Work Evaluation Table

<Use the same factors you have used in "Work Evaluation Table" to build your own "Proposed and Previous comparison table ">

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|  | **Work Goal** | **System's Components** | **System's Mechanism** | **Features**  **/Characteristics** | **C**  **o s t** | **Speed** | **S**  **e c u ri ty** | **Performance** | **Advantages** | **Li mit ati ons**  **/Di sad va nta ges** | **Platform** | **Results** |
| ZHIJUN MENG  LIFENG WANG  HAOCHEN LI  KAIPENG WANG  KAIPENG WANG | the aim is to create a smart drone that can fly by itself, learn from its surroundings, and make decisions to navigate safely through different environments | Construction of the Algorithmfor effective path planning  Stability and Convergence  Absatcle avoidence | UAV path planning algorithm utilizes POMDP, deep reinforcement learning with CNNs and RNNs, and a novel action selection strategy to enhance efficiency. An adaptive sampling mechanism improves learning stability. Simulation results show significant improvements over other algorithms. | This UAV path planning algorithm stands out for its ability to navigate in three dimensions, considering both horizontal and vertical actions. It formulates the problem as a Partially Observable Markov Decision Process, making decisions with incomplete information. The algorithm incorporates a probabilistic safety measure, evaluates performance in diverse environments, and introduces adaptive mechanisms for efficient learning. Its effectiveness in obstacle avoidance and applicability to limited sensor scenarios make it a robust solution for dynamic UAV navigation. | **-** | **-** | **-** | The performance will be dependent on algorithm used | The algorithm enhances UAV path planning by improving efficiency, learning, stability, and adaptability. It addresses partial observability, performs well in diverse environments, and does so with low computational cost, making it a valuable solution for UAV projects. | **-** | - | they used Deep Reinforcement Learning for effective path planning which is efficent then the old algorithms like A\* |

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| **Kevin Pluckter**  **Sebastian Scherer** | The goal or objective of this solution is to enable autonomous precision landing of unmanned aerial vehicles (UAVs) in unstructured and unknown environments, specifically at the UAV's starting position. The problem that needs to be solved is the reliance on GPS or odometry-based landing systems, which can be inaccurate and unreliable, especially in GPS-denied environments. The proposed solution aims to address this issue by using a downward-facing fisheye lens camera to accurately guide the drone back to its initial position without the need for a specific landing pattern | Take-off and Landing  Localization  Pose Estimation and Control  Safety Measures | The drone takes off, records key features, and during landing, uses these features to find its position by adjusting for tilt and estimating 3D space based on a flat assumption. It then guides itself back to the take-off position while considering safety measures in case of unexpected changes. The system's performance is evaluated through experiments in various environments. | This solution features efficient feature extraction, precise localization, and 3D pose estimation during drone landing. It incorporates safety measures, such as proactive ascension in case of scene changes. The system undergoes rigorous evaluation in diverse environments, comparing the performance of fisheye and pinhole lens cameras. | **-** | **-** | **-** | The validation results show high accuracy in landing the UVA at the safe place | This solution significantly improves drone precision and reliability in localization and landing, ensures safety through proactive measures, and offers versatility across diverse environments. The rigorous evaluation and camera comparison enhance its effectiveness in UAV projects. | **-** | **-** | The work presents a thorough approach to drone localization and landing. Critical analysis highlights strengths in feature extraction and safety measures but prompts consideration of limitations like the planar assumption and sensitivity to conditions |

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| **Xin Liu**  **Zhanyue Zhang** | The goal of this solution is to use a UAV to automatically detect, track, and accurately position a moving target. The problem to be solved is the state estimation of the target in a nonlinear system. | Vehicle Detection  Multitarget Tracking  Trajectory Processing and State Estimation  Cascade Matching | The process entails utilizing the YOLO v4 algorithm for vehicle detection, followed by employing the DeepSORT algorithm for multitarget tracking. Trajectories are processed, and the state of the target is estimated using the Mahalanobis distance matching method. Cascade matching is subsequently applied to address occlusions. The primary objective of this solution is to attain precise and real-time detection, tracking, and positioning of vehicles using UAVs in urban environments | This solution combines the YOLO v4 algorithm for accurate vehicle detection, DeepSORT for multitarget tracking, the Mahalanobis distance matching method for precise state estimation, and cascade matching to handle occlusions. Its objective is to achieve real-time and accurate detection, tracking, and positioning of vehicles using UAVs in urban environments. | **-** | **-** | **-** | UAV system's performance is affected differently based on whether it's a sunny day or a rainy da | positive impacts such as enhanced search capabilities, real-time monitoring, improved efficiency, data-driven decision making, and better collaboration among stakeholders. These benefits increase the chances of locating the missing child and contribute to the success of the project. | **-** | **-** | they tried improve the target detection by vision based and it is efficient |

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| **MUHAMMAD ARIF ARSHAD**  **SADDAM HUSSAIN KHAN1,**  **SULEMAN QAMAR  MUHAMMAD WALEED KHAN**  **IQBAL MURTZA**  **JEONGHWAN GWAK   ASIFULLAH KHAN** | The goal or objective of the proposed solution is to develop a deep Convolutional Neural Network (CNN) based strategy for drone navigation in complex and dynamic environments. The problem that needs to be solved is the safe and reliable navigation of unmanned aerial vehicles (UAVs) in challenging and unpredictable environments | Drone-STM-RENet  STM-based CNN blocks  Regression CNN  Deep learning techniques | Creating a drone navigation system requires the incorporation of machine learning, computer vision, GPS, and optical sensors, along with the implementation of SLAM for navigating urban environments. The steps involve gathering a varied dataset, labeling it for training, and designing a tailored Drone-STM-RENet neural network equipped with STM to enhance obstacle detection efficiency. Training and validation processes are crucial for ensuring the system's capability to navigate effectively in intricate surroundings. | Key features include the use of SLAM for robust urban navigation, a diverse dataset for training, and a specialized Drone-STM-RENet neural network with STM for efficient obstacle detection. The system is designed to process GPS, optical sensor, and camera data, providing a comprehensive and adaptable solution for navigating complex environments. | **-** | - | **-** | UAV system's performance is affected by The type and complexity of urban environments | This drone navigation solution positively impacts UAV projects by improving accuracy in urban environments through machine learning, computer vision, and SLAM. It ensures effective obstacle detection and avoidance, global navigation capability, adaptability to complex settings, real-time decision-making, and comprehensive sensor integration for a reliable and versatile system. | **-** | **-** | This drone navigation system shows innovation in addressing urban UAV challenges with machine learning and SLAM. Strengths include diverse dataset use and a specialized neural network. However, potential concerns include computational complexity, resource intensity, and sensor dependencies. |

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| **Abhishek Shara**  **Pankhuri Vanjni**  **Nikhil Paliwl**  **Wijerata Basna**  **Dushana Nalin K. Jayakody**  **Hwang-Cheng Wang** | The goal of the solution presented in the document is to improve the communication and networking capabilities of Unmanned Aerial Vehicles (UAVs). The problem that needs to be solved is the limited and inefficient communication infrastructure for UAVs, which hinders their ability to transmit data, receive control signals, and coordinate with ground operators | Communication Modules  Resource Handling Platforms  Networking Technologies | Creating a drone navigation system requires the incorporation of machine learning, computer vision, GPS, and optical sensors, along with the implementation of SLAM for navigating urban environments. The steps involve gathering a varied dataset, labeling it for training, and designing a tailored Drone-STM-RENet neural network equipped with STM to enhance obstacle detection efficiency. Training and validation processes are crucial for ensuring the system's capability to navigate effectively in intricate surroundings. | Efficient UAV communication solution featuring precise initialization, dynamic network discovery, reliable link establishment, optimized channel allocation, and seamless data transmission. | **-** | - | **-** | UAV system's performance is affected by the  environmental conditions | This solution enhances overall UAV project efficiency by optimizing communication, ensuring flexibility, and improving coordination, reliability, and resource utilization | **-** | **-** | The UAV communication solution shows promise with its focus on efficiency, coordination, and resource optimization. However, challenges like complexity, resource demands, vulnerability to interference, high initial costs, and security need careful consideration for successful implementation. |

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