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Parallel implementations of structural similarity based no-reference image quality assessment

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ABSTRACT

Automatic assessment of image quality has become increasingly important in numerous applications that utilize digital images. This is usually accomplished with no-reference image quality assessment (NR-IQA) techniques that use structural similarity (SSIM) index as a quality indicator. NR-IQA is computationally intensive because it generally involves image convolution and other time-consuming computations. A typical SSIM-based NR-IQA includes four computational operations: color to grayscale conversion, Gaussian blur, computation of image gradients with an 8-direction Sobel operator, and computation of SSIM indices of local windows in the image. Parallel computing using multi-core CPUs or many-core GPUs is often used to accelerate intensive computational problems. This research presents the design of three parallel implementations of SSIM-based NR-IQA methods to accelerate the computations. The first two utilize NVIDIA CUDA to implement all the operations as CUDA kernels, while the third uses Microsoft's Parallel Patterns Library to calculate mean similarity indices of local windows in the image. Experimental results showed that significant speedup can be achieved against the sequential method using all three methods, but it is more practical to use texture memory to perform the last task (similarity computation) because of its substantial enhancement in performance and its ease of scheduling when processing multiple images.

1. Introduction

Enabled by the ubiquity of digital photography technology, numerous images are generated every day for a wide range of applications, such as remote sensing, mobile apps, and surveillance and security applications. Degradations, such as noise, blocking artifacts, blurring, and fading, are introduced during image acquisition and processing procedures [1]. Detecting the degradation at the time of image acquisition is important to its subsequent applications, such as image analysis and visualization. Subjective methods of quality assessment are time-consuming, cumbersome, and expensive. Therefore, various automatic algorithms for objective quality assessment have been developed to evaluate the quality of images without human involvement.

Methods for objective image quality assessment can be classified into three categories: (1) full reference image quality assessment (FR-IQA), which assesses the quality of a potentially distorted image by comparing it with the original, believed to be undistorted version of the same image; (2) reduced reference image quality assessment (RR-IQA), which uses only limited features from a reference image instead of a full image to evaluate the quality of the distorted image; and (3) no-reference image quality assessment (NR-IQA), which assesses the quality of an image without the need of any reference image or its features [1].

The quality of an image is generally calculated by measuring the deviation of the image in question from the reference image. There exist a number of image quality metrics, such as Pearson correlation coefficient, Spearman correlation coefficient, root mean square error, and peak signal-to-noise ratio [1]. As original reference images are usually unavailable in most situations, the starting point of NR-IQA is to build a virtual "reference" image based on modeling statistics of the reference image, utilizing the characteristics of human visual system. Numerous NR-IQA methods have been developed [1–6]. For example, Wang and Sheikh [2] proposed a Structural Similarity (SSIM) Index for image quality assessment based on the degradation of structural information in the image, and it has been employed in some algorithms for no-reference image clarity assessment, such as [4] and [5].

Due to the ever-increasing size and resolution of digital images, image quality assessment can be computationally challenging

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for traditional single-core Central Processing Units (CPUs). Parallel computing is commonly utilized to accelerate intensive computations and various parallel computing methods have been developed. Traditional computer processors only had one CPU on each processor chip and parallel computing was implemented on parallel computers that had many processor chips or clusters that were networked workstations. Software libraries such as Message Passing Interface (MPI) were developed to facilitate parallel programing. With advances in hardware design and Very Large Scale Integrated Circuit (VLSI) technologies, a single processor VLSI chip now contains multiple cores, called multi-core or many-core processors. For example, an Intel Xeon processor can have as many as 24 cores on a single chip. Therefore, computations can be partitioned into multiple subtasks and then allocated to multiple cores on the same CPU chip for parallel processing. Graphics Processing Units (GPUs) are another category of computing hardware that are now widely used for parallel computing on personal computers, workstations, and clusters. GPUs were developed to mainly accelerate computer graphics related computations, such as affine transformations and rasterizations. In recent years, GPUs have been utilized for general purpose computing (GPGPU) such as computational fluid dynamics and machine learning. Various software tools have been developed to support parallel computing on multicore CPUs and GPUs. OpenMP, MPI, and Microsoft Parallel Patterns Library (PPL) are the major software libraries for developing parallel applications on multicore CPUs, while NVIDIA's Compute Unified Device Architecture (CUDA) and Khronos Group's Open Computing Language (OpenCL) for GPU-based parallel computing.

Although GPU computing has been utilized to accelerate general image processing computations, recent research on IQA largely focused on developing IQA metrics and so far GPUs have been seldom used to accelerate image quality assessment computations. In this research, SSIM-based methods are chosen for image quality assessment mainly for three reasons: (1) there have been many variations of SSIM-Based methods that have proven to be effective and can be easily modified for NR-IQA purposes; (2) SSIM-based methods contain several pixel-wise operations suitable for parallelization; and (3) these methods contain some operations that are suitable for execution on CPUs. This research analyzes several SSIM-based NR-IQA methods and designs three implementations of the NR-IQA algorithm, two of which use CUDA solely and the third uses both CUDA and PPL [7]. The paper then compares the performance enhancement of the three parallel implementations of NR-IQA.

The remainder of this paper is organized as follows. Section 2 introduces structural similarity and its application in no-reference image quality assessment. Section 3 describes the three parallel implementations of SSIM-based NR-IQA. Section 4 presents and analyzes experimental results. Finally, Section 5 draws the conclusion.

2. Methodology of SSIM-based NR-IQA

Structural similarity was proposed under the assumption that the human visual system (HVS) is highly adapted to extract structural information from the viewing field. Many researchers, including Wang and Sheikh [2], have proved that it outperforms most other image features. In this section, we present a brief introduction to the methodological framework of NR-IQA, and the application of structural similarity in NR-IQA.

2.1. Methodology of no-reference image quality assessment

As NR-IQA is the solution to measure the quality of images when reference images are unavailable, methods have been proposed to obtain virtual "reference" images. Blur estimation is one of those frequently used, which assumes that the difference between an already blurred image and its re-blurred image is less than that of a sharp image and its blurred version. Therefore, the key idea of such methods is to blur the initial image and observe the variation of their pixels [3]. The assessment often consists of the following steps [3–5]:

(1) Obtain the "reference" image by applying a low pass filter to the initial image. Existing research showed that there are more edges in sharp images, i.e., high frequency components in the frequency domain. The blur effect is caused by a loss of the high frequency content and it can be reproduced with a low-pass filter [3]. The filter kernel is generally obtained by a circular-symmetric Gaussian weighting function $W=\{w_i|i=1,2,\ldots,N\}$, normalized to unit sum $\Sigma w_i=1$.
(2) Identify the quality factors of the initial image and the blurred "reference" image, for example, luminance and spatial resolution, contrast and color range, gradation, flicker, and noise. In [3], intensity variation between neighboring pixels was used as the deviation metric. In [2], luminance, contrast and structure were used as components of structured similarity index.
(3) Compare and calculate the deviation between the initial image and the blurred "reference" image with the abovementioned quality factors. A high similarity between the original image and its blurred reference image means that the original image was already blurred, representing a low or poor quality of the original image.

2.2. Structural similarity and its application in NR-IQA

Structural similarity was proposed by Wang and Sheikh [2] based on the assumption that the pixels in natural images are highly structured and exhibit strong dependencies, and the structure of the objects in natural scenes could be represented by these dependencies. The similarities between images include luminance similarity, contrast similarity, and structural similarity. For any two images X and Y, the three abovementioned components are mathematically defined as follows [2].

$$\begin{cases} l(X,Y) = \dfrac{2\mu_X\mu_Y + C_1}{\mu_X^2+\mu_Y^2+C_1} \\ c(X,Y) = \dfrac{2\sigma_X\sigma_Y + C_2}{\sigma_X^2+\sigma_Y^2+C_2}, \\ s(X,Y) = \dfrac{\sigma_{XY}+C_3}{\sigma_X\sigma_Y+C_3} \end{cases} \quad (1)$$

where $\mu_X(\mu_Y)$ and $\sigma_X(\sigma_Y)$ are the mean and the standard deviation of X (Y) respectively, σ_{XY} is the covariance of X and Y. The small constants C_1,C_2, and C_3 are included to avoid instability when the denominators in Eq. (1) are very close to zero. The variables μ_X, σ_X, σ_{XY} are calculated as follows.

$$\begin{cases} \mu_X = \dfrac{1}{N}\displaystyle\sum_{i=0}^{N} X_i \\ \sigma_X = \left(\dfrac{1}{N-1}\displaystyle\sum_{i=0}^{N}(X_i-\mu_X)^2\right)^{1/2} \\ \sigma_{XY} = \left(\dfrac{1}{N-1}\displaystyle\sum_{i=0}^{N}(X_i-\mu_X)(Y_i-\mu_Y)\right)^{1/2} \end{cases}. \quad (2)$$

μ_Y and σ_Y are calculated in a manner similar to the calculation of μ_X and σ_X. The similarity between the two images is defined as follows.

$$\mathrm{SSIM}(X,Y) = [l(X,Y)]^{\alpha}[c(X,Y)]^{\beta}[s(X,Y)]^{\gamma}. \quad (3)$$