YALOVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

IMPROVING CLASSIFICATION ACCURACY OF QUICKBIRD IMAGERY

MASTER OF SCIENCE

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LIST OF ABBREVIATIONS

DT : Decision Tree
DWT : Discrete Wavelet Transform
GIHS : General Intensity Hue Saturation Transformation
IHS : Intensity Hue Saturation
MLC : Maximum Likelihood Classification
MS : Multispectral
NIR : Near Infra Red
PAN : Panchromatic
PCA : Principal Component Analysis
RBF : Radial Basis Function
RGB : Red Green Blue
SAM : Spectral Angle Mapper
SVM : Support Vector Machine

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IMPROVING CLASSIFICATION ACCURACY OF QUICKBIRD IMAGERY

SUMMARY

Fusion methods increase spatial resolution by combining panchromatic band with multi spectral data. In this study, the results belonging to several methods on multi spectral and panchromatic images are compared. The fusion methods common in literature Intensity-Hue Saturation (IHS), Principal Component Analysis (PCA) and wavelet transformation are used.

Supervised classification methods need prior examples for training of the algorithm to classify other unseen samples as opposed to unsupervised classification methods. Image classification is done with well-known supervised methods, e.g. Maximum Likelihood Classifier (MLC) and Support Vector Machines (SVM).

Fused images provide better spatial resolution. However, spectral distortions by introducing new colors or artificial structures called artifacts cause decrease in overall accuracy values especially with nonlinear classification methods such as SVM. Enhancement methods are proposed and tested to diminish classification errors caused by spectral distortions present in the fused image. A PCA-based image enhancement technique is found superior to other enhancement techniques applied.

Class separability is better after enhancements compared to the original reference satellite image. Using the classified result of the original multi spectral image as a benchmark, improvement in the overall accuracy of classification results of the enhanced fused images are observed. Higher classification accuracy is possible with the integration of image fusion and image enhancement methods into classification process. Results supporting the advancement are given in the related parts of the thesis.

QUICKBIRD GÖRÜNTÜLERİN SINIFLANDIRMA DOĞRULUĞUNUN İYİLEŞTİRİLMESİ

ÖZET

Çok bantlı ve pankromatik uydu görüntüleri görüntü birleştirme metotları ile birleştirilerek mekânsal çözünürlüğü yüksek zenginleştirilmiş yeni görüntüler elde edilebilmektedir. Bu çalışmada, çeşitli metodların çok bantlı ve pankromatik uydu görüntüleri üzerinde sonuçları incelenmiştir. Görüntü birleştirme yöntemi olarak literatürde çok yaygın olarak kullanılan yoğunluk renk dönüşümü, temel bileşenler analizi ve dalgacık dönüşümü görüntü birleştirme teknikleri kullanılmıştır.

Eğiticili sınıflandırma yöntemi, eğiticisiz sınıflandırmanın aksine, karşılaşılmamış olan ve dolayısıyla bilinmeyen örnekleri sınıflandırabilmek için algoritmayı eğitecek bilinen örnek verilere ihtiyaç duyar. Görüntü sınıflandırması için yaygın olarak bilinen eğiticili öğrenme algoritmalardan En Çok Olabilirlik ve Destek Vektör Makineleri kullanılmıştır.

Birleştirilmiş görüntüler daha iyi mekansal çözünürlüğe sahiptirler. Yeni renklerin ya da yapay yapıların eklenmesiyle oluşan spektral bozulmalar, özellikle Destek Vektör Makineleri gibi doğrusal olmayan sınıflandırma metotlarının genel doğruluğunu azaltır. Çalışmada, spektral bozulmalar ile oluşan sınıflandırma hatalarını azaltan görüntü iyileştirme metotları önerilmiş ve test edilmiştir. Temel bileşenler analizine dayanan bir görüntü zenginleştirme tekniği, uygulanan diğer tekniklere göre daha uygun bulunmuştur.

Görüntü iyileştirme teknikleri uygulandıktan sonra oluşan görüntüde sınıf ayrılabilirliği referans olarak alınan orijinal görüntüye göre daha yüksektir. Orijinal görüntünün sınıflandırılmış sonucu genel geçer bir karşılaştırma ölçüsü olan karşılaştırmalı değerlendirme tekniği kullanılarak, genel doğruluk alanındaki artma bulunmuştur. Görüntü birleştirme ve görüntü zenginleştirme metotlarının sınıflandırma sürecine dahil olması ile sınıflandırma algoritmalarının doğruluklarının arttırılmasının mümkün olduğu anlaşılmıştır. Bu bulguyu destekleyen sonuçlar tezin ilgili bölümlerinde verilmiştir.

1. INTRODUCTION

Image fusion could be defined as combination of images from different sensors with varying number of spectral bands, different temporal and spatial resolutions. The purpose of image fusion is to get more information by integrating image data acquired by different sensors rather than using a single image alone. The main objective of image fusion techniques could be spatial enhancement without effects of spectral distortions. Several image fusion techniques have been developed to utilize the data from different sensors with different spectral bands, different temporal and spatial resolutions (Pohl et al., 1998). While there are many studies in the use of image fusion for visual enhancement of satellite images, there are a limited number of studies focusing on classification accuracy improvement of remotely sensed data by prior application of fusion methods (Yang et al., 2009).

Classification methods are applied on every kind of data for better understanding and use of the data. Application of classification methods on satellite imagery is also very well known. Unsupervised classification methods have been applied on remote sensing data for a long time to eliminate human intervention. However, emergence of objective evaluation metrics allowed fair evaluation of supervised classification methods.

1.1 Purpose of the Thesis

In this thesis, fusion methods were applied prior to application of supervised classification methods to improve accuracy. In this context, commonly used methods like Principal Component Analysis (PCA) method, Discrete Wavelet Transform and Generalized Intensity-Hue-Saturation transformation (GIHS) are applied to the QuickBird PAN/MS image respectively. Also, a few convolution filters including Low-pass and High-pass kernels and de-noising method including PCA were employed to the fused imagery as a noise reduction processing. Finally, two different algorithms namely Maximum Likelihood Classification (MLC) and Support Vector Machines (SVM) were applied as supervised classification.

Spectral distortion and artificial structures called artifacts as the main problems of fusion methods need to be fixed for proper application of classification algorithms. Fusion methods increase spatial resolution providing more details for the classification process. In the thesis, a method is applied to reduce color distortions for diminishing error rates while increasing overall accuracy with better kappa statistics values.

1.2 Chapter Overview

Chapter 1 is a brief introduction to the subject together with research motivation and objectives. Chapter 2 is literature survey part. In Chapter 3, image enhancement and in Chapter 4, satellite image fusion methods are discussed in detail. The chapter includes application details of each method. The main purpose of Chapter 5 is explaining supervised classification methods. The mathematical background and application notes of the methods Maximum Likelihood Classification and Support Vector Machines are expressed. Chapter 6 includes detailed description of accuracy assessment metrics. Overall accuracy and kappa values are explained for complete understanding of the results. In Chapter 6, results are given and discussed. Finally, Chapter 7 is conclusion part showing the big picture and direction for future works.

2. LITERATURE SURVEY

This chapter is logically divided into two subtle subparts: the former one is dealing with literature review for satellite image fusion methods such as Generalized IHS, PCA-based and wavelet-based fusion methods; the latter is explaining the use of MLC and SVM supervised classification methods in literature and combined use of the methods.

Fusion methods have been commonly applied by remote sensing community to increase spatial and temporal resolution. Image fusion methods with considerable complexity are generally preferred. The fused images usually have more information about a component than individual images used in the fusion process. Image fusion is still a popular topic and applications continue to be developed by several researchers (Zhang et al., 1998; Scheunders et al., 2001; Rajan et al., 2002; Chan et al., 2003).

Absence of universal metrics for evaluation of fusion algorithms directs researchers through qualitative analysis like visual analysis. Despite efforts to assess quality of image fusion techniques and to develop new algorithms for fusion, there are still issues such as background noise levels and spectral distortions need to be resolved. These issues make fusion implementations harder, but applications with further attempts could benefit from image fusion (Zheng, 2010).

Principle Components Analysis based fusion method uses pixel values of all source images with different weights and averages the weighted pixel values to restore the same pixel location for the fused image. Optimization is basically achieved by the PCA technique. PCA is a statistical technique for converting an inter-correlated variable data set into a new dataset which is orthogonal with un-correlated values. This method decreases redundancy present in the data (Pohl et al., 1998). Decreasing redundancy and selecting feature space is desirable. However, discrimination capability of the classifiers is not to be sacrificed since classification errors are expected to be low (Benediktsson et al, 2003).

Discrete Wavelet Transform based method transforms source images to corresponding wavelet coefficient images at each scale level by DWT. By using a certain fusion rule, corresponding approximation coefficients and detail coefficients of the source image are fused at each level. The fusion rule could be as simple as addition or averaging or harder ones like PCA-based weighted averaging. The fused approximation and detail coefficients are then used at each level for the construction of final fused image via inverse wavelet transform (Wang et al., 2003 and Zeng et al., 2006).

Image enhancement techniques are used for effective display of image interpretation. Image enhancement techniques like spatial filtering radically improves the object separability in the images (Cetin and Musaoglu, 2009).

Comparison of contemporary image fusion techniques quantitatively for both spatial and spectral features is rare in literature. The detailed modeling of color space and grouping of PCA, wavelet and GIHS methods as IHS-like methods and explanation of color distortion problems are present in a work. The work could be considered a reference for new fusion techniques in the future (Tu et al., 2001).

By the help of high resolution satellite images, more details about the spatial features of land covers could be reached (Hwang, 2009). In literature, many techniques for the classification of high resolution remotely sensed images are reported (Tuia et al., 2009; Thomas et al., 2003; Mayunga et al., 2007).

Maximum likelihood classification could also be defined as use of probability histograms as discriminant functions yielding the highest probable class (Landgrebe, 2003). In a study, MLC is reported as the most stable method as compared to other methods like SVM and Decision Tree (DT) approach; MLC is least affected by training phase and training set size. SVM has good results, but supervision part of the classification dramatically affects overall accuracy (Guo and Zhang, 2008).

Support Vector Machines are well known in research community by their high discrimination capability of high dimensional data even with limited number of training samples (Camps-Valls et al., 2005; Gualtieri et al., 1998; Fauvel et al., 2006; Fauvel, 2007). SVM do not require preprocessing on data. SVM has good results on linear domain classification as well as multi-class classifications (Melgani and Bruzzone, 2004). Nonlinear cases could be handled as linear cases after a kernel transformation called kernel trick (Camps-Valls et al., 2006; Dundar et al., 2004; Chi, 2007). Types of kernels are linear, polynomial, radial basis function (RBF), and Sigmoid etc. Selection of the kernel is vital for proper results depending on the application type. SVM with Radial Basis Function (RBF) is preferable balancing complexity and accuracy for satellite imagery (Camps-Valls et al., 2007). RBF kernel function is superior over other kernel functions for satellite image classification (Hwang et al., 2009)

Since there are lots of applications dealing with individual applications of supervised classification algorithms on satellite images and we are focusing on the improvements made possible by prior application of fusion methods, we directly jump to applications including both of fusion methods and supervised classification algorithms at the same time. The use of contextual information in addition to statistical information increases classification accuracy. The neighborhood information increases classification accuracy better than Spectral Angle Mapper (SAM) method. Deriving new features depending on application is a novel application (Kavitha and Arivazgahan, 2010).

While many studies have been devoted to individual evaluations of fusion methods for visual enhancements, only a few ones focused on further use of fused data such as effects of fusion techniques on classification accuracy. Munechika et al. (1993) applied image ratio to improve merging process and found out that classification accuracy is increased by approximately 6 percent. They also expressed that color distortions did not necessarily affect the classification accuracy. Franklin and Blodgett (1993) noted that with the application of maximum likelihood classification method on fused images, an improvement of up to 9% is observed. Haack and Sloneckerr (1994) noted a huge increase in fused image classification accuracy to 94.1% as compared to original image classification accuracy of 69%. Sunar and Musaoglu (1998) investigated maximum likelihood classification accuracies of both original and fused images and noted a 6.5% increase in classification accuracy. Colditz et al. (2006) recently assessed classification results of various data obtained by different fusion methods and concluded that adaptive fusion method had the best performance; pca-based and wavelet-based approaches had acceptable results whereas IHS-based and Brovey transforms performed poorly because of spectral distortions. It is reported that wavelet resolution merge allowed better production of vegetation maps by automatic classification. Comparable or better spatial improvement and high potential for further classification applications are observable in wavelet fusion methods (Garguet-Duport, 1996).

In a research, an increase in classification accuracy is reported when mathematical morphology is applied prior to application of maximum likelihood classification algorithm (Yildirim et al., 2005).

3. IMAGE ENHANCEMENT

Image enhancement is a technique applied to improve appearance of the images. Some examples of image enhancement techniques are contrast enhancement to increase tonal discrimination between the pixels and spatial filtering to enhance specific patterns in spatial domain (Natural Resources, Canada, 2004). Spatial textures are reported to enhance classification accuracy for land-use mapping (Manian and Velez-Reyes, 2006).

3.1 Spatial Domain

3.1.1 Spatial Filtering

Spatial domain comprises collection of pixels that make up an image. Spatial domain operations are generally expressed as

$$g(x,y)=T\left[f(x,y)\right] \quad \textbf{(3.1)}$$

where g (x , y) is output function, f (x, y) is input image and T is the transformation function applied on image to get the desired output.

Neighborhood is an important term for applications on spatial domain and neighborhood (x, y) is defined as square or rectangular sub-image centered as (x, y). The center of the image is continuously moved from top left corner through right as the transformation operation is applied. Movement of the center provides the process to be applied on desired area (Gonzalez and Woods, 2002).

Filtering is extraction of useful information from a signal or an image based on predetermined criteria (Loy et al., 2001). Spatial filtering is application of filtering in spatial domain of an image. A window of predefined size is applied on a point (x, y) based on a chosen function to get the desired effect depending on application. Point (x, y) is moved as the function is performed and each result is stored as new value of the pixel. An example filter operation is shown in Figure 3.1.

w(-1,-1)	w(-1,0)	w(-1,1)
w(0,-1)	w(0,0)	w(0,1)
w(1,-1)	w(1,0)	w(1,1)

Coefficients

f(x-1,y-1)	f(x-1,y)	f(x-1,y+1)
f(x,y-1)	f(x, y)	f(x,y+1)
f(x+1,y-1)	f(x+1,y)	f(x+1,y+1)

Pixels

Figure 3.1 : Spatial filtering technique of 3x3 mask with coefficients and pixels in the image section (Gonzalez and Woods, 2002).

3.1.1.1 Linear Smoothing Filters

Smoothing filters are generally used to remove noise. Linear filters are known as averaging filters or low-pass filters. Linear spatial filter replaces a pixel value by average of gray levels of the neighboring pixels determined by filter mask (Yigitler, 2005). 3 x 3 and 5 x 5 averaging filters are common filters yielding average of pixels under the mask. Mean filter replaces center pixel by average of n x n neighborhood.

Noise level is reduced by application of linear filters. However, linear filters reduce sharp transitions in gray levels causing blur effect on edges which is not a desirable result. Mean filter tends to blur an image because of positive coefficients. Use of negative coefficients as in Laplacian type filters could enhance the image. Weighted averaging filter takes the center as most important pixel and other pixels are weighted inversely as a function of distance to the center.

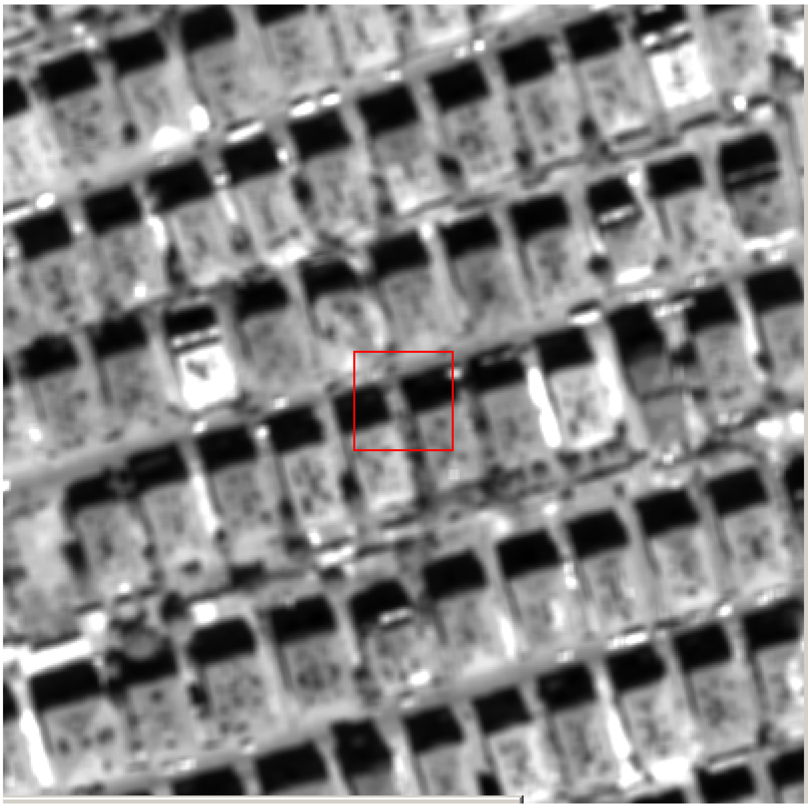

Figure 3.2 : The application of smoothing filter on panchromatic image.

The application of mean filter on panchromatic image is seen in Figure 3.2. Blurring effect of the filter is clearly visible. Sharp transitions which help classification algorithms to distinguish the objects by the edges are reduced. Thus, a way for smoothing without losing edge information is needed.

Proper use of mean filter is achieved with a method described in an article (Yildirim et al., 2005). The main problem of low-pass filtering is edge-detection problems including misplaced edges and undetected edges. Without the use of any edge detection algorithm, smoother images with preserved edges and thin lines are obtained. The algorithm described in the article is based on separation of noise and features. The residual image is the difference between an image and its smoothed version. Addition of the features in residual image on the smoothed image provides further smoothed image. The final image ideally has sharp edges as the original image with smoother regions inside them (Yildirim et al., 2005). Prior to application of classification works, fused image is smoothened with the technique. Color distortion problems are expected to be reduced with application of mean filter as an image enhancement method.

3.1.1.2 Nonlinear Smoothing Filters

Nonlinear filtering requires reordering of the area under filter mask based on predetermined function. Median filtering is a common application of nonlinear filtering. Median filter sorts the neighboring pixels and replaces the pixel value by median value. Median filter is good at reducing a random noise called salt and pepper effect. Less blurring is observed in the final image.

65	63	66
63	100	68
67	64	67

63	63	64	65	66	67	67	68	100

median

Figure 3.3 : Median filtering technique.

Median filter reduces binary noise and eliminates outliers. Sharp edges are preserved. Sorting process increases computational cost. A simple application of median filter is seen in Figure 3.3.

Post-processing filters are widely applied in remote sensing data classifications to further improve the results (Sonka et al., 1998).

3.2 Image Enhancement Based on PCA Technique

Multiresolution fusion process if spectral distortions can be avoided, could increase classification accuracy belonging to linear or moderately nonlinear classifiers. However, spatial and spectral artifacts inevitably embodied in fused images dramatically decrease classification accuracy of more powerful classifiers characterized by nonlinear discriminant functions. The problem is stated in a work, but the solution is not present in the article (Bruzzone et al., 2006).

Additionally, application of linear and nonlinear filters may not always give the desired results; thus, an image enhancement technique based on PCA transformation is proposed in the study. Fused images are transformed by PCA method and eigenvalues are examined. Depending on fusion method, number of Principal Component bands is decided. For PCA-based and GIHS-based fusion methods, first

4 PC bands carry enough information whereas for wavelet-based fusion method, 5th PC band is also required for better classification results. As seen in Table 3.1, 5th band may have necessary information to guide the advanced classification algorithms.

Table 3.1 Eigen Values of PC bands

	PCA-based Fusion		Wavelet-based Fusion		GIHS-based Fusion	
	Eigenvalue	Percentage	Eigenvalue	Percentage	Eigenvalue	Percentage
PC1	113065	78	115979	80	165818	83
PC2	18558	13	17907	12	18267	9
PC3	10174	7	5889	4	12532	6
PC4	3310	2	3187	2	3264	2
PC5	221	0	1815	1	220	0
PC6	2	0	220	0	12	0
PC7	0	0	48	0	3	0
PC8	0	0	26	0	1	0
PC9	0	0	12	0	0	0

As a preparation for Principal Components Transform, fused image bands, pan band and multispectral bands are merged. By combination of the bands, collecting all the information about the image is achieved. Total of 9 bands are formed by the transformation. As expected first four or five bands carry most of the information and we do not need to deal with the remaining bands which include noise.

Eigenvalues and eigenvectors are found generally by characteristic polinom method as Ax-λx=0 which could be written as (A-λ*I*)x=0 by multiplying with unit matrix I. Determinant of square matrix is equal to 0 and equation could be written as det(A-λI)=0. Roots of the characteristic function is found by the formula: $f(\lambda) = \lambda^n + c_1\lambda^{n-1} \ldots \ldots c_n$. The roots of the function is called eigenvalues belonging to A matrix. Eigenvectors could be found by solving the (A-λ*I*)x=0 with the eigenvalues.

$ECovE^T = V$ and $P_e = \sum_{k=1}^{n} d_k E_{ke}$ are main formulas for Principal Components calculations. E stands for Eigenvalues matrix, Cov stands for covariance matrix, V stands for Eigenvectors matrix sorted form the greatest to the lowest, T stands for transpose, P stands for output of principal component value at the specified band, k is used for representing a particular input band, n is total number of bands, and d input data file at the specified band.

Two ways are adapted for PCA-based enhancement as seen in Figures 3.4 and 3.5. In the first method, fused image, pan band and MS bands are merged, then transformation is applied and first PC band is directed to the classification algorithm. In the second method, merge operation is applied the same way above and selected number of PC bands were fed into classification algorithms.

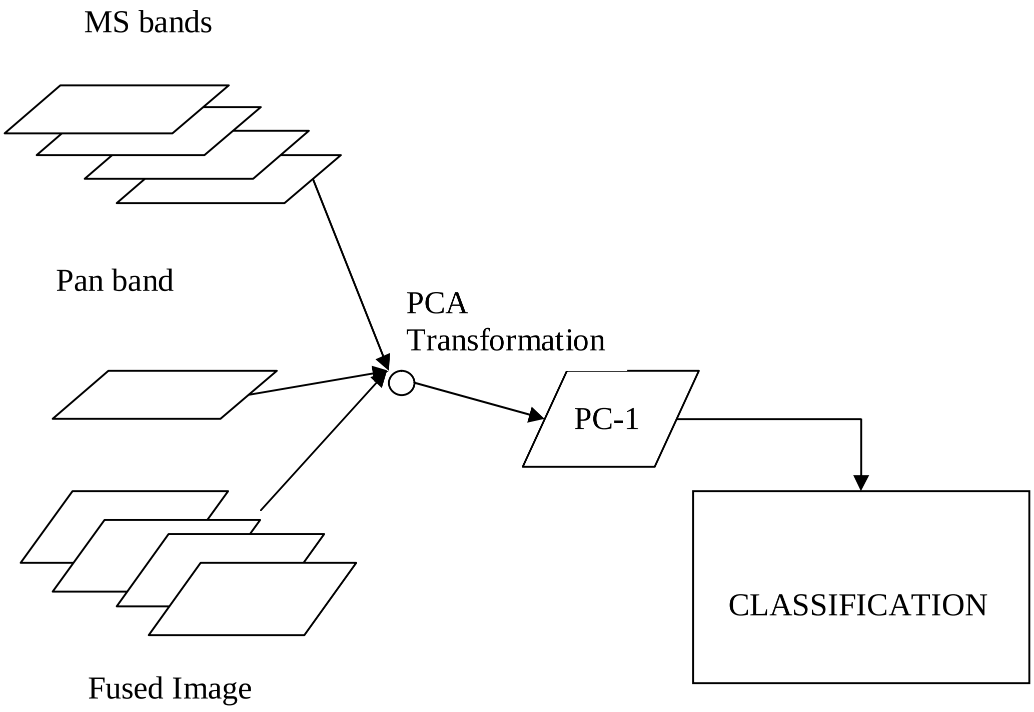

Figure 3.4 : PCA-based Image Enhancement, 1st method.

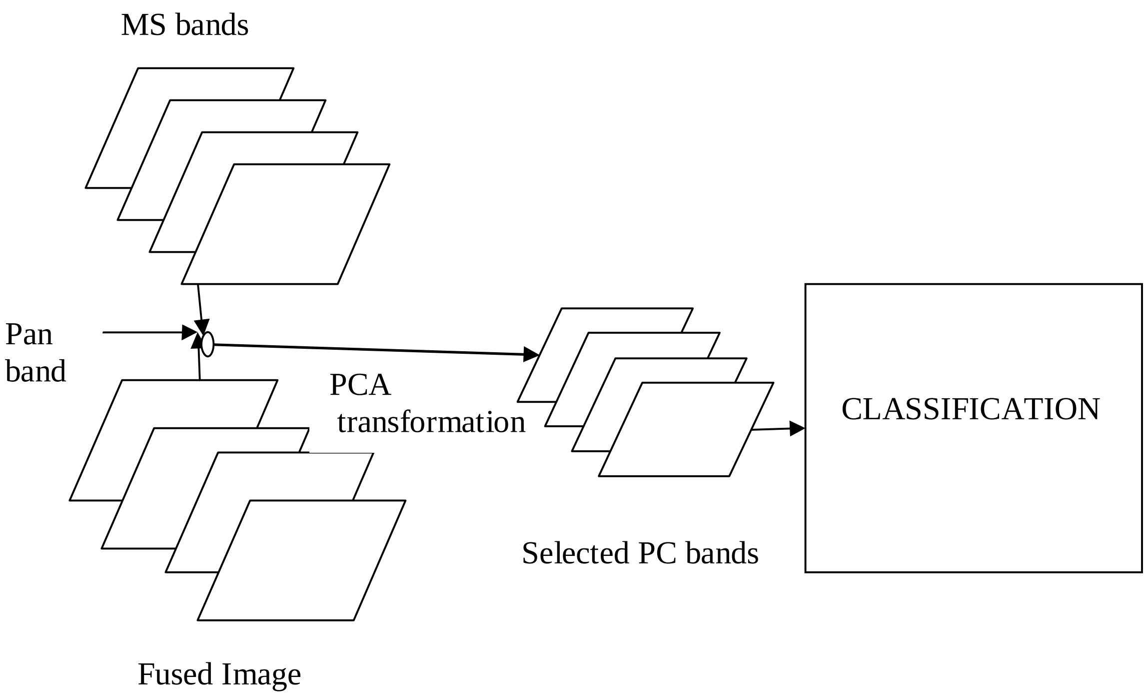

Figure 3.5 : PCA-based Image Enhancement, 2nd method.

3.3 Morphological Filters

Dilation and erosion operations are main components of morphological filters. Operations are defined as below:

$$\mathrm{D}\left(\mathrm{A},\mathrm{B}\right)=\max_{(j,k)\in B}(A(r-j,s-k)+B(j,k)) \tag{3.2}$$

$$\mathrm{E}\left(\mathrm{A},\mathrm{B}\right)=\min_{(j,k)\in B}(A(r+j,s+k)-B(j,k)) \tag{3.3}$$

In image processing applications, dilation filter constraints the size of bright features by correlation of darker nearby areas. Erosion limits the size of dark areas by surrounding lighter areas. Erosion and dilation operations are inverse operations of each other. The complement of erosion is equal to dilation of the complement (McAndrew, A., 2004). Opening and closing are other operations defined by erosion and dilation operations. Opening operation is the dilation of the erosion of an image. Closing operation is erosion of dilation of an image. The complement of opening operation is equal to closing of a complement and the complement of closing operation is equal to opening of a complement (McAndrew, A., 2004).

Skeletonization is a morphological algorithm showing all edges of the objects in the image. The skeleton of an image is created by morphological methods.

Thresholding is an algorithm to separate object from its background (Daryal and Kumar, 2010). Intensity difference in foreground and background pixels leads to create a binary image to take objects out of background (Watson et al., 1984)

Thresholding can be considered as a segmentation algorithm separating the pixels into two subgroups based on a threshold value. Intensity values greater than threshold are represented by black color as background and pixels with lower values are shown by white color as foreground object (Watson et al., 1984). The input of thresholding operation is generally a gray-scale image (Weiss, 2002).

Threshold selection must be carried out carefully not to lose any object information present in the image. Otsu method of threshold selection relies on exhaustive search to minimize intra-class variance. Intra-class variance is defined as weighted sum of variance of two classes. Weights are probabilities of two classes separated by a threshold t.

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \quad \textbf{(3.4)}$$

Otsu proved that minimizing the intra-class variance is equal to maximizing inter-class variance. Thus, equation becomes:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_2(t)]^2 \quad \textbf{(3.5)}$$

Application of thresholding algorithm together with skeletonization technique is seen in Figure 3.7. Original image is given as Figure 3.6 for comparison purposes.

Figure 3.6 : Original panchromatic image.

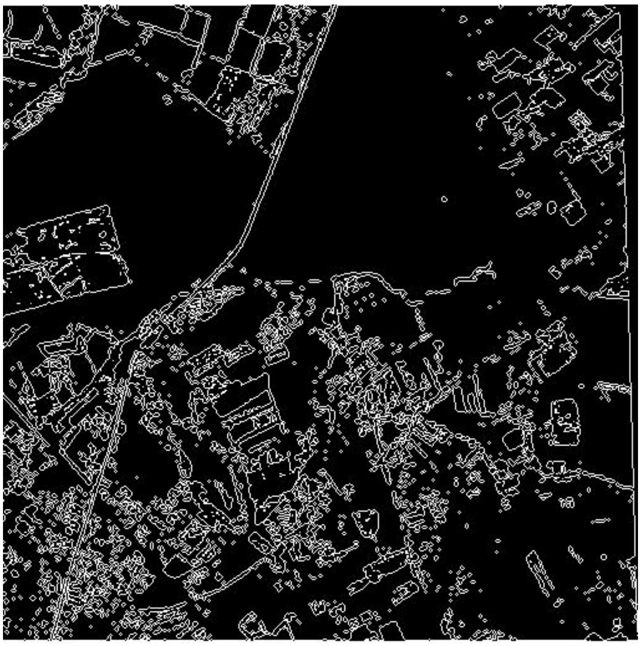

Figure 3.7 : Result of Otsu’s thresholding with Zhang-Suen’s thinning and Skeletonization algorithm.

The Zhang Suen’s algorithm for thinning is suitable for extracting straight lines from a raster, so may result in more desirable vectors from an original image which comprises mainly straight lines. Thus, it is preferable for satellite image works.

Thinning operation is mostly used for skeletonization. Since Zhang-Suen’s algorithm for thinning is relatively fast and easy to implement, it is preferred for applications. Thinning is normally applied to binary image and output is also a binary image. Residues of edge detectors are cleaned up with thinning by reducing all lines to single pixel thickness. Thinning operation uses structuring element which is a simple probe to handle the operations and its origin is compared with every possible pixel pair wise. If there is an exact match, the pixel is considered as background and its value is set to 0. Otherwise, nothing is changed (Medialogi, Gruppe 835).

The most important feature of Zhang-Suen’s thinning algorithm is that it preserves the topology by not changing the connectivity. Zhang-Suen’s algorithm is a fast parallel thinning consisting of two sub-iterations: the former one deletes the south-east boundary points and the north-west corner points while the latter one cuts off the north-west boundary points and the south-east corner points. The most favorable feature of the algorithm is preservation of end points and connectivity. The algorithm is used to get "skeleton" of the image with thinned edges. Iterative transformations are applied on the neighbors of the point (i, j) which are (i - 1, j), (i - 1, j + 1), (i, j + 1), (i + 1, j + 1), (i + 1, j), (i + 1, j - 1), (i, j - 1), and (i - 1, j - 1). All the contour points except the skeleton of the object are removed (Zhang and Suen, 1984).

The steps of the algorithm are as follows:

1. Its connectivity number is one.

2. It has at least two black neighbors and not more than six.

3. At least one of $I(i,j+1)$, $I(i-1,j)$ and $I(i,j-1)$ are background (white).

4. At least one of $I(i-1,j)$, $I(i+1,j)$ and $I(i,j-1)$ are background.

At the end of the sub iteration the marked pixels are deleted. Next sub iteration is a deletion or marking for deletion of pixel I (i, j) if the following four conditions are all true:

1. Its connectivity number is one.

2. It has at least two black neighbors and not more than six.

3. At least one of $I(i-1,j)$, $I(i,j+1)$ and $I(i+1,j)$ are background.

4. At least one of $I(i,j+1)$, $I(i+1,j)$ and $I(i,j-1)$ are background.

The marked pixels are deleted. If at the end of iteration, there is no pixel to delete, then skeleton is complete and program stops (Daryal and Kumar, 2010).

4. IMAGE FUSION METHODS

Definition of data fusion is “Data fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of ‘greater quality’ will depend upon the application” (Wald, 1999). Satellite image fusion is application of data fusion on satellite images.

The information obtained from an individual sensor may be incomplete and inconsistent; image fusion of multi-spectral remote sensing data with panchromatic satellite image could enhance classification process. It is important to integrate images with different spatial resolutions through image fusion for further applications such as land-use mapping (Xie et al., 2008).

4.1 GIHS Transform

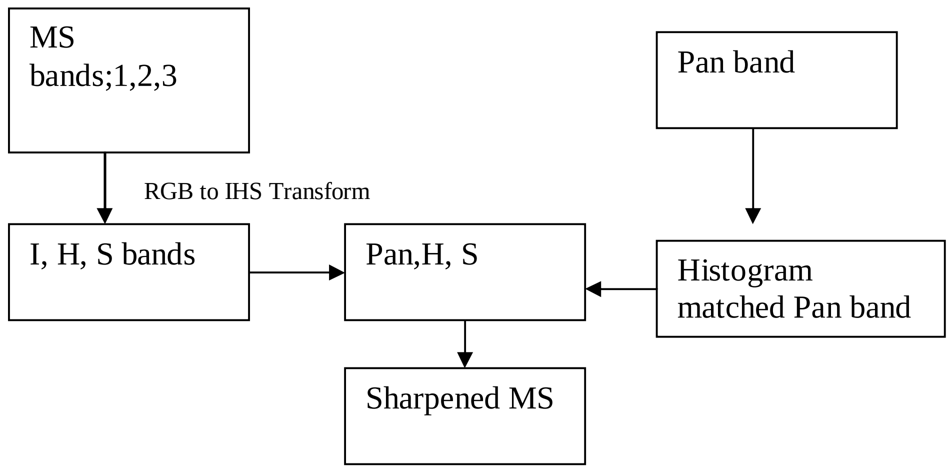

Figure 4.1 : IHS- based image fusion scheme (Stathaki, 2008).

Intensity Hue Saturation is very common method applied for image fusion. Red (R), Green (G) and Blue (B) bands of multispectral image is transformed to Intensity Hue Saturation (IHS) color space as explained by Carper and colleagues (1990). Basic framework of the IHS-based method is given in Figure 4.1.

$$\begin{pmatrix} I \\ V_1 \\ V_2 \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & \frac{-2}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} & 0 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{4.1}$$

$$H = \tan^{-1}\left(\frac{V_2}{V_1}\right) \tag{4.2}$$

$$S = \sqrt{V_1^2 + V_2^2} \tag{4.3}$$

I stands for Intensity component, H stands for Hue component and S stands for Saturation component; V_1 and V_2 are intermediate values. I component is replaced by panchromatic image and inverse transformation from IHS to RGB color space is applied.

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} = \begin{pmatrix} 1 & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{2}} \\ 1 & \frac{1}{\sqrt{6}} & -\frac{1}{2} \\ 1 & -\frac{2}{\sqrt{6}} & 0 \end{pmatrix} \begin{pmatrix} I \\ V_1 \\ V_2 \end{pmatrix} \tag{4.4}$$

Inverse transformation is achieved by using the coefficients of the above formula.

The problem with IHS fusion is that it assumes intensity component is constituted by even contributions of RGB channels (Yocky, 1996). This assumption causes spectral distortions.

IHS-based fusion is capable of handling large volumes of data such as satellite images. IHS can yield very satisfactory results with respectable spatial enhancement. However, spectral distortions are introduced as a change of colors between constitution of resampled and fused bands. The problem is not negligible for further applications such as classification algorithms. Especially vegetation areas which are more visible in NIR band due to reflectance are not taken into account in IHS transform. A generalized IHS fusion technique with spectral adjustment is introduced as a solution to the problem. The technique achieved better performance and image quality than the regular IHS method. In generalized IHS methods, NIR band is also used in calculations to mitigate color distortions before replacing I band (Tu et al., 2004).

$$\begin{pmatrix} R' \\ G' \\ B' \\ NIR' \end{pmatrix} = \begin{pmatrix} R + \delta' \\ G + \delta' \\ B + \delta' \\ NIR + \delta' \end{pmatrix} \tag{4.5}$$

where $\delta' = Pan - I' = Pan - (R + G + B + NIR) / 4$.

The fusion results of the method upgrade color quality by providing the highest spectral similarity to the multispectral image especially in vegetation areas. However, color distortions are somehow visible in more complicated structures such as buildings, roads and bare soil areas. There is a tradeoff between spectral enhancement and spatial quality and this method sacrifices the latter a little bit, but the solution is still feasible for color distortion problem (Tu et al., 2004).

4.2 Principal Component Substitution

Principal Components Analysis is a statistical technique to create an orthonormal reference axis formed by transformation of original values to describe the data without correlation. The coordinates of the pixels are linearly related to original ones and could easily be calculated. Principal components are formed by scaling functions and so PCA does not represent a unique characteristic of the data. First principal component carries much of the information about the data. Residual information is distributed among the other principal components as such the second one with highest information after the first one and so on. Use of correlation matrix instead of covariance matrix greatly improves the results and eliminates errors (G.Profeti, 1997).

In simplest terms; Principal Components Analysis is a transformation method to eliminate redundancy with representative data with the greatest variance and uncorrelated set of variables called principal components. The number of principal components is at most equal to number of original variables (Petrou and Petrou, 2010).

PCA transformation steps can be described as below (Kavitha and Arivazhagan, 2010, Principal Components Analysis):

1. Get image.

2. Calculate mean and covariance matrix.

3. Calculate Eigen vectors from the co-variance matrix.

4. Find Eigen values.

5. Order the covariance matrix by Eigen value highest.

6. Eigen vectors with highest Eigen value is the Principal Component, which contains significant information.

7. Lowest Eigen value components can be discarded.

4.3 Discrete Wavelet Transform

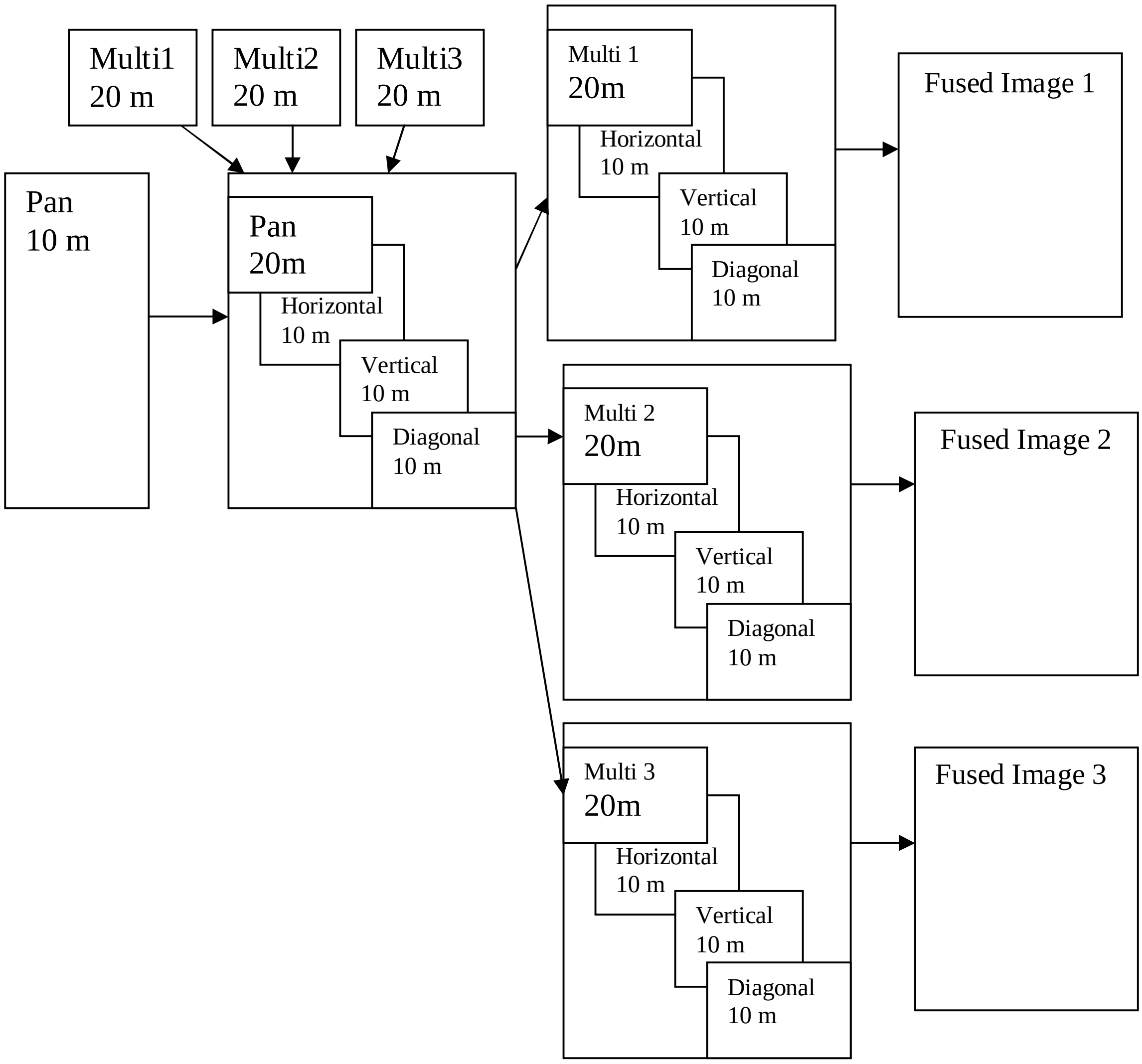

Figure 4.2 : Discrete Wavelet Transform based fusion method scheme

Discrete wavelet transform is wavelet transform of discretely sampled wavelets. DWT is preferable over Fourier transform in certain applications like our study because it captures location position in time in addition to frequency information. The most common DWT types are Haar wavelets and Daubechies wavelets. Haar wavelet is simply a recursive pairing up of 2^n numbers; difference is stored and sum is passed to provide the next scale, finally 2^{n-1} differences and one final sum is obtained. Daubechies wavelet defines recurrence relations repeatedly generating finer discrete sampling of mother wavelet function. Each resolution is twice that of previous scale (Chui, 1997).

DWT decomposition results in low-frequency coarse information and high-frequency detail information. Distribution of coefficients in the detail sub-bands have mean zero providing no change in the radiometry of the image obtained by the inverse transform (Li et al., 2002). The main principle of wavelet fusion is obtaining the best resolution without affecting the spectral contents of the image (Tu et al., 2001). This principle is based on multi resolution analysis of wavelet transforms (Mallat, 1998).

Widely applied wavelet-based method for remotely sensed data is based on Erdas Imagine software (King and Wang, 2001, Erdas Field Guide, 2010). High resolution panchromatic image is transformed into low resolution image components by using wavelet coefficients. Low resolution panchromatic band is replaced by original multispectral image. Inverse wavelet transform is applied on the final image to get the fused image part. This operation is repeated on each of the three bands of the multispectral image.

Briefly, image fusion provides a new way to extract land-use information for mapping by integrating multi-spectral and panchromatic images with different spatial resolutions to enhance quality of the image for further studies. For image fusion applications, getting high quality images with maximum detail and minimum color distortion is the essential point (Tu et al., 2004). Additionally, challenges of satellite image fusion are still considered an open research area.

Depending on the application, users may give different priorities to challenges: (1)some users may focus on color details for correct mapping, (2)some may expect an increase in classification accuracy, (3)some others may request fusion without color deficiencies for better visual analysis. Distinct techniques could be preferred based on the purpose of the application (Zhang, 2008).

There is a problem with determining the quality of fused images because no reference image is available for making a comparison (Collet et al., 2009).

5. SUPERVISED CLASSIFICATION

Classification of satellite image is defined as identifying and grouping of pixels with similar spectral features to map land-cover classes represented by these groups. Classified image is basically the thematic map of the original image. The theme is subject to selection allowing recognition of patterns in the mapping of the land-use (Pfister, 2004).

Supervised classification is basically techniques to classify objects into classes by considering the in-class similarities and interclass dissimilarities and identifying spectrally similar areas by training instances provided; then, using these spectral signatures to identify unseen instances (Remote Sensing Tutorial). Supervised classification needs a priori knowledge of location and identity of land-cover types used. Training areas need to represent full variability of the class. There are several factors affecting the spectral signature of a class which at the end affects the accuracy of thematic band (Tutorial: Fundamentals of Remote Sensing).

Supervised classification works as classifying objects into classes by help of training data. The term ‘supervised’ comes from educating the classifier to classify which part goes to which class by giving instances of each class prior to classification. In supervised training, pixels are selected based on spectral features and patterns. Additionally, auxilliary sources such as aerial photos and maps may be used in decision process (Erdas Field Guide, 2010). Basically, spectral signature of each class is stored by the supervised classification algorithm based on criteria predetermined. Every pixel is then compared with the signature and assigned as belonging to that class or not. In this study, Maximum Likelihood and Support Vector Machines algorithms are used to classify the high resolution satellite images.

Training and testing processes are vital for classification algorithms. Many studies reported that training of SVM is affected by training dataset size, kernel parameter settings and class separability (Huang et al., 2002).

Supervised classification of normal images is straightforward by the presence of the spectral reflectance in a specific frequency. However, the use of multiple frequency data called multi-spectral satellite images to classify the land use pattern classification is a challenge. With the overwhelming amount of data, classification tasks can come out as incomplete and sometimes with erroneous results. The methods of fusion need to be employed (Wıyarat, T., 2003). The ENVI-IDL extensions as wrapper classes available in literature could be used for parallel processing of operations on huge raw satellite data (Canty, M. J., 2010).

The fusion techniques used in this work could be applied as a part of a classification system since the resulting images enhance the original image data and reduces the noise.

The main objective of the classification is determining decision boundaries separating classes with different spectral features. Decision boundaries are formed by functions called discriminant functions which could be either linear or non-linear.

5.1 Maximum Likelihood Classification

Maximum Likelihood classifier is commonly used method in the applications of remote sensing as a parametric statistical method where supervision occurs by selecting sample areas. These areas are then stored numerically for the algorithm to divide the image into the respective most probable spectral classes. It is assumed that the distribution training data is Gaussian (normally distributed). The probability density functions of each class are used to assign an undefined pixel into the class of highest probability (Mustapha et al., 2010).

Maximum Likelihood Classification (MLC) method's prerequisite is that distribution of spectra needs to be normal for success with high accuracy levels. The graph associated with the density function needs to be bell-shaped to be normal (Gaussian).

$$P(\omega_i|x), i = 1, \dots, M \qquad (5.1)$$

$\omega_i, i = 1, ..., M$ and M represents total number of classes. The class of a pixel is calculated as a conditional probability where x is the position of the pixel.

$$x \in \omega_i \ if \ P(\omega_i|x) > P(\omega_j|x) \ for \ all \ j \neq i \qquad (5.2)$$

The probability P(ω_i |x) is the likelihood that the correct class is ω_i for a pixel positioned at x. The classification is performed as the following formula suggests:

$$P(\omega_i|x) = P(x|\omega_i)\, P(\omega_i)/P(x) \qquad (5.3)$$

The class is assigned to class with the highest probability. The algorithm of the Maximum likelihood method rooted at Bayes theorem.

A priori probabilities are needed for proper classification of the algorithm.

P (x|ω_i) is estimated from training data with Bayes theorem. P (ω_i) are called a priori probabilities and P (ω_i |x) are called posteriori probabilities.

$$x \in \ \omega_i \ if \ P(x|\omega_i)P(\omega_i) > \ P\left(x\middle|\omega_j\right)P\left(\omega_j\right) \ for \ all \ j \neq i \qquad (5.4)$$

Classification rule above could be written as shown above where P(x) has been removed as a common factor. The equation is more common in applications. Gaussian (normal) distribution assumption holds for multispectral and hyperspectral data making MLC a suitable technique for satellite image classification works.

$$D = \ln(a_c) - [0.5 \ln|Cov_c|] - [0.5(X - M_c)T(Cov_c - 1)(X - M_c)] \qquad (5.5)$$

The last equation is the main formula for Maximum Likelihood Classifier. The symbols are as follows: D is weighted distance (likelihood), c is a particular class, X is measurement vector of the candidate pixel, M_c is mean vector of sample of class c, a_c percent probability that a pixel is a member of class c, Cov_c covariance matrix and $|Cov_c|$ is determinant and Cov_c-1 inverse of it, ln is natural logarithm and T is transposition function. The pixel is assigned to the class with lowest D value (Erdas Field Guide, 2010).

5.2 Support Vector Machines

Support Vector Machine classification is based on statistical learning theory maximizing the distance between training samples of two classes. SVM has good generalization capacity with the approach even with a few training samples meeting expected accuracy levels (Kavitha and Arivazhagan, 2010).

Support Vector Machine is a non-parametric classifier by which no a priori knowledge of data distributions is assumed. This feature makes Support Vector

Machine Classification more powerful as compared to Maximum Likelihood Classification.

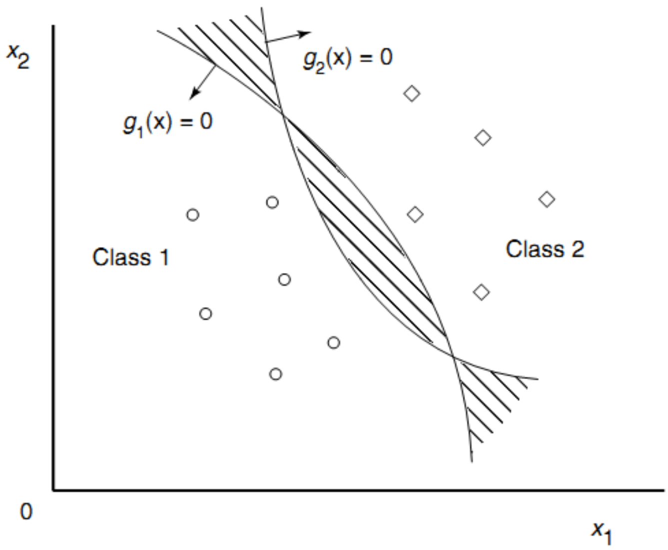

Figure 5.1 : Decision functions in a two dimensional space (Abe, 2005).

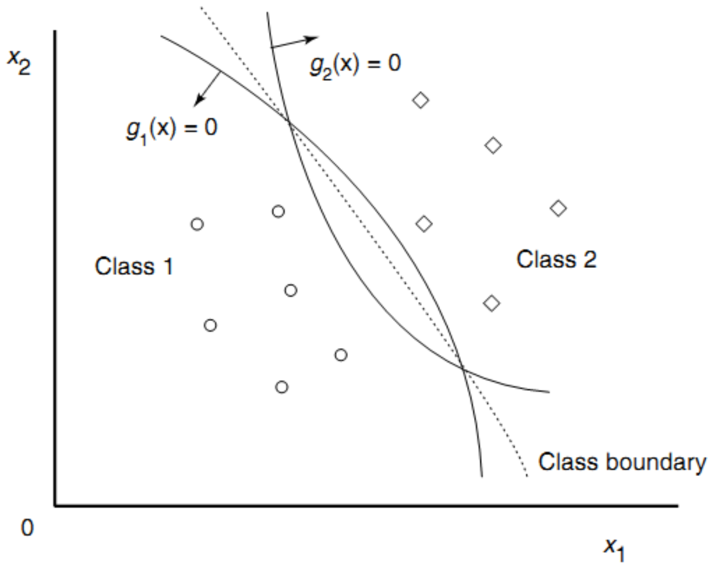

Figure 5.2 : Class boundary of decision functions in **Figure 5.1** (Abe, 2005).

x is classified into class one if the function $g_1(x) > 0$ and into class two if the function $g_2(x) > 0$. Consequently, class boundary is represented as:

$$g_1(x) = -g_2(x) = 0 \qquad (5.6)$$

If the decision function is linear $g_1(x)$ is:

$$g_1(x) = w^T x + b \qquad (5.7)$$

where w is an m-dimensional vector and b is a bias term. If one class is on the positive side of the hyperplane and the other one is on the negative side, then, calculations are straightforward and the problem is called as 'linearly separable'. In a support vector machine, decision function maximizing the generalization capability is preferred(Abe, 2005). Decision functions are chosen to maximize the distance from the training data assuming non-overlapping classes. The problem is a quadratic optimization problem of maximizing decision boundary and minimizing $½||w||^2$ with the condition $y_i (w^T x_i + b)>=+1$, for all i) (Demirci, 2007). Solution is achieved by Lagrance multipliers (Richard and Jia, 2006, Sepehri, 2011). Lagrance formulation is used for simpler solution and generalization to nonlinear cases (Demirci, 2007).

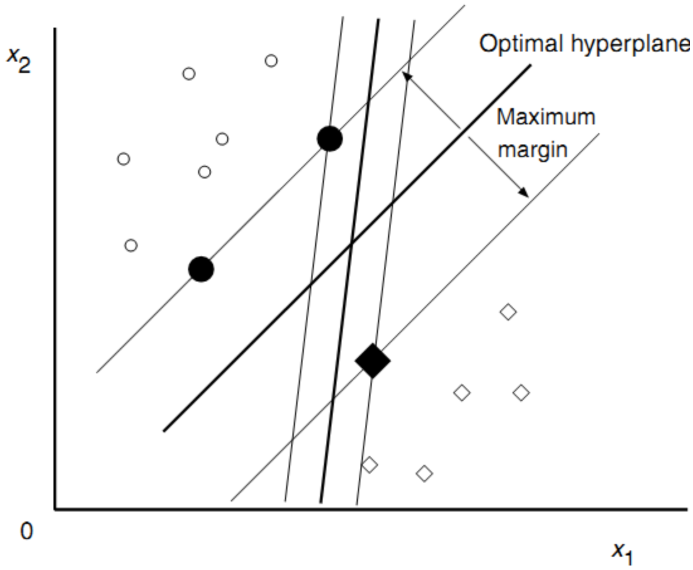

Figure 5.3 : Optimal separating hyperplane in a two-dimensional space (Abe, 2005).

Lagrance formulation is shown below. Lagrance multipliers as $\alpha_i >=0$ values are called positive Lagrance multipliers. The formulation stated below is hard to solve ; thus, transformation to dual problem with Karush-Kuhn-Tucker (KKT) conditions is applied. KKT conditions are stated below. Modifiying the equation 5.8 with considering the conditions, equation 5.11 is obtained (Demirci, 2007).

$$Lp = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{N} \propto_i y_i \left(w^T x_i + b\right) + \sum_{i=1}^{N} \propto_i \qquad (5.8)$$

$$\frac{\partial Lp}{\partial w} = 0 \Rightarrow w = \sum_i \propto_i y_i x_i \qquad (5.9)$$

$$\frac{\partial Lp}{\partial b} = 0 \Rightarrow \sum_i \propto_i y_i = 0 \qquad (5.10)$$

$$Ld = \sum_i \propto_i - \frac{1}{2}\sum_{i,j}^{N} \propto_i \propto_j y_i y_j x_i^T x_j \;; \quad \propto_i \geq 0, \forall\, i \qquad (5.11)$$

Solution of 5.11 with the condition is a quadratic optimization problem. Every training sample has a separate Lagrance multiplier and most of the Lagrance multipliers is zero. The x_i samples with a_i>0 values are support vectors.

There are cases where the training samples are not separable in two dimensional spaces. The cases are called not-linearly separable case and the feature space needs to be mapped to higher dimensional space with a kernel functions with a process called kernel trick.

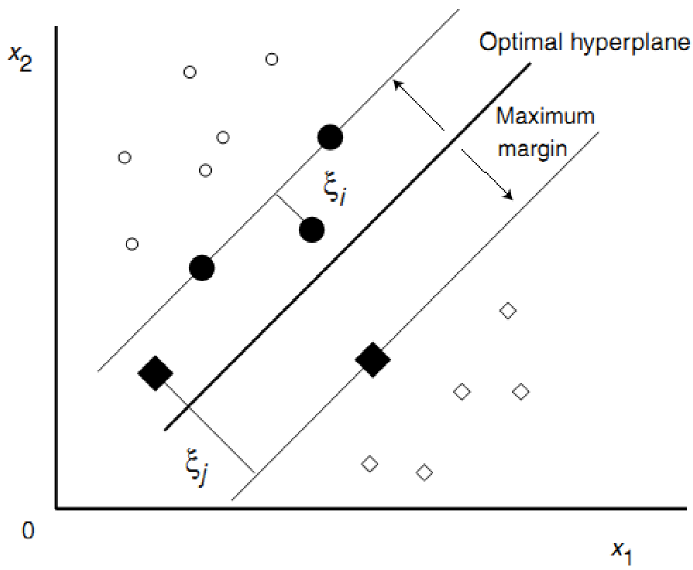

Figure 5.4 : Inseparable case in two dimensional space

(Abe, 2005).

Nonlinear classification is harder and requires mapping into a high dimensional space called feature space where optimal hyper-plane is determined. Nonlinear classification is achieved with the use of kernel functions. Seperating hyperplane is found in another hyperplane inducted by kernel function and other calculations are done in original space (Kavitha and Arivazhagan, 2010).

XOR function is an example of nonlinear separation. XOR function gives 1 when inputs are different and 0 otherwise. These points are not linearly separable that means a straight line cannot separate the training samples into classes. XOR gate is a straightforward example.

Table 5.1 : XOR gate.

X=(x1,x2)	Y
(1,1)	1
(-1,-1)	1
(1,-1)	-1
(-1,1)	-1

Feature space transformations are complicated; for the sake of simplicity, gate function will be used as an elementary example. A simple kernel trick for XOR gate is defining an x3 as x1*x2, so the cases are linearly separable in R^3. The plane z=0 has infinitely many decision surfaces as solutions to the modified XOR gate. An important capability of SVM is use of a non-linear function to map the training samples to a higher dimensional space called feature space. Once a linear decision surface is found in the feature space, non-linear separation is possible in the original space (A Brief Note on Support Vector Machines).

Table 5.2 : Modified XOR gate.

X=(x1,x2,x3)	Y
(1,1,1)	-1
(-1,-1,1)	-1
(1,-1,-1)	1
(-1,1,-1)	1

Nonlinear separation requires transformation of input values to higher dimensional feature space H with the function ϕ (Vapnik and Cortes, 1995). R^k->H and x_i->ϕ(i). As the dataset is transformed the higher dimensional space, working with the function ϕ is complicated and training algorithm can only be done with dot product, $\phi(x_i)\ .\ \phi(x_j)$. Kernel functions can be used instead of dot product (Huang et.al, 2002).

$$k(x_i, x_j) = \Phi(x_i).\Phi(x_j) \tag{5.12}$$

Classification now can be written in the form as in equation 5.13. Equation 5.14 states the value of a test sample of the system in testing phase where N_S is number of support vectors and s_i shows support vectors and K is kernel function. Radial basis functions (RBF) shown in equation 5.15 is most applied kernel function in satellite image classification works. γ is generally 1/N (Demirci, 2007).

$$w.\Phi(x_i) + b = 0 \tag{5.13}$$

$$f(x) = \sum_{i=1}^{Ns} \propto_i y_i\Phi(s_i)\Phi(x) + b = \sum_{i=1}^{Ns} \propto_i y_i K(s_i, x) + b \tag{5.14}$$

$$K(x_i, x_j) = \exp\left(-\gamma\left\|x_i^T - x_j\right\|^2\right) \tag{5.15}$$

To summarize, the objective of the SVM algorithm is to find the optimal separating hyperplane between classes by the help of the training samples. These training samples are called support vectors and others are discarded. In this way, an optimal hyperplane can be fitted even with fewer training samples with high classification accuracy (Nghi, 2008).

Support vector machines outperform other traditional classifiers as the dataset size is small and the number of input variables is high. Because of maximization of margin capability of support vector machines, high accuracy values are obtained with considerable performance (Abe, 2005).

6. ACCURACY ASSESMENT

Accuracy assessment is used to decide about accuracy of a classified image. Accuracy assessments used in this study are overall accuracy values and kappa statistics.

Confusion matrix provides valuable information about accuracy of each classification method. The success of classifier on each individual class could be observed by using confusion matrix (Ozturk and Cetin, 2011 General accuracy is calculated as $\sum X_{ii} / N$ where X_{ii} is diagonal elements in the marix and N is total number of observations. Kappa statistics contains valuable information to decide about success of each method. The Kappa coefficient is basically defined as the proportionate reduction in error generated by a classification process compared with the error of a completely random classification. The result of performing Kappa analysis is a KHAT analysis which is computed as below:

$$\widehat{K}=\frac{N\sum_{i=1}^{r}x_{ii} - \sum_{i=1}^{r}x_{i+} * x_{+i}}{N^2- \sum_{i=1}^{r}x_{i+} * x_{+i}} \qquad (6.1)$$

where r is number of rows in the matrix, x_{ii} is the number of observations in row i and column i, x_{i+} and x_{+i} are the marginal totals of row i and column i, respectively, and N is total number of observations (Congalton, 1991, Bishop et al.,1975).

It is reported that kappa values greater than 0.75 are considered to have a high degree of agreement beyond chance. Values below 0.40 have a low degree of agreement and values between 0.40 and 0.75 represent a fair to good level of agreement beyond chance alone.

There are five classes total. Color coding is as follows: red : building; green : vegetation; brown : bare land; cyan : road; white: shadow.

7. **RESULTS AND DISCUSSION**

7.1 Image Fusion Experimental Results

The Quickbird satellite image has a spatial resolution of 0.61 m and includes four spectral bands namely Red band (R), green band (G), blue band (B) and near infra-red band (NIR). The image in the studies is a subset of the satellite image acquired on 2009-30-08.

Implementation of PCA-based and wavelet-based fusion techniques are achieved by ERDAS, Inc. Imagine software (http://www.erdas.com/Homepage.aspx). Generalized IHS method is implemented by Matlab. MLC and SVM classification is done via Envi Software (*www.ittvis.com/ProductServices/ENVI.aspx*). ENVI-IDL extensions as wrapper classes are also employed for parallel processing of classification algorithms. Binarization, Thresholding, Thinning and Skeletonization algorithms are implemented by using Matlab.

Test cases are used to measure classification accuracy of the trained algorithms. Post-classification comparison is a useful technique (Cetin et al., 2008). Since the image fusion and image enhancement techniques employed together with classification algorithms, classification accuracy and kappa statistics values are higher as expected as shown by benchmarking the original image.

In literature, PCA-based and wavelet-based fusion methods are found more successful than IHS-based methods in general. As shown in Table 7.1, while PCA-based and wavelet-based fusion methods have comparable classification accuracy better than IHS-based method for maximum likelihood classification, wavelet-based method has higher classification accuracy than PCA-based and IHS-based fusion methods for support vector machines classification (Colditz et al, 2006).

Table 7.1 : Overall accuracies of image fusion methods(Colditz et al, 2006).

	IHS	PCA	Wavelet
MLC	62.05	81.21	81.02
SVM	68.69	77.04	79.51

Table 7.2 : Kappa accuracies for image fusion methods (Bruzzone et al., 2006).

	Original	GIHS
MLC	75.2	75.1
SVM	78.0	77.6

With PCA-based fusion method, some color distortions are observed. With wavelet based method, color information on the fused images are preserved, but it caused to reduce spatial details. However, wavelet-based method still had unusual effects. On the other hand, GIHS method showed poor spectral quality and had fingerprint-like structures called artifacts which severely affect further classification works. For that reason, color artifacts are reduced by application of smoothing filters. Smooth join of the smoothed image and fused image resulted in an image with better spectral quality which provided higher classification accuracy results.

Despite the problems, all the methods have comparable or better classification results. Especially with the application of smoothing as a post-classification filter, the results are much better. Smoothing filter is applied with a special care not to destroy edge information while smoothing the image. The effects of the artifacts are reduced by the application of the filter.

The results are given in Table 7.3 as a whole for comparison purposes. Mean Smoothed Fused Images did not show expected performance for overall accuracy and kappa values. Mean filter was modified to keep edge information for detection of objects by classification algorithms. Table 7.4 shows the results after application of mean filter. Since image enhancement using mean filter was not suitable, a new image enhancement method based on PCA transform is used in the applications.

Table 7.3 : Classification results for fused images.

	Fused Images			
	MLC		SVM	
	Acc.	Kappa	Acc.	Kappa
Original	77.00	70.56	84.25	79.79
PCA	90.24	88.00	92.90	91.13
DWT	93.33	91.67	93.30	91.63
GIHS	90.53	88.17	92.51	90.63

Table 7.4 Classification results mean filter image enhancements on fused images

	Smoothed Fused Images			
	MLC		SVM	
	Acc.	Kappa	Acc.	Kappa
Not applied on original image				
MeanSmoothedPCA	90.24	88	92.90	91.13
MeanSmoothedDWT	93.33	91.67	93.30	91.63
MeanSmoothedGIHS	90.53	88.17	92.51	90.63

The results of fusion algorithms were compared. Figure 7.1 is basically the original multispectral image.

Figure 7.1 : Original Multispectral Image.

The results belonging to original image are: for MLC classification, overall accuracy is 83.65%, kappa statistics is 0.79; for SVM classification, overall accuracy is 84.83%, kappa statistics is 0.80. These results are used as a benchmark to decide about the success of each fusion method and image enhancement methods. Over 80% accuracy is acceptable rate and kappa statistics are satisfactory, but further improvements on classification results are possible by the use of fusion methods and image enhancement techniques. Figure 7.2 includes resulting images of MLC and SVM classification algorithms on the original image.

Figure 7.2 : MLC vs SVM Classification of the Original Image

7.1.1 Wavelet-based Fusion Results:

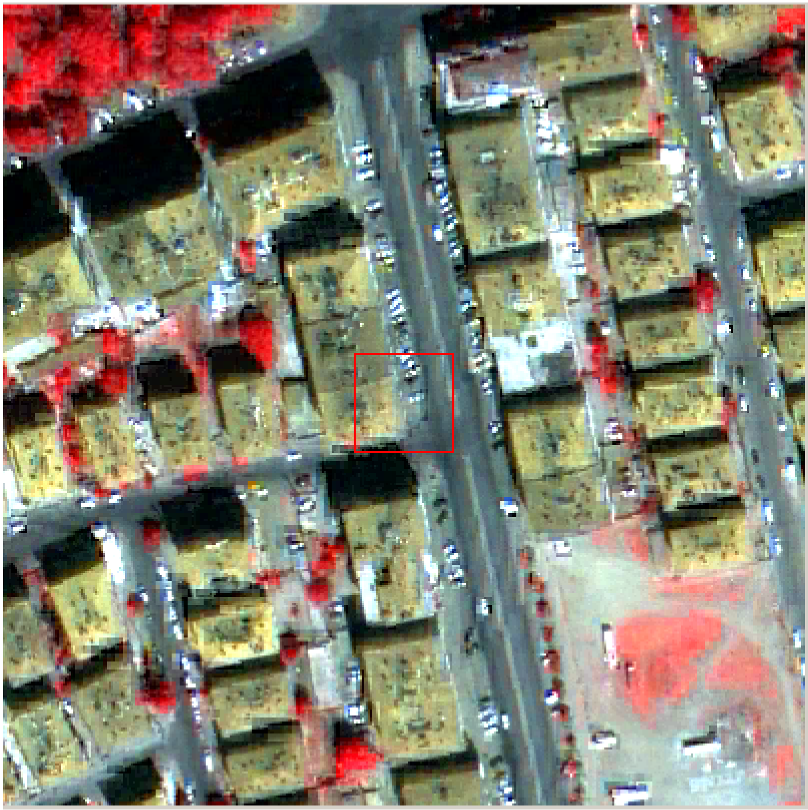

Figure 7.3 : DCW-based Fused Image.

Figure 7.3 is the resulting image of the wavelet-based fusion. Wavelet-based fused image has some blur effects causing confusion of neighboring complex classes such as buildings, road intersections and bare-soil areas. The desirable feature is that the vegetation areas of varying spectral features are clearly distinguishable increasing classification accuracy rate and kappa statistics values. Forests are also more visible providing better realization of forest areas which are somehow intermixed with other class types and often misclassified as the neighboring pixels.

Figure 7.4 : MLC vs. SVM Classification of DCW-based Fused Image.

Figure 7.4 illustrates MLC vs. SVM Classification Results of Wavelet-based Fused Image. There are only minor differences as seen in the illustrations of classification results and algorithms differ in separation of shadow and road classes. Wavelet resolution merge technique yields the highest accuracy levels among the compared fusion methods. Overall accuracy is increased to 93.33 % for MLC classification and to 93.30 % for SVM classification. Kappa statistics value is 0.92 for both of the algorithms.

7.1.2 PCA-based Fusion Results:

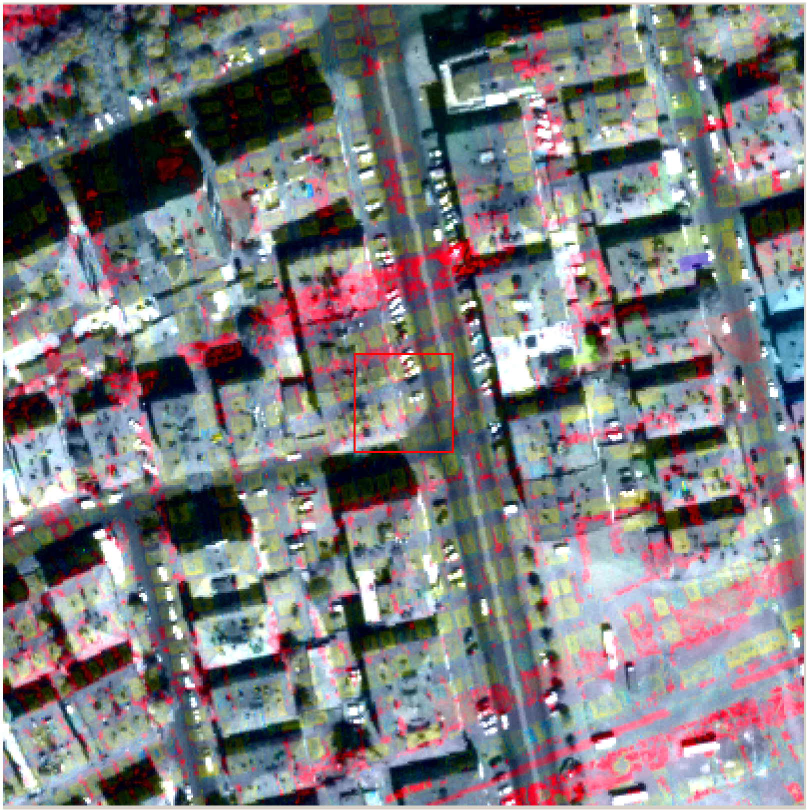

Figure 7.5 : PCA-based Fused Image.

PCA-based fusion resulting image is seen in Figure 7.5.

Figure 7.6 : MLC vs. SVM Classification of PCA-based Fused Image.

PCA-based fusion caused color distortions by introducing new color combinations not present in the original image. The artifacts are observed and are not in a level that can be underestimated. The spectral distortions are even visible to naked eye and cannot be ignored. Some other techniques need to be employed to get rid of effects of the artifacts.

Figure 7.6 shows MLC vs. SVM Classification Results of PCA-based Fused Image. Classification results are for MLC 90.24% overall accuracy with 0.88 kappa value and for SVM 92.90% overall accuracy with 0.91 kappa statistics value. Despite spectral distortions, the algorithms are still successful as compared to classification results of the original image.

7.1.3 Generalized IHS Fusion Results:

Figure 7.7 and Figure 7.8 are GIHS method resulted image and classification results.

Figure 7.7 : GIHS Fused Image.

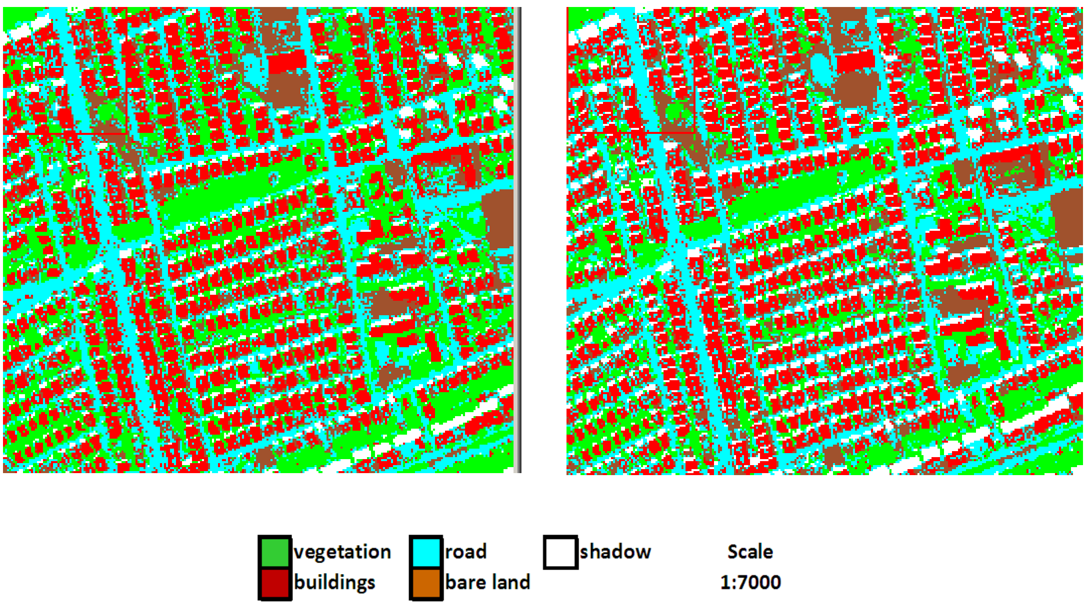

Figure 7.8 : MLC vs. SVM Classification of GIHS Fused Image.

The fused image includes spectral distortions not present in the original image. Some artificial structures called artifacts are present increasing the misclassification rate of classification algorithms. GIHS method still had better classification accuracy than the original image. Overall accuracy for MLC is 90.53% with 88.17% kappa values and for SVM is 92.51% with 90.63% kappa values.

7.2 Image Enhancement Experimental Results

Visual examination of the produced images is not enough for an objective evaluation. Therefore, overall accuracy and kappa statistics values of the confusion matrices are used for assesment of the classification results.

Since mean filtering technique of image enhancement did not give expected results, PCA-based image enhancement method is applied on the fused images.

7.2.1 PCA-based Image Enhancement Results:

7.2.1.1 First Method:

PCA-based image enhancement was more successful on the classification results of more powerful methods like support vector machines. As seen in Table 7.4, overall accuracy for wavelet-based fused image increased to 93.49 % with kappa value increased to 91.86 % as in Table 7.5 and Table 7.6. Similar situation is observed in Gihs-based fused image; with increasing overall accuracy of 93.17 % and with better kappa value of 91.46%. PCA-based fused image did not improve by enhancement method at all for any of the classification algorithms applied.

Table 7.5 : Overall accuracy values for 1st PCA-based enhancement method

	PCA-based Fused Image	Wavelet-based Fused Image	GIHS-based Fused Image
MLC	89.74	92.52	89.83
SVM	92.85	93.49	93.17

Table 7.6 : Kappa values for 1st PCA-based enhancement method

	PCA-based Fused Image	Wavelet-based Fused Image	GIHS-based Fused Image
MLC	87.19	90.65	87.29
SVM	91.06	91.86	91.46

7.2.1.2 Second Method:

Second type of the enhancement method in general has better results. As seen in Tables 7.7 and 7.8, with the application of the method, PCA-based fused image classification results were promoted to 92.94 % accuracy value with 91.18 % kappa value for MLC method and 94.64 % accuracy value with 93.3 % kappa value for SVM method. Wavelet-based method improved for SVM classification with 94.43 % overall accuracy value and 93.03 kappa value. Gihs-based fused image had advancements by 92.9 % accuracy value and 91.14 % kappa value for MLC method and by 94.67 % accuracy value and 93.33 % kappa value for SVM classification algorithm.

Table 7.7 : Overall accuracy values for 2nd PCA-based enhancement method

	PCA-based Fused Image	Wavelet-based Fused Image	GIHS-based Fused Image
MLC	92.94	91.43	92.9
SVM	94.64	94.43	94.67

Table 7.8 : Kappa values for 2nd PCA-based enhancement method

	PCA-based Fused Image	Wavelet- based Fused Image	GIHS-based Fused Image
MLC	91.18	89.29	91.14
SVM	93.3	93.03	93.33

Second method is preferable over the first method because the improvements are better and recorded with all type of fused images. SVM as a nonlinear classification algorithm showed better classification results than MLC which is known as linear or moderately linear classification method.

Image enhancements methods' results further advanced the use of image fusion methods. It is revealed that united application of image fusion and image enhancement methods provided high classification accuracies with good kappa statistics values as compared to the original satellite image. Binarization, thresholding (Otsu algorithm) and line detection by skeletonization elaborated the final image by visualizing the details present in the fused and enhanced image.

8. **CONCLUSION**

There is much information present in satellite images. Especially with the help of advanced sensor, more details could be obtained about land use. As illustrated in the thesis; with fusion methods, transformations and filtering techniques, the details could be revealed for further use such as land-use mapping.

The key concept is combining the panchromatic image with multispectral image to obtain an image with more spatial details together with color information. Signal/image processing techniques are applied in the transform domain images, and inverse transform is employed to obtain better images in the regular image domain. Averaging the resulting images by the help of smoothing filter in this domain per band further enhances the images by a large margin. With the algorithm to apply the morphological filter, the distortions were prevented and the edges preserved. Fused images are further enhanced so as having sharp edges as original and smoothed inner parts suitable for classification algorithms.

As the resulting fused images applied with PCA-based, wavelet-based and GIHS-based methods were tested with maximum likelihood classification and support vector machines methods, the effects on classification algorithms were observable. Image fusion methods clearly increase accuracy although some problems exist. The comparison by using the original image as benchmark illustrates the advances in the images by overall accuracy and kappa values. Wavelet resolution merge is the best fusion technique for accuracy comparisons among tested methods with little distortion and more details. Farther application of smoothing filters reveal more details as sharp edges separating objects as a further help classification algorithms for improving accuracy values.

With combined use of the image fusion and image enhancement techniques together with classification algorithms, overall classification accuracy and kappa statistics values increased as expected. Maximum Likelihood Classification which is a statistical parametric method and Support Vector Machines classification algorithm that is non-parametric in nature both demonstrated an improvement which could be considered as advancement for land-use mapping.

Smooth join of the enhanced image and fused image results in an image with better spectral quality in addition to spatial enhancements providing higher classification accuracy results. The final images are visibly enhanced with relatively low noise level compared to the original image. The image fusion and image enhancement methods could be integrated into existing classifier systems as optional processing steps. United approach is especially effective for advanced applications.

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