Towards Networked Airborne Computing in Uncertain Airspace: A Control and Networking Facilitated Distributed Computing Framework

Poznan Workshop, October 2024

Towards Networked Airborne Computing in Uncertain Airspace

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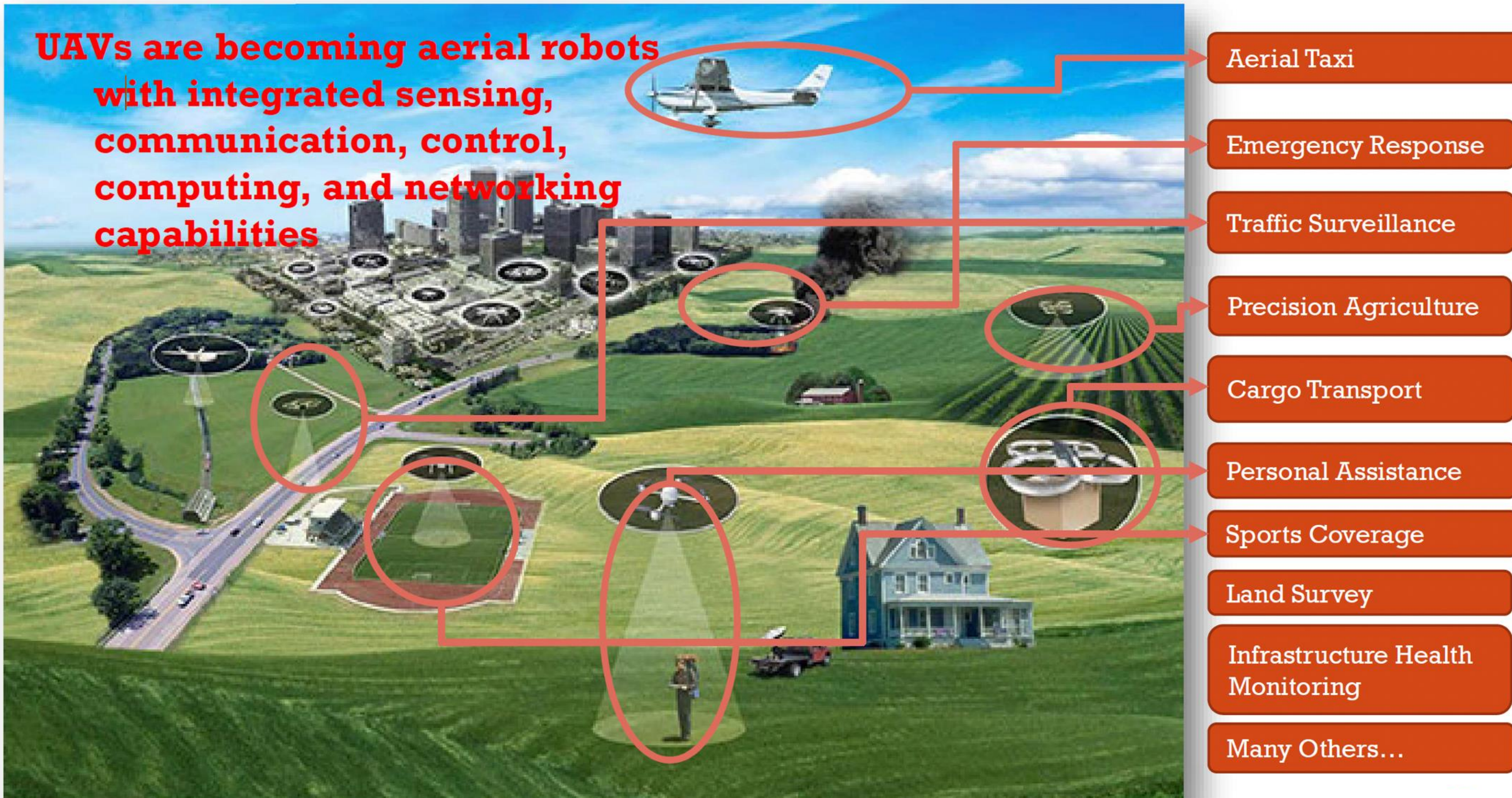
Introduction: Unmanned Aerial Vehicle

- UAVs, a.k.a., drones, have become quite common in our daily lives.

PC: Factor Daily, InterDrone, Amazon, Anuj Tiwari, DroneMate, WeTalkUAV

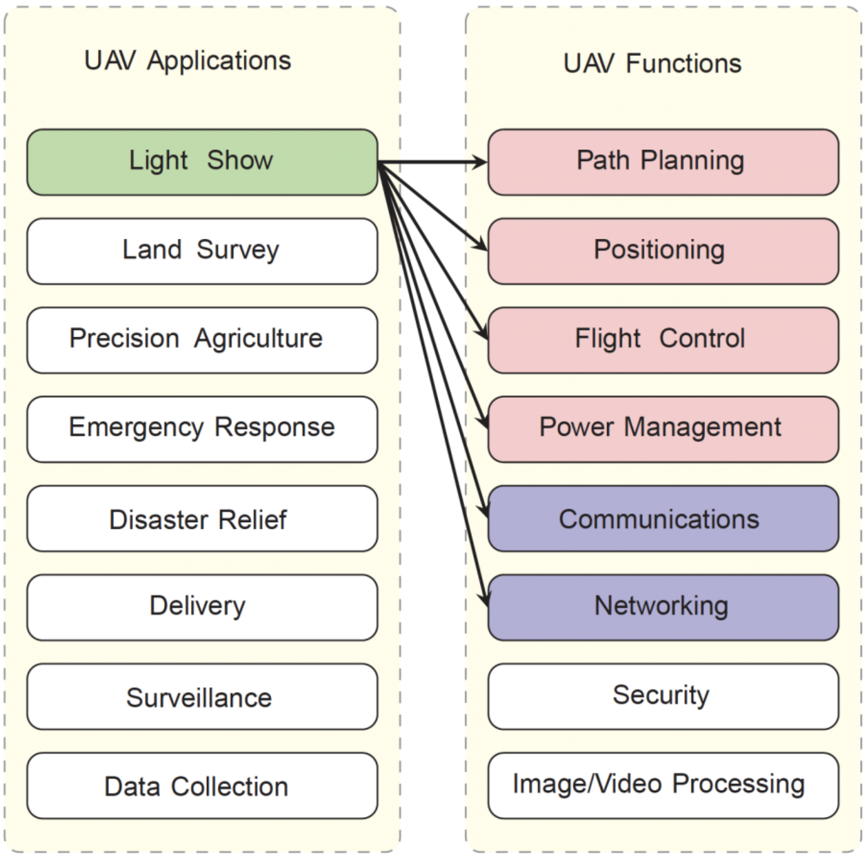
Networked UAVs



https://www.nasa.gov/ames/utm/

Introduction: Computing Need

- To realize a UAV application, it is necessary to design and implement multiple UAV functions.

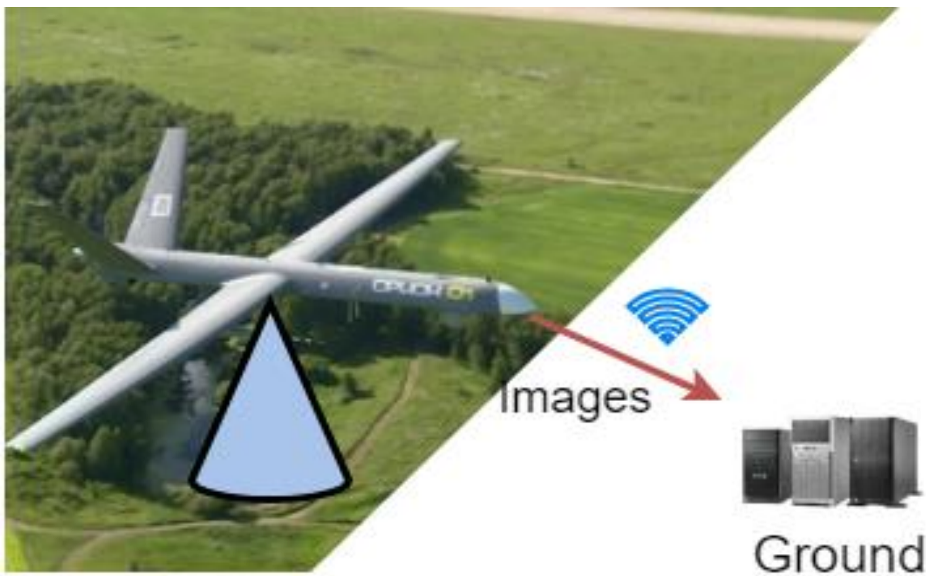


Many advanced UAV functions require considerable computing resources.

K. Lu, J. Xie, Y. Wan, S. Fu, "Towards UAV-Based Airborne Computing", IEEE Wireless Communications Magazine, Vol. 26, No. 6, pp. 172-179, 2019.

Introduction: Existing Solutions

- Many existing UAV platforms have limited computing capability.
- Computation-intensive tasks are offloaded to the ground station or the remote cloud.

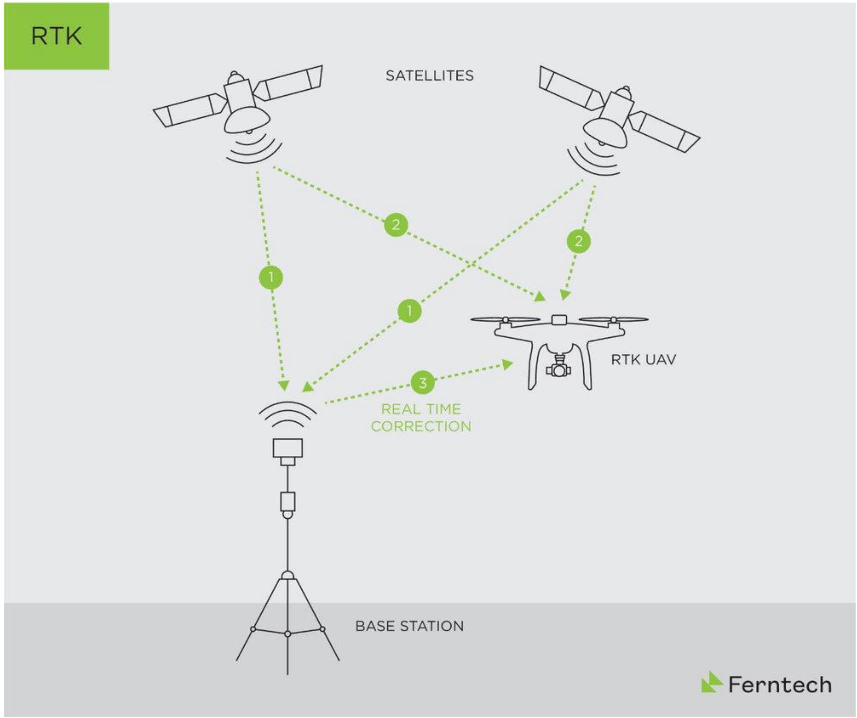


Issues:

- May lead to significant transmission delays or failures
- For high-bandwidth applications, such a computing model requires large communication bandwidths.

Introduction: Airborne Computing

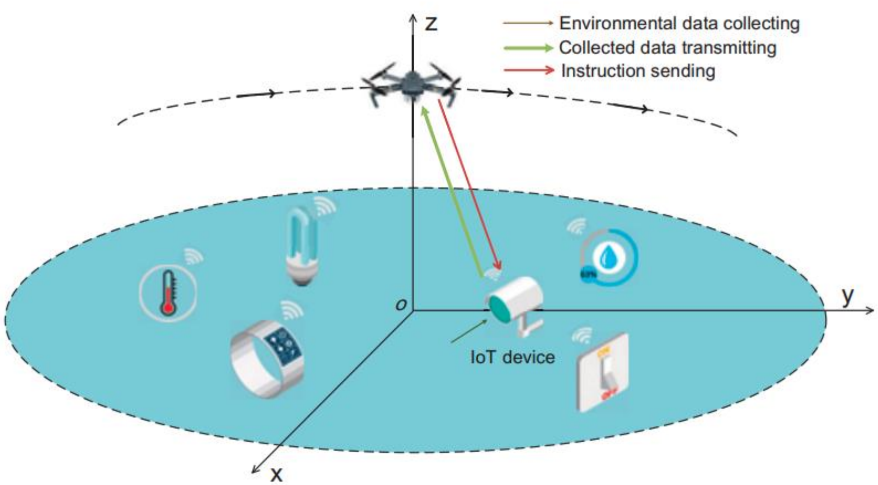
- Benefit existing UAV applications by enhancing UAV functions



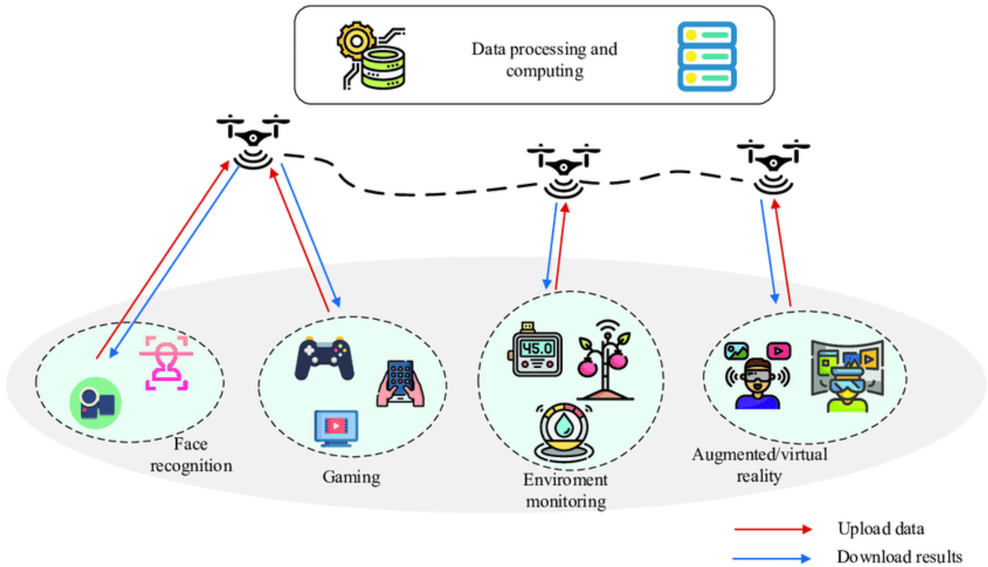
Y. Gu, M. Zhou, S. Fu, and Y. Wan, "Airborne WiFi Networks through Directional Antennae: An Experimental Study", in Proceedings of 2015 IEEE Wireless Communications and Networking Conference, New Orleans, LA, March 2015.
PC: Ferntech, Vision Systems

Introduction: Airborne Computing

- Benefit existing UAV applications by enhancing UAV functions
- Facilitate and enable new applications



IoT



UAV-assisted MEC

- Du, Yao, Kezhi Wang, Kun Yang, and Guopeng Zhang. "Energy-efficient resource allocation in UAV based MEC system for IoT devices." In 2018 IEEE Global Communications Conference (GLOBECOM), pp. 1-6. IEEE, 2018.
- Li, Linpei, Xiangming Wen, Zhaoming Lu, and Wenpeng Jing. "An energy efficient design of computation offloading enabled by UAV." Sensors 20, no. 12 (2020): 3363.

Networked Airborne Computing (NAC)

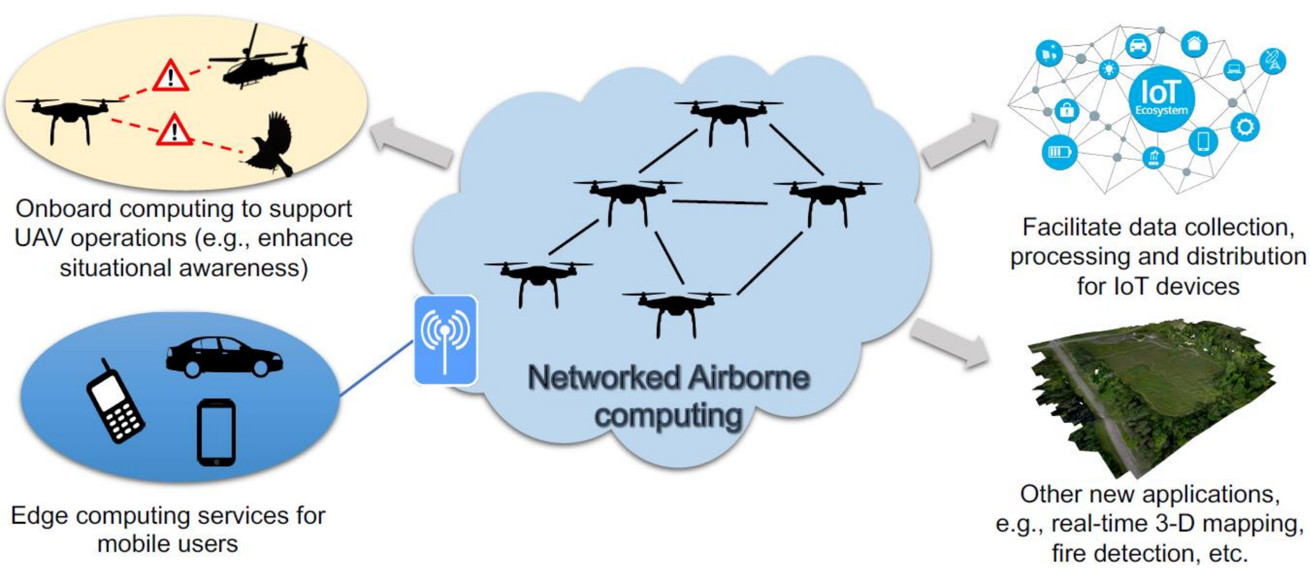
Challenge:

- Computing capacity of a single UAV is limited.

➡ multiple UAVs compute collaboratively

Networked Airborne Computing:

- Computing in the aerial layer through the airborne network



Technical Challenges

High 3-D mobility:

- Cause frequent network topology changes, link failures, data losses and task interruptions

High-dimensional uncertainty:

- Modulate the dynamics of the UAVs
- Disturb the communication among the UAVs

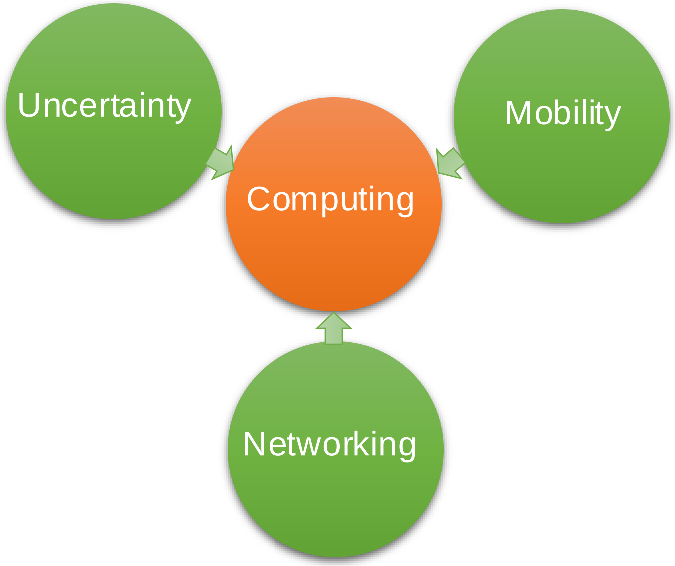
Strict safety requirement:

- UAVs are required to respond in a timely manner and satisfy mechanical and aerodynamic constraints

➡ Constrained designs employed by traditional mobile computing systems are not sufficient any more.

Control and Networking Facilitated Distributed Computing Framework

- Proactively exploits the **mobility**, **uncertainty**, and **networkin**g to enable high-performance designs
  - Mobility-aware coded distributed computing
  - Stochastic mobility control to facilitate robust computing under uncertainty
  - Networking design to facilitate scalable computing



Coded Distributed Computing

Traditional distributed computing:

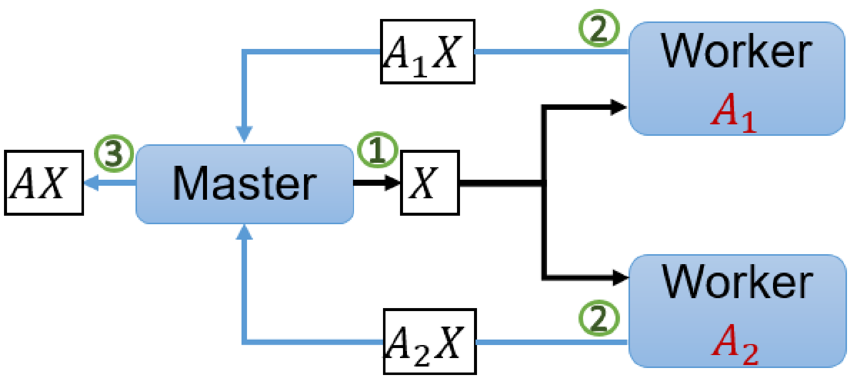
- allocate non-overlapping tasks to different computing nodes

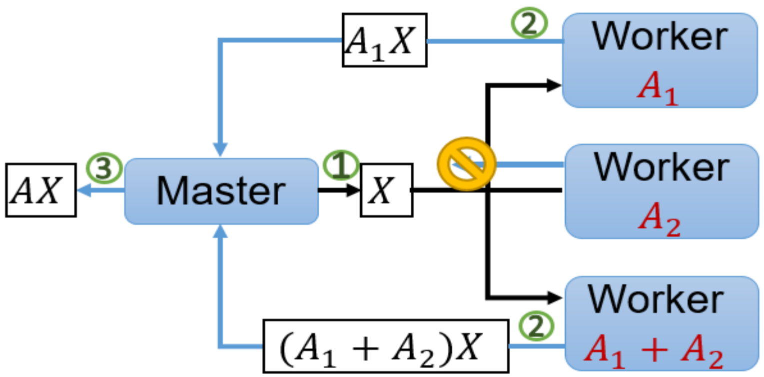
→ sensitive to system noises, e.g., stragglers

Coded distributed computing:

- Introduce redundancy into computation through erasure codes

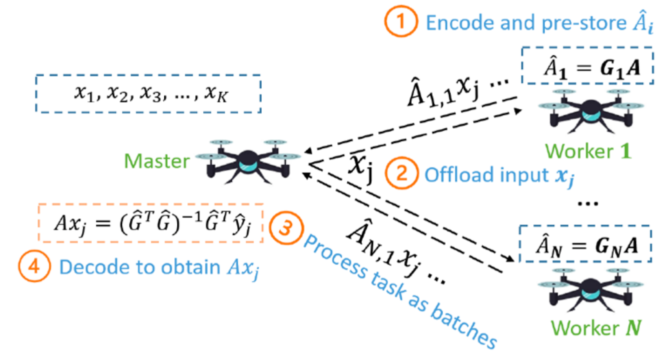
→ resilient to failures & higher efficiency

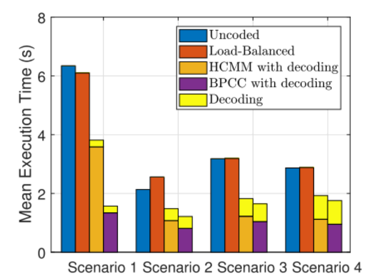


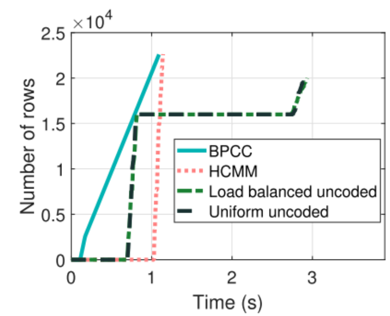


New Coded Distributed Computing Strategies

- **Batch Processing based Coded Computing for Static Networks**
  - Work for heterogeneous computing nodes.
  - Partial results are returned continuously, allowing quick response.
  - Resilient to node/link failures, topology changes, slowdowns, communication bottlenecks, and other network changes.





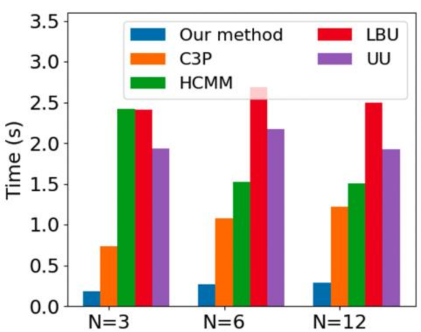


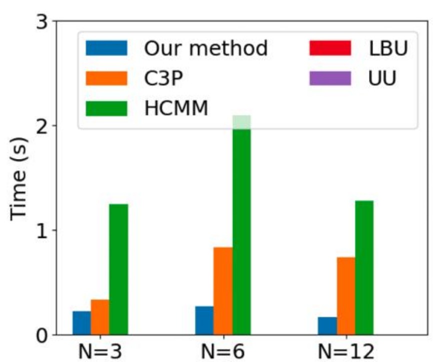
- *Experiment Results on Amazon EC2:*
  - Slow Nodes: BPCC achieves up to 79%, 78%, 62% improvements compared to Uncoded, Load-Balanced, HCMM, respectively.
  - Node failures: Uncoded, Load-Balanced fail all computation runs; BPCC has higher success rate and smaller mean execution time.

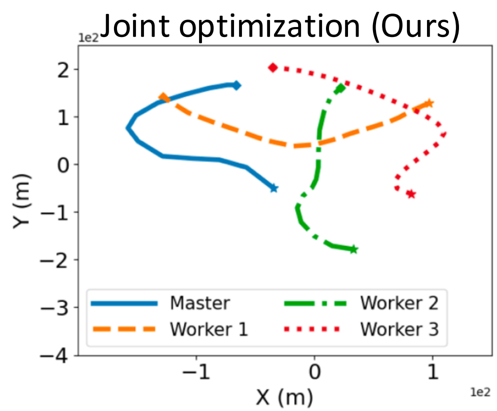
Mobility-Aware Coded Distributed Computing

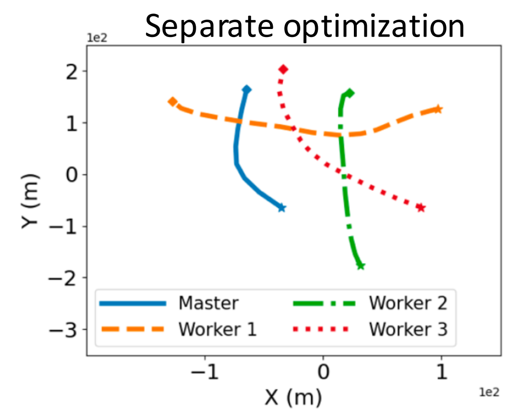
NAC Formation Scenarios:

- **Scenario One**: formed by UAVs operated by different owners in an opportunistic manner
  - e.g., when cargo drones owned by different companies are serving the same area.
  - *Mobility of the UAVs:* uncontrollable, unknown, and can be considered random.
- **Scenario Two:** formed by UAVs operated by the same owner
  - e.g., in multi-UAV applications like multi-UAV surveillance, search and rescue.
  - *Mobility of the UAVs:* controllable, and can be proactively planned by the owner to facilitate computing





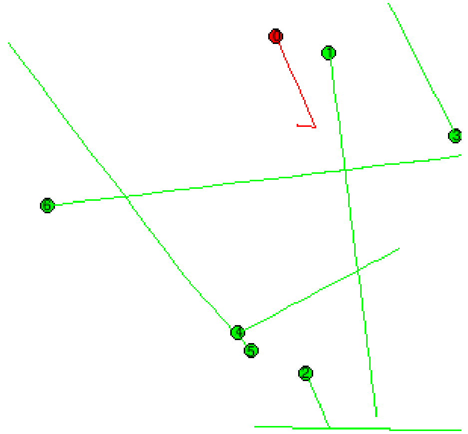




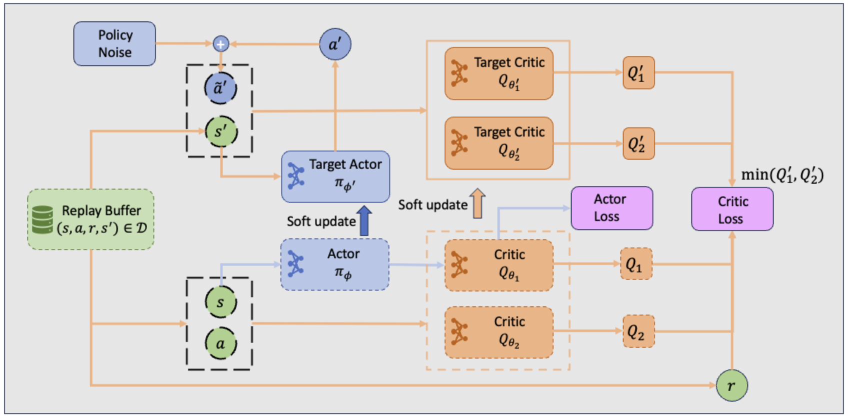
NAC with Random Mobility and Collision Avoidance

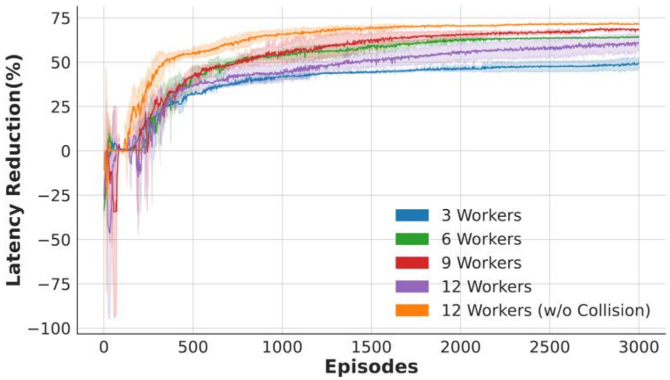
- **Limitations of the previous study:**
  - (1) UAVs maintain a consistent movement pattern throughput the execution of a particular task; (2) Motion interference between UAVs due to collision avoidance is not considered; (3) Simple matrix multiplication tasks were considered

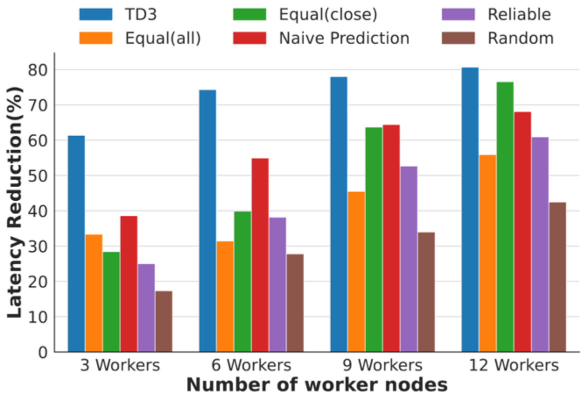
- **Mobility Model: Random direction with collision avoidance**



- **TD3-based Task Offloading:**

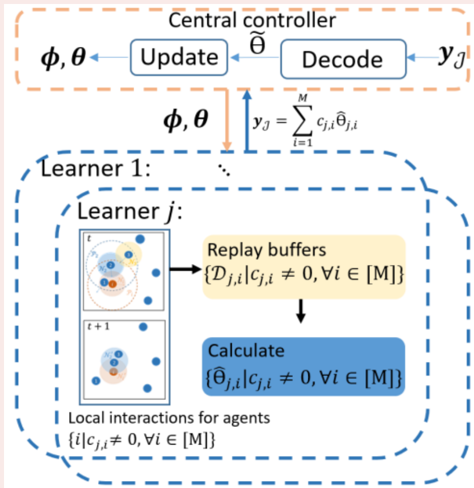




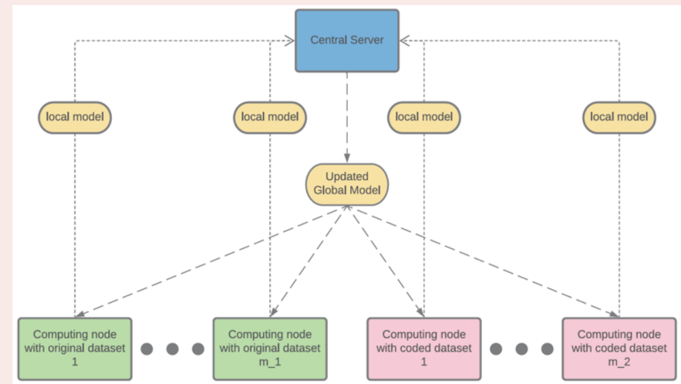


Beyond Matrix Multiplication

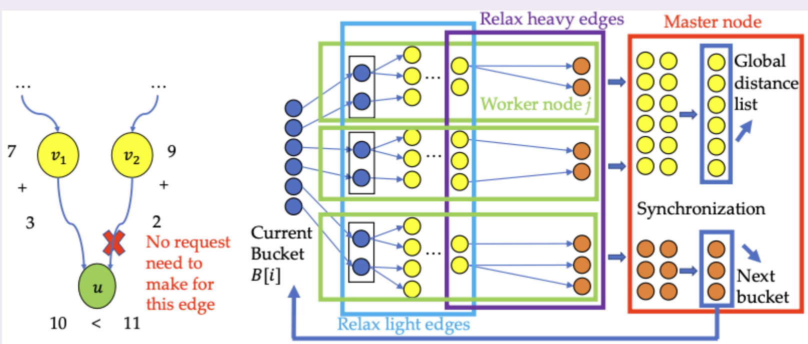
DARL1N: Distributed multi-Agent Reinforcement Learning with One-hop Neighbors



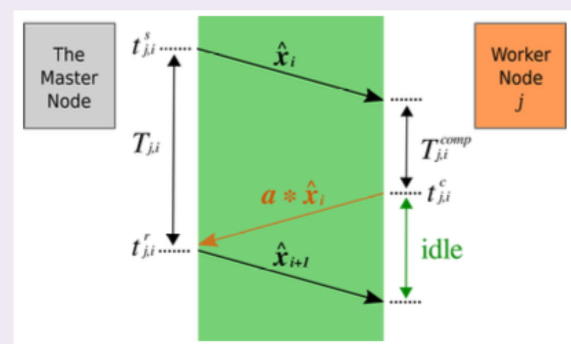
CFL-HC: Coded Federated Learning framework for the Heterogeneous Computing environment (CFL-HC).



Distributed Path Planning

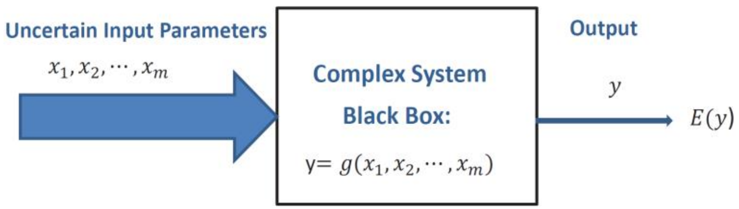


Dynamic Coded Distributed Convolution



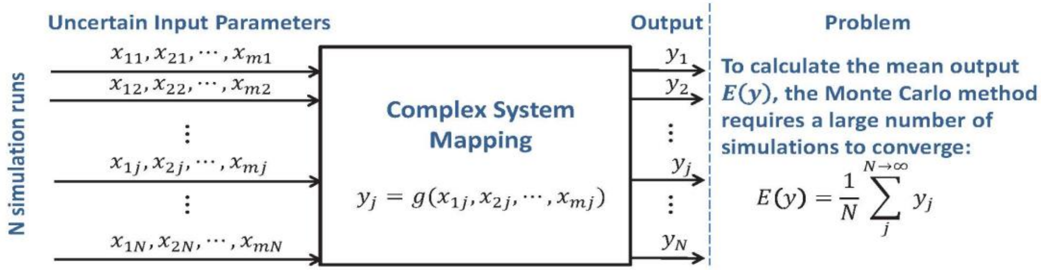
Scalable and Efficient Uncertainty Evaluation Method

- **Problem formulation:**

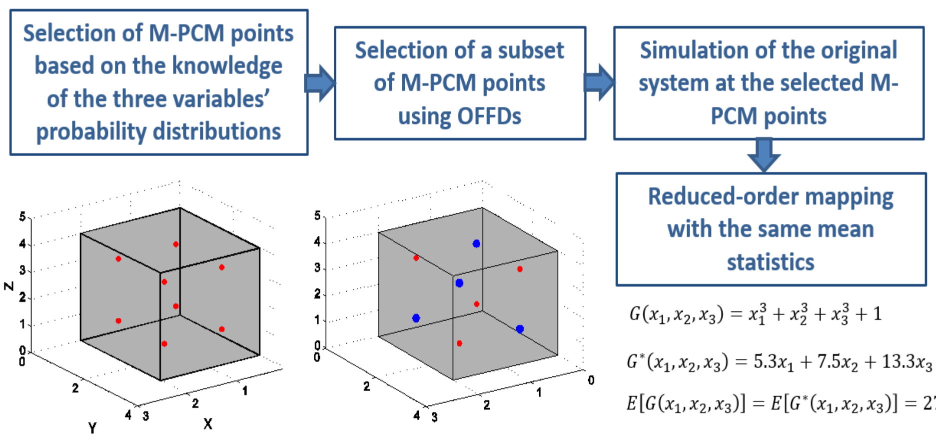


- **Monte Carlo simulation method**

High Computational Cost !!



- **M-PCM-OFFD**



$G(x_1, x_2, x_3) = x_1^3 + x_2^3 + x_3^3 + 1$

$G^*(x_1, x_2, x_3) = 5.3x_1 + 7.5x_2 + 13.3x_3 - 16.2$

$E[G(x_1, x_2, x_3)] = E[G^*(x_1, x_2, x_3)] = 27.1$

Reduce the number of simulations from

$$2^{2m} \rightarrow [2^{\lceil \log_2(m+1) \rceil}, 2^{m-1}]$$

Predict the correct mean output!

$$E[g(x_1, x_2, ..., x_m)] = E[g^*(x_1, x_2, ..., x_m)]$$

M-PCM-OFFD Based Stochastic Optimal Control

- Consider a generic dynamical system described by the following equation:

$$\mathbf{x}[k+1] = h_k(\mathbf{x}, \mathbf{u}, \mathbf{a})$$

- The stochastic optimal control problem is concerned with finding the optimal control policy π^*, that minimizes a total expected cost J, i.e., $\pi^* = \arg\min_{\pi} J$.

- **Finite-horizon control**

$$J_N(\mathbf{x}[0]) = E_{\mathbf{a}[0]}\{\cdots E_{\mathbf{a}[N-1]}\{\sum_{k=0}^{N-1} \alpha^k g_k(\mathbf{x}, \mathbf{u}) + \alpha^N q_N(\mathbf{x})\}\cdots\}$$

$$\pi^* = \{\mu_0^*, \mu_1^*, \ldots, \mu_{N-1}^*\}$$

- **Infinite-horizon control**

$$J(\mathbf{x}[k]) = E_{\mathbf{a}[k]}\{E_{\mathbf{a}[k+1]}\{\cdots E_{\mathbf{a}[\infty]}\{\sum_{i=k}^{\infty} \alpha^{i-k} g_i(\mathbf{x}, \mathbf{u})\}\cdots\}\}$$

$$\pi^* = \{\mu, \mu, \ldots\}$$

- **Key Idea:** Apply M-PCM-OFFD to discretize the uncertainty space

- **Finite-horizon Control:** Use backward-in-time methods: e.g., **dynamic programming**
  - Apply M-PCM-OFFD to approximate the value function

Bellman optimality equation:

Approximate using M-PCM-OFFD

$$V_k^*(\mathbf{x}[k]) = \min_{\pi} E_{\mathbf{a}[k]}\left[g_k(\mathbf{x}, \mathbf{u}) + \alpha V_{k+1}^*(\mathbf{x}[k+1])\right]$$

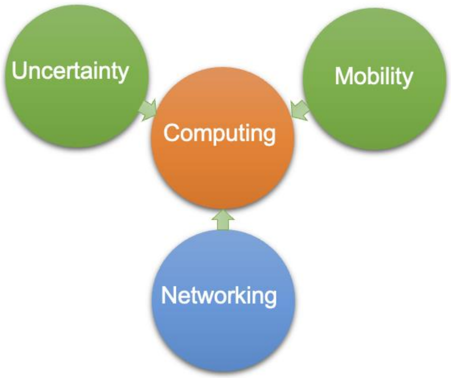
- **Infinite-horizon Control:** Use forward-in-time methods: e.g., **reinforcement learning**

Value update:

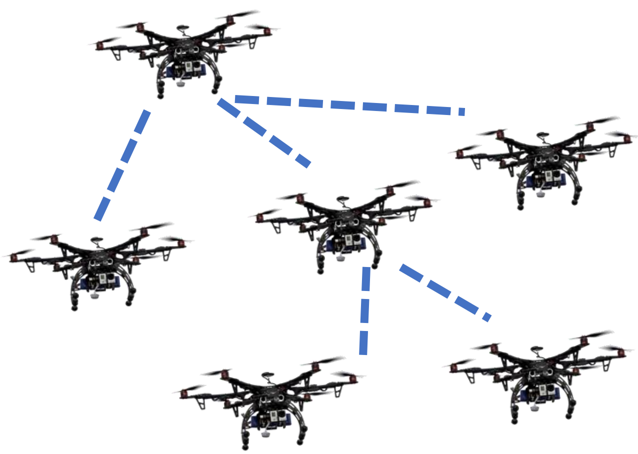
$$V_{j+1}(\mathbf{x}[k]) = E_{\mathbf{a}[k]}\left[g_k(\mathbf{x}, \mu_j(\mathbf{x})) + \alpha V_j(\mathbf{x}[k+1])\right]$$

The control solution optimal to the samples selected by M-PCM-OFFD is also optimal to all possible values of uncertain parameters under simple assumptions.

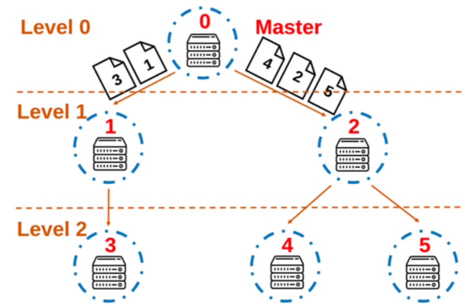
Networking Facilitates Computing



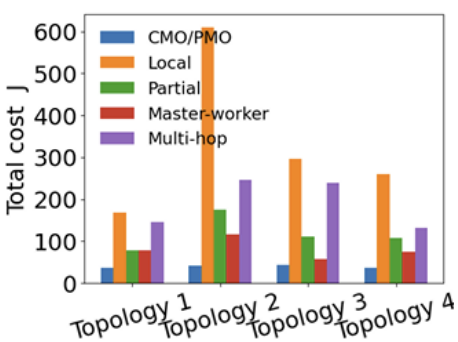
- **Motivation:** Traditional distributed computing limits resource sharing within one-hop neighborhoods.
- **Solution:** Explore resources at distant UAVs located multiple hops away.

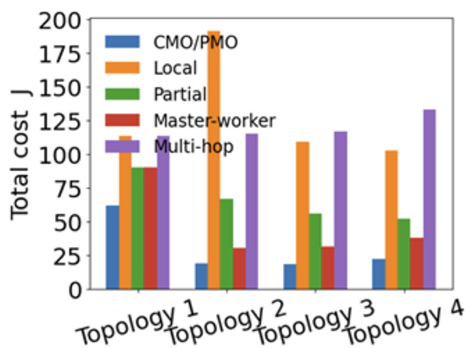


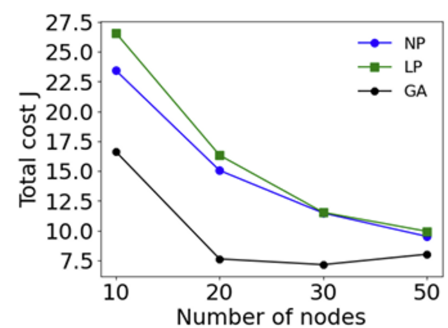
$$
\begin{aligned}
\mathcal{P}_0:\ & \min_{\boldsymbol{y},\boldsymbol{o}} \mathcal{J}(\boldsymbol{y},\boldsymbol{o}) & \\
s.t.\ & \sum_{i=0}^{N} y_i = Y & C1 \\
& 0 \leq y_i \leq Y, \forall i \in \mathcal{N} & C2 \\
& o_i \in \mathcal{N} \setminus \{0\}, \forall i \in \mathcal{N} \setminus \{0\} & C3 \\
& o_i \neq o_j, \forall i,j \in \mathcal{N} \setminus \{0\}, i \neq j & C4
\end{aligned}
$$

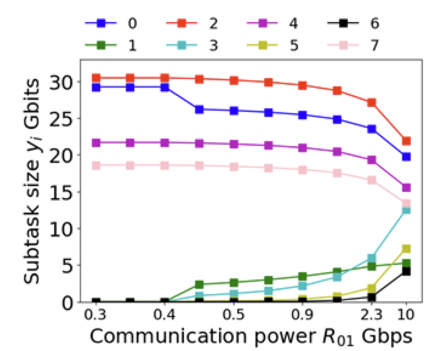


- Simulation results reveal that increasing the utilization of resources leads to better computing performance.



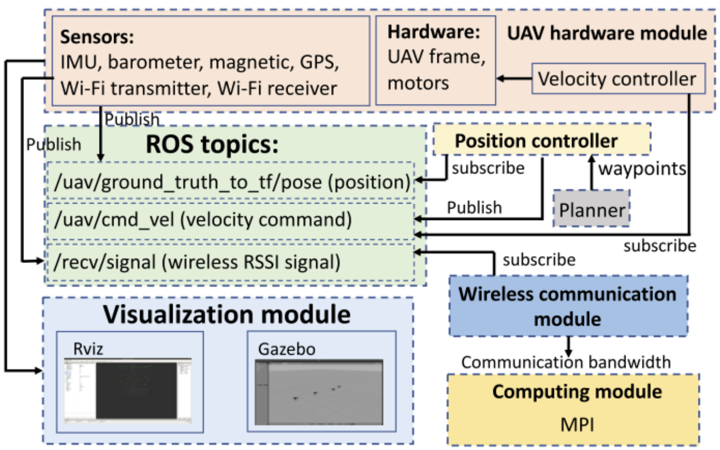


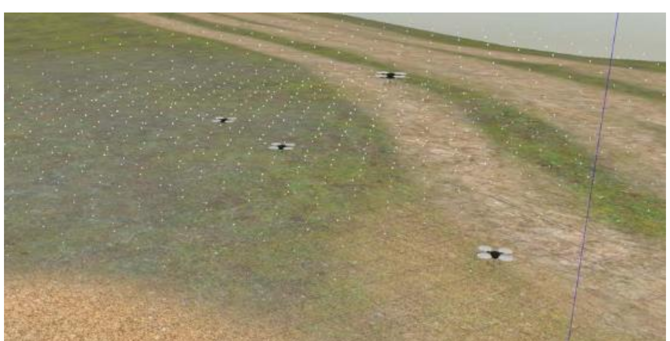


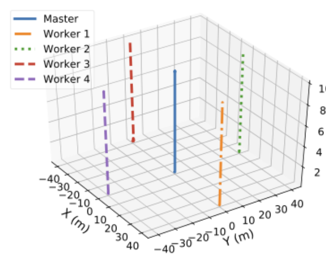


NAC Simulator Design

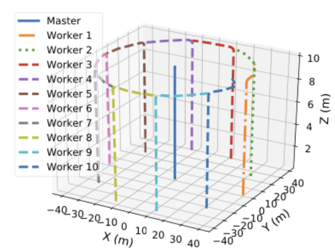
- A ROS and Gazebo-based simulator
- Five core modules:
  - UAV hardware module, controller module, wireless communication module, computing module and visualization model.







(a)



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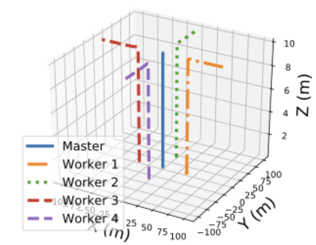

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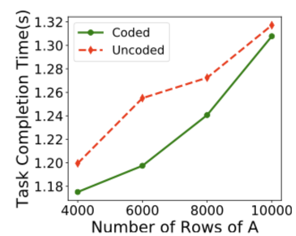
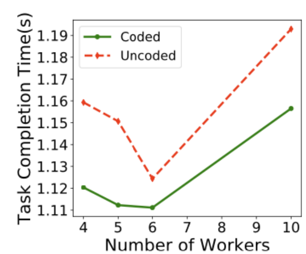
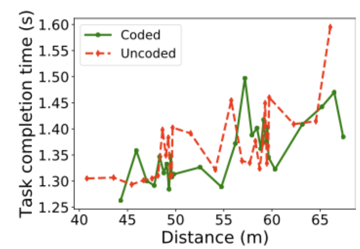
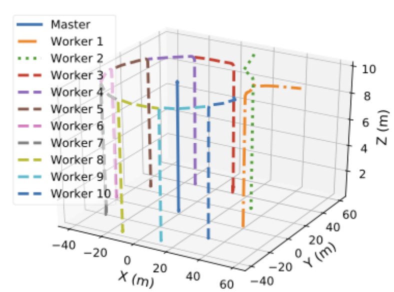




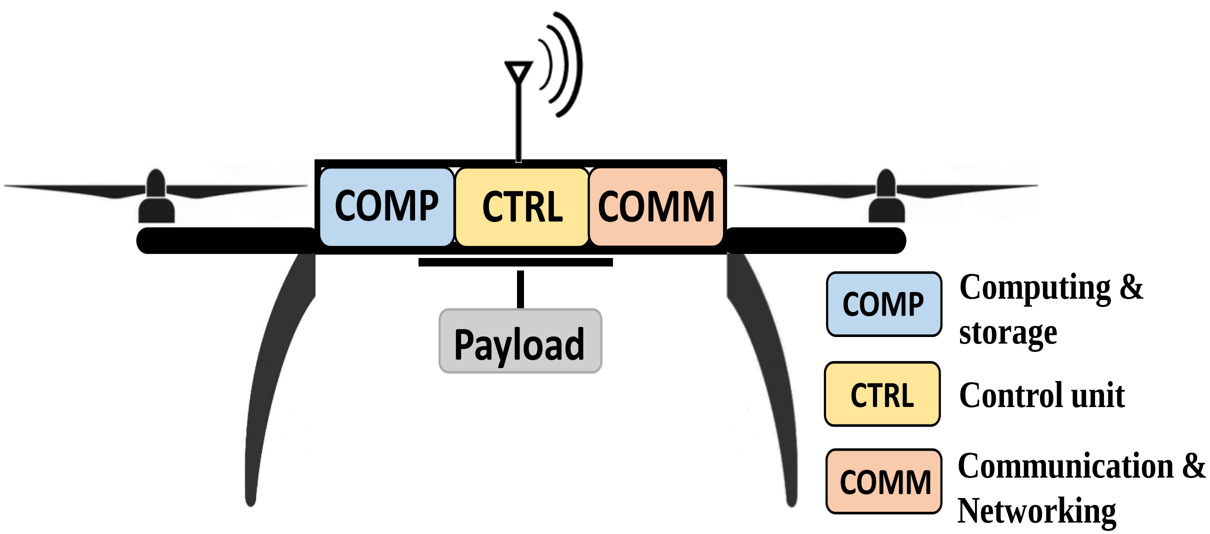




NAC Hardware Testbed Design

Four core units:

- **Quadcopter Unit:** lifting and mobility
- **Control Unit**: mobility control of UAV
- **Communication and Networking Unit**: long-range broadband communication
- **Computing Unit:** onboard processing and storage



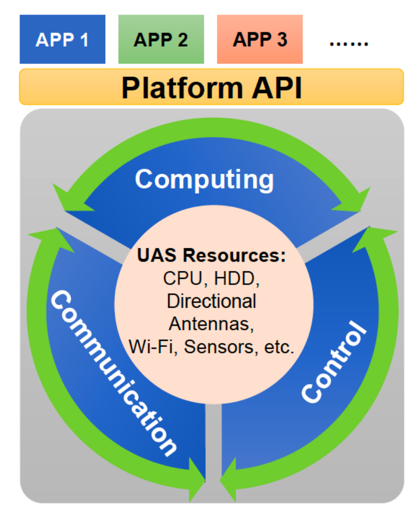
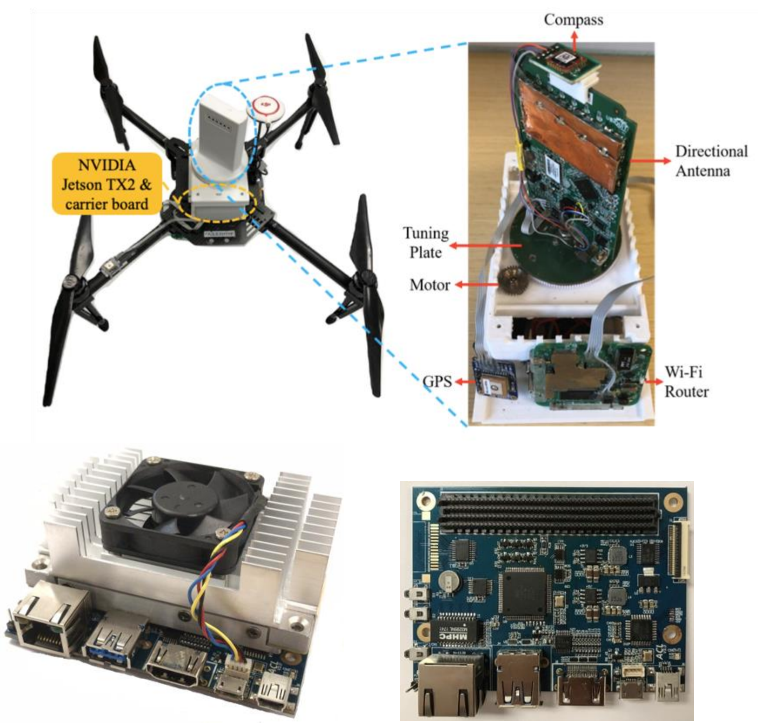


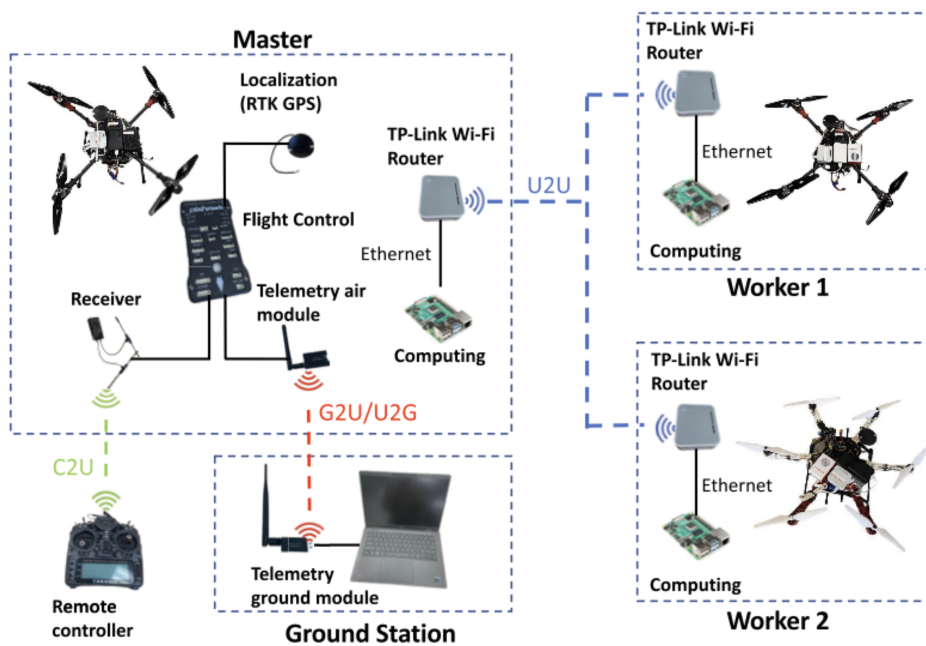
Fig. 1: System capability

This work is a collaboration between SDSU, UNT, UTA, and UPRM, supported by NSF CRI & CCRI programs.

Prototypes

- **Quadcopter Unit:** DJI Matrice 100/Tarot 650/DJI F550
- **Control Unit**: Pixhawk
- **Communication and Networking Unit**: Ubiquiti Nanostation Loco M5, Huawei WS323/TP-Link TL-WR902AC
- **Computing Unit:** Jetson TX2/Raspberry Pi 4
- **Localization Unit**: GPS/Here3 RTK

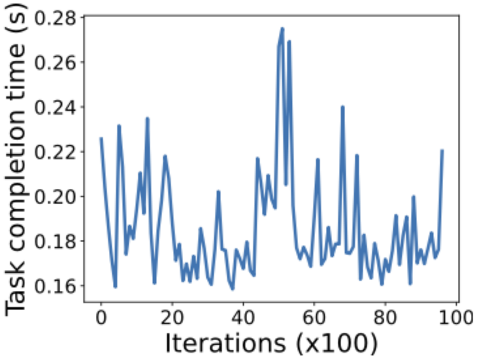


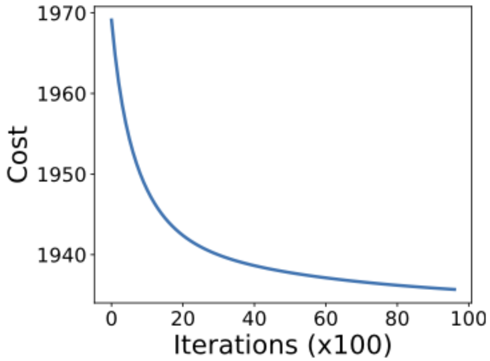


Project Website: https://utari.uta.edu/research/airborne/

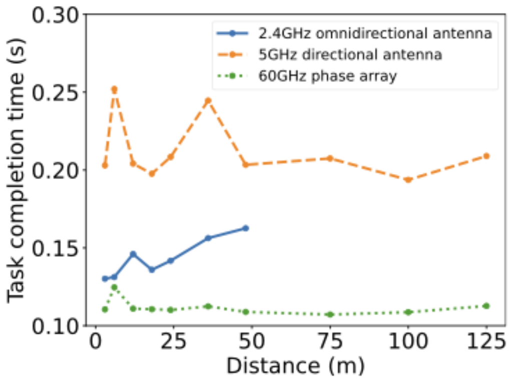
Flight Tests

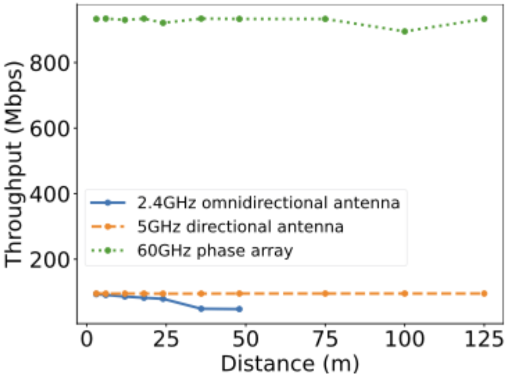
- Application in forest fire detection

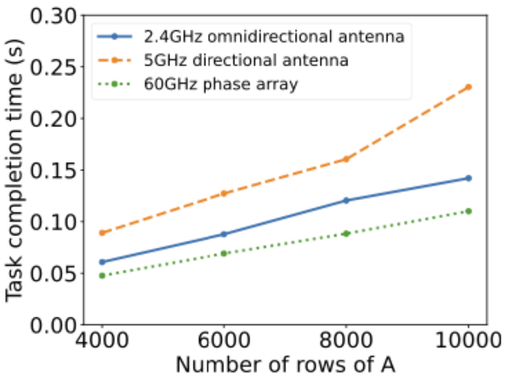




- Comparison of air-to-air communication techniques







➡ Explore millimeter-waves for air-to-air communications

Resources

Project website:

https://utari.uta.edu/research/airborne/

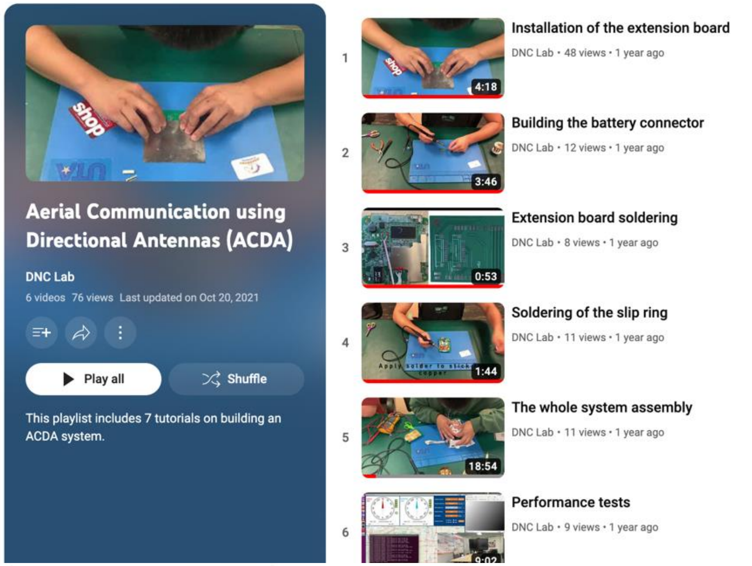
Technical Documentation and Tutorials

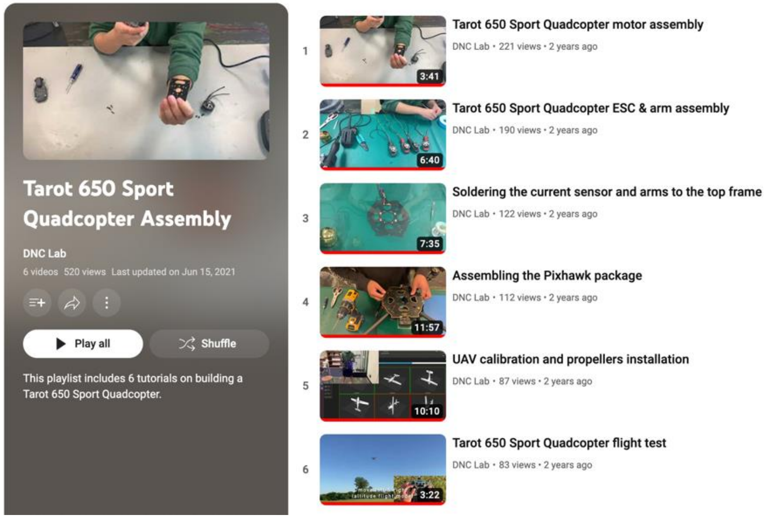
AIRBORNE COMPUTING NETWORKS

(NSF PROJECTS 1730675, 1730589, 1730570, 1730325)

- Aerial Communication using Directional Antennas (ACDA)
- Using MPI on Amazon EC2
- Tutorial on Networked UAV Computing Systems
- Aerial View Dataset
- Installation of KVM and Docker
- GNU Radio Installation Instruction
- Networked UAV Computing Systems Prototype II
- TX2 Carrier Board for UAVs Version II
- Comparison of Microcomputers
- Networked UAV Computing Systems Prototype I
- TX2 Carrier Board for UAVs Version I
- Comparison of Virtualization Techniques
- UAV Attitude Acquisition System

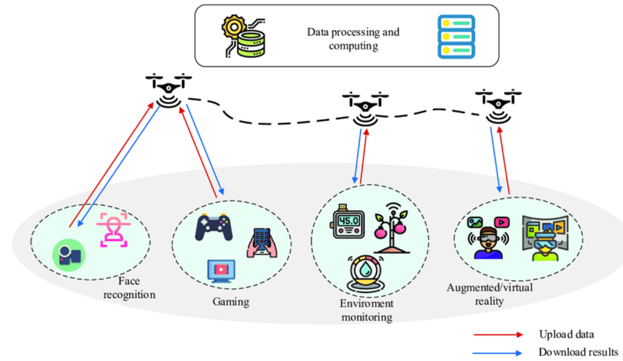
YouTube Videos:

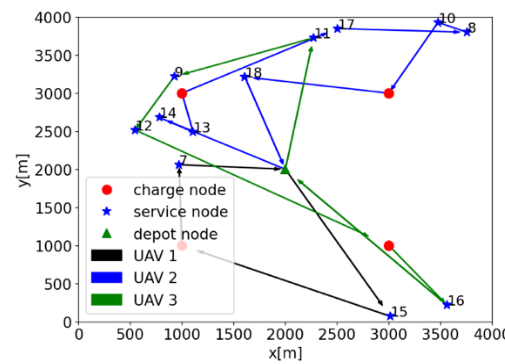


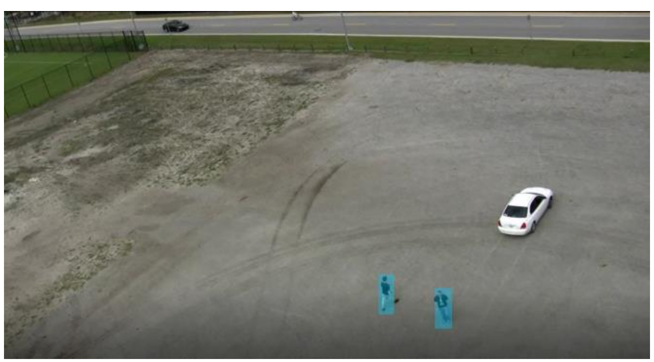


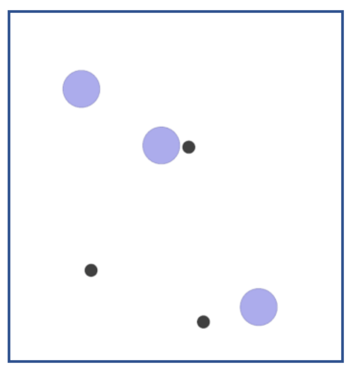
NAC Applications

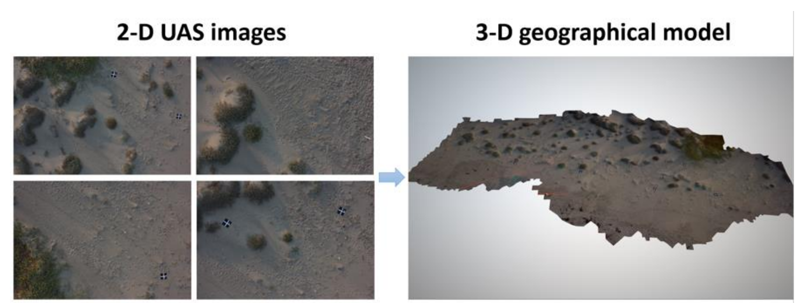
- ***Mobile/Multi-access Edge Computing:*** UAVs function as edge servers to provide computing services to ground users.
- ***Real-time surveillance of multiple targets***
- ***Multi-UAV coordinated navigation***
- ***Real-time 3D mapping***











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Acknowledgement

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