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Acceleration of super-resolution for multispectral images using self-example learning and sparse representation☆

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ABSTRACT

Super-resolution obtains a new high resolution image from single or multiple low-resolution images for the same scene. Recently compressive sensing has been successfully used in signal recovery. This paper investigates the potential reduction in execution time by selecting tasks that can be parallelized using general purpose computing on graphics processing units (GPGPU) and Compute Unified Device Architecture (CUDA). The self example based super-resolution method via sparse representation and morphological component analysis is proposed for satellite images. Orthogonal Matching Pursuit (OMP) is used in the high resolution image reconstruction phase. The complexity of each module in the OMP algorithm is analyzed and its bottlenecks are identified at the projection module and the least squares module. The projection module is accelerated by adopting a GPU tiled matrix vector multiplication. To speedup the least square module, a GPU implementation of the Jordan matrix inverse algorithm is adopted. Different experiments have been carried out on synthetic and satellite images. Extensive experimental comparisons were conducted with state-of-the-art super-resolution algorithms to validate the effectiveness of the proposed approach. The proposed GPU implementation for OMP is tested on NVS 5200M GPU on Intel ® Core(TM) i7 CPU. The GPU implementation accelerates the speedup compared to the CPU sequential implementation from 20× for small images to more than 40× for large image sizes.

1. Introduction

Single super-resolution (SSR) addresses the recovery of the high-resolution (HR) image from single low-resolution (LR) image. High resolution image reconstruction is considered a highly ill posed undetermined problem where the reconstruction process depends on prior knowledge from a single low resolution image. Existing super-resolution algorithms are categorized into two classes: Interpolation based and example based approaches. Modern SSR methods rely on supervised machine learning techniques to identify the relationship between low resolution image patches and high resolution image

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patches. Various machine learning algorithms had been adopted including the nearest neighbor approaches [1], manifold learning [2], dictionary learning, locally linear regression and convolutional networks [3].

Sparse representation proposed an effective and promising method for a broad range of applications including image de-noising, de-blurring and recently the super-resolution problem. Sparse representation was incorporated as prior knowledge in recent researches and become a hot topic in those researches. Super-resolution (SR) based on compressive algorithms has two distinct stages: training a dictionary then reconstructing the high resolution (HR) image by using the representations. Two types of databases are used for training the dictionary: External and internal. In external databases, different images patches are used to map between low and high resolutions. The internal database is always obtained from a single image. The low and high resolution patched pairs recur across different scales.

Parallel computing becomes increasingly more popular with different technologies used to boost the performance of the image processing, especially super-resolution. Different efficient computational methods were developed for real time applications. Different computing platforms have been investigated to handle this computation demand efficiently. Graphic processing unit (GPU) was introduced by NVIDIA to accelerate computing since 2005. It has been used to boost the compressed sensing algorithm in super-resolution.

The contribution of this paper is two-fold: First, we proposed an enhancement to self-example OMP based super-resolution method via sparse representation and morphological component analysis for satellite images. Second, we introduced an optimized GPU implementation on a GPGPU using the CUDA programming model. Two new GPU kernels are proposed to solve the bottlenecks of the OMP; matrix vector multiplication and the Jordan matrix inverse algorithm. The paper studies the behavior of both the sequential CPU and the parallel GPU implementations of the proposed OMP based super-resolution towards the state-of-art sequential interpolation methods (bi-cubic algorithm), the projection onto the convex sets (POCS) method [4], Freeman et al. [1] method, and Chang et al. [2] method. Both synthetic and real multi-spectral satellite images are used in the experiments to validate the results. The performance of the proposed OMP parallel implementation is evaluated against different parameters, such as acceleration rates, image quality, dictionary size, and self-similarity window.

The paper is organized as follows: In Section 2, the related work is discussed. In Section 3, the compressive sensing and its popular orthogonal matching pursuit (OMP) are illustrated. Section 4 describes the proposed parallel implementation of OMP algorithm. The experimental results are shown and discussed in Section 5. Finally, Section 6 concludes the paper.

2. Related work

Super-resolution techniques had been shifted from interpolation methods to learning based methods where a prior knowledge is incorporated to map the relation between the high resolution (HR) and low resolution (LR) patches in the training phase. Lei et al. [5] proposed a single Super-resolution for remote sensing, based upon a sparse signal representation and self-trained dictionary learning. A single input LR image was used in a self-trained dictionary leaning to exploit a prior knowledge instead of an external training database. They optimized the K-SVD algorithm to adopt the dictionary learning and the optimized OMP algorithm for image patches sparse coding, which reduces effectively the computational cost. The prior knowledge is updated gradually using the concept of course to fine resolutions to increase the magnification factor. Finally, the newly recovered HR image is back projected onto the resolution of the input LR image to further guarantee its consistency. Quickbird satellite image were used to demonstrate the effectiveness of the proposed algorithm. Experimental results indicated that the proposed algorithm outperformed the other related SR methods in both visually and PSNR values.

Yang et al. [3] proposed a single example based Super-resolution method that exploits the self-similarities and group structural information of image patches. Image pairs that were generated directly using an image pyramid to generate patch pairs are clustered for training a dictionary by enforcing group sparsity constraints underlying the image patches and the HR image was obtained by using the learned dictionary. Experimental results showed that the proposed method had superior performance over the state-of-the-art method. Bevilacqua et al. [6] presented an example based single image Super-resolution (SR) method without the need of an external dictionary of image examples. The dictionary was trained using the input LR image itself by using double pyramids. The reconstruction of the HR image is a multi-pass by to use a regression based method to directly map the low resolution (LR) input patches into their related high resolution (HR) output patches. Finally, iterative back projection is also employed to ensure consistency in each pass. Extensive experiments and comparisons with other state-of-the-art methods are conducted. The proposed algorithm showed visually pleasant up-scaling, with sharp edges and well reconstructed details, also, objective metrics like PSNR and SSIM indicated the best performance.

Recently, Self-Example has been investigated in different super-resolution techniques. Table 1 shows summary of different self-example based methods for reconstructions of images. Dang et al. [7] proposed a learning based super-resolution method that exploited the input image and its different down sampled scales to extract a set of training sample points using a min-max algorithm. The HR image patches were then reconstructed on a tangent space estimation of the local HR patch manifold. Experiments on different images are conducted to validate the effectiveness of the proposed method both quantitatively and visually.

Zhu et al. [8] proposed a novel algorithm for fast single image SR based on self-example patch based dictionary learning and sparse representation. The proposed strategy exploited the sparse signal representation theory in the framework of compressed sensing and dictionary learning of image patches. The obtained high resolution images have similar quality to other methods but with an increase in the computational efficiency. In [9], Wang et al. proposed a joint SR framework which exploits the advantages of external and self-example based training databases. Pan et al. [10] adopted structural