INVESTIGATION OF HYPERSPECTRAL IMAGINARY DATA FOR MINERAL DETECTION

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For everybody in my life that has support me to finish this project especially my dearest family, supervisor and friends

ABSTRACT

Hyperspectral unmixing (HU) is a very potential and increasingly popular preprocessing step for a wide range of hyperspectral application. Besides, it one of the important technique for hyperspectral data exploitation. Due to low spatial resolution of Hyperspectral cameras, microscopic material mixing, and multiple scattering, spectra measured by HSCs are mixtures of spectra of materials in a scene. Thus, accurate estimation is required using the hyperspectral unmixing algorithms. The linear mixing model is considered that assume hyperspectral image represented in the linear combination. However, this algorithm can perform all the chain involved in the hyperspectral unmixing process. The first chain is to the identification a set of pure spectral signature of the endmember. The second chain is to estimate the fractional abundances for each endmember for each pixel of the scene. These chains require an algorithm that highly desirable to avoid the propagation of error. The project is performed on a real HIS dataset as well on Airborne cuprite areas. Hence, this project attempt to propose a robust, stable, tractable, and accurate unmixing algorithm. The effectiveness of proposed method is confirmed through comparison with other algorithms, calculate the performance of unmixing by using spectral angle distance (SAD) under different noise level.

ABSTRAK

Hyperspectral unmixing (HU) adalah langkah preprocessing yang sangat berpotensi dan semakin popular untuk pelbagai aplikasi hyperspectral. Selain itu, ia merupakan salah satu teknik penting untuk eksploitasi data hyperspectral. Oleh kerana resolusi spatial kamera Hyperspectral yang rendah, pencampuran bahan mikroskopik, dan pelbagai hamburan, spektrum yang diukur oleh HSCs adalah campuran spektrum bahan di tempat kejadian. Oleh itu, anggaran tepat memerlukan algoritma hiperspectral unmixing. Model pencampuran linear dianggap sebagai menganggap imej hiperspectral yang ditunjukkan dalam gabungan linear. Walau bagaimanapun, algoritma ini boleh melakukan semua rantai yang terlibat dalam proses hiperspektral unmixing. Rantaian pertama adalah untuk mengenal pasti satu set tanda spektrum tulen endmember. Rantaian kedua adalah untuk menganggarkan jumlah pecahan bagi setiap endmember bagi setiap piksel tempat kejadian. Rantai ini memerlukan algoritma yang sangat diingini untuk mengelakkan penyebaran ralat. Projek ini dilakukan pada dataset HIS yang sebenar serta di kawasan cuprite Airborne. Oleh itu, percubaan projek ini mencadangkan algoritma yang mantap, stabil, boleh dikesan dan tepat. Keberkesanan kaedah yang dicadangkan disahkan melalui perbandingan dengan

algoritma lain, mengira prestasi unmixing dengan menggunakan jarak sudut spektrum (SAD) di bawah tahap bunyi yang berbeza.

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LIST OF SYMBOLS AND ABBREVIATIONS

HU	:	Hyperspectral Unmixing
NMF	:	Nonnegative Matrix Factorisation
LMM	:	Linear mixing model
NLLM	:	Nonlinear mixing model
PCA	:	Principle component analysis
CoNMF	:	Collaborative Nonnegative Matrix Factorisation
NFINDR	:	N-finder
SISAL	:	Simplex identification via variable splitting and augmented Lagrangian
LCTF	:	liquid-crystal tunable filter
HySime	:	Hyperspectral signal identification by minimum error
MV	:	Minimum volume
HSI	:	hyperspectral image
GPS	:	Global Positioning System
RTT	:	Radiative transfer theory
CCA	:	Convex cone analysis
SA	:	Annealing algorithm

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CHAPTER 1

INTRODUCTION

1.1 Background

This chapter describes the background of the study, which is an introduction to the research in hyperspectral imaginary data in precision agriculture. Then it followed by the problem statement of the study, research objectives, the scope of work and organization of the thesis.

1.2 Concept of Hyperspectral Imaging

The imaging concept is divided into two type which is multispectral and hyperspectral. Hyperspectral imaging is also known as other spectral imaging. It collects and processes the information from across the electromagnetic spectrum[1][2]. Besides, it has been widely used in the various scientific field. This concept enables capture of an image simultaneously in hundreds of narrow continuous spectral band. Moreover, the advantage of the hyperspectral imaging is to provide a large amount of data including of the complete spectrum of the ground object. The hyperspectral imaging is used in order to overcome the problem of resolution in part of the limitation of the sensors and the variability of the ground surface.

The observation of one pixel may contain several different substances causing it to be a “mixed pixel”. Furthermore, to utilize the hyperspectral information, the mixed pixel must be decomposed into a set of constituent spectra called endmember signatures and their corresponding proportions called abundances[1][3]. With the consistent improvement of imaging spectroscopy, hyperspectral pictures gathered by imaging spectrometers have caught progressively rich spatial, spectral, and outspread data, which advantage the hypothetical research on hyperspectral information analysis.

Nonetheless, the hyperspectral information basically contains a few hundreds of continuous spectral bands with limit wavelength intervals. However, there broadly exist mixed pixels attributable to the restricted spatial determination of the sensors of the sensor and the variation ground surface. Hence, the main goal is to make full utilization of the information. So, the hyperspectral unmixing has become an essential process, which deteriorates a mixed pixel into a gathering on constituent materials additionally called endmember and their relative proportions [4]. Hyperspectral unmixing (HU) alludes to any procedure that isolates the pixel spectra from a hyperspectral picture into a collection of constituent spectra, or spectral signatures, called endmembers and a set of fractional abundances, one set for each pixel[5]. The endmember are for the most part expected to represent the pure materials present in the images and the set of abundances, or simply abundances at every pixel to represent to the level of each endmember that is available in the pixel [6][7]

Besides, the hyperspectral imaging focusing on linear spectral unmixing is one of the essential tools to analyze remotely captured hyperspectral images form the specific scene [6]. The spectral unmixing is an essential strategy for hyperspectral information exploitation [1]. While this technique based on the suitable model signal. Generally, two model signal most used in the hyperspectral image is Linear Mixing Model and Nonlinear Mixing Model. Both signals have pros and cons but the Linear Mixing Model (LMM) has been the most prevalent device used to unmixing remotely detected hyperspectral information [8].

The LMM accept that every pixel can be deciphered as a linear mix of a given number of pure materials (i.e., endmembers) with their corresponding divisions alluded to as abundances. Notwithstanding, the weak of ability to represent temporal and spatial fluctuation between and among endmembers has been recognized as a major weakness of LMM with exist endmembers. In reality, endmember changeability has gotten impressive consideration in the most recent decade. The previously mentioned techniques expect to utilize endmembers in a more flexible manner, potentially joining different occasions of a given endmember, however, are as yet in view of LMM. Then again, there are additionally two models which rise above the LMM in the objective of including the natural endmember variance[9][10].

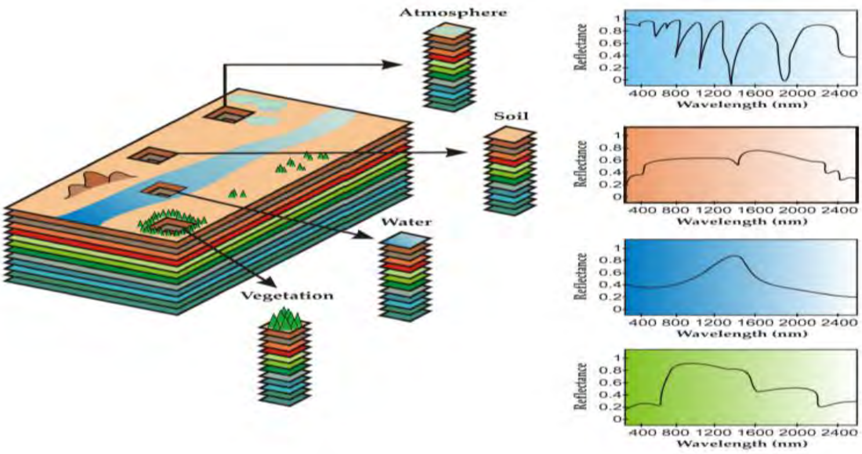

Figure 1.1 Hyperspectral concept [1]

Figure 1.1 outlines the measured data. Clearly, the data cube obtained from organizing the data into planes whereas each plane corresponds to radiance obtained through a spectral band for all pixels. Each spectral vector corresponds to the radiance acquired at a given scene for all spectral bands.

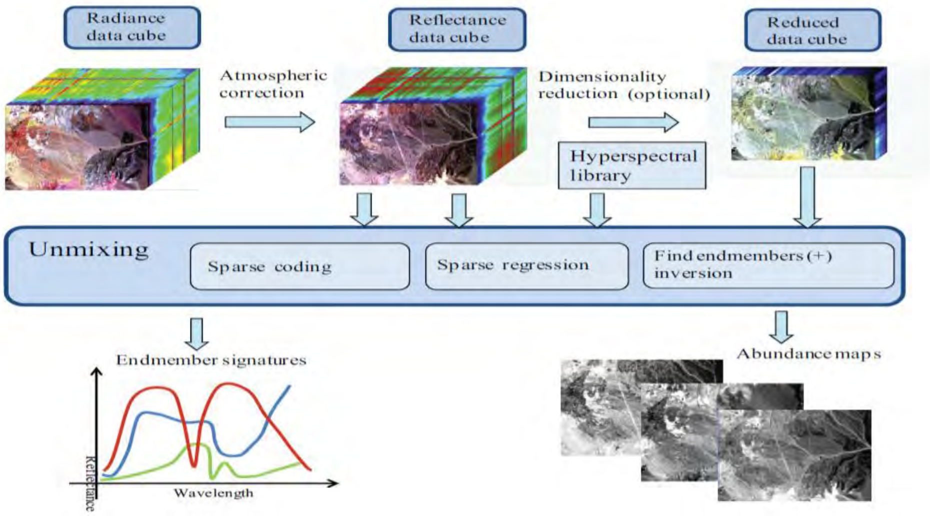

Figure 1.2 Processing step [1]

Figure 1.2 demonstrates the processing step over a hyperspectral to perform the unmixing process that involving four main step which is an atmospheric correction, dimensionality reduction, unmixing, and inversion.

The first step is considering the atmospheric correction of the radiance data cube. The atmosphere attenuates and scatters the light among the plane. Therefore, affects the radiance at the sensor. The atmospheric correction actually compensates for these impacts by changing radiance into reflectance, which is a characteristic property of the materials. We stress, however, that linear unmixing can be carried out directly on radiance data.

The next step is data reduction after converting the property of data cube. The basic concept is the reduction the multitudinous amounts of data down to the meaningful parts. It affects the dimensionality of the data cube where space spanned by spectra from an image is generally much lower than an available number of bands. It aims at identifying related subspaces to facilitate dimensionality reduction, improving algorithm performance and complexity and data storage. Furthermore, if the linear mixture model demonstrates is precise, the number of endmembers is one less than equal to the signal subspace dimension is a crucial figure in hyperspectral unmixing.

The next step is unmixing. Through the unmixing process, it consists of several steps especially identifying the endmembers in the scene and the fractional abundances at each pixel. Three basic approaches are used to address this problem. Each approach has a different method. First approaches refer to Geometrical approaches define that linearly mixed vectors are in a simplex set or in a positive cone. The second approach is the Statistical. This approach basically focuses on using parameter estimation techniques in order to predict endmember and abundance