MOPA: Modular Object Navigation with PointGoal Agents

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1. **Introduction and Related Work**

   Object navigation, a central task in embodied AI, involves agents interacting with environments to reach specific objects. MOPA (Modular Object Navigation with PointGoal Agents) proposes a modular approach, decomposing the task into object detection, map building, exploration, and navigation. This allows for efficient reuse of pre-trained models and facilitates adaptation to various environments and tasks.

   Related work in object navigation has explored various approaches, including end-to-end learning and modular architectures. While end-to-end learning achieves good performance, it lacks interpretability and adaptability. Modular approaches like MOPA offer better flexibility and explainability, but prior work often focuses on specific components, neglecting broader enhancements.

2. **Proposed Objectives**
   a. **Object Detection:**
      To surpass pre-trained detectors, we can explore three avenues: 1) building custom models (YOLO, SSD, EfficientDet) for flexibility with abundant data (e.g., Habitat_matterport); 2) leveraging semantic segmentation (DeepLab, U-Net) for richer object information; and 3) utilizing attention-based approaches (Transformers) to pinpoint key regions in cluttered scenes, potentially boosting accuracy.
   b. **Map Building:**
      We propose three map enhancements for improved navigation: 1) building a topological map capturing spatial relationships for efficient navigation, 2) incorporating temporal information about object dynamics in dynamic environments, and 3) utilizing probabilistic occupancy maps with uncertainty values for robustness against sensor noise.
   c. **Exploration:**
      We propose three exploration strategies for faster learning and discovery: 1) active learning, where exploration points minimize map uncertainty, 2) curriculum learning, where tasks gradually increase in difficulty for efficient learning, and 3) curiosity-driven exploration, encouraging the agent to uncover potentially valuable features through intrinsic motivation.
   d. **Navigation:**
      We propose three strategies for a more adaptive and efficient navigation system: 1) training our own PointGoal agent for tailored performance, 2) developing a modular navigation library with specialized pre-trained agents for different tasks, and 3) incorporating reinforcement learning or planning-based approaches for flexible and robust navigation.

3. **Timeline & Action Plan**
    a. **Literature Review and Initial Development (Pre-Midsem):**
        i. 1-2 Weeks: Conduct a comprehensive literature review in the areas of object detection, navigation, planning, and mapping, focusing on recent advancements and potential synergies with MOPA. Identify specific areas for improvement within the MOPA framework.
        ii. 3-4 Weeks: Implement the basic MOPA architecture using established libraries and frameworks. Familiarize ourselves with the code structure and functionality.
        iii. 5-6 Weeks: Integrate existing pre-trained models for object detection and navigation into the MOPA framework for initial performance evaluation.
    b. **Development and Implementation of Enhancements (Post-Midsem):**
        i. 7-8 Weeks: Choose two key modules for initial enhancement efforts.
        ii. 9-10 Weeks: Develop and implement code for the chosen enhancements (out of the 4 - detection, mapping, navigation, planning)
        iii. 11-12 Weeks: Integrate the developed enhancements into the MOPA framework and conduct preliminary testing and evaluation. Analyze the impact of individual enhancements on performance metrics.

Due to the uncertainty regarding compute/hardware support, providing a highly detailed timeline for Post-Midterm is challenging. However, the proposed roadmap establishes a clear direction and prioritizes key tasks within the available time frame.

4. **Literature**

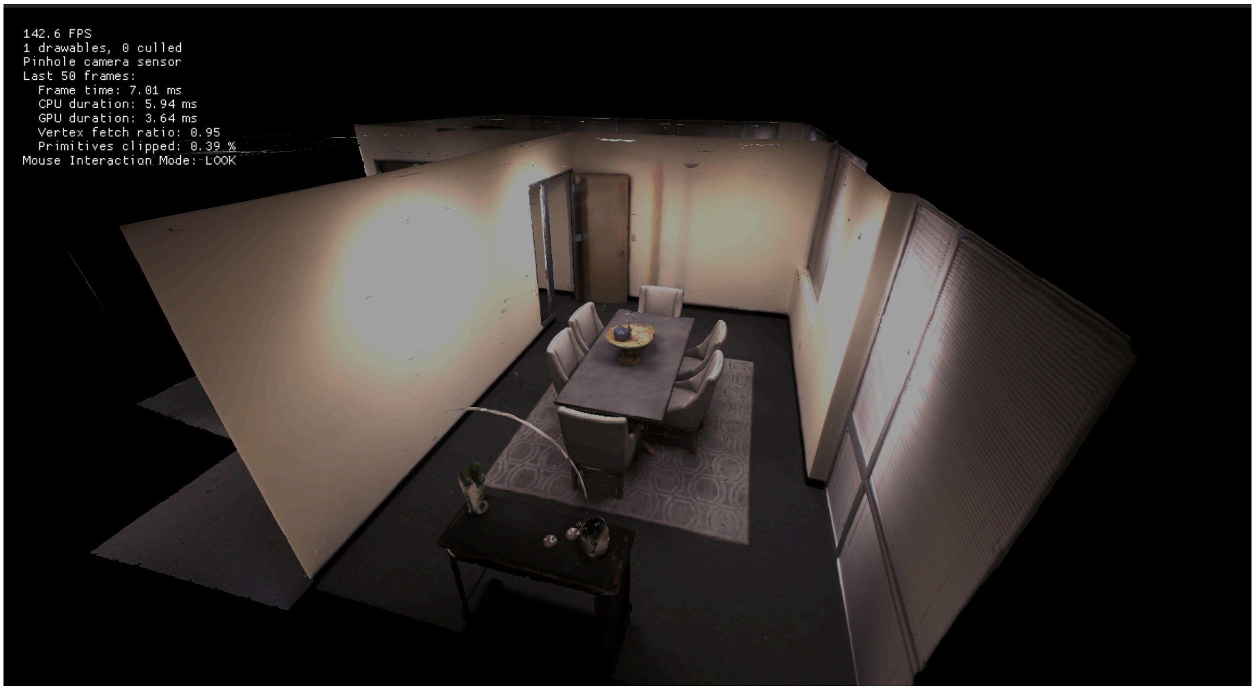
    a. Raychaudhuri, S., Campari, T., Jain, U., Savva, M., & Chang, A. X. (2024). MOPA: Modular object navigation with PointGoal agents. In Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 2547-2556).
    b. Savva, M., Kadian, A., Maksymets, O., Zhao, Y., Wijmans, E., Jain, B., ... & Malik, J. (2019). Habitat: A platform for embodied AI research. In Proceedings of the IEEE International Conference on Computer Vision (ICCV) (pp. 9339-9347).

5. **Environment**
    a. The project will utilize standard object navigation benchmarks (ObjectNav, Habitat) and potentially simulated environments for initial development and testing.
    b. Real-world robotic platforms might be integrated in later stages for validation and deployment.

Progress Report Mid-Semester

1. **Revised Timeline**
    - Literature Review
    - Setting up the environment
    - Narrowing down on the problem statement
    - Running sample tests using the HM3D and related datasets as mentioned in the paper
    - Evaluation of the given architecture against counterparts as mentioned in the paper

2. **Accomplishments**
    - Reviewed the literature
    - Successfully set up the environment
    - Tried experimenting with low-poly environments (still work in progress)



3. **Challenges and Limitations**
    - Hardware Limitations
    - Processing Power
    - Getting Dataset (requires access; already applied)
    - Shallow Understanding of the architecture (need some more work)

4. **Next Steps**
    - Continue experimenting with low-poly environments (e.g. Minecraft World)
    - Utilize the current framework to conduct the mentioned tests using the Matterport dataset
    - Test the navigation or exploration module with different existing algorithms