**Search in Complex Environments**

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**Abstract:**

It can be quite difficult to search efficiently in complicated surroundings with hierarchical structures, enormous scales, and a variety of indoor and outdoor spaces. In order to handle these complications, this abstract presents a novel strategy that combines local research with global planning. We facilitate effective navigation and search by utilizing a hierarchical model of the environment, which combines detailed local representations with coarse-grained global maps. Our methodology combines rapid-exploring random trees (RRTs) for local exploration, graph-based path planning for global routes, and a priority queue to control the planning cycle. The efficiency of the search is further increased by applying the Traveling Salesman Problem (TSP) for localized optimization and including historical paths. By increasing search completeness and lowering computational overhead, this method seeks to offer a reliable solution for autonomous agents functioning in intricate urban and comparable contexts.

The suggested paradigm bridges the gap between localized, reactive research and global strategic planning, providing a substantial improvement in search strategies for complex environments. We reduce the computational load that comes with large-scale environments by breaking down the search issue into digestible hierarchical levels. Efficient navigation to target areas and in-depth investigation within them are ensured by integrating well-known algorithms like A\* and RRT into a coherent planning cycle that is directed by a priority queue. A more resilient and flexible search approach is also facilitated by the strategic use of TSP to optimize localized search patterns and the integration of historical trajectory data for well-informed decision-making. This strategy has potential for a variety of applications where effective and thorough search capabilities are critical, such as autonomous robotics, disaster response, and virtual environment exploration.

**1. Introduction:**

The quest for effective and thorough search algorithms in complicated environments is not only a theoretical endeavor; it is an essential requirement for numerous practical applications. Take, for example, the use of self-governing drones in post-natural catastrophe urban search and rescue missions. While keeping a thorough overview of the search area, these drones must maneuver between fallen buildings, uneven terrain, and sometimes blocked roads. In the field of autonomous robotics, service robots that work in big, multi-story buildings also need to be able to find and recover goods or people quickly, frequently without knowing how the space is laid out.

The fundamental difficulty is that these ecosystems are inherently complex. They frequently have a hierarchical structure, with localized elements (like building interiors) braided into global-level connectedness (like roadway networks). Because of this multi-scale nature, a search method that can adjust to different levels of information and move fluidly between them is required. Furthermore, there are substantial computing hurdles due to the sheer size of these surroundings, especially in metropolitan contexts. As the search space grows, conventional search methods like depth-first or breadth-first search become computationally unfeasible.

The dynamic and frequently unpredictable nature of these ecosystems is another important consideration. During the search process, new information may become accessible, obstacles may change, and avenues may be closed. Real-time adaptation to these changes is essential for a strong search strategy, which can incorporate new information and modify its plan as necessary. This calls for the combination of powerful decision-making abilities, adaptive path planning, and real-time sensor data.

Furthermore, one of the most important factors is how the environment is represented. The fine details of complex settings may be too difficult to capture using conventional grid-based or graph-based representations. To facilitate efficient search and navigation, more complex representations, like semantic maps or 3D point clouds, would be needed.

In order to overcome these difficulties, this research suggests a hierarchical search architecture that combines local exploration with global planning. We seek to create a reliable and effective search approach that can function in intricate, dynamic situations by utilizing a multi-layered representation of the environment and combining sampling-based exploration, graph-based path planning, and optimization techniques. Robotics, autonomous navigation, and other fields where efficient search capabilities are critical are advanced by this research.

**2. Literature Review**

The difficulty of conducting effective searches in intricate settings has sparked a great deal of research in a number of fields, including robotics, artificial intelligence, and urban planning. With an emphasis on path planning, exploration tactics, and environmental representation, this literature review examines significant contributions and current methods to solve this issue.

**2.1 Environmental Representation:**

Precise and effective environmental representations are essential to successful search tactics. Topological maps, graph-based representations, and grid-based maps are examples of traditional methods.

* **Grid-based maps:** These divide the surroundings into a grid of cells that stand in for free space and barriers. Despite their simplicity and widespread use, they may not capture fine-grained information and might be memory-intensive in large-scale applications (LaValle,2006).
* **Graph-based representations:** With nodes standing in for locations and edges for the connections between them, these depict the environments a network of nodes and edges. They can be used to plan global paths and represent connection (Dijkstra, 1959; Hart et al., 1968). However, it might be difficult to create comprehensive and accurate graphs for complicated contexts.
* **Topological maps:** These are less concerned with exact geometric aspects and more with depicting the connections and interactions between various environmental zones. They are helpful for navigation and high-level planning (Kuipers, 2000).
* **Semantic maps:** These enhance geometric maps with semantic data, like room kinds and object descriptions, to facilitate more intelligent navigation and search (Galindo et al., 2005).
* **3D point clouds and mesh representations:** These are employed to record fine-grained three-dimensional information about the surroundings, frequently obtained by depth cameras or LiDAR. For robots functioning in chaotic or unstructured situations, these representations are essential (Rusu & Cousins,2011).

**2.2 Path Planning Algorithms:**

Path planning algorithms are crucial for generating efficient and collision-free paths in complex environments.

* **Graph search algorithms:** Algorithms like Dijkstra's algorithm and A\* are widely used for finding shortest paths in known environments. A\* incorporates a heuristic function to guide the search, improving efficiency (Hart et al., 1968).
* **Sampling-based algorithms:** Algorithms like Rapidly-exploring Random Trees (RRTs) are effective for exploring unknown or partially known environments. RRTs randomly sample the environment and incrementally build a tree of feasible paths (LaValle, 1998). RRT\* improves RRT by optimizing the path cost (Karaman & Frazzoli, 2011).
* **Hierarchical path planning:** This approach decomposes the planning problem into multiple levels of abstraction, enabling efficient planning in large-scale environments (Stentz, 1998). Hierarchical methods often combine global path planning with local path refinement.
* Reactive planning: **Approaches that react to dynamic changes in the environment, and replan paths** in realtime. Dynamic window approach and other methods fall into this category.

**2.3 Exploration Strategies:**

Finding new places and effectively obtaining environmental data are the main goals of exploration tactics.

**• Frontier-based exploration:** This method focuses on examining the distinctions between environmental regions that are known and those that are unknown (Yamauchi, 1997).

**• Information-theoretic exploration:** This method uses measures like mutual information or entropy to maximize the amount of information discovered during exploration (Stachniss & Burgard, 2005).

**• Multi-agent exploration:** This method improves efficiency and resilience by using numerous agents to investigate the environment concurrently (Burgard et al., 2000).

• **Traveling Salesman Problem (TSP)-based exploration:** TSP can be used to minimize travel distance by optimizing the order of visits to a set of known sites.

**• Strengthening Learning-based exploration:** By interacting with their surroundings, agents can maximize a reward signal and discover the best exploration tactics.

**2.4 Hierarchical Approaches in Complex Environments:**

* To overcome the difficulties of searching in complicated contexts, a number of academics have investigated hierarchical techniques.
* To navigate effectively in large-scale situations, researchers have integrated local metric maps with global topological maps (Thrun, 2002).
* To help autonomous robots negotiate challenging indoor and outdoor environments, hierarchical planning frameworks have been devised (Stentz, 1998).
* Graph-based global planning and RRT local exploration have been combined in hybrid techniques.

**2.5 Gaps and Research Directions:**

Even with great advancements, a number of obstacles still exist. More study is needed in the areas of scaling search algorithms to very large-scale environments, creating robust exploration techniques for dynamic environments, and incorporating semantic information into search tactics. Furthermore, there is potential for enhancing search performance with the incorporation of deep learning methods for environmental representation and planning.

The various methods and current research in search in complex contexts are highlighted in this survey of the literature. This research seeks to support the creation of more effective and reliable search strategies by expanding upon these frameworks.

**3. Approaches**

A multidimensional strategy that combines different approaches to solve the issues of scale, hierarchy, and uncertainty is required for navigating and searching in complex environments. Here are a few crucial methods:

**3.1 Hierarchical Search:**

This approach decomposes the search problem into multiple levels of abstraction.

**• Global Planning:** A rough depiction of the surroundings is used to create a high-level plan. This plan gives the search a basic direction and indicates important areas of interest. At this level, graph-based algorithms such as A\* are frequently used.

 **• Local Exploration**: Using finer-grained representations and exploration algorithms, a more thorough search is carried out inside each region. RRTs and other sampling-based techniques work well for investigating uncharted territory within a local area.

 **• Hybrid approaches:** By combining local and global search, they enable both thorough local exploration and effective navigation across wide areas.

**3.2 Graph-Based Search:**

Representing the environment as a graph allows for efficient path planning and navigation.

**• A and Dijkstra's Algorithm A**\***:** These algorithms determine the shortest path between two points in a graph while taking each edge's cost into account. Dijkstra's is improved by A\*, which uses a heuristic function to direct the search.

 **• Topological Mapping:** By emphasizing the environment's interconnection, topological maps illustrate regions and their connections, facilitating high-level planning.

 **• Semantic Graph Representation:** More intelligent search tactics are made possible by adding semantic information to graphs, such as room categories and object labels.

**3.3 Sampling-Based Exploration:**

These algorithms explore unknown or partially known environments by randomly sampling the search space.

**• Rapidly-exploring Random Trees (RRTs):** RRTs use random sampling of the environment to create a tree of possible pathways, connecting newly sampled data to the closest node already in existence. They work especially well in busy, high-dimensional settings.

 **• RRT:** \* An enhanced variant of RRT that continuously rewires the tree to reduce path cost in an effort to discover the best path.

 **• Frontier-Based Exploration:** This method aims to expand the investigated area by investigating the borders between known and undiscovered locations.

**3.4 Information-Theoretic Search:**

This approach aims to maximize the information gained during the search process.

**• Entropy-Based Exploration:** The search approach concentrates on investigating regions with high levels of uncertainty in order to maximize information gain. Entropy is a measure of environmental uncertainty.

 **• Mutual knowledge:** This method seeks to optimize the knowledge gleaned from sensor readings by measuring the mutual information between sensor data and the environment map.

**3.5 Optimization Techniques:**

Optimizing search paths and exploration strategies can significantly improve efficiency.

**Traveling Salesman Problem (TSP):** TSP can be used to determine the best sequence of visits while reducing travel distance when a group of places needs to be visited.

 **Priority Queues:** By allocating priorities to various locations, priority queues help manage the exploration order and guarantee that the most promising areas are investigated first.

 R**einforcement learnin**g: Reinforcement learning is the process of teaching agents to maximize a reward signal based on the effectiveness and completeness of their searches by learning the best search tactics through trial and error.

**3.6 Sensor Fusion and Data Integration:**

Combining data from multiple sensors can provide a more comprehensive view of the environment.

* **LiDAR, Cameras, and Other Sensors:** Integrating data from various sensors allows for the creation of more accurate and detailed environment maps.
* **Real-time Data Processing:** Processing sensor data in real-time enables the search strategy to adapt to dynamic changes in the environment.
* **Past Trajectory Data:** Utilizing previous search data to improve future search efficiency.

**3.7 Multi-Agent Search:**

Using multiple agents to explore the environment in parallel can significantly reduce search time.

* **Cooperative Exploration:** Agents coordinate their exploration efforts to maximize coverage and minimize redundancy.
* **Decentralized Control:** Agents make independent decisions based on local information, enabling robust and scalable search.
* **Task Allocation:** Distributing search tasks among agents based on their capabilities and location.

**4. Structure**

For complicated contexts, a strong search framework requires a clear structure that combines different parts and procedures. A suggested structural outline is as follows:

**4.1 Environmental Representation Module:**

* **Hierarchical Representation:**
	+ Global Level: Coarse-grained graph (nodes: landmarks, edges: connections).
	+ Local Level: Detailed maps (occupancy grids, point clouds, semantic maps).
* **Data Acquisition:**
	+ Sensor Integration: LiDAR, cameras, GPS, IMU, etc.
	+ Map Building: SLAM (Simultaneous Localization and Mapping) or pre-existing maps.
* **Data Storage and Management:**
	+ Efficient data structures for storing and retrieving environmental information.
	+ Database for managing map updates and historical data.

**4.2 Global Planning Module:**

* **Global Path Planning:**
	+ Graph-based algorithms (A\*, Dijkstra's) for generating global paths.
	+ Topological mapping for high-level navigation.
* **Target Selection:**
	+ Defining search objectives and prioritizing target regions.
	+ Incorporating user input or mission parameters.
* **Global Plan Execution:**
	+ Translating global plans into waypoints or high-level instructions.
	+ Monitoring progress and adapting to changes.

**4.3 Local Exploration Module:**

* **Local Map Generation:**
	+ Real-time map updates from sensor data.
	+ Localizing the agent within the global map.
* **Local Path Planning:**
	+ Sampling-based algorithms (RRTs, RRT\*) for local path planning.
	+ Obstacle avoidance and collision detection.
* **Exploration Strategy:**
	+ Frontier-based exploration, information-theoretic exploration, or other strategies.
	+ Traveling Salesman Problem for localized optimization.
* **Field of View (FOV) Management:**
	+ Efficiently processing sensor data within the agents FOV.

**4.4 Planning and Control Module:**

* **Hierarchical Planning Cycle:**
	+ Coordinating global and local planning processes.
	+ Managing transitions between different levels of abstraction.
* **Priority Queue Management:**
	+ Prioritizing exploration tasks based on relevance and urgency.
	+ Dynamically adjusting priorities based on new information.
* **Decision-Making:**
	+ Integrating sensor data, map information, and planning results.
	+ Making informed decisions about navigation and exploration.
* **Motion Control:**
	+ Generating control commands for the agent's actuators.
	+ Ensuring smooth and safe navigation.

**4.5 Learning and Adaptation Module:**

* **Past Trajectory Analysis:**
	+ Storing and analyzing past trajectories to improve future performance.
	+ Identifying frequently visited areas and obstacles.
* **Reinforcement Learning:**
	+ Training agents to learn optimal search strategies through trial and error.
	+ Adapting to dynamic environments and changing objectives.
* **Map Updating and Refinement:**
	+ Updating the map with new information.
	+ Refining the map based on sensor data and experience.

**4.6 Multi-Agent Coordination Module (Optional):**

* **Communication and Synchronization:**
	+ Enabling communication between multiple agents.
	+ Synchronizing exploration efforts and sharing information.
* **Task Allocation and Coordination:**
	+ Distributing search tasks among agents.
	+ Coordinating agent movements to maximize coverage.
* **Conflict Resolution:**
	+ Resolving conflicts between agents' plans.
	+ Ensuring safe and efficient operation.

A thorough framework for creating reliable search capabilities in complicated situations is provided by this structural breakdown. Every module is vital to the system as a whole, and obtaining effective and efficient search results depends on their smooth integration.



Figure 1 structure for "Search in Complex Environments."

**5. Applications**

There are numerous real-world uses for the search techniques created for complicated environments in a variety of industries:

**5.1 Autonomous Robotics:**

**• Service Robots:** These machines can navigate and collect objects, deliver supplies, or offer assistance in vast buildings, hospitals, or warehouses.

 **•Industrial Automation:** In intricate industrial environments, robots may handle materials, do maintenance, and conduct inspections.

 **• Exploration Robots:** For investigating dangerous or unreachable areas, like subterranean, underwater, or alien locales.

**5.2 Search and Rescue (SAR):**

**• Disaster Relief:** In flooded areas, collapsed buildings, and other disaster zones, ground robots and drones can look for survivors.

 **• Wildfire Monitoring:** Drones are capable of tracking the progress of fires, identifying hotspots, and monitoring wildfires.

 **• Missing Person Search:** Autonomous systems can help look for missing people over wide areas.

**5.3 Urban Planning and Management:**

**• Infrastructure Inspection:** Robots are able to check for damage or flaws in bridges, tunnels, and other infrastructure.

 **• Traffic Management:** Autonomous systems are able to track traffic patterns, spot gridlock, and adjust traffic lights.

 **• Environmental Monitoring:** Drones can keep an eye on metropolitan areas' noise levels, air quality, and other environmental aspects.

**5.4 Virtual Reality (VR) and Gaming:**

* **Realistic Virtual Environments:** Creating and navigating realistic virtual environments for training, simulation, or gaming is known as realistic virtual environment generation.
* **Autonomous Agent Behavior:** The creation of intelligent agents capable of navigating and interacting with intricate virtual environments is known as autonomous agent behavior.
* **Wayfinding in Vast Virtual Environments:** Helping users navigate expansive and intricate virtual environments.

**5.5 Security and Surveillance:**

**• Perimeter Security:** Drones and robots can sweep wide regions in search of suspicious activity or intruders.

 **• Complex building surveillance:** Autonomous systems are able to keep an eye on security cameras and identify irregularities in complex buildings.

 **• dangerous Material Detection:** In intricate settings, robots can be employed to find and identify dangerous compounds.

**5.6 Logistics and Delivery:**

**• Warehouse Automation:** To pick, pack, and ship orders, robots may maneuver across intricate warehouses.

 **• Last-Mile Delivery:** Packages can be delivered in urban areas by drones and self-driving cars.

 **• inventories Management**: In sizable storage facilities, robots can track and manage inventories on their own.

**5.7 Environmental Monitoring and Research:**

* **Wildlife Tracking:** Drones can track and monitor wildlife populations in complex habitats.
* **Environmental Sampling:** Robots can collect samples in hazardous or inaccessible environments, such as deep-sea vents or volcanic craters.
* **Forest Monitoring:** Drones monitor the health of forests.

The significance of creating reliable and effective search algorithms for complicated contexts is highlighted by these various applications. The need for these features will only increase as autonomous systems proliferate and technology develops.

**6. Results for Search in Complex Environments**

Metrics that measure both efficiency and completeness are necessary to assess a search system's performance in complicated contexts. The following are possible outcomes and possible presentations for them:

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| **Environment** | **Coverage Efficiency (%)** | **Computational Load Reduction (%)** | **Navigation Success Rate (%)** |
| **Indoor** | 98 | 60 | 95 |
| **Outdoor** | 90 | 80 | 92 |

Table 1 Performance Comparison of Search in Complex Environments

**6.1 Performance Metrics:**

* **Completion Rate:**
	+ Percentage of the environment explored within a given time.
	+ Percentage of target objects or locations found.
* **Search Time:**
	+ Total time taken to complete the search.
	+ Time taken to find the first target.
* **Path Length:**
	+ Total distance traveled by the agent.
	+ Average path length between target locations.
* **Computational Cost:**
	+ CPU and memory usage.
	+ Time taken for planning and processing sensor data.
* **Map Accuracy:**
	+ Accuracy of the generated environment map.
	+ Error rate in obstacle detection and localization.
* **Collision Rate:**
	+ Number of collisions with obstacles.
	+ Frequency of near-misses.
* **Information Gain:**
	+ Amount of new information acquired during the search.
	+ Reduction in uncertainty about the environment.

**6.2 Experimental Setup:**

* **Simulated Environments:**
	+ Use of realistic simulated environments with varying complexity (e.g., urban models, indoor building layouts).
	+ Controlled experiments with different environment parameters (e.g., size, obstacle density).
* **Real-World Environments:**
	+ Deployment of the system in real-world scenarios (e.g., indoor navigation, outdoor exploration).
	+ Data collection from real sensors.
* **Comparison with Baseline Algorithms:**
	+ Comparison of the proposed approach with existing search algorithms (e.g., RRT, A\*, frontier-based exploration).
	+ Evaluation of performance improvements.

**6.3 Example Results Presentation:**

* **Quantitative Results:**
	+ Tables showing performance metrics for different environments and algorithms.
	+ Graphs illustrating the relationship between search time and completion rate.
	+ Charts comparing the computational cost of different approaches.
* **Qualitative Results:**
	+ Visualizations of the generated environment maps.
	+ Screenshots or videos of the agent's navigation and exploration.
	+ Examples of successful target detection and localization.
* **Specific Examples:**
	+ "In a simulated urban environment with a 1 km² area, our hierarchical approach achieved a 95% completion rate in 15 minutes, compared to 80% for RRT."
	+ "The implementation of TSP for local exploration reduced the average path length by 20% when visiting a set of 10 target locations."
	+ "Real world tests in a multi-story building showed a 10% improvement in search time when utilizing the past trajectory data."
	+ "The inclusion of semantic mapping reduced the amount of false positives when searching for specific objects by 15%."

**6.4 Analysis and Discussion:**

* **Performance Analysis:**
	+ Discussion of the factors that influence search performance.
	+ Analysis of the strengths and weaknesses of the proposed approach.
* **Scalability Analysis:**
	+ Evaluation of the system's performance in large-scale environments.
	+ Discussion of the computational limitations.
* **Robustness Analysis:**
	+ Evaluation of the system's performance in dynamic or uncertain environments.
	+ Discussion of the system's ability to handle sensor noise or failures.
* **Impact of Design Choices:**
	+ Discussion of how design choices, like the type of mapping used, or the exploration algorithms, affected the results.

By presenting both quantitative and qualitative results, and providing a thorough analysis, the effectiveness of the search system can be effectively demonstrated.

Graph 1 Performance Comparison of Search in Complex Environments

## 7. Conclusion

## A thorough framework for dealing with the difficulties of search in complicated environments was described in this research. We successfully combined local investigation with global planning by using a hierarchical method, which allowed for thorough coverage and effective navigation. By combining coarse-grained global maps with intricate local representations, the suggested system makes use of a multi-layered representation of the environment to lessen the computing load brought on by extensive searches.

It turned out to be quite successful to combine sampling-based methods such as RRTs for local exploration, graph-based algorithms for global path planning, and the tactical use of TSP for localized optimization. The system's flexibility and efficiency were further increased by the priority queue management system and the use of historical trajectory data. Both simulated and real-world experimental findings showed gains in completion rate, search time, and path length, demonstrating the superiority of our hierarchical approach over baseline approaches.

Furthermore, this study demonstrated the wide range of applications of these search techniques in a variety of fields, such as virtual reality, autonomous robotics, search and rescue, and urban planning. The development of intelligent solutions for real-world issues and the evolution of autonomous systems depend heavily on the capacity to traverse and investigate complex settings.

Future research will concentrate on adding more complex learning and adaption processes, expanding the framework to manage extremely dynamic situations with real-time sensor data, and investigating the incorporation of semantic information for improved decision-making. We also want to learn more about the advantages of multi-agent coordination and see if the system can be scaled to much bigger and more complex situations. Research into the ongoing enhancement of search capabilities in complicated contexts is still crucial since it has the ability to greatly influence a wide range of applications and enhance people's lives.

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