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Hyper spectral Image Classification and Unfixing by using ART and SUNSPI Techniques

Nagarajan Munusamy, Rashmi. P. Karchi

Abstract: The Hyperspectral images extracts, collects and processes the information from across the electromagnetic spectrum. The main aim of the hyperspectral imaging is to get the spectrum from each pixel in the images, in the purpose to find the objects, materials, or detecting processes. The spectral range in the hyperspectral images gives the ability to identify chemical types on the environment of Mars more precisely than before. For extracting the hidden features in the mixed pixel, demonstrating state-of-the-art presentation when evaluate with freshly established hyper spectral image classification techniques. Then proposed method is experimentally calculated by using both pretended and actual hyperspectral datasets. The integration of Unmixing algorithm termed "Sparse Unmixing of Hyperspectral information with Spectral a Priori data" with the Singular Spectrum Analysis approach, to get the better result the Clustering by "Adaptively Regularized Kernel-Based Fuzzy C-Means" and Segmentation with "Watershed" of images is carried out and for the better level of classification is done using the ART classifier. The integration of these methods signifies an innovative contribution in the research field of hyperspectral imagery.

Index Terms: Clustering and Segmentation, Hyperspectral image classification, Mixed pixel, Unmixing.

I. INTRODUCTION

Form the past decades the hyper-spectral imaging has been the locale in the active examines improvement, and hyper-spectral images have been able merely to researches. Then hyper-spectral imaging system, Form the past decades the hyper-spectral imaging has been the locale in the active examines improvement, and hyper-spectral images have been able merely to researches. Then hyper-spectral imaging system has been entered the mainstream of the remote sensing. The applications of the hyper-spectral images have found many applications in resources of management, mineral exploration, agriculture and environment monitoring. But valuable utilize of the hyper-spectral images needs full knowledge on the nature and restrictions of facts and the different strategies for the dispensation and understanding it. The hyper-spectral images can be captured with the instrument known imaging spectrometers. The enlargements of these difficult sensors have concerned the convergence of two allied however distinctive technologies: spectroscopy and distant imaging of the Earth and terrestrial surfaces. The spectroscopy is learning of light that can be produced by or reflected as of resources and its difference in energy by wavelength as shown in Fig.1.

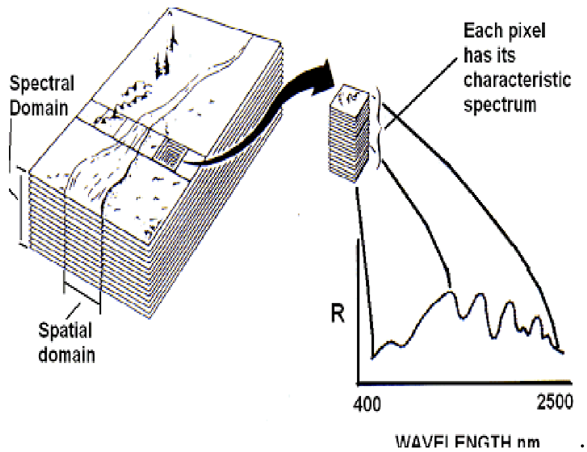

Fig. 1. Hyperspectral Imaging With Spectroscopy

In various digital images, sequential dimensions of minute areas can be done in a reliable geometric outline as the sensor stage moves and succeeding dispensation is necessary to gather them into an image. In anticipation of freshly, images are controlled to one or more comparatively broad wavelength bands with restrictions of detector designs with the desires of information storage, transmission, also processing. Newly progresses in this area have approved the plan of imagers that comprise spectral ranges and resolution equivalent to ground-based spectrometers. In purpose tracking techniques the abundance of elevated powered computer, the accessibility of expensive and good quality OMEGA instrument have formed a huge deal of attention in object tracking techniques present in hyper-spectral images. From the OMEGA instrument the two dimensional images are capture, due to inadequate spatial resolution of Hyper-spectral sensors mixed pixel arises. Spectral Unmixing is the process in which the measured spectrum of mixed pixel. Many methods have been proposed for the unmixing of hyper-spectral data and it can be classified and categorised in statistical, geometrical, and spares regression based approaches. The hyperspectral data processing requires the very large computational resources in terms of computation, storage, and I/O throughputs, particularly when real-time processing is considered. For the sparse unmixing of the hyperspectral images, a novel algorithm called Spares unmixing using spectral a priori information (SUnSPI) is proposed in this paper. This algorithm aims to find the optimal subset of endmembers scene. Newly, as more spectral libraries happen to openly obtainable, a semi-supervised advance, it takes the spectral records as a priori knowledge.

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* Correspondence Author
Nagarajan Munusamy*, Department of Multimedia and Web Technology, KSG College of Arts and Science, Coimbatore - 641015, Tamilnadu, India.
Rashmi. P.Karchi, Department of Computer Science, Bharathiar University, Coimbatore-641046, Tamilnadu, India.

Since from few decades so many researchers are working to improve the system performance, the referred research paper for the proposed work briefly explained in literature survey.

The rest of the paper is organized into four sections: section 2 reviews the developments in classification and unmixing of the hyperspectral imagery. The proposed model of hyperspectral image classification and unmixing by using ART and SUnSPI technique is described in section 3. The experimental results and analysis are given in section 4. The section 5 concludes the proposed work.

II. LITERATURE REVIEW

In this paper Olivier Eches et.al [1] have discussed on the new algorithm for the hyper-spectral image unmixing. A Bayesian model is introduced to exploit this correlation. This image is to be unmixed, if supposed to be separated in to classes where the property of abundance coefficient is consistent. A Markov Random Field (MRF) can be projected in the replica for spatial dependence of pixels in any class. Provisionally upon a specified class, every pixel can be modelled by the traditional linear mixing form by additive white Gaussian noise. This scheme can be investigated well known linear mixing form. In this parameter include abundances for every pixel, the variances and means of the abundances for every class, also a classification map signifying the classes of every pixel in an image. The accuracy of the proposed methods can be illustrated on synthetic and actual data.

In this paper Shaohui Mei et.al [2] author discussed on the spectral variation that are reflective in distantly intellect images suitable to changeable imaging circumstances. The broad attendance of that spectral difference degrades the presentation of hyper spectral study, such as categorization with spectral unmixing. This low-rank matrix approach can be used to ease spectral difference for the hyper-spectral image study. The hyper-spectral image information is decomposed into the low-rank matrix with the sparse matrix, and it can be supposed that intrinsic spectral characteristics are representing by low-rank matrix and spectral difference can be accommodated with sparse matrix. As a result, the presentation of image analysis is enhanced by effective on the low-rank matrix.

In this paper Paris V. Giampouras et.al [3] author have discussed on the unmixing of the hyper-spectral data in which a novel unmixing algorithm are introduced for the improvement of identification of the materials present in the hyper-spectral images. Mainly two unmixing technique have been proposed in this paper, in an effort to utilize both spatial correlation with sparse representation of pixels are lying in homogeneous areas of hyper-spectral images. The resultant normalized cost purpose is minimizing with a) an incremental proximal sparse with low-rank unmixing algorithm b) the technique based on irregular minimization system of multiplier (ADMM).

In this paper Xiong Xu et.al [4] author have discussed on the various unmixing of hyper-spectral images in this the Subpixel mapping algorithms has been extensively exploited to establish the spatial allocation of various land-cover classes in mixed pixels at the subpixel scale with adapting low-resolution fractional abundance maps (approximated by a linear assortment model) into the better classification maps. It has been evident that the exploited abundance map has a strong force on succeeding subpixel mapping process. Conversely, partial notice has been agreed to contact of dissimilar features in spectral unmixing form on subpixel mapping presentation. A detailed quantitative estimation of dissimilar aspect in linear spectral combination study, such criterion employed to decide the kinds of pixels, the profusion sum-to-one restraint in unmixing, and correctness of exploited abundance maps, is examined.

In our previous survey work presented in [5], it is described the summary of the different spectral unmixing models and algorithms with the state-of-the-art technologies employed for the Hyperspectral unmixing of mars dataset captured with several instruments.

In this paper Sicong Liu et.al [6] author have presented a fresh multitemporal spectral unmixing (MSU) method to attend the demanding multiple-change discovery crisis in bi-temporal hyper-spectral images[7-15]. The proposed method gives the spectral-temporal variations at a subpixel level. The measured Change Detection (CD) crisis can be analyzed in a multitemporal area, where the bitemporal spectral combination forms described to analyze the spectral composition in a pixel. Distinct multitemporal end members (MT-EMs) can be extracting according to the routine and unverified algorithm. Subsequently a vary study scheme can intended to differentiate alter and no-change MT-EMs. The end member grouping system can be applied to change MT-EMs to notice the sole modify classes. Finally, the measured multiple-change recognition trouble can be solving with analyzing abundances of change also no-change modules and their involvement to every pixel.

III. PROPOSED METHODOLOGY

This section descries about the procedure we have designed for Unmixing and classifying Hyperspectral images. The proposed system is divided into two phases namely, Testing and Training phase. Training phase involves learning the cropped Hyperspectral images by extracting features using Singular Spectrum Analysis (SSA) and storing in the knowledge base. In testing phase, the Hyperspectral image is pre-processed by using Singular Value Decomposition (SVD) algorithm. The Sparse Unmixing of Hyperspectral Data Using Spectral Priori Information (SUnSPI) is employed for Unmixing Hyperspectral images followed by feature extraction. These features are matched with already stored features in the knowledge base using ART Classifier. The block diagram of proposed system for Unmixing and classification of Hyperspectral image is shown in Fig. 2.

i. Training Phase: In this phase, Hyperspectral images are taken as input from the spectral library from hyperspectral reflectance dataset.

The spectral library consists of iron oxides ranging from 0.9 µm to 1.3 µm, Hydrated Minerals having spectral characteristics at 1.4, 1.9 and 2.5 µm, Surpentines spectra having very strong M shape duet absorptions at the 1.91 µm, Olivines spectra having spectral feature at 1 µm and other minerals spectral ranging from 0.2 to 2.02 µm. The materials falling in this spectral range the features are extracted using Singular Spectrum Analysis (SSA) method.

These extracted features are trained and stored in knowledge base for further validation.

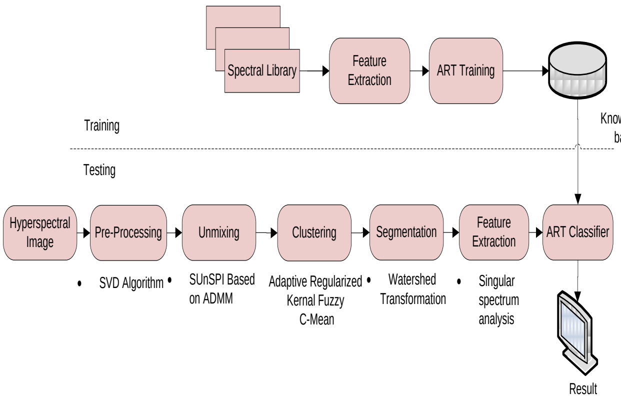

Fig. 2. Block diagram of proposed system for Unmixing and classification of Hyperspectral Image

ii. Testing phase: In testing phase, the Hyperspectral image is taken as an input and this image are pre-processed using the Singular Volume Decomposition algorithm. The size of the Hyperspectral images is reduced and also the significant reduction in complexity is done to facilitate the near real time processing speed. Unmixing of the hyper-spectral image is done using the "Sparse Unmixing of Hyperspectral Data Using Spectral a Priori Information" (SUnSPI) algorithm in which the mixed pixels are analysed and the materials present in the hyper-spectral images are differentiated for the proper classification and for the better improvement in the classification the clustering of the images is done using the "Adaptively Regularized Kernel-Based Fuzzy C-Means" (ARKFCM) technique in which cluster images are formed and the standard image is taken for the segmentation [16,17]. In the segmentation "Watershed segmentation" algorithm is used for the better classification as shown in Fig 2.

The next step is extracting features from these Hyperspectral images using Singular Spectrum Analysis approach. By eliminating noise components in extorting the characteristics, the discerning capability of characteristics will be enhanced significantly. SSA permits many possibilities for presenting considerable possible. In Hyperspectral image remote sensing, an application of SSA approach to each spectral pixel lead to a restoration procedure that enlarges the correctness in classification task. The main purpose of SSA is to decay a unique sequence into sub-series and some self-governing mechanism. Consequently, the main competence of SSA are as pursue: Periodicities with varying amplitudes and complex trends, discover the structures in tiny time sequence and envelopes of alternating signals, removal of episodic component, trends and smooth.

Using ART classifier, these extracted features are compared with the features stored in the knowledge base, which are generated during training phase. And the final results are validated by examining the classification accuracy. Series of real time neural network models are considered as the ART (Adaptive Resonance Theory), which provides both unsupervised and supervised learning[18,19], prediction, and detection and mainly with pattern recognition. This ART is designed for both analog and digital input patterns. Thus in our proposed system the ART for digital input patterns are utilized for better level of classification and for better classification and recognition rate.

A. Sparse Unmixing of Hyperspectral Data Using Spectral A Priori Information

Let $A \in R^{L\times m}$ indicate the spectral library, where L represents the amount of the bands, and m represents the amount of spectral signature in library. The linear sparse unmixing form supposes that the experiential range vector of the mixed pixel $y \in R_L$ is a linear arrangement of only the little spectral signature in spectral library, i.e.

$$y=Ax+n \tag{1}$$

In the SUnSPI model, the assumption is made that a few resources in spectral library is recognized to be real in hyper-spectral scene. Assume S={1,….,m} is the set of the indices of every spectral signature in spectral library, P ⊂S represents the position of the indices equivalent to resources that known to be real in scene, and S/P={x ∊ S/x ∉P} represents the set dissimilarity of and P. Let X_P indicate the rows of the X that contain the indices as of the set P. To integrate the ethereal a priori data into the sparse unmixing form, we must assurance that spectral signature indexed with P is active in representative the hyper-spectral facts; the other spectral signature may possibly or may not be energetic, however only a few of them must be vigorous since of the subspace personality of hyper-spectral information. This pole of analysis leads us to believe enforce the row sparsity of $X^{(S/P)}$ though departure X_P only.

$$\text{Min}_X \frac{1}{2}\|AX - Y\|_F^2 + \lambda_S \sum_{t=1}^{K}\|x_t\|_1 + \lambda_P \sum_{t\in\frac{S}{P}}\|x^t\|_2$$

$$\text{subject to: } X \geq 0. \tag{2}$$

Here, $\|X\|_1$ and $\|X\|_{2,1}$ to denote $\sum_{t=1}^{K}\|x_t\|_1$ and $\sum_{t=1}^{m}\|x^t\|_2$ respectively $H \in R^{m\times m}$ is a diagonal matrix associated to place **P**:

$$h_{ii} = \begin{cases} 0, if\ i\ \in P \\ 1, otherwise \end{cases} \tag{3}$$

Where h_{ii} represents the i-th diagonal aspect of **H**. therefore, we comprise $\sum_{i\in\frac{S}{P}}\|x^t\|_2 = \|HX\|_{2,1}$. Then SUnSPI form in Eq. (2) is written in subsequent equal form:

$$\underset{X}{\text{Min}} \frac{1}{2}\|AX - Y\|_F^2 + \lambda_S\|X\|_1 + \lambda_P\|HX\|_{2,1} + l_R + (X) \tag{4}$$

Where, $l_R + (X)$ represents the indicator purpose: $l_R + (X)$ zero if $X \geq 0$ is satisfy with $+\infty$ or else.

Then optimization trouble in Eq. (4) has subsequent equivalent formula:

$$\min_{U,V} \frac{1}{2}\|V_1 - Y\|_F^2 + \lambda_S\|V_2\|_1 + \lambda_P\|V_3\|_{2,1} + l_R + (V_4) \tag{5}$$

Subject to:

$$V_1 = AU$$
$$V_2 = U$$
$$V_3 = HU$$
$$V_4 = U$$

Where

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$$V = \begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \end{bmatrix} \qquad (6)$$

Assume that **I** represent identity matrix by appropriate size. Then it can be write Eq. (5) in a extra dense form: $\min_{U,V} g(V)$ Subject to:

$$GU + BV = 0 \qquad (7)$$

Where

$$g(V) \equiv \frac{1}{2}\|V_1 - Y\|_F^2 + \lambda_S\|V_2\|_1 + \lambda_P\|V_3\|_{2,1} + l_R + (V_4)$$

$$G = \begin{bmatrix} A \\ I \\ H \\ I \end{bmatrix}, B = \begin{bmatrix} -I & 0 & 0 & 0 \\ 0 & -I & 0 & 0 \\ 0 & 0 & -I & 0 \\ 0 & 0 & 0 & -I \end{bmatrix} \qquad (8)$$

The ADMM algorithm for solving the problem in Eq. (7) is shown in Algorithm 1, where

$$l(U, V, D) \equiv g(V) + \frac{\mu}{2}\|GU + BV - D\|_F^2 \qquad (9)$$

is the enlarged Lagrangian for crisis in Eq. (7). Here,μ>0 the increased Lagrangian penalty parameter also μD denotes the Lagrange multipliers associated to constriction GU+ BV = 0. In every iteration, ADMM algorithm consecutively reduces l to U and V, and next informs Lagrange multipliers.

By update μ with keeping a relation among ADMM primitive enduring standard and dual remaining norm in an agreed positive period, both are join to zero. Here the method make use of the KKT conditions to derive the primitive and dual residuals for the ADMM. Primary, the primal variable should be possible, which leads to the circumstance:

$$GU^* + BV^* = 0 \qquad (10)$$

Where U^* and $V^*$are the optimal solution of the problem in Eq. (7). After that, the dual variable must assure the Lagrange multiplier (or dual feasibility) form

$$0 \in \partial g(V^*) - B^T\lambda^* \qquad (11)$$
$$0 = -G^T\lambda^* \qquad (12)$$

Where $\partial g(V^*)$means the subdifferential of the convex purpose g at (V^*),$\lambda \equiv \mu D$ is Lagrange multipliers for the problem in Eq. (7).

As of the optimality state for the Step 4 of technique 1, then paper have

$$0 \in \partial g\left(V^{(k+1)}\right) + \mu B^T\left(GU^{(k+1)} + BV^{(k+1)}\right) \qquad (13)$$
$$= \partial g\left(V^{(k+1)}\right) - \mu B^T D^{(k+1)} \qquad (14)$$
$$= \partial g\left(V^{(k+1)}\right) - B^T\lambda^{(k+1)} \qquad (15)$$

Thus, the dual optimality condition in Eq. (11) is satisfied by $V^{((k+1))}$ and $\lambda^{((k+1))}$at end of the every iteration of an algorithm 1.

To meet the dual optimality condition in Eq. (12), the method exploit the optimality state for Step 3 of algorithm 1:

$$0 = \mu G^T\left(GU^{(k+1)} + BV^{(k)} - D^{(k)}\right) \qquad (16)$$
$$= -\mu G^T D^{(k+1)} - \mu G^T B\left(V^{(k+1)} - V^{(k)}\right) \qquad (17)$$
$$= -G^T\lambda^{(k+1)} - \mu G^T B\left(V^{(k+1)} - V^{(k)}\right) \qquad (18)$$

Thus, after each iteration of Algorithm 1, paper have

$$\mu G^T B\left(V^{(k+1)} - V^{(k)}\right) = -G^T\lambda^{(k+1)} \qquad (19)$$

Finally, the primal residual ($r^{((k))}$) and dual residual ($d^{((k))}$) which calculate how fine iterates of an algorithm 1 assure the KKT circumstances can described as:

$$r^{(k)} = GU^{(k)} + BV^{(k)} \qquad (20)$$
$$d^{(k)} = \mu G^T B\left(V^{(k)} - V^{(k-1)}\right) \qquad (21)$$

Now, the detailed SUnSPI algorithm is done by expanding the augmented Lagrangian in Eq. (9):

$$\begin{aligned} &l(U, V_1, V_2, V_3, V_4, D_1, D_2, D_3, D_4) \\ &= \frac{1}{2}\|V_1 - Y\|_F^2 + \lambda_S\|V_2\|_1 + \lambda_P\|V_3\|_{2,1} + l_R + (V_4) \\ &\quad + \frac{\mu}{2}\|AU - V_1 - D_1\|_F^2 + \frac{\mu}{2}\|U - V_2 - D_2\|_F^2 \\ &\quad + \frac{\mu}{2}\|HU - V_3 - D_3\|_F^2 + \frac{\mu}{2}\|U - V_4 - D_4\|_F^2 \qquad (22) \end{aligned}$$

In each iteration of the ADMM scheme, sequentially minimize the function l in Eq. (22) to U, V_1, V_2, V_3 and V_4, next update the Lagrange multipliers. The proposed method first execute an optimization above the changeable **U**.

By ignoring the conditions in purpose function in Eq. (22) that do not contain variable **U**, will get the reduced optimization problem:

$$\begin{aligned} U^{(k+1)} \leftarrow arg \min_U \frac{\mu}{2}\left\|AU - V_1^{(k)} - D_1^{(k)}\right\|_F^2 + \frac{\mu}{2}\left\|AU - V_2^{(k)} - D_2^{(k)}\right\|_F^2 \\ + \frac{\mu}{2}\left\|AU - V_3^{(k)} - D_3^{(k)}\right\|_F^2 + \frac{\mu}{2}\left\|AU - V_4^{(k)} - D_4^{(k)}\right\|_F^2 \qquad (23) \end{aligned}$$

This has closed form solution:

$$\begin{aligned} U^{(k+1)} \leftarrow (A^T A + 2I + H)^{-1}[A^T(V_1^k + D_1^k + V_2^{(k)} + D_2^{(k)} \\ + H\left(V_3^{(k)} + D_3^{(k)}\right) + V_4^{(k)} + D_4^{(k)}] \qquad (24) \end{aligned}$$

Here the method exploit the fact that **H** is a diagonal matrix with diagonal elements 0 or 1, which means $H^T = H$ and $H^T H = H$ .Further the values of variables V_1, V_2, V_3 and V_4 are computed in each iteration. To update **V**1, the reduced optimization problem is

$$V_1^{(k+1)} \leftarrow arg \min_{V_1} \frac{1}{2}\|V_1 - Y\|_F^2 + \frac{\mu}{2}\left\|AU^{(k)} - V_1 - D_1^{(k)}\right\|_F^2 \qquad (25)$$

$$V_1^{(k+1)} \leftarrow \frac{1}{1+\mu}\left[Y + \mu\left(AU^{(k)} - D_1^{(k)}\right)\right] \qquad (26)$$

Similarly, the reduced optimization problem for V_2 is

$$V_1^{(k+1)} \leftarrow arg \min_{V_2} \lambda_S\|V_2\|_1 + \frac{\mu}{2}\left\|U^{(k)} - V_2 - D_2^{(k)}\right\|_F^2 \qquad (27)$$

whose solution represents the *soft threshold*:

$$V_2^{(k+1)} \leftarrow soft\left(\xi_2, \frac{\lambda_S}{\mu}\right) \qquad (28)$$

Where $\xi_2 = U^{(k)} - D_2^{(k)}$ and soft $(\cdot, \tau)$ indicates the component-wise submission of the function of the soft-threshold $y \rightarrow sign(y)\max\{|y| - \tau, 0\}$. To update V_3, the reduced optimization problem is

$$V_3^{(k+1)} \leftarrow \arg\min_{V_3} \lambda_P \|V_3\|_{2,1} + \frac{\mu}{2}\left\|HU^{(k)} - V_3 - D_3^{(k)}\right\|_F^2 \qquad (29)$$

Whose solution represents a well-recognized *vect-soft threshold*, applied separately to every row *r* of inform changeable.

$$V_3^{(k+1)} \leftarrow vect - soft\left(\xi_3, \frac{\lambda_P}{\mu}\right) \qquad (30)$$

Where $HU^{(k)} - D_3^{(k)}$ and vect-soft $(\cdot, \tau)$ are the row-wise appliance of vect-soft-threshold purpose $y \rightarrow y\max\{\|y\|_2 - \tau, 0\} / (\max\{\|y\|_2 - \tau, 0\} + \tau)$. To compute V_4 solve the following optimization problem

$$V_4^{(k+1)} \leftarrow \arg\min_{V_4} l_R + V_4 + \|V_3\|_{2,1} + \frac{\mu}{2}\left\|U^{(k)} - V_4 - D_4^{(k)}\right\|_F^2 \qquad (31)$$

whose solution is the projection of $U^{(k)} - D_4^{(k)}$ onto the nonnegative orthant:

$$V_4^{(k+1)} \leftarrow \max\left\{U^{(k)} - D_4^{(k)}, 0\right\} \qquad (32)$$

After updating **U** and **V** in each iteration, should update the Lagrange multipliers. The whole process of SUnSPI algorithm is shown in Algorithm 1.

Algorithm 1 Pseudocode of the SUnSPI algorithm

1. Initialization:
2. set k= 0, choose $\mu > 0$, $U^0, V_1^0, V2^0, V3^0, V_4^0, D_1^0, D_2^0, D_3^0, D_4^0$
3. repeat:
4. Compute $U^{(k+1)}$ via Eq. (24)
5. Compute $V_1^{(k+1)}$ via Eq. (26)
6. Compute $V_2^{(k+1)}$ via Eq. (28)
7. Compute $V_3^{(k+1)}$ via Eq. (30)
8. Compute $V_4^{(k+1)}$ via Eq. (32)
9. $D_1^{(k+1)} = D_1^{(k)} - AU^{(k+1)} + V_1^{(k+1)}$
10. $D_2^{(k+1)} = D_2^{(k)} - U^{(k+1)} + V_2^{(k+1)}$
11. $D_3^{(k+1)} = D_3^{(k)} - HU^{(k+1)} + V_3^{(k+1)}$
12. $D_4^{(k+1)} = D_4^{(k)} - U^{(k+1)} + V_4^{(k+1)}$
13. Update iteration: $k = k+1$
14. Until some stopping criterion is satisfied.

The obtained results from Unmixing method are then processed using the clustering algorithm for the better classification of the materials present in the hyper-spectral images.

B. Adaptively Regularized Kernel-Based Fuzzy C-Means

An adaptively regularized kernel-based fuzzy C-means clustering framework can be proposed for the segmentation of materials present in the mars images. The framework can be worked on the three bases in which the local standard grayscale individual restored through the grayscale of the median filter, average filter and devised slanted images, correspondingly. The techniques are employing the heterogeneity of greyscales in neighbourhood and develop this evaluate for restricted contextual information and restore the measure Euclidean distance by Gaussian radial basis kernel function. The compensation of algorithm is adaptiveness to restricted context, improved robustness to protect image particulars, self-government of clustering parameter, and reduced computational expenses[20,21].

In proposed frame work the adaptively regularized kernel-based FCM framework is denoted as ARKFCM. In this first calculation is the adaptive regularization parameters φ_i associated with every pixel to control the contextual information. The objective function is defined as

$$J_{ARKFCM} = 2\left[\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^m (1 - K(x_i, v_j)) + \sum_{i=1}^{N}\sum_{j=1}^{c} \varphi_i u_{ij}^m \left(1 - K(\bar{x}_i, v_j)\right)\right]$$

The minimization of J_{ARKFCM} (u,v) can be calculated through an alternate optimization procedure using

$$u_{ij} = \frac{\left(\left(1 - K(x_i, v_j)\right) + \varphi_i\left(1 - K(\bar{x}_i, v_j)\right)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(\left(1 - K(x_i, v_k)\right) + \varphi_i\left(1 - K(\bar{x}_i, v_k)\right)\right)^{-1/(m-1)}}$$

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}^m \left(K(x_i, v_j)x_i + \varphi_i K(\bar{x}_i, v_j)\bar{x}_i\right)}{\sum_{i=1}^{N} u_{ij}^m \left(K(x_i, v_j) + \varphi_i K(\bar{x}_i, v_j)\right)}$$

When $\bar{x}$ is replaced with the grayscale of the average/median filter of the original image, the algorithm is denoted as $ARKFCM_1/ARKFCM_2$. When $\bar{x}_i$ is replaced with the weighted image $\bar{\xi}_i$, the algorithm is denoted as $ARKFCM_w$.

The main steps for the proposed algorithms are as follows:

1) Initialize threshold $\varepsilon = 0.001$, $m = 2$, loop counter t=0, v, and $u^{(0)}$
2) Calculate the adaptive regularization parameter φ_i.
3) Calculate $\bar{xi}$ for $ARKFCM_1$ and $ARKFCM_2$ or ξ_i for $ARKFCM_w$.
4) Calculate cluster canters $v_j^{(t)}$ and $u^{(t)}$
5) Calculate the membership function $u^{(t+1)}$
6) If $\max\left\|u^{t+1} - u^t\right\| < \varepsilon$ or $t > 100$ then stop; otherwise, update t=t+1 and go to step (4).

C. Segmentation using Watershed Algorithm

The clustered image is chosen in such a way that it should contain the more information about the material. Further the clustered images are processed with the Watershed segmentation algorithm in which the differentiation of the materials is done.

Let $u(x, y)$ with $(x, y) \in R^2$, be a scalar function recitation an image *I*. Then, morphological of gradient of I is,

$$\delta_D u = (u \oplus D) - (u \ominus D) \tag{33}$$

where $(u \oplus D)$ and $(u \ominus D)$ are the elementary dilation and erosion of u respectively by the formation part D. The morphological Laplacian specified by

$$\Delta_D u = (u \oplus D) - 2u + (u \ominus D) \tag{34}$$

In morphological Laplacian permits us to differentiate authority zones of minima and suprema: areas with $\Delta_D u < 0$ are measured as pressure zones of suprema, though areas by $\Delta_D u > 0$ are influence zones of minima. Then $\Delta_D u = 0$ permits us to understand edge location, and signify necessary assets for structure of morphological filter. The essential design is to relate also dilation or erosion to an image I, depending on either the pixel can be located in the pressure zone of the maximum or a minimum.

D. Singular spectrum analysis

The output of the Watershed Segmentation algorithm is given for the Feature extraction in that the extraction of features from these Hyperspectral images is done using Singular Spectrum Analysis approach. By eliminating noise component in extorting the quality, the discerning capability of characteristics will be enhanced significantly. Singular spectrum analysis aspire to provide enhanced renovation of spectral pixel in Hyperspectral imaging, by resources of major Eigen value components while reducing the noisy components. Feature extraction by singular spectrum analysis approach results in better classification.

E. Adaptive Resonance Theory (ART) Classifier

ART Classifier is used of the better classification of the hyper spectral images in which it uses the unlabelled instances similar to any other decision list classifier. Starting from head of list, a specified instance can be checked sequentially beside each rule until and unless an identical rule can obtained. Eventually any instance would arrive at the matching rule possibly counting a incurable default rule with that rule can considered with mainly general class that establish in training information as of that rule created. The unacceptable values are mechanically sent to else branch, when building the classifier, because they are not enclosed by exposed association rules. When classify the data for some attributes with unknown values, a different method could be followed. When there are no associated rules, ART classifier will end up in a default class value. The even worst case is when the association rules cover every examples in input dataset for building the list, a specified case could direct to nowhere in decision list. That instance would be considered with most general class in training information covered by the current sub-list in this improbable, but possible, case.

When there is a large dataset, the ART classifier will give the better accuracy when compared to other classifier. Seamlessly they can handle primary keys in the input data as well as noise. The organization rule mining methods entangled in ART provide an easy and effectual device to undertake a broad assortment of circumstances with no require using more precise, compound and artificial methods to resolve every trouble. RT represents the scalable and competent. Dissimilar traditional decision list of the inducers, which study system one at the time, ART simultaneously, determines the several rules. Besides, ART do not suffer as of the I/O blockage familiar to option rule and decision of the list inducer, because it uses a competent association rule mining method to produce hypothesis. Therefore the ART represents appropriate for the handling massive datasets typically establish in the real-world struggles.

IV. Experimentation

The performance of the proposed system is tested with real time image. The given input image is shows in Fig. 3.

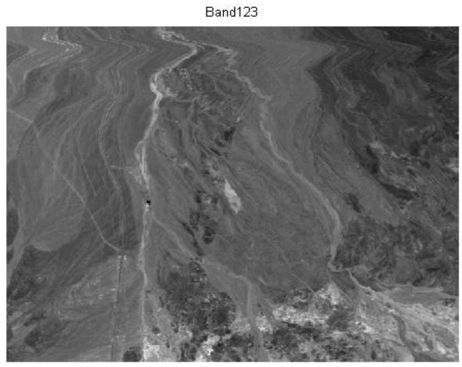


Fig. 3. Input Image

For the respective input image, the resultant segmented is presented in Fig. 4.

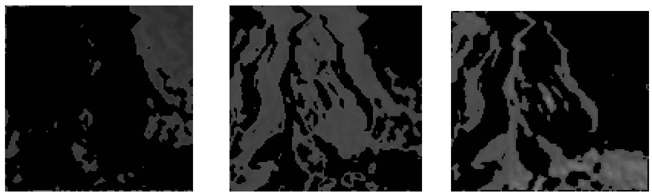
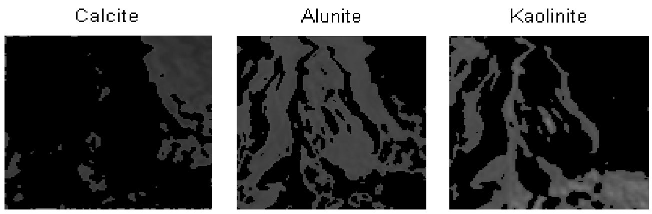


Fig.4. Segmented Output of the Input Image

The resultant classified mineral outputs images are presented in Fig. 5. Respective classified output is presented in Fig. 6.



(a) (b) (c)

Fig.5. Segmented Output of (a) Calcite (b) Alunite (c) Kaolinite

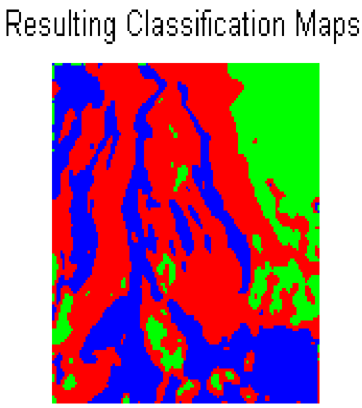


Fig. 6. Classification Output Map

Further other soft computing techniques like support vector machines, fuzzy logic, symbolic data analysis[22] and deep learning mechanisms can be explored for better classification and categorization as compared to ART classifier.

V. CONCLUSION

The proposed method presented novel algorithms for Unmixing with classification of Hyperspectral images. For pre-processing the Hyperspectral data, singular value decomposition (SVD) algorithm is employed. A new algorithm term SUnSPI is used for the Unmixing of Hyperspectral information. Then output of SUnSPI clustered by using "Adaptively Regularized Kernel-Based Fuzzy C-Means" and clustered images are segmented using the Watershed algorithm and the segmented images are feature extracted. The obtained features form singular spectrum analysis is then matched with features stored in the knowledge base using ART Classifier. In ART classifier the input patterns is utilized for better level of classification. This method is exposed to offer accurate classification of hyper-spectral descriptions in both spectral as well as spatial field in short span of time.

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AUTHORS PROFILE

Dr. Nagarajan Munusamy is currently Head and Associate Professor, Department of Multimedia and Web Technology, KSG College of Arts and Science, Coimbatore, Tamil Nadu, India . He has completed Ph.D in Computer Science in 2012. He has published many reputed International Journals and has an experience more than 15 years in the Industry and Academic. His research area includes Wireless Sensor Networks, Remote Sensing, Image Processing and Network Security.

Rashmi P. Karchi received her Bachelor's Degree in Computer Science from Karnatak University, Dharwad, Karnataka State, India, M.Sc in Statistics from Karnatak University, Dharwad, Karnataka State, India. M.Tech degree in Computer Cognition and Technology from Mysore University, Mysuru, Karnataka State, India, and currently pursuing her Ph.D in Computer Science from Bharathiar University, Coimbatore, Tamilnadu, India. Her areas of interest are Biometrics, Image processing, Signal Processing, Remote Sensing, Hyperspectral Image Analysis and Statistics.