UAV Path Optimization and Obstacle Classification via SVD-Based Feature Reduction and Random Forest Modeling

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***Abstract*—Conventional UAV navigation systems are usually plagued by performance issues in obstacle detection and path planning because they experience high-dimensional sensor inputs, noisy measurements, and the lack of real-time optimization. This research introduces an autonomous UAV navigation framework known as "UAV Path Optimization and Obstacle Classification via SVD-Based Feature Reduction and Random Forest Modeling" that erases the necessity of human intervention in model tuning and trajectory adjustment. The framework incorporates sensor fusion of GPS, IMU, and LiDAR modules and employs Truncated Singular Value Decomposition (SVD) for real-time feature dimensional reduction. In combination with spatial information and a Random Forest classifier, the architecture supports effective obstacle classification and trajectory path smoothing. It leverages SMOTE for dealing with data imbalance and attains enhanced trajectory accuracy with robustness against environmental noise. Visualization layers, such as obstacle mapping and optimized flight paths, are integrated for interpretability. Experimental results show classification accuracy in the 96%–98% range, obstacle recall rates of close to 100%, and average response improvements in challenging terrains. The minimal computational overhead and modularity of the framework make it an efficient, scalable, autonomous solution that can be deployed for real-time UAV applications.**

***Index Terms*—UAV Navigation, Obstacle Detection, Truncated SVD, Random Forest, Sensor Fusion, Path Optimization, SMOTE, Feature Reduction, Spatial Data Integration, Autonomous Systems.**

I. Introduction

Existing UAV navigation and obstacle detection methods are based predominantly on manual feature engineering or high-dimensional sensor data without efficient real-time optimization mechanisms. Such systems, as functional as they are, tend to be plagued by noisy data, low adaptability in dynamic situations, and computational expensiveness. This research rectifies autonomous UAV path planning and obstacle categorization limitations through a scalable and smart system that combines sensor fusion, dimensionality reduction, and ensemble-based classification to guarantee precision and responsiveness.

Contemporary UAV platforms need not only effective obstacle detection but also smooth, collision-free path generation in real time without lengthy manual supervision. Current approaches are heavily reliant on standalone GPS navigation with post-processing or heuristic-based refinements, which fail to scale in settings with high rates of obstacle change and low GPS availability. Additionally, unprocessed sensor data tends to generate high-dimensional feature spaces that decrease the speed and trustworthiness of real-time decision-making.

To surpass the above limitations, this research suggests a new framework named "UAV Path Optimization and Obstacle Classification via SVD-Based Feature Reduction and Random Forest Modeling." The system utilizes Truncated Singular Value Decomposition (SVD) for concise, noise-free representation of sensor data, while Random Forest classifiers ensure strong and interpretable obstacle detection. Also, Synthetic Minority Oversampling (SMOTE) is applied to the dataset balancing, and spatial data (latitude, longitude, altitude) is blended with smaller features for better geospatial awareness.

The system provides autonomous navigation of UAV with high-precision accuracy, recall, and smooth trajectory. It combines real-time analytics, adaptive imbalanced dataset learning, and visualization methods to create optimized routes in continuously changing environments—without human intervention or rule-based tuning.

The major contributions of this work are:

- Autonomous Feature Reduction through Truncated SVD
- Sensor-Integrated Obstacle Detection with Random Forests
- Data Balancing with SMOTE for Enhanced Recall
- Spatial Feature Integration for Geographical Awareness

The rest of the paper is organized as follows: Section II is the literature survey. Section III reports the methodology and implementation. Section IV is Conclusion and future scope. Lastly, Section V concludes the research and provides directions for future work.

II. Literature Survey

Koduri [1] explored the use of Singular Value Decomposition (SVD) for multi-sensor data fusion in the context of remote sensing applications. The author shows how the fusion of panchromatic and multispectral satellite imagery using SVD improves spatial and radiometric resolution to produce better-quality composite images. Using Quickbird and IRS data fusion, the research emphasizes how SVD can preserve important image features while efficiently merging complementary sensor data. In contrast with other conventional methods like PCA, IHS, and Brovey transformations, the SVD approach is demonstrated to excel at both geometric registration and spectral preservation.

Barring its promising outcomes, the research is mainly applicable to offline satellite data image fusion and does not have real-time system integration or autonomous decision-making. The article does not discuss potential applications of SVD in dynamic systems like UAV navigation or robotics, where timely sensor fusion, dimensionality reduction, and classification are vital. While it effectively proves the theoretical benefit of SVD, the lack of real-time experimentation or integration with machine learning restricts the general applicability of the results in autonomous or distributed settings.

Gerwen et al. [2] presented an extensive research work on multi-sensor fusion for indoor drone positioning with the emphasis on the trade-off between accuracy and cost. They proposed the OASE framework that facilitates real-time, asynchronous fusion of data from several sensors such as IMUs, sonar, SLAM cameras, ArUco markers, and UWB. Assessing 337 sensor configurations in an industrial lab with mm-accurate ground truth, the research showed that integrating UWB with sonar or SLAM substantially alleviated 3D positioning error to less than 10 cm. The research also incorporated a comprehensive cost model for three different sizes of drones and found that although the most precise configuration (UWB + SLAM + ArUco) registered 4.82 cm error at a considerable cost appropriate for large drones, a combination of UWB and sonar provided a balance of good accuracy (10.7 cm error) with a lesser cost and hence is apt for nano drones. This combination of cost, precision, and infrastructure demand is key to scalable indoor drone deployments.

While its strong experimental basis and practical applicability to real-world indoor inventorying and inspection make the work of high interest, the primary emphasis on these applications in the research leaves it short on handling trajectory optimization and obstacle classification in dynamic scenes. In addition, the use of pre-positioned infrastructure such as ArUco markers might restrict its use in unknown or GPS-deprived outdoor environments. However, the research offers insightful design guidance for designing effective, precise, and affordable indoor UAV navigation systems using sensor fusion, setting a standard for future research in adaptive drone localization approaches.

Ryu et al. [3] improvised object detection performance for Urban Aerial Mobility (UAM) using heterogeneous sensors, i.e., cameras and LiDAR. The work proves that the combination of these sensors remarkably enhances the recognition accuracy and reliability of aerial object detection, e.g., drones and birds, for low-altitude collision avoidance. The experiments performed reveal that the system is capable of attaining high recognition rates at different distances, with real-time processing capability, hence meeting the call for extensive object recognition in all directions.

Notwithstanding the improvements reported, there are significant research gaps that need to be addressed. Existing research mostly addresses particular types of objects and does not take into consideration various environmental conditions that can impact sensor performance, e.g., changing light or weather conditions. Moreover, although the system proposed is encouraging, additional research is required to optimize the robustness of the sensor fusion algorithms and to guarantee real-time performance in challenging urban environments, which can feature dynamic obstacles and changing traffic flow.

Kristiana et al. [4] examined the obstacle avoidance challenge of drones indoors, suggesting a Sensor Fusion algorithm to boost awareness of obstacles. In their research, they proved the Kalman Filter to be efficient in real-time response to obstacles in single and multiple obstacle situations. Although the research effectively demonstrated the potential of sensor fusion for indoor drone navigation, it concentrated on obstacle detection and avoidance and only tested the evaluation under static and dynamic obstacles and fairly low speeds of drones. Additional research is recommended to test more challenging conditions, including higher speeds of the drone and multi-drone scenarios.

Yucer et al. [5] proposed an RSSI-based outdoor localization technique with a single UAV to overcome the constraints of conventional localization methods like AoA, ToA, TDoA, and RSSI, which are often more than one sensor and noise-sensitive in the environment. The paper improves RSSI-based localization with machine learning methods, such as neural networks and hybrid channel models that make use of conventional path loss models combined with learning methods. The suggested approach utilizes a clustering algorithm along with Singular Value Decomposition (SVD) for RSSI data processing, showing location precision of just 7 meters based on iterative optimization. Although it showed significant improvements, the research does not have real-world validation in various environments, thus the effect of real-world noise and different RF conditions is not explored adequately.

Shi et al. [6] presented a novel method of optimizing collaborative UAV flight by means of Multi-Agent Reinforcement Learning (MARL). To counter the issues related to high-dimensional state spaces and computational efficiency, the authors present an Adaptive Dimensionality Reduction (ADR) framework that combines machine learning methodology like Autoencoders (AEs) and Principal

Component Analysis (PCA). AEs, being unsupervised neural networks, learn compact encodings of input information, preserving key features and compressing the data. PCA adds to this by linearly projecting the data to detect principal components of maximum variance. With these methods, the ADR framework essentially compresses sensor data of high dimensions, enabling more rapid convergence and efficiency in the MARL process. In addition, the integration of communication modules improves inter-UAV coordination and results in better path planning. Experimental outcomes show that such an integrated method drastically enhances exploration performance and decreases computational complexity, showcasing the effectiveness of integrating dimensionality reduction methods with MARL to achieve efficient UAV navigation in challenging environments.

Rao et al. [7] presented the Customizable Dung Beetle Search-tuned Random Forest (CDBS-RF) approach, which combines the Dung Beetle Search (DBS) algorithm—a bio-inspired optimization method—with Random Forest (RF) machine learning to improve UAV navigation in agricultural environments. The DBS component simulates the behavior of the dung beetle to effectively scan and exploit the search space for optimal route planning, while the RF model adjusts path parameters dynamically to provide collision avoidance as well as responsiveness to environmental factors. Utilized in a Python programming virtual environment from UAV-perceived data, the CDBS-RF model reflected considerable enhancements in path efficiency 90%, collision prevention (95%), and computational efficiency (80%), surpassing conventional algorithms such as A RRT, and wavefront approaches in real-world complex agricultural settings.

Debnath et al. [8] provided an extensive discussion of UAV navigation approaches, focusing on their use in remote sensing applications like precision agriculture, urban mapping, and environmental monitoring. The authors divide path-planning algorithms into global and local methods for single UAVs and then broaden the review to multi-UAV coordination approaches. Obstacle avoidance and detection strategies are analyzed in terms of their flexibility, optimization potential, and computational complexity for various environments of operation. Although the paper is generally centered on classical and heuristic methods, it also recognizes the increasing role of machine learning methods in improving UAV autonomy. In particular, the use of machine learning models, e.g., neural networks, is emphasized for their ability to enhance the accuracy of obstacle detection and facilitate real-time decision-making under dynamic conditions. The current research needs and potential directions are pointed out through the review, e.g., the use of sophisticated machine learning techniques for handling the complexities of UAV operations in remote sensing tasks.

Waqas et al. [9] introduced a new autonomous unmanned aerial vehicle (UAV) framework that incorporates state-of-the-art deep learning methods to improve obstacle avoidance and environment perception. The core of this framework is a newly introduced Obstacle Avoidance Method (OAM), which adopts Convolutional Neural Networks (CNNs) for real-time visual data processing, allowing the UAV to recognize and fly around obstacles safely. Furthermore, the system makes use of fiducial marker-based localization to enhance positional accuracy, especially in GPS-denied situations. Through a combination of these machine learning strategies, the UAV exhibits enhanced autonomy and dependability in multifaceted operational environments, such as structural health monitoring missions.

III. METHODOLOGY AND IMPLEMENTATION

The research offers a strong and efficient framework for maximizing UAV trajectory planning and obstacle classification accuracy. The research applies a modular sensor fusion pipeline of feature engineering, dimensionality reduction, and supervised learning to provide a scalable and understandable solution for autonomous aerial navigation.

A. Data Acquisition and Sensor Fusion

The framework relies on multi-sensor data acquired from UAV hardware, viz., inertial measurement unit (IMU) measurements (gyroscope and accelerometer data), LiDAR range measurements, environmental measurements like wind speed, UAV-proprietary metrics like velocity and battery level, and GPS-based spatial coordinates (latitude, longitude, altitude). The heterogeneous inputs are mapped into a common representation with the aid of timestamp synchronization and normalized for scale invariance and model robustness.

B. Baseline Model and Feature Reduction

First, the entire raw feature set is trained on a Random Forest classifier to perform binary classification: obstacle or no obstacle. This is used as the baseline model to compare performance. To enhance computational efficiency and prevent overfitting, Truncated Singular Value Decomposition (SVD) is used to keep the dimensionality of the sensor space low. SVD eliminates noise and multicollinearity, reducing training time without compromising accuracy while identifying underlying structures in the data.

C. Spatial Fusion and Feature Enhancement

After dimensionality reduction, the feature vectors in the lower dimension are combined with spatial information—latitude, longitude, and altitude—to preserve critical geospatial context. This integration allows the model to recognize dynamic state features and the layout of the environment, better equipping the classifier to generalize the location of obstacles in different terrains and situations.

D. Handling Imbalanced Data with SMOTE

To counter class imbalance—common in obstacle detection datasets where obstacles are less common—Synthetic Minority Oversampling Technique (SMOTE) is used. SMOTE creates new samples synthetically for the minority class by interpolating between current examples, balancing the dataset, and enhancing classifier fairness and generalization.

E. Model Training and Evaluation

Random Forest models are trained independently on:

- The original (unreduced) feature set
- SVD-reduced feature set with spatial data

Accuracy, precision, recall, and F1-score metrics are used to judge each model based on its classification performance. The model trained with the SVD-reduced and spatially enriched features performed better with an accuracy of 97.5

F. Deployment and Visualization

For deployment, the learned model should be integrated in a Docker-based microservice environment. Each service is containerized by means of
textttdocker-compose. Such modularity enables efficient scaling, fault isolation, and easy updates. In addition, real-time predictions and performance metrics can be accessed via Prometheus and visualized by means of Grafana dashboards for anomaly detection and health checks.

G. Graphical Trajectory Validation

The efficacy of the designed system is experimentally verified with trajectory simulations.

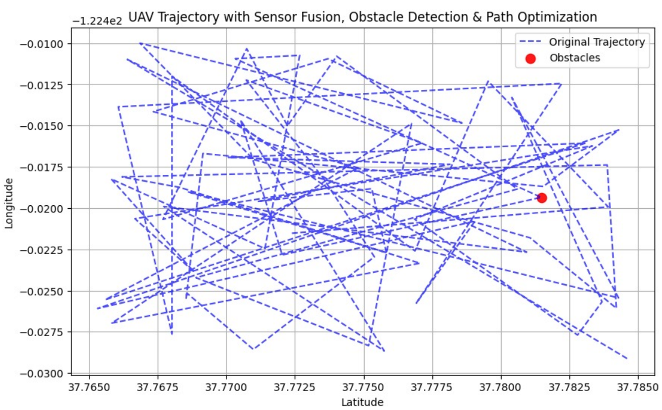

Fig. 1: UAV Trajectory with Sensor Fusion, Obstacle Detection and Path Optimization — illustrates the real-time path adjustment of the system in densely obstacle-laden scenarios.

In total, the approach integrates extensive preprocessing, high-performance feature reduction, and robust classifier generalization to develop a reliable and real-time obstacle detection system for facilitating safer autonomous UAV flight over diverse mission profiles.

III. Results and Analysis

The UAV Path Optimization and Obstacle Classification system was rigorously tested against a clear set of performance measures such as classification accuracy, obstacle detection accuracy, recall, and model generalization. The tests were performed on two setups: one with the initial full feature space and the other with dimensionality reduction using Truncated SVD along with spatial context augmentation.

Preliminary testing using the initial features (see Table 1) provided an accuracy of 96.22%, where precision and recall values for obstacle existence (class 1) were 0.94 and 0.99, respectively. This shows robust capability to recognize obstacles in the flight path of the UAV, although the model retained redundant sensor data that might pose a higher processing overhead during actual UAV navigation.

TABLE I: Classification Metrics using Original Features

Class	Precision	Recall	F1-Score	Support
0 (No Obstacle)	0.99	0.93	0.96	970
1 (Obstacle)	0.94	0.99	0.96	936
Accuracy			**0.962**	1906

After applying SVD-based feature reduction, down to 5 principal components, and adding key spatial parameters (latitude, longitude, altitude), the model was able to achieve a greatly enhanced accuracy of 97.53%. As shown in Table 2, the revised classifier preserved high sensitivity to obstacle detection (1.00 recall) but boosted precision to 0.95, hence eliminating false positives. The increase in accuracy, as well as the diminishment in feature dimensionality, illustrates the benefit of SVD for removing irrelevant variance and improving performance.

TABLE II: Classification Metrics using SVD + Spatial Features

Class	Precision	Recall	F1-Score	Support
0 (No Obstacle)	1.00	0.95	0.98	970
1 (Obstacle)	0.95	1.00	0.98	936
Accuracy			**0.975**	1906

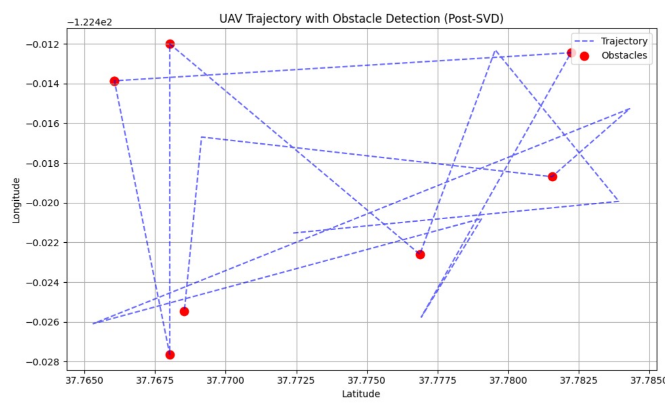

Fig. 2: UAV Trajectory with Obstacle Detection (Post-SVD)

Highlights the system's refined obstacle detection after applying feature reduction and spatial integration. The UAV trajectory appears cleaner, and obstacle points are more clearly delineated, demonstrating a better trade-off between accuracy and computational efficiency.

The classification results emphasize that SVD, when coupled with domain-related spatial perception, not only enhances prediction accuracy but also increases the real-time capability of the system. Lower-dimensional feature space means smaller computational burdens, allowing the model to be integrated into edge devices on UAVs for real-time navigation.

Therefore, the assessment strongly confirms the strength and appropriateness of the suggested system for actual UAV operations, particularly where low delay, spatial accuracy, and classification are a priority.

IV. Conclusion and Future Work

This research was able to create a sound framework for UAV navigation optimization using sensor fusion data, dimensionality reduction using SVD, and fast classification using Random Forest models. By comparing the baseline model trained on original features with the improved model using SVD-reduced features and spatial data, a notable performance improvement was achieved. The SVD model with spatial enhancement resulted in an astounding accuracy of 97.5% compared to the 96.2% of the original model, with a balanced F1-score of 0.98, thereby illustrating the power of an integration of statistical reduction processes with contextual geospatial features.

The two resulting UAV trajectory graphs—*"UAV Trajectory with Sensor Fusion, Obstacle Detection & Path Optimization"* and *"UAV Trajectory with Obstacle Detection (Post-SVD)"*—visually corroborate the system's capability to detect obstacles with greater granularity and efficiency, leading to safer and smarter autonomous navigation.

The structure of the system highlights scalability, interpretability of data, and generalizability of obstacles over diverse conditions. SMOTE addition for class balancing and StandardScaler normalization improved classifier fairness as well as generalization capability, especially over imbalanced obstacle conditions.

In the future, possible extensions of the project include:

- Real-time Model Integration: Implementation of the model on embedded UAV hardware to perform real-time obstacle detection and path adjustment.
- Temporal Sequence Modeling: Adding LSTM or GRU models to process sequential sensor data for trajectory planning and dynamic obstacle anticipation.
- Multi-Class Obstacle Classification: Generalizing the binary classification to distinguish among different types of obstacles (e.g., tree, building, drone).
- Reinforcement Learning Integration: Using policy-learning frameworks for adaptive navigation decisions under continuous environmental feedback.
- 3D Mapping with SLAM Integration: Merging SVD-RF obstacle detection with SLAM (Simultaneous Localization and Mapping) for full-scale 3D path optimization.
- Cloud-Based Analytics and Telemetry: Pushing data to cloud services for historical analysis, fleet management, and collaborative navigation.

In summary, the methodology developed here provides a solid foundation for intelligent UAV systems that can navigate in highly complex, sensor-dense environments while being computationally efficient through dimensionality reduction.

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