International Conference on Control, Engineering & Information Technology (CEIT'13)
Proceedings Engineering & Technology - Vol.2, pp.73-77, 2013

Nonlinear data separation and fusion for multispectral image classification

Hela Elmannai[#*1], Mohamed Anis Loghmari[#2], Mohamed Saber Naceur[#3]

[#] *Laboratoire de Teledetection et Systeme d informations a Reference spatiale, University of Tunis El Manar*
[*] *Ecole Superieure de Communication de Tunis, Tunisia*

[1] hela.elmannai@gmail.com
[2] MohamedAnis.loghmari@isi.rnu.tn
[3] Saber.Naceur@insat.rnu.tn

***Abstract*—The presented work deals with the problem of remote sensing data separation and fusion. Multispectral images are acquired from different bands. The collected radiances are the results of many reflections due to the land heterogeneity and the atmosphere. The mixture phenomenon is therefore nonlinear. This work aims to find an adequate nonlinear separation model based on Bayesian inferences. Sources are considered as gaussians and the nonlinearity is implemented by one hidden layer neuron network. The extracted sources have initially the same dimension as the observations. To reduce the Hughes phenomenon illness a dimension reduction algorithm will be proposed. We will select a subset of sources that describe efficiently the ground truth. The resulting source set will be called primary sources. After that, remain sources will be used to smooth the primary source classification results. The major goal of the presented work is to perform a powerful land characterization that describes the land more efficiently than observations**

***Keywords*— Remote sensing imaging; Hughes phenomenon; Source separation; Bayesian model; Dimension reduction; Data fusion; classification.**

I. Introduction

Data processing fields were motivated by remote sensing imaging development. The major interest is finding a reduced and efficient presentation for the collected observations. Blind source separation have motivated many researches [1] [2] [3]. Considering the physical phenomenon of emitted radiances by soil elements. Many reflections affect the radiances due to the soil heterogeneity, the atmosphere layer and clouds. Collected signals by satellite are therefore a nonlinear mixture of underlying soil radiances.

The presented nonlinear source separation approach within this work tends to approximate the nonlinear mixture phenomenon and to find jointly estimated sources. Although many simpler separation model were implemented based on many assumptions and approximations, nonlinear blind source separations is more realistic and complex.

Recalling that major goal is data classification, the dimension drawbacks decreases the classification accuracy [4]. Hughes phenomenon dues to the small ratio of training samples compared to the feature number. Therefore dimension reduction is an a determinative step for classifications. In this work, we will propose a new dimension reduction method that will discriminate sources in two categories: primary sources and secondary sources. Classification task will be leaded firstly by primary sources. Second, fusion task will contribute to ameliorate classification results taking into account the spatial information.

The paper will be organized as fellows. First, we will present the general approach for remote sensing image classification. Mainly approach phases will be then detailed. Secondly, we will present the source separation method. Thirdly, we will deal with the dimension reduction algorithm. The last step consist on a fusion algorithm that ameliorate the classified image in the reduced dimension by exploiting "remaining information's" in the source space. Experimental results will be detailed and analyzed in the sixth part. The paper ends with conclusion.

II. General Approach Presentation

The presented work deals with the multispectral image classification in a separated space. The given approach will give a reliable classification that exploit both nonlinear source separation concept and decision fusion method.

Given N observations, the source separation process will perform a nonlinear separation that provides non correlated sources through a Bayesian resolution scheme and a multilayer nonlinearity approximation. Obtained sources will pass by the dimension reduction algorithm that will distinguish a source subset that describe the ground-truth more efficiently than using all sources. The output for this phase are the primary source set and the reaming sources called secondary sources. After that the scene will be classified in the primary source space sue to the reliable land cover characterization that provides this reduced space. In parallel, the scene will be clustered in the secondary source space to give a spatial information for each pixel.

Given the segmented scene, the classified scene will be "updated" by a decisional fusion algorithm. Fusion scheme concerns always the source space and concerns each pixel label for a "smoothed" classified scene.

Fig. 1 gives the method flowchart from observation to the classified scene. The major method phases will be detailed in the rest of the paper.

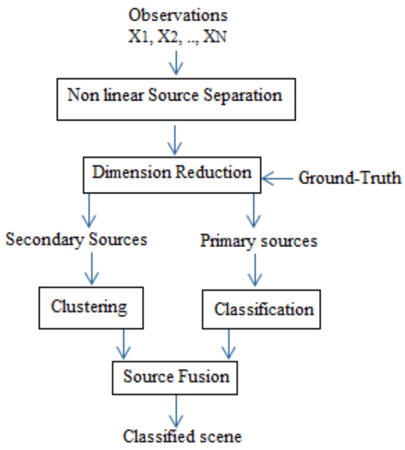


Fig. 1.General approach phases

III. NONLINEAR SEAPARATION BY BAYESIAN INFERENCES AND NEURON NETWORKS

Blind source separation methods aims to recover underlying factors for observations without any assumptions. Linear separation model are widely used for remote sensed imagery. The linear assumption consider pixels are linear mixture of material signature. Principal Component Analysis (PCA) is based on generating uncorrelated factors through linear mapping by maximizing their variances. Sources are restricted in this approach to be Gaussian [5].

Realistic nonlinear mixture phenomenon needs nonlinear approaches. In fact, many nonlinear distortions occur and a noise term may impact observations. Therefore, we considerate a nonlinear version of PCA method including additional noise. The resulting model have interested many researches namely Burel works [6] that propose a perceptron mapping and a mutual information minimizing. Other works used other dependencies measures [7].

In this work, we present a nonlinear mapping with additional noise. The nonlinearity is approximated by one hidden layer perceptron. Sources are gaussians. The prior information's describing latent factors and the likelihood that lies observations to unknown factors will be used to approximated posterior factors distributions.

Considering N observed images $X(t)=[\ x_1(t),\ x_2(t),\ldots,\ x_N(t)]^T$, ^{T} is the transposition operator. Unknown sources $S(t)=[\ s_1(t),\ s_2(t),\ldots,\ s_M(t)]^T$ are related to observations by a nonlinear mixing function f and are corrupted by an additional noise $\eta(t)$. Therefore the nonlinear relation relaying observations to sources is presented in Eq. 1. For a resolvable system $M \leq N$.

$$X(t)=f(S(t)) + \eta(t) \quad \text{where} \quad f: \Re^M \rightarrow \Re^N \qquad (1)$$

The generated model is called as Nonlinear Factor Analysis. The nonlinear mapping is approximated by a Multilayer Perceptron (MLP) with one hidden layer. MLP network approximation for nonlinearity offers flexible mapping model than other classic approximations namely Taylor or Fournier series. The activation function for nonlinear hidden neurons is denoted φ. The mapping model is therefore

$$X(t)= B\,\varphi\,(A\,S(t)+a) + b+\eta(t) \qquad (2)$$

A and B are weight matrices for first and second layer, a and b are correspondent biases. Let Θ be the vector of unknown parameters including sources, noise, weight matrices and biases. Each parameter is supposed to be Gaussian parameterized by its mean and variance. The separation method principle consist on approximating unknown parameters distributions by Bayesian inferences. Bayesian Ensemble learning scheme updates posterior distributions for unknown parameters iteratively [8]. The misfit function to minimize during iterations measures the mutual information between true posterior probability density function $p(\Theta|X)$ and their approximations $q(\Theta|X)$. The corresponding function is called Kullback-Leibler (KL) divergence and is defined in Eq.3

$$KL\,(\,p(\theta|X\,), q(\theta|X\,)) = \int_{\Re} p(\theta|X\,)\log\frac{p(\theta|X\,)}{q(\theta|X\,)}dX \qquad (3)$$

IV. SOURCE SPACE DIMENSION REDUCTION

Major existent dimension reduction algorithms have interested observations reduction. Reduced space has fewer dimension. To reduce Hughes phenomenon without meaningful information loss, several algorithms were implemented. Simpler approaches selected less correlated observations. Mathematical approaches aim to compress observations by transformations. PCA and SOBI algorithms are linear dimension reduction algorithms. Other approaches are nonlinear like Kernel-PCA and Sommon method. Other methods aims to minimize samples distance in observation space and their transform.

In the presented work we aim to reduce the source space dimension. Initial dimension is equal to observation dimension. To characterize the information in source space we will classify the observed scene in source space and compute the classification good classification rate. Recalling that classification in observation space may cause many manifolds due to radiance distortions.

The proposed dimension reduction process aim to reduce the source number by distinguishing a source subset that describe better the land covers than the initial source space. The algorithm input are the ground truth and the obtained sources. Iteratively a new source combination will be generated, classified by supervised algorithm and compared to the ground truth. The process will be repeated for all possible source set combination. The set performing the best classification good identification rate belongs to the reduced space. Sources that appear in the reduced source space are called "primary sources". Remain sources that doesn't belongs to the reduced space are called "secondary-sources".

Let PS denoted the primary sources and SS denoted secondary source. PS and SS constitute the source space as presented in Eq. 4 . PS are deduced by Eq. 4 where Cs denotes the source combination set.

$$Source \quad Space = PS \bigcup SS \tag{4}$$

$$PS = Arg \max_{C \in Cs}(Classification \quad Accuracy) \tag{5}$$

Considering the case of 4 observations. There are 4 obtained sources and Source Space={s_1, s_2, s_3, s_4} . The possible source combinations are Cs={ {s_1}, {s_2},{s_3},{s_4},{s_1, s_2},{s_1, s_3},{s_1, s_4},{s_2, s_3},{s_2, s_4},{s_3, s_4},{s_1, s_2, s_3},{s_1, s_2, s_4}, {s_1, s_3, s_4},{s_2, s_3, s_4}, {s_1, s_2, s_3, s_4 }}.

V. Source Fusion

Fusion methods could concern data, features or decisions. Fig.2 presented different fusion levels [9].

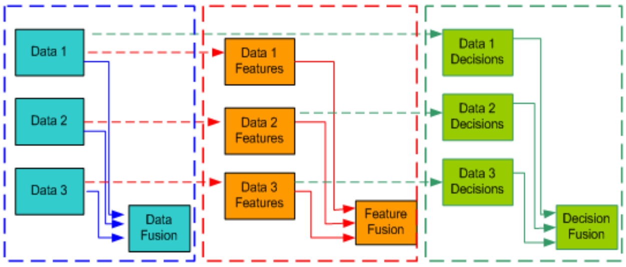


Fig. 2.Fusion levels

For remote sensing observations, data can be different observation bands, aerial image and land elevation. Feature fusion is based on a transformation to a future space and then feature fusion. The higher fusion level concerns decision which could be classification labels or pattern recognition. Most existent works concerns data fusion or feature fusion in the observation space which causes many miss-classified pixels due to band correlation and radiance distortion.

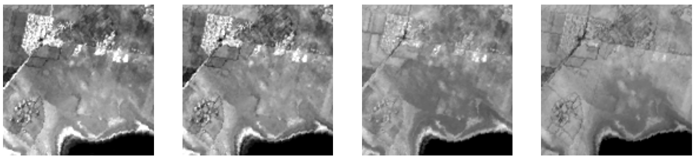
The presented work present a fusion scheme in the source space. Fusion concerns the decision level. Primary source classification result will be smoothed by secondary source segmentation result Therefore each pixel will be classified in primary space taking into account the spatial information from secondary sources. Let x denoted a pixel. SP the primary sources space and SS the secondary sources space. The probability that a pixel belongs to a class in the primary space is denoted p(PS) et p(SS) denoted the probability that a pixel belongs to a cluster in the secondary space. Therefore the Bayes theorem gives Eq. 6.

$$p(x|PS) = \frac{p(x|SS)\,p(SS)}{p(PS)} \tag{6}$$

Classification in the primary source will be updated with the segmented secondary sources to compensate the eventual loosed information by dimension reduction in the source space.

VI. Experiments and Analysis

The observations are SPOT-4 images and present a semi-arid zone located in Kairouan in Tunisia. The scene is 4 bands and the spatial resolution is 20 x 20 m. Channels are from visible to infrared .The region presented many heterogeneous land cover like vegetations, urban areas, barren soil and wetland.



(a) (b) (c) (d)

Fig. 3. Image of SPOT-4, (a) Band 1 . (b) Band 2 . (c) Band 3. (d) Band 4.

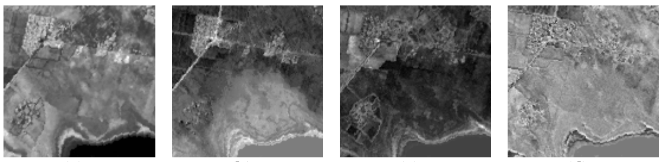
Table I presents the image band correlation. Spatial correlation affects considerably the scene classification or interpretation and may cause many miss-classified regions. Given a SPOT 4 observation images, the proposed nonlinear source separation method gives the sources presented in Fig. 4. The separation process generate non correlated sources as presented in Table II.

TABLE I. Bands Correlation

	Band 1	Band 2	Band 3	Band 4
Band 1	1	0.9496	0.7531	0.6502
Band 2	0.9496	1	0.8275	0.8050
Band 3	0.7531	0.8275	1	0.8685
Band 4	0.6502	0.8050	0.8685	1

TABLE II. Source Correlation

	Source 1	Source 2	Source 3	Source 4
Source 1	1	0.0065	-0.0130	-0.0268
Source 2	0.0065	1	0.0246	0.0297
Source 3	-0.0130	0.0246	1	0
Source 4	-0.0268	0.0297	0	1



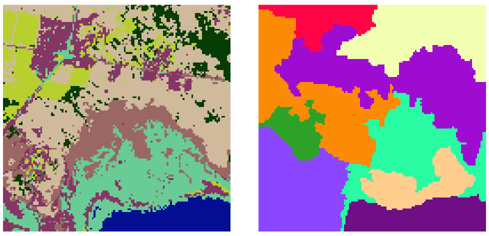
(a) (b) (c) (d)

Fig. 4. Source images. (a) Source image 1. (b) Source image 2. (c) Source image 3. (d) Source image 4.

The provided ground-truth for the study area will establish the supervised classification for the sources classification during the Dimension reduction process. The best accuracy is reached by the combination {s_2,s_3}. The accuracy for this combination is about 94,79%. The band classification good classification rate is 85,01% (Fig. 6 (a)). Therefore using source space suites better with the classification application then using observations. The generated primary source space is PS= {s_2, s_3}. The secondary source space is SS={s_1, s_4}.

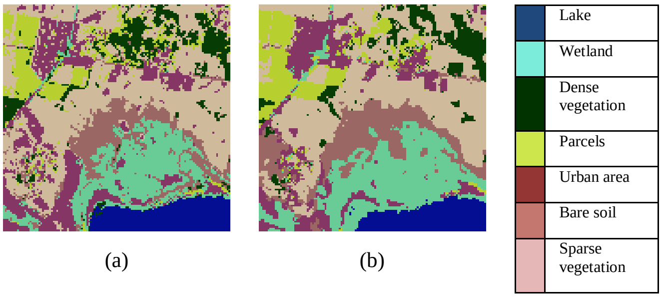
Ones the image is classified in the primary space PS (Fig. 5 (a), the scene will be segmented in the secondary space SS (

Fig. 5 (b)). Fig. 5 (a), (b) presents therefore the fusion algorithm inputs. This phase is a classification fusion decision that will produce an advanced classification scene as presented in Fig. 6 (b). The obtained accuracy after the fusion step is 96,70%.



(a) (b)

Fig. 5. Fusion phase inputs. (a) Classified image in PS space. (b) Cluster image in SS space.



(a) (b)

Fig. 6. (a) Classified image in Observations space. (b) Classified image in Source space after fusion method.

Fig. 7 and Fig. 8 illustrate the commission and omission error rates for lake, wetland, dense vegetation, parcels, urban area, bare soil and sparse vegetation. Classification in primary source space gives letter commission error rate for all classes compared to classification in observation space. The proposed method ameliorates the classification quality and provides letter commission error rates than classification in observation space and in primary space. The commission error is particularly great in the urban and sparse vegetation in observation classification. That means many pixels are classified as urban areas or sparse vegetation although they belongs really to other class. This impact is considerably reduced in the proposed approach.

For the omission errors, major pixel classes are "omitted" by the classification in observation space specially wetlands, urban areas, bare soil and vegetations. These classes are heterogeneous which causes many manifolds in observation space. The omission errors are letter in the proposed approach.

Therefore, the proposed classification method gives better classification result due to the nonlinear source separation process that provides another space that characterizes more precisely the land cover. The fusion scheme ameliorates classification result by taking into account the spatial information for pixels.

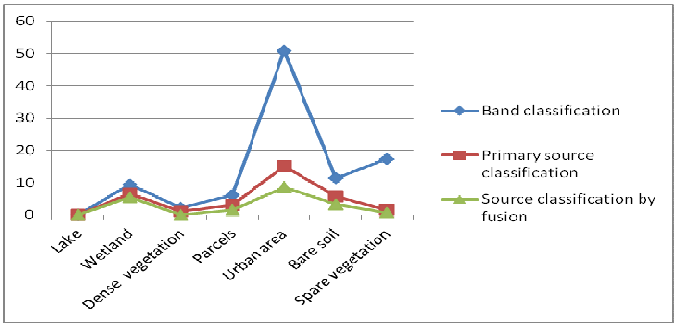


Fig. 7. Commission error by class for Band classification, primary source classification and proposed approach

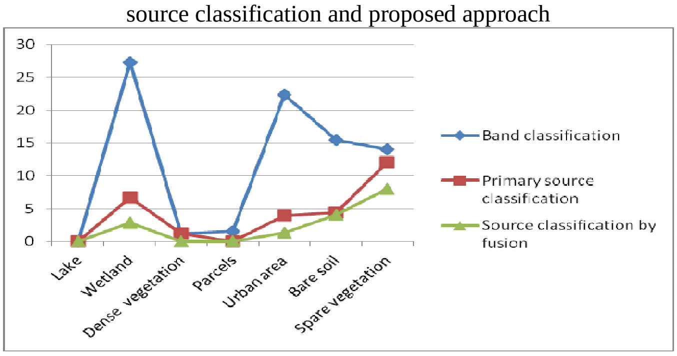


Fig. 8. Omission error by class for Band classification, primary source classification and proposed approach

VII. CONCLUSION

The proposed work presented a new approach for multispectral data classification. The general approach starts with a Bayesian nonlinear source separation that provides a new characteristic space. Obtained sources will go through a dimension reduction process and fusion scheme to ameliorate classification accuracy.

This work contribute in giving new remote sensing image analysis by estimating the nonlinear mapping that relies hidden sources to observations. Compared to observation classification we note that source space describes more precisely the land cover. To profit from dimension reduction, the proposed approach could be extended to hyperspectral images.

ACKNOWLEDGMENT

This work has been financially supported by the Ministry of Higher Education and Scientific Research in Tunisia.

REFERENCES

[1] N. Dobigeon, A. O.Hero and J-Y. Tourneret, " Hierarchical Bayesian Sparse Image Reconstruction With Application to MRFM", *IEEE transactions on Image Processing*, Vol. 18, NO. 9, September 2009.

[2] A. Halimi, Y. Altmann, N. Dobigeon and J-Y. Tourneret, "Nonlinear Unmixing of Hyperspectral Images Using a Generalized Bilinear Model", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 49, No. 11, November 2011.

[3] M. A. Loghmari, M. S. Naceur and M. R. Boussema ,"A Spectral and Spatial Source Separation of Multispectral Images", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 44, No. 12, November 2006.

[4] A. M. Fereidoun and Y.Zhang, "Robust Hyperspectral Classification Using Relevance Vector Machine", *IEEE Transactions on Geoscience and Remote Sensing*, VOL. 49, NO. 6, p. 2100- 2110, June 2011.

[5] M. J. Beal, "Variational algorithms for approximate Bayesian inference", Doctor of Philosophy thesis of the University of London, p 106-122, May 2003.

[6] p106-122G. Burel, “Blind separation of sources: A nonlinear neural algorithm,” *Neural Networks*, vol. 5, p. 937–947, 1992.

[7] A. Honkela, “Advances in variational Bayesian Nonlinear Blind Source Separation”, Dissertation for the degree of Doctor of Science in Technology, Helsinki University of Technology, Espoo, p. 44-61, 2005.

[8] H. Lappalainen and A. Honkela, “Bayesian nonlinear independent component analysis by multi-layer perceptrons ”, Advances in Independent Component Analysis. Springer-Verlag , Berlin, Edition Girolami, p.93-21, 2000.

[9] A. Martin, G. Sevellec and I. Leblond,"Characteristics vs decision fusion for sea-bottom characterization", *Colloque Caracterisation in-situ des fonds marins*, Brest, France, 2004.