Adaptive Noise-Type Routing for CNN Denoising

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Motivation and Problem Statement

Real-world images are often degraded by diverse noise types such as Gaussian, salt-and-pepper, Poisson, or compression artifacts. Traditional CNN-based denoisers are typically trained for a single noise model, which limits their robustness and generalization. A unified model struggles to adapt to different or mixed noise conditions. This project addresses the problem by developing a noise-type adaptive CNN that identifies the noise class and routes the input through specialized denoising branches.

Research Objectives

1. Develop a noise-type adaptive CNN framework that predicts the noise type present in an input image and applies a specialized denoising branch tuned for that type.
2. Evaluate the denoised images by comparing directly to the corresponding clean ground-truth images (original, noise-free dataset images)
3. Test the model's performance across multiple noise types (Gaussian, salt-and-pepper, Poisson, and potential motion blur or JPEG artifacts) and mixed-noise settings.
4. Analyze whether adaptive routing improves reconstruction quality compared to a single unified model when evaluated against clean ground-truth images.

State of the Art, and your Key Novelty

1. **Noise-type awareness:** Directly measures the denoiser's ability to reconstruct clean images, eliminating reliance on comparisons with other models.

2. **Adaptive multi-branch design:** Dynamically routes inputs to noise-type-specific modules or blends outputs, optimized purely for reconstruction quality. This places a focus on generalization without depending on a single fixed-architecture denoiser.

Impact, Outcomes, Achievements

1. **Impact:** Shows that noise-type adaptive CNNs can more effectively recover clean images under varied noise conditions and provides a transparent, ground-truth–based evaluation framework for denoising research.

2. **Outcomes:** A trained adaptive denoising system evaluated on image datasets with multiple synthetic noise types; results include metrics and visual comparisons to original clean images.

3. **Achievements:** End-to-end implementation of a noise-type classifier with adaptive denoising branches, creation of a reproducible benchmark with quantitative and qualitative results.

Action Plan

Phase 1 (Sep 12 – Oct 1):

Goal: Setup and prototype

- Set up environment and dataset loaders (MNIST, CIFAR-10/100, STL-10, etc)
- Implement synthetic noise generators (Gaussian, salt-and-pepper, Poisson, etc)
- Train baseline denoisers and begin implementation of noise-type classifier with basic routing

Deliverable: Prototype pipeline with sample denoised outputs

Phase 2 (Oct 2 – Nov 6):

Goal: Build full adaptive model and run experiments

- Implement multi-branch adaptive CNN with routing/blending mechanism
- Train model across multiple noise types and datasets
- Evaluate denoised images against clean ground-truth

Deliverable: Trained adaptive model and experimental results

Phase 3 (Nov 7 – Dec 2):

Goal: Analyze results, write report, and prepare presentation

- Analyze quantitative & qualitative results; generate figures (confusion matrix, error curves, etc)
- Write final technical report/paper with methods, experiments, results, and discussion
- Finalize code repository and pre-trained models (README.md, etc)
- Prep presentation

Deliverable: Complete report, reproducible code, and presentation ready