RESEARCH STATEMENT

Qin Yang (RickYang2014@gmail.com, qy03103@uga.edu)
Research Demonstration: https://rickyang2014.wixsite.com/qinyang/research

My research interests span the areas of multi-agent systems (MAS), multi-robot systems (MRS), distributed artificial intelligence (DAI) and Swarm Intelligence. A common thread in my research is in understanding the theory of relationships between agents' motivation, behaviors, and strategies adapting to complex environments and design the scalable architectures implemented in AI agent (like robot). I care about basic research that leads to fundamental new concepts resorted to mathematical methods of proof borrowed from Artificial Intelligence (AI), Robotics, Information and System Theory, Algorithms, Machine Learning, Game theory, Statistics, and Probabilistic Graphical Models (PGM).

Most of my current research application fields and lab-in-the-field experiments test insights from MAS/MRS cooperative planning and control and the design of innovation decision-making and learning architectures and algorithms simulating in AI agents or demonstrating on real robots and sensor networks.

Broadly speaking, my research belongs to the area of *Multi-Agent/Robot Systems* and *Artificial Intelligence* (which deals with the fundamental principles of architecture design), an upcoming field which is still in its infancy and whose theoretical foundations are just being laid.

Background and Current Works

It is natural that most large and complex systems are created from a set of smaller components, each of which is simpler than the system as a whole. The functioning of a complex system depends on the interaction between its constituent components. Multi-agent systems (MAS) could play a pivotal role in the potential and realization of future intelligent workspaces, especially building so-called human-artificial social systems, such as self-driving cars and multi-robot systems (MRS) aids for autonomy. For example, MRS cooperative working on exploration, disaster, or emergency scenarios, including complex, hazardous, dynamic changing, and adversarial environments like the urban search and rescue missions (USAR) and explore domain. However, integrating task requirements, low-level planning and control, and high-level decision making and learning in MAS to present reasonable strategies adapting to complex environments is still a challenge.

In my Ph.D studies, I attempt to lay a theoretical framework for this field. My thesis discusses a principled MAS cooperation framework, termed the Self-Adaptive Swarm System (SASS), which bridges communication, planning, execution, decision-making, and learning in the distributed MAS.

In particular, the main novel technical contributions of this thesis are as follow: defining Robot Needs Hierarchy to model the agent's motivation and requirements; offering a priority-based distributed Negotiation-Agreement Mechanism for realizing multi-agent task assignments, avoiding plan conflicts effectively; providing several Atomic Operations for MAS cooperation to achieve complex tasks through a series of simple sub-tasks; introducing the needs-based agent trust model – Relative Needs Entropy – analyzing the reliability and stability of relationships in MAS cooperation; building a new hierarchical network model called Game-theoretic Utility Tree to realize game-theoretic solutions in the presence of adversarial MAS; creating the Bayesian Strategy Networks (BSN) through Deep Reinforcement Learning (DRL) obtaining the optimal strategy combinations for MAS cooperation in various scenarios. Most of my work has greatly benefited from interaction with a number of colleagues and my advisor. I describe my work as below.

Self-Adaptive Swarm System (SASS)

Natural systems (living beings) and artificial systems (robotic agents) are characterized by apparently complex behaviors that emerge as a result of often nonlinear spatiotemporal interactions among a large number of components at different levels of organization [1]. Simple principles acting at the agent level can result in complex behavior at the global level in a swarm system, which has enjoyed both widespread academic interest and commercial success, especially in MAS/MRS.

However, observing the existence of theories and techniques, there are still three open questions about those systems:

1. *What is complexity?*
2. *What is intelligence?*
3. *Which kinds of complex systems can lead to intelligence?*

From the system theory perspective, we regard *Complexity* as certain relationships building in the interaction between and within various elements of systems. From an individual angle, agent or element principles acting might change system behaviors and inner/outer-relationships. Especially for the self-organized systems, their behaviors based on the current needs or systems' utilities present the global behaviors adapting to specific scenarios, which lead to certain intelligence. A good example is *Swarm Intelligence*, the collective behavior of distributed and self-organized systems [2].

To drive advanced intelligence and automation systems, the MAS needs to be combined with auxiliary controllers to handle conflicts, decompose the complicated task, and organize agents' behaviors and relationships, representing more complex strategies adapting to dynamic changes in the task assignments. In my Ph.D research, I propose a MAS/MRS cooperation concept, Self-Adaptive Swarm System (SASS) [3, 4], that combines the parts of the perception, communication, planning, and execution to address this gap. And I introduce three novel concepts in SASS:

1. ***Robot Needs Hierarchy*** To model an artificial intelligence agent's motivations and needs, I classify the *Robot Needs Hierarchy* as five different levels: *safety needs* (collision avoidance, human-safety control, etc.); *basic needs* (energy, time constraints, etc.); *capability* (heterogeneity, hardware differences, etc.); *teaming* (global utility, team performance, etc.); and *self-upgrade* (learning).
2. ***Negotiation-Agreement Mechanism*** I propose a *distributed Negotiation-Agreement* mechanism for selection (task assignment), formation (shape control), and routing (path planning) through automated planning of state-action sequences, helping MAS solve the conflicts in cooperation.
3. ***Atomic Operations*** By decomposing the complex tasks into a series of simple sub-tasks based on the *Atomic Operations*: *Selection*, *Formation*, and *Routing*, agents can recursively achieve all sub-tasks until MAS completes the mission.

The experimental analysis showed that the needs-based cooperation mechanism outperformed state-of-the-art methods in maximizing global team utility and reducing conflicts in planning and negotiation.

Relative Needs Entropy (RNE) Agent Trust Model

Trust describes the interdependent relationship between agents [5], which can help us better understand the dynamics of cooperation and competition, the resolution of conflicts, and the facilitation of economic exchange [6]. In different computing fields, trust is different based on various perspectives. However, in computational agents, these models do not involve the trustor's characteristics but focus on forming trust based on past behavior [7].

More generally, in MAS, it reflects agents' mission satisfaction, organizational group member behaviors and consensus, and task performance at the individual level. Moreover, trust has been associated with system-level analysis, such as reward and function at the organized group structure in a specific situation, the conflict solving of heterogeneous and diverse needs, and the system evolution through learning from interaction and adaptation. Although modeling trust has been studied from various perspectives and involves many different factors, it is still challenging to develop a conclusive trust model that incorporates all of these factors. Especially current trust models do not establish a substantial and clear connection between the agent's behaviors and motivations.

To bridge the gaps, based on the *Robot Needs Hierarchy* model, I introduce a general agent trust model – *Relative Needs Entropy (RNE)* [8, 9], which describes the reliability and stability of the relationships between agents in MAS cooperation. Like the information entropy, considering intelligent agents representing different needs in interaction, especially for the heterogeneous MRS, I define the needs entropy as the difference or distance of needs distribution between agents in a specific scenario for individuals or groups.

From the statistics perspective, the RNE can be regarded as calculating the similarity of high-dimensional samples from the robot needs vector. *A lower RNE value means that the trust level between agents or groups is higher because their needs are well-aligned and there is low difference (distance) in their needs distributions.* Similarly, a higher RNE value will mean that the needs distributions are diverse, and there exists a low trust level between the agent or groups because of their misalignment in their motivations, which are similar to each other.

We verify this trust model in a simulated urban search and rescue (USAR) mission to achieve multi-robot grouping based on trust level within the robots in a group. We analyze the relative mission performance against state-of-the-art methods which use energy capability (battery level) [4] or the spatial proximity (i.e., the inter-distance) between the robots for distributed task allocation [10]. The results show that the RNE trust model helps the system reassign the resources and gathers agents with similar capabilities, needs, and interests to fulfill suitable tasks, improving system performance and letting each group member's abilities be fully utilized. Like human society, the MAS/MRS can make the best possible use of resources and materials based on trust-based cooperation models.

Game-theoretic Utility Tree (GUT) Agent Decision-Making Model

Multiagent systems (MAS) [11] that cooperate with each other show *Distributed Intelligence*, which refers to systems of entities working together to reason, plan, solve problems, think abstractly, comprehend ideas and language, and learn [12]. In the system, an individual agent is aware of other group members and actively shares and integrates its needs, goals, actions, plans, and strategies to achieve a common goal and benefit the entire group. They can maximize global system utility together and guarantee sustainable development for each group member [13].

Systems with a wide variety of agent heterogeneity and communication abilities can be studied, and collaborative and adversarial issues also can be combined in a real-time situation [14]. Under the presence of adversarial agents, opponents can prevent agents from achieving global and local tasks, even impair individual or system necessary capabilities or normal functions [15].

MAS research domains focus on solving path planning problems for avoiding static or dynamical obstacles and formation control from the unintentional adversary perspective. For intentional adversaries, the "pursuit domain" [16] primarily deals with how to guide one or a group of pursuers to catch one or a group of moving evaders. Similarly, the robot soccer domain [17] deals with how one group of robots win over another group of robots on a common game element. Nevertheless, it is more realistic and practical for MAS to organize more complex relationships and behaviors, achieving given tasks with higher success probability and lower costs in adversarial environments.

Game Theory is the science of strategy, which provides a theoretical framework to conceive social situations among competing players and produce optimal decision-making of independent and competing actors in a strategic setting [18]. In order to help for cooperative MAS decisions in complex and adversarial environments, I propose a new hierarchical network-based model called Game-theoretic Utility Tree (GUT) [19], which decomposes a complex big game into conditional dependent simple small games and presents them as a tree structure. We can always find an optimal strategy trajectory against the adversary in the current situation through the GUT by calculating the Nash Equilibrium in the corresponding sub-games distributed in each level. GUT consists of *Game-theoretic Utility Computation Units* distributed in multiple levels by decomposing team strategies, thereby significantly lowering the game-theoretic operations in strategy space dimension. It combines with a new payoff measure based on agent needs for real-time strategy games and the core principles of *Game Theory*, and *Utility Theory* [20]. Furthermore, I present an *Explore Game Domain*, which measures the performance of MAS achieving tasks from the perspective of balancing the success probability and system costs.

I evaluate the GUT approach against state-of-the-art methods that greedily rely on rewards of the composite actions. Conclusive results on extensive numerical simulations indicate that GUT can organize more complex relationships among MAS cooperation, helping the group achieve challenging tasks with lower costs and higher winning rates. I also demonstrated the applicability of the GUT in the Robotarium [21] (a simulator-hardware testbed for multi-robot systems) on two different domains: Explore domain and Pursuit-Evasion domain. The performances verified the effectiveness of the GUT in the real robot application and validated that the GUT could effectively organize MAS cooperation strategies, helping the group with fewer advantages achieve higher performance.

Bayesian Strategy Net (BSN) with Deep Reinforcement Learning (DRL)

Adopting reasonable strategies is crucial for an intelligent agent with limited resources working in hazardous, unstructured, and dynamic changing environments to improve the system utility, decrease the overall cost, and increase mission success probability. Especially in the application domains such as exploration, disaster rescue, and emergency scenarios, the agent needs to dynamically switch its strategies based on the priority of its goals and needs adapting to various situations. Organizing the agent's behaviors and actions to represent complex strategies is challenging to achieve adaption in policy learning through interaction.

In the *SASS*, *Robot Needs Hierarchy* is the foundation. It surveys the system's utility from individual needs. Balancing the rewards between agents and groups for MAS through interaction and adaptation in cooperation optimizes the global system's utility and guarantees sustainable development for each group member, much like human society does [22]. Considering helping *SASS* self-evolution, individuals need to upgrade themselves from interaction, cooperation, and adaptation to achieve the highest level needs – *learning*.

Furthermore, I propose a decomposing strategy technique through a Bayesian net termed *Bayesian Strategy Net* (BSN), forming intricate relationships between atomic actions and building the corresponding Deep Reinforcement Learning (DRL) model to account for this unique action decomposition by training different sub-policies for atomic actions. Here, multiple actors jointly generate the global policy while a single critic evaluates the rewards from the environment on the joint strategy. The proposed approach can be extended to multi-agent strategies and will help the agents optimize its utilities and rewards in the mission in an more efficient and robust manner.

Future Works — A Research Agenda

In the course of my research, the SASS as a novel DAI model, the planning and control govern the individual low-level *safety* and *basic* needs; *capability* and *teaming* needs are the preconditions and requirements of MAS cooperation in decision-making for achieving tasks; through *learning*, agents can upgrade by itself based on the experiences and lead to the self-evolution of the whole system. However, I have noticed that optimizing the communication architecture in MAS cooperation and efficient learning mechanisms are the main challenge. I envisage the field of *MAS/MRS* extended to DAI created from the ground up, building upon the foundations of a number of fields including those mentioned above.

In the near future, I am interested in the principles involved in designing basic system architecture and learning algorithms through machine learning, demonstrating them on real AI agents (like robot) or sensor networks. These include the system performance, robustness, adaptability, generality, and the efficiency in scalability etc. My research will focus on how these basic and large components can be built in a scalable MAS while maintaining performance guarantees. Simultaneously, I intend to deeply understand how to organize multi-layer relationships building in agents' interactions, presenting more complex behaviors or strategies adapting to various environments.

In the future, though performance and scalability will remain key in MAS cooperation, I also intend to look at the issue – the robust agent trust network, which will become more relevant. Since compared with the natural intelligent agent, when the AI agent becomes more advanced and intelligent, it also represents more complex, multilayered, and diverse needs in evolution such as individual security, health, friendship, love, respect, recognition. When we consider intelligent agents, like robots, working as a team or cooperating with human beings, organizing their needs building certain reliable and stable relationships such as trust is a precondition for robot-robot and human-robot collaboration in complex and uncertain environments. It also involves the topics such as AI safety and information security.

Furthermore, my research will involve a good mix of futuristic and present day research. One part of my work will focus on fundamentally different proposals and radical solutions. In contrast, the other part of my work on practical systems has immediate relevance and impact in industry. I am excited at the prospect of learning, contributing, giving shape and making an impact in this upcoming and challenging field.

References

[1] S. A. Levin, "Ecosystems and the biosphere as complex adaptive systems," *Ecosystems*, vol. 1, no. 5, pp. 431–436, 1998.

[2] H. Hamann and H. Wörn, "A framework of space–time continuous models for algorithm design in swarm robotics," *Swarm Intelligence*, vol. 2, no. 2-4, pp. 209–239, 2008.

[3] Q. Yang, Z. Luo, W. Song, and R. Parasuraman, "Self-Reactive Planning of Multi-Robots with Dynamic Task Assignments," in *IEEE International Symposium on Multi-Robot and Multi-Agent Systems (MRS) 2019*, 2019. Extended Abstract.

[4] Q. Yang and R. Parasuraman, "Hierarchical needs based self-adaptive framework for cooperative multi-robot system," in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 2991–2998, IEEE, 2020.

[5] R. L. Swinth, "The establishment of the trust relationship," *Journal of conflict resolution*, vol. 11, no. 3, pp. 335–344, 1967.

[6] R. J. Lewicki, E. C. Tomlinson, and N. Gillespie, "Models of interpersonal trust development: Theoretical approaches, empirical evidence, and future directions," *Journal of management*, vol. 32, no. 6, pp. 991–1022, 2006.

[7] J.-H. Cho, K. Chan, and S. Adali, "A survey on trust modeling," *ACM Computing Surveys (CSUR)*, vol. 48, no. 2, pp. 1–40, 2015.

[8] Q. Yang and R. Parasuraman, "Needs-driven heterogeneous multi-robot cooperation in rescue missions," in *2020 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, pp. 252–259, IEEE, 2020.

[9] Q. Yang and R. Parasuraman, "How can robots trust each other for better cooperation? a relative needs entropy based robot-robot trust assessment model," in *2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, IEEE.

[10] R. Parasuraman, J. Kim, S. Luo, and B.-C. Min, "Multipoint rendezvous in multirobot systems," *IEEE transactions on cybernetics*, vol. 50, no. 1, pp. 310–323, 2018.

[11] M. Wooldridge, *An introduction to multiagent systems*. John wiley & sons, 2009.

[12] L. E. Parker, "Distributed intelligence: Overview of the field and its application in multi-robot systems.," in *AAAI Fall Symposium: Regarding the Intelligence in Distributed Intelligent Systems*, pp. 1–6, 2007.

[13] J. Shen, X. Zhang, and V. Lesser, "Degree of local cooperation and its implication on global utility," in *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 2*, pp. 546–553, Citeseer, 2004.

[14] P. Stone and M. Veloso, "Multiagent systems: A survey from a machine learning perspective," *Autonomous Robots*, vol. 8, no. 3, pp. 345–383, 2000.

[15] M. Jun and R. D'Andrea, "Path planning for unmanned aerial vehicles in uncertain and adversarial environments," in *Cooperative control: models, applications and algorithms*, pp. 95–110, Springer, 2003.

[16] T. H. Chung, G. A. Hollinger, and V. Isler, "Search and pursuit-evasion in mobile robotics," *Autonomous robots*, vol. 31, no. 4, p. 299, 2011.

[17] S. Nadarajah and K. Sundaraj, "A survey on team strategies in robot soccer: team strategies and role description," *Artificial Intelligence Review*, vol. 40, no. 3, pp. 271–304, 2013.

[18] R. B. Myerson, *Game theory*. Harvard university press, 2013.

[19] Q. Yang and R. Parasuraman, "A game-theoretic utility network for cooperative multi-agent decisions in adversarial environments," *arXiv preprint arXiv:2004.10950*, 2020.

[20] P. C. Fishburn, "Utility theory for decision making," tech. rep., Research analysis corp McLean VA, 1970.

[21] S. Wilson, P. Glotfelter, L. Wang, S. Mayya, G. Notomista, M. Mote, and M. Egerstedt, "The robotarium: Globally impactful opportunities, challenges, and lessons learned in remote-access, distributed control of multirobot systems," *IEEE Control Systems Magazine*, vol. 40, no. 1, pp. 26–44, 2020.

[22] Q. Yang, "Self-adaptive swarm system (sass)," in *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI-21*, pp. 5040–5041, International Joint Conferences on Artificial Intelligence Organization, 8 2021. Doctoral Consortium.