

# Chronological Advancement in Image Processing from Lime Stone Mofits to Superpixel Classification

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## Article history

Received: 22-07-2015

Revised: 23-12-2015

Accepted: 28-12-2015

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**Abstract:** Image processing is widely used method for representation and extraction of information. To get the information from the areas and objects which are not possible to be physically contact directly remote sensing image processing is used. While extracting the information from the remote sensed images the major issues that affect the accuracy of the classification is the presence of mixed pixels (reflecting more than one spectral signature) in image. In this study, we have summarized the various eras of image processing from its origin and also give the various techniques and methods used to solve the problem of mixed pixels. In this study, a new algorithm is proposed to solve the mixed pixel problem by using PSO based Fuzzy C-mean and Biogeographical Based Optimization (BBO). This proposed algorithm will improve the classification of mixed pixels as compared to the literature.

**Keywords:** Image, Image Processing, DIP, RSI, Mixed Pixels

## Introduction

Origin of images was in the Near East (region roughly correspond to modern Iraq, southeast Turkey, southwest Iran) from ca. 10,000 to 4500 BCE. In this period the skull was separated from the dead body and later was modeled by using clay. After that in 6000 BCE the feminine principle was represented through images made by using clay. In 4<sup>th</sup> millennium BCE Uruk and Susa depict that visual communication had extensive importance in urban societies. In 2900-2350 BCE the information was expressed by using symbols. They used limestone (known as Stele-of-Vulture) to depict the victory of city-state Lagash over their neighbor city Umma. The lime stone represented many war and religious scene. In 1600-1200 BCE the business between the regions increased which motivated the production of images because like jewelry, ivories and metal utensils images were also the prime object of exchange between the regions. With this the visual traditional float in other places also. Mofits (recurring of symbol that has symbolic significance in story) form their place in the symbolic systems.

In 1717 (circa) a mixture of chalk and silver nitric in nitric acid was used by Johann Heinrich Schulze to make sun prints of words because when sunlight pass through this mixture it will darken. In 1800 (circa) Thomas Wedgwood produced silhouettes and shadow images by using durable surface coated with a light-sensitive

chemical. But he failed to make them permanent. Nicéphore Niépce succeed in generating negative image on paper coated with silver chloride (1816). He created the first fixed permanent image without camera or lens by direct connecting printing with sunlight in 1822 which was destroyed later. In 1835 the Silver chloride camera negatives and two step negative-positive procedures produced by Henry Fox Talbot. This is presently used in most of non-electronic photography. Daguerreotype process (by Louis Daguerre) was publically introduced in 1839 which generate highly detailed permanent photographs on copper sheets plated with silver. In 1841 he improved his earlier process by making paper negative process which reduces less exposure time. Edmond Becquerel in 1848 make first full color image, but the colors faded away right before the viewer view it because of the sensitiveness to light.

The first RGB model image was introduced in 1855 by James Clerk Maxwell. In 1876 the science of sensitometer (by Hurter and Driffield) begins which evaluate the sensitivity of photographic emulsions. Celluloid film base was introduced in 1887 and the first ease to use camera came in 1888 (Kodak n°1 box camera). In 1891 based on the phenomenon of interference, the method of reproducing colors photographically was announced. While working with Thomas Edison, William Kennedy Laurie Dickson developed the motion picture camera “kinetosocopic” in

1891. In 1895 cinematograph was invented by Augustus and Louis Lumiere. Point-and-shoot box camera which is user reloadable and inexpensive was introduced by Kodak (1900). In 1907 the first commercial color photography product "Autochrome" plate was introduced and in 1902 telephotography technology which reduced the images to signal to send them on wire to other location was devised and in 1922 the transmission of images was done intercontinental. Vladimir K. Zworykin patented Cathode Ray Tube (CRT) in 1907 and in 1922 he gives the demonstration of first television system. The charge delivered by micro-photo-cells of CRT can be scanned and saved. Alexander Matveevich Poniatoft in 1927 researched on the registration of images and sound on magnetic tapes. By using high-frequency bias-technic given by Walter Bruch (father of PAL- phase alternation line) Poniatoft developed a better system. In 1951 the first image was recorded by using TV cameras and converts in electronic pulses, write it on Video Tape Recorder (VTR). About 35 mm format of still photography was introduced by Leica in 1925. Flowers and Trees the first full color cartoon made by using Technicolor by Disney in 1932. From 1942 to 1954 many new technology based cameras were introduced for better image capturing like Kodacolor, Hasselblad, Polaroid instant camera, SLR camera with pentaprism, Leica M and so on. Kirsch *et al.* (1957) acquired first digital computer scanned image.

In 1947-58 as technology shifted from analog electron valves to digital switches, from hot vacuum tube (1904) to small cool transistor (1925-1947) decrease circuit size increase speed. In 1969 at Bell Lab (NJ) Boyle and Smith create an image by using 8-pixel Charged-Couple-Device (CCD) and 8 by 8 pixels CCD in 1972. In this CCD ([http://www.nist.gov/public\\_affairs/releases/image\\_052407.cfm](http://www.nist.gov/public_affairs/releases/image_052407.cfm)) the image is created without any chemical and mechanical steps directly from the light just by the counting number of photon of lights falling on Silicon Chip. 1994, Mike Collette develop scanback using Kodak tri-lines CCD array. Scanback by single operator create superior images at great resolution.

As images became a major source of information so to gather the information about the object or phenomenon to which physically contact is not possible- the remote sensing images through satellite began. The first image from space was taken in 1946 by V-2 flight (U.S.). When U.S. and Soviet Union develop imagery Satellite systems (1950) and the technology of sensors improved multi-spectral range and CIR images are now possible to capture. In 1959 the first artificial satellite Sputnik-1 was launched. In 1960 to 1972 first satellite based reconnaissance program (US Corona Program) was launched. Commercial market of satellite imagery start in 1970 with ERTS-Landsat-1 and Landsat-2 in 1975 with MSS and 80 meter Ground Sample Distance or pixel size (GSD). These two satellites are used for

various civil applications. Landsat-4(1982) and Landsat-5(1984) improved GSD by 30 m. France launch their SPOT-1 (1986) and Spot-2(1990) with 20 m GSD. Commercial use of remote sensing expands into high resolution satellite images. In 1992 Russia's first (KVR100) high resolution satellite imagery with 2 m GSD was launched. By Landsat-7 in 1997 U.S. declassified satellite imagery system which acquires 30 meter GSD with 15 m GSD PAN and EROS-1A(2000), QuikBird(2002), OrbView(2003), U.S Eros series, ENVISAT-1(2001), SPOT-5(2002) fully contributed in improving high resolution imagery. Today more than 50% worldwide market consuming remote sensing satellite images. The various applications of remote sensing are shown in Table 1.

### *Image Processing*

Imagery is a way to represent the information by picturing rather than describing (Fodor, 1981). Image processing is the process in which input will be an image and some mathematical operations performed on it to get the output image or some parameters or characteristics related to the image. Mathematical operation can be performed on any form of the signal. Image processing generally refer to digital (optical) and analog image processing. Analog image processing is to process an image through electrical mean- a continuous wave of analog signals. The best example of analog image processing is television. Second is Digital Image Processing (DIP) in which digital computers are used to process an image and convert it to digital form for further processing. In this study image processing refer to digital image processing. Digital image processing is multidisciplinary science that makes the use of principles from various fields like, computer science, surface physics, mathematics, optics and psychophysics. In DIP image is represent as 2-dimension signals and series of operations are performed over it to get the desired result. In DIP image passed through three main phase: Pre-processing, enhancement and display, information extraction. There are various techniques used while processing a digital image.

### *Remote Sensing Satellite Image Processing*

Remote sensing is a process of earth observation. It extracts the information about an object, area or phenomena with being physical contact with it. The best example of remote sensing is human eye, sense of smell or hearing. The Remote Sensing (RS) has become more associated with the measuring the interaction between earth surface and electromagnetic energy. Various techniques used to capture the images of earth surface in various Electromagnetic Spectrum (EMS)'s wavelength regions. RS is used to detect the objects or features of earth surface by recording the radiant energy emitted by the surface or object.

Different amount of energy is emitted by different object in different bands of electromagnetic spectrum which is depending on the surface roughness, angle of incidence, wavelength of radiant energy and physical, chemical and structural properties of the surface material. RS is multi-disciplinary science of optics, photography, computer, telecommunication, spectroscopy, satellite launching. The combination of all these technologies is known as Remote sensing system.

To make the use of satellite images in these areas there are various operations performed over the satellite images to get the appropriate information like.

The most basic operation that can be performed is classification. There are many approaches used to improve the classification accuracy of an image. But the major issues in the classification of high resolution multispectral image are mixed pixels that reduce the accuracy of the classification. In a satellite image the pixels that do not follow spectral features of one class of the image (like water, vegetation) or the pixels that reflect the characteristics of multiple classes are known as mixed pixels and pure pixels are those which are in the inference region of one class. Various techniques or operations performed on images are discussed in Table 2.

Table 1. Applications of remote sensing Satellite Image processing

Sr. No	Application area	Features
1	Agriculture	arable land acreage determination, salinity, soil composition determination, crop condition monitoring, dynamic crop development monitoring and forecasting
2	Forestry	Spatial distribution of forest, drive forest acreage, mature and over mature forest discrimination, tree species composition, monitoring of died-back areas during pests control.
3	Intelligent Transportation Systems (ITS)	Travel information, traffic management, Commercial Vehicle Operations, Electronic Toll management, transit management.
4	Moving	Tracking of moving objects for security and surveillance. Moving
5	Object tracking	object tracking objects enables to identify motion parameters.
5	Defense surveillance	Different formation of naval vessels of ocean surface, separate the different objects present in water body from the image based on the parameters such as, length, breath, area, perimeter, compactness and directions.
6	Weather forecasting	Detect clouds, cyclones, growing thunderclouds, forest fire smoke and volcanic ash, etc. From satellite measurements meteorological parameters like humidity profiles, wind velocity and lightning can also be derived

Table 2. Image processing techniques

Sr. No	Year	Techniques	Methods
1	1958	Classification (C)	FLD, L <sub>reg</sub> , NB <sub>c</sub> , P, SVM, LS <sub>SVM</sub> , Q <sub>c</sub> , K <sub>est</sub> , K <sub>nn</sub> , Boost <sub>malgo</sub> , D <sub>trec</sub> , Rand <sub>for</sub> , N <sub>N</sub> , LVQ
2	1966	Feature Extraction (FEx)	PCA, Semi <sub>Emb</sub> , MDR, MS <sub>learn</sub> , N <sub>L</sub> DR, I <sub>map</sub> , K <sub>PCA</sub> , M <sub>PCA</sub> , LSA, PLS, ICA, A <sub>ecoder</sub>
3	1962	Pattern Recognition (PREc)	Classification Algorithms: LDA, QDA, Max <sub>EC</sub> , D <sub>trec</sub> , NBC, N <sub>N</sub> , SVM, GEX <sub>prog</sub> , Clustering Algorithms: C <sub>MM</sub> , DLM, H <sub>c</sub> , KM <sub>cl</sub> , CO <sub>CL</sub> , K <sub>PCA</sub> Ensemble Learning Algorithms: Boost <sub>malgo</sub> , Boost <sub>agg</sub> , E <sub>avg</sub> , B <sub>N</sub> , MRF, MSL <sub>algo</sub> , MPCA, RVSL <sub>algo</sub> , Kal <sub>f</sub> , Part <sub>f</sub> , Regression Algorithms: GP <sub>reg</sub> , L <sub>reg</sub> , N <sub>N</sub> , DLM, ICA, PCA Sequence Labeling Algorithms: CRFs, HMMs, MEMMs, R <sub>NN</sub> , HMMs,

FLD-Fisher's linear discriminant, L<sub>reg</sub> - Logistic regression, NB<sub>c</sub> - Naive Bayes classifier, P- Perceptron, SVM- Support vector machines, LS<sub>SVM</sub> - Least squares support vector machines, Q<sub>c</sub> - Quadratic classifiers, K<sub>est</sub> - Kernel estimation, K<sub>nn</sub> - K-nearest neighbor, Boost<sub>malgo</sub>- Boosting (meta-algorithm), D<sub>trec</sub>-Decision trees, Rand<sub>for</sub>-Random Forests, N<sub>N</sub>- Neural networks, LVQ- Learning vector quantization, PCA- Principal component analysis, Semi<sub>Emb</sub> - Semidefinite Embedding, MDR - Multifactor Dimensionality Reduction, MS<sub>learn</sub> - Multilinear Subspace Learning, N<sub>L</sub>DR - Nonlinear Dimensionality Reduction, I<sub>map</sub> - Isomap, K<sub>PCA</sub> - Kernel PCA, M<sub>PCA</sub> - Multilinear PCA, LSA - Latent Semantic Analysis, PLS - Partial Least Squares, ICA - Independent Component Analysis, A<sub>ecoder</sub> - Autoencoder, LDA- Linear Discriminant Analysis, QDA- Quadratic Discriminant Analysis, Max<sub>EC</sub>- Maximum Entropy Classifier, D<sub>trec</sub>- Decision Trees, K<sub>EstKNN</sub> - Kernel Estimation And K-Nearest-Neighbor Algorithms, NBC- Naive Bayes Classifier, N<sub>N</sub>- Neural Networks, GEX<sub>prog</sub>-Gene Expression Programming, C<sub>MM</sub> - Categorical Mixture Models, DLM- Deep Learning Methods, H<sub>c</sub> - Hierarchical Clustering, KM<sub>cl</sub>- K-Means Clustering, CO<sub>CL</sub>- Correlation Clustering, K<sub>PCA</sub> - Kernel Principal Component Analysis, Boost<sub>malgo</sub>- Boosting (Meta-Algorithm), Boost<sub>agg</sub> - Bootstrap Aggregating, E<sub>avg</sub>- Ensemble Averaging, B<sub>N</sub> - Bayesian Networks, MRF- Markov Random Fields, MPCA- Multilinear Principal Component Analysis, RVSL<sub>algo</sub>- Real-Valued Sequence Labeling Algorithms, Kal<sub>f</sub>-Kalman Filters, Part<sub>f</sub>-Particle Filters, R<sub>algo</sub>- Regression Algorithms, GP<sub>reg</sub>- Gaussian Process Regression, L<sub>reg</sub> - Linear Regression, N<sub>N</sub> - Neural Networks, DML- Deep Learning Methods, ICA- Independent Component Analysis, PCA- Principal Components Analysis, Conditional Random Fields (CRFs), Hidden Markov Models (HMMs), Maximum Entropy Markov Models (MEMMs), Recurrent Neural Networks (R<sub>NN</sub>), Hidden Markov Models (HMMs)

### *Problem of Mixed Pixel*

Classification of remotely sensed data is an important task that is used in multiple practical applications like; monitoring and management of natural disasters, crop mapping, security and defense, object identification and etc. so to perfume the classification of this data at high level of accuracy is important to achieve. Objective of the classification process is to label each pixel to an appropriate class. But when spectral resolution increase while capturing hyperspectral images the spatial resolution usually gets to decrease and lead to the problem in hyperspectral images classification that is known as Mixed Pixel. A hyperspectral image with low spatial resolution image has two types of pixels: Pure and Mixed pixels. Pure pixels are those that represent a single class of the earth 'surface on the image. Mixed Pixels are defined as the pixels that reflect the more than one spectral signature of the earth surface (known as endmembers). Mixed pixels response to more the one class features. To get the accurate information classification of both pure and mixed pixels to their appropriate classes is required. Various techniques are used and proposed for this purpose in last decades.

### **Literature Review**

From the last two decade the application areas of satellite image processing are expanding rapidly. Many researchers have proposed and developed many techniques to extract the information from satellite images that can be useful in different applications. In this section we try to summarize the work done on mixed pixel problem in satellite images from initial years to now.

Viglione (1968) have explained that imagery from different types of sensor is required to serve various discipline and environment constraints. But the issues of concern is that the data captured by theses sensors lack in commonality. The compatibility issues in registration and resolution seemed to be insuperable, So to overcome the problem of in utilizing all image data (from different sensors) to achieve the data classification use a specific sensor as primary sensor which interrogate the data of other sensor for support and verifying information. Hemami *et al.* (1970) focused on classification of objects from an image by generation of template using regression analysis. Experiment was carried over four class problem; ellipses, rectangle, concave crescents and convex crescent. Nonlinear regression analysis is used for achieving pictorial pattern recognition. Paola and Schowengerdt (1995) compare the two classification

techniques for urban land use. Test site (Tucson, Oakland) accuracy of both classification techniques was similar. But by examine the class regions and density plots in decision space of Tucson the map generated by neural network was visually more accurate. On other hand for Oakland map generated by both techniques was visually and numerically similar. From analysis of this paper the conclusion is that the neural network is more robust and superior in classification of land use that cover more spectral signature-mixed pixel classification. The only drawback of neural network over maximum-likelihood is that to minimize mean square error a large training time is required. Kalviainen *et al.* (1996) proposed a method of identification of pure pixels from mixed pixels by using Randomized Hough Transform (RHT). In presence of outliers in large dataset the deterministic Hough is slow and for that least square method cannot cope. RHT has advantages over deterministic Hough like it store data in tree structure not in accumulator array which make it memory efficient. Irrespective of number of sample used in RHT its fixed requirement in CPU time is its big advantage over deterministic Hough.

Zhang and Foody (1998) used fuzzy approach for land cover classification of sub-urban characteristics from remote sensing satellite images by applying the both hard and fuzzy evaluation techniques. Results show that fuzzy phenomena and their evaluations allow locational and quantitative examinations of misclassified data. Issues in this are that fuzzy technique required ground data of pixels for classification which increase the complexity and cost. Bosdogianni *et al.* (1998) proposed Hypothesis Testing Hough Transform (HTHT) for mixed pixel classification. As in their previous approach (Hough Transform) has disadvantage that the performance of HT decreased when outliers are not presents. But HTHT will perform equally with and without the presence of outliers. HTHT has advantage over standard Hough transform that is it used continues accumulator function rather than discrete accumulator array function used in standard Hough Transform. Drawback of this approach is that it will not perform well when dataset is large and number of pure pixel classes is more. Ji and Jensen (1999) proposed a hybrid technique of 'subpixel processor and layered classifier to detect' spectral fractions of impassable components of large number of mixed urban pixels and generis characteristics of few uncommon urban pixels. As subpixel analysis compute from total radiance of pixel the urban impedance by extracting background spectra and then testing the remaining

spectrum against the signature spectrum. Some difficulties arise while managing spectral divergency of various urban features. To overcome this issues the layered classifications which is used to find extreme cases is used in combination with subpixel analysis. Kappa coefficient is used to check the performance. Hu *et al.* (1999) a new method Total Least-Square (TLS) is introduced to solve the first level to find the Least Square problem (LS) End-Member Spectra (EMS) of two successive. For the second issues is to the find the land Cover Class Proportions (CCP's) from the identified EMS Quadratic Programming (QP) is used. As compare with previously proposed method given by Settle and Drake Preliminary (approximated solution based on Lagrange Multiplier (LM)) TLS based computed EMS will give better prediction for CCP. To estimate CPP's from noisy observation QP method perform better as compare to LM method. But if only linear algebraic matrix operations are required then LM is preferable as it is computationally less complex then QP.

Foody (2000) resolve mixed pixel problem from remote sensing image by using soft/ fuzzy techniques the main strength of pixel membership display to class works for fractional coverage of class as surrogate. The classification accuracy based on the relationship between class membership strength and related fractional coverage. Issue in this is that the measure of class membership can be done in training stage. So, the untrained classes will influence on the accuracy. Fuzzy C- Mean (FCM) and Possibilistic- C- Mean (PCM) are used for the classification of land cover. Both algorithms perform equally when the classes are trained. But FCM's performance degrades when untrained classes are encounter. On the other hand PCM will give the absolute measure of class membership strength when the untrained classes are encounter. PCM works on the distance value calculated in pixel and centroid of class alongside with the product of FCM analysis. It is observed that the combination of both algorithm improve the performance of land cover classification. The summarization of the methods used for mxed pixels are listed in Table 3.

Faraklioti and Petrou (2001) proposed illumination = invariant statistics for mixed pixel classification. When there is a change in statics of the reflectance values of real mixed scene due to change is roughness and illumination linear mixing model will not be applicable. As the topology and radiometric will not be concern with the roughness issues so change in that will not provide the solution. A mixture model has proposed with new illumination invariant statistics

which will not be influenced by the illumination conditions. Input to the model will be statistical data of pure classes, roughness of the surface of these classes, data about the level of illumination in shadowed regions. This data will be extracted from the training scenes. Hsieh *et al.* (2001) formulated methods for calculation of pure pixels' class spectral covariance and mixed pixels' spectral responses using linear mixing model. The impact of parameters like ratio of Ground Sampling Distance (G.S.D) with Field Width (F.W.), the reference class variance, the growth order of class variance with decreasing ratio on classification error are evaluated. This opposite effect for the error found in overall classification as compared to the ratio of G.S.D to F.W. may result in valley phenomenon. Our results further show that the optimum ratio increases with increasing growth order and increasing reference variance. In this study the experiment perform on simulated data shows that with decreasing the G.S.D to F.W. there is decrease encountered firstly in overall classification error. When it reaches to a threshold value i.e. minima, thereafter an increase may be encountered by further decreasing the ratio. This results represent that the commonly used per pixel classifier may not have the advantage of the information available in high resolution imagery. Chang (2002) proposed a new approach where signature Vectors which are chosen as targets are constrained instead of abundance fractions. This approach referred to as target signature constrained pixel classification. It works on three aspects. (1) From sensor array processing point of view which was known as CEM and further referred to as LCMV, (2) from pattern classification point of view known as LCDA. It use classification technique similar to Fishers linear discriminant analysis which imposed constrain on each of the target signature vector along a predefined direction, (3) Linear spectral mixture analysis point of view known as FV method. Chiang and Chang (2002) proposed a new method which directly extract end member signature from abundance fractional images known as "Histogram based mixed-to-pure pixel conversion (HMPVC)". It works on the threshold value to separate image background from end member signature. This threshold is a value of confidence coefficient which is found when an abundance fractional image is taken as input and the resulting histograms' probability distribution is taken into account.. Further the performance of HMPVC is compare with utility of HMPVC with other mixed pixel methodologies. Kasetkasem *et al.* (2003) the problem n of mixed pixel classification is to know the

within class proportion. Author has presented Markov Random Fields (MRF) as a new classification approach for sub-pixels. MRF helps in generation of fine resolution Land Cover Map (LCM) from less detailed resolution. MRF leads to accurate characterization of classes' spatial distribution. This approach performs more accurately and efficiently as compare to maximum likelihood classifier. Naceur *et al.* (2004) proposed a method to decompose mixed pixel from RSI and retrieve the compositional information from it. The main objective of this method is to return the different sources coving the scanned area. Issus in restoring these sources is the presence of mixture of physically independent components. In this study two statistical methods are used for getting the independence between the different sources. (1) Based off on the reduction of the spatial source correlations, (2) based on the joint maximization of the fourth-order cumulants. JADE and SOBI algorithms are used

for source separations. These algorithms model the sensibility according to different spectral bands which results in more information about spectral signature represented by the corresponding source image. After the sources images the linear mixture model is apply to them for classification/decomposition of mixed pixels. Kosaka *et al.* (2005) proposed a method for periodically distributed hyperspectral senor images-Independent Component Analysis (ICA)- aided mixed pixel analysis. From the mixed pixel data this method also estimates pure spectra and the coverage of endmember. A prior knowledge can be estimated from ICA process which is effective for scaling factor formulation of independent component and independent to the variety of crop. Issues are the only when in the large shadow of crop the number of verities of crop is two or more then independence will be affected. So to identify the shadow which is crop type dependent investigate crop pattern (Table 4).

Table 3. Summary of techniques used for mixed pixel classification (1968-2000)

Paper	Image type	Technique	Tool	Pros	Cons
Paola and Schowengerdt (1995)	LTM	Max <sub>LH</sub> , N <sub>N</sub>	Sun SPARCstation 10	Par <sub>comp</sub> , Rob	L <sub>tt</sub>
Kalviainen <i>et al.</i> (1996)	RHT	NA	FlexCP	M <sub>eff</sub>	Lack <sub>guide</sub>
Bosdogianni <i>et al.</i> (1996)	LTM	SHT	NA	Tol <sub>Lolier</sub>	NA Ldb <sub>PCL</sub>
Zhang and Foody (1998)	SPOT HRV and LTM	FCM	VAX/VMS	High <sub>infoacc</sub>	High <sub>cc</sub>
Bosdogianni <i>et al.</i> (1998)	LTM	HTHT	NA	P <sub>pab</sub> Outlier	NA Ldb <sub>PCL</sub>
Ji and Jensen (1999)	LTM, SPOT PAN Images, HSRAI images	SubP <sub>p</sub> Layered <sub>classifier</sub>	NA	Map <sub>urlmp</sub>	Multi D <sub>cal</sub> , C <sub>macc</sub>
Hu <i>et al.</i> (1999)	LTM	TLS, QP	MatLab	Better <sub>CCPE</sub> EasyC <sub>Nob</sub>	H <sub>CT</sub>
Foody (2000)	ATM	PCM	NA	Acc <sub>utdb</sub>	H <sub>c</sub>

LTM-Landsat ThermalMapper, Max<sub>LH</sub>- Maximum-likelihood, N<sub>N</sub> -Neural Network, Par<sub>comp</sub>- parallel computing, Rob-Robust, L<sub>tt</sub>- Large training time, RHT- Randomized Hough Transformation, FlexCP- Flexible CPU time, M<sub>eff</sub>- Memory efficient., L<sub>olier</sub>- large number of outliers, Lack<sub>guide</sub>- Lack of guidelines, SHT- Statistic Hough Transform, Tol<sub>Lolier</sub>- Tolerate large amount of Outliers, NA Ldb<sub>PCL</sub>- Not applicable for large dataset of pure pixels classes, FCM-Fuzzy C-mean, High<sub>infoacc</sub> -High Accuracy, igh<sub>cc</sub>-High Cost and Complexity, HTHT- Hypothesis testing Hough Transform, P<sub>pab</sub>Outlier- perform better in presence and absent of outlier, NA Ldb<sub>PCL</sub>. Not perform better when Large number of pure classes, ATM- Airborne thematic mapper, PCM- Problistic c mean, Acc<sub>utdb</sub>- Accurate in untrained classes, H<sub>c</sub>- High complexity, SubP<sub>p</sub>- Subpixel processor, Layered<sub>classifier</sub> -Layered Classifier, SRO<sub>coanalysis</sub>- Spearman rank-order correlation analysis, Map<sub>urlmp</sub>- Map urban imperviousness of each pixel, MultiD<sub>cal</sub>- Multidate calibration, C<sub>macc</sub>- change map accuracy, TLS- Total Least Square, QP- Quadratic Programming, Better<sub>CCPE</sub>- Better CCP estimation, easy, EasyC<sub>Nob</sub>- compute for noisy, H<sub>CT</sub>- High computation time.

Table 4. Summary of techniques used for mixed pixel classification (2001-2005)

Paper	Image type	Technique	Tool	Pros	Cons
Faraklioti and Petrou (2001)	S <sub>sc</sub>	IIS	NA	NotInf <sub>cill</sub>	Dis <sub>Guas</sub> HOS <sub>NI</sub>
Chang (2002)	AVIRIS, HYDICE	LCMV, BRLCMV, LCDA, FV, OSP	NA	Imp <sub>class</sub>	NA
Chiang and Chang (2002)	HyDICE	HMPC-OSP and HMPC-CEM	NA	FCA <sub>EE</sub>	NA
Kasetkasem <i>et al.</i> (2003)	M <sub>sp</sub> , PAN	MRF	NA	Better <sub>Class</sub>	NA
Naceur <i>et al.</i> (2004)	SAR, HRVIR	2-D JADE, 2-D SOBI	NA	Eff <sub>repInfo</sub>	NA
Kosaka <i>et al.</i> (2005)	LTM	ICA-aided	MATLAB	EffEstCP <sub>unkm</sub>	IndEff <sub>shod</sub>

S<sub>sc</sub>- Simulated scenes, IIS- illumination = invariant statistics, NotInf<sub>cill</sub>- Not influenced by change in illumination, Dis<sub>Guas</sub>-HOS<sub>NI</sub>-distribution is Gaussian the higher order statics will not give more, Imp<sub>class</sub>- Improve classification, HMPC-OSP- Histogram Based mixed -to- pure conversion based orthogonal sub space projection, HMPC-CEM- HMPC based constrained energy minimization, FCA<sub>EE</sub>- Fully computer automated, endmember extraction, MRF- Markov Random field, Better<sub>Class</sub>- Better Classification, Eff<sub>repInfo</sub>- Effective representation of information, EffEstCP<sub>unkm</sub>- Effective estimate covering plant is unknown, IndEff<sub>shod</sub>- Independence affected as shadow relies on type of vegetation

Chang and Ji (2006) has proposed an enhancement of Fisher's linear discriminant analysis which is known as Fisher's Linear Spectral Mixture Analysis (LSMA). The new FLSMA based on constrains; "Feature- Vector Constrains FLSMA (FVC-FLSMA) and Abundance Constraint FLSMA (AC-FLSMA)" will give more optimal solution. Because of the pattern intraclass classification the scatter matrix in FLSMA is more efficient then the data correlation matrix used in LSMA. Fisher's ratio is used as classification criteria in FLSMA which is more efficient then LSE and SNR used in LSMA. Miao *et al.* (2007) propose an unsupervised decomposition algorithm Gradient Descent Maximum Entropy (GDME) which is derived from classic maximum entropy principle for effective and robust estimation of mixed pixels. This algorithmic rule can Diamond State crease the negative entropy by de mistreatment the hybrid of GLSE based mostly} is that the combination of a world Least sq. Error (GLSE) based endmember detection and per-pixel abundance learning supported a distinction operate (which scale back the negative entropy). This algorithm is basically decomposing mixed pixels by addressing the importance of maximum entropy principle from geometric point and demonstrate that the GDME provide more accurate results when end members signatures are close to each other as compare to least square methods.

**Algorithm\_1:** Unsupervised Gradient Descent MaxEnt(GDME)

Input:  $f$ , starting value  $x_1$ , termination tolerances

For  $t = 1, 2, \dots, \text{maxIters}$ :

- Compute the search direction  $d_t = -\nabla f(x_t)$
- If  $\|d_t\| < \varepsilon_g$  then:  
return "Converged to critical point", output  $x_t$
- Find  $\alpha_t$  so that  $f(x_t + \alpha_t d_t) < f(x_t)$  using line search
- If  $\|\alpha_t d_t\| < \varepsilon_x$  then:  
return "Converged in  $x$ ", output  $x_t$
- Let  $x_{t+1} = x_t + \alpha_t d_t$

Return "Max number of iterations reached", output

$x_{\text{maxIters}}$

Liu *et al.* (2007) introduce an algorithm of Bayesian Self-Organizing Map (BSOM) which estimates the parameters of Gaussian Mixture Model (GMM) for the decomposition of mixed pixels of remote sensed images. For high precision of unmixing the range of Gaussian distribution is extended by using 3omega variance adjustment method. The efficiency of proposed method is compared with FCM on the basis of RMSE, correlation coefficient, computation time and robusticity to noise. Then proposed method is also checked on real data which show that it unmix the mixed pixels in

shorter computation time. Tang *et al.* (2007) has done a comparative study on the performance of various algorithms for detecting in 3D data the depth discontinuities and mixed pixels. The algorithms are Normal angle filter, Edge length filter, Boundary removal variation, clone of influence algorithm. This paper shows that depth detection algorithm can be converted to mixed pixel detection algorithm and vice versa. Performance evaluation of various algorithms is performed on test patches extracted from varieties of scene are used. Results shows that the surface normal angle based algorithms perform better than all other algorithms mentioned before. Godbaz *et al.* (2008) has used Heterodyne Beat Waveform (HBW's) harmonic content for identification of range of multiple return values as well as for identification of the intensity of each pixel. The mixed pixel problem originating out of multiple source light integration to single pixel is solved using this method. Basically these pixels are found around the edges of objects. The problem of mixed pixel has affected the performance of continuous wave range imagers based upon Full-Field Amplitude Modulation (FFAM). This system also uses the application of Levy-Fullager (LF) method. Heterodyne Beat Waveform (HBW) is fed as an input to LF and harmonic content is extracted in AMCW lidar system results which shows that there is improvement in separating multiple ranging sources as well as the overall ranging error improves by 30%. Ge *et al.* (2009) proposed an algorithm which is capable of producing fine grained information of land covers with spatial distributions by extracting fractional values within the mixed problems by using soft classification. This is used for computing the region ration of the endmember component of mixed element and their neighbor elements. This mapping is done by three steps: (1) Identify the position of vertices of polygonal shape that square measure on the central pixel's boundary; (2) determine the position of vertices of polygon inside the central pixel; (3) find the geographical area of endmember elements. Proposed algorithm is tested on both synthetic and artificial images. Due to the existence of subpixel mapping error in this methodology when tested on synthetic images is due to the degradation process for calculation area proportion. Tao *et al.* (2009) has proposed a simplex based algorithm to overcome the draw of N-FINDER (i.e., Computing Complexity) that was widely used for mixed pixels decomposition due to its simplicity and effectiveness. The proposed algorithm is an improvement to N-FINDER basically in two aspects: (1) it replace the matrix determinant calculation of N-FINDER with an iterative Gram-Schmidt orthogonalization for searching of endmember. Which make the algorithm to run very fast with less computing time and ensure the stable end results;

(2) it helps in proper calculation of number of endmembers and the automatic classification of mixed pixels from the actual image.

**Algorithm 2:** Orthogonal Bases Approach (OBA)

INPUT  $X \equiv [x_1, x_2, \dots, x_N]$   
 //Initialization:  
 1)  $e_0 = \text{argmax}_i(|x_i|)$   
 2)  $e_1 = \text{argmax}_i(|x_i - e_0|)$   
 3)  $\alpha_1 = e_1 - e_0, \beta_1 = \alpha_1$   
 4)  $l_i = x_i - e_0, (i = 1, \dots, N)$   
 5)  $\gamma_1 i = l_i - ((l_i \cdot \beta_1)/(\beta_1 \cdot \beta_1))\beta_1, (i = 1, \dots, N)$   
 6) Set iteration index  $k = 1$   
 //main loop  
 while stopping condition is not met do  
 7)  $e_{k+1} = \text{argmax}_i(|\gamma_k i(x_i)|)$   
 8)  $\beta_{k+1} = \text{argmax}_i(|\gamma_k i|)$   
 9) Update  $\gamma_k i + 1 = \gamma_k i - ((l_i \cdot \beta_{k+1})/(\beta_{k+1} \cdot \beta_{k+1}))\beta_{k+1},$   
 ( $i = 1, \dots, N$ )  
 10) Increase  $k$  by 1  
 end

Larkins *et al.* (2009) proposed an algorithm to solve the mixed pixel problem in point cloud images. This proposed algorithm will not discard mixed pixel but restore them to their appropriate location. In this approach mixed pixels are identified and projected on the surface they belongs to by segmentation of the region around the mixed pixel into two classes by using Otsu threshold technique. This algorithm is tested on simulated and original images and result shows that this technique robust and accurate in allotment of mixed pixel to their correct position, but he issue in this is that if classes in neighborhood of mixed pixels are three then Otsu threshold method will not work well in this situation. Linga *et al.* (2009) used fuzzy theory for classification of mixed pixels to their proper class. In this the experiment is performed on TM remote sensing images. First in the pre-processing of remote sensing images is performed by removing noise from it through Minimum Noise Fraction transformation (MNF). After that pure pixel are identified by using Pixel Purity Index (PPI). Then based on endmember (by using PPI) mixed pixels are decomposed by applying fuzzy technique. Result is analyzed and compare with maximum likelihood method and prove that fuzzy classification approach perform more efficient then maximum likelihood.

Mei *et al.* (2010) has proposed Multi-channel Hopfield Neural Network (MHNN) to decompose mixed pixels. This MHNN handle all pixels in image synchronously rather than using the procedure of per-pixel. To improve the unmixing this approach used stopping criterion of Noise Energy Percentage (NEP) instead of empirically selecting the number of

iteration. Results shows that MHNN perform better then Fully Constrained Least Square (FCLS), Hopfield Neural Network (HNN), Gradient Descent Maximum Entropy (GDME) and on a single computer different real world application can used this algorithm with acceptable cost.

**Algorithm 3:** MHNN-Algorithm

Data: Mixture data  $R_{b \times o}$   
 Result: Abundance matrix  $A_{c \times o}$

// Initialization  
 Set  $\delta, \eta$  and  $\lambda$  under unsupervised/supervised way:  
 Add pseudo band to spectral vector in R and M  
 Set the block synapses  $W_{c \times c}$  and the biases  $I_{c \times o}$   
 $A = \frac{I_{c \times o}}{c};$   
 // Set stopping criterion  
 Estimate the SNR of the image;  
 Calculate the NEP stopping criterion (Nep) for MHNN  
 Calculate the current NEP ( $c_{Nep}$ )  
 //MHNN iteration for matrix analysis  
 While  $c_{Nep} > Nep$   
 Update the input of neurons:  $U_{c \times o} = U_{last} + \eta \times (WA + I);$   
 Update the state of neurons:  $A_{c \times o} = f(U);$   
 Update the current NEP ( $c_{Nep}$ );  
 End

Jin *et al.* (2010) has purposed a new method derived from Fisher Discriminant Null Space (FDNS) to decompos mixed pixels when endmember have spectral variability. FDNS find linear transformation of spectra, which reduce variability within endmebergroup and increase the difference between other endmember groups. Experiment has shown that FDNS perform with more accuracy then PPI method.

**Algorithm 4:** FDNS

Step1) Selecting certain numbers of pure-pixel spectra by using PPI calculation. The candidates are classified to each endmember group through interactive clustering analysis and regarded as the training samples.

Step 2) Analyzing the original spectra through the FDNS to obtain  $p-1$  optimal discriminant vectors.

Step 3) Projecting both the mixed-pixel spectra and the endmember spectra to the null space by the transformation matrix  $W$  of the FDNS and then unmixing the mixed pixels by FCLS to get the end member fractions.

Zhang *et al.* (2011) has proposed a new way to represents the relationship between pixels, which is



given by directed and weighted graph. This converts the problem to shortest path optimization from endmember extraction and solved by using “Ant Colony Optimization” technique. This algorithm performs better than N-Finder and VCA for extraction of mixed pixels. Panchal and Gupta (2011) used Biogeography Based Optimization (BBO) algorithm for classification of mixed pixel from remote sensed images. Values of seven band of RS image are used in this algorithm which bitterly observed land features and show that mixed pixel resolution is highly influenced by spectral bands. BBO is built on local search of individual from the population to utilize adequate information of neighborhood in range of mixed pixels.

**Algorithm\_5:** Biogeography Based Optimization (BBO)  
 Input- Dataset of Pure and mixed pixels of land features.  
 Output- All mixed pixels are classified.

```
i. Condition = no of different sets of mixed pixel //
Initialization
ii. Reading training data set of all pure pixels. // Data set
of Water-vegetation, urban-rocky, urban- Vegetation are
taken//
iii. Reading training data set of all mixed pixels.
iv. While (condition! = 0)
{
pxl = no of pixels in mixed training data set taken. //
taking one unique set of MP for each Iteration for
condition*/

v. Original_HSI_1 = mean (standard deviation of each
Band DN values of pure pixel data set of class_1 of
which a mixed pixel corresponds)
vi. Original_HSI_2 = mean (standard deviation of each
band DN values of pure pixel data set of class_2 of
which a mixed pixel corresponds)
vii. for (j = 0; j<pxl; j++)
{
Add pixel [pxl] from mixed pixel to tables of both the
pure pixel of which the Mixed pixel corresponds.
//Emigration//
Calculate New_HSI_1, New_HSI_2 // after Addition
Deviation_1 = Original_HSI_1- New_HSI_1;
Deviation_2 = Original_HSI_2- New_HSI_2;
If (Deviation_1<Deviation_2)
{
Classify Pixel [pxl] as Class 1;
//Immigration//
Else
Classify Pixel [pxl] as class_2;
//Immigration//
}
}
```

```
}
viii. [End]
```

Ursani *et al.* (2012) proposed a procedure which is based on spectral and textural features for classification and segmentation of a set of multispectral and high resolution satellite- borne panchromatic images. This method uses k-mean for segmentation and neural network classifier for classification. Proposed algorithm is faster than the region based and objects oriented method. In comparison to textural based classification the combination of both spectral and textural improve the classification process by 27% (accuracy). Su *et al.* (2012) proposed an algorithm with combination of the positive attributes of Contouring and Hopfield Neural Network (HNN) to decompose the mixed pixel problem known to CHNN. This method overcome the limitations of contouring and HNN methods like; the limitation of contouring method is the unmaintained class proportional information and HNN produces unrealistic serrates boundary. The proposed algorithm -CHNN fit the contour on pre- final product generated by HNN. The results show that the combination of Contouring and Hopfield Neural Network (CHNN) produced more efficient results and compare to Contouring and Hopfield neural network when used individually. Arora and Tiwari (2013) purposed a new super resolution mapping algorithm which is based inverse Euclidean distance. In this method spatial distribution of abundance fraction is adjusted to find the subpixel targets. This method overcomes the limitations of Linear Mixture Model (LMM). Advantage of this new method is its less and near constant CPU time with increase in complexity and improved classification accuracy. Disadvantage of this method is that it is not using non-linear Euclidean Distance method lies only on linear Euclidean Distance method.

King and Younan (2006) anew mixels classification technique is proposed that is derived from the information of neighboring pixels. In this method multiple endmemeber models are used to extract a subset of original endmember based on which each pixel of image is unmixed. Then mixed pixel classification is further refined by assuming that neighboring pixels of that mixed pixel contain similar end members. RSME and four other metrics (procedure’s accuracy, User’s accuracy, Pessimistic accuracy, Optimistic accuracy), are used for performance evaluation of the proposed method. Result shows that this new method gives better result as compare to conventional method (Maselli). Sriwilai *et al.* (2013) proposed a level set based super resolution mapping algorithm. This method segment the image based on region based methods (level set method) and reduces the isolated pixels. In this approach first for

each class find mean and covariance matrix using area boundary from ground truth image. Then perform the segmentation by using level set method by and maximum likelihood classifier the results shows that performance of proposed method (75.18%) is better than MLC (63.68%). Itoh and Iwasaki (2013) has combine End-member Extraction Algorithm (EEA) with continuum removal. This combination is more effective in finding and identifying material known and unknown and evaluation the abundances. First remove noise band and select bands manually, then enhance absorption features by using continuum removal method, in last on continuum removed spectra apply orthogonal projection for dimensionality reduction and Split Augmented Lagrangian (SISAL) end member extraction algorithm. Result is compare with and without using continuum removal and it shows that EEA works with continuum removal. Cerra *et al.* (2014) proposed a novel Supervised Metric Learning (SML) which is a machine learning algorithm to find the target pixels based on from hyperspectral images. SML learn distance metric by using supervised distance maximization to increase the distance between negative (background) and positive (mixed pixels with target signatures) samples and then used similarity propagation constraint to classify negative sample to background and all positive to the target. Once the identification of the target samples is done, then on positive samples smoothness regularization is performed for maintaining their regional geometry in the obtain matrix. The results show that SML algorithm performs more effectively in target detection as compared to AMF and CEM algorithms. Xu *et al.* (2014) proposed a subpixel mapping framework MASSM to improve the accuracy of mapping based on Multi agent System (MAS) which deals with different types of mixed pixels. In this framework three kinds of agents are used to resolve the problem of subpixels mapping. Three agents are; Feature Detection Agents (FDA), Subpixel Mapping Agents (SMA) and Decision Agents (DA). First create FDs to find pure pixels, boundary pixels and linear subpixel by calculating MLI. Then different SMA is applied to different types of pixels generated from FDA for subpixel mapping. Now as different types of mixed pixels are presented so for single agent with single function best result will not be possible to generate. So for this issue MASSM use DA to coordinate the confusion during implementing FDA and SMA. Experiment shows that MASSM gives improved accuracy as compared to HC, BP algorithms. Li *et al.* (2014) proposed a new model based on spatial-temporal Markov Random Field (MRF) and super Resolution Mapping (STMRF\_SRM). Because it builds the mapping forest knowledge of huge space combination of timely updated coarse spatial resolution pictures and

previous medium spatial resolution pictures at low expense. STMRF\_SRM first smooth spatial land covers classes for spatially neighboring subpixels and maintains temporal links of temporally neighboring subpixels in bitemporal images. Kappa coefficient is used for performance measure. Omission error and commission error are used to check the accuracy.

#### Algorithm\_6. TMRF\_SRM

- 1) The endmember spectra are extracted. The coarse spatial resolution images are unmixed and the SR map is initiated in terms of the fraction images.
- 2) The transition probability matrix is calculated.
- 3) The subpixel labels are updated in terms of (4) of the entire image. The land cover type for each subpixel that contributes to the minimal posterior energy is accepted as the label of this subpixel.
- 4) The iteration is terminated until less than 0.1% of the total number of subpixels is changed after two consecutive iterations; otherwise, return to Step (2). The flow chart of the STMRF\_SRM mode

Cubero-Castan *et al.* (2015) proposed a new novel approach to estimate the mixed pixel material's temperature and analysis of the linear spectral mixture in thermal infrared domain. Two methods Temperature and Emissivity Separation (TES) and Thermal Remote sensing Unmixing for Subpixel Temperature (TRUST) are used for estimation of pure pixel and mixed pixel temperature.

#### Algorithm\_7: Hybrid of TES and TRUST

- i. Classify the coregisterd hyperspectral image acquired in visible domain which results in pure pixel localization
- ii. Apply TES algorithm to estimate temperature and emissivity of pure pixels
- iii. The TRUST is used to estimate temperature of material inside the mixed pixels
- iv. Abundance is calculated by minimization of the reconstruction error of mixed pixel radiance.

Guerra *et al.* (2015) proposed an algorithm of Gram-Schmidt method which is derived from orthogonal projections. Known as FUN algorithm for unmixing. This algorithm is easy to implement on hardware as it is not perform the complex matrix operation, has high level of parallelization and reutilize the information. FUN algorithm first extract endmember and estimate their number then calculate abundances. FUN algorithms' performance is compared with HySIME, VCA and FCLUS algorithms and results show that the accuracy for extraction and estimation of endmember is better than the others. FUN calculates abundance much faster than FCLUS.

**Algorithm 8:** Process to extract endmember

Input:  $M = [r_1, r_2, \dots, r_{N_p}]$ ,  $\alpha = 1$   
 $E = []$ ; {endmember extraction}  
 $Q = []$ ; {Endmembers' GramSchmidtOrthogonalization}  
 $U = []$ ; {Endmembers' GramSchmidtOrthonormalization}  
 $X = [x_1, x_2, \dots, x_{N_p}] = M$  {Auxiliary copy of the hyperspectral cube}  
 $e_1 = x_j$  where  $x_j$  is the pixel of hyperspectral image selection as first endmember according to the initialization criterion; {Select first endmember}  
 $q_1 = e_1$ ;  
 $u_1 = q_1 / \|q_1\|$ ;  
 $E = [e_1]$ ;  
 $Q = [q_1]$ ;  
 $U = [u_1]$ ;  
 $P = 1$ ; {Number of endmember found}  
 $Exit = 0$ ;  
 While  $Exit = 0$  do  
   For  $j = 1$  to  $N_p$  do  
      $x_j = x_j - (x_j \circ U_p) \cdot U_p$ ;  
      $\delta_j = 100 \cdot x_j / \|r_j\|$ ;  
 End  
 If  $\max(\delta) \leq \alpha$  then  
    $Exit = 1$ ;  
 else  
    $j_{max} = \text{argmax}(\delta_j)$ ;  
    $p = p + 1$ ;  
    $q_p = x_{j_{max}}$ ;  
    $\mu_p = x_{j_{max}} / \|r_j\|$ ;  
    $e_p = r_{j_{max}}$ ;  
 end  
 end  
 Output:

$P$ , {number of endmember}  
 $E = [e_1, e_2, \dots, e_p]$ , {endmembers}  
 $Q = [q_1, q_2, \dots, q_p]$ , {Orthogonalizedendmembers}  
 $U = [u_1, u_2, \dots, u_p]$ , {Orthonormalizedendmembers}

**Algorithm 9:** Process to obtain the abundances

Inputs:  $M = [r_1, r_2, \dots, r_{N_p}]$ ,  $p, E = [e_1, e_2, \dots, e_p]$   
 $E = [E, E]$ ;  
 $Norms = []$ ,  $U = []$ ,  $Q = []$ ,  $U^* = []$ ,  $Q^{**} = []$ ;  
 for  $k = 2$  to  $p + 1$  do  
    $U_1 = E_k / \|E_k\|$ ;  
 for  $j = 2$  to  $p$  do  
    $x = E_{k+j-1}$ ;  
   for  $i = 1$  to  $j - 1$  do

$q_x = x - (x \circ q_j) \cdot q_j$ ;  
 end  
 $U_j = q_j / \|q_j\|$ ;  
 end  
 $Norms = [Norms, \|q_p\|]$ ;  
 $U^* = [U^*, U_p]$ ;  
 end  
 for  $i = 1$  to  $p$  do  
    $Q_i^* = U_i / Norms_i$ ;  
 end  
 $A = (Q^*)^T \cdot IMG; \{Abundances\}$

Outputs: Abundances

Yuan *et al.* (2015) has introduced Substance Dependence constrained Sparse Nonnegative Matrix Factorization (SDSNMF) method which work on spatial information and substance dependence of hyperspectral data. In this algorithm similarities in given hyperspectral data is used in unmixing process. The characteristics like substance dependence constraint, stability of decomposition and antinoise make SDSNMF to perform better than other algorithms.

**Algorithm 10:** SDSNMF for HyperspectralUnmixing

Input:  
 The observed mixture data  $X \in RL \times N$ , the number of Endmembers  $P$  and the parameters  $\lambda_1, \lambda_2, \lambda_3$ .  
 Output:  
 Endmember signature matrix  $A$  and abundance matrix  $S$ .  
 1: Initialize  $A$  and  $S$  by the initializing rules mentioned before. Rescale each column of  $S$  to unit norm and make  $w_{ii} = 0$ .  
 2: Update  $A$ ,  $S$  and  $W$  by the updating rules in (15), (19), and (22) until the iteration ends;  
 3: End.

Chen *et al.* (2015) a new algorithmic rule Hybrid constraint of pure and mixed pixels (HCPMP) for allocation of land cover categories for soft then exhausting super resolution mapping (STHSRM) supported multiple shift pictures (MSI). 1st HCPMP realize the categories of subpixel by mistreatment data from each mixed pixels from MSIs and pure pixels of auxiliary pictures in MSIs. The remainder of mixed pixels square measure allotted to their categories by mistreatment ton in HCPMP. This take some massive computation time however generate higher and correct SRM map as compared to different algorithms like; DH, UOS and HAVF. This methodology work higher for top resolution pictures as compared to low resolution pictures (Table 5).

Table 5. Summary of techniques used for mixed pixel classification [2006-2015]

References	Data type	Technique	Tool	Pros	Cons
Chang and Ji (2006)	AVIRIS	FLSMA	NA	AccPattern <sub>class</sub>	Rely <sub>TS</sub>
Núñez <i>et al.</i> (2006)	PAN	à trous	NA	Robt	NA
Miao <i>et al.</i> (2007)	HIS	GDME	NA	AppL-NL, Flex	L <sub>CT</sub>
Liu <i>et al.</i> (2007)	LEMT+ RSI	BSOM, 3 omega	NA	L <sub>CT</sub> , H <sub>acc</sub>	C
Ge <i>et al.</i> (2009)	TM 5	S <sub>class</sub>	Microsoft Visual Studio.NET	P <sub>loc</sub> Red <sub>uncert</sub>	SPM <sub>error</sub>
Tao <i>et al.</i> (2009)	HIS	OBA	NA	L <sub>CT</sub> , Auto <sub>unmix</sub>	V <sub>based</sub>
Mei <i>et al.</i> (2010)	AVIRIS	MHNN	MATLAB	RWA <sub>sc</sub> , F <sub>CT</sub>	NA
Jin <i>et al.</i> (2010)	AVIRIS	FDNS	NA	BDecomp <sub>acc</sub> , L <sub>rmse</sub>	H <sub>cc</sub>
Zhang <i>et al.</i> (2011)	AVIRIS	ACO	NA	Post <sub>feed</sub> , G <sub>search</sub> , St	Lack <sub>model</sub> , CS <sub>slow</sub>
Panchal and Gupta (2011)	RSI	BBO	Matlab	R, Share <sub>InfoNeigh</sub>	Comp, T <sub>cons</sub>
Ursani <i>et al.</i> (2012)	QuickBird images	KMC, N <sub>N</sub>	NA	F <sub>comp</sub>	M <sub>class</sub>
Su <i>et al.</i> (2012)	PAN images	CHNN	NA	Acc <sub>bound</sub>	Sens <sub>parset</sub>
Arora and Tiwari (2013)	AVIRIS	IED-SRM	NA	Const <sub>CPU-T</sub>	NA
King and Younan (2006)	DAP	N <sub>info</sub>	NA	Rob, Min <sub>rmse</sub>	ILR <sub>High</sub>
Khodadadzadeh <i>et al.</i> (2014)	AVIRIS	SVM, MLRsub, MRF <sub>reg</sub>	NA	Less <sub>sensitive</sub>	NA <sub>TampDB</sub>
Xu <i>et al.</i> (2014)	LTM	MASSM	NA	Dist <sub>Con<sub>psol</sub></sub> , G <sub>optimize</sub>	Acc <sub>dec</sub>
Li <i>et al.</i> (2014)	MODIS	ST-MRF	NA	Less <sub>exp</sub>	Hinfluenced <sub>weight</sub>
Cubero-Castan <i>et al.</i> (2015)	DUCAS	TES, TRUST	NA	Indep <sub>par</sub>	SI
Guerra <i>et al.</i> (2015)	AVIRIS	FUN Algorithm	NA	Less <sub>PT</sub> , Easy <sub>imp</sub>	Acc <sub>EndExt</sub>
Chen <i>et al.</i> (2015)	MSI, LTM	HCPM	NA	Less <sub>RT</sub>	NEff <sub>LRI</sub>

FLSMA- Fisher linear spectral mixture analysis, Acc - Accurate Patternclassification-, Rely<sub>TS</sub> - Relies on training sample, Robt- robust, GDME- Gradient Descent Maximum Entropy, AppL-NL- applicable to linear and non-linear data, Flex - flexible, BSOM- Bayesian Self-Organizing Map, L<sub>CT</sub> - less computation time, H<sub>acc</sub>- high accurate, C- complex, S<sub>class</sub> - soft classification, P<sub>loc</sub> - predict location of uncover, Red<sub>uncert</sub> - reduce uncertainty, SPM<sub>error</sub> - subpixel mapping error, OBA - Orthogonal based approach, L<sub>CT</sub> - less computation time, Auto<sub>unmix</sub>- automatic unmixing, V<sub>based</sub> - volume based, Fuzzy<sub>T</sub> - fuzzy theory, Class<sub>HP</sub> - Classification with high precision, Prior<sub>InfoNoCl</sub> - Prior information of number of clusters, MHNN - Multichannel Hopfield neural network, RWA<sub>sc</sub> - real world application on single computer at acceptable cost and time, F<sub>CT</sub> - feasible cost and time, FDNS - Fisher's discernment null space, BDecomp<sub>acc</sub>- Better decomposition accuracy, L<sub>rmse</sub> - less rmse, H<sub>cc</sub> - high computational cost, ACO - ant colony optimization, Post<sub>feed</sub> - positive feedback, G<sub>search</sub>, - global search, St - stability, Lack<sub>model</sub> - lack of model, CS<sub>slow</sub>- computation speed slow, BBO- biogeography based optimization, R- Robustness, Share<sub>InfoNeigh</sub> - sharing information with neighbor, Comp - complex, T<sub>cons</sub> - time consuming, F<sub>comp</sub> - Faster computation, M<sub>class</sub> - Misclassification, KMC - k mean clustering, N<sub>N</sub> - neural Network, CHNN- Contouring and Hopfield neural network, Acc<sub>bound</sub> - accurate boundaries, Sens<sub>parset</sub> sensitive to parameter setting, IED-SRM - inverse Euclidean distance based super-resolution, Const<sub>CPU-T</sub> - constant CPU processing time, SVM- support vector machine, MLRsub-, MRF<sub>reg</sub> - markov random field regularization, Less<sub>sensitive</sub>- Less sensitive to quality of sample, NA<sub>TampDB</sub> - not applicable on temporal dataset, MASSM- Multiagent system based subpixel mapping, Dist<sub>Con<sub>psol</sub></sub> - Distributed and concurrent problem solving, G<sub>optimize</sub> - global optimization, Acc<sub>dec</sub>- Accuracy decrease, ST-MRF - Spatial Temporal markov random field, Less<sub>exp</sub>- less expensive, Hinfluenced<sub>weight</sub> - Highly influenced on weighting coefficients and nonlinear parameters, TES - Temperature and Emissivity Separation, TRUST- Thermal Remote sensing Unmixing for Subpixel Temperature, Indep<sub>par</sub> - independence to parameter, SI - slow, Less<sub>PT</sub>- less processing time, Easy<sub>imp</sub> - easy to implement, Acc<sub>EndExt</sub> - accuracy depends on endmember extraction, SDSNMF - Substance dependence constrained sparse nonnegative matrix factorization, A<sub>N</sub> - antinoise, HCPM- Hybrid constraints of pure and mixed pixels, Less<sub>RT</sub>- less run time, NEff<sub>LRI</sub> - Not effective for low resolution images, N<sub>info</sub>- neighboring information

From the comprehensive review of literature outline that remote sensed satellite image processing has vast application areas. To extract the information from satellite images there are many techniques are available depending on the application. To perform any operation on remote sensed satellite images classification of objects or data from the image is basic step. Many algorithms are presented for classifying an image but the performance of these classifiers is not up-to the level because of the existence of mixed pixels in the remote sensed images. Multiple techniques are proposed to resolve this problem but efficient and accurate results are not achieved. Most of the already proposed algorithms assume that the mixed pixels are of homogenous type and in small number. But this is not true, so to classify all mixed pixels to their respective class one by one is time consuming and cumbersome. This research is focused to overcome these shortcomings of literature.

## Problem Formulation

In remote sensed image processing challenging task is to resolve mixed problem. The pixel which shows the properties of more than one class is known as mixed pixel. On the other hand the pixel with properties of single class is pure pixel. To overcome the shortcoming of previously developed approaches a new algorithm is proposed.

### Proposed Algorithm\_11: Supapixel Classification

1. Input multiresolution remote sensed satellite image
2. Identification of mixed pixels and pure pixels from the input image by using LSSVM
3. Clustering of mixed pixels by using PSO-based-FCM. (because all mixed pixels are not homogenous in nature)
4. Classification of mixed pixels clusters to their particular class by using BBO

In the proposed approach for classification of mixed pixel the first step is to identification of pure and mixed pixels from the image. For clustering of the similar features that classify mixed pixel from pure pixel is done by using Self Organizing Map (SOM) and model is trained by using least Square Support Vector Machine (LSSVM).

To overcome the shortcoming analyzed from the survey that all mixed pixels are not of similar type. Based on the similarity clustering of mixed pixels are done by using Particle Swarm Optimization based Fuzzy C Mean (PSO-FCM). By making the cluster now it is not required to check each mixed pixel for labeling. Set a sample size from the cluster like  $1/5^{\text{th}}$  of the pixels to be examined for classification if these entire pixels belong to same class then label the complete cluster with that particular class. This assigning of labels to pixel is done by using BBO.

## Conclusion

Image processing is a research area which has its own legacy. But it has a great scope of research. It come a long distance from humble techniques like addition, generating negative or histogram processing to the problem of superpixel classification. In paper we summarized the work done by various researchers in the field of image processing and proposed an algorithm for superpixel classification.

## Acknowledgement

My sincere thanks to Ms. ShrutiGujral, Mr. Harjeet Singh and Mr. Sumit Sharma for their constant support

## Author's Contributions

**Er. Sumit Kaur:** Analysis of sorveg, proposed the algorithm.

**R.K. Bansal:** Review the artical and proposed algorithm.

## Ethics

This article contained original material. The data present in this article is not published anywhere else. This article is approved by corresponding author that there is no ethical issue in it.

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