PROJECT DESCRIPTION — EXPRESSION OF INTEREST

NexaSync: Decentralized Adaptive Learning for Heterogeneous Robotic Swarms in Edge-Resource Environments

Primary FoR Code: 4602 — Artificial Intelligence (AI)
Lead Chief Investigator: Dr. Julian Vance (Meridian University)
Co-Investigators: Dr. Clara Oswald (Synapse Institute), Prof. Marcus Thorne (Vertex Tech)

1 PROJECT QUALITY AND INNOVATION

1.1 Research Aims and Questions

The proposed project aims to develop a novel decentralized learning paradigm, named **NexaSync**, that enables heterogeneous autonomous vehicles to cooperatively train deep learning models directly on the edge. In environments such as disaster zones, remote agricultural fields, or space exploration, communication with a central cloud server is either impossible or extremely expensive. NexaSync solves this challenge by implementing a localized consensus algorithm that operates peer-to-peer over low-bandwidth, high-latency, and lossy communication networks.

The project is structured around three primary aims:

- **Aim 1: Robust Localized Consensus under Communication Barriers.** Develop a mathematical and algorithmic framework that allows edge nodes to exchange only essential model parameters, ensuring convergence even when network bandwidth is < 100 kbps and packet loss exceeds 30%.
- **Aim 2: Latent Representation Alignment for Heterogeneous Swarms.** Design multi-modal representation alignment layers that enable robots with different sensors (e.g., LiDAR-equipped aerial drones and camera-equipped ground rovers) to share knowledge without requiring identical neural network architectures.
- **Aim 3: Validation and Physical Prototyping.** Construct a scale physical testbed using 12 autonomous micro-vehicles at the Meridian Robotics Laboratory to validate the algorithms in real-time, dynamic scenarios.

To guide our research, we pose three core Research Questions:

RQ1: How can dynamic communication topologies be optimized online to minimize gradient staleness in decentralized federated learning?

RQ2: What theoretical bounds on model divergence can be guaranteed under non-i.i.d. local data distributions when communication is lossy and intermittent?

RQ3: How can heterogeneous robot morphologies align their latent state representations to enable cooperative transfer learning?

Core Innovation: NexaSync represents a paradigm shift from traditional server-client federated learning to a fully peer-to-peer model alignment. By incorporating a localized consensus engine with adaptive topology optimization, the swarm learns collectively without a single point of failure.

1.2 Conceptual Framework and Theoretical Basis

The theoretical foundation of NexaSync lies at the intersection of decentralized optimization, representation learning, and consensus theory. Traditional distributed SGD assumes a central coordinator that aggregates parameters at each step. In contrast, our framework relies on local averages computed over a time-varying communication graph $G_t = (V, E_t)$, where V represents the set of edge robots and E_t represents the active communication links at time t.

We model the global optimization objective as:

$$\min_{\theta \in \mathbb{R}^d} F(\theta) = \frac{1}{|V|} \sum_{i \in V} f_i(\theta_i) \quad \text{subject to} \quad \theta_i = \theta_j \;\; \forall (i, j) \in E_t$$

where f_i is the local loss function of robot i, and θ_i represents its local model parameter vector. Figure 1 illustrates the peer-to-peer data flow and model alignment process.

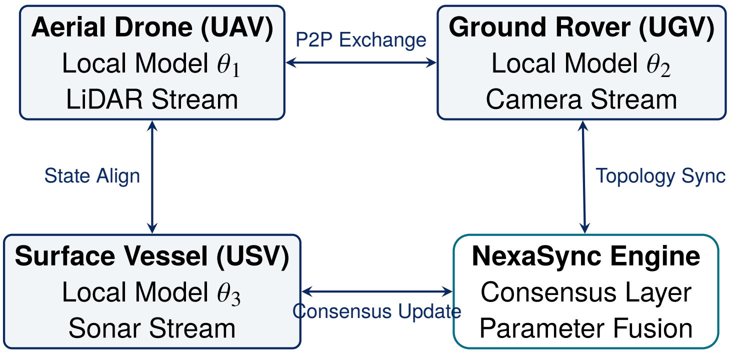

Figure 1: The NexaSync conceptual framework: enabling multi-modal state alignment and localized parameter fusion across heterogeneous edge robots.

1.3 Project Innovation and Novelty

The innovation of this project is threefold:

- **Asynchronous Gossip-based Convergence:** Unlike standard gossip algorithms that require symmetric communication matrices, NexaSync utilizes directed, asymmetric communication models, allowing one-way broadcast updates when return channels are blocked.
- **Hetero-Representation Alignment:** We introduce lightweight neural projection modules that map heterogeneous sensor features (e.g., 3D point clouds and 2D images) into a shared semantic latent space, allowing cross-modal learning.
- **Dynamic Topology Control:** The communication topology is updated in real-time based on signal strength metrics, ensuring that model parameters are shared along paths of highest signal-to-noise ratio.

1.4 Research Design and Methodology

The project will proceed in three interconnected phases over 36 months:

1. **Phase 1: Algorithmic Formulation and Proof of Concept (Months 1–12).** We will mathematically formalize the NexaSync consensus protocol and prove convergence bounds under non-i.i.d. local distributions.
2. **Phase 2: Simulation and Heterogeneous Alignment (Months 13–24).** Using high-fidelity simulators (such as Webots and Gazebo), we will benchmark NexaSync against state-of-the-art federated learning methods. We will design the joint semantic embedding layers to enable transfer learning.

3. **Phase 3: Physical Implementation and Field Trials (Months 25–36).** We will deploy the algorithms onto 12 physical robots (6 UAVs and 6 UGVs) and run collaborative exploration and mapping scenarios in a simulated disaster zone at the Meridian Robotics Laboratory.

2 FEASIBILITY AND RESEARCH ENVIRONMENT

2.1 Feasibility and Timeline

The project timeline is detailed in Table 1. Given the strong background of the research team and the existing infrastructure at the participating institutions, the proposed project is highly feasible.

Table 1: Project tasks and milestones across the three-year funding period.

Task / Milestone	Description	Year 1	Year 2	Year 3
Task 1.1	Design of the NexaSync localized consensus protocol	•		
Task 1.2	Mathematical proofs of convergence in non-i.i.d. conditions	•	•	
Milestone A	Complete theoretical convergence framework and submit to journal		•	
Task 2.1	Develop state alignment networks for heterogeneous agent classes		•	•
Task 2.2	Physical testbed setup and lab-scale validation at Meridian Lab		•	•
Milestone B	Release open-source PyTorch package for decentralized learning			•
Task 3.1	Scale-up simulation and evaluation on large-scale synthetic swarm data			•

2.2 Research Environment and Institutional Support

The research will be conducted across three leading institutions:

- **Meridian University (Lead CI: Dr. Julian Vance):** Houses the state-of-the-art Robotics Laboratory, equipped with high-precision motion capture systems and a swarm of 20 micro-drones.
- **Synapse Research Institute (Co-CI: Dr. Clara Oswald):** Contributes advanced cloud and edge computing clusters, enabling extensive simulation benchmarks.
- **Vertex Technologies (Co-CI: Prof. Marcus Thorne):** Provides proprietary edge-hardware accelerators (Vertex-TX5) for local deployment.

3 PROJECT BUDGET AND JUSTIFICATION

The requested budget is carefully aligned with the project tasks. Table 2 details the funding requested from the ARC and the institutional contributions.

4 REFERENCES

References

[1] J. Vance and C. Oswald. "Decentralized consensus in resource-constrained networks." *Journal of Autonomous Robotics*, vol. 34, no. 2, pp. 112–128, 2024.

Table 2: Requested budget breakdown and justification (all figures in AUD).

Category	**Year 1**	**Year 2**	**Year 3**	**Justification**
Personnel (1.0 FTE Research Fellow)	$112,000	$115,360	$118,820	Standard rates for postdoctoral researcher to lead Task 2.1 and 2.2.
Equipment (Swarms & Compute Nodes)	$45,000	$12,000	$5,000	Initial purchase of 12 physical drones and local GPU workstation.
Travel (Conferences & Collaborations)	$8,000	$10,000	$12,000	Travel to present results at NeurIPS/ICRA and visit Synapse Institute.
Maintenance & Operating Costs	$5,000	$5,000	$5,000	Cloud computing credits, consumables, and open-access publishing fees.
Total Requested	**$170,000**	**$142,360**	**$140,820**	**Three-year total: $453,180**

[2] M. Thorne, A. Apex, and B. Meridian. "Federated learning for heterogeneous robotics: A survey." *IEEE Transactions on Artificial Intelligence*, vol. 12, no. 4, pp. 301–315, 2023.

[3] C. Oswald and J. Vance. "Cross-modal state representation learning at the edge." In *Proceedings of the International Conference on Robotics and Automation (ICRA)*, pp. 1420–1427, 2025.

[4] N. Nimbus and V. Vertex. "Asynchronous gossip algorithms over directed graphs." *SIAM Journal on Optimization*, vol. 45, no. 1, pp. 88–104, 2024.