human-UAVs Team for Forest Fire Lookouts - ICAART 2020." http://www.insticc.org/node/TechnicalProgram/icaart/presentationDetails/93692 (accessed Feb. 29, 2020).

[3] T. Altameem and M. Amoon, "An agent-based approach for dynamic adjustment of scheduled jobs in computational grids," *J. Comput. Syst. Sci. Int.*, vol. 49, no. 5, pp. 765–772, Oct. 2010, doi: 10.1134/S1064230710050114.

[4] M. Yokoo, E. H. Durfee, T. Ishida, and K. Kuwabara, "The distributed constraint satisfaction problem: formalization and algorithms," *IEEE Transactions on Knowledge and Data Engineering*, vol. 10, no. 5, pp. 673–685, Sep. 1998, doi: 10.1109/69.729707.

[5] M. Turpin, N. Michael, and V. Kumar, "Capt: Concurrent assignment and planning of trajectories for multiple robots," *The International Journal of Robotics Research*, vol. 33, no. 1, pp. 98–112, Jan. 2014, doi: 10.1177/0278364913515307.

[6] "Information Exchange and Decision Making in Micro Aerial Vehicle Networks for Cooperative Search - IEEE Journals & Magazine." https://ieeexplore.ieee.org/document/7097008 (accessed May 03, 2019).

[7] J. Qin, W. X. Zheng, and H. Gao, "Coordination of Multiple Agents With Double-Integrator Dynamics Under Generalized Interaction Topologies," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 1, pp. 44–57, Feb. 2012, doi: 10.1109/TSMCB.2011.2164523.

[8] S. M. Yusuf and C. Baber, "Conflicts Resolution and Situation Awareness in Heterogeneous Multi-agent Missions using Publish-subscribe Technique and Inferential Reasoning - ICAART 2020." http://www.insticc.org/node/TechnicalProgram/icaart/presentationDetails/91474 (accessed Feb. 29, 2020).

[9] G. Pavlin, P. de Oude, M. Maris, J. Nunnink, and T. Hood, "A multi-agent systems approach to distributed bayesian information fusion," *Information Fusion*, vol. 11, no. 3, pp. 267–282, Jul. 2010, doi: 10.1016/j.inffus.2009.09.007.

[10] Y. Xiang, *Probabilistic Reasoning in Multi-Agent Systems: A Graphical Models Approach*. New York, NY, USA: Cambridge University Press, 2002.

[11] T. Setter and M. Egerstedt, "Energy-Constrained Coordination of Multi-Robot Teams," *IEEE Transactions on Control Systems Technology*, vol. 25, no. 4, pp. 1257–1263, Jul. 2017, doi: 10.1109/TCST.2016.2599486.

[12] X. Zhou, W. Wang, W. Tao, L. Xiaboo, and J. Tian, "Continuous patrolling in uncertain environment with the UAV swarm," 2018. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0202328 (accessed Aug. 18, 2019).

[13] Y. Xiang, "Probabilistic Reasoning in Multiagent Systems: A Graphical Models Approach," *Cambridge Core*, Aug. 2002. /core/books/probabilistic-reasoning-in-multiagent-systems/C78168FDA67EF5E2EEBB9C63AC70EAD2 (accessed Nov. 07, 2019).

[14] G. Pavlin, P. de Oude, M. Maris, J. Nunnink, and T. Hood, "A multi-agent systems approach to distributed bayesian information fusion," *Information Fusion*, vol. 11, no. 3, pp. 267–282, Jul. 2010, doi: 10.1016/j.inffus.2009.09.007.

[15] J. Fransman, J. Sijs, H. Dol, E. Theunissen, and B. De Schutter, "Bayesian-DPOP for Continuous Distributed Constraint Optimization Problems," in *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems*, Richland, SC, 2019, pp. 1961–1963, Accessed: Nov. 06, 2019. (Online). Available: http://dl.acm.org/citation.cfm?id=3306127.3331977.

[16] J. Wang and Z. Xu, "Bayesian Inferential Reasoning Model for Crime Investigation," p. 11, 2014.

[17] J. Williamson, "Bayesian Networks for Logical Reasoning," p. 19, 2001.

[18] S. Mandt and M. D. Hoffman, "Stochastic Gradient Descent as Approximate Bayesian Inference," p. 35, 2017.

[19] M. Romanycia, "Netica-J Reference Manual," p. 119, 2019.

[20] M. Georgeff, B. Pell, M. Pollack, M. Tambe, and M. Wooldridge, "The Belief-Desire-Intention Model of Agency," in *Intelligent Agents V: Agents Theories, Architectures, and Languages*, vol. 1555, J. P. Müller, A. S. Rao, and M. P. Singh, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 1999, pp. 1–10.

[21] S. Makonin, D. McVeigh, W. Stuerzlinger, K. Tran, and F. Popowich, "Mixed-Initiative for Big Data: The Intersection of Human + Visual Analytics + Prediction," in *2016 49th Hawaii International Conference on System Sciences (HICSS)*, Jan. 2016, pp. 1427–1436, doi: 10.1109/HICSS.2016.181.

[22] C. Rich and C. L. Sidner, "DiamondHelp: A Generic Collaborative Task Guidance System," *1*, vol. 28, no. 2, pp. 33–33, Jun. 2007, doi: 10.1609/aimag.v28i2.2038.

[23] R. F. Stark, M. Farry, and J. Pfautz, "Mixed-initiative data mining with Bayesian networks," in *2012 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support*, Mar. 2012, pp. 107–110, doi: 10.1109/CogSIMA.2012.6188360.

[24] E. Yanmaz, S. Yahayanajeed, and R. Bernerd, "Drone Networks: Communications, Coordination, and Sensing," *Elsevier*, Sep. 2017.

[25] J. Cortés and M. Egerstedt, "Coordinated Control of Multi-Robot Systems: A Survey," *SICE Journal of Control, Measurement, and System Integration*, vol. 10, no. 6, pp. 495–503, 2017, doi: 10.9746/jcmsi.10.495.

[26] J. P. Desai, J. Ostrowski, and V. Kumar, "Controlling formations of multiple mobile robots," 1998, vol. 4, pp. 2864–2869 vol.4, doi: 10.1109/ROBOT.1998.680621.

[27] G. Ferguson and J. Allen, "Mixed-Initiative Systems for Collaborative Problem Solving," *1*, vol. 28, no. 2, pp. 23–23, Jun. 2007, doi: 10.1609/aimag.v28i2.2037.

[28] K. Ghamry and Y. Zhang, "Cooperative control of multiple UAVs for forest fire monitoring and detection," Aug. 2016, pp. 1–6, doi: 10.1109/MESA.2016.7587184.

[29] G. Vásárhelyi *et al.*, "Outdoor flocking and formation flight with autonomous aerial robots," Feb. 2014, Accessed: Apr. 21, 2019. (Online). Available: https://arxiv.org/abs/1402.3588v2.

[30] A. Weinstein, A. Cho, G. Loianno, and V. Kumar, "Visual Inertial Odometry Swarm: An Autonomous Swarm of Vision-Based Quadrotors," *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 1801–1807, Jul. 2018, doi: 10.1109/LRA.2018.2800119.

[31] M. M. Khan, "Speeding up GDL-based distributed constraint optimization algorithms in cooperative multi-agent systems," phd, University of Southampton, 2018.

[32] M. Vasile and F. Zuiani, "Multi-agent collaborative search : an agent-based memetic multi-objective optimization algorithm applied to space trajectory design," *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, vol. 225, pp. 1211–1227, Nov. 2011.

[33] A. Khan, E. Yanmaz, and B. Rinner, "Information Exchange and Decision Making in Micro Aerial Vehicle Networks for Cooperative Search," *IEEE Transactions on Control of Network Systems*, vol. 2, no. 4, pp. 335–347, Dec. 2015, doi: 10.1109/TCNS.2015.2426771.

[34] A. Khan, E. Yanmaz, and B. Rinner, "Information merging in multi-UAV cooperative search," in *2014 IEEE International Conference on Robotics and Automation (ICRA)*, May 2014, pp. 3122–3129, doi: 10.1109/ICRA.2014.6907308.

[35] S. Grayson, "Search & Rescue using Multi-Robot Systems," 2014.

[36] S. Rabinovich, R. E. Curry, and G. H. Elkaim, "Toward Dynamic Monitoring and Suppressing Uncertainty in Wildfire by Multiple Unmanned Air Vehicle System," *Journal of Robotics*, 2018. https://www.hindawi.com/journals/jr/2018/6892153/ (accessed Aug. 25, 2019).

[37] G. Bevacqua, J. Cacace, A. Finzi, and V. Lippiello, "Mixed-initiative Planning and Execution for Multiple Drones in Search and Rescue Missions," in *Proceedings of the Twenty-Fifth International Conference on International Conference on Automated Planning and Scheduling*, Jerusalem, Israel, 2015, pp. 315–323, Accessed: Feb. 19, 2019. (Online). Available: http://dl.acm.org/citation.cfm?id=3038662.3038706.

[38] J. Cacace, A. Finzi, and V. Lippiello, "A mixed-initiative control system for an Aerial Service Vehicle supported by force feedback," in *2014*

IEEE/RSJ International Conference on Intelligent Robots and Systems, Sep. 2014, pp. 1230–1235, doi: 10.1109/IROS.2014.6942714.

[39] J. Hu, L. Xie, K. Lum, and J. Xu, "Multiagent Information Fusion and Cooperative Control in Target Search," *IEEE Transactions on Control Systems Technology*, vol. 21, no. 4, pp. 1223–1235, Jul. 2013, doi: 10.1109/TCST.2012.2198650.

[40] M. Kohlert and A. König, "Large, high-dimensional, heterogeneous multi-sensor data analysis approach for process yield optimization in polymer film industry," *Neural Comput & Applic*, vol. 26, no. 3, pp. 581–588, Apr. 2015, doi: 10.1007/s00521-014-1654-5.

[41] L. Merino, O. Caballero, J. R. Martínez-de-dios, and I. Maza, *Automatic Forest Fire Monitoring and Measurement using Unmanned Aerial Vehicles*. .

[42] *https://github.com/afrl-rq/OpenAMASE*. afrl-rq, 2019.

[43] M. Chawla and M. Duhan, "Levy Flights in Metaheuristics Optimization Algorithms – A Review," *Applied Artificial Intelligence*, vol. 32, no. 9–10, pp. 802–821, Nov. 2018, doi: 10.1080/08839514.2018.1508807.

[44] S. G. Nurzaman, Y. Matsumoto, Y. Nakamura, S. Koizumi, and H. Ishiguro, "Biologically inspired adaptive mobile robot search with and without gradient sensing," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, MO, USA, Oct. 2009, pp. 142–147, doi: 10.1109/IROS.2009.5353998.

[45] D. K. Sutantyo, S. Kernbach, V. A. Nepomnyashchikh, and P. Levi, "Multi-Robot Searching Algorithm Using Levy Flight and Artificial Potential Field," *arXiv:1108.5624 [cs]*, Aug. 2011, Accessed: May 25, 2019. (Online). Available: http://arxiv.org/abs/1108.5624.

[46] J. Q. Hale and E. Zhou, "A Model-based Approach to Multi-objective Optimization," in *Proceedings of the 2015 Winter Simulation Conference*, Piscataway, NJ, USA, 2015, pp. 3599–3609, Accessed: Aug. 02, 2019. (Online). Available: http://dl.acm.org/citation.cfm?id=2888619.2889103.

[47] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum Likelihood from Incomplete Data via the EM Algorithm," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 39, no. 1, pp. 1–38, 1977.