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FQF-VTrack: Flexible Q-Fuzzy Vehicle Detection and Tracking in Aerial Surveillance

Geethalakshmi M[1], Karpagam[2] Venkata Mohan Reddy[3], Gopal Thangavel[4], S. Bala Krishnan[5], V. Sumangala[6]

[1]*Gnanam School of Business, Thanjavur, Tamil Nadu, India*
[2] *SRM Valliammai Engineering College, Kattankulathur, Tamil Nadu, India*
[3]*Saveetha School of Engineering, Saveetha University, Chennai, Tamil Nadu. India*
[4,5]*University of Technology and Applied Sciences, Nizwa, Oman.*
[6]*N.K.T National College of Education for Women, Chennai, Tamil Nadu. India*

Abstract
Accurate vehicle detection and tracking in low-illumination aerial surveillance remain challenging due to poor visibility, background complexity, shadow interference, and vehicle occlusions. Recent studies have employed Fuzzy C-Means (FCM), YOLO variants, SIFT, SURF, Kalman filtering, SORT, and Deep SORT to improve vehicle monitoring performance. However, existing approaches mainly utilize fuzzy logic at the segmentation stage and do not fully exploit advanced fuzzy group structures for uncertainty-aware decision making.

This paper proposes a Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack) for intelligent traffic surveillance using aerial and night-time images. The framework integrates image enhancement, Flexible Q-Fuzzy segmentation, YOLO-based vehicle detection, and Deep SORT-assisted object tracking. A novel Flexible Q-Fuzzy Inference Engine (FQFIE) is introduced to combine detection confidence, motion consistency, appearance similarity, and temporal continuity under uncertain environments. The inference mechanism is inspired by Flexible Q-Fuzzy Groups, Alpha Flexible Q-Fuzzy Subgroups, q-Rung Ortho pair Fuzzy Sets, and Intuitionistic Q-Fuzzy structures. The generated fuzzy membership values are used to preserve vehicle identities during partial occlusions and illumination transitions. Finally, fuzzy trajectory optimization is employed to estimate traffic flow patterns and vehicle movement directions. The proposed framework is expected to achieve robust vehicle detection and tracking accuracy while reducing identity switching and false associations in dense traffic scenarios. The methodology provides a new research direction that combines modern computer vision with advanced Flexible Q-Fuzzy mathematical structures for intelligent transportation and autonomous surveillance systems.

Keywords: Vehicle Detection, Vehicle Tracking, Flexible Q-Fuzzy Groups, DeepSORT, Night Surveillance, Intelligent Transportation Systems, q-Rung Orthopair Fuzzy Sets, Traffic Analytics.

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I. Introduction

The rapid growth of urban populations and transportation networks has significantly increased the number of vehicles operating on roadways, creating a strong demand for intelligent traffic surveillance systems. Vehicle detection and tracking have become essential components of modern Intelligent Transportation Systems (ITS) because they support traffic management, congestion analysis, accident prevention, route optimization, and public safety monitoring. Conventional surveillance systems rely on fixed cameras; however, aerial platforms and unmanned aerial vehicles (UAVs) provide wider coverage and greater flexibility for large-scale traffic monitoring (1)(2)(3).

Recent advances in computer vision and deep learning have improved the performance of vehicle monitoring systems. Deep learning models such as YOLO have demonstrated remarkable success in detecting vehicles under complex traffic conditions, while tracking algorithms such as SORT mechanisms can significantly enhance decision-making performance in uncertain intelligent systems and transportation applications (21)– (28).

Motivated by these observations, this paper proposes a Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack) for night-time aerial traffic surveillance. The proposed framework integrates image enhancement, Flexible Q-Fuzzy segmentation, YOLO-based vehicle detection, DeepSORT-assisted tracking, and a novel Flexible Q-Fuzzy Inference Engine for uncertainty-aware vehicle association. The framework utilizes Flexible Q-Fuzzy membership values to combine detection confidence, motion consistency, appearance similarity, and temporal continuity for robust vehicle tracking. Furthermore, fuzzy trajectory optimization is employed to improve traffic flow analysis and movement pattern estimation. By combining advanced computer vision techniques with modern Flexible Q-Fuzzy mathematical structures, the proposed approach aims to provide a reliable and intelligent solution for next-generation traffic surveillance systems (2)(3)(15)– (20)(29).

Contributions of the Paper

The main contributions of this work are as follows:

1. A novel **Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack)** is proposed for intelligent vehicle surveillance in aerial and night-time environments.
2. A Flexible Q-Fuzzy Inference Engine (FQFIE) is introduced to handle uncertainty in vehicle detection and multi-object tracking.
3. Flexible Q-Fuzzy Groups, Alpha Flexible Q-Fuzzy Subgroups, and q-Rung Ortho pair Fuzzy concepts are incorporated into the vehicle association process.
4. Deep learning-based vehicle detection is integrated with Deep SORT tracking and fuzzy confidence evaluation to improve identity preservation.
5. A fuzzy trajectory optimization model is developed for robust traffic-flow analysis and vehicle movement estimation.
6. The proposed framework establishes a new research direction that combines advanced fuzzy algebraic structures with intelligent transportation surveillance systems.

and DeepSORT have enabled continuous monitoring of vehicle trajectories across video frames (2)(3)(4)(5). Nevertheless, real-world surveillance environments continue to present several challenges, including illumination variations, night-time visibility limitations, weather disturbances, background clutter, shadows, scale variations, and partial or complete occlusions of vehicles. These factors often reduce detection accuracy and tracking consistency, particularly in aerial surveillance applications (1)(2)(3).

To overcome these challenges, researchers have introduced image enhancement techniques, feature extraction methods such as SIFT and SURF, fuzzy clustering approaches, and motion prediction models. The integration of Fuzzy C-Means (FCM) segmentation with deep learning detectors has shown promising results by reducing background complexity and improving foreground vehicle extraction. Similarly, DeepSORT combines appearance information and motion estimation to maintain vehicle identities across successive frames, thereby reducing identity switching during tracking (3)(6)(12).

Although fuzzy techniques have been successfully utilized for image segmentation and pattern recognition, most existing vehicle surveillance frameworks employ fuzzy logic only during preprocessing stages. Advanced fuzzy algebraic structures such as Fuzzy Dot Groups, Bipolar Anti Q-Fuzzy Groups, Flexible Q-Fuzzy Groups, Alpha Flexible Q-Fuzzy Subgroups, and Intuitionistic Q-Fuzzy Soft Structures have not been sufficiently explored in the context of intelligent vehicle detection and tracking systems (13)– (18). These mathematical frameworks offer powerful mechanisms for modelling uncertainty, ambiguity, and incomplete information, which are common characteristics of night-time and aerial surveillance environments.

In addition, q-Rung Orthopair Fuzzy Sets provide a more flexible representation of membership and non-membership degrees compared with traditional fuzzy and intuitionistic fuzzy models. Such fuzzy structures can effectively represent uncertain detection confidence values, ambiguous vehicle appearances, and inconsistent tracking observations. Consequently, they offer a promising foundation for improving vehicle association, identity preservation, and trajectory estimation under difficult traffic conditions (19)(20). Recent studies indicate that fuzzy reasoning

detection, $\mu_A(x)$ may represent the confidence that an object belongs to the vehicle class.
The basic fuzzy operations are $\mu_{A\cup B}(x) = \max\{\mu_A(x), \mu_B(x)\}$
$\mu_{A\cap B}(x) = \min\{\mu_A(x), \mu_B(x)\}$ *and* $\mu_{A^c}(x) = 1 - \mu_A(x)$. These operations provide the first mechanism for uncertainty aggregation in traffic surveillance systems.

2.3 Q-Fuzzy Sets (14)(15)
Q-Fuzzy Sets extend conventional fuzzy sets by introducing a parameter set Q.
Let $Q \neq \emptyset$ be a non-empty parameter space. A Q-Fuzzy Set is defined as $\mu: G \times Q \rightarrow [0,1]$, where G is a group and $q \in Q$.
In surveillance applications, $Q = \{Time, Velocity, Appearance, Illumination\}$
Thus $\mu(x, q)$ simultaneously captures membership and contextual information.
For a detected vehicle, $\mu(vehicle, q) = 0.85$ may indicate high vehicle confidence under a particular environmental condition.

2.4 Fuzzy Dot Groups(13)
The concept of Fuzzy Dot Groups was introduced by Solairaju et al.
Let $(G,\cdot)$ be a group. A fuzzy subset $\mu: G \rightarrow [0,1]$ is said to be a Fuzzy Dot Group if
$\mu(x \cdot y) \geq \min\{\mu(x), \mu(y)\}$ for every $x, y \in G$ and $\mu(x^{-1}) \geq \mu(x)$ for every $x \in G$.

Vehicle Confidence Aggregation
Suppose $C_d = Detection\ Confidence$, $C_a = Appearance\ Similarity$, and
$C_m = Motion\ Consistency$. Then $F = C_d \cdot C_a \cdot C_m$ is the fuzzy dot aggregation score.
Assume $\mu(C_d) = 0.90$, $\mu(C_a) = 0.84$, $\mu(C_m) = 0.78$, Then $\mu(F) \geq \min(0.90, 0.84, 0.78)$
$\mu(F) \geq 0.78$. This ensures that the combined evidence does not fall below the weakest major contributor, providing robustness during uncertain tracking situations.

2.5 Flexible Q-Fuzzy Groups(15)(16)
Flexible Q-Fuzzy Groups generalize Q-Fuzzy Groups by introducing adaptive membership behaviour. Let $\mu: G \times Q \rightarrow [0,1]$ be a Q-fuzzy mapping.
Then $\mu(x \circ y, q) \geq T(\mu(x, q), \mu(y, q))$ where $T(a, b)$ is a triangular norm.
Popular choices include

II. Related Work and Mathematical Foundations

The proposed Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack) integrates modern deep-learning-based vehicle surveillance with advanced fuzzy algebraic structures. Therefore, this section reviews existing vehicle detection and tracking approaches and develops the mathematical foundations required for the proposed framework. These foundations include Fuzzy Sets, Q-Fuzzy Sets, Fuzzy Dot Groups, Flexible Q-Fuzzy Groups, Alpha Flexible Q-Fuzzy Subgroups, Intuitionistic Q-Fuzzy Systems, and q-Rung Orthopair Fuzzy Sets. The resulting theory forms the basis of the proposed Flexible Q-Fuzzy Inference Engine presented in Section 3.

2.1 Vehicle Detection and Tracking in Intelligent Transportation Systems(2)(3)(29).

Vehicle detection and tracking are fundamental components of intelligent traffic surveillance systems. Traditional methods relied on background subtraction, Gaussian mixture models, edge detection, HOG descriptors, Haar features, SIFT features, SURF descriptors, and Support Vector Machines for object recognition and localization (1)(2)(3).

With the development of deep learning, object detection frameworks such as Faster R-CNN, SSD, YOLOv4, and YOLOv5 have significantly improved vehicle recognition performance. YOLO-based detectors have become particularly attractive owing to their real-time detection capability and high accuracy on aerial and road surveillance datasets (2)(3)(8)(9)(11).

Similarly, tracking algorithms evolved from Kalman filters and particle filters to SORT and DeepSORT methods. DeepSORT incorporates both motion and appearance information, providing more reliable vehicle identity preservation than conventional tracking approaches (4)(5). However, existing systems still struggle with uncertainty caused by low illumination, partial occlusion, motion blur, and complex backgrounds.

2.2 Classical Fuzzy Sets(21)(22).
The concept of fuzzy sets was introduced by Zadeh (21) to represent uncertainty mathematically. Let $X = \{x_1, x_2, \ldots, x_n\}$ be a universal set. A fuzzy set A is defined as
$A = \{(x, \mu_A(x)): x \in X\}$ where $\mu_A: X \rightarrow [0,1]$ is the membership function. For vehicle

2.8.2 Hesitation Degree

The hesitation degree is $\pi_q(x) = (1 - \mu^q(x) - \nu^q(x))^{1/q}$ For $\mu = 0.85, \nu = 0.60, q = 3$ we obtain $\pi_3 = (1 - 0.85^3 - 0.60^3)^{1/3} = (1 - 0.614 - 0.216)^{1/3} = 0.170^{1/3} = 0.554.$
This hesitation reflects uncertainty in vehicle identity assignment.

2.8.3 q-Rung Score Function

The ranking score proposed for q-rung decisions is $S(x) = \mu^q(x) - \nu^q(x)$(20).
For $\mu = 0.90, \nu = 0.30, q = 3, S(x) = 0.90^3 - 0.30^3 = 0.729 - 0.027 = 0.702.$
Large positive values indicate stronger confidence.

2.8.4 Accuracy Function

The q-rung accuracy function is $H(x) = \mu^q(x) + \nu^q(x)$. For $\mu = 0.85,\ \nu = 0.60, q = 3$

$$H(x) = 0.614 + 0.216 = 0.830.$$

The value measures certainty contained in the Ortho pair information.

2.8.5 Proposed q-Rung Vehicle Association Function

For vehicle tracking, let $\mu_T = Tracking\ Membership$ and $\nu_T = Tracking\ Rejection.$
Define $\mu_T = \lambda_1\mu_d + \lambda_2\mu_a + \lambda_3\mu_m + \lambda_4\mu_t$ subject to $\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1.$
The q-rung vehicle association score is $F_q = \mu_T^q - \nu_T^q$.Decision rule: $F_q > \tau$
Vehicle belongs to the trajectory. $F_q \le \tau$ Vehicle identity is reassigned.This equation forms the principal decision mechanism of the proposed FQF-VTrack framework.

2.9 Research Gap

The literature demonstrates that YOLO-based detectors and DeepSORT-based trackers achieve strong performance in traffic monitoring systems (2)(3)(5). However, these methods generally employ crisp confidence evaluation mechanisms and lack advanced uncertainty modeling capabilities. Existing fuzzy approaches mainly focus on image segmentation through FCM and do not exploit Flexible Q-Fuzzy Groups, Fuzzy Dot Groups, Alpha Flexible Q-Fuzzy Subgroups, Intuitionistic Q-Fuzzy Structures, or q-Rung Orthopair Fuzzy Sets during object association and identity preservation (3)(13)– (20).

Minimum T-Norm $T(a, b) = \min(a, b)$
Product T-Norm $T(a, b) = ab$
For three evidence sources μ_d, μ_a, μ_m the Flexible Q-Fuzzy confidence can be written as $\mu_V = \mu_d \times \mu_a \times \mu_m$. Assuming $\mu_d = 0.92, \mu_a = 0.86, \mu_m = 0.80$
then $\mu_V = 0.92 \times 0.86 \times 0.80 = 0.633$.This value acts as the final fuzzy vehicle confidence.

2.6 Alpha Flexible Q-Fuzzy Subgroups(17)

Alpha Flexible Q-Fuzzy Subgroups provide threshold-based decision regions.
For $\alpha \in [0,1]$ the α-cut is defined as $A_\alpha = \{x \in G: \mu(x, q) \ge \alpha\}$.
Examples: $A_{0.90} = Reliable\ Vehicles, A_{0.75} = Moderately\ Reliable\ Vehicles$
$A_{0.50} = Uncertain\ Vehicles.$ Thus, tracking decisions can be made according to confidence categories.

2.7 Intuitionistic Q-Fuzzy Structures(18)

Intuitionistic fuzzy theory introduces both membership and non-membership functions.
For every object x, $\mu(x) + \nu(x) \le 1$, where $\mu(x) = membership$ and $\nu(x) = nonmembership$.The hesitation degree is $\pi(x) = 1 - \mu(x) - \nu(x)$.
Suppose $\mu(x) = 0.82$ and $\nu(x) = 0.10$ then $\pi(x) = 0.08$.Small hesitation implies a reliable vehicle association.

2.8 q-Rung Orthopair Fuzzy Sets(19)(20)

Among modern fuzzy models, q-Rung Orthopair Fuzzy Sets (q-ROFS) provide the largest uncertainty representation space and therefore are highly suitable for vehicle surveillance systems.A q-rung orthopair fuzzy set is defined by $A = \{(x, \mu_A(x), \nu_A(x)) : x \in X\}$
where $\mu_A(x) \in [0,1]$ and $\nu_A(x) \in [0,1]$ satisfy $\mu_A^q(x) + \nu_A^q(x) \le 1$.

2.8.1 Generalized Orthopair Constraint

Unlike intuitionistic fuzzy sets, $\mu + \nu \le 1$ and Pythagorean fuzzy sets, $\mu^2 + \nu^2 \le 1$,
q-rung sets use $\mu^q + \nu^q \le 1$.This creates a significantly larger feasible decision region.
For example, $\mu = 0.85, \nu = 0.75$.Intuitionistic Check $0.85 + 0.75 = 1.60$ Not valid.Pythagorean Check $0.85^2 + 0.75^2 = 1.285$ Not valid.
q-Rung Check ($q = 5$) $0.85^5 + 0.75^5 = 0.4437 + 0.2373 = 0.681 < 1$.Valid.
Therefore q-rung models provide greater flexibility for uncertain decisions.

Orthopair Fuzzy Sets into the vehicle association process (2)(3)(13)– (20).

The proposed framework consists of six major modules:

1. Image Enhancement
2. Flexible Q-Fuzzy Segmentation
3. YOLO-Based Vehicle Detection
4. Flexible Q-Fuzzy Inference Engine
5. DeepSORT Vehicle Tracking
6. Fuzzy Trajectory Optimization

3.2 Image Enhancement

Night-time aerial images frequently suffer from low brightness, poor contrast, fog effects,
motion blur,sensor noise. To improve vehicle visibility, every image frame is pre-processed using adaptive gamma correction. For an input image$I(x,y)$, the enhanced output image is given by$I_e(x,y) = I(x,y)^{\gamma}$Where$\gamma = \frac{\log(0.5)}{\log(S/255)}andS = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)$represents image brightness.The enhanced image produces improved foreground visibility and stronger vehicle feature representation before segmentation.

3.3 Flexible Q-Fuzzy Segmentation

After enhancement, a Flexible Q-Fuzzy Segmentation process is introduced.
Unlike conventional FCM segmentation, the proposed model includes environmental context through Q-fuzzy membership assignment.

Therefore, the proposed FQF-VTrack framework introduces a novel Flexible Q-Fuzzy Inference Engine that combines detection confidence, appearance similarity, motion consistency, and temporal continuity using Fuzzy Dot Group aggregation, Flexible Q-Fuzzy reasoning, and q-Rung Orthopair decision functions. This mathematical integration constitutes the primary novelty of the proposed research and forms the theoretical foundation for the methodology presented in Section 3.

III. Proposed Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack)

3.1 Overview of the Proposed Framework

The proposed Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack) is designed to perform robust vehicle detection, tracking, and trajectory analysis in night-time aerial surveillance environments. The framework combines image enhancement, Flexible Q-Fuzzy segmentation, YOLO-based vehicle detection, DeepSORT tracking, and a novel Flexible Q-Fuzzy Inference Engine (FQFIE). The major goal is to address uncertainty arising from illumination variation, occlusion, blurred vehicle appearances, and complex traffic scenarios. The framework extends existing vehicle surveillance approaches by integrating Flexible Q-Fuzzy Groups, Alpha Flexible Q-Fuzzy Subgroups, Fuzzy Dot Groups, and q-Rung

Let$Q = \{L, T, V, O\}$where$L$= illumination,T= time,V= velocity,O= occlusion factor.
The segmentation membership function is$\mu_S(x,q): X \times Q \to [0,1]$
The Flexible Q-Fuzzy clustering objective becomes$J = \sum_{i=1}^{c}\sum_{j=1}^{n} \mu_{ij}^{m}(q) \parallel x_j - v_i \parallel^2$
where$v_i$represents cluster centres.Membership update:$\mu_{ij}(q) = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}}$
The segmented image retains vehicle regions while suppressing irrelevant background information.

3.4 YOLO-Based Vehicle Detection

After segmentation, vehicle localization is performed using a YOLO detector.
For every image frame$I_t$the detector produces a set of vehicle observations
$D_t = \{d_1, d_2, \dots, d_n\}$where$d_i = (x_i, y_i, w_i, h_i, c_i)andx_i, y_i$are bounding-box coordinates,$w_i, h_i$are width and height,c_i is detector confidence.Vehicle confidence membership is defined as$\mu_d(d_i) = c_i$. For example,$c_i = 0.91$implies$\mu_d = 0.91$.Only detections satisfying$\mu_d > \theta_d$are retained.Typical threshold, $\theta_d = 0.5$.This stage provides the initial candidate vehicle set for tracking.

3.5 Vehicle Appearance Feature Extraction

Each vehicle is represented through appearance characteristics.Let$F_i = [f_1, f_2, \dots, f_n]$be the feature

1.The hesitation degree is$\pi_V = \left(1 - \mu_V^q - \nu_V^q\right)^{1/q}$.For$q = 5, \mu_V = 0.87, \nu_V = 0.50, \pi_V = (1 - 0.498 - 0.031)^{1/5} = 0.861$.
The q-rung score function becomes$S_V = \mu_V^q - \nu_V^q$.Vehicle assignment rule:$S_V > \tau$ Accept current identity.$S_V \leq \tau$Generate new identity.This model significantly improves robustness in ambiguous tracking situations**.**

3.10 Alpha Flexible Q-Fuzzy Trajectory Preservation

The α-cut mechanism removes unreliable vehicle tracks.Define$T_\alpha = \{v: \mu_V(v) \geq \alpha\}$.
For$\alpha = 0.80$only strong trajectories remain.The resulting track set has improved reliability and reduced identity switching.

3.11 Fuzzy Trajectory Optimization

Each vehicle trajectory is represented as$P_i = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$.
The fuzzy trajectory weight is$W_i = \frac{1}{n} \sum_{k=1}^{n} \mu_V\ (k)$.Trajectory smoothness is defined by$TS_i = \frac{1}{n-1} \sum_{k=1}^{n-1} \sqrt{(x_{k+1} - x_k)^2 + (y_{k+1} - y_k)^2}$.The optimized trajectory confidence becomes$TC_i = W_i \times TS_i$.Trajectories with low confidence are eliminated, while high-confidence trajectories are retained for traffic-flow estimation.

3.12 Proposed Algorithm

Algorithm: FQF-VTrackInput: Enhanced aerial frame sequence$I = \{I_1, I_2, \dots, I_n\}$
Output: Detected vehicles, tracked vehicle IDs, optimized trajectories.
Steps

1. Apply adaptive image enhancement.
2. Perform Flexible Q-Fuzzy segmentation.
3. Detect vehicles using YOLO.
4. Extract appearance descriptors.
5. Predict motion using DeepSORT-Kalman filter.
6. Compute: Detection membership μ_d, Appearance membership μ_a, Motion membership $\mu_m$and Temporal membership μ_t
7. Calculate Flexible Q-Fuzzy confidence:$\mu_V = \lambda_1\mu_d + \lambda_2\mu_a + \lambda_3\mu_m + \lambda_4\mu_t$
   Evaluate q-Rung score:$S_V = \mu_V^q - \nu_V^q$Preserve or reassign identities, apply α-vector extracted from vehicle i.Appearance similarity between two vehicles is $Sim_A = \frac{F_i \cdot F_j}{||F_i||||F_j||}$. The corresponding fuzzy membership becomes$\mu_a = Sim_A$.

Example$Sim_A = 0.87$thus$\mu_a = 0.87$.The appearance score evaluates visual similarity across consecutive frames.

3.6 Motion Estimation Module

Vehicle motion is estimated through DeepSORT prediction.Suppose the vehicle state vector is$x_t = [u, v, s, r, \dot{u}, \dot{v}, \dot{s}]^T$where$u, v$= centroid coordinates,$s$= area,$r$= aspect ratio.
Kalman prediction:$x_t^- = Ax_{t-1}$, Covariance prediction:$P_t^- = AP_{t-1}A^T + Q$.
Motion consistency score:$\mu_m = \exp\left(-\frac{||p_t - \hat{p}_t||^2}{\sigma_m}\right)$, where$\hat{p}_t$is the predicted position.
High motion consistency yields high fuzzy membership values.

3.7 Temporal Continuity Module

Vehicle existence over time contributes important information.The temporal continuity score is defined as$\mu_t = \frac{N_s}{N_s + N_l}$where$N_s$= successful matches, and N_l= lost matches.A vehicle continuously observed throughout several frames obtains a larger temporal membership.

3.8 Flexible Q-Fuzzy Inference Engine (FQFIE)

The Flexible Q-Fuzzy Inference Engine is the core novelty of the proposed framework.
Four evidence sources are considered:$\mu_d = Detection$, $\mu_a = Appearance$, $\mu_m = Motion$ and $\mu_t = Temporal$. The Fuzzy Dot aggregation becomes$F = \mu_d \cdot \mu_a \cdot \mu_m \cdot \mu_t$
According to Fuzzy Dot Group theory,$\mu(F) \geq \min\{\mu_d, \mu_a, \mu_m, \mu_t\}$. The Flexible Q-Fuzzy confidence is defined as$\mu_V = \lambda_1\mu_d + \lambda_2\mu_a + \lambda_3\mu_m + \lambda_4\mu_t$, subject to$\sum_{i=1}^{4} \lambda_i = 1$.
Typical values:$\lambda_1 = 0.35$, $\lambda_2 = 0.25$, $\lambda_3 = 0.25$ and $\lambda_4 = 0.15$.Therefore$\mu_V = 0.35\mu_d + 0.25\mu_a + 0.25\mu_m + 0.15\mu_t$.This score becomes the principal vehicle association confidence.

3.9 q-Rung Orthopair Vehicle Association Model

To further model uncertainty, the proposed framework adopts q-Rung Orthopair Fuzzy Sets.
Let$\mu_V$represent vehicle-association membership.Let$\nu_V$represent vehicle-rejection membership.The orthopair condition is$\mu_V^q + \nu_V^q \leq$

for vehicle monitoring and trajectory analysis in aerial surveillance studies.

4.3 Dataset Partitioning

The datasets are divided into70%70\%70%,Training Set15%15\%15%,
Validation Set15%15\%15%,Testing Set
To improve robustness, data augmentation is applied using, Rotation, Horizontal flipping, Brightness enhancement, Gaussian noise injection and Contrast variation
These augmentations simulate real surveillance conditions and improve generalization capability.

4.4 Performance Metrics

To comprehensively evaluate the effectiveness of the proposed Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack), both conventional computer vision performance measures and newly proposed fuzzy reliability measures are employed. The evaluation framework analyzes detection performance, tracking capability, trajectory consistency, identity preservation, and uncertainty management. Unlike existing YOLO–DeepSORT frameworks that mainly utilize precision and recall, the proposed model additionally evaluates fuzzy confidence preservation through Flexible Q-Fuzzy and q-Rung Orthopair measures.

4.4.1 Precision

Precision measures the proportion of correctly detected vehicles among all detected vehicles.
$Precision = \frac{TP}{TP+FP}$where$TP$= True Positive detections and FP= False Positive detections
The precision value lies within$0 \leq Precision \leq 1$, A higher precision value indicates fewer false vehicle detections.Derivation, suppose$N_d$represents total detections and$N_c$represents correct detections.Then$N_d = TP + FP$Substituting,$Precision = \frac{TP}{N_d}$.
For example,$TP = 920,\ FP = 80$then$Precision = \frac{920}{920+80} = 0.92$or 92%.
A higher precision value demonstrates effective rejection of non-vehicle objects.

4.4.2 Recall

Recall represents the proportion of true vehicles successfully identified by the system.
$Recall = \frac{TP}{TP+FN}$where$FN$denotes False Negative detections.
Derivation, Let$N_a$be total actual vehicles.Then$N_a = TP + FN$. Thus,$Recall = \frac{TP}{N_a}$

cut trajectory filtering and generate optimized traffic trajectories.

3.13 Computational Complexity

For an image sequence containing N frames:Flexible Q-Fuzzy Segmentation$O(Nc)$ YOLO Detection$O(Nd)$, DeepSORT Tracking$O(Nm)$, Fuzzy Inference$O(N)$, Overall complexity:$O(N(c+d+m))$which remains suitable for real-time intelligent transportation and aerial surveillance applications.

IV. Experimental Design and Performance Evaluation

4.1 Experimental Environment

The proposed Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack) is evaluated for vehicle detection, vehicle tracking, identity preservation, and trajectory estimation in night-time aerial surveillance environments. The framework is implemented using Python and deep-learning libraries with YOLO for vehicle detection and DeepSORT for tracking. The experiments utilize UAV-based traffic surveillance datasets that contain diverse traffic scenarios, illumination conditions, moving vehicles, occlusions, and varying traffic densities
The evaluation focuses on, Vehicle Detection Accuracy. Vehicle Tracking Accuracy. Identity Preservation Accuracy.Fuzzy Association Reliability. Trajectory Estimation Quality. Computational Efficiency.

4.2 Datasets Description

The proposed framework is validated using publicly available aerial surveillance datasets.

4.2.1 UAVDT Dataset

The UAVDT dataset contains aerial traffic videos captured using unmanned aerial vehicles in urban environments. The dataset includesHighways, Intersections, Urban roads and Congested traffic scenes
The dataset contains large-scale vehicle variations, illumination changes, shadows, and occlusion scenarios that make it suitable for evaluating robust surveillance systems

4.2.2 KIT-AIS Dataset

The KIT-AIS dataset consists of aerial traffic image sequences collected by airborne platforms.
Vehicle categories includeCars, Trucks, Buses, Cyclists and Minibuses. The dataset is widely used

Suppose$LostIDs = 120$, and$RecoveredIDs = 108$then$IRR = 90\%$. High IRR demonstrates robust re-identification capability.

4.5 Proposed Flexible Q-Fuzzy Evaluation Measures
Conventional metrics do not evaluate uncertainty handling. Therefore, two additional metrics are introduced.

4.5.1 Flexible Confidence Index (FCI)
The Flexible Confidence Index evaluates the average confidence of all vehicle associations.
$FCI = \frac{1}{N}\sum_{i=1}^{N} \mu_V\,(i)$where$\mu_V(i)$is the Flexible Q-Fuzzy confidence.Derivation,
The proposed confidence is$\mu_V = \lambda_1\mu_d + \lambda_2\mu_a + \lambda_3\mu_m + \lambda_4\mu_t$With$\sum\lambda_i = 1$
Assume$\mu_d = 0.91$, $\mu_a = 0.87$, $\mu_m = 0.82$, $\mu_t = 0.79$
Then$\mu_V = 0.35(0.91) + 0.25(0.87) + 0.25(0.82) + 0.15(0.79) = 0.860$.
Thus,$FCI = 0.860$indicating robust tracking confidence.

4.5.2 Fuzzy Dot Aggregation Reliability (FDAR)
To measure the effectiveness of Fuzzy Dot Group aggregation, the following metric is introduced:$FDAR = \frac{\sum_{i=1}^{N}\mu(F_i)}{N}$, where$F_i = \mu_d \cdot \mu_a \cdot \mu_m \cdot \mu_t$
According to Fuzzy Dot Group theory,$\mu(F_i) \geq \min\{\mu_d, \mu_a, \mu_m, \mu_t\}$.Derivation,
Suppose$\mu_d = 0.92, \mu_a = 0.86, \mu_m = 0.83, \mu_t = 0.80$. Then$FDAR = 0.80$
This measures the reliability of multi-source confidence fusion.

4.5.3 q-Rung Association Reliability (QAR)
The q-Rung Association Reliability evaluates uncertainty-aware vehicle matching.
$QAR = \frac{1}{N}\sum_{i=1}^{N}(\mu_i^q - \nu_i^q)$, where$\mu_i$is membership and$\nu_i$is non-membership.
Derivation, for$q = 5$, $\mu = 0.87$, $\nu = 0.50$, we obtain$QAR = 0.87^5 - 0.50^5 = 0.498 - 0.031 = 0.467$. Positive values indicate reliable vehicle-track association.

4.5.4 q-Rung Hesitation Index (QHI)
The proposed q-Rung Hesitation Index quantifies uncertainty.$QHI = \frac{1}{N}\sum_{i=1}^{N}\pi_i$where$\pi_i = (1 - \mu_i^q - \nu_i^q)^{1/q}$Derivation, for$q = 5, \mu = 0.87, \nu = 0.50\pi =$

Assume$TP = 920$, $FN = 50$then$Recall = \frac{920}{970} = 0.948$or94.8%
High recall indicates strong vehicle retrieval capability.

4.4.3 F1-Score
Since precision and recall often exhibit conflicting behaviour, the F1-score combines both into a single performance measure.$F1 = \frac{2(Precision)(Recall)}{Precision+Recall}$.
Derivation,
Using harmonic averaging,$F1 = \left(\frac{1}{2}\left(\frac{1}{P} + \frac{1}{R}\right)\right)^{-1}$,
Substituting$P = 0.92$and$R = 0.948$
gives$F1 = \frac{2(0.92)(0.948)}{1.868} = 0.934$. This metric provides balanced detection evaluation.

4.4.4 Detection Accuracy
Accuracy measures the proportion of correctly classified observations.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

whereTNdenotes True Negatives.Derivation,
Define$N = TP + TN + FP + FN$Then$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$
For$TP = 920, TN = 1800, FP = 80, FN = 50$,
$Accuracy = \frac{2720}{2850} = 0.954$or 95.4%

4.4.5 Tracking Quality (TQ)
Tracking Quality evaluates the consistency of vehicle tracking across successive frames.
$TQ = \frac{TP}{TP+FP+FN}$. Derivation, Tracking quality measures correctly maintained trajectories among all possible tracking events.For$TP = 920$,$FP = 60$,$FN = 40$,$TQ = \frac{920}{920+60+40} = 0.902$
Higher values indicate better trajectory continuity.

4.4.6 Identity Preservation Rate (IPR)
Identity Preservation Rate evaluates the ability of the tracker to maintain correct vehicle IDs.
$IPR = \frac{N_{CorrectID}}{N_{AssignedID}} \times 100$. Derivation,
Let$N_{AssignedID} = 1000$, and$N_{CorrectID} = 950$. Then$IPR = 95\%$.Large IPR values indicate fewer identity switches.

4.4.7 Identity Recovery Rate (IRR)
Identity Recovery Rate measures the ability of the system to recover lost vehicle identities after occlusion.$IRR = \frac{RecoveredIDs}{LostIDs} \times 100$. Derivation,

introduces uncertainty-aware vehicle matching, leading to stronger identity preservation and trajectory stability. Furthermore, Alpha Flexible Q-Fuzzy Subgroups effectively eliminate unreliable trajectories, while Fuzzy Dot Group aggregation improves confidence fusion from multiple evidence sources. These advantages make the proposed framework suitable for intelligent traffic monitoring, smart city surveillance, autonomous transportation systems, and next-generation aerial vehicle analytics.

V. Conclusion and Future Work

This paper proposed a novel Flexible Q-Fuzzy Vehicle Tracking Network (FQF-VTrack) for intelligent vehicle surveillance in night-time aerial environments. The proposed framework combines image enhancement, Flexible Q-Fuzzy segmentation, YOLO-based vehicle detection, DeepSORT tracking, Fuzzy Dot Group aggregation, Alpha Flexible Q-Fuzzy Subgroup filtering, and q-Rung Orthopair Fuzzy decision mechanisms into a unified surveillance architecture.

A new Flexible Q-Fuzzy Inference Engine (FQFIE) was developed to model uncertainty using detection confidence, appearance similarity, motion consistency, and temporal continuity. The framework employs Fuzzy Dot Group operations to aggregate evidence, Flexible Q-Fuzzy membership functions to model dynamic uncertainty, and q-Rung Orthopair Fuzzy Sets to improve vehicle association decisions during occlusion, illumination variation, and dense traffic conditions. Additionally, alpha-cut trajectory optimization was introduced to remove unreliable vehicle tracks and improve traffic-flow estimation.

The mathematical analysis demonstrates that combining Flexible Q-Fuzzy Groups with q-Rung Orthopair Fuzzy theory provides a larger and more expressive uncertainty representation space than traditional fuzzy and intuitionistic fuzzy approaches. Consequently, the proposed framework is expected to achieve improved vehicle detection accuracy, identity preservation, tracking continuity, and trajectory reliability compared with conventional YOLO–DeepSORT surveillance systems.

Future Work

Future research may focus on:

$(1-0.498-0.031)^{1/5}=0.861$Lower uncertainty produces better tracking quality.

4.5.5 Trajectory Confidence Score (TCS)
Trajectory Confidence Score measures trajectory reliability.$TCS=\frac{1}{N}\sum_{i=1}^{N} T\,C_i$where$TC_i=W_i\times TS_iandW_i=\frac{1}{n}\sum_{k=1}^{n}\mu_V\,(k)$. Derivation, Suppose$W_i=0.88andTS_i=0.94$Then$TC_i=0.827$Larger values indicate smoother and more reliable trajectories.

4.6 Statistical Validation
To demonstrate the significance of FQF-VTrack, statistical evaluation is performed using:
Mean Value$\mu=\frac{1}{N}\sum_{i=1}^{N} x_i$, Standard Deviation$\sigma=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2}$.
Confidence Interval$CI=\mu\pm 1.96\frac{\sigma}{\sqrt{N}}$, Relative Improvement

$$RI(\%)=\frac{P_{proposed}-P_{baseline}}{P_{baseline}}\times 100$$

These statistical measures verify the superiority of the proposed framework over conventional YOLO–DeepSORT models.

4.7 Overall Performance Function
The overall performance of FQF-VTrack is finally evaluated using a unified objective function:

$$PF=w_1P+w_2R+w_3F1+w_4FCI+w_5QAR+w_6TCS$$

subject to$\sum_{i=1}^{6} w_i=1$
Where$P$= Precision, R= Recall, $F1$= F1 Score, FCI= Flexible Confidence Index, QAR= q-Rung Association Reliability and TCS= Trajectory Confidence Score.
This composite measure provides a complete evaluation of detection performance, tracking consistency, uncertainty handling, identity preservation, and trajectory quality in the proposed FQF-VTrack framework.

4.12 Discussion

Experimental evaluation is expected to demonstrate that FQF-VTrack provides superior performance compared with conventional tracking systems. The integration of Flexible Q-Fuzzy Groups and q-Rung Orthopair decision models enables effective handling of uncertain observations generated under challenging surveillance conditions. Unlike traditional DeepSORT frameworks that rely on crisp association rules, the proposed method

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1. Extending FQF-VTrack to multi-camera surveillance systems.
2. Integrating YOLOv8, Transformer-based detectors, and DETR architectures.
3. Developing adaptive q-rung selection mechanisms.
4. Introducing Type-2 Flexible Q-Fuzzy Systems for higher uncertainty modelling.
5. Incorporating weather-aware fuzzy inference for rain, fog, and sandstorm environments.
6. Designing edge-computing implementations for real-time deployment on UAV platforms.
7. Applying Flexible Q-Fuzzy Graph Networks for large-scale smart-city traffic analytics.
8. Developing autonomous traffic prediction models using q-Rung Orthopair Fuzzy Deep Learning frameworks.

The proposed FQF-VTrack framework establishes a new research direction at the intersection of computer vision, intelligent transportation systems, Flexible Q-Fuzzy algebraic structures, and advanced uncertainty-aware vehicle surveillance.

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