Learning Recovered Pattern from Region-Dependent Model for Hyperspectral Imagery

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Abstract—The Compressive-Projection Principle Component Analysis (CPPCA) technique which recovers hyperspectral image (HSI) data from random projection efficiently, has been proved to be significant in decreasing signal-sensing costs at the sender. Inspired by the fact that the spectral signature of the same ground cover is similar, and two pixels of the neighborhood are likely to belong to the same ground cover, this paper proposed a novel region-dependent approach CPPCA to recover HSI data. Due to the fact that the region map is critical to our proposed algorithm, herewith we employ a robust supervised Bayesian approach (LORSAL-MLL segmentation) which explores both the spectral and spatial information in an intuitive interpretation with small size samples to segment hyperspectral image into different regions. The CPPCA reconstruction procedure is then employed to each region independently other than each partition individually. The effectiveness and practicability of proposed region-dependent CPPCA (RDCPPCA) reconstructed algorithm is illustrated by real hyperspectral image data set with several criteria measurement.

Index Terms—Hyperspectral image segmentation, Hyperspectral image reconstruction, Compressive sensing, Principle component analysis.

I. INTRODUCTION

Hyperspectral image data [1] has become increasingly popular and attracted more attentions in high dimensional data analysis community, since this technology can be widely applied to landmarks analysis [2], target detection [3], and remote sensing [4] etc. One of the main challenging problems of HSI is its high dimensionality which conducts the expensive computational cost for data analysis [5]. Hence, it will be of great benefit if dimensionality reduction could occur before further processing, since many signal acquisition devices are often highly with limited computational resource [6]. These state-of-the-art techniques include principal component analysis (PCA) [7], discrete wavelet transform (DWT) [8], as well as kernel nonparametric weighted feature extraction (KNWFE) [9].

Conventional paradigm generally employs DWT at the sender. However, such kind of technique has found to be a disadvantage in those literatures are regularly of expensive computational cost and are required to reside on board the sender. This sender is usually housed within the sensing modality [10]. Recently, as a candidate transform sensing system, compressed sensing (CS) [11], which provides a framework for the recovery of sparse signal from data independent random projection, has been gotten popularity among many researchers around the world. Fowler et al. [4] developed compressive-projection PCA (CPPCA) for sparse signal recovery which integrates the PCA transformation with compressed sensing. Recently, W. Li [12] proposed a class-independent CPPCA strategy for hyperspectral image reconstruction. The principle behind class-independent CPPCA is that when the distribution of HSI data is multimodal, conventional CPPCA will recover the primary eigenvectors which represent the entire data set. On the contrary, class-independent CPPCA recovers the primary eigenvectors for each group individually. By doing so, the accuracy of receiver-side reconstruction for each category will be much more precise than conventional CPPCA. Nevertheless, according to our experiment, the class accuracy of classifier/clustering-based approaches is generally worse than the segmentation-based approaches. The main reason lies in the fact that classifier/clustering-based approaches treat each pixel of HSI data individually and thus ignore the fact that the pixels, who are with similar properties and adjacent to each other spatially, are likely to be the same land cover. In other words, two neighboring pixels are expected to have the same label.

Inspired by the fact that both supervised and unsupervised classification/clustering literatures discard the spatial information, we thus propose a novel segmentation based CPPCA recovered scheme which employs the segmentation methodologies to group pixels with similar properties and spatial locality other than classifier/clustering methodologies.

The remainder of this paper is organized as follows. We start with Section II which introduces the conventional CPPCA algorithm. In Section III, we present our region-dependent CPPCA approach, following with Section IV which reports the reconstructed results of the efficiency on real hyperspectral image data sets. And at final, we conclude our work with a few remarks and hints in Section V.

II. RELATED WORKS

The conventional CPPCA adopts the results of random projection to achieve a relative cheap computational cost. By doing so, the transformation procedure of HSI data is dramatically accelerated at the sender. However, the question at hand is how to recover the HSI data from the projection domain at the receiver with high efficiency. This work is summarized by J. Fowler [4] and W. Li [10], and we will give a brief introduce here.

A. CPPCA based reconstructed strategy at the Receiver

Let \( X = \{x_i\}_{i=1}^M \) be a dataset of \( M \) vectors to be analyzed, where each \( x_i \subset \mathbb{R}^N \) with zero mean. At the sender, an \( N \times D \)
orthogonal matrix $O_i$ is applied to each vector $x_i$ and thus produces an $D$-dimensional subspace: $f_i = O_i^T x_i (D \ll N)$. At the receiver, yet, only the orthogonal matrix $O_i$ and projected data $f_i$ is available. Suppose the same projected matrix is imposed on each $x_i$; at the sender, i.e. $O_i \equiv O$, then the covariance matrix over all dataset $X$ is given as:

$$\Sigma = X^T X / M$$ \hfill (1)

For a given vector $x_m$, PCA tries to find a linear transform: $f_m = W^T x_m$, where $W$ represents the $N$ unit length eigenvectors of $\Sigma$ in column wise:

$$\Sigma = W\Lambda W^T$$ \hfill (2)

On the other hand, suppose we have gained $K$ orthogonal vectors $o_k, k = 1,...,K$ which form the basis of $K$-dimensional subspace $O = [o_1, o_2, ... , o_K]$. Hence, the orthogonal projection of $x_m$ on to $O$ is $f_m = O^T x_m$. In order to make a relationship with the basis $\{o_k\}$, owing to $f_m = O^T x_m$, then we have $f_m = O f_m$. The covariance of projected vectors $F = [f_1, f_2, ... , f_M]$ is given by Eq.(3):

$$\hat{\Sigma} = \hat{F} \hat{F}^T / M = O^T X X^T O / M = O^T \Sigma O$$ \hfill (3)

The relationship between the eigenvectors of $\Sigma$ and $\hat{\Sigma}$ is described by Rayleigh-Ritz theory [4].

In order to recover the data randomly projected, the projection-onto-convex-sets(POCS) [12] is adopted for generating the eigenvectors. In this literature, the data vectors $X$ are firstly divided into multi-partitions $\{M_k\}$, where each partition is associated with a random orthogonal projection matrix $O_k$ aforementioned individually. Then, the projected vectors are transformed by Eq.(4):

$$F^{(k)} = O^{(k)}^T M^{(k)}$$ \hfill (4)

Eq.(4) will conduct a lightweight encoder at the sender-side terminal. However, in the decoder-side terminal, one has to approximate $W$ according to barely $\hat{\Sigma}$ without any information of $\Sigma$.

Since the covariance matrix of projected vectors can be calculated by $\hat{\Sigma}^{(j)} = \hat{F}^{(k)} \hat{F}^{(k)}^T / M^{(k)}$, the Ritz vectors [10] in each subspace $O^{(k)}$ are formed via spectral decomposition of projected covariance matrix $\hat{\Sigma}^{(k)}$. Moreover, suppose we have formed $J$ random $K$-dimensional orthogonal subspaces $O^{(1)}, O^{(2)}, ... , O^{(J)}$, each subspace $Q^{(j)}$ is formed individually under the assumption that $u^{(j)}_k \approx v^{(j)}_k$:

$$Q^{(k)} = O^{(k)} \oplus \text{span}\{u^{(j)}_k\}$$ \hfill (5)

The matric form of Eq.(5) can be expressed as Eq.(6):

$$Q^{(j)}_k = [u^{(j)}_k \ \ \text{NULL}(O^{(j)}_k)^T]$$ \hfill (6)

where the NULL(* ) marks as the null space in mathematics. As each $Q^{(k)}$ is convex and closed, the parallel form of POCS can be employed to produce an estimation of eigenvectors $W$ as

$$w^{(i)}_k = \frac{1}{J} \sum_{j=1}^{J} Q^{(j)}_k Q^{(j)}_k^T w^{(i-1)}_k, \ \ k = 1, ... , L$$ \hfill (7)

where the iteration of $w^{(0)}_k$ are initialized to the average of the Ritz vectors:

$$w^{(0)}_k = \frac{1}{J} \sum_{j=1}^{J} u^{(j)}_k$$ \hfill (8)

At final, the CPPCA decoder utilize the pseudo-inverse to recover the PCA coefficients:

$$\hat{X}^{(j)} = (O^{(j)}_k)^T \Psi \Sigma F^{(j)}$$ \hfill (9)

where $\Psi = [\hat{w}_1, \hat{w}_2, ... , \hat{w}_L]$.

As proposed by [4] and [12], the number of eigenvectors to be recovered is restrained to the heuristic:

$$L = \text{round}(\frac{S}{\log N})$$ \hfill (10)

III. PROPOSED REGION-DEPENDENT RECONSTRUCTION STRATEGY

We will perform our region-dependent strategy for HSI data reconstruction in this section. In our proposed region-dependent reconstructed model (see Fig.1), the hyperspectral images are first segmented into different regions, following the CPPCA reconstruction procedure over each region individually and independently at the receiver-side. The segmentation literature of region-dependent approach can be supervised or unsupervised. In this paper, we present a supervised segmentation to segment hyperspectral images into diverse regions before applying the CPPCA recovered procedure.

A. Supervised LORSAL-MLL Segmentation Algorithm

In the work of J.Li [5], a novel supervised Bayesian approach which explores both the spectral and spatial information in an intuitive interpretation is proposed. This approach involves two primary steps below:

- The learning stage of using multinomial logistic regression (MLR) to deduce the class distributions by variable splitting and augmented Lagrangian(LORSAL)
- The segmentation stage of inferring the classes from a posterior distribution which is built on the class distribution and on a multilevel logistic(MLL) prior.

This procedure formulates a computation of maximum posterior (MAP) which involves in maximizing the posterior distribution of classes. We impose the graph-cut-based $\alpha$-expansion algorithm to solve this problem.

Since we have to generate a region map from the projected data, the most straightforward modusoperandi is to recover the entire data first by CPPCA as shown in Fig.1. Let $x = [x_1, ... , x_n] \in \mathbb{R}^{d \times n}$ be the HSI of $D$-dimensional feature vectors and $y = [y_1, ... , y_n] \in \mathbb{R}^n$, the MLR is modeled as

$$p(y_i = k | x_i, \omega) \equiv \frac{\exp(\omega(k) h(x_i))}{\sum_{k=1}^{K} \exp(\omega(k) h(x_i))}$$ \hfill (11)

where $p(y_i | x_i, \omega)$ denotes the posterior, $h(x) \equiv [h_1(x), ... , h_l(x)]^T$ represents $l$ fixed functions of the input, and $\omega \equiv [\omega^{(1)}, ... , \omega^{(K)}]^T$ is the logistic regressors. In order to learn the distribution of class, the logistic
regressors $\omega$ must have to be estimated. According to spare MLR(SMLR) [13], the estimation of $\omega$ is equivalent to maximum a posterior of Eq.(12)

$$\hat{\omega} = \arg \max_{\omega} l(\omega) + \log p(\omega)$$  (12)

where $l(\omega)$ denotes the log-likelihood function:

$$l(\omega) \equiv \log \prod_{i=1}^{L} p(y_i|x_i, \omega)$$  (13)

$$p(\omega) \propto \exp(-\lambda ||\omega||_1)$$  (14)

In order to estimate the logistic regressor $\omega$ in Eq.(12) efficiently, the LORSAL [14] algorithm was employed. The Hammersly-Clifford theorem [15] implies that the distribution of Markov random field(MRF) is actually a Gibbs’s distribution whose form is as follows:

$$p(y) = \frac{e^{-\sum_{c \in C} V_c(y)}}{Z}$$  (15)

where $Z$ denotes the normalizing constant, $V_c(y)$ denotes the prior potentials for the set of cliques $c \in C$. The calculation of $V_c(y)$ is given by:

$$V_c(y) = \begin{cases} -v_y, & |c| = 1 \\ -\mu, & |c| > 1 \text{ and } \forall i,j \in c \ y_i = y_j \\ \mu, & |c| > 1 \text{ and } \exists i,j \in c \ y_i \neq y_j \end{cases} \text{ (16)}$$

where $\mu$ is constant with constraint $\mu \geq 0$.

Note that the function of Eq.(16) encourages piecewise smooth segmentation and provides solution in which adjacent pixels are likely to share the same label. That is, the spatial-contextual information has been included by adopting an isotropic MLL prior to the model. Suppose the classes are equiprobable, we have $e^{v_y} = e^{\mu}$ and $\mu = \mu/2 > 0$. A clique consists of a single pixel: $c = \{i\}$ or a pair of neighborhood pixels$(i,j): c = \{i,j\}$. We rewrite Eq.(15) as

$$p(y) = \frac{\mu(\sum_{(i,j) \in c} \delta(y_i-y_j))}{Z}$$  (17)
where \( \delta(y) \) denotes the unit impulse function

\[
\delta(y) = \begin{cases} 
0 & y = 0 \\
1 & y \neq 0 
\end{cases}
\] (18)

As discussed previously, we adopt LORSAL algorithm to learn \( p(y_i|x_i) \) and MLL to learn prior \( p(y) \). Finally, the MAP segmentation is formulated as

\[
\hat{y} = \arg \min_{y \in \mathcal{L}} \sum_{i \in \mathcal{S}} - \log p(y_i|\hat{\omega}) - \mu \sum_{i,j \in \mathcal{C}} \delta(y_i - y_j) 
\] (19)

where \( p(y_i|\hat{\omega}) \equiv p(y_i|x_i, \omega) \). The optimized problem of (19) can be solved by energy minimization algorithms, eg. \( \alpha \)-expansion algorithm [13].

**B. Region-dependent Recovered Strategy**

The region map has been generated via the aforementioned technique, where each pixel is labeled into one region and the continuity will be reserved spatially. Then each region will be adopted the CPPCA procedure individually and independently. Suppose we have generated \( R \) regions in the region map, the data set \( X \) is partitioned into \( J \) partitions \( X^{(1)}, X^{(2)}, \ldots, X^{(J)} \) via a modulo operation at the sender, namely:

\[
X^{(j)} = \{ x_i \in X \mid (i-1) \mod J = j - 1 \} \quad (20)
\]

Each partition \( X^{(j)} \) is then projected into \( F^{(j)} \) by Eq.(4). However, at the receiver, each \( F^{(j)} \) is further partitioned into \( r \) regions based on the region map of segmented result. Next, the CPPCA procedure is adopted several on each region. Assume \( F_r^{(j)} \) represents the \( r^{th} \) the region map \( R \) for the \( j^{th} \) partition, then the covariance becomes

\[
\hat{\Sigma}_r^{(j)} = \frac{F_r^{(j)} F_r^{(j)T}}{M_{(r,j)}} \quad (21)
\]

where \( M_{r,j} \) denotes the total number of vectors in \( F_r^{(j)} \). The corresponding Ritz vectors \( \mu_{(r,s)} \) can also be calculated. In order to recover the \( r^{th} \) HSI data region, Eq.(6) and Eq.(7) are rewritten as

\[
Q_{(r,s)}^{(j)} = [u_{(r,s)}^{(j)}] \quad NULL(O^{(j)T}) \quad (22)
\]

\[
\hat{w}_{(r,s)}^{(j)} = \frac{1}{j} \sum_{j=1}^{j} Q_{(r,s)}^{(j)} Q_{(r,s)}^{(j)T} \hat{w}_{(r,s)}^{(j-1)} \quad (23)
\]

Next, each \( \hat{X}_r^{(j)} \) is recovered as

\[
\hat{X}_r^{(j)} = (O^{(j)T} \Psi_r)^T F_r^{(j)} \quad (24)
\]

where \( \Psi_r = [\hat{\Psi}_{r,1}, \ldots, \hat{\Psi}_{r,L}] \) denotes the \( L \) recovered eigenvectors of class \( k \). The final data set \( X \) is achieved via combining all \( \hat{X}_r^{(j)} \) together.

To conclude this section, Algorithm shows the pseudocode of region-dependent reconstruction algorithm using supervised LORSAL-AL algorithm.

LORSAL-MLL Algorithm

1. **Encode HSI data via RP**
   - HSI data partition.
     - Use (20) to partition HSI data into \( J \) partitions.
   - Randomized projection.
     - Access the projected data via (4).

2. **Region map generation**
   - HSI data recover.
     - Use (6)(9) to recover the entire data set.
   - LORSAL.
     - Use (12) to estimate \( \hat{\omega} \):
       \[ \hat{\omega} = LORSAL(D_L, \lambda, \beta) \]
     - MLL spatial prior computation.
       - Use (17) to compute the prior:
         \[ P = \hat{p}(x, \hat{w}) \]
     - MAP estimator.
       - Use (19) to classify each pixel into region. This step leads to a region map for all pixels.
         \[ \hat{y} = \alpha - \text{Expansion}(P, \mu) \]

3. **Region-Dependent recovery**
   - Calculate \( Q_{(r,s)}^{(j)} \) via (22).
   - Recover each \( \hat{X}_r^{(j)} \) via (24).
   - Merge \( \hat{X}_r^{(j)} \) into final \( \hat{X} \).

**Output:** The final reconstructed representation \( \hat{X} \).

**IV. EXPERIMENT DESIGN AND RESULT ANALYSIS**

In this section, we demonstrate the performance of the proposed algorithm. The main objective of these experiments is to compare the performance of our method with conventional CPPCA method. It should be noted that the projected matrices used in our experiments are random generated via spare random projection, which followed by Gram-Schmidt orthogonalized procedure. Spare random projection is one kind of random matrices that the entries values are \( \sqrt{3}x \), where \( x \) is a random number taking from these values: \( -1 \) with probability \( 1/6 \), \( 0 \) with probability \( 2/3 \), and \( 1 \) with probability \( 1/6 \).

**A. Evaluation Criterion**

In this paper we only employ signal-to-noise ratio (SNR), spectral angle mapper (SAM) and normalized cross correlation (NCC) as criterion to evaluate the performance of reconstructed HSI data by the proposed method in contrast to conventional CPPCA methodology throughout the experiments. SNR determines the quality of image acquired at first hand. The higher SNR represents the higher reconstructed quality in image restored community. SAM measures the angle between the endmember vector and pixel spectrum vector. Smaller angles of SAM denote the closer matches to the spectrum to be referenced, while angles that far away from the referenced angle will indicate the mismatched relationship. The numerical value of NCC is between 0 and 1.0, of which 0 means that there won't be any correlation between two signals, yet 1.0 denotes the signals compared are ideally correlated [16].

**Algorithm:** Region-Dependent CPPCA using Supervised
B. Experimental Data Collection

The HSI dataset was used in this section, which called Salinas-A scene, consisting of pixels $[591 - 676] \times [158 - 240]$ for a size of $86 \times 83$, which totally contains 6 regions in the image scene. In this experiment, training data for LORSAL-MLL segmentation method are extracted (Roofs, Streets and Paths, Grass, Trees, and Water), which represents five main land cover regions.

C. Experimental Result

We set $J \equiv 20$ throughout this experiment. We divide every HSI dataset into 20 partitions both for conventional CPPCA and our proposed algorithm. Fig.(2) shows one pseudo-color image recovered by conventional CPPCA and our region-dependent CPPCA respectively for Salinas-A scene. Obviously, the geographic and distribution of land covers are approximately preserved in space.

![Fig. 2. Pseudo-color image of Salinas-A scene in recovered domain. (a) Recovered by CPPCA ($[R, G, B] = bands[#7, #97, #200]$) (b) recovered by our algorithm($[R, G, B] = bands[#7, #94, #195]$).](image)

In order to generate an accurate region map with less samples, we totally choose 500 samples from the labeled samples. Specially, we only choose 20 samples from each region. For the case when the available samples is less than 20 in a region, we choose half of the available samples instead. The missing samples are randomly choose from the remaining available samples. Tab.I shows the details of training samples in one random running case. The visual effect of segmentation performance by LORSAL-MLL method in the recovered domain is illustrated in Fig.3 (left: region map in gray scale, right: region map in pseudo-color). This map illustrates the effectiveness of supervised LORSAL-MLL method.

We measure the performance of the proposed region-dependent CPPCA by reporting signal-to-noise ratio (SNR), spectral angle mapper (SAM) and normalized cross correlation (NCC) between the recovered vectors and original vectors in Tab.II. Fig.4(a) presents the SNR, SAM and NCC versus subrate$^1$ of proposed method as a comparing to conventional CPPCA for Salinas-A scene. It can be observed from this figure that our method yields a significant improvement over the conventional CPPCA.

![Fig. 3. Segmented region map of Salinas-A scene in recovered domain by LORSAL-MLL method. (a)Region map in gray scale (b)Region map in pseudo-color](image)

V. Conclusion

This paper proposed a region-dependent algorithm which employs the supervised LORSAL-MLL segmentation to generate the region map. The region map would be used to guide our grouping procedure. The proposed strategy is validate in real hyperspectral image data set, and the performance is evaluated via SNR, SAM, and NCC. Comparing to the conventional CPPCA, our scheme works efficiently and yields better performance. The proposed scheme has been proved to be outstanding in performance. Hence, it is more suitable for HSI data transmission and compression task.

Further work will be considered to explorer certain mathematically statistical model to acquire the statistical dependent "region", i.e., contextual information. The contextual information can be gained through contextual composite covariance. We are also interested in other spectral based techniques, such as spectral clustering which has been proved to be more precise in imaging segmentation. The proposed region-dependent CPPCA is expected to extend another effective approach for simultaneous signal sensing and compression. The final destination is to reconstruct the projected signal with high precision and accuracy.

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\begin{table}[h]
\centering
\caption{Quantity of training samples for generating region map by LORSAL-MLL method in Salinas-A scene}
\begin{tabular}{|c|c|c|}
\hline
region index & training samples & labeled samples \tabularnewline
\hline
1 & 391 & 57 \tabularnewline
2 & 1343 & 110 \tabularnewline
3 & 616 & 63 \tabularnewline
4 & 1525 & 135 \tabularnewline
5 & 674 & 69 \tabularnewline
6 & 799 & 66 \tabularnewline
\hline
\textbf{total} & 5348 & 500 \tabularnewline
\hline
\end{tabular}
\end{table}

$^1$ subrate $= \frac{S}{P}$, where $S$ denotes the reserved bands while $P$ denotes the amount of bands.
Fig. 4. Average SNR, SAM, and NCC versus subrate for Salinas-A scene.

TABLE II

PERFORMANCE OF REGION-DEPENDENT CPPCA VERSUS CONVENTIONAL CPPCA FOR SALINAS-A SCENE

<table>
<thead>
<tr>
<th>Item</th>
<th>Subrate</th>
<th>0.15</th>
<th>0.20</th>
<th>0.25</th>
<th>0.30</th>
<th>0.35</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNR (dB)</td>
<td>CPPCA</td>
<td>12.04</td>
<td>29.50</td>
<td>30.24</td>
<td>33.53</td>
<td>34.95</td>
<td>37.38</td>
<td>38.70</td>
<td>39.66</td>
</tr>
<tr>
<td></td>
<td>RD-CPPCA</td>
<td>19.48</td>
<td>33.65</td>
<td>34.53</td>
<td>37.19</td>
<td>37.94</td>
<td>39.76</td>
<td>40.61</td>
<td>41.04</td>
</tr>
<tr>
<td>SAM (radians)</td>
<td>CPPCA</td>
<td>0.2705</td>
<td>0.2091</td>
<td>0.2093</td>
<td>0.2082</td>
<td>0.2081</td>
<td>0.2077</td>
<td>0.2076</td>
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</tr>
<tr>
<td></td>
<td>RD-CPPCA</td>
<td>0.1101</td>
<td>0.0134</td>
<td>0.01254</td>
<td>0.0091</td>
<td>0.0083</td>
<td>0.0067</td>
<td>0.0061</td>
<td>0.0058</td>
</tr>
<tr>
<td>NCC (0-1)</td>
<td>CPPCA</td>
<td>0.9126</td>
<td>0.9370</td>
<td>0.9370</td>
<td>0.9372</td>
<td>0.9371</td>
<td>0.9373</td>
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<tr>
<td></td>
<td>RD-CPPCA</td>
<td>0.9738</td>
<td>0.9995</td>
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