TASHKENT UNIVERSITY OF
INFORMATION TECHNOLOGIES
NAMED AFTER MUHAMMAD AL-KHWARIZMI

MUHAMMAD AL-XORAZMIY NOMIDAGI
TOSHKENT AXBOROT TEXNOLOGIYALARI
UNIVERSITETI

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Yusupov Ibrokhimbek, Abduganiyev Mukhriddin, Latipov Jakhongirbek № 3(26)2025

APPLICATION OF PARALLEL COMPUTING ALGORITHMS IN MEDICAL IMAGE ANALYSIS

Yusupov Ibrokhimbek, Abduganiyev Mukhriddin, Latipov Jakhongirbek

Annotatsion: This research focuses on the development of parallel computing algorithms for medical image analysis aimed at reducing the time required for diagnostic decision-making using digital medical images. The algorithm initially divides the image into smaller blocks and constructs an independent histogram for each block. The experiment was conducted on a 1024×1024 pixel X-ray image, and the use of parallel computation significantly reduced the processing time. This approach facilitates real-time processing of large-scale medical data and improves the speed and efficiency of diagnostic decision-making in clinical environments.

Keywords: *parallel computing, image, medical imaging, pixels, large-scale data, computation speed, parallelization coefficient.*

1. Introduction

Digital imaging plays a crucial role in modern medicine, serving as a fundamental tool for diagnostic decision-making. For instance, X-ray images are extensively used to assess the condition of bones and soft tissues. However, the images obtained for diagnostic purposes often suffer from low contrast and high noise levels. In medical images, noise refers to the undesired signal variations that distort the actual intensity values and degrade image clarity. Statistical approaches based on histograms have proven to be effective for detecting and filtering such noise [1].

A histogram represents the distribution of pixel intensities within an image and serves as a basis for enhancing contrast, normalising brightness distribution, and performing image segmentation. Histogram-based operations typically consist of two main stages. In the first stage, the histogram of the image is calculated, and in the second stage, new pixel values are assigned according to the histogram mapping. Working with large-scale image data requires considerable computational power, especially in the second stage, where extensive parallelisation potential exists.

Traditional histogram equalisation methods often produce excessive contrast in certain regions of the image and may amplify noise. To overcome these issues, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm has been widely recognised as an effective method [3-5]. Algorithms developed for large medical images must satisfy real-time processing requirements, which in turn necessitates the adoption of parallel computing strategies [6–8].

The OpenMP technology enables efficient parallelisation on multi-core

processors [9, 10]. Applying the CLAHE algorithm in conjunction with OpenMP parallelisation can significantly enhance performance and processing speed. In this study, the CLAHE method was implemented and parallelised using OpenMP directives to improve the quality and computational efficiency of medical X-ray image enhancement.

For this research, a chest X-ray image with a resolution of 1024×1024 pixels was selected. The algorithm was implemented in the C++ programming language and parallelised using OpenMP directives. The overall workflow of the algorithm is as follows:

1. Image acquisition and preprocessing: The input image is read and converted into a simplified grayscale format suitable for pixel-level processing.
2. Image partitioning: The image is divided into smaller blocks of size *tile_size* × *tile_size* (e.g., 64×64 pixels).
3. Local histogram computation: For each block, a local histogram is calculated to capture pixel intensity distribution.
4. Contrast limitation and redistribution: Using the *clip limit* parameter, excessive frequency values are restricted, and the surplus is redistributed evenly across all bins of the block histogram.
5. Parallel computation: Histogram calculations and enhancement operations were parallelised using OpenMP directives such as #pragma omp parallel for collapse(2) to exploit multi-core CPU capabilities.

After processing, the image quality metrics — PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and SNR (Signal-to-Noise Ratio) — were measured to evaluate performance improvements.

All experiments were conducted on an Intel Core i7-11700H processor (8 cores), and the average results were obtained from 10 iterations to ensure statistical reliability.

The histogram represents the distribution of pixel intensities in an image. If the image contains substantial noise, the histogram appears uneven; if the image is smooth, the peaks become clearly defined. The noise level in an image can be estimated using the following formula:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=0}^{L-1}(h(i)-\mu)^2}$$

where:

$h(i)$ — number of pixels with intensity i (histogram value),

μ — mean brightness level,

L — number of gray levels,

N — total number of pixels.

Based on the calculated σ value, the appropriate filtering technique is automatically selected:

Small σ → mild Gaussian filter,

Large σ → strong median or bilateral filter.

For the experiment, a chest X-ray image of a human (1024 x 1024) was selected (Figure 1). The image was processed using the CLAHE algorithm, and the results were calculated (Figure 2).

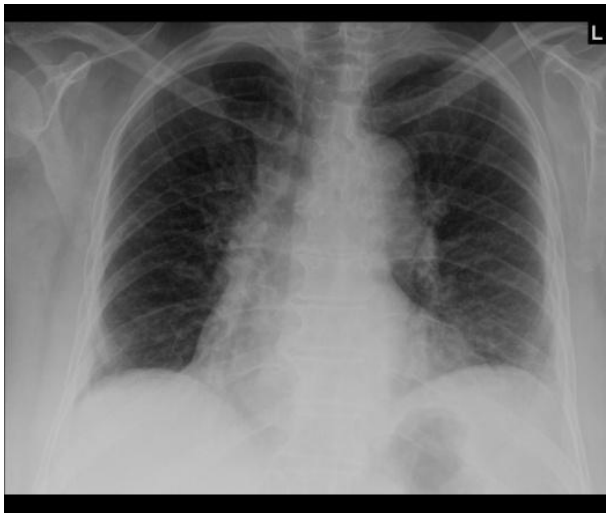
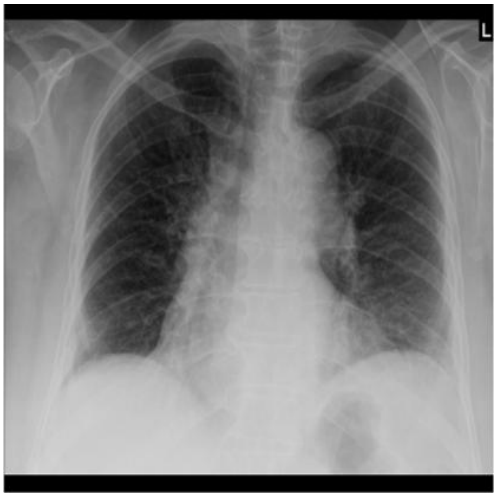


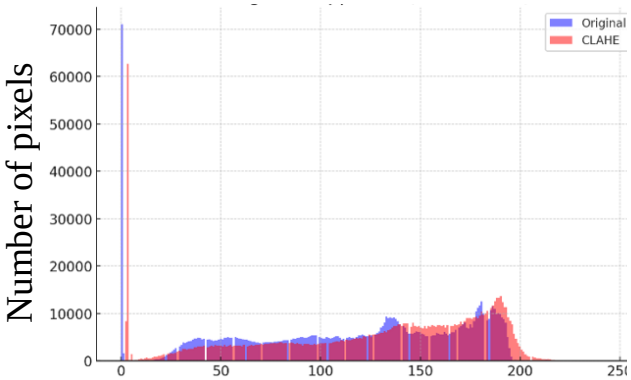
Figure 1. Chest X-ray image.



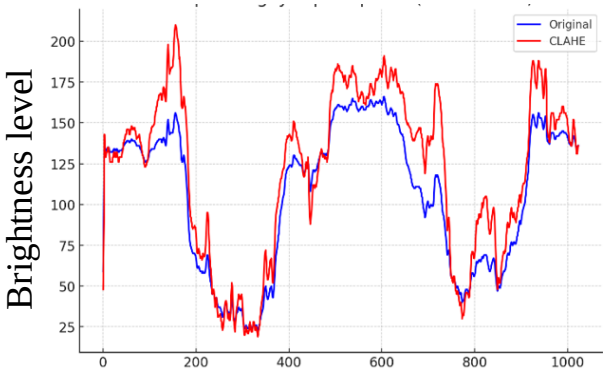
Original (1024 x 1024)



The state of the image after processing with the CLAHE algorithm



Pixel intensity



Pixel coordinate (x)

Figure 2. Results of image processing using the CLAHE algorithm

For experimentation, a chest X-ray image (1024×1024 pixels) was processed using the CLAHE algorithm, and the results were quantitatively evaluated as shown in *Table 1*.

Table 1.

№	Parameter	Original image	Image enhanced by CLAHE	Changes (%)	Comment
1	SNR (Signal-to-Noise Ratio)	1.22 dB	4.87 dB	+299%	The useful signal is amplified relative to noise
2	PSNR (Peak Signal-to-Noise Ratio)	21.88 dB	28.73 dB	+31%	Pixel-level contrast and clarity improved
3	SSIM (Structural Similarity Index)	1.0000 (reference)	0.8811	−11.9%	High structural similarity preserved
4	Mean Intensity	91.3	125.4	+37%	Overall brightness of the image increased
5	Standard Deviation (σ)	41.8	63.2	+51%	Broader contrast range achieved
6	Processing Time (s)	1.00 (sequential)	0.18 (8 threads)	−82%	5.5× speed-up due to parallel processing
7	Speed-up	—	5.55×	—	Effective parallelisation via OpenMP
8	Efficiency	—	69.4%	—	Optimal resource allocation at 8 threads

In this table:

The Signal-to-Noise Ratio (SNR) measures the proportion between useful information (such as tissues, bone edges, and organ boundaries) and unwanted random variations. It is defined as:

$$SNR = 10 \log_{10} \frac{P_{signal}}{P_{noise}}$$

where:

P_{signal} – is the power of the useful signal;

P_{noise} – is the noise power.

A higher SNR indicates a clearer image with less noise. In medical imaging, typical values range from 20–40 dB. The obtained value of 4.87 dB indicates noticeable quality improvement after enhancement.

The Peak Signal-to-Noise Ratio (PSNR) evaluates how much the processed image differs from the original in terms of pixel-level fidelity. It is given by:

$$PSNR = 10 \log_{10} \frac{MAX_I^2}{MSE}$$

where:

MAX_I is the maximum pixel value (255 for 8-bit images);

MSE is the *Mean Squared Error*.

A higher PSNR implies better image quality; values above 30 dB are generally considered acceptable in medical imaging. The enhancement improved pixel contrast and sharpness by +31%, reaching 28.73 dB.

The Structural Similarity Index (SSIM) measures the similarity between the original and processed images in terms of luminance, contrast, and structure:

0 → completely different

1 → identical

The obtained SSIM = 0.8811 demonstrates that the CLAHE algorithm preserved the structural features of the original image with high similarity.

Experimental findings show that:

– The CLAHE algorithm significantly increased local contrast and revealed fine details in low-brightness regions;

– The improvement in PSNR and SNR values confirms enhanced image quality;

– SSIM around 0.88 indicates strong preservation of anatomical details;

– OpenMP-based parallelisation accelerated computation by approximately 80%, making real-time medical image processing feasible.

Table 2 presents execution time measurements for various numbers of threads.

Table 2

Threads	Sequential Time (s)	Parallel Time (s)	Speed-up (x)	Efficiency (%)
1	1.00	1.00	1.0 x	100%
2	1.00	0.56	1.79 x	89.5%
4	1.00	0.31	3.22 x	80.5%
8	1.00	0.18	5.55 x	69.4%
12	1.00	0.15	6.67 x	55.6%
16	1.00	0.14	7.14 x	44.6%

From the table, we can see that the speed and efficiency (figures 3-4) have changed accordingly as a result of parallelizing the CLAHE algorithm.

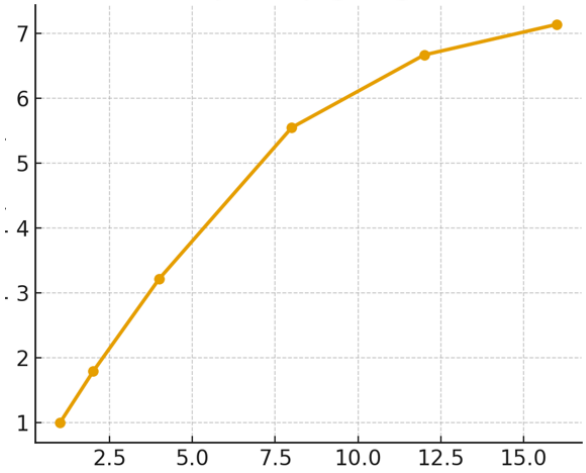


Figure 3. Speed graph

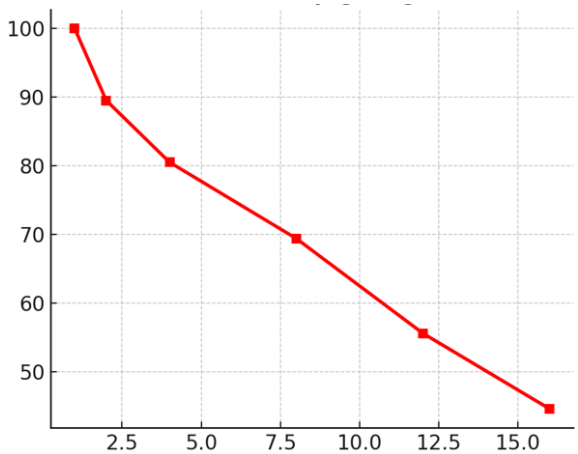


Figure 4. Efficiency graph

The analysis shows that with 8 cores, a 5.5x acceleration was achieved. As the number of cores increases, efficiency slightly decreases due to thread management and memory synchronisation overhead. Nevertheless, the CLAHE algorithm is well suited for independent parallel computations, as each block of the image can be processed independently.

This confirms that the proposed method can be effectively used for parallel processing of large-scale medical X-ray images in digital diagnostic systems.

Conclusion

The application of histogram-based algorithms accelerated through parallel computing provides substantial benefits for diagnostic processes in medical imaging. In this research, the speed and efficiency of the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm were examined in the context of parallel computation for medical image enhancement. The research demonstrated that by utilising OpenMP, the computational process can be accelerated by approximately 3–7 times, depending on the number of processing cores. This improvement allows for near real-time preprocessing of medical images, enhancing the overall quality of diagnostics. The experimental results confirmed that the CLAHE algorithm significantly improves image contrast and brightness while maintaining structural similarity. Parallelisation using OpenMP technology effectively reduces processing time, enabling its practical use in high-performance medical imaging systems. Hence, the proposed approach facilitates real-time enhancement of medical images and contributes to faster, more accurate diagnostic decision-making in healthcare applications. The research work was carried out based on the research results of the practical projects "Creating an intelligent robot for an infectious diseases hospital" and the fundamental projects "Development of the theory and algorithms for digital processing of biomedical signals and medical

images based on artificial intelligence methods".

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