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Literature Review: Transitioning Usage From BFS and DFS To Heuristic Search In The Modern Ai Era

Fahmy Syahputra[1], Elsa Sabrina[2], M Fajar Sahendra Chan[3*], Rifki Fali[4], M Fattah[5], Joko Hendratmo[6], M Fadhil Ardiansyah[7]

[1,2,3,4,5,6,7]*Universitas Negeri Medan, Kota Medan,Provinsi Sumatera Utara, Indonesia*
famybd@unimed.ac.id[1] , elsasabrina@unimed.ac.id[2] , fajar.5232451002@mhs.unimed.ac.id[3] , rifkifali.5233151020@mhs.unimed.ac.id[4] , fattah.5233151017@mhs.unimed.ac.id[5] , jokohendra.5232451004@mhs.unimed.ac.id[6], fadhil.5233351026@mhs.unimed.ac.id[7].*

Abstract

Uninformed search algorithms, specifically Breadth-First Search (BFS) and Depth-First Search (DFS), encounter significant scalability limitations when addressing complex problem spaces in modern Artificial Intelligence (AI) ecosystems. This study investigates the paradigm shift toward intelligent heuristic algorithms through a systematic literature review and comparative analysis of 24 recent academic sources. The evaluation focuses on three primary domains: logical problem solving, robotic navigation, and data infrastructure management. Results demonstrate that heuristic methods, such as A-Star and hybrid variants like PrunedBFS, offer superior time efficiency and memory optimization for autonomous navigation and massive computing tasks. Nevertheless, classic algorithms retain functional relevance for specific scenarios requiring exhaustive exploration. Furthermore, this study reveals that algorithmic evolution has fundamentally transformed digital infrastructure, driving a shift from Search Engine Optimization (SEO) to Answer Engine Optimization (AEO) and necessitating adaptive cybersecurity architectures. The research concludes that the future of AI development relies not on substitution, but on a collaborative synthesis integrating the robustness of classic methods with the adaptability of modern heuristics.

***Keywords**: AI Ecosystem, BFS and DFS, Intelligent Heuristics, Navigation Optimization, Search Algorithm.*

1. Introduction

This Breadth-First Search (BFS) and Depth-First Search (DFS) have long served as foundational algorithms for solving statespace problems in Artificial Intelligence (AI) and computer science research. Studies highlight that while BFS ensures completeness and optimality in unweighted graphs, it suffers from exponential space complexity, whereas DFS, though memory-efficient, cannot guarantee either optimality or completeness without cycle detection or depth limitation mechanisms [1]. Furthermore, these algorithms are categorized as uninformed search methods because they explore the search space without additional knowledge about the proximity or cost to the goal, making them inefficient in large and complex domains [2].

As problem scales in AI such as in automated planning, robotics, and multiagent navigation continue to grow exponentially, traditional uninformed methods like BFS and DFS encounter practical limitations in both time and memory consumption, necessitating the adoption of more intelligent and adaptive search mechanisms. To overcome such inefficiencies, the research community has increasingly shifted toward informed or heuristic-based search algorithms such as A-Star, which employ heuristic functions to estimate the remaining cost to the goal, thereby guiding node expansion more selectively and efficiently [3]. Theoretical studies show that when heuristics satisfy the admissible and consistent properties, algorithms such as A-Star can guarantee optimality while significantly reducing the number of explored nodes compared to uninformed search methods [4].

This paradigm shift is not merely a replacement of algorithms but rather a conceptual transformation in problem-solving strategies from exhaustive state-space exploration toward knowledge-based and learning-driven approaches. Consequently, the evolution from BFS and DFS to heuristic and hybrid search models marks a crucial milestone in the advancement of modern AI systems, directly addressing computationa and scalability challenges in increasingly complex and dynamic environments.
This challenge becomes even more apparent when viewed from a theoretical data structure perspective. Research by [5] shows that recognizing search trees generated by BFS and DFS is a difficult computational problem (NP-complete) in complex graphs such as bipartite

(space efficient) that enable BFS to run with linear memory O(m+n) bits [6], this approach often sacrifices execution time, making it insufficient for massive real-time applications. Therefore, a comprehensive review of the transition from uninformed to informed search methods is crucial for mapping the future direction of intelligent technology.

2. Research Method

This study uses a qualitative approach through a systematic literature review and comparative analysis of 19 selected academic sources covering the most recent publication period. This methodology was designed to evaluate the effectiveness of search algorithms in three main domains:

1. Logic and Game Problem Solving,
2. Physical Navigation and Robotics, and
3. Intelligent System Infrastructure and Data Management.

Data collection was carried out by extracting algorithm performance metrics such as time complexity, space complexity, and solution optimality from various experimental studies. We compared blind search algorithms (BFS, DFS) with heuristic algorithms (A-Star, Greedy, Collaborative Heuristic) in specific cases such as maze navigation, Sudoku puzzles, web crawling, and search engine optimization (SEO).

Data analysis is conducted descriptively to identify patterns of technological transition, where classical algorithms are being abandoned or modified, and where heuristic algorithms are becoming dominant. In addition, this study also reviews the impact of algorithm evolution on supporting infrastructure, such as cloud security and metadata management, to provide a holistic picture of the modern AI ecosystem.

3. Findings and Discussion

3.1. Computational efficiency in logic and game problems

In testing combinatorial logic problems such as Sudoku, heuristic search algorithms have proven to be far superior to traditional methods. [7] reported that heuristic algorithms were able to solve “Hard” level Sudoku puzzles in an average time of 1.07 seconds, much faster than BFS (8.35 seconds) and DFS (2.45 seconds). This advantage occurs because heuristics cut out irrelevant search spaces, while BFS gets stuck in broad exploration that consumes massive memory.

However, classical algorithms are not completely obsolete. In the combat strategy game Kamen Rider Decade, [8] found that BFS is more effective for defensive strategies because it can analyze all possible enemy attacks at one level of depth, while DFS tends to make quick decisions that risk defeat. This shows that in game scenarios with limited state space that require tactical caution, blind search still has functional relevance.

3.2. Optimization in Robotics and Spatial Navigation

In the domain of physical navigation, the transition to heuristics has a significant impact on energy and time efficiency. A comparative study on maze navigation by [9] shows that the A-Star algorithm produces the lowest path cost compared to BFS and DFS, making it the gold standard for autonomous navigation.

Further innovation is seen in the development of the Pony robot for indoor transportation. [10] developed the Pruned-BFS algorithm, a variant of BFS modified with pruning heuristics. Experimental results show that Pruned-BFS can reduce execution time by up to 50% and reduce the number of nodes visited by up to 70% compared to standard BFS. This proves that combining the basic logic of BFS with heuristic intelligence is key to cost-effective robotic navigation.

3.3. Section headings

The impact of search algorithms extends to global information management. In web crawling, [11] found that although BFS is more thorough in indexing files (949 files at a depth of 4), it takes a very long time (886 seconds) compared to DFS (233 seconds), requiring a hybrid algorithm to balance speed and coverage.

Furthermore, the information search landscape has evolved from SEO (Search Engine Optimization) to AEO (Answer Engine Optimization). [12].. note that AI-powered search engines now prioritize direct answers (zero-click searches) over mere links, forcing search algorithms to understand semantic context, not just keywords. This is supported by [13], who introduced the concept of GEO (Generative Engine Optimization) in response to the dominance of generative algorithms in presenting information.

To support these intelligent algorithms, computing infrastructure must also change. [14] emphasizes the need to redesign distributed systems to be compatible with the all-to-all communication patterns of modern AI models, leaving behind the old rigid paradigm. On the other hand, data security in this ecosystem is no longer static. [15] and [16] emphasize that modern security relies on dynamic access control and AI-based anomaly detection, not just data isolation.

3.4. Metadata Management and Cloud Security

AI has revolutionized metadata management from static manual processes to automated systems based on NLP, ML, and LLM. Open-source platforms such as DataGalaxy and DataHub adopt AI-driven features for cross-format metadata extraction, classification, and validation accelerating the process of metadata acquisition, search, and governance, as well as improving data quality and information discovery efficiency. AI also enables real-time metadata enrichment and maintenance, supporting cross-platform system interoperability and modern application domains[17].

The integration of AI into cloud security architecture enables the detection and prevention of advanced persistent threats (APTs) with over 99% accuracy using a combination of optimized CNN and bidirectional GRU. This system is capable of precisely recognizing attack patterns and anomalies through behavioral analysis, as well as managing user identities and access with real-time risk analysis-based adaptive authentication. AI also strengthens governance policies through automated compliance monitoring, smart key management, and zero-trust security systems for multi-layered clouds[16]
.

3.5. Performance Evaluation and Innovation of Heuristic Algorithms in Real-World Problems

Recent research shows that heuristic search algorithms such as A* (A-star), greedy search, and local search techniques (hill climbing, simulated annealing) consistently provide advantages in solving complex problems in various AI application domains. In experimental studies applied to Sudoku and the 8-puzzle, heuristic algorithms successfully solved problems with less time and fewer steps than BFS and DFS. [3] and [7] reported that the application of appropriate heuristics (e.g., Manhattan distance for the 8-puzzle) can improve efficiency by up to 99% in terms of time and memory compared to uniform cost search, and reduce the branching factor by more than 21% in high- level Sudoku cases.

3.6. Review of Modern Search Techniques and Their Implications

According to [18], AI search trends are evolving from uninformed methods (BFS, DFS) to informed and hybrid searches (A*, Greedy, etc.). The use of domain knowledge-based heuristics accelerates solutions but must still consider prediction quality to ensure that the resulting solutions remain optimal. Hybrid techniques, such as combining A* and local search, are increasingly relevant in handling large- scale problems and dynamically adapting solutions.
A comparative performance analysis concludes:

1. BFS is optimal on unweighted graphs but is not memory-efficient on a large scale.
2. DFS is suitable for deep exploration with limited memory, but there is a risk of loops and loss of optimal solutions.
3. Heuristic/A* offers minimum search with optimal results if the heuristics are accurate.
4. Hybrid and local search techniques are optimal for dynamic and iterative optimization.

3.7. Implications for AI Development and Implementation

The evolution of modern AI search techniques requires the selection of algorithms based on the type of problem, domain knowledge, and computational resource requirements. Implementation in various sectors (gaming, robotics, industry, decision support) confirms the synergy between heuristic and hybrid search innovations as a leap in efficiency in terms of time, computing power, and relevance in real- world scenarios[19].

4. Conclusion

The transition from uninformed search algorithms (BFS/DFS) to intelligent heuristic methods is an absolute response to data complexity and efficiency demands in the modern era. This study concludes three main points:

1. Heuristic Superiority: Heuristic algorithms (such as A-Star) and their variants (such as Pruned-BFS) offer significantly better time and memory efficiency for complex problems such as robotic navigation and large logic puzzles.
2. Specific Relevance: Classic algorithms (BFS/DFS) remain relevant for specific cases requiring comprehensive coverage (such as data crawling) or defensive strategies in games.
3. Ecosystem Transformation: The application of intelligent search algorithms has fundamentally changed digital infrastructure, from metadata management and proactive cybersecurity to the evolution of search engines into answer engines (AEO/GEO).

The future of algorithm development no longer lies in a binary choice between "blind" or "intelligent," but rather in a collaborative synthesis that combines the robustness of classical algorithms with the adaptability of heuristic methods

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