

A Parallelized Approach for Colorizing Grayscale Images

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Abstract — Image processing plays an integral role in the field of computer science and is incorporated in numerous applications such as remote sensing, medical imaging, image restoration, and machine vision. One of the challenging tasks in image processing is colorizing grayscale images. Restoring color in grayscale images aids in enhancing the visual cognition of image data such as medical images, surveillance images, and scientific illustrations. Compared to the relatively simpler process of converting color images to grayscale, the process of colorizing grayscale images is much more complex, is not based on any one particular method, and is significantly dependent on the human perception of color. Additionally, such a colorizing process is generally computation-intensive and tedious. Hence, a parallelized high-performance approach based on many-core programming and the CUDA platform is presented in this paper for colorizing grayscale images. The proposed approach has been developed with the objective of incorporation in huge image datasets (such as those obtained from satellites) and video frame sequences.

Keywords — image colorization, image processing, many-core programming, parallel processing.

I. INTRODUCTION

Perception of colors by the human eye is a psychophysiological process. Owing to the structure of the human eye, all colors are perceived as various combinations of the three primary colors, namely red (R), green (G), and blue (B) [1]. Three characteristics are generally employed for distinguishing one color from the other: hue (H), saturation (S), and brightness (I). Hue represents the dominant wavelength (and hence the color) in a mixture of light waves. Brightness (also called lightness or luminosity) refers to the intensity value of a particular hue. Saturation refers to the relative degree of white or black mixed with the hue. The HSI color model is an alternative representation of the RGB color model and closely resembles the human eye's perception of colors [2]. In the context of coordinate geometry, the HSI color model represents a cylindrical projection of the RGB color model, as depicted in Figure 1 [3].

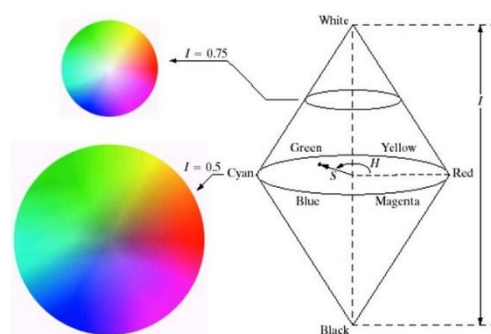


Fig 1: Geometrical representation of the HSI color model [3]

The color components of a pixel in a color image may either be represented by the HSI color space or by the RGB color space. However, the pixels of a grayscale image solely comprise intensity values. Hence, in order to convert a grayscale image into the corresponding color image, it is necessary to assign the hue and saturation values to each image pixel. Since different colors may have the same intensity value but vary in hue or saturation, the task of colorizing grayscale images does not have any one particular solution and often requires human interaction. The proposed approach addresses the said issue by incorporating a reference color image that can be employed for transferring color to the grayscale image. The intensity value of a grayscale pixel can be mapped with that of a similar color pixel in the reference image. However, it should be noted that similar intensity values could represent entirely different segments of the image. Hence, it is necessary to compare the chosen pixel's intensity value with that of the neighboring pixels for guiding the color mapping process. Depending on the number of neighbors being considered and the images' sizes, such a comparison process could be computation-intensive and tedious (especially in the case of large image datasets). To address this issue, the proposed approach incorporates parallelization of the color mapping task through many-core programming and the CUDA programming platform. The many-core processing paradigm emphasizes on enhancing the execution throughput of parallel applications. The many-core microprocessor design is exemplified by graphics processing units such as NVIDIA's GeForce and Tesla series, AMD's

Northern Island series, and ATI Radeon R300 series [4–6].

Since restoring color in grayscale images enhances the visual cognition of image data, employing the proposed parallelized high-performance approach for colorizing grayscale images can thereby be greatly beneficial while working with huge image datasets, such as those obtained from satellite imagery, surveillance imaging data, and medical imaging data, wherein a single image can be the size-range of gigabytes. In this paper, section II describes the proposed algorithmic approach in detail, and the obtained results are analyzed. Finally, section III elucidates the conclusions derived from the proposed study and future scope of work.

II. PARALLELIZED COLOR MAPPING FOR GRAYSCALE IMAGES AND RESULT ANALYSIS

An essential step for colorizing grayscale images is the assignment of hue and saturation values to each grayscale image pixel. As explained earlier in the introductory section, the proposed approach achieves this objective by mapping each grayscale image pixel to a particular color pixel of an input reference color image and considering the neighboring pixels of the chosen pixel for guiding the color mapping process. The proposed approach can algorithmically be described as follows:

Step 1: The target grayscale image and the reference color image are read and subsequently stored in the form of matrices.

Step 2: An appropriate sub-image is selected from the reference color image, and the RGB color values of each pixel in the sub-image are converted into the corresponding HSI values by applying the following equations [7–10]:

$$I = \frac{R + G + B}{3} \quad (1)$$

$$S = 1 - \frac{\min(R, G, B)}{I} \quad (2)$$

$$H = \cos^{-1} \sqrt{\frac{\frac{1}{2} \times ((R - G) + (R - B))}{(R - G)^2 + (R - B) \times (G - B)}} \quad (3)$$

Step 3: The intensity value of each grayscale image pixel is compared with the obtained I-values of the pixels in the reference color sub-image, and the best match is determined by comparing the mean I-values of the neighboring color pixels.

Step 4: The values of H and S from the best matched color pixel are transferred to the grayscale image pixel while retaining the original grayscale intensity value.

Step 5: As an optional step, the HSI values obtained in the previous step can be converted to the

corresponding RGB values by applying the following equations [7–10]:

$$R = I \times \left[1 + \left(\frac{S \times \cos(H)}{\cos(60 - H)} \right) \right] \quad (4)$$

$$G = I \times \left[1 + S - \left(\frac{S \times \cos(H)}{\cos(60 - H)} \right) \right] \quad (5)$$

$$B = I \times (1 - S) \quad (6)$$

Since the pixel operations described in Steps 2–5 are independent of each other, they can be parallelly processed, which in turn significantly reduces the computation time. While implementing the proposed approach, the binary search algorithm (with complexity of $O(\log n)$) was employed for determining the best pixel intensity match, two pixel neighborhoods of sizes 11×11 and 15×15 were applied, a reference color sub-image of size 500×500 pixels was selected, and the CUDA programming interface was employed for parallelizing the color mapping process. Figures 2(a) and 2(b) represent two sample target grayscale images [11], and Figure 2(c) depicts a reference color image. Figures 2(d) and 2(e) indicate the corresponding RGB color images obtained after parallelized colorization.

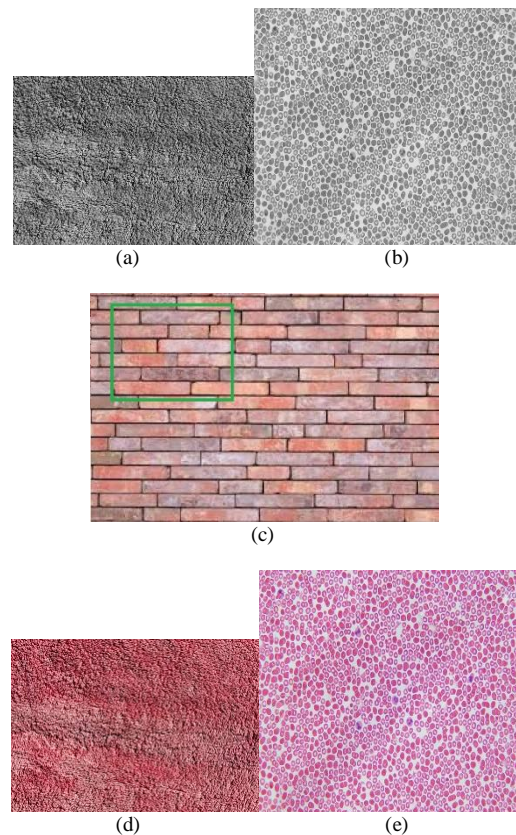


Fig 2: Parallelized colorization of grayscale images
(a) and (b): sample target grayscale images [11]
(c): reference color image

(d) and (e): corresponding colorized RGB images

Figure 2(a) represents the close-up image of a concrete wall surface, whereas Figure 2(b) represents an image of blood cells under the microscope. In Figure 2(c), the selected sub-image of the reference color image has been outlined in green for the purpose of clarity. It can be clearly observed from Figure 2(d) and Figure 2(e) that image colorization significantly aids in enhancing the visual cognition of the target grayscale images. Furthermore, selection of the reference color image greatly affects the quality of the final obtained colorized images. The original sizes of the two target grayscale images and the reference color image are 1087×2700 pixels, 2100×2100 pixels, and 2800×4000 pixels, respectively. While implementing the proposed approach, the pixel neighborhood of size 11×11 pixels was applied for Figure 2(a), whereas the pixel neighborhood of size 15×15 pixels was applied for Figure 2(b). It should be noted that during and after conversions between the RGB and HSI color models, the pixel values were accordingly scaled by multiplication with an appropriate factor. Furthermore, while implementing Step 3 of the proposed approach, the error difference (Δ) between the intensities of the matched pixels was measured during the binary search algorithm for determining the best pixel intensity match. If the grayscale pixel intensity for the i^{th} pixel is represented by I_{iG} , the intensity of a matching color pixel is represented by I_C , and N is the total number of pixels in the grayscale image, then Δ can be calculated as follows:

$$\Delta = \sqrt{(I_{iG} - I_C)^2}, \text{ where } 1 \leq i \leq N \quad (7)$$

For each grayscale image pixel, the minimum value of Δ (Δ_{min}) was estimated in the matching color pixels' neighborhood and the best matched intensity value was thereby determined. In order to test and evaluate the speed-up obtained through parallelized color mapping, parallelized and sequential versions of the proposed approach were tested on various multi-core and many-core platforms. The obtained results are summarized in Table I.

It can be observed from Table I that the parallelized color mapping process yields significantly superior results as compared with its sequential counterpart. If the NVIDIA Quadro 4000 platform is considered as the comparison benchmark, then it can be seen that an execution speed-up of approximately hundred times can be achieved. Such a tremendous execution speed-up indicates that the proposed parallelized approach for colorizing grayscale images can be potentially employed for processing large image datasets, such as frames of video sequences and surveillance image data. It should be noted that in the case of all the four test platforms, the processing time for Figure 2(b) is greater than that for Figure 2(a). This can be attributed to two

reasons. Firstly, the size of Figure 2(b) is larger than that of Figure 2(a), implying that a higher number of grayscale pixels need to be colorized. Secondly, while determining the best matched color pixel from the reference color sub-image, a neighborhood pixel region of size 15×15 pixels was applied for Figure 2(b), whereas a smaller neighborhood pixel region of size 11×11 pixels was applied for Figure 2(a). The latter aspect is also the plausible reason behind obtaining a lower mean value of $\Delta_{min}(\Delta_{mean})$ for Figure 2(b) because greater number of pixels were compared in the neighborhood region for determining the best color pixel match, thereby leading to a lower difference in the intensity values of the matched pixels. These observations suggest that a tradeoff exists between two aspects that need to be considered while parallelizing the color mapping process: size of the color pixel neighborhood region and the processing computation time. While determining the best pixel intensity match, increasing the size of the neighborhood region of color pixels around the matched color pixel can reduce the error in the matched intensity values but increase the computation time, and vice versa.

TABLE I
PERFORMANCE COMPARISON OF PARALLELIZED COLORIZATION FOR GRAYSCALE IMAGES

	Target grayscale image 1 (Fig 2(a))	Target grayscale image 2 (Fig 2(b))
Image size	1087 × 2700 pixels	2100 × 2100 pixels
Neighborhood color pixel matching region	11 × 11 pixels	15 × 15 pixels
Mean value of image pixel intensity (μ)	124.02	172.21
Mean obtained value of $\Delta_{min}(\Delta_{mean})$	1.182	0.753
Mean error in pixel intensity matching ($\frac{\Delta_{mean}}{\mu} \times 100$)	$\frac{1.182}{124.02} \times 100 = 0.95\%$	$\frac{0.753}{172.21} \times 100 = 0.44\%$
Test platform I: (parallelized execution) NVIDIA Quadro 4000 Compute capability: 2.0 No. of cores: 256 Clock speed: 2.8 GHz	Execution time = 0.009 s	Execution time = 0.014 s
Test platform II: (parallelized execution) NVIDIA Tesla C1060 Compute capability: 1.3 No. of cores: 240 Clock speed: 1.3 GHz	Execution time = 0.028 s	Execution time = 0.042 s
Test platform III: (sequential execution) Intel Xeon Model: X5570 Clock speed: 2.93 GHz	Execution time = 0.15 s	Execution time = 0.21 s

Test platform IV: (sequential execution) Itanium 2 Model: 1 Clock speed: 1.66 GHz	Execution time	Execution time
	= 1.12 s	= 1.38

III. CONCLUSIONS

Colorizing grayscale images is one of the challenging tasks of image processing and requires complex computations that are generally dependent on the human perception of color. In particular, the colorizing process becomes extremely tedious and computation-intensive while processing large image datasets. Hence, in this paper, a parallelized many-core processing approach based on the CUDA programming platform is proposed for colorizing grayscale images that addresses the said issues. Obtained results corroborate that compared to multi-core sequential processing, the proposed approach can achieve execution speed-ups up to approximately hundred times, with a pixel intensity matching error of less than 1%, which implies that the proposed approach can be potentially applied for colorizing large image datasets such as frames of video sequences, image surveillance data, and medical imagery.

As future scope of work, the proposed approach can be enhanced further so that multiple reference color images may be incorporated for colorizing a single grayscale image. Usage of multiple reference color images can lead to improved histogram equalization. Furthermore, the proposed approach can be merged with artificial intelligence and neural networking for “remembering” the pixel intensity mapping information, which can be incorporated with other “similar” grayscale images for their colorization.

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