FOG REMOVAL FROM HAZY IMAGES TO IMPROVE OBJECT DETECTION

PHASE 1: LITERATURE REVIEW AND PROPOSAL

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Literature Review:

Vision based perception in hazy and foggy environments remains a significant bottleneck for reliable deployment of object detection systems in real world scenarios. Traditional single image dehazing methods although they are capable of improving perceptual visibility but often fail to enhance and may even degrade downstream high level tasks due to their emphasis on low level restoration metrics such as PSNR and SSIM. Recent studies increasingly argue that dehazing must be rethought as a *task driven* or *domain adaptive* process that explicitly accounts for detection robustness under adverse weather conditions. The emerging body of work can be categorized into three converging lines of research: detection friendly dehazing, physics and depth informed domain adaptation and joint dehazing detection optimization.

Li *et al.*'s TPAMI work represents a major step in task-driven restoration with the introduction of BAD-Net, a detection friendly dehazing framework that integrates self supervised haze robust losses and iterative data refinement to benefit object detection in real hazy scenes [1]. Using RTTS, VOChaze, and synthetic Cityscapes based hazy datasets, BAD Net demonstrates consistent mAP improvements over conventional pipelines in which generic dehazing is followed by a detector. Their findings highlight the inadequacy of dehazing algorithms that optimize only for visual clarity, reinforcing evidence from Demir *et al.*'s recent evaluation study which shows that many classical and deep dehazing algorithms improve image quality while harming detection or tracking performance [10]. Such results motivate the broader shift toward task aware and jointly trained architectures.

A parallel direction leverages **unsupervised domain adaptation (UDA)** to bridge the distribution gap between clear weather training sets and adverse weather test domains. Sindagi *et al.* propose a physics-aware UDA approach that embeds weather priors into a prior adversarial training objective, supported by residual feature recovery modules to handle haze and rain [2]. Evaluations on Foggy Cityscapes, Rainy Cityscapes, RTTS, and UFDD show notable mAP gains over conventional UDA baselines. Yang *et al.* extend this paradigm by incorporating depth consistency, fog transmission modeling, and background reconstruction losses into the adaptation pipeline [3]. By enforcing geometric and atmospheric constraints their method preserves scene structure under synthetic and real fog, producing more reliable object detection results and demonstrating 3+ mAP improvement over previous DA techniques. Relatedly, the FIFO framework, although developed for semantic segmentation, introduces fog pass filter modules that generate fog-invariant features across varying densities, providing concepts transferable to detection backbones [4].

A third and increasingly influential line of inquiry explores **joint or tightly coupled dehazing detection frameworks**. Morales *et al.* investigate efficient dehazing for real time vision systems through feature forwarding modules illustrating that lightweight designs can integrate seamlessly with detection pipelines without large computational overhead [5]. Qiu *et al.* propose IDOD YOLOv7 wherein an AOD style defogger and a SAIP enhancement module are trained jointly with a YOLOv7 detector to improve precision recall performance in foggy traffic scenes [6]. In the safety domain, Liu *et al.* introduce DST-DETR, combining a PAOD Net dehazer with a DETR style detector for helmet detection in foggy construction imagery, achieving near real time operation while outperforming detector-only baselines [7].

Recent task driven frameworks emphasize **mutual guidance** between restoration and detection. FriendNet explicitly couples dehazing and detection through shared guidance maps and joint losses, showing improved robustness over pre-processing-based approaches [8]. Similarly, DDNet introduces detection-oriented architectural and loss-level modifications, demonstrating that dehazing networks trained with detection supervision can outperform general-purpose models such as FFA-Net [11], HardGAN [12], and DehazeFormer [13] when evaluated on Foggy-Cityscapes, RTTS, and related benchmarks [9].

Collectively, these advances illustrate a decisive shift from traditional image centric dehazing toward task-driven, domain-adaptive, and jointly optimized approaches. Physics-informed priors, depth cues, fog-invariant representations, and cross task coupling all contribute to improved robustness of object detectors operating in degraded visual conditions. The literature strongly suggests that designing dehazing modules in isolation is insufficient; instead, effective hazy scene object detection requires integrating restoration objectives with semantic-level constraints. This trend provides a foundation for developing next-generation dehazing frameworks explicitly tailored to maximize downstream detection performance in real-world hazy environments.

Review & Feasibility Note — Image Fog Removal

I. Introduction

Image fog removal aims to restore scene visibility degraded by atmospheric scattering, enabling more reliable perception in outdoor environments. This task is critical for embedded systems deployed in traffic monitoring, robotics, and autonomous platforms, where resource limited hardware such as the Jetson Nano must operate in real time. Efficient, accurate dehazing techniques balancing computational footprint and restoration quality are therefore of practical importance.

II. Review of Selected Techniques

1. Classical Method: Dark Channel Prior / CAP

Classical prior based techniques such as the **Dark Channel Prior (DCP)** and its widely referenced variants under the umbrella of classical "CAP" approaches (e.g., color attenuation prior, contrast-atmospheric priors) estimate atmospheric light and transmission maps using handcrafted priors. These methods are computationally inexpensive relative to deep networks and require no training, making them attractive for embedded deployment. However, they tend to produce artifacts such as halos, color distortions, and over-saturation when tested on diverse scenes. Their reliance on strong assumptions (e.g., local patch dark intensity) limits performance under heterogeneous lighting or dense fog.

2. Deep Learning Based Method: FFA-Net

FFA-Net (Feature Fusion Attention Network) by Qin *et al*. [1] represents a modern learning based dehazing framework achieving high PSNR/SSIM across synthetic benchmarks. It uses **attention based feature fusion**, a **multi path design**, and **pixel level attention**,enabling the network to adaptively select fog relevant features while suppressing noise. Compared to classical priors, FFA-Net produces clearer, more natural outputs and generalizes better to real hazy images. However, the original architecture is **computationally heavy**, with tens of millions of parameters and relatively high memory usage, making direct deployment on a Jetson Nano challenging without pruning, quantization, or a reduced variant.

Criterion	**CAP**	**FFA-Net**
Training Required	No	Yes (GPU needed initially, but inference only on Jetson)
Runtime Complexity	Low–moderate (CPU-friendly)	High (requires TensorRT optimization or model slimming)
Quality	Moderate, prone to artifacts	High-quality restoration, SOTA-level

Ease of Implementation	Very High	Medium–High (requires DL pipeline + deployment steps)
Suitability for Jetson Nano	Excellent	Moderate with optimizations

CAP provides a clear, fast baseline and is ideal for benchmarking or fallback quality. FFA-Net offers state of the art performance but requires engineering effort for real time or near real time inference on edge hardware.

Implementing **both** techniques is feasible provided the project focuses on **re implementation and optimization** rather than novel deep algorithm development from scratch. Key considerations:

3.Feasible Components

1. **CAP implementation**
   a. Straightforward Python/C++ coding.
   b. Real time on Jetson Nano achievable.
   c. Good as a classical benchmark.
2. **FFA-Net implementation (inference only)**
   a. We will use pretrained weights from the original paper or re-train on a GPU.
   b. Port to Jetson Nano using:
      i. TensorRT conversion
      ii. FP16 or INT8 quantization
      iii. Model slimming (e.g., reducing channels or number of attention modules)
   c. Achievable in 10–12 weeks with group collaboration.
3. **Our contribution / research gap**
   a. **Efficient adaptation of a heavy dehazing model (FFA-Net) to resource-constrained hardware**.
   b. **Comparative study of classical vs. modern models on embedded deployment** (speed, power, latency, quality).
   c. **Evaluation on real foggy outdoor scenes** expanding beyond synthetic datasets.
   d. Optional: lightweight redesign of FFA-Net modules (channel reduction, depth reduction).

Risk	Mitigation
Jetson Nano cannot run full FFA-Net	Use reduced-width variant, prune weights, quantize with TensorRT
Training time too long	Train off device or use pretrained models
Memory limits (4 GB)	Run inference-only, simplify architecture, use swap if needed

Conclusion:

Implementing CAP + an optimized FFA-Net on Jetson Nano is **appropriate and achievable** for our semester project. The tasks balance classical and deep learning methods allow meaningful experimentation,and offer a publishable contribution. Furthermore, It is resource efficient dehazing for embedded perception.

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Declaration:

“ChatGPT (Deep Research Mode) was used to search, verify, and summarize research papers and to generate the narrative literature review. All links were opened and confirmed by the team. All reviewed papers were added to the GitHub repository under /docs/references.”