A Method for Recovering Near Infrared Information from RGB Measurements with Application in Precision Agriculture

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***Abstract*—In this work we develop a cost-efficient coupled dictionary learning based method for reconstructing multispectral images using only a single RGB commercial camera, without requiring the sensitivity function of the camera sensor. Considering the very high cost, the acquisition time and reduced mobility of multispectral cameras we claim that this is a very attractive option. In contrast to other approaches, the proposed method is not limited only to spectral bands inside the visible spectrum, but it also considers an even more challenging task, that is the reconstruction of spectral bands outside the visible range closer to the near-infrared wavelengths of the spectrum. Extensive experiments with real data demonstrate the effectiveness and applicability of the proposed method in the precision agriculture domain. To this end, we calculate one of the most widely used vegetation indices, the normalized difference vegetation index (NVDI), which may be used for plant health monitoring.**

***Index Terms*—Multispectral Imaging, Near infrared bands, Coupled dictionary learning, NDVI, RGB images**

I. Introduction

Over the last years, multispectral imaging has proven to be remarkably beneficial to various computer vision applications, ranging from remote sensing [1], medical imaging and autonomous driving to precision agriculture and land health surveillance [2]. Contrary to mainstream RGB cameras, which can capture only three spectral bands, the aim of multispectral imaging is to exploit the abundant spectral information which underlies the electromagnetic spectrum, providing much more detailed spectral resolution. Typically, a multispectral camera can offer 5 to 15 spectral bands in the visible and near-infrared electromagnetic spectrum. However, this high spectral resolution is accompanied with several limitations. In particular, the cost of the multispectral cameras is very high and they exhibit various mobility limitations due to their weight and the need for special hardware equipment. This may be an obstacle for real applications.

Considering the aforementioned limitations, in this paper, we propose a low-cost and efficient method to infer detailed spectral information outside the visible spectrum range by employing only an RGB camera. Our ultimate goal is to develop a novel coupled dictionary learning method which exploits the spectral information without the need for a multispectral camera during the system's operation. Using only an RGB camera, the proposed system is able to reconstruct accurately the most informative spectral bands for various applications such as monitoring the health of the crop. To this end, we examine the validity of our method in a real-world application for detecting plant diseases. In more details, having reconstructed spectral bands in the near infrared spectrum, we calculate one of the most widely used vegetation indices, namely the normalized difference vegetation index (NDVI) [3], which can reveal valuable information concerning the health of the under examined plants [4].

Plant diseases have been a thorny and perplexing problem in the agricultural domain with tremendous economic and environmental impacts worldwide [5]. Advances in signal processing have provided an opportunity to extend and ameliorate automatic systems so as to monitor plant health and identify pathogens [6], [7]. In recent years, in precision agriculture [7], multispectral and hyperspectral imaging provide new insights into the complicated pathogen-host system, enabling researchers to investigate the reflectance properties of the plants in various wavelengths of the electromagnetic spectrum (visible, near infrared), thereby leading to more efficient methods for plant disease detection [7], [8].

To sum up, the key contribution of the proposed work is two-fold:

- A novel method is proposed which based on visible (RGB) data provides effective spectral reconstruction for spectral bands beyond the visible spectrum. Particularly, unlike previously presented that focus on reconstructing spectral bands inside the visible range, our method enables the recovery of near infrared spectral bands, i.e., bands beyond the spectral reach of the RGB camera.
- Application of the proposed method to obtain spectral data for a plant disease detection task in a real greenhouse setting by calculating the NDVI index, which is very useful for monitoring plant health.

The remainder of the paper is organized as follows. Section 2 presents an overview of the related literature. Section 3 describes the proposed technique for reconstructing multispectral bands via RGB data. Section 4 presents some experimental results that demonstrate the efficacy of the proposed framework.

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Finally, section 5 concludes the paper.

II. Related work

In literature, there are a plethora of studies tackling the problem of recovering spectral information inside the visible spectrum, by exploiting only RGB measurements. Nguyen *et al.* [9], employed a radial basis network to learn a non-linear mapping from RGB to multispectral measurements. Arad *et al.* [10] proposed a dictionary learning based method, utilizing the sparsity of the multispectral images. In particular, they used a dictionary from hyperspectral priors and the corresponding RGB projections via the known sensitivity function of the RGB camera to recover hyperspectral signals through RGB intensities. Furthermore, Oh *et al.* [11] utilized the different sensitivity functions of multiple RGB cameras to reconstruct hyperspectral images. Later, Wu *et al.* [12] employed adjusted anchored neighborhood regression for extracting hyperspectral information. Akhtar *et al.* [13] used Gaussian processes for recovering spectral details. In recent years, as increasing amounts of spectral-data have become available, deep learning based approaches have emerged. Alvarez-Gila *et al.* [14] employed Generative Adversarial Networks to reconstruct the spectral information through RGB images. Kaya *et al.* [15] proposed a CNN-based model to recover spectral signals without any priors about the scene conditions. Peng *et al.* [16] employed a residual pixel attention network for recovering spectral information. Shi *et al.* [17] proposed a residual advanced CNN to reconstruct the spectral information through RGB images. Yan *et al.* [18] introduced a methodology based on the U-net-based architecture, namely C2H-Net, to recover hyperspectral images from their RGB measurements. Zhao *et al.* [19] used a hierarchical regression network (HRNet) to reconstruct spectral details. Li *et al.* [20] employed an adaptive weighted attention network (AWAN) for spectral reconstruction, exploiting the knowledge of the RGB camera sensitivity function.

It should be highlighted that the above mentioned approaches focus only on recovering spectral bands inside the visible spectral range. However, in numerous scenarios and settings, such as plant health monitoring [3], [8] and medical applications [21], the most informative spectral bands belong outside the visible spectrum. Hence, in this study, *unlike the other studies in literature*, we focus on developing an efficient coupled dictionary learning method, tackling an even more difficult problem, which is the recovery of spectral information outside the visible range. In particular, the proposed method is able not only to reconstruct spectral bands inside the visible spectrum, but more importantly, to recover bands in the near infrared range.

Overall, this paper provides valuable evidence that such a challenging problem, that is the reconstruction of spectral bands beyond the visible spectrum, is feasible with significant practical value as it can be implemented in some real-world applications.

III. MULTISPECTRAL RECONSTRUCTION FROM RGB DATA

We propose a cost-efficient and accurate technique for reconstructing spectral information in the near-infrared spectrum, via an RGB camera, thus reducing the dependency on multispectral cameras in real-world applications.

A. Problem formulation

Consider an RGB image, denoted by $\boldsymbol{I}_{rgb} \in \mathbb{R}^{n1 \times n2 \times 3}$. Our principal goal is to recover a multispectral image $\boldsymbol{I}_{ms} \in \mathbb{R}^{n1 \times n2 \times B}$ which corresponds to the same natural scene, where where B corresponds to the spectral channels. Hence, our focus is to ameliorate the spectral resolution (dimension) of the RGB image by reconstructing spectral bands in the near infrared spectrum, which are the most informative for the application at hand. The formulation of the considered problem can be expressed as follows:

$$\boldsymbol{I}_{ms} = \mathcal{F}(\boldsymbol{I}_{rgb}), \tag{1}$$

where $\mathcal{F}$ denotes the the mapping function between the RGB space and the multispectral space. Based on training data, our aim is to accurately model this unknown transformation function by employing a coupled dictionary learning methodology.

B. Coupled Dictionary learning based method

Building upon the inherent sparsity of the natural images [22], [10], we propose a sparse coupled dictionary learning method to model the unknown relationship between the RGB and the multispectral measurements. Concretely, given an RGB training set $\boldsymbol{X} : \{x_i\}_{i=1}^N$, where $x_i \in \mathbb{R}^d$ is an RGB patch (size $\sqrt{p} \times \sqrt{p} \times 3$ and held as a column vector of length d), and the corresponding multispectral training set $\boldsymbol{Y} : \{y_i\}_{i=1}^N$, where $y_i \in \mathbb{R}^l$ is a spectral patch (size $\sqrt{p} \times \sqrt{p} \times B$ and held as a column vector of length l), the optimum pair of coupled dictionaries $\boldsymbol{D}_x \in \mathbb{R}^{d \times K}$ and $\boldsymbol{D}_y \in \mathbb{R}^{l \times K}$ can be estimated for any coupled signal pair $\{x_i, y_i\}$ by solving the following objective function:

$$\begin{aligned} &\min_{\boldsymbol{D}_x, \boldsymbol{D}_y, \boldsymbol{G}} \|\boldsymbol{X} - \boldsymbol{D}_x \boldsymbol{G}\|_F^2 + \|\boldsymbol{Y} - \boldsymbol{D}_y \boldsymbol{G}\|_F^2 \\ &s.t. \|\boldsymbol{G}(:, i)\|_0 \leq T_o \; \forall\, i = 1, ..., N, \\ &\|\boldsymbol{D}_x(:, j)\|_2^2 \leq 1, \; \|\boldsymbol{D}_y(:, j)\|_2^2 \leq 1 \; \forall\, j = 1, ..., K\,, \end{aligned} \tag{2}$$

where $G(:, i)$ is the ith sparse coding column vector corresponding to the ith coupled pair signals $\{x_i, y_i\}$, $\boldsymbol{D}_x(:, j)$ and $\boldsymbol{D}_y(:, j)$ stand for the jth atom of the respective dictionary.

However, the reconstruction of spectral bands outside the visible spectrum using only RGB measurements constitutes *a really challenging ill-posed problem, since the information captured by RGB cameras does not practically extend to the IR range.* Thus, instead of learning a large pair of of large dictionaries, say, $\boldsymbol{D}_x$ and $\boldsymbol{D}_y$ to represent the RGB data $\boldsymbol{X}$ and the multispectral data $\boldsymbol{Y}$ respectively, our proposed method aims to reduce the size of the coupled dictionaries and make the atoms of the dictionaries more effective in representing the multispectral and the RGB data. In light of this, we cluster the training dataset into M clusters using the Kmeans++

algorithm, where each cluster contains similar multispectral data and the corresponding RGB measurements. Thus, having grouped the data into clusters in this method we learn smaller coupled dictionaries for each cluster independently.

Let $\boldsymbol{X}^m$ and $\boldsymbol{Y}^m$ denote the RGB and the multispectral training data in the m-th cluster. The coupled dictionaries are expressed as $\boldsymbol{D}_x^m$, $\boldsymbol{D}_y^m$ and they can be obtained by solving the optimization problem in (3). Nevertheless, instead of learning the dictionaries jointly, we start with the RGB data $\boldsymbol{X}^m$ constructing the RGB dictionary $\boldsymbol{D}_x^m$ based on the classic single feature space dictionary learning problem:

$$\begin{aligned} &\min_{\boldsymbol{D}_x^m, \boldsymbol{G}_m} \|\boldsymbol{X}^m - \boldsymbol{D}_x^m \boldsymbol{G}_m\|_F^2 \\ &s.t. \ \|\boldsymbol{G}_m(:,i)\|_0 \leq T_o, \ \|\boldsymbol{D}_x^m(:,j)\|_2^2 \leq 1. \end{aligned} \tag{3}$$

The problem in relation (3) can be effectively tackled via the K-SVD dictionary learning algorithm [23], whereas the sparse coding stage can be performed using the Batch-OMP algorithm [24]. After learning the dictionary $\boldsymbol{D}_x^m$ and sparse coding matrix $\boldsymbol{G}^m$, the corresponding spectral dictionary $\boldsymbol{D}_y^m$ is estimated as follows:

$$\underset{\boldsymbol{D}_y^m}{min} \left\|\boldsymbol{Y}^m - \boldsymbol{D}_y^m \boldsymbol{G}_m\right\|_F^2 \tag{4}$$

The closed form solution of problem (4) is given by

$$\boldsymbol{D}_y^m = \boldsymbol{Y}^m \boldsymbol{G}_m^+ = \boldsymbol{Y}^m \boldsymbol{G}_m^T (\boldsymbol{G}_m \boldsymbol{G}_m^T)^{-1}. \tag{5}$$

C. Efficient Multispectral Recovery

Given a new testing RGB image, say $\boldsymbol{X}_{new}$, the following methodology is used to recover the corresponding multispectral image of the scene. The RGB image is divided into non-overlapping patches size $\sqrt{p} \times \sqrt{p} \times 3$ (held as a column vectors of length d). For each patch x_i encountered in the RGB image, its nearest cluster in the training set is found and the corresponding RGB dictionary is employed to represent it. Then, all patches in the examined image that belong to the m-th cluster can be expressed as

$$\boldsymbol{X}_{new}^m = \boldsymbol{D}_x^m \boldsymbol{G}_m, \tag{6}$$

where $\boldsymbol{G}_m$ denote the sparse representation matrix for the testing RGB data in the m-th cluster. Note that the sparse representation matrix can be calculated by using some sparse coding algorithm such as batch-OMP [24].

Considering that the proposed method can be used for processing large volumes of data, such as health-plant monitoring, the computational complexity of the existing sparse coding algorithms may become a critical issue, thus rendering the reconstruction of the multispectral image an extremely slow procedure. In particular the sparse coding algorithms treat the patches that belong to the m-th cluster independently ignoring that they demonstrate strong similarity properties. In light of this, and **only** for the sparse coding procedure during the testing stage we use the algorithm presented in [25], which employs a block-processing strategy and reduces notably the required computational complexity, thus making our method ideal for online applications.

Having effectively estimated the sparse matrix $\boldsymbol{G}_m$, the corresponding multispectral data of the m-th cluster can be reconstructed by

$$\boldsymbol{Y}_{new}^m = \boldsymbol{D}_y^m \boldsymbol{G}_m. \tag{7}$$

Thus, the overall multispectral image can be recovered by gathering the reconstructed data from all the M clusters.

IV. EXPERIMENTAL PART

As it has already been mentioned, *unlike the other studies in literature* that reconstruct spectral data only in the visible spectrum range, our proposed method tackles an even more difficult and practical problem, which is the recovery of spectral information outside the visible range (based on data in the visible). For this reason, the proposed method could not be compared with the recent studies discussed in the introduction, as these tackle in fact different problems. To validate our method, we conducted experiments in the precision agriculture domain, by estimating near infrared bands and by calculating the NDVI index.

A. Dataset and Parameter Setting

Our dataset includes 100 8-bit multispectral images from different tomato plants. Specifically, the multispectral camera provided three spectral bands in the visible spectrum, namely the 460 nm, 540 nm and 630 nm and one in the near infrared spectrum, namely the 850 nm. The spatial resolution of each image is 1770x2368 pixels. In addition, each multispectral image has a corresponding RGB image.

Concerning the implementation, the number of the clusters was set to $M = 35$. The dictionaries employed $K = 64$ atoms, while the sparsity level was 12. A patch size of 3×3×3 (or length 27 in vector form) and 3×3×4 (or length 36 in vector form) was employed to divide the RGB and multispectral images into non overlapping patches respectively. These parameters were determined to be ideal via exploration of the parameter space. A 5-fold cross-validation was employed to determine the parameters and the performance of our method, splitting the dataset into training, validation and test set. Finally, the reconstruction performance between the ground truth and the estimated images, is quantified by the Relative Root Mean Square Error (RMSE), normalized by the ground truth luminance, Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) metrics. The simulations were performed using Matlab (2019a), running on a PC with an Intel i7-8700 CPU at 3.40 GHz with 16 GB of RAM.

B. Numerical Results

Figure 1 demonstrates the high quality of the reconstructed near infrared spectral band at 850nm by illustrating a comparison with ground truth images. It is worth noting that the errors maps are depicted on a scale of $[0 - 0.2]$ instead of the standard scale $[0 - 1]$, as the error is very small, which indicates the effectiveness of the proposed method. The above mentioned results are consistent with the quantitative analysis summarized in Table I, since our method achieves high PSNR

TABLE I: Average reconstruction results for the 850 nm near infrared spectral band.

Metrics	PSNR	SSIM [0-1]	RMSE [0-1]
Proposed method	32.17	0.9663	0.0251

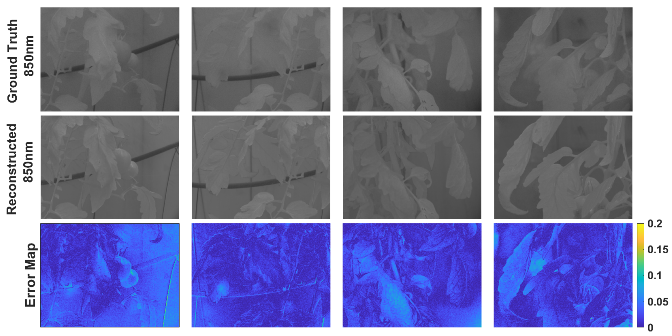

Fig. 1: The ground truth and reconstructed images in 850 nm near infrared spectral band. In row one we present the 850nm ground truth, in row 2 the reconstructed in 850 nm and in row 3 the error. Error maps are depicted on a scale of [0-0.2] instead of the standard scale [0-1], as the error is very small.

and SSIM (more than 0.95 and closer to 1) values and low error rate in terms of RMSE metric. Figure 2 illustrates the sensitivity of the proposed method to the selection of the parameters, namely the number of clusters (M), the number of the dictionary atoms (K) and the sparsity level. To examine the parameters, the dataset was divided into two parts: 50% for the training and 50% for testing and vise versa. The number of the clusters appears to have a significant impact on the accuracy of our method, as it offers a huge dimensionality reduction on size of the dictionaries, making the atoms of the dictionaries more compact and efficient to represent the RGB and near infrared data. It is evident that the best results occur when large cluster size and smaller dictionaries are employed. Thus, the cluster size was set to 35 and the number of atoms was set to 64 for later tests. On the other hand, the sparsity level has a low influence on the PSNR of the proposed method. For that reason, we didn't consider values greater than 12, as they would impact only the computational complexity of the method. Hence, the sparsity level was set to 12 balancing between the accuracy and the computational complexity.

To further demonstrate the efficacy and applicability of the proposed method, we conducted experiments in the precision agriculture domain, by calculating the normalized difference vegetation index (NDVI) [3]. To estimate the vegetation index, we calculate also the three spectral bands inside the visible range (460, 540 and 630 nm) . In particular, Figure 3 depicts the ground truth NDVI index using the spectral bands in the 650 nm and 850 nm captured via the multispectral camera and the estimated NDVI index calculated via the corresponding reconstructed spectral bands. The histograms of the ground truth and reconstructed NDVI indices are also presented. It is evident that the proposed method is able to accurately

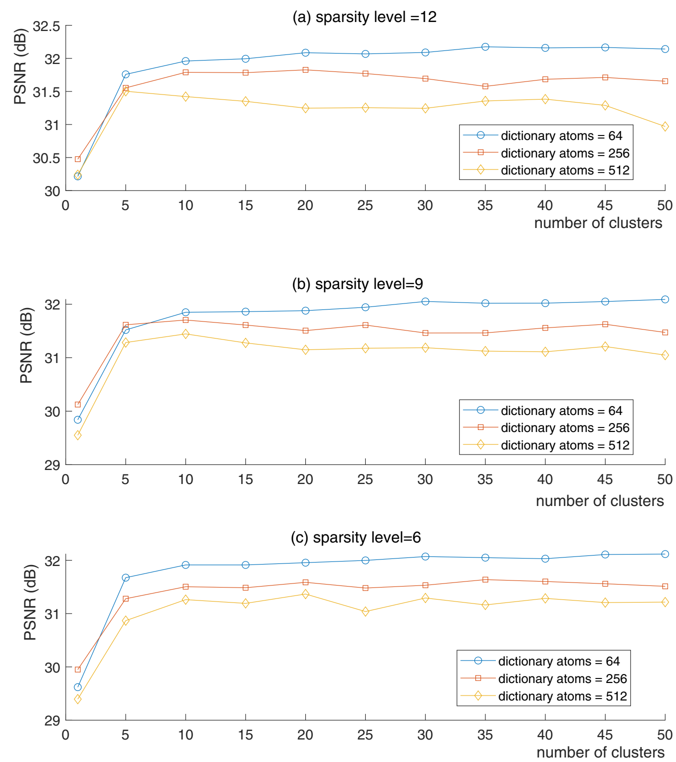

Fig. 2: Influence of the clusters number and the dictionary size on the performance of the proposed method, employing (a) sparsity level = 12, (b) sparsity level =9 and (c) sparsity level = 6.

estimate the NDVI index, providing comparable results with the multispectral camera. Finally, regarding the computational complexity of our method, the reconstruction of a multispectral image of size 1770x2368x4 requires only **7** seconds, thus rendering the method ideal for online applications.

V. Conclusions

We developed an efficient coupled dictionary learning based method for precisely reconstructing multispectral images using a single RGB commercial camera. On the contrary to other methods, our methodology focuses on reconstructing spectral bands outside the visible spectrum, namely bands closer to the near-infrared wavelengths of the spectrum. Considering the very high cost, the acquisition time and reduced mobility of multispectral cameras we claim that this is a very attractive option. Furthermore, we demonstrated its application in a real setting for estimating one of the most widely used vegetation indices, the normalized difference vegetation index (NVDI) and showed that it can be used as a significantly cheaper and far more usable alternative to installing a spectral camera, which gives comparable results.The datasets used in the experimental part will soon become publicly available.

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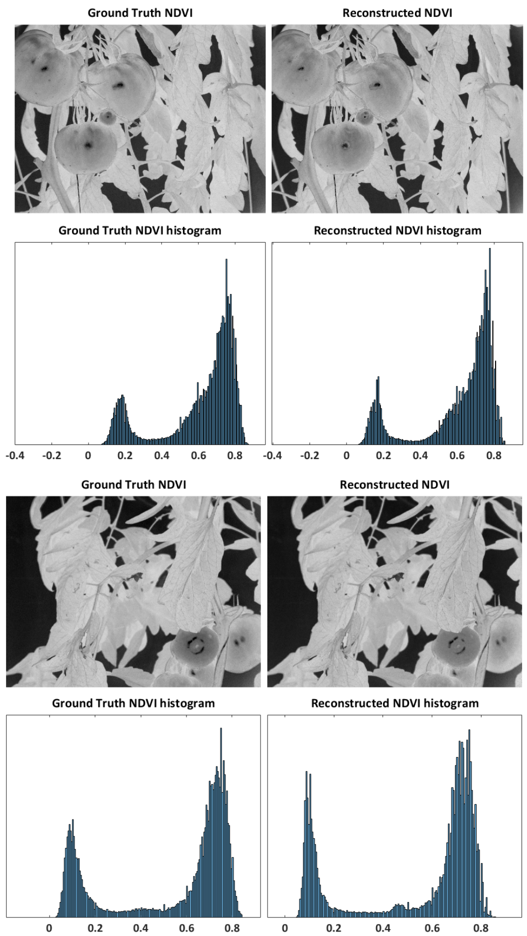

Fig. 3: The ground-truth NDVI index using the spectral bands in the 650 nm and 850 nm captured via the multispectral camera vs. the estimated NDVI index given by the corresponding reconstructed spectral bands. Along with the NDVI images, the corresponding histograms of the NDVI indices are shown to further clarify the quality of the reconstructed NDVI index.

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