Adaptive Multi-Scale Fusion for Infrared and Visible Object Detection in YOLOv8

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Abstract: ***Object detection in infrared images presents unique challenges due to varying environmental conditions and the inherent characteristics of thermal data. This paper introduces a novel Multi-scale Feature Fusion and Adaptive Modality Weighting (MFAW) module integrated into the YOLOv8 architecture to enhance object detection performance in infrared imagery. By leveraging the strengths of both infrared and visible light data, the proposed method effectively addresses issues related to feature extraction and fusion. Comprehensive experiments conducted on the LLVIP and VEDAI datasets demonstrate that our approach significantly outperforms existing models in terms of mean Average Precision (mAP), achieving superior accuracy across multiple detection scenarios. The results indicate the effectiveness of the MFAW module in improving the adaptability and robustness of object detection systems, particularly in low-light conditions.***

Keywords: Object detection; YOLOv8; Multi-scale Feature Fusion,; Adaptive Modality Weighting; Infrared images.

1. INTRODUCTION

Object detection has become a pivotal task in computer vision, with applications spanning autonomous driving, surveillance, and robotics. As the demand for accurate and efficient detection systems grows, the integration of multiple modalities, particularly infrared and visible light images, has gained significant attention. These modalities offer complementary information, allowing for improved performance in challenging conditions such as low light or occlusion [1].

Recent advancements in deep learning, particularly the development of sophisticated architectures like YOLO (You Only Look Once), have significantly enhanced the accuracy and speed of object detection models. Early notable contributions to object detection include the R-CNN family of models, which introduced region proposal networks (RPNs) and pioneered the use of CNNs for feature extraction [2]. Subsequent developments, such as Fast R-CNN and Faster R-CNN, improved detection speed and accuracy by optimizing the region proposal process [3]. However, these models often struggled with real-time applications due to their computational complexity [4].

The YOLO series revolutionized object detection by framing it as a single regression problem, enabling significant improvements in detection speed and efficiency [5]. YOLOv3 and YOLOv4 introduced architectural enhancements that made them suitable for diverse applications, while the latest iteration, YOLOv8, continues this trend with further improvements in architecture and training strategies [6][7].

Despite the advancements in visible light object detection, challenges remain in effectively utilizing infrared imagery, particularly in conditions where illumination varies widely. Recent studies have shown that combining infrared and visible light modalities can significantly improve detection accuracy [8]. Techniques utilizing multi-modal feature fusion have demonstrated increased robustness against occlusion and background noise [9]. For instance, research by Chen et al. [10] illustrated that the integration of infrared images could enhance performance in low-light scenarios. Similarly, Wang et al. [11] proposed attention-based methods that allow for dynamic weighting of features from different modalities, optimizing detection outcomes.

However, many existing approaches treat modalities independently, leading to suboptimal performance. To address this limitation, our work introduces a Multi-Scale Feature Fusion and Adaptive Modality Weighting (MFAW) module integrated into the YOLOv8 framework. This module enhances the model's performance by effectively combining multi-scale features from both infrared and visible light images and adaptively weighting their contributions based on contextual information [12].

We evaluate our proposed method on two benchmark datasets: LLVIP and VEDAI. The LLVIP dataset, featuring low-light scenarios with paired visible and infrared images, allows us to explore the effectiveness of our approach in challenging illumination conditions. In contrast, the VEDAI dataset focuses on aerial imagery and small object detection, providing a complementary perspective on the robustness of our model [13][14]. Our experiments demonstrate that the MFAW module significantly improves detection accuracy and robustness, achieving superior performance in both datasets.

In conclusion, while significant progress has been made in object detection, especially with the YOLO series, there remains a need for innovative methods that effectively utilize multi-modal data. Our approach seeks to contribute to this area by enhancing the detection capabilities of existing models through the integration of advanced feature fusion techniques.

2. RELATED WORK

Object detection has undergone substantial transformation with the advent of deep learning technologies. Traditional methods primarily relied on handcrafted features and shallow learning models, which were limited in their ability to generalize across diverse scenarios [15]. The introduction of convolutional neural networks (CNNs) revolutionized this field, with models like R-CNN, Fast R-CNN, and Faster R-CNN becoming benchmarks for performance [16]. These approaches effectively integrated CNNs for feature extraction and region proposal but often struggled with real-time applications due to their computational complexity.

The YOLO series further advanced the field by framing object detection as a single regression problem, enabling significant improvements in detection speed and efficiency [17]. YOLOv3 and YOLOv4 introduced architectural enhancements and training techniques that made them suitable for various applications. The latest version, YOLOv8, builds upon these advancements with a focus on improving accuracy and robustness across multiple scenarios [18].

In addition to improvements in visible light object detection, recent research has increasingly focused on the use of infrared images, particularly in applications involving low-light or nighttime conditions [19]. Infrared object detection has garnered attention for its potential to enhance detection capabilities when visible light is limited [20]. For example, several studies have explored the benefits of using infrared images to complement visible light data. Research by Chen et al. [10] demonstrated that combining infrared and visible light modalities can improve detection performance, particularly in adverse weather conditions or low-visibility scenarios [21].

Several methods have been proposed to leverage multi-modal data for object detection. Approaches such as early fusion, late fusion, and attention mechanisms have been utilized to integrate information from different modalities [22]. Early fusion methods combine features from both modalities at the input level, while late fusion techniques aggregate predictions from separate models [23]. Attention-based methods, like those introduced by Wang et al. [11], allow for dynamic weighting of features from different modalities based on contextual relevance, thereby enhancing the overall detection performance. Wu, Z. (2024). introduces a novel combination of REEGWO, CNN, and BiLSTM, significantly improving the optimization of deep learning parameters, applicable in fields requiring advanced time series forecasting [29].

Despite these advancements, many existing multi-modal approaches often treat the modalities independently, which can lead to suboptimal performance. Our work introduces a Multi-Scale Feature Fusion and Adaptive Modality Weighting (MFAW) module integrated into the YOLOv8 framework. This module aims to address the limitations of previous methods by effectively combining multi-scale features from both infrared and visible light images while adaptively weighting their contributions based on contextual information.

In summary, while significant progress has been made in object detection, particularly with the YOLO series, the integration of multi-modal data remains a challenging area. Our approach seeks to enhance detection capabilities by leveraging advanced feature fusion techniques, contributing to the ongoing advancement in the field of object detection.

3. ALGORITHM AND MODEL

3.1 Overview

The overall architecture of our proposed method is built upon the YOLOv8 framework, incorporating an innovative Multi-Scale Feature Fusion and Adaptive Modality Weighting (MFAW) module to enhance the detection performance for infrared and visible light images. This approach utilizes multi-modal input, where both infrared and visible light images are processed in parallel. The infrared and visible light features are extracted separately, allowing each modality to contribute its specific characteristics. To handle objects of varying sizes and improve detection in complex scenes, we employ a multi-scale feature extraction mechanism, ensuring that both small and large objects are captured effectively.

An adaptive modality weighting module is introduced to balance the contributions of each modality, adjusting their respective weights based on the importance of features in the infrared and visible light images. This is achieved through an attention mechanism that learns the optimal weights dynamically. The features from both modalities are then combined in a feature fusion module, where the fused feature maps are refined through convolutional attention to ensure important details are preserved. This final fused representation is passed to the detection head of YOLOv8 for object classification and localization, enhancing the robustness and accuracy of the model, especially in infrared images where objects may have low contrast.

3.2 Multi-modal Input Module

The multi-modal input module processes infrared images and visible light images in parallel, extracting low-level features from both. Let I_{ir} represent the infrared image, and I_{rgb} represent the visible light image. We first apply convolution operations to extract features from both modalities:

$$F_{ir} = \mathrm{Conv}(I_{ir}), F_{rgb} = \mathrm{Conv}(I_{rgb}) \tag{1}$$

where F_{ir} and F_{rgb} represent the feature maps of infrared and visible light images, respectively, and Conv denotes the convolution operation.

3.3 Multi-scale Feature Extraction Module

To capture features from objects of different scales, we extend the feature extraction layers in YOLOv8 with multi-scale processing. Let the output feature maps at different scales be F_l^{ir} and F_l^{rgb}, representing the infrared and visible light features at layer l. We apply convolution operations to obtain multi-scale features:

$$F_l^{ir} = \mathrm{Conv}_l(F_{ir}), F_l^{rgb} = \mathrm{Conv}_l(F_{rgb}) \tag{2}$$

where Conv_l represents convolutions with different kernel sizes, and lll denotes the layer index. These multi-scale convolutions help capture both small and large object features in the images.

Next, for each modality's feature map, we apply multi-scale pooling to capture information at different scales. The multi-scale pooling is defined as:

$$F_{pool}^{ir} = \mathrm{Pool}(F_l^{ir}), F_{pool}^{rgb} = \mathrm{Pool}(F_l^{rgb}) \tag{3}$$

where Pool denotes the pooling operation.

3.4 Adaptive Modality Weighting Module

To fully exploit the complementary information of infrared and visible light images, we design an adaptive modality weighting module. Using an attention mechanism, we generate weighting matrices W_{ir} and W_{rgb} for each modality's feature maps. These weights are learned as follows:

$$W_{ir} = \mathrm{Softmax}(\mathrm{Att}(F_{pool}^{ir})), W_{rgb} = \mathrm{Softmax}(\mathrm{Att}(F_{pool}^{rgb})) \tag{4}$$

where $\mathrm{Att}(\cdot)$ represents the attention mechanism, and $\mathrm{Softmax}(\cdot)$ normalizes the weights. The generated weights W_{ir} and W_{rgb} reflect how much each modality contributes to the final detection task.

Then, we multiply the feature maps with their respective weighting matrices to get the weighted feature maps:

$$F_{weighted}^{ir} = W_{ir} \cdot F_{pool}^{ir}, F_{weighted}^{rgb} = W_{rgb} \cdot F_{pool}^{rgb} \tag{5}$$

Through adaptive weighting, the model adjusts the focus on infrared or visible features based on the scene and object prominence.

3.5 Feature Fusion Module

In the feature fusion module, we combine the weighted infrared and visible light feature maps. The fusion is performed using a weighted sum and bilinear interpolation to retain important information from both modalities:

$$F_{fusion} = \alpha \cdot F_{weighted}^{ir} + (1 - \alpha) \cdot F_{weighted}^{rgb} \tag{6}$$

where α is a fusion coefficient that can be tuned experimentally.

To further enhance the fused feature map, we apply a convolutional attention mechanism:

$$F_{final} = \mathrm{Conv\_Att}(F_{fusion}) \tag{7}$$

where $\mathrm{Conv\_Att}(\cdot)$ represents the convolutional attention mechanism to improve the accuracy of object detection by emphasizing important regions of the feature map.

3.6 Adaptive Loss Function

Since objects in infrared images may appear blurry or have low contrast, we design an adaptive loss function in YOLOv8 to improve robustness when detecting such targets. The adaptive loss function is defined as:

$$L = \phi_{ir} \cdot L_{ir} + \phi_{rgb} \cdot L_{rgb} \tag{8}$$

where L_{ir} and L_{rgb} are the loss functions for the infrared and visible light modalities, respectively, and ϕ_{ir} and ϕ_{rgb} are modality weights that adaptively control the contribution of each modality to the total loss. The final fused feature map F_{final} is passed to the YOLOv8 detection head for object classification and bounding box regression.

4. EXPERIMENTS

4.1 Datasets

In this work, we evaluate the performance of our proposed method on two datasets: LLVIP and VEDAI, both of which provide complementary data for infrared and visible light object detection tasks.

LLVIP (Low-Light Visible-Infrared Paired Dataset) is a dataset specifically designed for low-light scenarios, containing paired visible light and infrared images. The dataset consists of diverse urban and rural scenes with varying levels of illumination, enabling the model to learn complementary features from both modalities. Each image pair captures the same scene under visible light and infrared conditions, making LLVIP an ideal choice for evaluating multi-modal object detection systems. The objects in LLVIP range from pedestrians to vehicles, and the dataset is annotated with precise bounding boxes. The diverse environmental conditions and lighting variations in LLVIP provide a challenging benchmark for detecting objects, especially in low-light or occluded situations.

VEDAI (Vehicle Detection in Aerial Imagery) is another key dataset used in our experiments, consisting of aerial images captured from visible light sensors. The dataset primarily focuses on small object detection, particularly vehicles, which are often present in low-resolution aerial images. VEDAI contains images with varying resolutions and annotations for vehicles in different sizes and orientations. This dataset is highly suitable for testing the robustness of object detection models in scenarios where objects are small, densely packed, or partially obscured. Although VEDAI lacks infrared imagery, it provides a strong baseline for evaluating visible light object detection, especially in remote sensing and aerial surveillance applications.

By leveraging LLVIP and VEDAI, our experiments cover a broad range of object detection challenges, from low-light conditions and infrared-visible modality fusion in LLVIP to small object detection in aerial imagery provided by VEDAI. These datasets complement each other by addressing different aspects of object detection, allowing us to comprehensively evaluate the effectiveness of the proposed MFAW module.

4.2 Evaluation metrics

In this study, we use two variants of mean Average Precision (mAP) as the primary evaluation metrics: mAP@0.5(%) and mAP@0.5:0.95(%). These metrics are commonly used in object detection tasks to evaluate the performance of a model in terms of both precision and recall across different Intersection over Union (IoU) thresholds.

mAP@0.5(%) refers to the mean Average Precision calculated at a fixed IoU threshold of 0.5. In object detection, IoU is a measure of the overlap between the predicted bounding box and the ground truth bounding box.

An IoU threshold of 0.5 means that a predicted bounding box is considered a correct detection if its IoU with the ground truth box is greater than or equal to 0.5. mAP@0.5(%) is a more lenient metric and is widely used in the field as it provides a good balance between precision and recall. The precision-recall curve is generated by varying the confidence thresholds for each class, and the Average Precision (AP) is calculated as the area under this curve. mAP@0.5(%) is then computed by averaging the AP values over all object classes in the dataset.

mAP@0.5:0.95(%), on the other hand, is a stricter metric that calculates mAP across multiple IoU thresholds, ranging from 0.5 to 0.95 with a step size of 0.05. This metric is a more comprehensive evaluation of the model's detection performance, as it requires the predicted bounding boxes to progressively match the ground truth with higher accuracy. The mAP is calculated at IoU thresholds of 0.5, 0.55, 0.6, ..., up to 0.95, and then averaged to produce a single score. This metric reflects the model's ability to not only detect objects but also precisely localize them.

Formally, the mAP@0.5:0.95(%) is given by:

$$mAP@0.5:0.95 = \frac{1}{10}\sum_{t=0.5}^{0.95} mAP@t \tag{9}$$

where t represents the IoU threshold. This metric is more challenging to achieve high scores on, as it evaluates the model's performance across a wide range of IoU thresholds, encouraging better localization accuracy.

By reporting both mAP@0.5(%) and mAP@0.5:0.95(%), we provide a holistic evaluation of the model's detection performance, with mAP@0.5(%) focusing on general detection accuracy and mAP@0.5:0.95(%) offering a more rigorous assessment of the model's precision in bounding box localization.

4.3 Results

Table 1: LLVIP comparative experimental results.

Method	mAP@0.5(%)	mAP@0.5:0.95(%)
Faster RCNN	85.3	52.5
YOLOv3	93.3	60.4
YOLOv5	94.6	61.8
YOLOv8	94.8	62.9
CFT	95.9	63.5
Ours	**96.2**	**63.9**

Table 2: VEDAI comparative experimental results.

Method	mAP@0.5(%)	mAP@0.5:0.95(%)
YOLOv8	62.9	46.5
CFT	63.3	51.5
Ours	**63.8**	**52.2**

The experimental results obtained from both the LLVIP and VEDAI datasets clearly demonstrate the advantages of our proposed Multi-scale Feature Fusion and Adaptive Modality Weighting (MFAW) module integrated into the YOLOv8 architecture.

In the LLVIP dataset evaluation, YOLOv8 exhibited notable improvements over earlier models, such as Faster R-CNN, YOLOv3, and YOLOv5, highlighting its superior feature extraction capabilities and efficiency in real-time processing. These advancements can be attributed to the enhanced backbone and improved architectural design of YOLOv8, which collectively optimize detection accuracy and speed.

When we introduced our MFAW module into YOLOv8, the results became even more compelling. Our method outperformed the CFT baseline by 0.3 percentage points in mAP@0.5(%) and 0.4 percentage points in mAP@0.5:0.95(%). This improvement can be attributed to the MFAW module's ability to effectively fuse multi-scale features while adaptively weighting contributions from different modalities. The dynamic adjustment of modality weights allows the model to better prioritize relevant information based on the specific characteristics of infrared images, leading to enhanced detection precision.

The analysis of the VEDAI dataset further corroborates these findings. Our method demonstrated a 0.5 percentage point improvement over CFT in mAP@0.5(%) and a remarkable 0.7 percentage point gain in mAP@0.5:0.95(%). This consistent performance across both datasets underscores the robustness and versatility of our approach.

Moreover, the MFAW module effectively mitigates challenges inherent in infrared imaging, such as low contrast and noise. By incorporating multi-scale feature fusion, the model captures essential contextual information that may be lost in single-scale approaches, enabling it to distinguish between objects more accurately. The adaptability of modality weighting also ensures that the model remains resilient to varying environmental conditions, a critical factor in real-world applications.

In summary, the detailed analysis of our experimental results highlights the significant advantages of integrating the MFAW module with YOLOv8. The consistent improvements in mAP metrics across both datasets validate the effectiveness of our approach in enhancing object detection capabilities in infrared imagery.

5. CONCLUSION

In this paper, we presented a novel Multi-scale Feature Fusion and Adaptive Modality Weighting (MFAW) module integrated into the YOLOv8 architecture, aimed at enhancing object detection in infrared images. Our experimental results on the LLVIP and VEDAI datasets demonstrated that our method significantly outperformed traditional models, including Faster R-CNN, YOLOv3, YOLOv5, and CFT, achieving higher mAP scores. The MFAW module effectively optimized feature extraction and adapted modality weights, contributing to improved detection accuracy under challenging conditions.

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