A NEW APPLICATION OF PIXEL PURITY INDEX TO UNSUPERVISED MULTISPECTRAL IMAGE CLASSIFICATION

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ABSTRACT

Two major challenging issues arise in unsupervised classification. One is how to generate desired knowledge directly from the data in an unsupervised manner. The other is how to find an appropriate follow-up classifier to use the obtained unsupervised knowledge to perform supervised classification. This paper presents a new approach to unsupervised classification for multispectral imagery. To address the first issue the pixel purity index (PPI) which is commonly used in hyperspeftral imaging for endmember extraction is used to find a good set of initial training samples without prior knowledge. To address the second issue the PPI-found samples are then used as training samples for a support vector machine to find a good set of training samples for a follow-up supervised classifier, Fisher's linear discriminate analysis (FLDA) which performs classification iteratively to produce final results. The experimental results show the proposed approach has great promise in unsupervised classification.

1. INTRODUCTION

Unsupervised multispectral image classification is generally more difficult than unsupervised hyperspectral image classification because of several reasons. One is due to the lack of spectral resolution which results in mixed pixels. Second, also due to low spatial resolution many materials substances often appear at subpixel scale in which case no spatial information can be used for classification. Third and most importantly, with a small number of spectral channels used for multispectral data acquisition classification must largely rely on spatial correlation rather than spectral information as the case of hyperspectral imagery. As a result, endmember extraction which has received considerable interest in hyperspectral imaging has no role in multispectral imaging since an endmemmber defined as a pure spectral signature is rare in multispectral data. However, this does not exclude endmember extraction from its application to multsipectral imagery. This paper presents a new and interesting application of an endmember extraction algorithm, pixel purity index (PPI) which is commonly used in hyperspectral imagery and available in a popular ENVI software system originally developed by Analytical Imaging and Geophysics (AIG) [1] to unsupervised multispectral image classification. Instead of finding endmembers in multispectral images the PPI is used to find initial training samples that can be refined by a support vector machine (SVM) [3]. Since the SVM is supervised and requires training samples for classification, the PPI-extracted samples provide a good set of training samples for the SVM. The samples classified by the SVM are then used as training samples for Fisher's linear discriminant analysis (FLDA) for further classification. In order to fine tune classification the FLDA is repeatedly applied in an iterative manner until two consecutive runs produce the same classification results. The resulting FLDA is referred to as iterative FLDA (IFLDA). The idea of the IFLDA is similar to that used by the ISODATA [4] or C-means clustering algorithm which also performs iteratively to find final clusters. In order to demonstrate the utility of the proposed unsupervised multispectral image classification algorithm which implements IFLDA coupled with PPI, a SPOT multispectral data is used for experiment. The results show that our proposed algorithm has potential in solving unsupervised issues often encountered in multispectral image analysis.

2. UNSUPERVISED PPI-IFLDA CLASSIFICATION ALGORITHM

It has been shown in [2] that potential target pixels can be only captured by spectral statistics of high orders. In order to do so the data must be pre-process to remove the first and second orders of statistics prior to the implementation of PPI.

The data sphering is the common practice used for this purpose, specifically for independent component analysis (ICA) by making the sample zero to remove the 1st order of statistics as well as making the data variance of each band image unity to remove the 2nd order of statistics. After the data is sphered, the PPI is then applied to find all the samples with their PPI counts, $N_{\mathrm{PPI}}(\mathbf{r})$ greater than zero, denoted by $\mathbf{r}_i^{\mathrm{PPI}}$, i.e., $N_{\mathrm{PPI}}(\mathbf{r}_i^{\mathrm{PPI}}) > 0$. The set of $\{\mathbf{r}_i^{\mathrm{PPI}}\}$ is used as initial training samples for an SVM to produce a final set of training samples, denoted by $\{\mathbf{r}_i^{\mathrm{training}}\}$ for a follow-up supervised classifier, Fisher's linear discriminant analysis (FLDA) [4] which will be implemented iteratively.

Unsupervised PPI-IFLDA Classification Algorithm
1. Initial condition: Set the number for classes to the number of spectral bands.
2. Sphere the data.
3. Operate PPI on the sphered data to find $\{\mathbf{r}_i^{\mathrm{PPI}}\}$.
4. Implement an SVM using $\{\mathbf{r}_i^{\mathrm{PPI}}\}$ as training samples to produce a final set of training samples $\{\mathbf{r}_i^{\mathrm{training}}\}$.
5. Apply FLDA using $\{\mathbf{r}_i^{\mathrm{training}}\}$ as training samples to perform supervised classification.
6. Repeat step 5 until two consecutive runs of FLDA produce the same classification results.

It should be noted that the procedure of running steps 5 and 6 is called Iterative FLDA (IFLDA). Fig. 2 depicts a flow chart of the Unsupervised PPI-IFLDA Classification Algorithm.

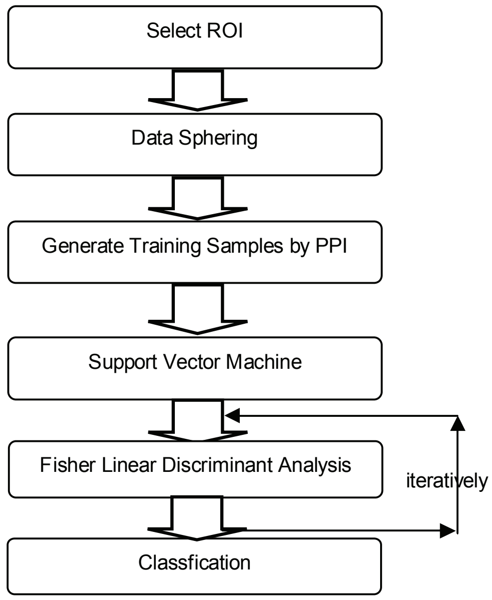
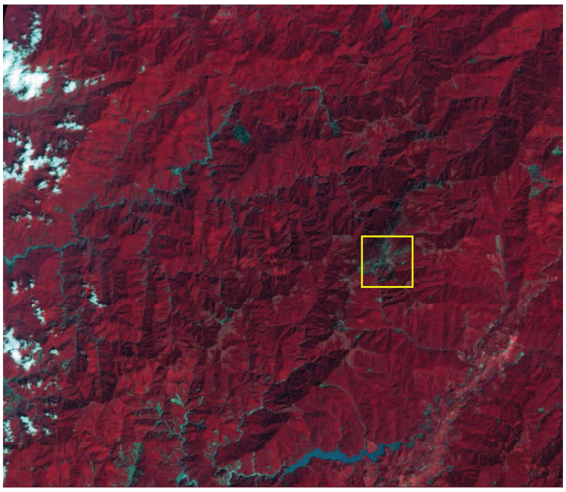


Figure 2. Flow chart of Unsupervised PPI-IFLDA Classification Algorithm

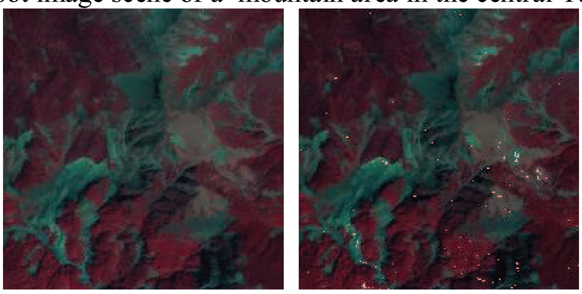
Two comments are noteworthy.
1. Since multispectral imagery has a small number of dimensions, the PPI does not perform dimensionality reduction as generally done in hyperspectral imagers.
2. Due to unavailability of prior knowledge the number of classes to be classified is unknown. In this case, a general guideline is to set the number of classes to the number of spectral bands used for data acquisition. However, it can be adjusted once prior knowledge is available.

3. IMAGE EXPERIMENTS

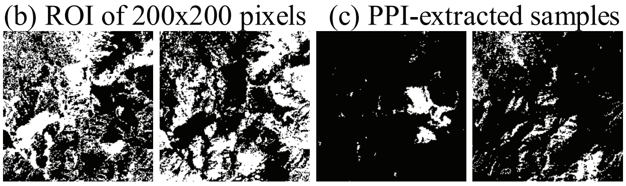
A 4-band SPOT image scene with ground sampling distance of 10m and size of 32420mx37540m taken in 2008 over a mountain area in the central part of Taiwan is shown in Fig. 3(a) where a region of interest (ROI) in Fig. 3(b) marked by square was selected for data analysis. The terrain in the ROI was collapsed with a severe landslide disaster caused by a devastating earthquake, called 911 occurred on September 11, 1999 where a large area of the forest within this ROI was flattened and vanished.



(a) Spot image scene of a mountain area in the central Taiwan



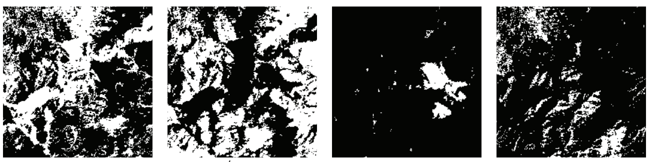
(b) ROI of 200x200 pixels (c) PPI-extracted samples



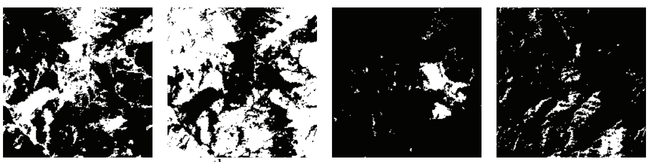
(d) training samples of 4 classes produced by SVM

Figure 3. A SPOT image of a mountain area

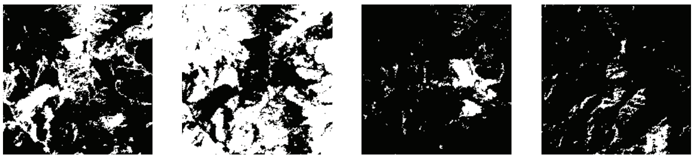
Fig. 3(c) shows the bright samples extracted by the PPI with their PPI counts greater than zero. These PPI-extracted samples are then used as training samples for an RBF kernel-based SVM to refine training samples into 4 classes shown in Fig. 3(d) where the number of classes, 4 was determined by the number of bands which is 4. The samples classified by the SVM in Fig. 3(d) were assumed to be training samples for each of 4 classes for a follow-up supervised FLDA. Fig. 4 shows the classification results of the IFLDA with 5 iteration results produced by the FLDA.



1^{st} iteration of FLDA



4^{th} iteration of FLDA

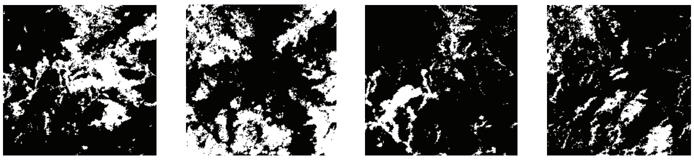


bare land vegetation low density grass shadow

5^{th} iteration and final classification results

Figure 4. Classification by IFLDA using PPI

Since no prior knowledge was used, the google Earth was used to verify the results where the 4 classes were identified as bare land, vegetation, shadow and low density grass. Interestingly, according to the ground truth conducted by an aerial view these 4 classes were very close to what they are found. In order to further demonstrate the effectiveness of our proposed algorithm, the commonly used unsupervised clustering algorithm, fuzzy C-means was also implemented for comparison by removing find training samples for IFLDA. Fig. 5 shows the 4-class classification results which were poor compared to those in Fig. 4.



bare land vegetation low density grass shadow

Figure 5. Classification by IFLDA using fuzzy C-means

The above experiments provide evidence that the IFLDA coupled with PPI can be very effective in unsupervised multispectral classification where no prior knowledge is given. There were other experiments conduced for other selected ROIs and the conclusions were similar. So, their results are not included here.

4. CONCLUSIONS

This paper investigates issues of unsupervised classification in multispectral imagery and further develops a new approach which implements the PPI to find initial training samples with no need of prior knowledge. These PPI-found training samples are then further refined by an SVM to produce a final set of training samples for a follow-up supervised FLDA. In order to fine tune the classification results, a new version of the FLDA is also developed, called iterative FLD (IFLDA) which implements FLDA iteratively until two consecutive runs produce the ame classification results. There are several new contributions made in this paper. One is the use of the PPI to find initial training samples. The PPI has been widely used in hyperspectral data exploitation, but its application to multispectral imagery has not been explored. A second contribution is to use an SVM to refine training samples instead of performing classification. A third contribution is to develop an iterative version of FLDA which can further improve classification results. Finally and most importantly, the proposed PPI-IFLDA works very effectively according to our conducted experiments.

5. REFERENCES

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