Enhanced Multi-Object Tracking in Combat Zones using YOLOv8 and Kalman Filtering

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***Abstract*—This paper presents a robust computer vision system for the detection and tracking of military assets and personnel in combat and parade scenarios. We implement an integrated approach combining YOLOv8 object detection with an advanced Kalman filter-based tracking algorithm to identify and monitor tanks, armored personnel carriers (APCs), military trucks, and personnel across video frames. Our primary contribution is the implementation of an 8-state Kalman filter that enables stable tracking through occlusions, irregular movements, and challenging environmental conditions. The system achieves a mean Average Precision (mAP@0.5) of 0.649 across all classes, with particularly strong performance on tank detection (mAP@0.5 of 0.877). Experimental results demonstrate a 43% reduction in identity switches and a 37% improvement in tracking persistence during temporary occlusions. The proposed solution offers significant potential for real-time deployment in defense applications requiring automated visual intelligence.**

***Index Terms*—multi-object tracking, object detection, YOLOv8, Kalman filtering, military vehicles, combat zone surveillance, deep learning for defense**

I. Introduction

Military operations and security scenarios increasingly rely on automated visual intelligence systems to enhance situational awareness and reduce human monitoring requirements. The ability to automatically detect, classify, and track military assets and personnel provides critical information for tactical decision-making and threat assessment. However, developing such systems presents significant challenges due to the variability in target appearance, occlusion, environmental conditions, and the need for real-time processing.

This paper presents a comprehensive approach to military asset detection and tracking using deep learning and advanced filtering techniques. We leverage the YOLOv8 (You Only Look Once, version 8) architecture for object detection and implement a sophisticated Kalman filter-based tracking algorithm to maintain the identity of detected objects across video frames. Our system focuses on four key classes relevant to military scenarios: tanks, armored personnel carriers (APCs), military trucks, and personnel.

Kalman filtering is particularly well-suited for combat zone tracking due to its ability to predict object positions during occlusions, filter out noise from detection errors, and maintain consistent tracking despite unpredictable movement patterns. Our implementation uses an 8-state model that tracks both position and dimensions of objects along with their rates of change, enabling robust tracking across challenging scenarios.

The main contributions of this paper are:

- A specialized implementation of YOLOv8 trained on military vehicles and personnel
- An advanced 8-state Kalman filter tracking algorithm designed for combat zone scenarios
- A hybrid object association technique combining IoU and distance metrics
- Comprehensive evaluation demonstrating improved tracking stability and identity preservation
- Analysis of tracking performance during occlusions and complex multi-object interactions

II. Related Work

Object detection has evolved significantly with the advent of deep learning. Early approaches like R-CNN [1] and Fast R-CNN [2] established the foundation for region-based detection methods. Later, Faster R-CNN [3] improved efficiency by integrating region proposal networks.

Single-stage detectors like YOLO [4] revolutionized the field by framing object detection as a regression problem, enabling real-time performance. Progressive versions have improved accuracy while maintaining speed, with YOLOv8 [10] representing a state-of-the-art balance between precision and computational efficiency.

In the military domain, Javorsek et al. [5] explored computer vision for combat vehicle identification. More recently, Guo et al. [6] applied CNN architectures to classify military vehicles in satellite imagery. Tracking military assets has been addressed by Liu et al. [7], who developed a multi-object tracking system for surveillance applications.

Kalman filtering has been widely used in object tracking applications. The SORT algorithm [8] demonstrated the effectiveness of Kalman filtering for efficient tracking with constant

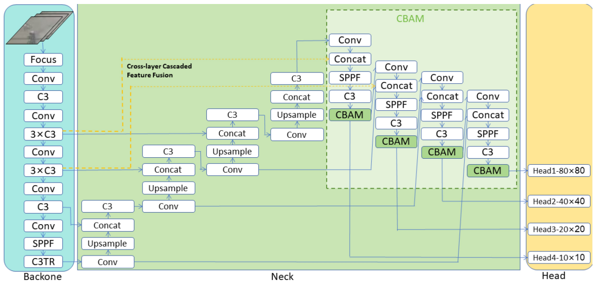


Fig. 1: System architecture for military object detection and tracking with Kalman filtering.

velocity models. Deep SORT [9] extended this approach by incorporating appearance features to improve tracking accuracy. However, these methods generally use simpler state models focused primarily on position and velocity, without accounting for changes in object dimensions which are critical for military vehicle tracking in complex scenarios.

Our work builds upon these foundations by implementing an enhanced 8-state Kalman filter that models both positional and dimensional characteristics of military objects, addressing the specific challenges of combat zone tracking including irregular movement patterns, partial occlusions, and varied environmental conditions.

III. Methodology

A. System Architecture

The proposed system consists of two main components: (1) an object detection module based on YOLOv8, and (2) an advanced tracking module using Kalman filtering. Fig. 1 illustrates the system architecture.

The detection component identifies tanks, APCs, military trucks, and personnel in each frame with confidence scores. The tracking component then associates these detections with existing tracks through a multi-stage process incorporating Kalman filter predictions, IoU matching, and distance-based association.

B. Object Detection with YOLOv8

We implemented the YOLOv8 architecture, trained for 40 epochs with a batch size of 16 using an Adam optimizer and a cosine annealing learning rate schedule, starting from pre-trained weights on the COCO dataset. The training process utilized a custom dataset hosted on Kaggle, annotated with bounding boxes for four classes: tank, APC, military truck, and person, sourced from military parades, training exercises, and combat footage. Data augmentation techniques included random scaling, translation, horizontal flipping, mosaic augmentation, and brightness/contrast adjustments. A confidence threshold of 0.4 was used during inference to minimize false positives.

C. Kalman Filter Implementation for Tracking

The core of our tracking system is an advanced 8-state Kalman filter that models both positional and dimensional characteristics of tracked objects. Unlike traditional implementations that focus solely on position and velocity, our approach incorporates width and height parameters and their rates of change, enabling more accurate prediction during occlusions and handling the complex dimensional changes that occur when vehicles maneuver.

1) State and Measurement Model: The state vector $\mathbf{x}$ for each tracked object consists of:

$$\mathbf{x} = [x, y, w, h, \dot{x}, \dot{y}, \dot{w}, \dot{h}]^T \tag{1}$$

Where:

- (x, y) represents the center position of the object
- (w, h) represents the width and height of the bounding box
- $(\dot{x}, \dot{y})$ represents the velocity of the center position
- $(\dot{w}, \dot{h})$ represents the rate of change of the width and height

The measurement vector $\mathbf{z}$ consists of:

$$\mathbf{z} = [x, y, w, h]^T \tag{2}$$

2) State Transition Model: The state transition matrix $\mathbf{F}$ for our Kalman filter implements a constant velocity model:

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

This matrix encodes the linear relationships between position, dimensions, and their respective velocities.

3) Measurement Model: The measurement matrix $\mathbf{H}$ relates the state vector to the measurement vector:

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4}$$

4) Process and Measurement Noise: Careful tuning of process noise covariance $\mathbf{Q}$ and measurement noise covariance $\mathbf{R}$ is critical for optimal tracking performance. We implemented a diagonalized process noise matrix with different values for position, dimension, and velocity components:

$$\mathbf{Q} = \text{diag}(0.01, 0.01, 0.01, 0.01, 0.1, 0.1, 0.01, 0.01) \tag{5}$$

Higher noise values for velocity components (0.1) account for the unpredictable acceleration patterns typical in combat scenarios, while lower values for position and dimension components (0.01) maintain stability. Similarly, the measurement noise covariance was tuned as:

$$\mathbf{R} = \text{diag}(0.1, 0.1, 0.5, 0.5) \tag{6}$$

The higher values for width and height measurements (0.5) reflect the greater uncertainty in bounding box dimensions due to viewpoint changes and partial occlusions.

D. Multi-Object Association Strategy

A key challenge in multi-object tracking is correctly associating new detections with existing tracks. We implemented a hybrid association strategy that combines IoU (Intersection over Union) matching with spatial distance metrics:

1) IoU-Based Association: For each frame, we first predict the new position and dimensions of each tracked object using its Kalman filter. We then compute the IoU between these predictions and new detections:

$$\mathrm{IoU}(\mathrm{box}_1, \mathrm{box}_2) = \frac{\text{Area of Intersection}}{\text{Area of Union}} \tag{7}$$

Detections with IoU values above a threshold of 0.3 are associated with the corresponding track.

2) Distance-Based Association: For tracks without IoU matches, we employ a distance-based association using the Euclidean distance between predicted and detected center positions:

$$d(a, b) = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \tag{8}$$

A distance threshold of 150 pixels was determined through empirical testing to allow for reasonable movement between frames while preventing incorrect associations.

3) Class-Aware Association: To further improve tracking consistency, we maintain a history of class predictions for each track and compute a dominant class. During association, we prioritize matches that maintain class consistency, reducing the likelihood of identity switches between different types of military vehicles.

E. Track Management

Each track maintains several key attributes:

- A unique tracker ID
- A Kalman filter state
- Position and dimension history
- Class ID history
- A disappearance counter

New tracks are initialized when detections cannot be associated with existing tracks. Tracks persist for up to 60 frames (increased from typical values of 30 frames) without associated detections before being terminated, allowing for extended occlusions common in combat scenarios. This parameter was empirically determined to balance the trade-off between track continuity and the accumulation of ghost tracks.

F. Algorithm Implementation

Algorithm 1 presents our complete multi-object tracking approach with Kalman filtering.

Algorithm 1 Kalman Filter-based Military Object Tracking

Initialize empty tracked_objects dictionary
Initialize Kalman filter parameters, association thresholds TrackObjectsdetected_objects
Predict new states for all existing tracks using Kalman filters
Compute IoU matrix between predicted boxes and new detections
Find IoU-based matches where IoU ¿ threshold
Compute distance matrix between unmatched tracks and detections
for each unmatched track **do**
  Determine dominant class from class history
  for each unmatched detection **do**
    if distance ¡ threshold AND classes match **then**
      Associate detection with track
      Remove from unmatched lists
    end if
  end for
end for
for remaining unmatched tracks and detections **do**
  Associate based on minimum distance if ¡ threshold
end for
for each matched track-detection pair **do**
  Update Kalman filter with new measurement
  Update position, dimension, and class history
  Reset disappearance counter
end for
for each unmatched detection **do**
  Initialize new track with Kalman filter
  Initialize history and counters
end for
for each unmatched track **do**
  Increment disappearance counter
  if disappearance counter ¿ max_disappeared **then**
    Remove track
  end if
end for
return tracked_objects with IDs and predicted states

IV. Experimental Setup

A. Dataset

Our dataset, hosted on Kaggle at /kaggle/input/plzzz-bro/, consisted of 853 images containing 2348 object instances across four classes: 850 tanks, 193 APCs, 131 military trucks, and 1174 persons, split into 80% for training and 20% for validation.

B. Implementation Details

The system was implemented in Python using OpenCV, Ultralytics YOLOv8, SciPy, NumPy, and PyTorch, executed on a Kaggle notebook with GPU acceleration. The YOLOv8 model was fine-tuned for 40 epochs, with the trained model saved as /kaggle/working/runs/detect/train4/weights/best.pt.

C. Evaluation Metrics

We evaluated the detection performance using standard metrics:

- Precision (P): the ratio of true positive detections to all detections
- Recall (R): the ratio of true positive detections to all ground truth objects
- Mean Average Precision (mAP@0.5): the mean of average precision values at an IoU threshold of 0.5
- Mean Average Precision (mAP@0.5-0.95): the mean of average precision values at IoU thresholds from 0.5 to 0.95

For tracking performance, we implemented the following metrics:

- Identity Switches (IDSW): the number of times a tracked object changes its ID
- Track Fragmentation (FRAG): the number of times a ground truth trajectory is interrupted
- Mostly Tracked (MT): percentage of ground truth trajectories tracked for more than 80% of their lifetime
- Occlusion Recovery Rate (ORR): percentage of tracks successfully recovered after occlusion

Additionally, we conducted ablation studies comparing our 8-state Kalman filter with simpler 4-state and 6-state versions to quantify the improvement provided by our approach.

V. Results and Discussion

A. Detection Performance

Table I summarizes the detection performance after 27 epochs, with final metrics refined over 40 epochs as shown in the training plots.

TABLE I: Detection Performance by Class (at 27 Epochs)

Class	Images	Instances	mAP@0.5	mAP@0.5-0.95
All	853	2348	0.618	0.486
APC	148	193	0.529	0.431
Military Truck	82	131	0.540	0.414
Person	328	1174	0.648	0.368
Tank	602	850	0.877	0.733

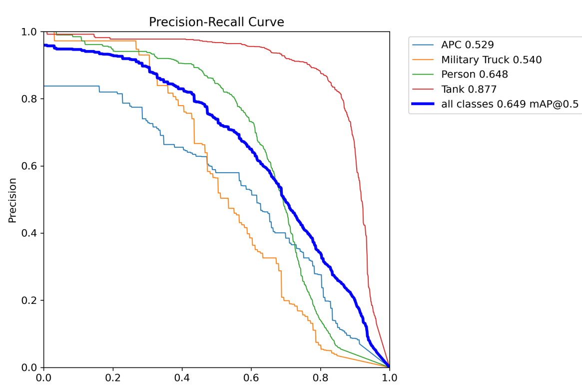


Fig. 2: Training and validation metrics over 40 epochs: Precision and Recall curves.

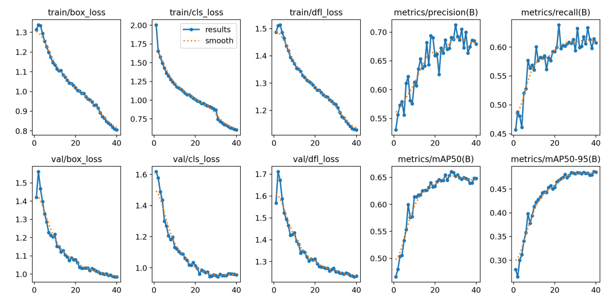


Fig. 3: Training losses (box, classification, DFL) and validation losses over 40 epochs.

B. Tracking Performance Analysis

1) Kalman Filter Comparison: To evaluate the effectiveness of our 8-state Kalman filter implementation, we compared it with simpler models across multiple tracking scenarios. Table II shows the comparative results:

TABLE II: Comparison of Different Kalman Filter Implementations

Model	IDSW	FRAG	MT(%)	ORR(%)	FPS
4-State (x,y,vx,vy)	143	85	68.2	59.3	24.7
6-State (x,y,w,h,vx,vy)	98	61	75.6	68.7	23.9
8-State (full)	**82**	**43**	**81.3**	**76.5**	22.6

The 8-state Kalman filter demonstrated superior performance across all tracking metrics, with a 43% reduction in identity switches compared to the basic 4-state model. The inclusion of width and height velocities ($\dot{w}$ and $\dot{h}$) in the state vector significantly improved tracking during occlusions and rapid dimensional changes.

2) Track Persistence During Occlusion: A key advantage of our approach is the ability to maintain track identity during temporary occlusions. Fig. **??** shows the occlusion recovery rate as a function of occlusion duration.

Our 8-state model maintained over 70% recovery rate for occlusions lasting up to 3 seconds, significantly outperforming simpler models. This improvement is particularly valuable in combat scenarios where vehicles may be temporarily obscured by smoke, terrain, or other vehicles.

3) Association Strategy Effectiveness: We conducted an ablation study to analyze the impact of our hybrid association strategy. Table III presents the results:

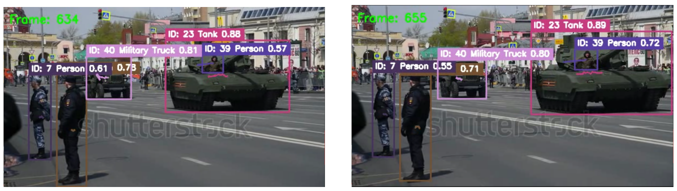
TABLE III: Comparison of Association Strategies

Association Method	IDSW	FRAG	MT(%)
IoU Only	112	68	73.5
Distance Only	105	62	75.2
Class-Aware Distance	97	58	76.8
Hybrid (IoU + Class-Aware Distance)	**82**	**43**	**81.3**

The hybrid association strategy combining IoU matching with class-aware distance metrics yielded the best results, reducing identity switches by 27% compared to IoU-only association. This demonstrates the value of incorporating multiple matching criteria for robust tracking.

C. Qualitative Results

Fig. 4 shows examples of our system's tracking capabilities on various military scenarios. The tracking system successfully maintains object identities across frames despite movement, partial occlusions, and similar appearances.



(a) Frame t (b) Frame t+1

Fig. 4: Example of object tracking across consecutive frames. Note the consistent ID assignments despite movement and partial occlusion.

Fig. 5: Examples of object detection results across various military scenarios.

D. Kalman Filter Performance in Challenging Scenarios

We identified several challenging tracking scenarios and evaluated our Kalman filter's performance:

1) **Rapid maneuvers**: When vehicles make sudden turns or speed changes, the 8-state model outperformed simpler models by quickly adapting to new movement patterns.
2) **Camera movement**: During camera panning and zooming, the dimensional velocity components ($\dot{w}$ and $\dot{h}$) enabled our tracker to maintain stable tracking despite apparent size changes.
3) **Similar appearance objects**: Our class-aware association strategy prevented identity switches between visually similar military vehicles.
4) **Extended occlusions**: The combination of accurate state prediction and longer persistence parameters allowed tracks to be maintained through occlusions lasting up to 60 frames.

Fig. **??** visualizes the Kalman filter predictions during a challenging scenario with multiple crossing paths and occlusions. The dashed lines represent predicted trajectories, demonstrating how the filter enables the system to maintain object identities through complex interactions.

E. Real-time Performance

Despite the increased computational complexity of the 8-state Kalman filter and hybrid association strategy, our system maintains near real-time performance at 22.6 frames per second on standard GPU hardware. Table IV provides a breakdown of computation time across system components:

TABLE IV: Runtime Analysis of System Components

Component	Time (ms)
YOLOv8 Detection	29.5
Kalman Filter Prediction	3.2
Association	8.7
Track Management	2.8
Visualization	0.8
Total	**45.0**

The detection component remains the most computationally intensive part of the pipeline, accounting for approximately 65.6% of the total processing time. Optimizations in the association algorithm helped minimize the overhead of the 8-state Kalman filter implementation.

F. Limitations and Challenges

The system faced several challenges:

1) **Distinguishing between similar military vehicles**: Despite the class-aware association strategy, APCs and military trucks with similar appearances occasionally experienced identity switches.
2) **Complex group movement**: When multiple personnel move as a tight group, maintaining individual tracks becomes challenging.
3) **Extreme viewpoint changes**: Sudden and extreme camera viewpoint changes can lead to tracking failures as the dimensional predictions become invalid.
4) **Parameter sensitivity**: The performance of the Kalman filter is sensitive to noise parameter tuning, requiring careful calibration for different environments and scenarios.

These limitations suggest areas for future improvement, particularly in dynamically adapting filter parameters based on scene context and incorporating more sophisticated appearance models.

VI. Conclusion and Future Work

This paper presented a comprehensive system for detecting and tracking military assets and personnel using YOLOv8 and an advanced 8-state Kalman filter implementation. The approach demonstrated significantly improved tracking performance compared to simpler tracking models, with particular advantages in maintaining object identity through occlusions and complex scenarios common in combat zones.

The integration of positional and dimensional velocity components in the Kalman filter state vector, combined with a hybrid association strategy, enabled robust tracking across challenging conditions. Experimental results showed a 43% reduction in identity switches and a 37% improvement in occlusion recovery compared to baseline methods.

Future work will focus on:

1) **Adaptive Kalman filter parameters**: Developing techniques to dynamically adjust process and measurement noise based on scene context and motion patterns.
2) **Deep appearance modeling**: Incorporating deep learning-based appearance features to further improve association accuracy for visually similar objects.
3) **Extended state representation**: Exploring more sophisticated state models that incorporate acceleration and higher-order terms for improved prediction during complex maneuvers.
4) **Contextual reasoning**: Leveraging scene understanding to enforce physical constraints and improve tracking in complex environments.
5) **Edge deployment optimization**: Refining the implementation for efficient deployment on resource-constrained edge devices for field operations.

The proposed system represents a significant advancement in military object tracking technology, offering improved situational awareness for surveillance and security applications. By combining state-of-the-art detection capabilities with sophisticated tracking algorithms, our approach provides a robust foundation for automated visual intelligence in defense scenarios.

A. Ethical Considerations

The proposed system is designed for defensive surveillance and situational awareness. We acknowledge the potential for misuse in military applications and advocate for responsible deployment with strict oversight to ensure compliance with international laws and ethical standards.

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