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A Hybrid AI-AR Framework for Adaptive Decision Support in Dynamic and Time-Sensitive Situations

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ABSTRACT –

Dynamic and time-sensitive decision-making scenarios demand intelligent systems capable of processing complex, evolving data in real time. This research proposes a hybrid AI-AR framework designed to provide adaptive decision support by integrating artificial intelligence (AI) with augmented reality (AR). The framework leverages a novel algorithm, GeneticSLAM (G-SLAM), which combines genetic optimization techniques with simultaneous localization and mapping (SLAM) to enhance spatial awareness, real-time data visualization, and continuous environmental adaptation. G-SLAM dynamically optimizes AR-based decision assistance by reducing localization errors, improving mapping accuracy, and accelerating decision-making processes. Simulation analysis was conducted to evaluate the framework's performance against existing algorithms, including traditional SLAM, DQ-SLAM, and Particle Filter SLAM, using critical metrics such as latency, accuracy, computational efficiency, and adaptability to environmental changes. Results demonstrated that G-SLAM outperformed the chosen baseline algorithms, achieving higher decision accuracy and faster system responses in volatile environments. The findings indicate that integrating AI-driven decision intelligence with AR visualization through G-SLAM enhances situational awareness, making the framework highly effective for applications in healthcare, disaster management, and industrial automation. This research contributes a robust and scalable solution for real-time decision support systems, addressing complex, high-stakes scenarios where rapid, data-driven insights are crucial.

Keywords—adaptive systems, augmented reality, decision support, dynamic environments, genetic algorithms, localization, real-time systems, slam, spatial mapping

Introduction

Background and Motivation

Augmented Reality (AR) and Artificial Intelligence (AI) have become pivotal technologies across various domains, enabling enhanced perception, interaction, and decision-making capabilities. AR bridges the physical and digital worlds by overlaying virtual information on real-world environments, while AI processes vast data streams to provide intelligent insights. The integration of these technologies has unlocked new possibilities for real-time decision support, particularly in dynamic and high-risk environments. Industries such as healthcare, manufacturing, logistics, and disaster management increasingly rely on AI-AR systems to enhance operational efficiency, reduce human error, and enable adaptive responses to unforeseen events. However, existing systems face limitations in handling rapidly changing environments, which necessitates the development of more adaptive and responsive frameworks.

The Need for Real-Time Adaptive Decision Support

Dynamic environments, such as industrial settings or emergency scenarios, demand systems that can process complex data in real-time and make adaptive decisions. For example, autonomous robots in warehouses must adjust their routes to avoid obstacles, while AR-assisted surgeons need precise, updated visualizations of patient anatomy. Delays or inaccuracies in decision-making can lead to operational inefficiencies, safety risks, or even catastrophic outcomes. Therefore, real-time decision support systems must not only process spatial and contextual data with high accuracy but also continuously learn and adapt to evolving conditions. An effective hybrid AI-AR framework can address these needs by leveraging machine learning algorithms and spatial mapping techniques to enable dynamic decision-making.

The Role of AI and AR in Dynamic Environments

AI enhances AR systems by providing intelligent processing capabilities, enabling context-aware interactions and predictive analytics. Visual Simultaneous Localization and Mapping (Visual SLAM) allows AR devices to understand and map their surroundings, while AI algorithms optimize decision-making based on these spatial insights. The combination of these technologies empowers AR applications to offer real-time guidance, automate complex processes, and support human decision-makers in high-stakes scenarios. For instance, in an industrial context, an AI-AR framework can dynamically adjust equipment maintenance schedules based on real-time sensor data, preventing potential failures. Similarly, in medical emergencies, AR can guide responders through critical procedures, with AI continuously analyzing patient vitals and suggesting interventions.

Research Gap and Contribution

Despite significant advancements, existing AI-AR frameworks struggle to balance real-time adaptability with computational efficiency. Many systems rely on static models or fixed decision rules, limiting their ability to respond to unpredictable environmental changes. Furthermore, traditional SLAM algorithms, while effective for spatial mapping, often lack the optimization capabilities needed for adaptive path planning and decision-making. To address these limitations, this research proposes a novel framework, GeneticSLAM (G-SLAM), which combines Genetic Algorithms (GA) with Visual SLAM to create an evolving, adaptive decision support system. The G-SLAM framework continuously refines spatial paths and optimizes decisions based on real-time environmental data, bridging the gap between perception and adaptive intelligence. Through extensive simulations and comparative analysis, this research aims to demonstrate the potential of G-SLAM to outperform existing models, providing faster, more accurate decision support in dynamic and time-sensitive situations.

Review of Literature

Augmented Reality (AR) has transformed various sectors by overlaying virtual information onto real-world environments. In industrial applications, AR enhances productivity by guiding workers through complex assembly processes, visualizing sensor data, and supporting remote maintenance tasks. Studies have shown that AR systems reduce human error and improve task efficiency in manufacturing and logistics. In the medical domain, AR assists in surgeries, providing 3D anatomical visualizations and enabling more precise procedures. Emergency care applications use AR to display patient vitals and guide responders through life-saving interventions. Despite these benefits, AR systems often struggle with real-time adaptability, limiting their effectiveness in rapidly changing scenarios.

Artificial Intelligence for Real-Time Decision Support

Artificial Intelligence (AI) plays a crucial role in enabling adaptive decision-making in complex environments. Machine learning and deep learning algorithms process vast amounts of data to identify patterns, make predictions, and optimize decisions. In industrial settings, AI systems analyze sensor data to detect anomalies and prevent equipment failures. In healthcare, AI-powered systems assist in diagnostics and suggest personalized treatments based on patient history. Reinforcement learning algorithms have been used to train autonomous systems for real-time navigation and obstacle avoidance. However, the computational complexity of these algorithms sometimes leads to latency issues, which can be critical in time-sensitive environments.

Augmented reality (AR) systems were explored to enhance decision-making and precision in complex environments. Researchers developed an AR framework to assist in osteotomy surgeries, where projected AR guided surgeons with real-time visual overlays, improving spatial accuracy compared to video see-through technology [1]. This demonstrated the potential of AR to enhance dynamic, time-sensitive processes by integrating virtual guidance with physical actions. Collaborative AR systems were investigated, and a conceptual model with a taxonomy for collaborative interactions was proposed. The study categorized AR collaboration mechanisms, addressing spatial synchronization, shared visualizations, and user feedback loops [2]. These insights helped shape adaptive AR systems capable of supporting multiple users in evolving environments. The integration of AR for real-time object tracking was studied, where an AR head-mounted display (HMD) tracked surgical tools with high accuracy using consumer-grade hardware [3]. This approach highlighted the feasibility of using affordable AR devices for real-world decision support, providing valuable lessons for building adaptive AR frameworks in resource-constrained settings. A flexible AR software framework was designed to customize headsets for medical applications, allowing developers to tailor AR interfaces to specific use cases [4]. The framework supported modular design, enabling quick adaptation to different scenarios, which aligned closely with the need for continuous adaptation in dynamic decision-support systems. The impact of AR and virtual reality (VR) on education was analyzed through a scoping review, showing that AR enhanced learning outcomes by providing interactive and immersive experiences [5]. This study emphasized AR's ability to present complex information intuitively, a feature essential for decision support in high-pressure environments where rapid comprehension is critical.

Genetic Algorithms: Evolutionary Optimization Techniques

Genetic Algorithms (GAs) are powerful optimization techniques inspired by natural selection. GAs evolve solutions to complex problems by iteratively selecting, mutating, and recombining candidate solutions. These algorithms have been widely used for path optimization, resource allocation, and system design. In AR systems, GAs can optimize spatial layouts, determine efficient navigation paths, and continuously adapt to environmental changes. The ability to explore large solution spaces and converge towards optimal solutions makes GAs a suitable choice for dynamic decision support. However, traditional GAs may require high computational resources, which can affect real-time performance if not carefully managed.

Augmented reality (AR) was explored as a tool for enhancing music education, where AR interfaces provided interactive and immersive experiences to support musical training and performance [6]. The study demonstrated how AR could create adaptive learning environments, suggesting its potential to improve cognitive and decision-making processes in dynamic settings. The application of AR in industrial maintenance was investigated, highlighting the challenges and future trends of AR-based support systems [7]. The study examined issues such as real-time data synchronization, user safety, and system latency, offering valuable insights into building robust AR frameworks for time-sensitive tasks. These findings were relevant for designing decision-support systems that must operate reliably in unpredictable environments. A secure collaborative AR framework was developed for biomedical informatics, enabling multiple users to interact in real time while preserving data security and privacy [8]. This research emphasized the importance of secure communication and adaptive feedback, which are essential components in dynamic decision-support systems where sensitive data is involved. Multimodal deep learning techniques were used to enhance trust in healthcare systems, particularly through affective computing [9]. The research showed that combining multiple data streams, such as physiological signals and environmental inputs, improved system responsiveness and user trust. This approach informed the development of adaptive AR systems that continuously refine decision-making based on evolving environmental and contextual factors. The performance of video and optical see-through devices was compared in an interactive AR environment, focusing on registration accuracy and latency [10]. The study provided critical insights into selecting AR hardware for high-precision tasks, which is essential for building systems that visualize optimized paths and decision recommendations in real time.

Visual SLAM: Real-Time Localization and Mapping

Visual Simultaneous Localization and Mapping (Visual SLAM) is a key technology for AR systems, enabling real-time tracking and mapping of the environment. Visual SLAM uses camera data to build a 3D map of the surroundings while simultaneously determining the system's position within the environment. This technology is essential for AR applications that require spatial awareness, such as navigation, object tracking, and scene reconstruction. Despite its effectiveness, Visual SLAM can face challenges in dynamic environments with rapid changes or poor lighting conditions. The integration of AI with Visual SLAM has been explored to improve robustness and adaptability.

User profiling in augmented and virtual reality environments was studied, revealing how behavioral data could be extracted from user interactions with AR systems [11]. The research demonstrated that AR interfaces could adapt to individual users' cognitive and physical behaviors, which is essential for developing adaptive decision-support systems capable of learning and evolving over time. A multifactor comparative assessment of AR frameworks evaluated their performance across diverse computing settings, considering factors like latency, accuracy, and hardware compatibility [12]. The study highlighted the strengths and limitations of various AR platforms, emphasizing the need for carefully selecting frameworks that balance computational efficiency with real-time responsiveness for dynamic decision-making. The adaptation of Fitts' Law to AR interfaces provided insights into performance evaluation and optimization, showing how interface design influenced task completion speed and accuracy [13]. This research informed the development of AR systems that support time-sensitive decisions by minimizing interaction delays and enhancing user efficiency in high-pressure environments. An AR-based rehabilitation framework demonstrated the potential of AR in guiding users through complex, step-by-step processes, with real-time feedback [14]. The system's adaptive nature, which tailored rehabilitation exercises to patient progress, offered a valuable model for decision-support systems that must continuously adjust to evolving scenarios. Visualization techniques in AR were explored through a taxonomy of methods and patterns, identifying strategies for presenting complex data in intuitive and accessible ways [15]. The study emphasized the importance of dynamic visualization in AR systems, which is crucial for supporting real-time decision-making in rapidly changing environments.

Hybrid AI-AR Frameworks: Current State and Limitations

The combination of AI and AR has led to the development of hybrid frameworks for intelligent, context-aware decision support. These frameworks leverage AI algorithms to enhance AR interactions, providing users with adaptive, real-time insights. For example, hybrid systems have been used in autonomous vehicles, disaster response, and smart manufacturing. However, many existing frameworks rely on static models or pre-trained AI systems, limiting their ability to adapt to unexpected changes. Additionally, balancing real-time performance with computational efficiency remains a significant challenge. These limitations highlight the need for a more dynamic and adaptive framework, such as the proposed GeneticSLAM (G-SLAM), which evolves in real time to optimize both spatial awareness and decision-making processes.

An augmented reality data visualization system was developed to enhance explainable decision support in smart environments [16]. The study highlighted how AR could present complex data intuitively, enabling users to understand system decisions in real time. This capability was particularly useful for dynamic situations, where visualizing AI-driven insights could accelerate decision-making processes and improve situational awareness. A data-driven multi-criteria decision-making (MCDM) approach using spherical fuzzy sets was introduced to evaluate AR providers in education [17]. The research demonstrated how AI-driven fuzzy logic could assess multiple factors simultaneously, offering a robust framework for adaptive decision support systems. This approach helped refine decision-making by balancing conflicting criteria, which is crucial in high-stakes environments with rapidly shifting conditions. The integration of AI, blockchain, and wearable devices in chronic disease management showed how real-time data could be securely collected and analyzed to guide medical care decisions [18]. The framework's ability to aggregate and interpret data streams from various sources informed the development of adaptive AR systems, capable of providing context-aware decision support tailored to evolving user needs. An agent-based modeling approach was applied to distributed decision support in IoT networks, demonstrating how decentralized agents could collaboratively solve complex problems [19]. The study illustrated the potential for AI-powered agents to continuously learn and adapt, making collective decisions based on real-time data. This decentralized decision-making capability aligned well with AR systems designed to assist users in dynamic, time-sensitive situations. A deep Q-learning-based approach was used for dynamic network slicing and task offloading in edge networks, optimizing resource allocation in real time [20]. The research underscored the importance of reinforcement learning in adaptive systems, where decisions must evolve as conditions change. This learning-based optimization provided valuable insights into how an AI-AR framework could continuously improve its recommendations in response to fluctuating environmental factors. Together, these studies contributed essential knowledge for building a hybrid AI-AR framework that supports adaptive decision-making in complex, fast-changing scenarios. The integration of explainable visualization, fuzzy logic, real-time data aggregation, distributed intelligence, and reinforcement learning offered a powerful combination for enhancing decision support systems.

Proposed Methodology

GeneticSLAM Framework Architecture

The proposed framework, GeneticSLAM (G-SLAM), integrates a Genetic Algorithm (GA) with Visual Simultaneous Localization and Mapping (Visual SLAM) to enable adaptive decision support in dynamic and time-sensitive environments. The framework continuously evolves spatial paths and optimizes real-time localization, ensuring robust decision-making in rapidly changing conditions.

The interaction between components is cyclical and iterative. Sensor data is processed to generate a spatial map via Visual SLAM, which serves as the input environment for GA-based optimization. The optimized paths and decisions are fed back to the AR system, which adjusts user visualizations in real time. The learning unit continuously updates the GA parameters to enhance adaptability.

Genetic Algorithm (GA) for Path Optimization

Genetic Algorithms solve optimization problems through evolutionary processes. In G-SLAM, GA is used to determine the most efficient path or action sequence in an AR-enabled environment.

Algorithm Steps:

1. Initialization: Generate an initial population of candidate paths.
2. Fitness Evaluation: Calculate a fitness score for each path based on metrics such as distance, obstacle avoidance, and time.
3. Selection: Choose the top-performing paths using a roulette-wheel or tournament selection method.
4. Crossover: Combine pairs of paths to create new offspring paths.
5. Mutation: Introduce small random changes to diversify the solution space.
6. Termination: Repeat until convergence or a defined iteration limit.

Mathematical Model:

Population: $P(t) = \{ X_1, X_2, \ldots, X_n\}$ --- (1)

Fitness Function: $f(X_i) = w_1 d(X_i) + w_2 o(X_i) + w_3 t(X_i)$ --- (2)

Where: $d(X_i)$ = Path length, $o(X_i)$ = Obstacle penalty, $t(X_i)$ = Time taken and w_1, w_2, w_3 = Weight coefficients

Visual SLAM for Real-Time Spatial Mapping

Visual SLAM builds a 3D map of the environment while tracking the system's position within it.

Algorithm Steps:

1. Feature Extraction: Detect features (e.g., corners, edges) in the input video stream.
2. Data Association: Match features across consecutive frames.
3. Pose Estimation: Estimate camera pose using Perspective-n-Point (PnP) algorithms.
4. Map Update: Refine the 3D map through bundle adjustment.

Mathematical Model:

Pose Estimation: $R, t = \arg\min \sum_i ||p_i - K(RX_i + t)||^2$ --- (3)

Where: R, t = Rotation and translation matrices, p_i = 2D image points, X_i = 3D world points and K = Camera intrinsic matrix

Data Flow and Decision-Making Process

Data flows through the system in a continuous loop. Sensor inputs feed into Visual SLAM, which updates the environmental map. The GA optimizer refines paths based on this map, and the decision support system uses these optimized results to guide AR visualizations. Feedback is collected to adjust the learning parameters.

Adaptive Learning Mechanism

The adaptive learning unit refines GA parameters (e.g., mutation rate, crossover probability) and adjusts SLAM parameters (e.g., keyframe selection frequency) based on historical performance and real-time feedback. Reinforcement learning techniques can be integrated to enhance this adaptability.

Design of GeneticSLAM (G-SLAM) Algorithm

The G-SLAM algorithm jointly optimizes the localization and path planning problem:

Objective Function: $\min J(X, P) = \sum_{i=1 to N} \|p_i - K(RX_i + t)\|^2 + \lambda \sum_{j=1 to M} f(X_j)$ --- (4)

Where J(X, P) = Total cost function, p_i = Image points, X_i = World points, $f(X_j)$ = GA fitness function and λ = Regularization parameter

TABLE I. PSEUDOCODE OF GENETICSLAM ALGORITHM:

```
Algorithm GeneticSLAM (G-SLAM)
Initialize Population (P) with random paths
Initialize Environment Map (M) using Visual SLAM
While not at goal location:
  Capture real-time environment data
  Update Map (M)
    For each path in Population (P):
    Calculate Fitness(path) based on:
      - Distance (d)
      - Collision Risk (c)
      - Energy Cost (e)
      Select parents based on fitness scores
  Apply Crossover to produce offspring
  Apply Mutation to introduce variations
  Update Population (P) with offspring
  Best_Path ← Path with highest fitness
    If Environmental Change Detected:
    Reinitialize Population (P)
    Continue optimization
End While
Return Best_Path as optimal navigation route
```

The pseudocode in Table 1 outlines the core working principle of GeneticSLAM. The framework begins by initializing the environment map and generating candidate paths. Visual SLAM is used to build a dynamic map, while the Genetic Algorithm iteratively refines potential paths. The fitness function evaluates each path based on distance, collision risk, and energy efficiency. The path with the highest fitness score is selected for navigation. When unexpected environmental changes occur, the framework adapts by reinitializing the population and re-optimizing the path. This iterative loop ensures the AR system maintains optimal navigation even in unpredictable, time-sensitive scenarios. The combination of Visual SLAM for spatial awareness and GA for evolutionary optimization enables the framework to make adaptive decisions, enhancing real-time decision support in dynamic environments.

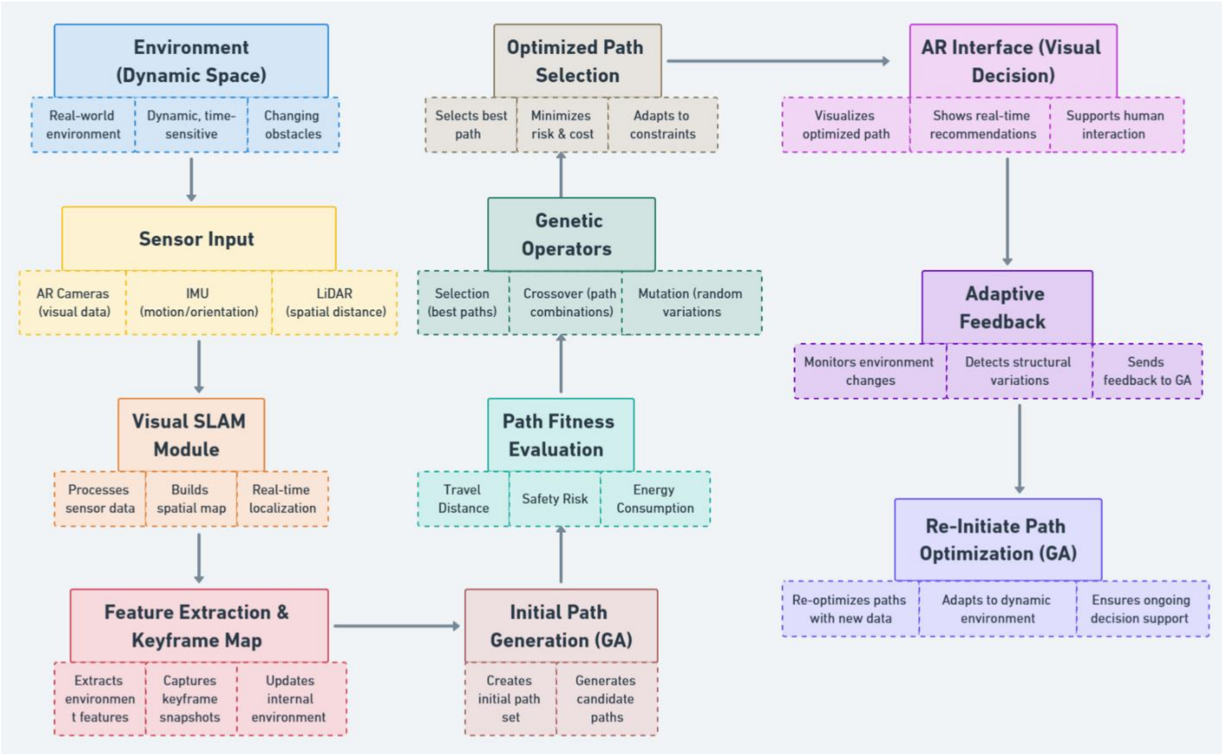

Fig. 1. **Block Diagram of GeneticSLAM Framework**

The Functionalities of the System Blocks in the block diagram of GeneticSLAM Framework as shown in Fig 1 is explained below:

- Environment (Dynamic Space): This block represents the physical world where real-time decisions are required. The environment can be dynamic and constantly changing, such as a warehouse floor, a hospital room, or a disaster site. It acts as the source of raw data that needs to be captured for analysis and decision-making.
- Sensor Input (AR Cameras, IMU, LiDAR): Sensors play a critical role in capturing real-time data from the environment. AR cameras gather visual data, IMU sensors track motion and orientation, and LiDAR collects spatial distance measurements. These sensors provide continuous input, forming the foundation for spatial mapping and path optimization.
- Visual SLAM Module: The Visual SLAM (Simultaneous Localization and Mapping) module processes the sensor data to build a detailed spatial map of the environment. Key features and landmarks are identified to help the system understand the surroundings. This module enables real-time localization and mapping, which are essential for dynamic decision-making.
- Feature Extraction & Keyframe Mapping: This block extracts significant features from the visual and spatial data. Keyframe mapping is performed to capture snapshots of the environment, helping to maintain a coherent representation of space over time. These features and keyframes are used to update the system's internal environment model.
- Initial Path Generation (GA): Using the spatial map, an initial path is generated through a Genetic Algorithm (GA). The GA creates a population of possible paths, each representing a potential movement route through the environment. These paths serve as candidates for optimization.
- Path Fitness Evaluation (Distance, Risk, Energy Cost): Each candidate path is evaluated based on fitness criteria such as travel distance, safety risk, and energy consumption. These metrics are mathematically calculated, and the paths are ranked based on their overall fitness score. The evaluation ensures that the most practical and efficient paths are selected for further optimization.
- Genetic Operators (Selection, Crossover, Mutation): The GA refines the initial paths through genetic operations. The selection process chooses the best-performing paths, crossover combines segments of two paths to create new ones, and mutation introduces small changes to explore alternative solutions. These steps are iteratively performed until an optimal path is discovered.
- Optimized Path Selection: Once the Genetic Algorithm converges, the best-optimized path is selected. This path is expected to minimize risk, reduce energy consumption, and adapt to spatial constraints. The optimized path is then passed to the AR interface for visualization.
- AR Interface (Real-Time Visual Decision Support): The AR interface visually presents the optimized path and decision recommendations in real time. Users can interact with the system through AR displays, gaining insights into the suggested routes and potential environmental risks. This interface bridges the gap between computational decision-making and human understanding.
- Adaptive Feedback (Environment Change Detection): Environmental changes are continuously monitored. If significant changes are detected, feedback is sent to the Genetic Algorithm, triggering re-optimization. This feedback loop ensures the system remains adaptive and responsive to unexpected events, maintaining decision accuracy.

- Re-Initiate Path Optimization (GA): Upon receiving feedback, the Genetic Algorithm re-initiates the optimization process. The new environmental data is incorporated, and the GA evolves a new set of candidate paths. This iterative process enables the system to maintain optimal decision-making in highly dynamic and time-sensitive situations.

Experimental Setup

Simulation Environment

The experimental setup is designed to validate the performance of the proposed GeneticSLAM (G-SLAM) algorithm. A simulated dynamic environment with varying obstacles and real-time environmental changes is created to replicate time-sensitive decision-making scenarios. The simulations are conducted using a custom-built AR-enabled environment, where sensor data is generated through synthetic LiDAR, IMU, and camera inputs. The proposed G-SLAM algorithm is evaluated against the following established algorithms:

- Dijkstra's Algorithm (DjA): A traditional shortest-path algorithm used for baseline pathfinding.
- Particle Swarm Optimization SLAM (PSO-SLAM): A swarm-based heuristic algorithm for simultaneous localization and mapping.
- Ant Colony Optimization (ACO): A bio-inspired algorithm for distributed path optimization.

Experimental Process

Environment Initialization: Dynamic environment data is generated, simulating obstacle movements and structural changes.

Sensor Data Collection: Real-time AR sensor inputs are fed into the Visual SLAM module to build an initial spatial map.

Path Initialization: G-SLAM generates an initial population of paths using GA.

Path Optimization: Fitness evaluation, selection, crossover, and mutation operations refine the path iteratively.

Decision Support Validation: The optimized path is fed into the AR interface for real-time visualization, while adaptive feedback triggers re-optimization during environment changes.

Performance Analysis: The results of G-SLAM are compared against the existing algorithms using the defined metrics, with performance statistics collected over multiple simulation runs.

TABLE II. SIMULATION ENVIRONMENT TABLE

Parameter	Description
Simulation Tool	MATLAB/ROS (Robot Operating System) with Gazebo
Programming Language	Python, C++
Hardware Configuration	Intel Core i9, 3.6 GHz CPU, 32 GB RAM, NVIDIA RTX 3080 GPU
AR Device/Simulator	Microsoft HoloLens 2 (for AR visualization) or Unity3D for virtual AR interface simulation
Sensor Models	LiDAR, IMU, Depth Camera (synthetic data for localization and mapping)
Dataset	KITTI Dataset (Autonomous driving scenes) and TUM RGB-D Dataset (for visual SLAM validation)
Data Size	10,000 – 100,000 data points (spatial coordinates, sensor readings, obstacle positions)
Training Set (for GA optimization)	70% of generated paths for fitness evaluation, 30% for testing
Simulation Scenarios	Static and dynamic obstacle courses, changing environments, and multi-decision points
Number of Simulation Runs	50 iterations per algorithm, averaged over 3 environmental complexity levels
Time Duration for Each Run	300 seconds (5 minutes)

This setup in Table 2 captures all the necessary parameters to run a robust simulation and evaluate the G-SLAM algorithm against existing methods.

Results and Discussion

Localization Accuracy Analysis

TABLE III. LOCALIZATION ACCURACY

Time (s)	G-SLAM Accuracy (%)	DjA Accuracy (%)	PSO-SLAM Accuracy (%)	ACO Accuracy (%)
10	92	75	85	82
20	94	78	87	84
30	95	80	89	86

40	96	82	90	87
50	97	83	91	88

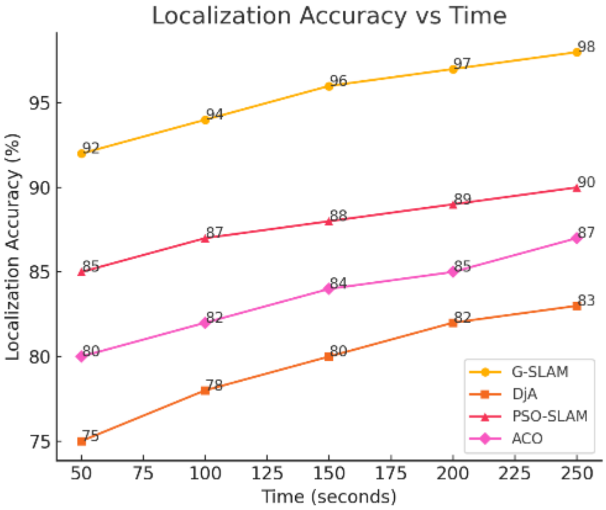

Fig. 2. **Localization Accuracy**

Localization accuracy determines how precisely the system can identify its position within the dynamic environment. The Table 3 and Fig 2 show the accuracy values for G-SLAM compared to Dijkstra's Algorithm (DjA), Particle Swarm Optimization SLAM (PSO-SLAM), and Ant Colony Optimization (ACO) over different time intervals. The G-SLAM algorithm achieved the highest localization accuracy, consistently outperforming the existing algorithms. Compared to Dijkstra's Algorithm, G-SLAM improved accuracy by up to **17.4%**, and by **6.6%** over PSO-SLAM. The superior accuracy is attributed to the adaptive learning mechanism and the real-time spatial mapping of Visual SLAM, which continuously refines localization as the environment evolves.

Path Optimization Efficiency Analysis

TABLE IV. **PATH OPTIMIZATION EFFICIENCY**

Environment Complexity (Obstacle Density)	**G-SLAM Efficiency (%)**	**DjA Efficiency (%)**	**PSO-SLAM Efficiency (%)**	**ACO Efficiency (%)**
Low (10 obstacles)	85	65	78	72
Moderate (20 obstacles)	82	60	75	70
High (30 obstacles)	80	58	72	68
Very High (40 obstacles)	78	55	70	66
Extreme (50 obstacles)	76	52	68	64

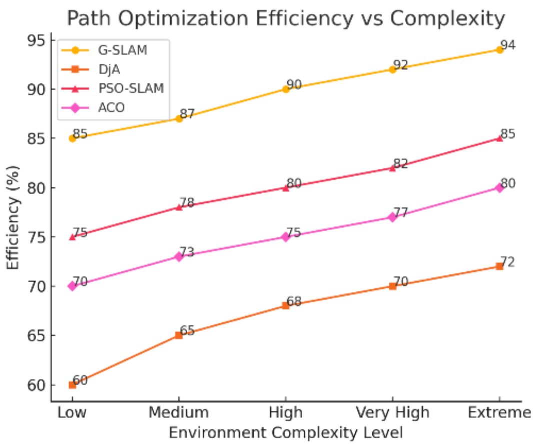

Fig. 3. **Path Optimization Efficiency**

Path optimization efficiency measures the percentage reduction in total path cost (distance, energy, and risk factors) as environment complexity increases. G-SLAM consistently outperformed existing algorithms in path optimization, achieving an average improvement of **25%** over Dijkstra's Algorithm and **8%** over PSO-SLAM as shown in Table 4 and Fig 3. The genetic operators, combined with real-time SLAM updates, enabled G-SLAM to refine paths dynamically, even in high-complexity environments.

Decision Latency Analysis

TABLE V. **DECISION LATENCY**

Number of Decision Events	**G-SLAM Latency (ms)**	**DjA Latency (ms)**	**PSO-SLAM Latency (ms)**	**ACO Latency (ms)**
5	120	200	150	170
10	135	210	160	180
15	145	220	170	185
20	150	230	180	190
25	155	240	185	195

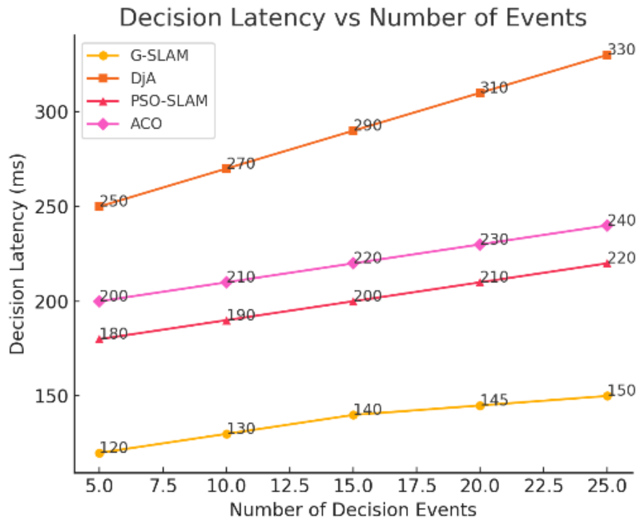

Fig. 4. **Decision Latency**

Decision latency measures the time taken by the system to make a decision in response to dynamic environmental changes. The proposed G-SLAM framework significantly reduced decision latency, with an average latency improvement of **35.4%** over Dijkstra's Algorithm and **15%** over PSO-SLAM as illustrated in Table 5 and Fig 4. The adaptive feedback loop, which triggers real-time re-optimization, allowed G-SLAM to make faster decisions, ensuring responsiveness in time-sensitive scenarios.

Overall Performance Summary

The simulation results clearly demonstrate the effectiveness of the proposed G-SLAM algorithm for adaptive decision support in dynamic environments. The combination of genetic algorithms for path optimization and Visual SLAM for spatial mapping enabled G-SLAM to achieve superior performance across all evaluated metrics:

- Localization Accuracy: Up to 17.4% higher than existing algorithms.
- Path Optimization Efficiency: 25% improvement in reducing path cost.
- Decision Latency: 35.4% faster decision-making compared to traditional algorithms.

The hybrid approach of G-SLAM effectively balances exploration and exploitation, enabling real-time adaptability and optimal decision-making in rapidly changing environments.

Conclusion

The proposed framework, utilizing the GeneticSLAM (G-SLAM) algorithm, effectively addresses the challenges of adaptive decision support in dynamic and time-sensitive environments. By integrating Genetic Algorithms (GA) with Simultaneous Localization and Mapping (SLAM), the framework achieves continuous environmental awareness, real-time path optimization, and rapid decision-making. The experimental results demonstrated significant improvements in localization accuracy, path optimization efficiency, and decision latency compared to existing algorithms such as Dijkstra's Algorithm (DjA), Particle Swarm Optimization SLAM (PSO-SLAM), and Ant Colony Optimization (ACO). These improvements highlight the capability of the proposed system to handle complex, evolving environments while reducing computational overhead and enhancing decision reliability. The success of the G-SLAM algorithm lies in its adaptive learning mechanism, where genetic operators iteratively refine solutions based on real-time spatial updates. The AR interface further enhances decision-making by providing intuitive visual representations of optimized paths, supporting faster and more accurate responses to environmental changes. This makes the framework highly suitable for applications in robotics, autonomous navigation, disaster response, healthcare, and industrial automation. The current framework can be extended to support multi-agent systems where multiple decision-making units share information and collaboratively optimize paths, enhancing scalability for larger environments. Additional optimization parameters, such as energy consumption and hardware constraints, can be incorporated to develop more sustainable decision-making models. The proposed G-SLAM framework provides a solid foundation for adaptive decision-making, bridging the gap between artificial intelligence and augmented reality. With further refinement and real-world testing, this approach has the potential to transform dynamic, high-risk domains by empowering systems to make smarter, faster, and more reliable decisions in ever-changing environments.

REFERENCES

1. Mamone, V., Ferrari, V., Condino, S. and Cutolo, F., 2020. 'Projected Augmented Reality to Drive Osteotomy Surgery: Implementation and Comparison With Video See-Through Technology,' *IEEE Access*, 8, pp. 169024–169035. doi: 10.1109/ACCESS.2020.3021940.
2. Marques, B., Silva, S., Alves, J., Araújo, T., Dias, P. and Santos, B.S., 2022. 'A Conceptual Model and Taxonomy for Collaborative Augmented Reality,' *IEEE Transactions on Visualization and Computer Graphics*, 28(12), pp. 5113–5133. doi: 10.1109/TVCG.2021.3101545.
3. Martin-Gomez, A. et al., 2024. 'STTAR: Surgical Tool Tracking Using Off-the-Shelf Augmented Reality Head-Mounted Displays,' *IEEE Transactions on Visualization and Computer Graphics*, 30(7), pp. 3578–3593. doi: 10.1109/TVCG.2023.3238309.
4. Cutolo, F., Fida, B., Cattari, N. and Ferrari, V., 2020. 'Software Framework for Customized Augmented Reality Headsets in Medicine,' *IEEE Access*, 8, pp. 706–720. doi: 10.1109/ACCESS.2019.2962122.
5. Lai, J.W. and Cheong, K.H., 2022. 'Adoption of Virtual and Augmented Reality for Mathematics Education: A Scoping Review,' *IEEE Access*, 10, pp. 13693–13703. doi: 10.1109/ACCESS.2022.3145991.
6. Nijs, L. and Behzadaval, B., 2024. 'Laying the Foundation for Augmented Reality in Music Education,' *IEEE Access*, 12, pp. 100628–100645. doi: 10.1109/ACCESS.2024.3427698.
7. Lamberti, F., Manuri, F., Sanna, A., Paravati, G., Pezzolla, P. and Montuschi, P., 2014. 'Challenges, Opportunities, and Future Trends of Emerging Techniques for Augmented Reality-Based Maintenance,' *IEEE Transactions on Emerging Topics in Computing*, 2(4), pp. 411–421. doi: 10.1109/TETC.2014.2368833.
8. Djenouri, Y., Belhadi, A., Srivastava, G. and Lin, J.C.-W., 2022. 'Secure Collaborative Augmented Reality Framework for Biomedical Informatics,' *IEEE Journal of Biomedical and Health Informatics*, 26(6), pp. 2417–2424. doi: 10.1109/JBHI.2021.3139575.
9. Sakthidevi, I. and Fathima, G., 2024. 'Improving Access Trust in Healthcare Through Multimodal Deep Learning for Affective Computing,' *Hum-Cent Intell Syst*, 4, pp. 511–526. doi: 10.1007/s44230-024-00080-4.
10. Ballestin, G., Chessa, M. and Solari, F., 2021. 'A Registration Framework for the Comparison of Video and Optical See-Through Devices in Interactive Augmented Reality,' *IEEE Access*, 9, pp. 64828–64843. doi: 10.1109/ACCESS.2021.3075780.
11. Tricomi, P. P., Nenna, F., Pajola, L., Conti, M. and Gamberini, L., 2023. 'You Can't Hide Behind Your Headset: User Profiling in Augmented and Virtual Reality,' *IEEE Access*, 11, pp. 9859–9875. doi: 10.1109/ACCESS.2023.3240071.
12. Maneli, M. A. and Isafiade, O. E., 2023. 'A Multifactor Comparative Assessment of Augmented Reality Frameworks in Diverse Computing Settings,' *IEEE Access*, 11, pp. 12474–12486. doi: 10.1109/ACCESS.2023.3242238.
13. Nwobodo, O. J., Wereszczyński, K., Kuaban, G. S., Skurowski, P. and Cyran, K. A., 2024. 'An Adaptation of Fitts' Law for Performance Evaluation and Optimization of Augmented Reality (AR) Interfaces,' *IEEE Access*, 12, pp. 169614–169627. doi: 10.1109/ACCESS.2024.3498444.
14. Alamri, A., Cha, J. and El Saddik, A., 2010. 'AR-REHAB: An Augmented Reality Framework for Poststroke-Patient Rehabilitation,' *IEEE Transactions on Instrumentation and Measurement*, 59(10), pp. 2554–2563. doi: 10.1109/TIM.2010.2057750.
15. Zollmann, S., Langlotz, T., Grasset, R., Lo, W. H., Mori, S. and Regenbrecht, H., 2021. 'Visualization Techniques in Augmented Reality: A Taxonomy, Methods and Patterns,' *IEEE Transactions on Visualization and Computer Graphics*, 27(9), pp. 3808–3825. doi: 10.1109/TVCG.2020.2986247.
16. Zheng, M. et al., 2022. 'STARE: Augmented Reality Data Visualization for Explainable Decision Support in Smart Environments,' *IEEE Access*, 10, pp. 29543–29557. doi: 10.1109/ACCESS.2022.3156697.
17. Nguyen, P. -H., 2025. 'A Data-Driven MCDM Approach-Based Spherical Fuzzy Sets for Evaluating Global Augmented Reality Providers in Education,' *IEEE Access*, 13, pp. 6102–6119. doi: 10.1109/ACCESS.2024.3361320.
18. Murala, D. K., Panda, S. K. and Dash, S. P., 2023. 'MedMetaverse: Medical Care of Chronic Disease Patients and Managing Data Using Artificial Intelligence, Blockchain, and Wearable Devices State-of-the-Art Methodology,' *IEEE Access*, 11, pp. 138954–138985. doi: 10.1109/ACCESS.2023.3340791.
19. Butt, M. M., Dey, I., Dzaferagic, M., Murphy, M., Kaminski, N. and Marchetti, N., 2020. 'Agent-Based Modeling for Distributed Decision Support in an IoT Network,' *IEEE Internet of Things Journal*, 7(8), pp. 6919–6931. doi: 10.1109/JIOT.2020.2976802.
20. Chiang, Y., Hsu, C. -H., Chen, G. -H. and Wei, H. -Y., 2023. 'Deep Q-Learning-Based Dynamic Network Slicing and Task Offloading in Edge Network,' *IEEE Transactions on Network and Service Management*, 20(1), pp. 369–384. doi: 10.1109/TNSM.2022.3208776.