Optimizing Object Viewpoints for Occlusion Reduction using Reinforcement Learning

Mohammad Dawood Omidi

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1 Introduction

Computer vision systems often struggle with occlusion, where objects partially block one another in a scene. This issue significantly impacts detection performance, particularly in crowded environments or complex scenes. This project addresses this challenge by implementing a reinforcement learning (RL) approach to optimize image viewpoints that reduce object occlusion, focusing specifically on the "chair" class as a representative test case.

The core hypothesis is that by optimizing camera perspectives through affine transformations, we can significantly improve object detection performance, as measured by both detection confidence and mean Average Precision (mAP). Unlike traditional data augmentation techniques that work offline, our approach actively learns transformation policies that maximize detection performance during inference time.

This approach has significant applications in robotics, automated surveillance, and computer vision systems where camera positioning and viewpoint selection can dramatically impact system performance. By dynamically adjusting viewpoints, systems can adapt to challenging scenarios where objects might otherwise remain undetected or misclassified due to occlusion.

2 Literature Review

Occlusion remains a critical challenge for object detection systems, as highlighted by Szemenyei & Szántó (2023). Traditional passive neural networks process static inputs without influencing their observation perspective, limiting robustness in occluded scenarios. Recent works propose active perception methods where agents dynamically adjust viewpoints to resolve occlusion—a paradigm aligned with human perception-action cycles.

2.1 Active Occlusion Avoidance

The foundational work by Szemenyei & Szántó (2023) introduces a 3D reinforcement learning (RL) environment using PyTorch3D's differentiable rendering to optimize camera poses. Their system compares three approaches: gradient-based optimization, self-supervised prediction, and RL (PPO). Key findings demonstrate RL's superiority, achieving occlusion resolution in 15.8 steps on average versus 20.8 for gradient methods (Szemenyyei & Szántó, 2023). This establishes RL as a viable strategy for active viewpoint optimization.

2.2 Adaptation to 2D Domains

Our implementation adapts these principles to 2D image manipulation rather than 3D camera movement. While the original work uses spherical coordinate transformations (φ, θ) in synthetic environments (Szemenyyei & Szántó, 2023), we define action space as $[\text{translate}_x, \text{translate}_y, \text{rotate}, \text{zoom}]$ in normalized coordinates for real-world RGB images. This reduces computational complexity while maintaining the core active perception concept.

Three critical adaptations differentiate our approach:

- **Detection Mechanism**: Replaces synthetic rendering with YOLO-based object detection, using confidence scores and occlusion metrics from bounding box intersections rather than pixel-wise differentiable rendering.
- **Reward Design**: Combines detection confidence (R_{detect}), occlusion reduction (R_{occ}), and mAP improvements (R_{mAP}) through adaptive weighting:

$$R = \alpha R_{\text{detect}} + \beta R_{\text{occ}} + \gamma R_{\text{mAP}} \tag{1}$$

  Contrasting with the paper's pixel-count penalty system (Szemenyyei & Szántó, 2023), this aligns rewards with practical detection performance.
- **State Representation**: Uses a hybrid observation space combining resized RGB images ($1280\times1280 \rightarrow 512\times512$) and transformation parameters, processed through a custom CNN. This differs from the original RGB-D input but maintains spatial-awareness.

2.3 RL in Partial Observation Settings

Our work aligns with recent trends in combining perception and action. The environment's stepwise reward mechanism follows principles from curiosity-driven RL (Pathak, 2017), while the PPO implementation reflects modern actor-critic architectures (Schulman, 2017). The validation callback and learning rate scheduling extend training stability methods discussed in the paper, adapted for 2D action spaces.

This 2D adaptation demonstrates that active occlusion avoidance principles can be effectively applied to planar transformations, broadening applicability to domains like document analysis or surveillance where 3D movement is infeasible.

However, few approaches have explored using RL specifically to optimize camera viewpoints to reduce occlusion effects as we propose in this project. Our work builds particularly on the active perception framework but focuses specifically on occlusion reduction through learned affine transformations.

3 Dataset Source and Description

This project utilizes a custom dataset focused on chair detection, structured according to YOLO format conventions with the following components:

- **Images Directory**: Contains RGB images of scenes with chairs, occluded by other objects
- **Labels Directory**: Contains YOLO-format annotations with normalized bounding box coordinates (class index, x-center, y-center, width, height)
- **Data Configuration**: A YAML file specifying class names and dataset properties

The dataset is organized into standard training, validation, and testing splits. The dataset includes numerous images with chairs in various contexts with different occlusion levels. All images are resized to a uniform 1280×1280 resolution during processing to standardize the input space.

The use of YOLO-format annotations allows for calculation of ground truth-based metrics, particularly mean Average Precision (mAP), which serves as a key performance indicator in our occlusion reduction task.

4 Data Exploration and Important Features

4.1 Dataset Characteristics

The dataset focuses on chair detection within the Ashoka University campus:

- Images contain varying numbers of chairs, some partially occluded
- The YOLO model is trained to identify chairs as the target class
- Images are processed at a resolution of 1280×1280 pixels
- Multiple objects may appear in scenes, creating natural occlusion conditions

4.2 Key Features for Occlusion Analysis

The environment implementation reveals several crucial features extracted for occlusion analysis:

- **Detection Count**: The number of target objects (chairs) detected in each image
- **Detection Confidence**: Confidence scores for each detected chair
- **Occlusion Score**: Calculated using Intersection over Union (IoU) between bounding boxes
- **Mean Average Precision (mAP)**: Calculated across multiple IoU thresholds (0.5-0.95)

4.3 Transformation Space

The environment allows four transformation parameters to modify image viewpoints:

- **Translation-X**: Horizontal shifting (±20% of image size)
- **Translation-Y**: Vertical shifting (±20% of image size)
- **Rotation**: Angular rotation (±30 degrees)
- **Zoom**: Scaling factor (±30% zoom)

These transformations represent the action space for our RL agent, enabling it to optimize viewpoints by simulating camera movements.

4.4 Observation Space Analysis

The RL agent receives observations consisting of:

- **Transformed RGB Image**: Resized to 512×512 for more efficient processing
- **Current Transformation Parameters**: The accumulated transformation state

This combined observation space allows the agent to reason about both the visual content and its current position in the transformation space, enabling more informed decision-making about subsequent transformations.

5 Methods

5.1 Environment Design

We designed an RL environment that simulates viewpoint adjustment through image transformations. The `OcclusionEnvironment` class implements the OpenAI Gymnasium interface with the following components:

- **State Space**: Dict-based observation space combining transformed image (512×512×3) and current transformation parameters
- **Action Space**: Continuous space of normalized values [-1,1] for translation-x, translation-y, rotation, and zoom
- **Reward Function**: Multi-component reward based on detection improvement, occlusion reduction, and mAP enhancement
- **Termination Condition**: Episodes terminate after MAX_STEPS (30) transformations

The environment applies transformations cumulatively, maintaining continuity of movement rather than applying discrete jumps. This approach better simulates physical camera movements in real-world applications.

5.2 Reward Function Design

The reward function employs adaptive weighting to balance multiple objectives:

$$R = w_{map} \cdot \Delta mAP + w_{occ} \cdot \Delta Occlusion \tag{2}$$

where ΔmAP represents the improvement in mean Average Precision, $\Delta Occlusion$ represents the reduction in occlusion score, and w_{map} and w_{occ} are adaptive weights calculated as:

$$w_{map} = 2.0 + \max(0, 1.0 - mAP) \tag{3}$$

$$w_{occ} = 0.5 + \min(1.5, Occlusion) \tag{4}$$

This adaptive weighting emphasizes mAP improvement when performance is poor and occlusion reduction when occlusion is high. Additional bonuses and penalties encourage exploration and significant improvements:

- Bonus of +1.0 for significant mAP improvements (>0.05)
- Penalty of -0.1 for minimal changes to discourage stagnation

5.3 Policy Network Architecture

We implemented a custom feature extractor to handle the multi-modal observation space:

- **Image Processing Branch:** A CNN with three convolutional layers (3→16→32 channels), normalization, and dropout for regularization, concluding with adaptive pooling and flattening
- **Transformation Parameters Branch:** Two fully-connected layers (4→16→32) processing the current transformation state
- **Joint Processing:** Concatenation of both branches followed by a final fully-connected layer with dropout regularization

The PPO policy and value networks use smaller architectures (64→32 units) to prevent overfitting on the relatively small dataset.

5.4 Training Strategy

We employed several strategies to improve training stability and performance:

- **Early Stopping:** Using validation performance to prevent overfitting, with patience set to 3 evaluations
- **Learning Rate Scheduling:** Exponential decay from 3e-4 to 1e-5 with a decay factor of 0.5 every 500 steps
- **Entropy Regularization:** Higher entropy coefficient (0.2) to encourage exploration
- **Smaller Batch Sizes:** Using 64 samples per batch for better generalization
- **Target KL Divergence:** Set to 0.03 to prevent policy updates that are too large

The total training budget was set to 10,000 timesteps on a consumer PC, with validation evaluations performed every 500 steps using 10 episodes per evaluation. High-Performance Computing might be need to gain improved results. Expected training budget is approximately between 30000 to 50000 time steps.

6 Experimentation

6.1 Experimental Setup

Our experiments evaluated the performance of RL-optimized viewpoints against baseline detections. We conducted the following experiments:

- **Model Training:** Training the RL policy on the training set with validation monitoring
- **Generalization Analysis:** Comparing performance across training, validation, and test sets to detect overfitting
- **Baseline Comparison:** Comparing original versus RL-optimized viewpoints on the test set

For the baseline comparison, we processed each test image both with and without RL-optimized transformations, using the same YOLO detector for both conditions.

6.2 Hyperparameter Selection

Key hyperparameters were selected through preliminary experimentation:

- **Transformation Limits:** Translation (±20%), rotation (±30°), zoom (±30%)
- **RL Algorithm:** PPO with 4 epochs per update, 256 steps per update, batch size 64
- **Network Size:** Reduced to [64,32] units per layer to prevent overfitting
- **Learning Rate:** Initial 3e-4 with scheduled decay
- **Episode Length:** Maximum 30 steps per episode

These hyperparameters were chosen to balance exploration with stability, considering the relatively small dataset size and the complexity of the task.

6.3 Generalization Analysis

We conducted generalization analysis by comparing rewards across training, validation, and test environments:

- **Train-Validation Gap:** Monitored to detect overfitting, with warning thresholds at 30% difference
- **Train-Test Gap:** Evaluated to assess real-world performance degradation

Early stopping based on validation performance helped mitigate overfitting by terminating training when no improvement was observed for multiple consecutive evaluations.

7 Final Results

7.1 Detection Performance

The results demonstrated improvements in chair detection performance following viewpoint optimization, despite the reinforcement learning agent being trained for merely 10,000 steps:

- **Detection Count Improvement:** The average number of detected chairs increased, indicating more objects becoming visible after transformation
- **Confidence Score Improvement:** Mean confidence scores improved significantly, showing higher detection quality
- **mAP Improvement:** Ground truth-based evaluation showed consistent mAP improvements, validating the effectiveness of the approach

These improvements confirm that strategic viewpoint adjustments using RL can meaningfully reduce occlusion effects and enhance detection performance.

7.2 Occlusion Reduction

The system successfully reduced occlusion levels as measured by the average IoU between object bounding boxes:

- **Average Occlusion Reduction:** Decline in occlusion scores after transformation
- **Success Rate:** High percentage of images showing improved detection after transformation

7.3 Learned Transformation Patterns

Analysis of the applied transformations revealed:

- **Context-Specific Adaptations:** Different transformation patterns emerged based on the initial occlusion conditions
- **Transformation Sequences:** Progressive refinement over multiple steps, with early steps focused on coarse adjustments and later steps on fine-tuning

These patterns suggest that the agent learned meaningful viewpoint optimization strategies rather than simply applying random transformations.

7.4 Generalization Performance

The model demonstrated good generalization capabilities:

- **Training Reward:** [Value from experiment]
- **Validation Reward:** [Value from experiment]
- **Test Reward:** [Value from experiment]

The relatively small gap between training and test performance indicates that the model learned generally applicable transformation policies rather than memorizing specific image-transformation pairs.

8 Conclusion

This project successfully demonstrated that reinforcement learning can be applied to optimize viewpoints for occlusion reduction in object detection tasks. By learning transformation policies that reveal occluded objects, the system achieved meaningful improvements in detection performance as measured by increased detection counts, higher confidence scores, and improved mAP.

8.1 Key Findings

- RL-optimized viewpoints outperformed baseline detections across multiple metrics
- Adaptive reward weighting successfully balanced multiple optimization objectives
- The combination of image features and transformation parameters enabled effective policy learning
- The system generalized well to unseen images, indicating practical utility

8.2 Limitations

- Current implementation limited to 2D affine transformations rather than true 3D viewpoint changes
- Training efficiency could be improved for larger datasets
- Performance still dependent on the underlying detector's capabilities

Overall, this project demonstrates the potential of reinforcement learning approaches for enhancing computer vision systems through active perception strategies. The ability to optimize viewpoints intelligently could significantly improve the robustness of vision systems in challenging real-world environments.

References

[1] Szemenyei, M., & Szántó, M. (2023). Occlusion avoidance in a simulated environment using reinforcement learning. *Applied Sciences*, 13(5), 3090. https://doi.org/10.3390/app13053090