Parallel Implementation of Spatial–Spectral Endmember Extraction on Graphic Processing Units

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***Abstract*—The identification of pure spectral signatures (endmembers) in remotely sensed hyperspectral images has traditionally focused on the spectral information alone. Recently, techniques such as the spatial–spectral endmember extraction (SSEE) have incorporated both the spectral and the spatial information contained in the scene. Since hyperspectral images contain very detailed information in the spatial and spectral domain, the integration of these two sources of information generally comes with a significant increase in computational complexity. In this paper, we develop a new computationally efficient implementation of SSEE using commodity graphics processing units (GPUs). The relevance of GPUs comes from their very low cost, compact size, and the possibility to obtain significant acceleration factors by exploiting properly the GPU hardware architecture. Our experimental results, focused on evaluating the candidate endmembers produced by SSEE and also the computational performance of the GPU implementation, indicated significant acceleration factors that allow exploiting the SSEE method in computationally efficient fashion.**

***Index Terms*—Graphics processing units (GPUs), hyperspectral imaging, spatial–spectral endmember extraction (SSEE).**

I. Introduction

SPECTRAL unmixing [1] is an important technique for the exploitation of remotely sensed hyperspectral datasets. Over the last years, many techniques have been developed for the identification of pure spectral constituents (called endmembers in unmixing jargon) and their corresponding fractional abundances at a subpixel level [2]. The remaining problem is how to automatically identify endmembers, which are representative of both the spectral and the spatial information contained in the scene. For instance, it is generally difficult to obtain endmembers, which are representative in spatial sense, as endmember identification algorithms are often driven by the spectral information alone and are therefore sensitive to noise, outliers, and anomalous endmembers [3].

To address this issue, several strategies have been proposed in order to guide the endmember identification process to spatially homogeneous areas, expected to contain the purest signatures available in the scene [4]–[6]. For this purpose, several spectral–spatial techniques have been developed for the identification of endmembers in hyperspectral scenes.

One of the first algorithms in the literature designed to integrate the spatial and the spectral information was the automatic morphological endmember extraction (AMEE) [4], which used extended morphological operations of erosion and dilation to account for endmembers that are sufficiently pure (in spectral terms) and cover a large area (in spatial sense). The algorithm had several shortcomings, including the need to define a spatial search area around each pixel in the scene and its computational complexity. Another important method is the spatial–spectral endmember extraction (SSEE) [5], which uses spatial constraints to improve the relative spectral contrast of endmember spectra that have minimal unique spectral information, thus improving the potential for these subtle, yet potentially important endmembers to be selected. With the SSEE, the spatial characteristics of image pixels are used to increase the relative spectral contrast between spectrally similar, but spatially independent endmembers.

Finally, several spatial preprocessing (SPP) methods have been used prior to endmember identification [7]–[9]. These methods are intended to be combined with a spectral-based endmember extraction algorithm. The SPP in [7] introduces the spatial information in the endmember extraction process, so that the preprocessing can be combined with classic methods for endmember identification [10]. The main idea behind this preprocessing is to estimate, for each input pixel vector, a scalar factor, which is related to the spatial similarity between that pixel and its spatial neighbors, defined in a spatial window that defines a neighborhood around each pixel vector, and then use this scalar factor to spatially weigh the spectral information associated to the pixel. An extension of this concept was

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