A Critical Performance Evaluation of Classification Methods with Modified JPEG Decompressed Multiband Images

Ch. Ramesh[1], Dr. N.B. Venkateswarlus[2] and Dr. J.V.R. Murthy[3]

[1] Aditya Institute of Technology and Management/JNTUK

Received: 15 December 2012 Accepted: 1 January 2013 Published: 15 January 2013

Abstract

Effective utilization of bandwidth andstorage space is important in imaging applicationsincluding remote sensing. Remote sensingapplications use multi-sensory, multi-band, multiresolution images. Usually, remote sensingapplications uses image classification results fortheir analysis and decision making. In this paper wepropose a new JPEG based image compressionalgorithm based on filters. Proposed algorithmperformance is evaluated in relation to conventionalJPEG algorithm. In order to envisage the effect ofcompression on classification performance, MaximumLikelihood, Mahalanobis and Euclidean distanceclassifiers performance is evaluated with originalimage data, conventional JPEG compressed data andthe compressed image data with the proposedmethod. Experiments are carried out with manymulti-band images. Our experiments supports thatthe classification accuracies of compressed imagesare at par with original image data.

Index terms— joint photo experts group (jpeg), filters, maximum likelihood, mahalanobis, euclidean, confusion matrix, kappa coefficient.

1 Introduction

n the recent years use of remote sensingsatellite data for urban planning, military,weather forecast, robotics, automatednavigation system, remote surveillance hasincreased by many fold in addition toconventional applications such as naturalresources management. These applications involve acquisition, communication, storage and processing ofterrible number of images of earth surface.This situation is becoming more aggravatedbecause of increased pixel resolution, graylevel resolution, band resolutions and reducedrepetition cycle of satellite. All of these development demands more band width fordownlink lines of satellite in addition to moredisk space for storage.

In communications, data compression techniques under the name hood of imagecoding are widely used to reduce thecommunication bandwidth bottlenecks duringdata communication. For instance, JPEGstandard is used for still image compression [1], MPEG is used for video compression [2]. Also, while communicating data from satellites toground stations some compression methods areused [3].

A typical image processing system isas shown in Figure 1 that is commonlyemployed for remote sensing applications. It isvery common that most of the applicationscientists using original image data for theirprocessing. In majority of remote sensing applications, results of classification are theultimate interest [4].

In this study, we propose to study howthe classification results will vary if we usecompressed image data instead of originalimage data. Usually applications such as landuse classifications assumes samples of a groupwill be having small random variations in theirpixel values while samples of different groupsto be having contrastingly different pixelvalues. Because of the increased pixel and graylevel resolutions, samples of a group may behaving similar pixel values. Moreover, they willbe having high level of spatial auto correlation.Evidently, majority of compression methods exploits this auto correlation to achieve highcompression ratios with acceptable PSNR (PeakSignal to Noise Ratio) values [5].

Our proposed Algorithm is based onfiltering concept [6]. In this Algorithm insteadof sending the original image, we send thefiltered image. In general, the number ofuseful DCT coefficients will become more if 8x8image blocks contain lot of variations in values,otherwise only few DCT coefficients will bemeaningful. If we apply filtering on image itgets smoothened, that is variation of the pixelvalues of a block reduces. It is attractive forpoint of view of compression as the number ofmeaningful DCT coefficients are going toreduce. Thus we are achieving compression benefit. We have compared the compression performance of our algorithm with conventional JPEG algorithm with variety ofmulti band images.

Also in this study, we evaluate theclassification performance of popularclassification algorithms like Maximum Likelihood, Mahalanobis and Euclidian distanceby taking original image data, conventional Our paper work is organized as follows.Section II introduces the standard JPEGalgorithm. Section III explains proposedcompression algorithm. Section IV illustratesthe selected classification algorithms. Section Vincludes details about our experimentationsand results. Section VI contains conclusionsabout our research work II.

2 Brief Overview of JPEG Encoding/ Decoding System

JPEG is a well known standardized image compression technique. JPEG loses informationso the decompressed picture is not the same asthe original one. The main reason for use ofJPEG is to reduce the size of image files.Reducing image files is an important procedurefor transmitting files across networks orarchiving libraries. Usually JPEG can removethe less important data before thecompression; hence JPEG is able to compressimages meaningfully, which produces a hugedifference in the transmission time and the diskspace. Figure **??** shows the basic Architecture ofJPEG compression system. Here is a briefoverview of the JPEG compression system. [5] The image is first subdivided into pixelblocks of size 8X8, which are processed left toright, top to bottom. As each 8X8 block or subimage is encountered, its 64 pixels are levelshifted by subtracting the quantity L/2, whereL is the Gray level resolution of the image . The2-D Forward Discrete Cosine Transform (FDCT)(Eq-1) [5]of the block is then computed,quantized using 64 corresponding step sizevalues from the quantization table in Figure 3 [7]. After quantization the DCT coefficientsare rearranged in a zigzag sequence order as shown in the Figure **??**. [7] Since the one-dimensional reorderedarray generated under the zigzag pattern ofFigure 3 is qualitatively arranged according toincreasing spatial frequency, the JPEG codingprocedure is designed to take the advantage ofthe long runs of zeros that normally result fromthe reordering. In particular, the nonzero ACcoefficients (the term AC denotes all transformcoefficients with the exception of the zeroth orDC coefficient) are coded using a variablelengthcode that defines the coefficient's valueand number of preceding zeros. The DCcoefficient is difference coded relative to theDC coefficient of the previous sub image. The decompression process performs aninverse procedure. It decodes the Huffmancodes. Then, it makes the inversion of theQuantization step. In this stage, the decoderraises the small numbers by multiplying themby the quantization coefficients. The resultsare not accurate, but they are close to theoriginal numbers of the DCT coefficients. AnInverse Discrete Cosine Transform (IDCT) (Eq.4) [7] is performed on the data received from theprevious step. Finally add L/2 to each subimage. Place the sub images in their correctpositions. (4) The error between the original imageand reconstructed image is calculated in termsof Peak signal to noise ratio (PSNR) = 10 log10 Mean filtering [8] is a simple, intuitiveand easy to implement method of imagesmoothing i.e. reducing the amount of variationbetween one pixel and the next or surroundingpixels. It is often used to reduce noise inimage. The idea of mean filtering is simply toreplace each pixel in an image with the meanvalue of its neighbors including itself. This hasthe effect of eliminating pixel values which areunrepresentative of their surroundings. Usually,3x3 neighborhoods of pixels are consideredwhile calculating mean filtered value of anypixel.(L2/MSE) (5)**(6)**? = ? = ? ? ? ? ? ? ? + ? ? ? ? ? ? + = 1 0 1 0 2) 1 2 (cos 2) 1 2 (cos) , ( ) ( ) ( ) , (N x N y N v y N u x y x f v u v u C ? ? ? ? for u, v = 0, 1, 2, ... , N -1 ? ? ? > = = 0 / 2 0 / 1) (u for N u for N u ? ? ? ? > = = 0 / 2 0 / 1) (v for N v for N v ? ?? ? = ? = ? ? ? ? ? ? + ? ? ? ? ? ? ? + = 1 0 1 0 2) 1 2 (cos 2) 1 2 (cos) , ( ) ( ) ( ) , (?N u N v N v y N u x v u C v u y x f ? ? ? ? [ ]

Median filter [9] is normally used to reducenoise in an image like the mean filter.However, it often does a better job than themean filter in preserving useful detail in theimage. Like the mean filter, the median filterconsiders each pixel in the image in turn andlooks at its neighbors to decide whether or notits representative of its surroundings. Insteadof simply replacing the pixel value with themean of neighboring pixel values, it replaces itwith the median of those values.

An outlier [10] is an observation that isnumerically distant from the rest of the data.In an image, a pixel value is very different fromits surrounding pixels, it can be called asoutlier.

From basic statistics, we know that apopulations sample values with someconfidence level can be given as mean ± C*P, where C is weighing factor (critical value) and P is standard deviation of the population. Table-1 shows the commonly used ConfidenceLevels and Corresponding Critical Values [11].In our outlier based algorithms, we take thesesimple confidence limits of normal distributionin deciding whether a pixel is outlier or not. Ifthe pixel is observed to be outlier with thegiven confidence level, we may retain else wemay take its mean filtered or median filtered value. ? Apply mean filtering with a little variation tothe given original image using 3x3 window. Foreach pixel, calculate average and standarddeviation of its neighboring 3x3 pixels. If apixels value is observed to be outlier (not inthe range of Mean ± C*P) then its value is takenas itself else mean is taken as its filtered value. ? Apply DCT on the outliermean filteredimage.

3 d) OutlierMedianDCT Algorithm

? Apply median filtering with a little variationto the given original image using 3x3 window.For each pixel, calculate median and standarddeviation of its neighboring 3x3 pixels. If apixels value is observed to be outlier (not inthe range of Median ± C*P) then its value istaken as itself else median is taken as itsfiltered value. ? Apply DCT on the outliermedian filteredimage.

4 IV.

5 Popular Classification Algorithms a) Maximum Likelihood Classifier

Let w 1 ,w 2 , . . . , w m denote m distinctpopulations (classes) with known d-dimensionalprobability density functions p 1 (X), p 2 (X), ... p m (X), respectively. The a priori probabilitiesthat an observation is selected frompopulations w 1 , w 2 , . . . ,w m are denoted by q l ,q 2 , ..., q m , respectively **??**12]. According tothe Bayesian ML classification rule, assumingequal costs for misclassifications, a random ddimensional pixel vector X is classified as classw k (7) Assuming equal a priori probabilities for all theclasses, decision rule (7) becomes:(8)

In Equations (**??**) and (8), the probability densityp k (X) will be given as: ( ) Year) , (?y x f q k p k (X) = max{q i P i (X)} for i = 1, 2 . . . ., m. p k (X) = max{p i (X)}, i = 1, 2 , . . . , m 2 / 1 2 /) 2 (1) (? = k d k X p ? ? ? ? ? ? 1)]. ( ) .(2 / 1 exp[k k T k M X M X X b) Mahalanobis Classifier**37**

According to this classifier a ddimensionalrandom pixel vector (X) will be assigned to thegroup to which it is nearest [13]. Each group ischaracterized by its mean vector, which iscalculated from training data. Nearness isdetermined by the Mahalanobis distancebetween the group mean and X. Inmathematical terms, the same classificationrule can be represented as: **??**10) where i = (1, 2, . . . C) groups if d i (X)<d j (X) forall j U i where (11) and M i s mean vector of i th group indicatesvector should be transposed.

-1 is the inverseof the pooled covariance matrix.

6 c) Euclidian Distance Classifier

According to this classifier a random ddimensionalpixel vector (X) will be assigned tothe group to which it is nearest [14]. Eachgroup is characterized by its mean vector,which is calculated from training data.Nearness is determined by the Euclideandistance between the group mean and X. Inmathematical terms, the same classificationrule can be represented as: **??**12) Where i = (1, 2, . . . C) groups if d i (X)<d j (X) forall j U i where (13) and M i is mean vector of i th group. T indicatesvector should be transposed V.

7 Experimentations and Results

For the purpose of experimental work,Landsat TM data from USGS data base"www.usgs.gov" is used. Confusion matrix [15] is used to assessthe accuracy of an image classification. Thestrength of a confusion matrix is that it identifiesthe nature of the classification errors, as well astheir quantities. In confusion matrix rowscorrespond to classes in the test set, columnscorrespond to classes in the classification result.The diagonal elements in the matrix representthe number of correctly classified pixels of eachclass. The off-diagonal elements representmisclassified pixels. The overall accuracy iscalculated as the total number of correctlyclassified pixels divided by the total number of test pixels.Year i w X ? i (X) = (X-M i) T ? -1 (X-M i d i w X ? i (X) = (X-M i) T (X-M i d

Another measure which can be extractedfrom a confusion matrix is the kappa coefficient [16] which is a popular measure to estimateagreement in categorical data. The motivation ofthis measure is to extract from the correctlyclassified percentage the actual percentageexpected by chance. Thus, this coefficient iscalculated as (14) cm1,, cm2, ??? cmnare the column 1, 2 ????n marginals rm 1 ,rm 2 , ??? rm n are the row 1, 2 ———nmarginals n is the total number of test pixels.

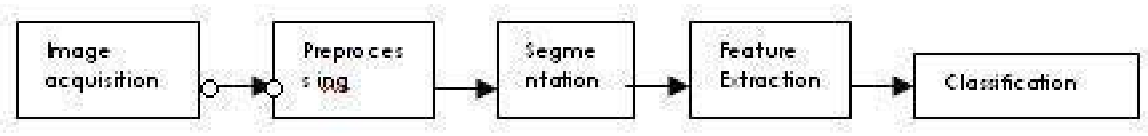
The higher the value of kappa, the betterthe classification performance. If all informationclasses are correctly identified, kappa takes thevalue 1. As the offdiagonal entries increase, thevalue of kappa decreases. For classification two data sets were used. Onewas a 1048 X 920 (Owensvalley image) LandsatTM with all 7 bands. The second data setcontained 500 samples of four ground types,Dense scrub, Rock, Forest and Open scrub of thesame scene. This second data set is used to observe the classification accuracy. All the 2000set patterns were classified simultaneously withthe Maximum Likelihood, Mahalanobis andMinimum distance classifiers. Classificationperformance of all the classifiers is displayed intables 4, 5 & 6. Figure 6 shows the Overallaccuracy of all the classifiers. It is observed thatclassification performance on proposedcompression images is almost same as JPEGstandard compression images and original images. [1] [2]

[1] F obal Journal of Researches in EngineeringGl Volume

[2]

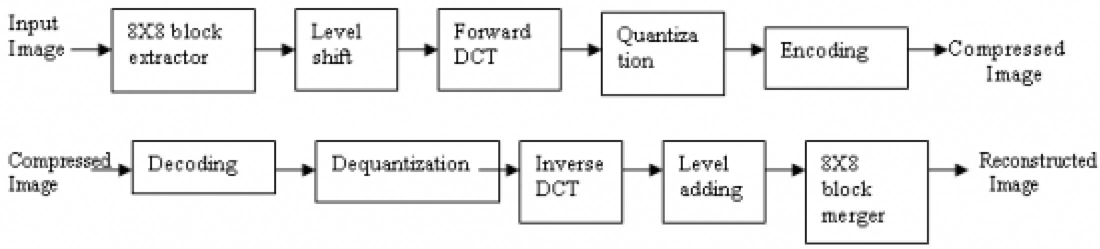
1

Figure 1: Figure 1 :



34

Figure 2: Figure 3 :Figure 4 :



1

Figure 3: Table 1 :

16	11	10	16	24	40	51	61
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

Figure 4:

5

Confidence Level	80%	90%	95%	98%	99%	99.8%	99.9%
Critical Values	1.28	1.645	1.96	2.33	2.58	3.08	3.27

Figure 5: Figure 5 :

6

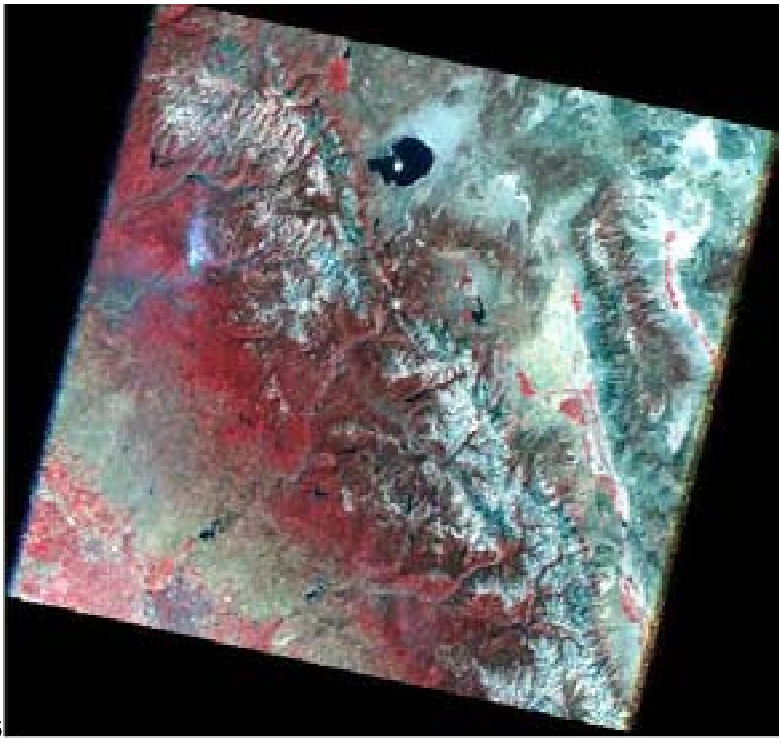


Figure 6: Figure 6 :

2
I
XIII Issue XVI Version
( )

[Note: YearFigure 2 : Basic Architecture of JPEG Compression ??]

Figure 7: A Critical Performance Evaluation of Classification Methods with Modified JPEG Decompressed Multiband Images

Experiments arecarried out under MS Windows XP version 2002,SP3 edition. The experimental system isequipped with Intel core 2 Duo 2.60 GHzprocessor with 1 GB RAM. Using ERDAS Imagine8.6 (copy rightsÃ?"1991-2002, Lieca Geo systems)Training sites are labeled. Programs are writtenin C language under Microsoft Visual Studio2005 version 8.0.

We have carried out extensivesimulations with the selected images andproposed algorithms. Table 2 shows theCompression Benefit and PSNR values ofMeanDCT algorithm VsOutlierMeanDCTalgorithm. With all the images we found thatMeanDCT and OutlierMeanDCT algorithms havebetter compression ratios as compared toconventional JPEG coding. The PSNR loss inMeanDCT and OutlierMeanDCT algorithms isnegligible as compared to conventional JPEGcoding. While comparing MeanDCT and thecorresponding Outlier DCT, CompressionBenefits are observed to beMeanDCT>OutlierMeanDCT (for C=1.28 to 2.58).As the value of C increases in the Outlier,Compression Benefit increases. For C=3.08 to3.27 Compression Benefit in MeanDCT andOutlierMeanDCT is almost same. PSNR in MeanDCT<OutlierMeanDCT(for C=1.28 to 2.58).As the value of C decreases in the Outlier,

PSNRincreases. For C=3.08 to 3.27 PSNR in MeanDCTand OutlierMeanDCT is almost same. Fig5 Showsthe sample (Owensvalley) Original image, JPEGcompressed image, Proposed compresse dimage

(Mean filtered approach).

2 I XIII Issue XVI Version ( )

[Note: A Critical]

Figure 8: Performance Evaluation of Classification Methods with Modified JPEG Decompressed Multiband Images

2

Figure 9: Table 2 :

A Critical Performance Evaluation of Cl

Multiband
Images
No. o
Bits 55910
357508
357508
No. o
Bits 24958
232905
232911
No. o
Bits 99113
583964
583964

Image Bolivia7 Monolake6 % of Saving % of Saving PSNR % of Loss PSNR 46.608 37.557 37.557 Conven

3

shows the Compression Benefit and PSNR values of Median DCT algorithm Vs Median DCT algorithm. With all the images we found that Median DCT and Outlier Median DCTalgorithms have better compression ratios as compared to conventional JPEG coding. The PSNR loss in Median DCT, Compression Benefits are observed tobe MedianDCT>OutlierMedianDCT(for C=1.28 to 2. the value of C increases in the Outlier,Compression Benefit increases. For C=3.08 to 3.27 Compression Benefit in MedianDCT andOutlierMedianDCT is s PSNR in MedianDCT<OutlierMedianDCT(for C= DCT and OutlierMedianDCT algorithms is very less as compared to conventional JPEG coding. While com

% of Loss - 3.400 0.400 3.400

Figure 11: Table 3

3

JPEG

Figure 12: Table 3 :

		No. of Bits	708596		492900	492901				492901	501063	
	Owens valley 57	% of Saving PSNR % of Loss	-30.718	-	30.439	30.439	28.639	28.639	6.768 6.768	30.439 28.639 6.768	29.287	27.74
		No. of Bits	4249620	3032712	3032716	3032711	3069953	3130758	3276024	3475985	3793053	
		% of Saving	-		28.635	28.635				28.635	27.759	26.32
Year 2 I XIII Issue XVI Version ( )	Total	PSNR	32.530		29.877	29.877				29.877	29.922	29.97
		% of Loss	-		8.155		8.155			8.155	8.017	
		K	= e P P e ? ? 0 P 1									

Figure 13: A Critical Performance Evaluation of Classification Methods with Modified JPEG Decompressed Multiband Images

4

Original Image

Figure 14: Table 4 :

5

Spectral Class	Correct Classification (%)	Original Image Number of Samples used	1	Classified as group 2 3		4
1. Dense scrub	100	500	500	0	0	0
2. Rock	95.4	500	20	477	3	0
3. Forest	100	500	0	0	500	0
4. Open scrub	100	500	0	0	0	5
Misclassification= 1.15 %	Overall accuracy= 98.85 %		Kappa coefficient=0.9846			
	Conventional JPEG Compression image					
Spectral Class	Correct Classification (%)	Number of Samples used	1	Classified as group 2 3		4
1. Dense scrub	98.2	500	491	6	3	0
2. Rock	93	500	23	465	12	0
3. Forest	96.8	500	8	8	484	0
4. Open scrub	99.8	500	1	0	0	4
Misclassification= 3.05 %	Overall accuracy=96.95%			Kappa coefficient=0.9593		
proposed compression image(Mean filtered approach)						
Spectral Class	Correct Classification (%)	Number of Samples used	1	Classified as group 2 3		4
1. Dense scrub	98.6	500	493	4	1	2
2. Rock	78.4	500	81	392	27	0
3. Forest	96.2	500	18	1	481	0
4. Open scrub	100	500	0	0	0	5
Misclassification= 6.7%	Overall accuracy= 93.3 %		Kappa coefficient=0.9106			

Figure 15: Table 5 :

6

		Original Image				
Spectral Class	Correct Classification (%)	Number of Samples used	1	Classified as group 2 3		4
1. Dense scrub	97.2	500	486	1	0	13
2. Rock	71.8	500	118	359	5	18
3. Forest	100	500	0	0	500	0
4. Open scrub	100	500	0	0	0	50
Misclassification= 7.75%		Overall accuracy=92.25%		Kappa coefficient=0.8966		
		Conventional JPEG compression image				
Spectral Class	Correct Classification (%)	Number of Samples used	1	Classified as group 2 3		4
1. Dense scrub	93.6	500	468	4	5	23
2. Rock	51.2	500	101	256	69	74
3. Forest	98.6	500	7	0	493	0
4. Open scrub	100	500	0	0	0	50
Misclassification= 14.15%		Overall accuracy=85.85 %		Kappa coefficient=0.811		
	proposed compression image(Mean filtered approach)					
Spectral Class	Correct Classification (%)	Number of Samples used	1	Classified as group 2 3		4
1. Dense scrub	91	500	455	5	6	34
2. Rock	48.8	500	79	244	90	87
3. Forest	96	500	18	2	480	0
4. Open scrub	99.6	500	2	0	0	49
Misclassification= 16.15%		Overall accuracy= 83.85 %		Kappa coefficient=0.784		

Figure 16: Table 6 :

VI.

.1 Conclusions

In this paper, a new filtering basedJPEG compression algorithm is proposed. Wehave compared our proposed algorithm withStandard JPEG compression. From ourexperiments it is evident that our approachgives better compression ratios compared toStandard JPEG. The PSNR resulting from ourapproach is slightly less than Standard JPEGapproach. Also the Classification accuracy oforiginal images, Conventional JPEGcompression images and proposed compression images are almost same.

If a typical satellite mission goal isclassification only, then we can sendcompressed images from satellite which savesbandwidth requirements of a satellite mission.Also, storage requirement reduces by manyfolds as we will be storing compressed imagesonly. This indirectly reduces powerrequirement needs of the storage system. Inaddition, loading and storing of images takesless time compared to original images, thus response times of imaging systems increases.

[Anthony] , J Anthony . Viera, MD.

[Nb Venkateswarlu and Psvsk Raju ()] 'A newfast classifier for remotely sensed imagery'. & Nb Venkateswarlu , Psvsk Raju . *International Journal of Remote Sensing* 1993. 14 (2) p. .

[Nguyen] *Detecting Computer -InducedErrors in Remote-Sensing JPEG CompressionAlgorithms*, Cung Nguyen .

[Ch et al. (2012)] 'Filter Augmented JPEGAlgorithms: A Critical Performance Study forImproving Bandwidth'. Ch , Dr N B Ramesh , Dr J V R Venkateswarlu , Murthy . factor:0.821. *IJCA* :0975-8887. December 2012. 60 (17) .

[Gonzalez and Woods ()] R C Gonzalez , R E Woods . *Digital Image Processing*, (2 nd Edition Addison Wesley, USAISBN) 1993sz. p. .

[Huang et al. (2010)] Bormin Huang , Antonlo J Plaza , Joan Serra-Sagrista , Chulhee Lee , L I Younsong . *Shen-En Qlan Editors Proceedings of SPIE "Satellite Datacompression, communications, and ProcessingVI*, (San Dlego, California, United States) august 2010.

[Morton and Canty] *Image Analysis,Classification and Change Detection in Remote Sensing: With Algorithms for ENVI/IDL*, . J Morton , Canty . (A CRCpress company)

[Hankerson et al.] *Introduction to information theoryand data compression*, Darrel Hankerson , Greg A Harris , D Peter , JohnsonJr . (second edition. A CRCpress company)

[Jensen] *Introductory Digital Image Processing A Remote Sensing Perspective"Second Edition*, John R Jensen . Prentice Hall.

[Watkinson ()] *MPEG Handbook" Taylor & Francis*, John Watkinson . 2004.

[NB Venkateswarlu PSVSK Raju Three Stage ML Classifier ()] 'NB Venkateswarlu& PSVSK Raju'. `http://www.stat.yale.edu/courses/1997-98/101/con-fint.html2` *Three Stage ML Classifier*, 1991. 24 p. .

[Garrett (2005)] 'Understanding Interobserver Agreement:The Kappa Statistic'. Joanne M Garrett , Phd . *Family Medicine ResearchSeries* May 2005. 360.

[Venkateswarlu and Psvsk Raju ()] 'Winograd' smethod:a perspective for somepattern recognition problems'. N B Venkateswarlu , & Psvsk Raju . *PatternRecognition Letters* 1994. 15 p. .