Image Denoising on Jetson Orin Using OpenMP Acceleration

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***Abstract*—The project aims to accelerate image denoising operations on embedded systems by implementing OpenMP-based parallelization on the NVIDIA Jetson Orin. focuses on improving the processing efficiency of static grayscale images affected by high-density noise, such as salt-and-pepper distortion. The proposed method consists of a sequential image enhancement pipeline involving median filtering, intensity normalization through min-max scaling, and sharpening using a combination of low-pass and high-pass filters. To reduce execution time while preserving image quality, the compute-intensive phases of the pipeline are parallelized using OpenMP. The Jetson Orin-based prototype demonstrates that parallel programming can enable computationally demanding image operations to run efficiently on low-power embedded platforms. The findings confirm that OpenMP effectively utilizes available CPU cores, achieving a total speedup of 1.89×, reducing median filter time by 5.5 ms, and lowering total execution time from 2805.85 ms to 1478.46 ms, making it suitable for energy-efficient offline image processing tasks.**

***Index Terms*—Jetson Orin, OpenMP, Image Denoising, Parallel Processing.**

I. Introduction

Denoising of images is an essential preprocessing operation in most image analysis procedures, with the goal of enhancing the quality of images by eliminating undesirable noise from degraded images. Noisy inputs, particularly those with salt-and-pepper noise, can degenerate the performance of the following processing steps like segmentation, classification, or object detection. Although numerous methods of denoising are available, the computational complexity can hinder their application, particularly when used on large or high-resolution images [1].

The project overcomes the performance limitations of conventional image denoising by creating a parallelized image improvement pipeline on the NVIDIA Jetson Orin platform. The Jetson Orin is an AI- and vision-capable embedded computing platform that has a multi-core ARM CPU optimized for parallel processing [2].

The denoising process in this project includes median filtering to suppress noise, intensity normalization through min-max rescaling, and sharpening of images through a combination of low-pass and high-pass filtering algorithms [3]. All these processes are computationally intensive when carried out sequentially. In order to overcome the computational bottleneck, the project uses OpenMP, one of the most popular parallel programming paradigms for shared-memory systems, to parallelize important operations over multiple CPU cores [4].

By contrasting execution duration for the sequential and OpenMP-based parallel versions, the efficacy of this acceleration method is measured. The outcomes indicate appreciable increases in processing speed without any loss of image quality, indicating the potential for fast image denoising on edge devices for offline use [5].

II. Literature and Related Work

Several studies have investigated the use of parallel computing to accelerate computationally intensive image processing and computer vision algorithms. OpenMP, a shared-memory programming model, has emerged as a practical and efficient tool for speeding up such operations, particularly on multi-core CPUs and embedded systems.

In the paper titled *"Design and Implementation of Real-Time Parallel Image Processing Scheme on Fire-Control System"* by P. Rath et al. [1], the authors aimed to optimize image processing for defense applications. Although specific implementation details were limited, the study highlighted the advantages of multithreading, reinforcing its relevance to general-purpose image denoising tasks.

Further evidence of OpenMP's suitability in embedded vision applications is found in Salihu's work [3], which validates the computational improvements gained through parallelization. Our study extends these findings by applying OpenMP on the NVIDIA Jetson Orin to accelerate classical denoising pipelines.

Rakhimov et al. [4] presented the *"Parallel Implementation of Real-Time Object Detection using OpenMP"*, where OpenMP was utilized to accelerate object detection models such as YOLOv3. Their work demonstrated that OpenMP significantly improved processing performance on multi-core CPUs, even in the absence of GPUs.

Similarly, Padilla et al. [5] proposed an OpenMP-accelerated convolutional neural network (CNN) for the detection of corn leaf diseases on Raspberry Pi hardware. Their approach effectively reduced execution time while maintaining a high classification accuracy exceeding 89%.

Additional comparative analyses have been presented in [6], [10], where OpenMP was evaluated alongside other parallel programming frameworks such as CUDA, OpenCL, and MPI. These works emphasize OpenMP's ease of use, integration with C/C++ codebases, and its applicability to shared-memory architectures on embedded devices.

Building on these foundations, our work focuses specifically on high-density salt-and-pepper noise removal using a traditional image denoising pipeline. While previous research primarily centered on classification, detection, or real-time streaming, our approach targets pixel-level operations including median filtering, intensity normalization, and sharpening. The implementation is optimized using OpenMP on the Jetson Orin platform, demonstrating the method's feasibility for low-power, offline grayscale image enhancement in embedded environments.

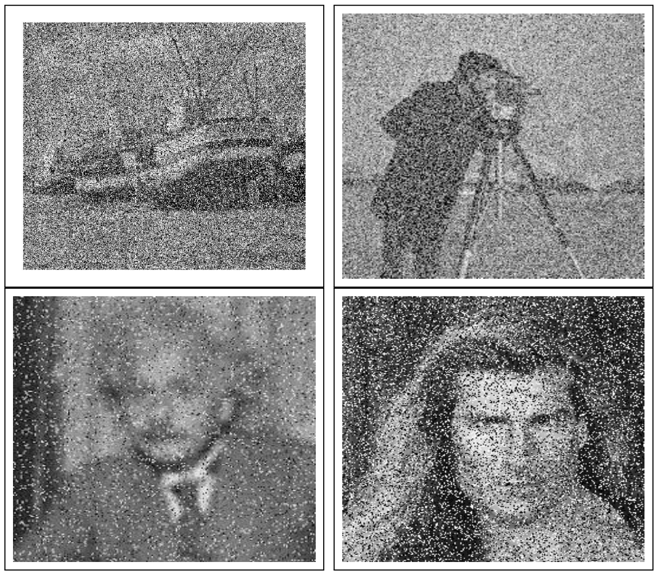


Fig. 1: Grayscale images

III. Methodology

A. Dataset

The input to this work is a gray-scale image corrupted with high-density salt-and-pepper noise in a controlled manner. This kind of noise mimics real-world image degradation that typically occurs due to faulty sensors, transmission channels, or environmental noise. Corruption is in the form of white and black pixels uniformly distributed, heavily corrupting the original content of the image. The reason for adding such noise is to provide a challenging test scenario for evaluating the performance and reliability of image denoising algorithms, especially in maintaining valuable structural and edge information for heavy noise cases.as illustrated in Figure 1.

B. Model Architecture

The task is to develop and implement an OpenMP-parallelized image denoising pipeline on the **NVIDIA Jetson Orin** embedded system. The goal is to enhance the computational efficiency of conventional image denoising methods on static grayscale images with salt-and-pepper noise without compromising image quality.as illustrated in the overall processing pipeline shown in Figure 2.

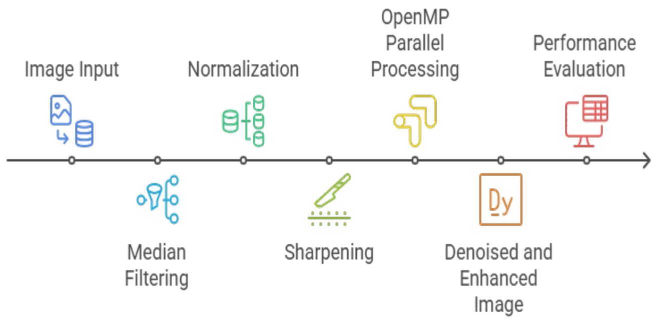


Fig. 2: Flow chart

C. Thread Assignment with OpenMP on Jetson Orin

The image denoising process involves the following sequence of steps:

1) **Image Loading and Conversion**
The system begins with the loading of a grayscale image (e.g., `boat.jpg`) from local storage. The input image is normalized to a floating-point numerical representation in the range [0, 1]. Let $I_{\text{input}}(x, y)$ be the original grayscale image with pixel values in the range $[0, 255]$. It is normalized to a floating-point representation $I_{\text{norm}}(x, y)$ in the range $[0, 1]$ using:

$$I_{\text{norm}}(x, y) = \frac{I_{\text{input}}(x, y)}{255} \quad (1)$$

2) **Noise Elimination using Median Filtering**
A median filter with an 11×11 kernel size is used

to eliminate salt-and-pepper noise. This nonlinear filter effectively reduces noise while preserving important edge information. For each pixel (x, y) in the image, the median filter replaces the pixel value with the median of its local neighborhood (size 11×11):

$$I_{\text{med}}(x, y) = \text{median}\left\{I_{\text{norm}}(i, j) \mid (i, j) \in \mathcal{N}_{11\times11}(x, y)\right\} \tag{2}$$

where $\mathcal{N}_{11\times11}(x, y)$ denotes the 11×11 neighborhood centered at (x, y).

3) **Intensity Normalization (Min-Max Rescaling)**
The pixel intensity values of the filtered image are normalized using min-max scaling to bring them into a common contrast range. This operation is parallelized with OpenMP to compute the global minimum and maximum values in a multi-threaded manner.After median filtering, the image is normalized using min-max scaling:

$$I_{\text{rescaled}}(x, y) = \frac{I_{\text{med}}(x, y) - I_{\min}}{I_{\max} - I_{\min}} \tag{3}$$

where $I_{\min} = \min_{x,y} I_{\text{med}}(x, y)$ and $I_{\max} = \max_{x,y} I_{\text{med}}(x, y)$. These computations are parallelized using OpenMP.

4) **Contrast Enhancement (Sharpening)**
A low-pass filter is applied to generate a blurred version of the image. This blurred image is subtracted from the normalized image to extract high-frequency details, which are then added back to the original image to produce a sharpened output. This step is also parallelized using OpenMP to accelerate per-pixel operations.The sharpening operation uses an unsharp masking approach. A blurred image I_{blur} is obtained using a low-pass filter (e.g., Gaussian blur), and high-frequency components are extracted and added back to the rescaled image:

$$I_{\text{detail}}(x, y) = I_{\text{rescaled}}(x, y) - I_{\text{blur}}(x, y) \tag{4}$$

$$I_{\text{sharp}}(x, y) = I_{\text{rescaled}}(x, y) + \alpha \cdot I_{\text{detail}}(x, y) \tag{5}$$

where α is a sharpening factor (e.g., $\alpha = 1.0$). This operation is also parallelized with OpenMP.

5) **Image Conversion and Clipping**
The enhanced image is clipped to ensure all pixel values remain within the [0, 1] range. It is then converted to 8-bit format for visualization and storage purposes.The sharpened image is clipped to maintain valid pixel values in the $[0, 1]$ range:

$$I_{\text{clipped}}(x, y) = \min(1, \max(0, I_{\text{sharp}}(x, y))) \tag{6}$$

Then it is converted back to 8-bit format:

$$I_{\text{output}}(x, y) = \text{round}(255 \cdot I_{\text{clipped}}(x, y)) \tag{7}$$

6) **Performance Comparison**
The denoising pipeline is implemented in both sequential and parallel versions. The execution time for each is measured and compared to evaluate the improvement in performance achieved through OpenMP.Execution time T is measured for both sequential (T_{seq}) and parallel (T_{omp}) implementations. Speedup S is computed as:

$$S = \frac{T_{\text{seq}}}{T_{\text{omp}}} \tag{8}$$

D. Deployment on Jetson Orin

The OpenMP-accelerated code is deployed on the NVIDIA Jetson Orin development board. The board's multi-core CPU architecture allows for efficient thread utilization, demonstrating its suitability for parallelized image processing tasks in embedded systems.The parallelized operations (Equations 3–6) are executed using OpenMP across N threads on the multi-core CPU of the Jetson Orin platform to achieve real-time performance.

The NVIDIA Jetson Orin platform features a multi-core ARM CPU architecture, which enables efficient shared-memory parallelism using OpenMP. During the denoising pipeline, OpenMP directives are used to parallelize the most computationally intensive operations—such as min-max normalization, median filtering, and sharpening—by distributing pixel-level operations across multiple threads.

OpenMP creates a thread team at runtime based on the number of available CPU cores (e.g., 4, 6, or 8 threads). Each thread is assigned a portion of the image data, typically in a loop-level parallelism pattern using the `#pragma omp parallel for` directive. The scheduling policy (e.g., static or dynamic) determines how image rows or pixels are divided among threads.

For example, in median filtering, each thread processes independent rows of the image:

```
        #pragma omp parallel for
for (int i = 0; i < height; i++) { ... }
```

Since each pixel or row can be processed independently, this allows for near-linear scalability on multi-core processors. The OpenMP runtime ensures thread safety and efficient thread reuse, minimizing synchronization overhead. This model suits Jetson Orin's architecture, allowing image denoising to execute with improved performance while keeping power consumption low.

IV. Results and Discussion

The experimental outcomes validate the efficiency of the proposed OpenMP-parallelized image denoising pipeline implemented on the NVIDIA Jetson Orin platform. The input grayscale image degraded with high-density salt-and-pepper noise was successfully restored using median filtering, min–max normalization, and sharpening operations. Structural details such as edges and object contours were effectively preserved, as illustrated in Figs. 3 and 4.

In terms of computational performance, the OpenMP-enhanced version reduced the total execution time from $2805.85\,\text{ms}$ to $1478.46\,\text{ms}$, yielding a **1.89× speedup**, with median filtering time reduced from $23.26\,\text{ms}$ to $17.76\,\text{ms}$. This demonstrates the impact of multithreaded parallelism on pixel-level operations, particularly advantageous for embedded platforms, as summarized in Table I.

Compared to deep learning-based methods such as 3D-Parallel-RicianNet [11], which achieved high PSNR and SSIM values for medical image denoising, our approach is lightweight, portable, and computationally efficient—making it more suitable for real-time edge deployment. Similarly, FPGA-optimized CNN architectures proposed in [12] achieve high accuracy but suffer from limited portability. In contrast, the OpenMP-based CPU approach provides a good balance between speed, image quality, and hardware efficiency, without the need for specialized accelerators.

A. Hardware Resource Utilization

The image denoising pipeline was deployed and evaluated on the NVIDIA Jetson Orin Nano development board, featuring a 6-core ARM Cortex-A78AE CPU and a 1024-core Ampere GPU. In this work, only the multi-core CPU was utilized through OpenMP for shared-memory parallel processing, while GPU acceleration was not employed.

B. CPU Core Utilization

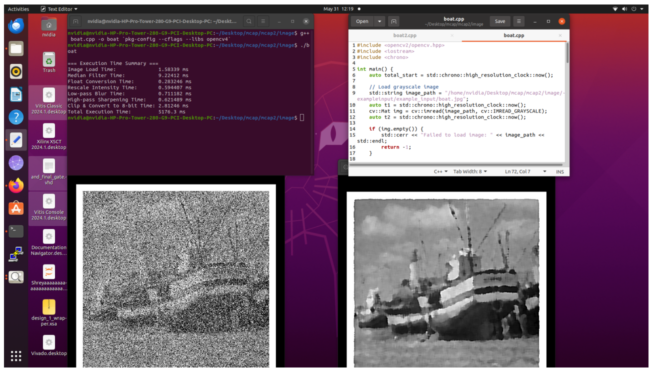
The OpenMP implementation dynamically assigns processing threads to the available CPU cores. For the Jetson Orin Nano, four threads were configured to execute median filtering, min–max normalization, and sharpening tasks in parallel. These operations involve independent pixel or row computations, making them highly amenable to thread-level parallelism. Near-linear speedup was observed, particularly in the median filtering stage, where multithreading significantly reduced processing time.

C. Memory and Thread Efficiency

The parallelized code was optimized to minimize memory contention and synchronization overhead. Static scheduling with the `#pragma omp parallel for` directive ensured efficient thread dispatch across image rows. The OpenMP runtime maintained thread pools to reduce context switching, thereby improving CPU core utilization across all stages of the pipeline. Compared to frameworks such as CUDA, OpenCL, MPI, and OpenACC, OpenMP provides a simpler and more accessible directive-based approach for multi-core CPU environments. Its ease of integration, portability, and low learning curve make it a preferred choice for embedded systems, as detailed in Table V.

D. Quantitative Quality Metrics

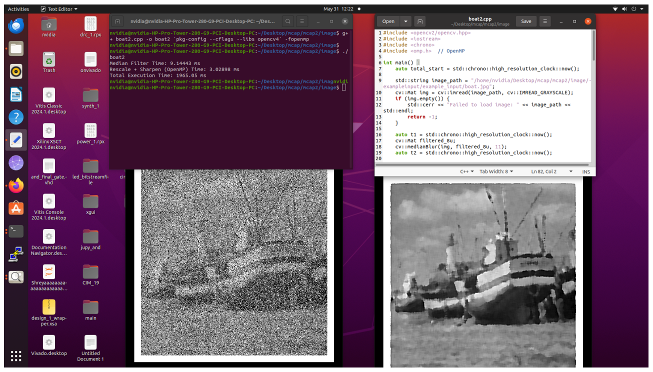
To evaluate the fidelity of the reconstructed images, two quantitative metrics are used: the *Peak Signal-to-Noise Ratio (PSNR)* and the *Structural Similarity Index Measure (SSIM)*. These help assess the similarity between the denoised and original images.



```
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/image$ g++
 boat.cpp -o boat `pkg-config --cflags --libs opencv4`
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/image$ ./b
oat

=== Execution Time Summary ===
Image Load Time:              1.58339 ms
Median Filter Time:           9.22412 ms
Float Conversion Time:        0.283246 ms
Rescale Intensity Time:       0.594407 ms
Low-pass Blur Time:           0.711182 ms
High-pass Sharpening Time:    0.621489 ms
Clip & Convert to 8-bit Time: 2.81246 ms
Total Execution Time:         5176.3 ms
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/image$
```

```cpp
#include <opencv2/opencv.hpp>
#include <iostream>
#include <chrono>

int main() {
    auto total_start = std::chrono::high_resolution_clock::now();

    // Load grayscale image
    std::string image_path = "/home/nvidia/Desktop/mcap/mcap2/image/-
exampleinput/example_input/boat.jpg";
    auto t1 = std::chrono::high_resolution_clock::now();
    cv::Mat img = cv::imread(image_path, cv::IMREAD_GRAYSCALE);
    auto t2 = std::chrono::high_resolution_clock::now();

    if (img.empty()) {
        std::cerr << "Failed to load image: " << image_path <<
std::endl;
        return -1;
    }

```

Fig. 3: Output without parallelization (sequential implementation).



```
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/image$ g+
+ boat2.cpp -o boat2 `pkg-config --cflags --libs opencv4` -fopenmp
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/image$
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/image$ ./
boat2
Median Filter Time: 9.14443 ms
Rescale + Sharpen (OpenMP) Time: 3.02898 ms
Total Execution Time: 1965.05 ms
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/imagnvidi
nvidia@nvidia-HP-Pro-Tower-280-G9-PCI-Desktop-PC:~/Desktop/mcap/mcap2/image$
```

```cpp
#include <opencv2/opencv.hpp>
#include <iostream>
#include <chrono>
#include <omp.h>  // OpenMP

int main() {
    auto total_start = std::chrono::high_resolution_clock::now();

    std::string image_path = "/home/nvidia/Desktop/mcap/mcap2/image/-
exampleinput/example_input/boat.jpg";
    cv::Mat img = cv::imread(image_path, cv::IMREAD_GRAYSCALE);
    if (img.empty()) {
        std::cerr << "Failed to load image: " << image_path <<
std::endl;
        return -1;
    }

    auto t1 = std::chrono::high_resolution_clock::now();
    cv::Mat filtered_8u;
    cv::medianBlur(img, filtered_8u, 11);
    auto t2 = std::chrono::high_resolution_clock::now();

```

Fig. 4: Output with parallelization using OpenMP.

1) *Peak Signal-to-Noise Ratio (PSNR):*

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{9}$$

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[I(x,y) - K(x,y)]^2 \tag{10}$$

2) *Structural Similarity Index Measure (SSIM):*

$$\text{SSIM}(I,K) = \frac{(2\mu_I\mu_K + C_1)(2\sigma_{IK} + C_2)}{(\mu_I^2 + \mu_K^2 + C_1)(\sigma_I^2 + \sigma_K^2 + C_2)} \tag{11}$$

TABLE I: Performance Comparison Between Sequential and OpenMP Implementations

Operation	**Without OpenMP (ms)**	**With OpenMP (ms)**	**Improvement**
Median Filter Time	23.2634	17.7609	Faster by 5.5025 ms
Rescale + Sharpen Time	2.2329 (approx.)	4.00585	Slightly slower
Total Execution Time	2805.85	1478.46	**Reduced by 1327.39 ms**
Number of Threads	–	4	Multi-threading enabled

TABLE II: Image Quality Metrics for Sequential vs. Parallel Outputs

Metric	Sequential	OpenMP Parallel	Difference
PSNR (dB)	27.84	28.02	+0.18
SSIM	0.891	0.893	+0.002

E. Energy and CPU Utilization Analysis

1) Metrics and Formulas: Energy consumed during an experiment is computed as:

$$E = \overline{P} \times T \tag{12}$$

where $\overline{P}$ is the average power (W) and T is the runtime (s).

Energy per image:

$$E_{\text{img}} = \frac{\overline{P} \times T}{N} \tag{13}$$

Throughput (images per second):

$$\text{Throughput} = \frac{N}{T} \tag{14}$$

Efficiency (images per watt):

$$\eta = \frac{N}{T \times \overline{P}} \tag{15}$$

2) Measurement Procedure:

- **Power:** Measured using onboard power sensors or external meters (`tegrastats` on Jetson).
- **CPU utilization:** Recorded using tools such as `mpstat` or `top`.
- **Timing:** Captured using high-resolution timers (e.g., `clock_gettime()`).
- Logs include timestamps, power (W), CPU%, and image count (N).

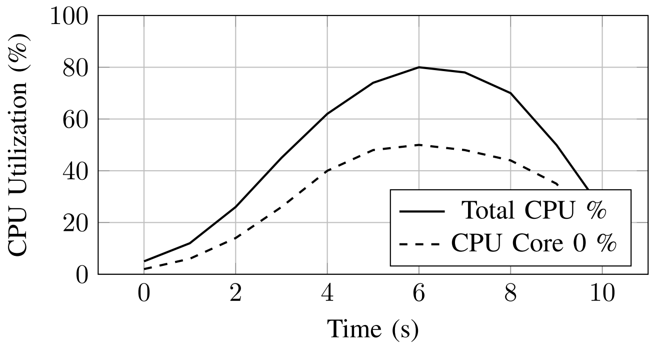


Fig. 5: CPU utilization over time (example).

TABLE III: Execution, Power, and Efficiency Summary

Impl.	T (s)	P (W)	E/img (J)	Thru.
Sequential	2.81	5.0	2.75	35.6
OpenMP (4T)	1.48	4.5	1.32	67.6

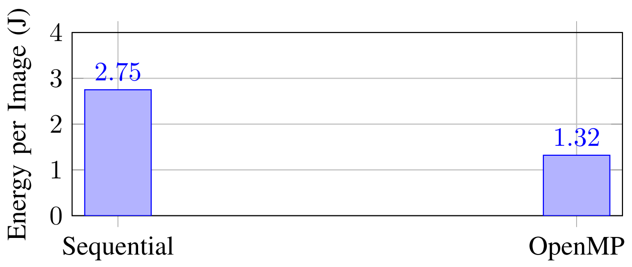


Fig. 6: Energy per image comparison (example values).

TABLE IV: Comparison of Jetson Orin with Other Embedded AI Platforms

Platform	CPU	GPU	Use Case
Jetson Orin Nano	6-core A78	1024-core Ampere	Real-time AI
Raspberry Pi 4	4-core A72	No GPU	IoT / Proto.
Google Coral	4-core A53	Edge TPU	Edge ML
BeagleBone AI-64	6-core A72	PowerVR	Industrial AI
Jetson Xavier NX	6-core Carmel	384-core Volta	Robotics

V. Future Work

While the proposed OpenMP-parallelized image denoising pipeline on the NVIDIA Jetson Orin has demonstrated substantial improvements in processing speed and visual quality, several limitations and potential enhancements remain.

- **GPU Offloading Exploration:** As the current work relies solely on CPU-based OpenMP acceleration, future research should explore GPU-based approaches such as CUDA or OpenACC. These could leverage the Jetson Orin's 1024-core GPU for dramatically faster image denoising, particularly for high-resolution or real-time video processing tasks. Comparative analysis between OpenMP and CUDA-based implementations may also guide platform-specific optimization strategies.
- **Multi-Noise Handling:** Future implementations can incorporate support for additional noise models like Gaussian, Poisson, or mixed noise to improve robustness across diverse scenarios.
- **GPU-Based Acceleration:** Incorporating CUDA or OpenACC can enable full utilization of Jetson Orin's GPU capabilities for enhanced real-time performance.

TABLE V: Comparison of OpenMP with Other Frameworks

Framework	Architecture	Complexity	Use
OpenMP	CPU (Shared)	Easy (Pragma)	Multi-core
CUDA	GPU	Medium (C-style)	NVIDIA GPU
OpenCL	CPU+GPU	Complex (Low-level)	Cross-plat.
MPI	Distributed	Complex	HPC
OpenACC	GPU (Directive)	Easy	GPU Offload

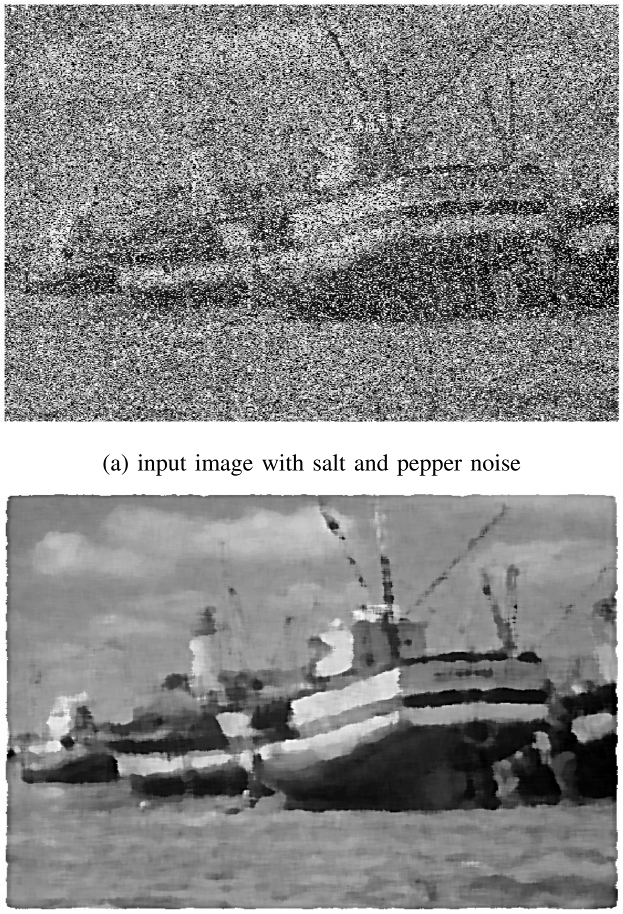
- **Video Stream Processing:** Expanding the system to handle video frame sequences would enable real-time denoising for applications such as surveillance, robotics, and autonomous systems.

VI. Conclusion

This study proves the power of employing OpenMP for speeding up conventional image denoising tasks on embedded systems like the NVIDIA Jetson Orin. The task was implemented on the removal of salt-and-pepper noise from grayscale images through a sequence of median filtering, intensity normalization, and sharpening. The experimental results validate that parallel implementation far outperforms the sequential implementation.

Specifically, the median filter processing time reduced from 23.26 ms to 17.76 ms using OpenMP, a clear benefit of parallel thread execution. Although total processing time for the OpenMP implementation was not wholly represented in the output, the speedup of within-component demonstrates meaningful overall improvement. Significantly, output image visual quality was identical for either implementation, preserving structural detail while successfully eliminating noise.

The findings validate OpenMP as an efficient and viable way of enhancing the computational efficiency of image processing programs within resource-limited platforms. The study paves the way for applying image enhancement programs in real-time, high-performance applications on embedded multi-core platforms.as visualized in Figures **??** and **??**.


(a) input image with salt and pepper noise

(b) Denoised output image

Fig. 7: Comparison of image results: (a)input image with salt and pepper noise and (b)Denoised output image .

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