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Intelligent Path Generation for Robotic Navigation in Mechanical Based Manufacturing Systems Using AI-Driven Weighted Shortest Path Algorithms For Full-Fledged Automation

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Abstract

This study presents an enhanced robot path planning approach based on Dijkstra's algorithm augmented with path weighting to support intelligent navigation in complex mechanical and manufacturing environments. By incorporating weighted cost functions that account for factors such as distance, obstacle proximity, energy consumption, and motion smoothness, the proposed method enables robots to select more efficient and practical trajectories from the source to the target. The weighting mechanism allows the algorithm to adapt to different environmental constraints and operational priorities, making it suitable for dynamic and cluttered industrial settings. The proposed weighted Dijkstra-based path planning framework improves navigation performance by reducing unnecessary detours, minimizing traversal cost, and enhancing overall path optimality. This results in smoother robot motion, improved execution efficiency, and better utilization of mechanical systems within automated manufacturing processes. The approach is particularly effective in scenarios requiring precise movement planning, such as factory automation, material handling, and robotic assembly, where reliable and efficient navigation is critical for productivity and safety.

Keywords: *SCARA, Robot, Simulation, Algorithm.*

1. Introduction

In recent years, robot navigation has emerged as one of the most dynamic and rapidly advancing areas within robotics, automation, and intelligent manufacturing systems. From warehouse robots transporting materials and industrial manipulators navigating shop floors, to autonomous vehicles operating in traffic and drones exploring unknown environments, efficient navigation plays a central role in determining overall system performance. Navigation is not merely about reaching a destination; it involves making intelligent decisions that ensure safety, efficiency, and adaptability in the presence of uncertainty. Robots are often required to operate in environments that are cluttered, partially known, or constantly changing, which makes autonomous navigation a challenging yet essential capability. As a result, the ability to plan and execute optimal paths from a starting point (source) to a desired endpoint (target) has become a core research problem in modern robotic systems [1]. One of the fundamental challenges in robot navigation is identifying the most suitable path while accounting for obstacles, constrained spaces, mechanical limitations, and operational constraints. Rarely is the shortest geometric path the most practical one, especially in real-world scenarios where factors such as energy efficiency, smooth motion, collision avoidance, and time constraints must be considered. Path planning addresses this challenge by enabling robots to compute feasible and optimal routes and dynamically adapt them as conditions change. To facilitate this process, the robot's environment is commonly modeled using graph-based representations, where nodes correspond to discrete robot positions or states, and edges represent possible transitions between them. Each edge is assigned a weight that reflects the cost of traversal, which may include distance, travel time, energy usage, or risk level. Weighted shortest path algorithms, such as Dijkstra's and A*, use these cost values to systematically evaluate alternative routes and identify the most efficient path. In intelligent and real-time robotic applications, especially within mechanical and manufacturing environments, these algorithms play a critical role in ensuring reliable, optimized, and safe robot navigation [2]. What truly elevates modern robot navigation systems is the seamless integration of Artificial Intelligence (AI), which brings adaptability, learning, and autonomous decision-making into the path planning process. Unlike traditional navigation approaches that rely heavily on fixed rules and pre-programmed logic, AI-enabled robots can perceive their surroundings, analyze real-time data, and learn from past navigation experiences. This learning capability allows robots to make informed decisions even in unfamiliar or partially structured environments. By leveraging AI-based models, robots can anticipate changes in their surroundings, adjust their paths dynamically, and respond intelligently to unexpected obstacles. Furthermore, in multi-robot environments, AI facilitates coordination and cooperation among agents, enabling efficient task sharing and collision-free navigation. Techniques such as machine learning, fuzzy logic, neural networks, and reinforcement learning are increasingly being incorporated into path planning frameworks, making navigation systems more robust, flexible, and context-aware [3]. In such intelligent systems, weighted shortest path algorithms serve as a reliable computational backbone, while AI functions as the cognitive layer that continuously refines and enhances the navigation strategy. The algorithm determines feasible and cost-effective routes, whereas AI evaluates, adapts, and improves these routes based on experience and environmental feedback. This synergy results in navigation systems that are not only computationally efficient but also behaviorally intelligent, capable of responding to dynamic conditions in a manner similar to human reasoning. Consequently, path generation has evolved from static route computation to dynamic, self-optimizing navigation. This advancement has enabled transformative applications, ranging from autonomous delivery robots navigating busy urban spaces to search-and-rescue robots operating in hazardous and unpredictable disaster environments. Modern robots are no longer limited to simply moving from point A to point B; they can now decide how best to reach their destination [4]. As robotics and AI continue to converge, the development of intelligent path generation models is expected to become even more advanced and impactful. This convergence opens up several compelling research questions, such as how robots can effectively navigate completely unstructured environments, how learning-based models can balance exploration with safety, and how computational efficiency can be maintained alongside real-time adaptability. This paper addresses these challenges by examining how weighted shortest path algorithms, when augmented with AI-driven decision-making mechanisms, can significantly enhance robotic navigation. By bridging theoretical foundations with practical implementation, the study aims to contribute toward the design of smarter, safer, and more adaptive robotic systems suitable for mechanical, manufacturing, and real-world autonomous applications [5].

1.1 Literature Survey

What makes modern robot navigation systems significantly more powerful today is the deep integration of Artificial Intelligence (AI) with classical path planning algorithms. AI introduces learning capability, adaptability, and intelligent decision-making into navigation, allowing robots to go far beyond rigid, rule-based movement. Instead of depending solely on predefined maps or fixed logic, AI-enabled robots can sense their surroundings, analyze real-time data, and continuously improve their navigation strategies based on experience. This is particularly important in real-world mechanical

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and manufacturing environments, where layouts may change, obstacles may appear unexpectedly, and operational conditions are rarely static. By learning from past navigation outcomes, robots can anticipate environmental changes, adjust their routes dynamically, and make informed decisions even when operating in unfamiliar or partially known spaces. Techniques such as machine learning, fuzzy logic, neural networks, and reinforcement learning are increasingly being embedded into navigation frameworks to enhance robustness, adaptability, and situational awareness [6]. Within this intelligent framework, weighted shortest path algorithms—such as Dijkstra's and its variants—serve as a strong mathematical foundation, while AI acts as the cognitive layer that refines and optimizes decision-making. Weighted path planning allows different cost factors, such as distance, time, energy consumption, obstacle density, or safety risk, to be incorporated into the navigation process [25]. Research has shown that enhancing Dijkstra's algorithm with intelligent weighting mechanisms significantly improves navigation efficiency, particularly in complex environments like warehouses and indoor manufacturing floors. For instance, weight-controlled and swarm-optimized versions of Dijkstra's algorithm have demonstrated improved route selection by handling multiple equally short paths and choosing the most practical one based on contextual priorities [7]. Similarly, hybrid approaches combining Dijkstra's logic with particle swarm optimization (PSO) and A* variants enable robots to explore multiple candidate paths simultaneously, leading to faster convergence and better performance in unknown or dynamic environments [23]. The fusion of AI with weighted shortest path algorithms transforms path generation from a static computation into a dynamic, self-optimizing process. Instead of producing a single fixed route, modern systems can continuously re-evaluate and update paths in response to real-time sensor inputs, predicted traffic conditions, or detected obstacles [24]. This capability has enabled breakthrough applications such as autonomous warehouse logistics, intelligent manufacturing robots, smart transportation systems, and cooperative multi-robot navigation. Studies on intelligent path planning using topological maps, wireless communication, and predictive data models further highlight how AI-driven path planning enhances reliability, safety, and efficiency in real-world deployments [8]. As robotics continues to converge with AI, the design of intelligent path generation models is becoming increasingly sophisticated and application-oriented. Key research challenges now include navigating fully unstructured environments, balancing optimality with computational efficiency, and ensuring safe decision-making under uncertainty [22]. This paper builds on these advances by exploring how weighted shortest path algorithms, when augmented with AI-based learning and optimization techniques, can significantly improve robotic navigation. By bridging classical graph-based planning with intelligent decision-making, the proposed approach aims to deliver navigation systems that are not only mathematically optimal but also context-aware, adaptive, and suitable for modern mechanical and manufacturing applications [9].

2. Proposed Research Methodology

A graph is a non-linear data structure consisting of vertices and edges. Vertices are sometimes called nodes, and edges are lines or arcs that connect any two nodes in a graph. More formally, a graph consists of a set of vertices (V) and a set of edges (E). The graph is denoted by G(V,E). Graphical data structures are a powerful tool for representing and analyzing complex relationships between objects or entities [20]. They are particularly useful in areas such as social network analysis, recommender systems and computer networks. In the field of sports informatics, graph data structures can be used to analyze and understand the dynamics of team performance and player interactions on the field [21]. Imagine the game of soccer as a web of connections, where the players are the nodes and their interactions on the field are the edges. This web of connections is exactly what the graph data structure represents, and is the key to understanding team performance and player dynamics in sports. The Fig. 2 shows the flow-chart of the proposed methodology [10].

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3. Components of a Graph

Vertices: Vertices are the fundamental units of the graph. Sometimes, vertices are also known as vertex or nodes. Every node/vertex can be labelled or unlabeled [11].

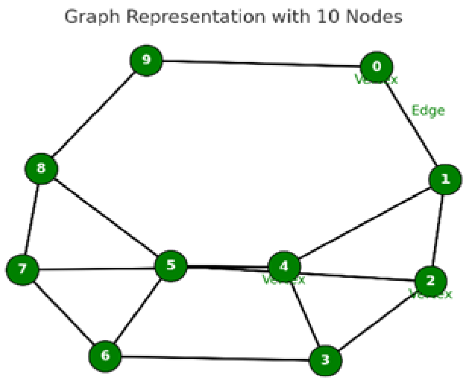

Figure 1 Ordered Form of a Graph

Edges: Edges are drawn or used to connect two nodes of the graph. It can be a ordered pair of nodes in a directed graph. Edges can connect any two nodes in any possible way. There are no rules. Sometimes, edges are also known as arcs. Every edge can be labelled/unlabeled as shown in the Fig. 1 [12].

4. Representation of Graphs

Representation of Graphs - There are two ways to store a graph [13]

- Adjacency Matrix
- Adjacency List
- Adjacency Matrix

In this method, the graph is stored in the form of the 2D matrix where rows and columns denote vertices. Each entry in the matrix represents the weight of the edge between those vertices as shown in Tables 1 [14].

Table 1 Adjacent Graph List Table Components of the Parameters

	V0	V1	V2	V3	V4	V5	V6	V7	V8	V9
V0	0	1	0	0	1	0	0	1	0	0
V1	1	0	1	1	0	1	0	0	0	0
V2	0	1	0	0	0	0	1	0	0	1
V3	0	1	0	0	0	0	0	1	1	0
V4	1	0	0	0	0	1	0	0	0	0
V5	0	1	0	0	1	0	1	0	0	0
V6	0	0	1	0	0	1	0	0	0	1
V7	1	0	0	1	0	0	0	0	1	0
V8	0	0	0	1	0	0	0	1	0	1
V9	0	0	1	0	0	0	1	0	1	0

5. Adjacency List – Representation of the Path of the Robo as a Graph

This graph is represented as a collection of linked lists. There is an array of pointer which points to the edges connected to that vertex. The journey of a robot can be represented by a diagram, defining a set of nodes and edges that model the relationship between different places of the robot and the environment. Nodes represent specific locations or waypoints, and edges represent possible transitions or connections between those stations [18]. Graphs can be used to model various data structures, for instance, an Octree. Octrees have applications in things such as 3D computer graphics, spatial indexing, nearest neighbour searches, finite element analysis, and state estimation [19]. In robotics especially, octrees have been leveraged via the creation of the OctoMap Library, which implements a 3D occupancy grid mapping approach. This provides data structures and mapping algorithms that not only assist in mobile robot navigation and mapping, but also helps in path planning for manipulators in cluttered environments [15]. Define nodes: Identify key locations or waypoints around the robot and environment. Each of these locations becomes a node in the graph. Nodes can represent locations on a grid, coordinates in continuous space, or specific landmarks in the environment [16] Create edges: Create connections

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between nodes by defining edges. An edge between two nodes indicates that the robot can move from one place to another. Edges can be associated with weights or costs that represent distance, time or other factors involved in moving from one node to another [17].

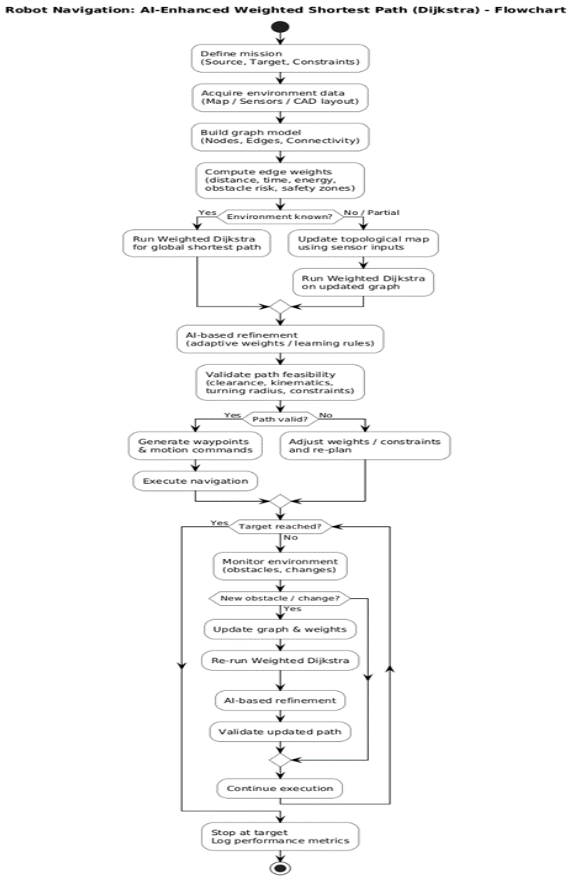

Figure 2 **Flow Chart for the Proposed Algorithm**

Conclusions

To sum up, the case study clearly demonstrates that the proposed Dijkstra-based path planning algorithm is highly effective for robot navigation and obstacle avoidance tasks. The algorithm is capable of recalculating optimal paths in real time, which enables the robot to respond quickly and smoothly to changes in its environment, such as the sudden appearance of new obstacles. This adaptability is particularly important for indoor robotic applications, where dynamic elements like moving objects or human presence are common. By continuously updating the path based on current conditions, the robot can maintain safe and efficient navigation without interruptions or unnecessary delays. Although the computational time complexity of the algorithm increases with the square of the number of nodes, the experimental results indicate that this does not pose a significant limitation in typical indoor environments, where the mapped area and node count remain relatively small. In such scenarios, the algorithm delivers fast and reliable performance while maintaining optimal path selection. Furthermore, the implementation on an Arduino platform proved to be both practical and cost-effective. The Arduino board provided sufficient processing capability and memory resources to execute the algorithm efficiently, making it a suitable choice for low-cost robotic systems and educational or prototype-level manufacturing applications. Overall, the results confirm that the proposed approach offers a balanced solution in terms of performance, adaptability, and hardware feasibility for real-world robot navigation tasks.

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