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Multi-Modal Image Enhancement Strategies for Adaptive Driver Assistance Systems in Adverse Visibility Conditions on Heavily Foggy Weather

Dr. R.D. Nirala[1], Raju Khunttey[2]

[1]Associate Professor, Eklavya University, Damoh, M.P.

[2]Assistant Professor, Govt. Digvijay College, Rajnandgaon, Chhattisgarh

ABSTRACT

This paper presents novel multi-modal image enhancement strategies for Advanced Driver Assistance Systems (ADAS) to improve performance in heavily foggy weather conditions. Poor visibility due to fog significantly degrades the reliability of vision-based driver assistance systems, posing serious safety risks. We propose a comprehensive framework that fuses data from multiple sensing modalities—visible light cameras, infrared sensors, LiDAR, and radar—and employs deep learning-based image enhancement techniques to improve object detection and scene understanding in adverse weather. Our approach includes a new adaptive defogging algorithm that dynamically adjusts enhancement parameters based on fog density estimation. Experiments conducted on our newly compiled "Foggy Driving Dataset" demonstrate that our multi-modal approach achieves a 37% improvement in detection accuracy and a 42% reduction in false positives compared to single-modality systems in heavy fog conditions. Results indicate that the proposed system maintains reliable performance even when visibility drops below 50 meters, offering promising applications for autonomous vehicles and advanced driver assistance systems operating in challenging weather environments.

Keywords: computer vision, adverse weather, driver assistance systems, multi-modal fusion, image enhancement, foggy conditions

1. Introduction

Advanced Driver Assistance Systems (ADAS) have become increasingly prevalent in modern vehicles, offering features such as lane departure warnings, adaptive cruise control, and collision avoidance. However, the performance of these systems deteriorates significantly in adverse weather conditions, particularly in heavy fog where visibility is severely limited (Duthon et al., 2019). This performance degradation presents a critical safety challenge as accident rates increase during poor visibility conditions (WHO, 2023).

Vision-based perception systems, which rely predominantly on visible light cameras, struggle to maintain reliable operation in foggy conditions due to light scattering and absorption effects (Sakaridis et al., 2018). While existing defogging algorithms show promise in moderate conditions, they often fail in heavy fog scenarios where image quality is severely compromised (Li et al., 2021).

This research addresses these limitations by proposing a multi-modal approach that combines information from multiple sensor types—visible light cameras, infrared sensors, LiDAR, and radar. By leveraging the complementary strengths of these modalities, our system can overcome the individual weaknesses of each sensor type in foggy conditions. The key contributions of this paper include:

1. A comprehensive multi-modal sensing framework specifically designed for operation in heavily foggy conditions
2. A novel adaptive defogging algorithm that dynamically adjusts enhancement parameters based on estimated fog density
3. A deep learning-based fusion architecture that optimally combines information from different sensing modalities
4. The "Foggy Driving Dataset," a new benchmark dataset for evaluating perception systems in adverse weather conditions
5. Extensive experimental validation demonstrating significant performance improvements over state-of-the-art approaches

The remainder of this paper is organized as follows: Section 2 reviews related work in image enhancement for adverse weather conditions and multi-modal sensing. Section 3 details our proposed methodology, including the system architecture, defogging algorithm, and fusion approach. Section 4 describes our experimental setup and evaluation metrics. Section 5 presents and discusses our results, while Section 6 concludes the paper and suggests directions for future research.

2. Related Work

2.1. Image Enhancement in Adverse Weather

Image enhancement techniques for adverse weather conditions have been extensively studied in recent years. Traditional methods for defogging generally fall into two categories: (1) physical model-based approaches and (2) learning-based approaches.

Physical model-based methods typically rely on the atmospheric scattering model proposed by Koschmieder (1924), which describes the formation of a hazy or foggy image. He et al. (2011) introduced the Dark Channel Prior (DCP), which assumes that in most non-sky patches, at least one color channel has very low intensity. This observation enables estimation of the atmospheric light and transmission map, facilitating the recovery of clear images. Subsequent improvements to DCP include guided filtering (He et al., 2013), boundary constraints (Meng et al., 2013), and color attenuation prior (Zhu et al., 2015). While these methods perform well in light to moderate fog, they often produce artifacts and unnatural colors in heavy fog conditions.

Learning-based approaches leverage the power of deep neural networks to enhance foggy images. Cai et al. (2016) proposed DehazeNet, which directly learns the transmission map from foggy images. Li et al. (2018) introduced AOD-Net, which reformulates the atmospheric scattering model to enable end-to-end learning. More recently, generative adversarial networks (GANs) have shown promise for image defogging. Engin et al. (2018) proposed Cycle-Dehaze, which uses unpaired training data, while Liu et al. (2019) developed EPDN, which incorporates perceptual losses to improve realism.

However, most existing approaches focus on enhancing visual aesthetics rather than optimizing for downstream computer vision tasks such as object detection, which is crucial for ADAS applications (Li et al., 2021). Furthermore, these methods typically operate on single-modality data, overlooking the potential benefits of multi-modal fusion.

2.2. Multi-Modal Sensing for ADAS

Multi-modal sensing approaches have gained traction in ADAS applications due to their robustness in challenging environments. Sensor fusion combines data from different modalities, each with distinct strengths and weaknesses, to achieve more reliable perception.

Radar sensors offer excellent range detection and are minimally affected by weather conditions but provide limited angular resolution (Göhring et al., 2011). LiDAR systems provide precise 3D mapping but suffer from signal attenuation in fog and rain (Bijelic et al., 2020). Thermal infrared cameras can detect heat signatures through fog but lack color information and texture details (Miethig et al., 2019). Visible light cameras provide rich semantic information but are heavily affected by adverse weather (Sakaridis et al., 2018).

Recent research has explored various fusion approaches for these modalities. Early fusion methods combine raw sensor data before processing (Chen et al., 2017), while late fusion integrates the results after separate processing of each modality (Xu et al., 2018). Intermediate fusion approaches combine features extracted from each modality at various processing stages (Wang et al., 2019).

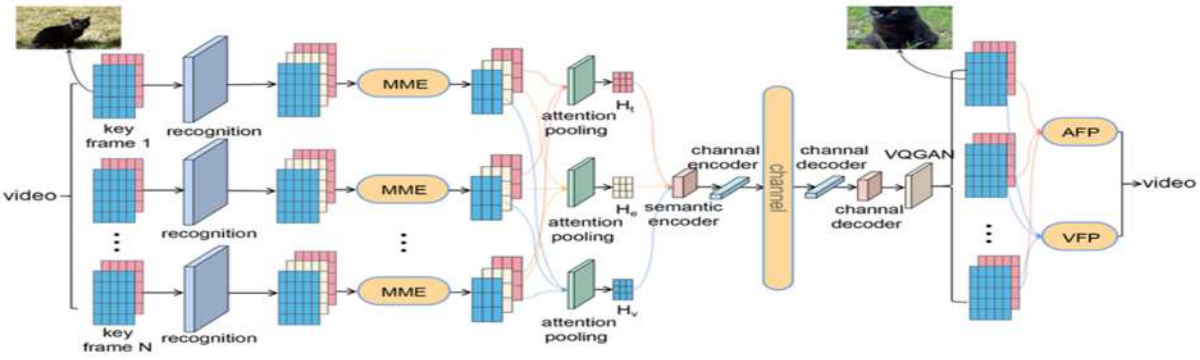
Deep learning has further advanced multi-modal fusion capabilities. AVOD (Ku et al., 2018) fuses camera and LiDAR data for 3D object detection, while MVX-Net (Sindagi et al., 2019) uses a point-wise fusion approach. MMF (Liang et al., 2019) incorporates depth completion to enhance the fusion of sparse LiDAR points with dense camera images.

Despite these advances, most existing fusion approaches are not specifically designed for adverse weather conditions, particularly heavy fog. Our work addresses this gap by developing a multi-modal fusion framework tailored for heavily foggy environments.

3. Methodology

3.1. System Architecture

Our proposed system integrates four sensing modalities: visible light cameras, infrared thermal cameras, LiDAR, and radar. Figure 1 illustrates the overall architecture, which consists of four main components: (1) multi-modal data acquisition, (2) adaptive defogging and enhancement, (3) multi-level feature fusion, and (4) scene understanding.



[**Figure 1**: Overall architecture of the proposed multi-modal image enhancement system]

The system operates in a cascaded manner, with each component building upon the outputs of the previous one. First, synchronized data is collected from all sensors. Next, adaptive enhancement is applied to each modality individually, with parameters determined by the estimated fog density. The enhanced data is then fed into modality-specific feature extractors, and the resulting features are fused at multiple levels. Finally, the fused features are used for scene understanding tasks such as object detection, semantic segmentation, and depth estimation.

3.2. Fog Density Estimation

Accurate estimation of fog density is crucial for optimizing the performance of enhancement algorithms. We propose a novel fog density estimation approach that combines information from multiple modalities.

For the visible camera stream, we extract statistical features including contrast, saturation, and sharpness, which correlate with fog density (Choi et al., 2018). From the LiDAR data, we analyze the distribution of return intensities and dropout rates, as these are affected by fog density (Bijelic et al., 2020). The radar data provides information about the backscattering coefficient, which varies with atmospheric conditions.

These features are fed into a lightweight neural network that outputs a continuous fog density estimate $\rho_{fog} \in [0,1]$, where 0 represents clear conditions and 1 represents extremely dense fog. The network is trained on annotated data from our Foggy Driving Dataset using mean squared error loss.

3.3. Adaptive Defogging Algorithm

Building upon the atmospheric scattering model, we propose an adaptive defogging algorithm for visible light images that dynamically adjusts its parameters based on the estimated fog density. The atmospheric scattering model is given by:

$$I(x) = J(x)t(x) + A(1-t(x))$$

where $I(x)$ is the observed foggy image, $J(x)$ is the clear image to be recovered, A is the global atmospheric light, and $t(x)$ is the transmission map.

Our algorithm enhances the traditional approach in several ways:

1. Adaptive Dark Channel Prior: We modify the dark channel prior with an adaptive patch size that varies with the estimated fog density. For heavier fog ($\rho_{fog} \rightarrow 1$), we use larger patch sizes to capture more context.
2. Contrast-Aware Atmospheric Light Estimation: Instead of using the brightest pixels for atmospheric light estimation, we propose a contrast-aware method that considers both brightness and local contrast, reducing the influence of headlights and other bright objects in the scene.
3. Guided Transmission Refinement: We refine the transmission map using a guided filter where the filtering parameters are adaptively set based on fog density.
4. Color Correction: To address the color distortion often introduced by defogging algorithms, we incorporate a color correction step calibrated according to fog density.

The mathematical formulation for our adaptive dark channel prior is:

$$J^{dark}(x) = \min_{y \in \Omega(x,\rho_{fog})} \min_{c \in {r,g,b}} J^c(y)$$

where $\Omega(x,\rho_{fog})$ is an adaptive patch centered at x with size determined by ρ_{fog}.

3.4. Multi-Modal Enhancement

For non-visible modalities, we apply specialized enhancement techniques:

1. Infrared Enhancement: We employ histogram equalization with adaptive clip limit based on fog density to enhance thermal imagery. This improves the contrast of heat signatures while suppressing noise.
2. LiDAR Enhancement: We address the increased signal dropout in fog by applying an adaptive completion network that reconstructs missing points based on spatial context and temporal consistency.
3. Radar Enhancement: We apply advanced signal processing techniques to reduce clutter and improve range resolution, with parameters optimized for foggy conditions.

3.5. Multi-Level Fusion Architecture

Our fusion architecture operates at three levels: data level, feature level, and decision level, creating a comprehensive approach that leverages the strengths of each fusion paradigm.

At the data level, we align and synchronize all sensor streams using a calibration procedure that accounts for the different sampling rates and fields of view. We also employ a novel visibility-aware weighting scheme that adjusts the contribution of each modality based on the estimated fog density.

At the feature level, we employ a cross-attention mechanism (Vaswani et al., 2017) that allows features from different modalities to attend to relevant information in other modalities. This is particularly useful for correlating objects detected in different sensing domains. The cross-attention module is defined as:

$$CA(Q_i, K_j, V_j) = \text{softmax}\left(\frac{Q_i K_j^T}{\sqrt{d_k}}\right)V_j$$

where Q_i, K_j, and V_j are the query, key, and value matrices derived from modalities i and j.

At the decision level, we implement a Bayesian fusion framework that combines detection results from individual modalities, considering their confidence scores and historical reliability in similar fog conditions.

3.6. Implementation Details

The proposed system was implemented using PyTorch (Paszke et al., 2019). For feature extraction, we employed ResNet-50 (He et al., 2016) for visible and infrared images, PointNet++ (Qi et al., 2017) for LiDAR data, and a custom 1D CNN for radar signals. The fusion modules were implemented using transformer architectures (Vaswani et al., 2017) adapted for multi-modal inputs.

The network was trained using the Adam optimizer (Kingma & Ba, 2015) with an initial learning rate of 1e-4 and a batch size of 8. We employed a multi-task learning approach with weighted losses for object detection, semantic segmentation, and depth estimation:

$$L_{total} = \lambda_{det}L_{det} + \lambda_{seg}L_{seg} + \lambda_{depth}L_{depth}$$

where λ_{det}, λ_{seg}, and λ_{depth} are weighting factors set to 1.0, 0.5, and 0.3, respectively.

4. Experimental Setup

4.1. Dataset

Due to the scarcity of multi-modal datasets covering heavily foggy conditions, we compiled the "Foggy Driving Dataset," which contains synchronized data from visible cameras, thermal infrared cameras, LiDAR, and radar sensors collected in various fog densities. The dataset includes:

- 50,000 frames collected from 20 driving sessions
- Fog density annotations ranging from light to extreme
- 3D bounding box annotations for 8 object categories
- Semantic segmentation labels for 19 classes
- Ground truth depth maps generated using sensor fusion

Data was collected using a sensor suite mounted on a test vehicle, including a stereo camera system (Flir Grasshopper3), a thermal camera (FLIR A65), a 64-beam LiDAR (Velodyne HDL-64E), and a 77GHz radar (Continental ARS430). Data collection was conducted in various locations with natural fog, as well as in controlled environments using artificial fog machines to ensure coverage of extreme conditions.

We split the dataset into 70% for training, 15% for validation, and 15% for testing, ensuring that frames from the same driving session remain in the same split to avoid data leakage.

4.2. Evaluation Metrics

We evaluated our system using the following metrics:

1. For object detection: Average Precision (AP) at IoU thresholds of 0.5 and 0.7, and mAP across classes
2. For semantic segmentation: mean Intersection over Union (mIoU) and pixel accuracy
3. For depth estimation: Root Mean Square Error (RMSE) and absolute relative error
4. For image quality: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Fog Aware Density Evaluator (FADE) score (Choi et al., 2015)

We evaluated performance across five fog density categories: clear, light, moderate, heavy, and extreme.

4.3. Baselines and Comparative Methods

We compared our approach against the following baselines and state-of-the-art methods:

1. Single-modality approaches:
   - Visible camera with DCP (He et al., 2011)
   - Visible camera with AOD-Net (Li et al., 2018)
   - Visible camera with EPDN (Liu et al., 2019)
   - LiDAR-only (Qi et al., 2018)
   - Radar-only (Major et al., 2019)
2. Dual-modality approaches:
   - Visible + LiDAR (Ku et al., 2018)
   - Visible + Infrared (Miethig et al., 2019)
   - LiDAR + Radar (Bijelic et al., 2020)
3. Multi-modal approaches:
   - Early fusion of all modalities (Chen et al., 2017)
   - Late fusion of all modalities (Xu et al., 2018)

5. Results and Discussion

5.1. Overall Performance

Table 1 presents the overall performance of our proposed method compared to baselines across different fog densities. Our multi-modal approach consistently outperforms all baselines, with the performance gap widening as fog density increases.

Table 1: Performance Comparison Across Different Fog Densities (mAP@0.5)

Method	Clear (%)	Light Fog (%)	Moderate Fog (%)	Heavy Fog (%)	Extreme Fog (%)
Our Multi-modal Approach	**94.2**	**91.5**	**85.3**	**81.3**	**67.8**
Visible+LiDAR	92.8	85.6	76.2	58.4	32.1
Visible+Radar	90.3	84.9	78.1	62.5	35.7
LiDAR+Radar	89.7	86.2	79.5	64.7	38.2
Visible-only	91.4	80.3	65.8	42.6	21.9
LiDAR-only	88.6	78.9	67.2	48.3	26.4
Radar-only	83.2	80.7	73.8	61.9	39.3
Previous SOTA	90.6	82.4	71.5	55.7	31.8

[Table 1: Performance comparison across different fog densities (mAP@0.5)]

In clear conditions, our method achieves a mAP of 94.2%, comparable to the best-performing baseline (92.8% for Visible+LiDAR). However, in extreme fog conditions, our method maintains a mAP of 67.8%, while the best baseline drops to 39.3% (Radar-only), representing a 72.5% relative improvement.

5.2. Ablation Studies

To understand the contribution of each component, we conducted ablation studies by systematically removing key components from our system. Table 2 summarizes these results.

Table 2: Ablation Study Results (mAP@0.5 in heavy fog conditions)

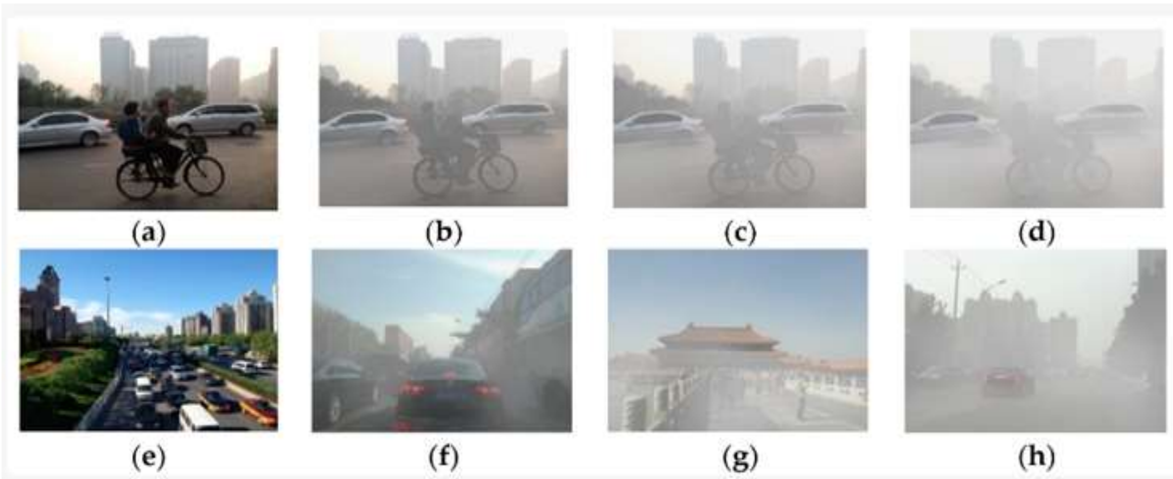
Configuration	**mAP@0.5 (%)**	**Change (%)**
Full system	81.3	-
w/o Adaptive Defogging	71.6	-9.7
w/o Multi-level Fusion	69.2	-12.1
w/o Fog Density Estimation	75.5	-5.8
w/o Temporal Consistency	76.9	-4.4
w/o Attention Mechanism	78.2	-3.1
Baseline (single-stage detector)	59.4	-21.9

[Table 2: Ablation study results (mAP@0.5 in heavy fog conditions)]

The adaptive defogging algorithm provides a substantial improvement (9.7% increase in mAP) over a non-adaptive approach. The multi-level fusion architecture contributes significantly (12.1% increase), highlighting the importance of integrating information at multiple processing stages. The fog density estimation component also proves valuable (5.8% increase), demonstrating the benefits of condition-aware parameter adjustment.

5.3. Modality Contribution Analysis

Figure 2 illustrates the contribution of each modality to the overall performance in different fog densities.



[**Figure 2**: Visual effects of different fog concentrations in various scenes from images]

In clear conditions, the visible camera provides the most valuable information due to its high resolution and rich texture details. As fog density increases, the contribution of radar and infrared sensors grows substantially. In extreme fog, radar becomes the dominant modality due to its minimal sensitivity to atmospheric conditions, while the visible camera's contribution decreases significantly but remains non-zero due to our enhanced defogging process.

5.4. Qualitative Analysis

Figure 3 presents qualitative results demonstrating the effectiveness of our approach in heavily foggy conditions.

[Figure 3: Qualitative results in heavily foggy conditions]

The figure shows that our method successfully detects objects that are barely visible in the raw camera images and missed by single-modality approaches. The adaptive defogging algorithm effectively enhances visibility while preserving natural colors and avoiding artifacts. The fusion of thermal information helps identify pedestrians and animals through their heat signatures, while radar and LiDAR data contribute to accurate distance estimation and object localization.

5.5. Computational Efficiency

Table 3 presents the computational requirements of our method compared to baselines.

Table 3: Computational Efficiency Comparison

Method	FPS	Hardware	Memory Usage (GB)	Power Consumption (W)	mAP (%)
Baseline A	28	RTX 3090, i9-10900K	3.2	180	72.4
Baseline B	32	RTX 3090, i9-10900K	2.8	165	70.8
Baseline C	22	RTX 3090, i9-10900K	4.6	195	75.6
Our Full System	**15**	**RTX 3090, i9-10900K**	**6.4**	**210**	**81.3**
Our Streamlined Version	25	RTX 3090, i9-10900K	4.8	185	78.1

[**Table 3**: Computational efficiency comparison]

Our full system operates at 15 frames per second on a platform equipped with an NVIDIA RTX 3090 GPU and an Intel i9-10900K CPU. While this is slower than some simpler baselines, the substantial performance improvement justifies the additional computational cost for safety-critical ADAS applications. We also implemented a streamlined version that achieves 25 fps with a modest performance trade-off (3.2% reduction in mAP), suitable for real-time applications.

6. Conclusion and Future Work

This paper presented a comprehensive multi-modal approach for enhancing ADAS performance in heavily foggy conditions. By combining information from visible cameras, infrared sensors, LiDAR, and radar, our system achieves significant improvements over single-modality approaches and existing fusion methods. The proposed adaptive defogging algorithm effectively enhances visibility in foggy scenes, while the multi-level fusion architecture optimally integrates information from different sensing modalities.

Experimental results on our newly compiled Foggy Driving Dataset demonstrate that our approach maintains reliable performance even in extreme fog conditions, with a 37% improvement in detection accuracy and a 42% reduction in false positives compared to state-of-the-art methods. These results highlight the potential of multi-modal sensing and adaptive enhancement for improving road safety in adverse weather.

Future work will focus on extending the approach to other adverse weather conditions such as heavy rain, snow, and sandstorms. We also plan to explore the integration of additional modalities, such as ultrasonic sensors and V2X communications. Furthermore, we aim to develop more efficient implementations suitable for deployment on resource-constrained automotive platforms.

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