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A FRAMEWORK FOR COOPERATIVE DYNAMIC TASK ASSESSMENT FOR COTSBOT AUVs

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ABSTRACT-This project presents a proposed framework aimed at collaborative and dynamic allocation of tasks for a specific group of self-governing underwater vehicles known as autonomous underwater vehicles (AUVs). These AUVs are utilized to manage the proliferation of Crown-Of-Thorns starfish (COTS) on the Great Barrier Reef situated in Australia. The concept of constrained task allocation is employed to reframe the supervision and regulation of COTS into a challenge where a central task involves eradicating clusters of COTS using the injection mechanism integrated into the COTSbot AUVs. The operational setting, encompassing underwater topography, COTS clusters, and shorelines, is mapped probabilistically. The COTSbot AUVs are then collaboratively deployed to target as many COTS clusters as possible within a designated mission timeframe, utilizing an inventive heuristic technique termed Heuristic Fleet Cooperation (HFC). To substantiate the efficiency and dependability of the proposed collaborative task allocation algorithm for COTS eradication in the Great Barrier Reef, comprehensive simulations and quantitative performance evaluations are conducted.

INTRODUCTION

In recent times, there has been a surge in the popularity of autonomous underwater vehicles (AUVs), finding diverse applications in oceanographic surveys such as mine detection, offshore infrastructure maintenance, mapping, Data collection, sampling, and monitoring. These AUVs offer valuable tools for environmental scientists to collect underwater data on marine organisms and phenomena like silt movement in damaged ecosystems. The Australian government and environmental groups have consistently emphasized the significance of monitoring underwater ecosystems and biodiversity, given the unique ecological composition of the country's marine environments. The severe impact of Crown-Of-Thorns starfish (COTS) has led to the loss of over 50% of coral in the Great Barrier Reef, posing a significant challenge for the Queensland government. Nonetheless, various solutions are being explored to address this issue. Traditional methods of manually removing starfish by human divers are both operationally inefficient and logistically impractical. In response, a specialized type of AUV called the COTSbot AUV, developed by the University of

Queensland and Queensland University of Technology (QUT), has been introduced. This AUV is equipped with vision-based technology and an injection arm to autonomously eliminate COTS within the Great Barrier Reef. Initial evaluations of this AUV have shown promising outcomes, demonstrating its effectiveness in safeguarding coral against the COTS population compared to conventional approaches. However, there is potential for further enhancement in its performance, particularly through the cooperative deployment of a fleet of COTSbot AUVs in the Great Barrier Reef region. The objective of this whitepaper is to explore the utilization of the COTSbot AUV within the context of Multi-Robot Task Assignment (MRTA). This pertains to optimizing the behavior of multiple robots in an economical manner, in terms of cost and time, to address specific challenges associated with controlling COTS in the Great Barrier Reef.

PROBLEM STATEMENT

In Byron Bay, Australia, a distressing situation is unfolding as the Great Barrier Reef faces a severe threat. The reef, already vulnerable due to rising ocean temperatures, is now under attack by voracious starfish. The Great Barrier Reef Marine Park Authority has reported that these deadly crown-of-thorns starfish are consuming parts of the massive reef system. These starfish, which are a native species, can occasionally experience population explosions that put the reef at risk. Alarming reports reveal their presence on 37 sections of the southerly Swain Reef, situated over 60 miles offshore. The significance of this threat cannot be underestimated. Fred Nucifora, a spokesperson for the park authority, emphasized that any form of stress or danger to coral in the Great Barrier Reef is a matter of concern. The Great Barrier Reef stands as one of the most expansive living structures on Earth and is even visible from space. This reef is not just a natural wonder; it is a vibrant ecosystem inhabited by an array of species, including sharks, turtles, and whales. Beyond its ecological importance, the Great Barrier Reef holds immense economic value for Australia. It contributes to around 70,000 jobs and generates billions of dollars annually through tourism revenue. The challenge posed by these crown-of-thorns starfish further compounds the existing threats posed by climate change and underscores the urgency of conservation efforts to preserve this invaluable natural treasure.

Ordinarily, starfish contribute to the diversity of the reef by consuming faster-growing coral species, creating space for slower-growing ones to flourish. However, during outbreaks, these starfish can consume coral—a polyp that constructs the limestone reefs on which they coexist—faster than the coral can reproduce. To achieve this, starfish have an adaptable stomach that envelops and consumes the coral. A single starfish can consume its body diameter in coral nightly. In 2012, a control program was initiated, resulting in the removal of over 600,000 starfish from the northern and central reef regions. Starfish predation, coupled with tropical cyclones and bleaching, accounted for almost half of the reef's coral cover decline between 1985 and 2012, according to a study. The current outbreak's cause remains uncertain, with one theory suggesting that nutrient-rich water from the deep sea is being transported up to the shelf, coinciding with starfish larvae growth. This resurgence of starfish outbreak coincides with warnings from scientists about coral bleaching—a consequence of elevated ocean temperatures—placing stress on the reef's ecosystem. Recent research highlighted that the frequency of coral bleaching has intensified to the extent that reefs no longer have adequate recovery time between events. Active control of the starfish population through culling is currently the most viable and scalable measure, involving divers who inject the starfish with solutions containing bile salts or white vinegar to eliminate them without harming other marine life. The Australian government has committed significant funds to this endeavor, with an allocation of 14.4 million Australian dollars for an additional control vessel. Since 2012, a total of 34.4 million Australian dollars has been dedicated to

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addressing this issue. Coral reefs are naturally subject to cycles of change, encompassing both mortality and rejuvenation. The pivotal question raised by Hugh Sweatman, a scientist from the Australian Institute of Marine Sciences, is the timeline within which these reefs can recuperate.

METHOD FOR DETECTI NG COTS

A technique for detecting Crown-of-Thorns starfish (COTS) involves the following steps:

- **Image Capture**: Utilize underwater imaging technology, such as cameras mounted on autonomous underwater vehicles (AUVs) or remotely operated vehicles (ROVs), to capture high-resolution images of the underwater environment.
- **Image Analysis**: Process the captured images using image analysis software capable of identifying COTS. This software can be equipped with machine learning algorithms to recognize distinct features of COTS, including their color, size, and arm arrangement.
- **Pattern Recognition**: Apply pattern recognition algorithms to the analyzed images to differentiate COTS from other marine organisms and the background. This could involve comparing patterns in the images against a database of known COTS images.
- **Feature Extraction**: Extract relevant features from the detected objects in the images, such as the number of arms, spines, and overall shape, to further enhance the accuracy of COTS identification.
- **Classification**: Employ a classification algorithm, such as a convolutional neural network (CNN), to categorize the detected objects as COTS or non-COTS based on the extracted features and patterns.
- **Thresholding**: Set appropriate threshold values to minimize false positives and negatives, ensuring accurate detection of COTS while reducing the likelihood of misidentification.
- **Real-Time Monitoring**: Implement real-time monitoring capabilities to continuously analyze incoming images and promptly identify COTS presence, allowing for rapid response and mitigation efforts.
- **Integration with AUVs or ROVs**: Integrate the detection system with autonomous underwater vehicles (AUVs) or remotely operated vehicles (ROVs) to enable efficient and targeted surveying of large underwater areas.
- **Data Collection and Reporting**: Record and store detection results, including location and density of COTS, for further analysis and decision-making.
- **Validation and Improvement**: Continuously validate the accuracy of the detection method through comparisons with manual identification and expert validation. Iteratively refine the algorithm and system based on feedback and new data.

By combining advanced imaging technology, machine learning, and accurate pattern recognition, this method can offer an effective and automated way to detect Crown-of-Thorns starfish in underwater environments, aiding in the conservation and management of delicate marine ecosystems.

EXISTING SYSTEM

COTSbot is an underwater robotic system developed to manage populations of the crown-of-thorns starfish (COTS) within the Great Barrier Reef, a vast and globally significant coral reef ecosystem.The software architecture of COTSbot encompasses the assortment of programs and algorithms responsible for governing the robot's actions and facilitating its designated tasks. COTSbot AUVs exhibit a broad spectrum of potential uses, encompassing underwater exploration, environmental surveillance, and search and rescue operations.

EXISTING SYSTEM ALGORITHM

Faster R-CNN:

Faster R-CNN stands as a prominent object detection model within the realm of computer vision and deep learning. It represents an advancement of the well-known R-CNN (Region-based Convolutional Neural Network) model.

The fundamental breakthrough of Faster R-CNN lies in the incorporation of a Region Proposal Network (RPN), which functions as a fully convolutional network capable of swiftly producing region proposals, significantly outpacing the selective search algorithm utilized in the conventional R-CNN approach.

Faster R-CNN has garnered renown for its exceptional precision and efficiency, finding extensive utility in domains like autonomous vehicles, robotics, and surveillance setups.

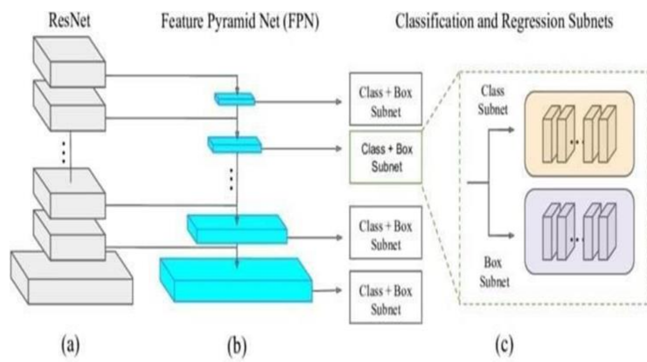
DRAWBACKS OF EXISTING SYSTEM

- Challenges in detecting diminutive objects.
- Restrictions in identifying atypical shapes.
- Constraints in achieving comprehensive applicability.
- Extended training duration.

PROPOSED SYSTEM

- RetinaNet emerges as a fitting algorithm for detecting COTS due to its remarkable accuracy and efficiency.
- The algorithm can be educated on an extensive collection of COTS images to grasp the unique attributes of the starfish, subsequently operationalized on the COTSBOT for real-time COTS detection.
- The incorporation of RetinaNet can substantially elevate the COTSBOT's detection efficacy, facilitating broader reef coverage within reduced timeframes.

PROPOSED SYSTEM ARCHITECTURE



PROPOSED SYSTEM ALGORITHM

RetinaNet:

- RetinaNet operates as an object detection algorithm employing a one-stage deep neural network architecture to discern objects within images.
- RetinaNet leverages a feature pyramid network (FPN) for extracting features across various scales from an input image. It subsequently employs classification and regression subnetworks for each feature map, predicting the presence and spatial coordinates of objects.

ADVANTAGES OF PROPOSED SYSTEM

- Elevated precision levels.
- Inclusion of a Feature Pyramid Network facilitating detection across diverse object sizes.
- Integration of Focal Loss function addressing imbalances in class distribution.
- Utilization of a one-stage architecture.

METHODOLOGY

Introduction

In the proposed system, the primary focus lies in generating sets of positive or negative video instances, termed "bags," for the purpose of training. These instances are extracted from the available dataset. Subsequently, features are extracted from these videos, and rankings are assigned to these bags. This ranking process aids in the classification of bags as containing starfish or not. The process involves

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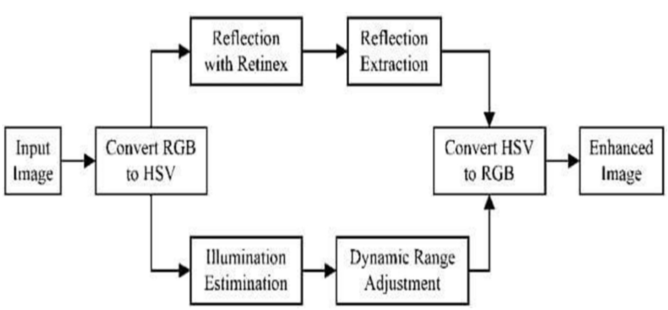
training the system on regular videos to learn and create deep representations. A Convolutional Neural Network (CNN) is employed within this architecture. A CNN is a type of neural network that specializes in compressing information from the input layer into a compact code, referred to as a deep representation. This compressed code is then reconstructed to closely resemble the original data. In the context of the system, CNN is utilized to identify the starfish by analyzing reconstruction errors and assessing the likelihood of the deep representations. Ultimately, when an image containing a starfish is detected, it is transmitted to a control room. At this stage, estimations and calculations related to the starfish's presence or attributes are performed. This process encompasses various stages, including bag ranking, CNN-based deep representation, reconstruction error analysis, and control room assessment.

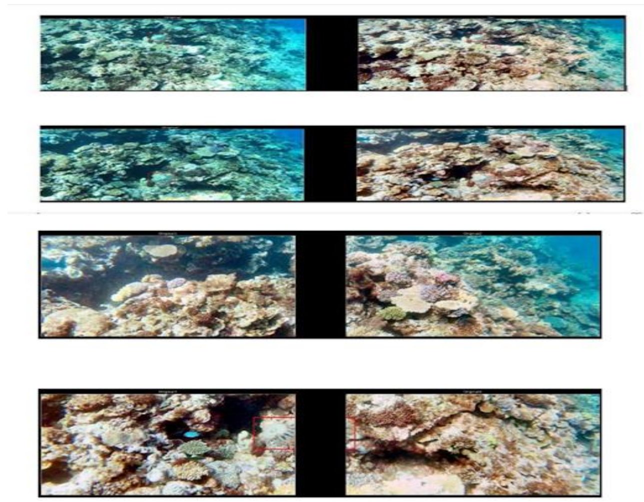
Block Diagram



Preprocessing:

Images exhibit variability in terms of their dimensions and proportions. Moreover, they originate from diverse sources.

- In light of these variations, it becomes essential to engage in pre-processing steps when handling image data. The RGB encoding format is widely utilized, particularly for "natural images." Furthermore, one of the initial steps in data pre-processing involves standardizing image sizes to ensure uniformity.
- In this context, we've employed an auto-resizing approach during training. This technique ensures that all images within the dataset are transformed into a consistent resolution.



Feature Extraction:

Feature extraction is a valuable process employed to streamline resource consumption during processing, while retaining crucial and pertinent information. This technique aids in diminishing redundant data during analysis, leading to enhanced efficiency. Furthermore, by curtailing data volume and the computational effort required to construct feature combinations, feature extraction accelerates the pace of learning and the generalization stages within the machine learning process.

Convolutional Neural Network

- In the realm of deep learning, a Convolutional Neural Network (CNN) stands as a specialized form of deep neural networks that specializes in processing datasets to derive insightful information. It is applicable to various data types such as images, sounds, and videos. The core elements of CNN encompass a local receptive field, shared weights and biases, and activation and pooling layers. In CNN, the training process commences with training neural networks using an extensive dataset, which allows the CNN to discern salient features from input data. Upon receiving input, the initial step involves image preprocessing. Subsequently, the feature extraction phase leverages the stored dataset to deduce significant features. The final stage entails data classification, leading to the presentation of outcomes as results. This process integrates data input, feature extraction, and classification to yield valuable insights.

- A CNN is capable of handling input data that aligns with the training data and patterns stored within the neural network.
- CNNs find application in tasks such as image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing.

Dataset

A significant advantage of employing CNNs in contrast to traditional NNs is the elimination of the need to flatten input images into 1D arrays. CNNs can operate directly with 2D image data, preserving the inherent "spatial" attributes of images. In this context, we're utilizing the Kaggle underwater dataset, which encompasses two distinct categories: "starfish found" and "starfish not found."

Pre-Processing Steps

The pre-processing procedures encompassed resizing, patch extraction, and augmentation steps. The initial pre-processing stage aimed to standardize the dimensions of input images. Given the variation in image shapes and sizes, all images were resized to a uniform 224x224 pixel square. This was achieved by maintaining the aspect ratios while applying zero-padding. The second pre-processing phase involved the utilization of patches, which are cropped segments of each image. The selection of patches was determined by bounding boxes, ensuring the inclusion of adequate starfish found and starfish not found segments for subsequent analysis. Furthermore, data augmentation was exclusively applied to the training dataset. This augmentation involved creating mirror images by horizontally flipping images, as well as rotating them by angles of -30, -10, 10, and 30 degrees. These processes contribute to enhancing the diversity and richness of the training dataset, thereby augmenting the model's ability to generalize effectively.

Image Labeling And Dataset Distributions

Each subject's images underwent dual labeling procedures, independently classified into either "STAR FISH" or "NOT A STAR FISH" categories. The first round of labeling occurred using the original images on a picture archiving communication system (PACS). Subsequently, a second round of labeling was conducted using the resized images utilized for actual learning purposes. The dataset was partitioned into an internal dataset and a temporal dataset, the latter reserved for test evaluation. The internal dataset was further divided randomly into training (70%), validation (15%), and test (15%) subsets. The distribution of the internal test dataset was evenly balanced, comprising 50% starfish images and 50% non-starfish images. This comprehensive partitioning and labeling process constituted a structured foundation for subsequent analysis and evaluation of the model's performance.

IMPLEMENTATION MODULES

Certainly, here's an outline of potential modules for the implementation of the described system:

➢ **Data Preprocessing Module:**
- Resize images to a standardized size (e.g., 224x224 pixels).
- Extract patches using bounding boxes to capture relevant regions.
- Apply data augmentation techniques like horizontal flipping and rotation.

➢ **Labeling Module:**
- Assign "STAR FISH" or "NOT A STAR FISH" labels to images based on dual labeling procedures.

➢ **Dataset Splitting Module:**
- Split the internal dataset into training, validation, and test subsets in a 70-15-15 ratio.

➢ **Convolutional Neural Network (CNN) Architecture:**
- Define the CNN architecture with layers like convolutional, pooling, and fully connected layers.
- Apply activation functions and appropriate regularization techniques.

➢ **Training Module:**
- Train the CNN using the training subset.
- Use validation subset to fine-tune hyperparameters and prevent overfitting.

➢ **Testing Module:**
- Evaluate the trained CNN on the test dataset (internal test dataset) to assess its performance.

- **Performance Evaluation Module:**
  - Calculate metrics like accuracy, precision, recall, and F1-score.
  - Generate a confusion matrix to visualize the classification results.
- **Deployment Module:**
  - Deploy the trained model for real-time detection of starfish in new images.
  - Implement a mechanism to send detected images to a control room for further analysis.
- **User Interface (Optional):**
  - Develop a user interface for user interaction and visualization of results.
- **Integration and Reporting Module:**
  - Integrate the entire system, ensuring smooth flow of data and processes.
  - Generate comprehensive reports summarizing system performance and detected instances.

These modules collectively constitute the framework for implementing the described system that detects starfish using CNNs and specialized preprocessing techniques.

Thonny IDE:

The passage provides information about the Thonny Integrated Development Environment (IDE):

- **Thonny Overview:** Thonny is described as a small and lightweight Integrated Development Environment (IDE) designed for simplicity and fast performance. It aims to minimize dependencies on other packages and desktop environments, making it easy to run.

- **Dependencies:** Thonny relies on the GTK2 toolkit for its graphical interface. It requires the GTK2 runtime libraries to be installed. Additionally, for compiling Thonny, GTK (version 2.6.0 or later), Pango, Glib, and ATK libraries and header files are needed.
- **Compilation:** To compile Thonny, the passage provides instructions for running the configure script followed by make and make install commands. It mentions that the configure script supports various common options.
- **Compile Time Options:** The passage notes that there are compile-time options available, which are specified in the src/Thonny.h file.
- **System Compatibility:** Thonny has been successfully compiled and tested on various systems, including different versions of Debian, Fedora, Linux From Scratch, FreeBSD, and Microsoft Windows.
- **Startup Behavior:** Thonny loads files from the previous session at startup by default. This behavior can be disabled through the preferences dialog. Recent files are accessible from the file menu.
- **Running Multiple Instances:** Users can start multiple instances of Thonny, but only the first instance will load files from the previous session. Subsequent instances will detect the first running instance and open files in it.
- **Terminal Widget:** Thonny includes a terminal widget (VTE) at the bottom, which provides basic terminal functionality. The presence of the terminal widget depends on the availability of libvte.so. Users can disable the use of the terminal widget via a command line option.
- **Project Settings:** Thonny allows users to define project settings that are used for the Make and Run commands. These settings are saved with the project and will be used when the project is reopened.
- **Execute Command:** The Execute command runs executable files, shell scripts, or interpreted scripts in a terminal window. After execution, the terminal window prompts users to review the output before closing.
- **Compile and Build Commands:** The Compile and Build commands allow users to add include paths, compile flags, library names and paths, and other arguments. This enables customization of compilation and execution behavior.
- **Printing Files:** Users can print files by passing the filename to a command. However, printed documents won't include syntax highlighting.

Overall, the passage provides insights into Thonny's features, compilation process, usage instructions, and customization options.

FUTUREWORK

Certainly, here are some potential areas of future development for the Cotsbot AUV (Autonomous Underwater Vehicle):

- **Enhanced Detection and Removal Capabilities:** To improve its effectiveness in detecting and removing crown-of-thorns starfish, the AUV could be equipped with more advanced sensors, such as hyperspectral imaging or machine vision, enabling more accurate detection and targeting. Additionally, it could employ improved methods for removing the starfish without causing harm to the surrounding ecosystem.
- **Advanced Swarm Technology:** The Cotsbot AUV could be part of a coordinated swarm of autonomous vehicles, including both underwater and surface units. These units could communicate and collaborate using advanced swarm algorithms, enabling them to cover larger areas efficiently and work together to tackle coral reef threats.
- **Integration of AI and Machine Learning:** By integrating artificial intelligence and machine learning, the AUV's capabilities could be significantly enhanced. It could learn to adapt its strategies based on real-time data, refine its targeting accuracy, and even predict crown-of-thorns starfish behavior patterns to proactively counter their impact.
- **Expanded Monitoring and Conservation:** Beyond its current focus on removing crown-of-thorns starfish, the AUV could be repurposed for broader environmental monitoring and conservation efforts. It could collect data on water quality, temperature, pollution, and other factors affecting coral health. This data could contribute to a better understanding of coral reef ecosystems and aid conservation initiatives.
- **Remote Operation and Control:** Developing remote operation capabilities for the AUV would allow operators to control and monitor the vehicle from a distance. This could be particularly valuable for deploying the AUV in remote or dangerous locations, reducing risks to human divers.
- **Enhanced Energy Efficiency:** Research and development efforts could focus on improving the AUV's energy efficiency, allowing it to operate for longer durations and cover larger areas before needing to recharge or resurface.
- **Real-time Data Transmission:** Enabling real-time data transmission from the AUV to a central control station could provide researchers with immediate insights into the health of coral reefs. This data could be used to make timely decisions and respond to emerging threats.
- **Collaboration with Marine Biologists:** Collaborating closely with marine biologists and conservationists could lead to the development of specialized sensors and tools that cater to the unique needs of coral reef ecosystems. This interdisciplinary approach could result in more effective conservation strategies.
- **Public Awareness and Education:** The AUV's capabilities and findings could be used to raise public awareness about the importance of coral reefs and the threats they face. Educational programs and public engagement initiatives could help promote conservation efforts.
- **Continuous Innovation:** As technology evolves, new sensors, materials, and algorithms may become available. Continuously updating and innovating the AUV's capabilities could keep it at the forefront of coral reef conservation efforts.

These developments have the potential to transform the Cotsbot AUV into a versatile tool for safeguarding not only coral reefs but also marine ecosystems at large.

CONCLUSION

The paper proposes a novel solution to address the environmental challenge of controlling crown-of-thorns starfish (COTS) populations in Australia's Great Barrier Reef. The proposed solution involves the development of a cooperative mission planner algorithm tailored for a specific type of underwater vehicle known as COTSbot AUVs (Autonomous Underwater Vehicles). The algorithm's performance was thoroughly evaluated through extensive simulation studies. The core problem of managing COTS populations is approached as a constrained task assignment problem. The algorithm leverages the cooperative capabilities of the COTSbot AUVs to maximize the completion of tasks related to controlling COTS. By working together, the AUVs aim to efficiently address the COTS problem and mitigate its impact on the reef ecosystem. Key aspects addressed in the paper include:

- **Algorithm Development:** The paper introduces a cooperative mission planner algorithm designed to optimize the distribution of tasks among the COTSbot AUVs. This algorithm facilitates coordinated task execution for efficient COTS control.
- **Comparison with Non-Cooperative Approach:** The paper evaluates the performance of the cooperative approach by comparing it to individual-based or non-cooperative methods of COTS control. The results highlight the advantages of collaboration and the effectiveness of the proposed planner algorithm.
- **Robustness Testing:** To assess the robustness of the cooperative planner, Monte Carlo simulations are conducted. These simulations introduce variations in the topology of COTS clusters, mimicking real-world uncertainties and challenges. The algorithm's stability and adaptability in handling such variations are confirmed through these simulations.
- **Comparison with Benchmark Method:** The paper compares the proposed cooperative algorithm, referred to as the HFC algorithm, with a benchmark method based on a genetic algorithm (GA) for task assignment. The HFC algorithm demonstrates superior performance compared to the GA-based approach.
- **Future Directions:** The paper concludes by discussing potential future extensions of the study, including field trials and real-world evaluations of the proposed planner algorithm. These practical trials would provide valuable insights into the algorithm's effectiveness and applicability in real-world scenarios.

In summary, the paper presents a comprehensive approach to addressing the COTS problem through the cooperative operation of COTSbot AUVs. The proposed cooperative mission planner algorithm is shown to be effective in simulation studies, offering advantages over non-cooperative methods and benchmark approaches. The study sets the stage for potential field trials and further advancements in the field of underwater autonomous systems for environmental conservation.

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