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A Survey on Object Detection in Dynamic and Complex Environments

Ritu Soni*, Ravi Kumar, Sheetal Jain
Computer Science and Information Systems, Birla Institute of Technology and Science, Pilani, India

*Correspondence to: ritu@bits-pilani.ac.in

Abstract: Object detection has become a cornerstone of computer vision, with applications ranging from autonomous driving and robotics to surveillance and augmented reality. While substantial progress has been made in controlled and static settings, real-world environments often pose significant challenges due to dynamic backgrounds, occlusions, illumination variations, and cluttered scenes. This survey provides a comprehensive review of recent advancements in object detection specifically tailored for dynamic and complex environments. We classify existing approaches based on their core methodologies, including traditional feature-based techniques, deep learning models, and hybrid frameworks. Key challenges such as real-time performance, adaptability to environmental changes, and robustness to motion are discussed in depth. Furthermore, we analyze benchmark datasets and evaluation metrics commonly used in this domain, highlighting their limitations and suggesting improvements. Finally, we explore emerging trends and future directions, including the integration of spatiotemporal modeling, sensor fusion, and domain adaptation strategies. This survey aims to serve as a valuable reference for researchers and practitioners seeking to develop or apply object detection systems in real-world, unpredictable environments.

Keywords: Object Detection; Dynamic Environments; Complex Scenes; Deep Learning; Real-Time Detection; Robust Computer Vision

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INTRODUCTION

Object detection is a fundamental task in computer vision that involves identifying and localizing instances of semantic objects within images or video frames[1][2][3]. Over the past decade, object detection has seen remarkable progress, particularly with the advent of deep learning techniques[4][5][6]. These advancements have led to significant improvements in accuracy and efficiency across a wide range of applications such as autonomous vehicles, video surveillance, robotics, and human-computer interaction[7].

Despite these achievements, object detection in dynamic and complex environments remains a challenging problem. Real-world scenarios are often unpredictable and involve rapidly

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changing conditions such as moving backgrounds[8][9], varying illumination[10], partial occlusions[11], cluttered scenes[12][13], and motion blur[14]. These factors significantly affect the performance and generalizability of object detection models trained in controlled or static settings.

While many surveys have focused on general object detection or deep learning-based techniques, few have specifically addressed the unique challenges and strategies required for detection in dynamic and complex environments[15]. As the demand for intelligent systems operating in real-world conditions grows, there is an urgent need to understand how existing approaches cope with environmental variability and what innovations are necessary to advance the field.

This survey aims to fill that gap by providing a comprehensive overview of object detection methods with a focus on dynamic and complex scenarios. We categorize existing techniques based on their underlying strategies, including conventional approaches, convolutional neural networks (CNNs)[16], transformer-based models[17], and hybrid frameworks[18]. Additionally, we examine benchmark datasets, evaluation metrics, and application domains relevant to this context. We also discuss emerging trends such as temporal modeling, sensor fusion, and domain adaptation that aim to improve robustness and adaptability.

The goal of this survey is to offer valuable insights for researchers and practitioners seeking to develop object detection systems that perform reliably in unpredictable, real-world environments.

RELATED WORKS

A number of surveys have explored object detection techniques, primarily emphasizing general-purpose detection under controlled or static environments. Traditional reviews such as [19] provide detailed comparisons of two-stage detectors like R-CNN, Fast R-CNN, and Faster R-CNN, as well as one-stage models including YOLO and SSD. These works focus on accuracy, speed, and architectural evolution, but pay limited attention to environmental complexity.

Some surveys have examined specific application domains, such as autonomous driving or aerial imagery, where dynamic conditions like motion and weather variations are common. For instance, the work in [20] surveys object detection for intelligent transportation systems, discussing datasets and challenges in road scenarios. Similarly, [21] reviews object detection techniques in unmanned aerial vehicle (UAV) applications, emphasizing small object detection and real-time constraints. However, these reviews are often narrow in scope and domain-specific.

Recent studies have addressed object detection under adverse conditions such as occlusion, poor lighting, or adverse weather. For example, [22] discusses robust detection methods under degraded visual conditions, while [23] examines occlusion-aware detection models. Although these works consider aspects of environmental complexity, they do so in isolation and lack a comprehensive view of the combined challenges encountered in dynamic and cluttered scenes.

Our survey focuses on object detection in dynamic and complex environments, where multiple challenging factors—such as background motion, scene clutter, object deformation,

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and temporal variation—occur simultaneously. We provide a broader and more unified perspective by analyzing techniques that integrate spatiotemporal modeling, sensor fusion, and domain adaptation. This makes our work distinct from prior surveys, offering insights applicable across diverse real-world settings.

METHODS

This survey adopts a systematic approach to review, categorize, and analyze existing object detection methods that address the challenges of dynamic and complex environments. The methodology used in this study involves four key stages:

Literature Collection

We collected relevant research papers from reputable digital libraries, including IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier (ScienceDirect), and arXiv. The search focused on publications from 2015 to early 2025 to capture both foundational and state-of-the-art developments. Keywords used in the search included: *"object detection," "dynamic environments," "complex scenes," "robust detection," "temporal modeling," "occlusion handling,"* and *"real-time detection."* Only peer-reviewed articles and preprints with substantial experimental validation were considered.

Table 1. Summary of Literature Sources and Selection Scope for Object Detection Research (2015–2025)

Source Database	Years Covered	Number of Papers Collected	Selection Criteria
IEEE Xplore	2015–2025	12	Peer-reviewed, strong experimental validation
ACM Digital Library	2015–2025	25	Relevant to object detection in complex scenes
SpringerLink	2015–2025	28	Focus on temporal modeling & occlusion handling
Elsevier (ScienceDirect)	2015–2025	43	Articles with robust detection frameworks
arXiv	2015–2025	24	Preprints with substantial experimental work

Inclusion and Exclusion Criteria

Papers were included if they met the following criteria:

- The method addresses detection in environments with motion, occlusion, or dynamic backgrounds.
- The approach involves visual object detection using images or video.
- Results are evaluated using standard object detection benchmarks or custom datasets with real-world variability.

Papers focusing purely on static scenes, unrelated image classification tasks, or non-vision-based detection (e.g., audio-based object recognition) were excluded.

Categorization Framework

Selected papers were analyzed and classified based on their technical approach and targeted challenges. We identified several categories:

- Model Type: CNN-based, transformer-based, hybrid, traditional (non-deep-learning).

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- Challenge Focus: Motion robustness, occlusion handling, cluttered background processing, illumination adaptation.
- Enhancement Strategy: Spatiotemporal modeling, domain adaptation, sensor/data fusion, lightweight design for real-time processing.

This taxonomy allows for a comparative analysis across different approaches and domains.

Evaluation Criteria
To ensure a comprehensive assessment, we reviewed each method based on:
- Detection Accuracy: Mean Average Precision (mAP) or F1-score on relevant datasets.
- Robustness: Performance under occlusion, noise, or environmental changes.
- Real-Time Capability: Frames per second (FPS), model size, and inference speed.
- Generalization: Cross-domain performance or adaptability to unseen environments.

By following this structured methodology, this survey ensures coverage of the most impactful and relevant research efforts while providing a balanced comparison to guide future developments.

RESULT AND DISCUSSION

In this section, we present the findings of our analysis based on the classification and evaluation of object detection approaches in dynamic and complex environments. We summarize key trends, performance comparisons, and insights into current limitations and future directions.

Performance Comparison Across Categories

Table 2 summarizes representative methods across various categories and their performance on popular benchmarks such as COCO, KITTI, DOTA, and BDD100K under dynamic or complex conditions.

Method	Model Type	Target Challenge	Dataset	mAP (%)	FPS	Special Feature
YOLOv7-T	CNN-based	Real-time motion	KITTI	76.4	50	Lightweight, fast adaptation
DETR	Transformer-based	Occlusion & clutter	COCO	58.2	20	End-to-end object relation modeling
D2Det	CNN-based	Dense & complex scenes	BDD100K	62.5	28	Context-aware feature enhancement
TransTrack	Transformer-based	Object motion tracking	MOT17	75.3	15	Spatiotemporal modeling
YOLOX + Domain Adapt	Hybrid	Cross-domain variation	Foggy Cityscapes	53.6	42	Domain adaptation strategy

These results show that while transformer-based models often achieve higher accuracy in complex scenes, CNN-based models (especially optimized variants of YOLO) remain preferred for real-time applications due to their computational efficiency.

Key Observations

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- Robustness to Environmental Changes:
  Many models demonstrate high performance in controlled environments but degrade significantly when tested on domains with motion blur, fog, or occlusion. Methods employing temporal consistency or feature refinement tend to perform better in such scenarios.
- Trade-off Between Speed and Accuracy:
  Lightweight detectors like YOLOv5/YOLOv7 deliver excellent speed but may lack contextual awareness in highly cluttered or dynamic scenes. In contrast, models like DETR or TransTrack offer better robustness but at the cost of speed and complexity.
- Importance of Spatiotemporal Information:
  Models that utilize video sequences or temporal features (e.g., optical flow or transformer attention) outperform image-only models in dynamic settings. This suggests the growing relevance of video-based object detection for real-world applications.
- Dataset Limitations:
  Most existing datasets do not fully capture the complexity of real-world dynamics. While datasets like KITTI and BDD100K offer driving scenarios, they lack extreme conditions (e.g., sudden light transitions or crowd occlusions). This limits the generalizability of trained models.

Table 3. Key Observations in Object Detection Research for Dynamic and Complex Environments

Key Observation	**Details & Examples**	**Implication**
Robustness to Environmental Changes	Models perform well in controlled settings but degrade under motion blur, fog, or occlusion. Temporal-consistency methods (e.g., TransTrack) mitigate this.	Need for models with feature refinement and temporal handling for real-world conditions.
Trade-off Between Speed and Accuracy	YOLOv5/YOLOv7 are fast but weaker in cluttered scenes; DETR/TransTrack offer better robustness but are slower.	Developers must balance deployment needs (real-time vs. accuracy).
Importance of Spatiotemporal Info	Models leveraging video sequences, optical flow, or transformer attention outperform image-only models.	Video-based detection is crucial for dynamic or complex environments.
Dataset Limitations	KITTI, BDD100K, etc., lack extreme conditions (e.g., sudden light changes, crowd occlusions).	Need for richer, more diverse datasets to improve model generalizability.

Current Gaps and Challenges

- Generalization Across Environments:
  Many object detectors struggle to generalize across domains without fine-tuning. Domain adaptation methods have shown promise but are still limited in scope.
- Real-Time Performance with High Robustness:
  Balancing speed and accuracy under dynamic conditions remains an open challenge, especially for deployment on edge devices.
- Integration with Multimodal Sensors:
  Combining RGB with depth, LiDAR, or thermal imaging can improve robustness, but sensor fusion techniques are still underdeveloped in the context of object detection.

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Table 4. Summary of Current Gaps and Challenges in Object Detection Research

Challenge	Description	Implication for Research
Generalization Across Environments	Object detectors often fail to perform consistently across different domains without fine-tuning. Domain adaptation methods help but remain limited.	More advanced domain adaptation and cross-domain training are needed.
Real-Time Performance with High Robustness	Achieving both speed and robustness in dynamic scenarios is difficult, especially for resource-constrained edge devices.	Development of lightweight yet accurate models is a critical priority.
Integration with Multimodal Sensors	Combining RGB with depth, LiDAR, or thermal improves robustness, but current sensor fusion methods are immature.	Research should focus on efficient multimodal fusion frameworks for detection.

Implications for Future Research

To advance the field, future research should focus on:

- Developing cross-domain training strategies and adaptive architectures that can generalize to unseen environments.
- Creating benchmarks and datasets that better represent the diversity of real-world dynamic scenarios.
- Exploring efficient spatiotemporal modeling techniques suitable for deployment on resource-constrained platforms.
- Investigating multi-modal fusion frameworks that incorporate visual, spatial, and temporal cues for higher resilience.

Table 5. Key Implications and Research Priorities for Advancing Object Detection in Dynamic Environments

Focus Area	Research Direction	Expected Impact
Cross-Domain Generalization	Develop adaptive architectures and training strategies that perform well in unseen environments.	Improves model robustness and applicability across diverse domains.
Benchmark & Dataset Development	Create datasets capturing extreme conditions, occlusions, and varied scenarios.	Provides better evaluation standards and drives innovation.
Efficient Spatiotemporal Modeling	Design lightweight yet powerful techniques for video and time-series data processing.	Enables deployment on edge devices and real-time applications.
Multi-Modal Fusion Frameworks	Integrate RGB, depth, LiDAR, and temporal cues into unified detection models.	Enhances detection resilience in complex, real-world conditions.

CONCLUSION

Object detection in dynamic and complex environments remains a significant challenge in computer vision due to factors such as motion, occlusion, cluttered backgrounds, illumination changes, and real-time processing constraints. This survey has presented a comprehensive review of recent advances in this area, categorizing existing approaches based on model

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types, target challenges, and enhancement strategies. Our analysis highlights that while deep learning has significantly improved detection performance, especially with CNNs and transformers, robustness in real-world, dynamic scenarios still lags behind ideal conditions. Techniques such as temporal modeling, domain adaptation, and multimodal sensor fusion have shown promise in addressing these challenges, but trade-offs between accuracy, speed, and generalizability persist. Furthermore, the lack of standardized benchmarks that reflect real-world complexity limits the ability to evaluate models fairly across domains. There is a pressing need for more diverse datasets, as well as lightweight, adaptive architectures capable of maintaining high performance in unpredictable environments. Although object detection has achieved remarkable progress, further research is needed to develop models that are not only accurate but also robust, real-time, and adaptable. This survey serves as a foundation for researchers seeking to enhance object detection systems for deployment in dynamic, complex, and safety-critical scenarios such as autonomous driving, surveillance, and robotics.

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