Assessment of large scale urban mapping from airborne hyperspectral data based on SVM and ANN

LAMYAA GAMAL EL-DEEN TAHA1 and ATTIA ABD AL FATTAH SHAHIN2

Abstract—Hyperspectral imaging has tremendous application such areas as mineral identification, crop classification, land use planning, environment monitoring, and military reconnaissance.
In this research the potential of airborne hyperspectral data for large scale urban mapping was evaluated in order to know to what scale of airborne hyperspectral data is suitable for map production.
Geometric correction using direct georefrencing and atmospheric correction have been performed. After that feature selection has been applied.
Quality of rectification has been assessed using DGPS check points. A program has been developed using paython language for assessment of geopositioning accuracy of airborne hyperspectral data. The results revealed that the total RMS of airborne hyperspectral data was 0.4 m. The RMS was within the required standard map accuracy for a map 1:1000 according to the map accuracy standards of NMAS. Planimetric vector map has been produced manually and automatically. For automatic map production a comparison between two subpixel classifiers (Support vector machines (SVM) and artificial neural network (ANN)) was carried out. Quantitative accuracy assessments of the classification results were performed. Experiment shows that, Support vector machine technique outperformed neural network technique in terms of the overall classification accuracy and kappa coefficient. The overall accuracy of the Support vector machine method was 98%, and kappa coefficient was 0.96 and the overall accuracy of the neural network method was 96%, and kappa coefficient was 0.94. After that morphological operations were performed in order to remove noise followed by raster to vector conversion.
The results of the SVM and the results of the neural network classification were compared and showed an increase in accuracy of land use discrimination using SVM.
In conclusion by analysis of the results, it is obvious that the manual map production method is faster than the automatic methods and automatic methods needs manual editing compared to the resulted vector map from on screen digitizing.

***Keywords*—**Airborne hyperspectral data- Radiometric Correction- Geometric Correction-Atmospheric Correction-direct georefrencing-large scale mapping-ANN-SVM.

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INTRODUCTION

The '' hyper''in the hyperspectral means ''over '' as in too many and refers to a large number of measured wavelengths bands.

Imaging spectroscopy, also known as hyperspectral imaging, is concerned with the measurement, analysis, and interpretation of spectra acquired from a given scene (or specific object) at a short, medium or long distance by an airborne or satellite sensor. Since the development of imaging spectrometry in the early 1980s, hyperspectral remote sensing has become an important tool for earth observations. It employs hyperspectral sensors to collect two dimensional spatial images over many contiguous spectral bands containing the visible, near-infrared, and shortwave infrared spectral bands (Li et al,2012). The main advantage of hyperspectral remote sensing is the amount of spectral detail it provides.
Althought Hyperspectral remote sensing deals with imaging at narrow and large number of spectral bands (Navalgund et al. ,2007). In contrast to traditional multispectral sensors such as Landsat-TM, Spot-MX or IRS-LISS that collect spectral data in a few spectral bands (less than 20 spectrally discontinuous channels), the hyperspectral sensors are expected to improve our ability to observe the earth surface . Such as increasing the classification accuracy. The development and application of hyperspectral techniques request more advanced approaches to process the hyperspectral remote sensing data with large dimensions (Jun et al. 2008). However, in practice, the data processing approaches that have so far been successfully applied to other multispectral data may not be effective for hyperspectral data processing (Pu and Gong,2004).

An adequate preprocessing of hyperspectral data is a mandatory prerequisite to extract useful information from hyperspectral data. It includes geometric and radiometric correction.

Airborne data are provided as an image cube accompanied by an auxiliary data stream of differential positioning (DGPS) and inertial navigation system data (INS). The first provides sbumeter accurate position data of the sensor during acquisition (x,y and z) ,the latter information on roll ,pitch and yaw movements of the platform(Φ,ω, assuming a correct synchronization between scan lines and auxiliary data, it is possible to calculate the acquisition geometry for every pixel.

Accurate ground truth allows for high quality assessment of geometrically corrected data sets (Rashed and Jurgens,2010).

Precise Radiometric preprocessing is required. Atmospheric correction of hyperspectral data is mandatory for conversion of radiance to reflectance.

In general, hyperspectral imaging is used for a broad range of applications in remote sensing. To date, a majority of research has focused on natural targets such as vegetation and minerals. Far less research has focused on urban areas using hyperspectral data.

The Spectral characteristics of urban surfaces are known to be complex. Hyperspectral data offer capabilities of improved spectral and spatial urban mapping capabilities (Herold et al.,2004).

For each pixel within a hyperspectral image, a continuous spectrum is sampled and can be used to identify materials by their reflectance(Hsu and Burke ,2003).

Since the increase of spectral bands and spectral resolution makes it possible to reduce overlap between different classes, and therefore greatly enhances the potential to discriminate subtle spectral difference of different objects that multispectral imaging cannot achieve (Xu et al.,2007).

The dynamic development of urban areas requires production and frequent updating of the existing databases. Standard approaches are mostly based on field investigations and visual interpretation of aerial photographs. Since they are time consuming and expensive, mapping activities often cannot keep up with the pace of urban development. Thus, there is a big need for the development of innovative techniques allowing automated identification of urban surface materials (Heiden et al. ,2007) .

New opportunities have been opened up with the availability of airborne hyperspectral remote sensing data characterized by a high spatial and spectral information content. Several studies show the basic potential and new challenges of such data for spectral differentiation of urban surface materials (Ben-Dor, 2001; Heiden et al., 2001; Roberts & Herold, 2004).

Acquisition of hyperspectral data from an airborne platform is expensive as they require ad hoc flights, and they are usually feasible to acquire data only over a small area due to the limited ground projected field of view. This means that the use of these data over large areas become problematic, due to costs and difficulties related to the different spectral responses associated with images acquired at different spectral timings and days (eg. this makes the mosaicking and radiometric correction phase difficult) (Dalponte et al.,2012)

As new airborne systems and spaceborne sensors become operational, improved digital image processing techniques are needed to handle the expected increase in hyperspectral remotely sensed data volume in a computationally efficient manner (Filippi and Jensen,2006) .

Hyperspectral data contain a mix of pure and mixed pixels. A mixed pixel is a picture element representing an area occupied by more than one ground cover type (Roosta and Saradjian ,2007) which have been recognized as a problem affecting the effective use of remotely sensed data in urban land use/ land cover classification (Lu and Weng ,2006) Usually classification of mixed pixels leads to errors that make the subsequent area estimation inaccurate. These errors are caused by the premise of classification that all pixels are pure, i.e. consisting of a single ground cover type, while in fact they are not(Roosta and Saradjian ,2007).

Several automatic classification techniques have been proposed (Stoica and Neagoe ,2013).

Traditional pixel-based classification algorithms are often not capable to resolve mixed pixel problem. Since the traditional hard classifier can label each pixel only with one class, urban impervious surfaces (e.g.buildings) can only be recorded as either present or absent.

The existence of mixed pixels led to the development of numerous methods of subpixel classifiers in which each pixel is allocated to all classes in varying proportions. Among the most popular techniques for subpixel classification are artificial neural networks and support vector machines (SVM).

Unlike statistically based pattern recognition classifiers, ANNs require no assumption regarding the statistical distribution of the input pattern classes, and they are relatively noise tolerant and entail a massively parallel structure (Filippi and Jensen,2006).

Another subpixel classifier is support vector machines (SVM). It has been very successful in pattern recognition. It is a non-parametric classifiers have the additional advantage that they are able to simultaneously minimize the empirical classification error and maximize the class separation using various transformations of hyperplanes. This allows SVM to better deal with data of high dimensionality and classes with a feature space of multimodal distribution producing often better results in comparison to other parametric or non-parametric methods (Yuhendra et al,2010).

The representation of urban surface materials in hyperspectral image data is also characterized by a high within-class variability (Heiden et al., 2005). This is due to several factors, such as color, coating, degradation and illumination of the material as well as preprocessing of the image data. The highest number of spectrally distinct materials and the greatest variability can be found for roof materials. This is caused by the wide range of available roofing materials and varying orientations of the roofs towards the sun and the sensor.

Reference spectra for surface materials can be retrieved from field measurements or derived from image data.

This research is concerned with the investigation of large scale mapping from airborne hyperspectral data in order to know to what scale of airborne hyperspectral data is suitable for map production.

In this study, the geometric accuracy of hyperspectral data has been assessed as well as feature compilation. Planimetric accuracy of rectified hyperspectral data has been compared to the National Map Accuracy Standards (NMAS) which were established in 1941 by the USA and revised in 1947.

Georectification using direct georefrencing has been performed. Atmospheric effect has been corrected. Noise has been reduced using Minimum noise fraction (MNF). GCPs have been collected using static DGPS. This will be followed by assessment of the quality of rectification using check points. After that optimal bands (feature selection) that are located at wavelengths that are known to be useful for discriminating urban have been selected. Manual Production of planimetric map has been performed.

In this research also automatic map production has been conducted. Firstly a comparison between two nonparametric subpixel classifiers artificial neural networks (ANNs) and support vector machines (SVM) for classification of hyperspectral data has been carried out. After that morphological operations were performed in order to remove noise then raster to vector conversion.

I. AIRBORNE HYPERSPECTRAL DATA

A. Basic difference between Multispectral and airborne hyperspectral data

Hyperspectral data differ from multispectral data in the number of bands and band widths.

One can obtain different spatial resolution from airborne hyperspectral data depending on the flight height also the spatial resolution is better than the available satellite images till now.

Airborne hyperspectral data depends on direct georefrencing which decrease the cost of field work compared to satellite images.

Order of satellite image take long time specially for new acquisition tasks for urgent problems on the other hand acquisition of airborne hyperspectral data is fast.

B.Spatial resolution of Airborne hyperspectral data

Spatial resolution defines the level of spatial detail depicted in an image. This may be described as a measure of the smallness of objects on the ground that may be distinguished as separate entities in the image, with the smallest object necessarily being larger than a single pixel. In this sense, spatial resolution is directly related to image pixel size.

Spatial resolution of hyperspectral data is a function of sensor altitude, detector size, focal size and system configuration (Weng,2012).

Spatial resolution = coverage/1600 Equation 1

Where: coverage =2*height* tan (FOV °)

In our study area:

coverage =2*1000* tan (17 °)=611.46

Spatial resolution = 611.46/1600 =0.38m

C. HySpex Airborne hyperspectral imaging system

The VNIR-1600 and SWIR-320i modules have been integrated into an aircraft, where GPS and INS data are logged continuously to enable geometric correction and georeferencing of the images (Baarstad et al., 2005). Fig1.shows HySpex camera NEO VNIR & SWIR. Fig2. illustrates the hyperspectral imaging concept. Fig3. illustrates spectral bands of hyperspectral data.

Fig1. HySpex camera NEO VNIR & SWIR.

The HySpex covering the visible and near infrared (VNIR) as well as short wave infrared (SWIR) ranges, from 0.4 to 2.5 µm. Table1 shows spatial, spectral and radiometric characteristics of HySpex airborne system.

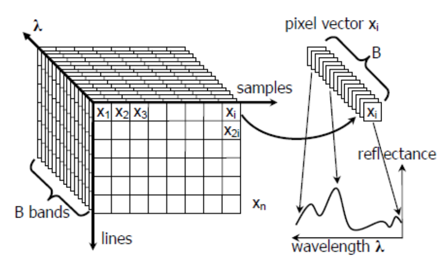

Fig2. The hyperspectral imaging concept.

Fig3. Spectral bands of hyperspectral data.

Table 1. Spatial ,spectral and radiometric characteristics of HySpex airborne system.

Spatial configuration			
	VNIR-1600		SWIR-320m -e
Instant field of view (IFOV) milliradian	0.36 mr along track 0.18 mr across track		0.75 mr along track 0.75 mr along track
Field of view (FOV)	17 degrees across track		14 degrees across track
Spectral configuration			
Module	**Spectral range**	**Average spectral Number (sampling interval)** nanometre	**Number of bands**
VNIR (visible near infrared)	0.4-1 µm	3.7nm	160 binning mode (2,4,8)
SWIR(shortwave infrared region)	1-2.5 µm	6.25 nm	256
Radiometric configuration			
VNIR	12 bits		
SWIR	14 bits		

(Hyspex,2010)

II. STUDY AREA AND DATA SET

The site chosen for study is located in Aswan Governorate-Egypt. Hyperspectral data VNIR image concurrently with SWIR image was acquired in 11/03/2013 using airborne hyperspectral data from HySpex system. The test site covers an area of about 1 km^2. This area has a very representative urban scene.

The positions and attitude data are measured in real time during data acquisition, using a GPS and Inertial Measurement Unit (IMU) onboard.

Twenty five Differential GPS points obtained with 10 cm accuracy in X,Y,Z were used for quality validation of geometric correction.

II. III.METHODOLOGY

1-Flight planning.
2-Processing of hyperspectral data (geometrically, radiometrically).
3-Collection of GCPs using DGPS.
4-Assessment of geometric correction quality using check points (horizontal accuracy)
5- Development of a program using paython language for assessment of geopositioning accuracy.
6- Manual production of planimetric map.
7-Spectral endmembers collection.
8-classification of the rectified image using ANN and SVM.
9-Comparison between classification performances.
10-Production of planimetric map.
11-Assessment of cartographic potential of hyperspectral data.

A. *Flight planning*

Flight operations in Aswan in 11/03/2013 were surveyed with the following survey specifications:
Approximate ground speed 160 knots (296 km/h)
Flight altitude =1000 m
IFOV ('pixel size') 0.38 m.
For the HySpex instrument the instant field of view (IFOV) of 0.38 m corresponds to a flight altitude of 1000 m at which the scanner's swath width (the area to be imaged across the flight track) is approximately 1 km^2 . Fig4. shows flight operations.

A.1.Flight planning precautions

- Calibration airborne hyperspectral camera every year.
- Check calibration of airborne GPS (rover) & base also calibration of IGI
- Rover &base work simultaneously
- Subscription of omnistar
- Check aircraft maintenance before flight.
- Check of recording capacity before flight.
- Side lap and gaps

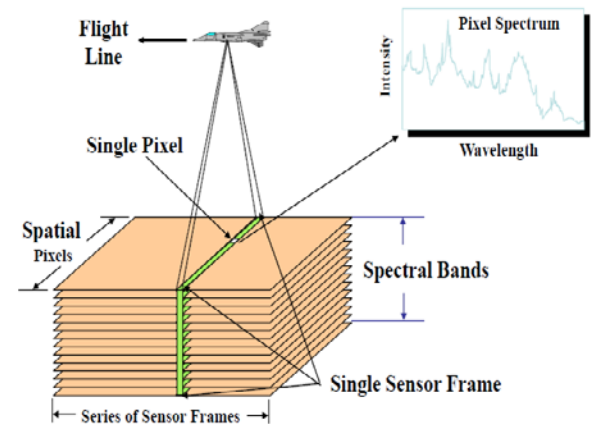

Fig4. Flight operations.

B. *Pre-processing of hyperspectral data*

An adequate preprocessing of hyperspectral data is a mandatory prerequisite to extract useful information from hyperspectral data. The large volume and complexity of the data generated by the hyperspectral sensors mean that it required large processing time.

The data has been subjected to geometric and atmospheric corrections to provide the basis for detailed analysis. The geometric correction is accomplished before the atmospheric correction.

B.1.Geometric correction

Accurate georeferenced image data is crucial to link the image to the reference data (Kempeneers,2007).

The VNIR-1600 and SWIR-320i modules have been integrated into an aircraft, where GPS and INS data are logged continuously to enable geometric correction and georeferencing of the images. Fig5. shows Pushbroom technique.

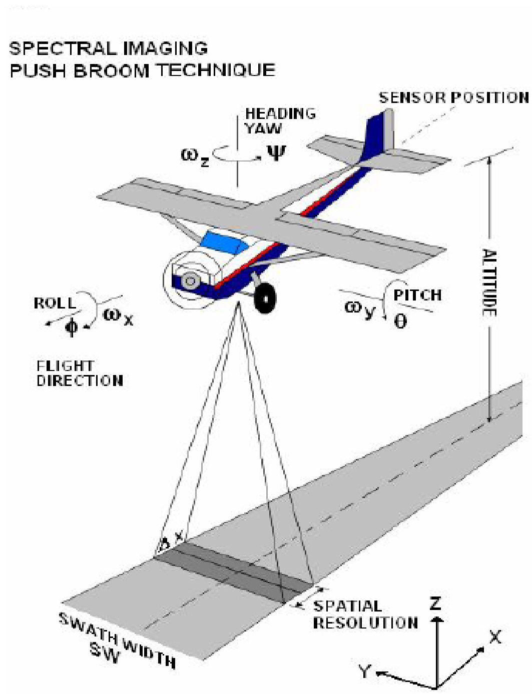

Fig5.Pushbroom technique.

Geometric correction has been performed by direct georeferencing using PARGE (PARametric Geocoding, ReSe Applications Schäpfler and RSL, University of Zurich) software. The PARGE outputs for each Hyper image include *.igm files (Lat/Long Geographic LUT for ENVI) and *.sca files (scan zenith/azimuth angles and the altitude for ENVI).

Distortions may be caused by the geometric characteristics of the sensor itself, variation in the position and orientation of the sensor (pitch, yaw and roll) and relief displacements (Garfagnoli et al.,2013) .

B.2. Atmospheric correction

The pre-processing of the data involved atmospheric correction using ATCOR 4, a program based on radiative transfer modelling of MODTRAN. That accounts for flat and rugged terrain, and includes haze/cirrus detection and removal algorithms(Storch et al.,2008). Fig 6. shows rectified VNIR image.

Fig 6.Rectified VNIR image flight line (frame) (strip).

C.Assessment of geometric correction

The accuracy of this rectification result is crucial for overlaying the data with existing data sets, maps, or in geographic information systems (GIS) and using them for evaluations like change detection, map updating, and others (Storch et al.,2008).

So it is important to evaluate the planimetric accuracy of rectified image. Twenty five well distributed DGPS check points were used for this purpose. The X and Y coordinates of check points in the rectified image were measured, and then compared with the corresponding coordinates from differential GPS surveys. Fig 7.illustrates distribution of DGPS check points on rectified VNIR image of the study area.

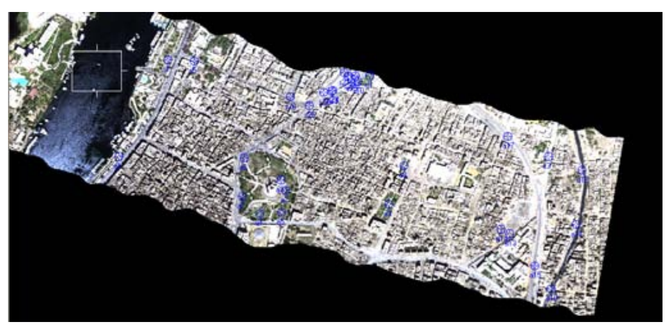

Fig 7.Distribution of DGPS check points on rectified VNIR image of the study area.

C..1.Development of a program using paython language for assessment of geopositioning accuracy

A program has been developed using paython language for assessment of geopositioning accuracy and used for assessment of the result of direct georefrencing. Table 2 provides RMST values of check points of VNIR image rectification using twenty five check points (units in meter).

Table 2. RMST values of check points of VNIR image rectification using twenty five check points (units in meter).

Number of check points	RMST of DGPS check points(m)
25	0.4

D .Feature selection

Spectral band selection is one of the problems in hyperspectral data. Although there may be hundreds of bands available for analysis, not all bands in the whole spectrum contain the discriminatory information for classification. In some parts of the spectrum, certain material might have sole spectral reflectance feature; on the other parts of the spectrum, the uniqueness of its spectral reflectance might be not very significant. Furthermore, the high dimensionality inevitably results in a larger volume of data.

The main objective of band selection is to remove the redundant spectral bands whilst not degrading the interpretation and classification accuracy (Guo et al., 2005).

Optimal bands have been selected from VNIR image. ENVI 5 software has been used for this purpose.

E. Map standards

The NMAS has stated that the planimetric accuracy requirements for a certain map scale are as follows:
RMST(m) = Scale number x 0.3 (mm); Equation 2
where:
RMST (m) = the planimetric accuracy (horizontal accuracy) Equation 3
Scale of map=1/scale number Equation 4 (Afify ,2005; Saati et a.l, 2008)
Table 3.shows map scales and standards.

Table 3.Map scales and standard.

Scale	Horizontal accuracy
1:1000	0.2
1:2500	0.40
1:5000	1
1:10000	2
1:25000	12.5
1:50000	25
1:100000	50
1:250000	200
1:500000	500
1:1000000	1000

(Mahmoud, 2004)

F. Information content

An indication of the information contents is the ground resolution (pixel size). The relation between the required GSD and the map scale is a key point for economic data acquisition (Jacobsen,2009). One selects the flight height according to the required map scale in order to preserve the planimetric accuracy of the map (i.e.0.2mm at the map scale) (Thomas ,2002). Other reference applies a rule of thumb for the relation of the pixel size and the map scale which is, 0.05 up to 0.1mm pixel size in the map scale for panchromatic image. With color images the interpretation is quite simpler, so the pixel size of color image may be larger by 1.5(Topan, et al.,2004).

G. Assessment of Mapping Capability

Assessment of Mapping Capability of VNIR image has been performed.

G.1.Assessment of map scale that produced from VNIR image

according to NMAS:
0.3*S/1000= 0.4

The scale that produced from VNIR image is 1333 □ 1:1000

From table 2, one can see that the horizontal accuracy of rectified VNIR image is consistent with the standard horizontal accuracy of 1:1000 map scale.

This means a root mean square error of planimetric accuracy of VNIR image equals to 0.4 m must be realized for the production of map scale 1333 □ 1:1000

Also the information content of the VNIR image is consistent with the map scale of 1:1000.

H .Planimetric large scale map production

Large scale map has been produced from two techniques. The first technique is manual map production and the second technique is automatic classification using neural network (ANN) and support vector machines (SVM).

H.1.Manual map production

Large scale map has been produced from airborne hyperspectral rectified data by visual interpretation using ArcGIS10. Fig8. shows vector map of the first study area 1:1000 map.

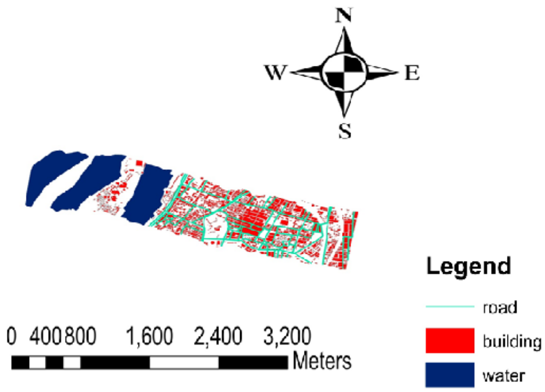

Fig 8.Vector map of the first study area 1:1000 map.

H.2. Automatic map production

H.2. 1.Automatic techniques

Image classification is automatically procedures that to categorize all pixels in an image into land cover classes. The experiment was done with two classifiers: ANN and SVM, and their results were compared.

H.2.1. 1.Neural Networks

Statistical techniques widely use the normal distribution assumption for remote sensing image classification. However, geographical phenomena do not occur randomly in nature and frequently are not displayed in the image data with a normal distribution. Neural networks learn whatever distribution present in the training data; consequently, they can be successfully applied instead of statistical methods. Neural networks have several advantages over classical statistical algorithms are the following:

• Neural classifiers do not require initial hypotheses on the data distribution and they are able to learn non-linear and discontinuous input data;
• Neural networks can adapt easily to input data containing texture information;
• Architecture of neural networks is very flexible, so it can be easily adapted for improving the performances of a particular application;
• The neural classifiers are generally more accurate than the statistical ones (Neagoe and Strugaru,2008; Stoica and Neagoe ,2013).

The multilayer perceptron (MLP) feed-forward artificial neural network is used. In a MLP, there are three types of layer, each consisting of processing nodes or neurons, these layers are fully interconnected to each other, except that there are no interconnections between nodes within the same layer. These layers are known as the input, hidden and output layers, respectively. All the neurons, except those in the input layer, perform two processing functions- collecting the activation signals of the neurons in the previous layer and generating an activation signal as the input to the next layer.
The neurons in the input layer only send signals to the next layer. The input layer nodes correspond to individual data sources, Hidden layers are used for computations, and the values associated with each node are estimated from the sum of the multiplications between input node values and weights of the links connected to that node. The output layer includes a set of nodes to represent the classes to be recognized (Jitendrudu,2005)

H.2.1.1.1.Training process of the ANN

Training the network determines the optimum weights and bias values for a given dataset. In this study we have used the backpropagation learning algorithm (BP) which is a supervised training algorithm for training the network. In BP algorithm the initial weights are randomly selected, then the calculated output of the network is compared with the expected output for each observation. The mean square error for all the observations in the training data set is calculated and then the ANN weights are modified according to the generalized delta rule, so that the total error is distributed among the different nodes of the network. The whole process is repeated, with weights being recalculated at every iteration, until the error is minimal, or else is lower than a given threshold value (Jitendrudu,2005).
Fig 9.shows conceptual model of Backpropagation algorithm.

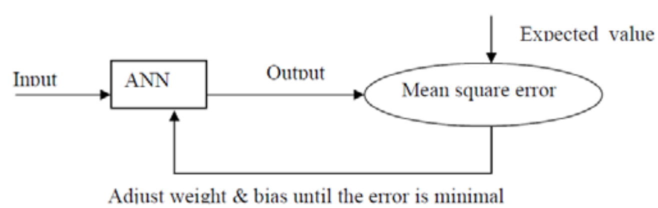

Fig 9. Conceptual model of Backpropagation algorithm.

Supervised neural network classification has been performed by utilizing neural network (feed-forward neural network with back propagation learning) that is available in ENVI 5 software.
After determining the number and type of classes to be studied, training samples have been collected in each class about thirty signatures in each of the eight classes “Roads, buildings, vegetation, water, desert, shadow, cars and boats”. The training data for two separate classes should not overlap. In the implementation of the ANN, a training threshold contribution value of 0.9, a training rate of 0.2, a training momentum of 0.9 and a training RMS exit criteria of 0.1 were used. The number of training iterations was set to 1000. Fig10. shows parameter of neural network. Fig11. indicates neural network RMS plot.

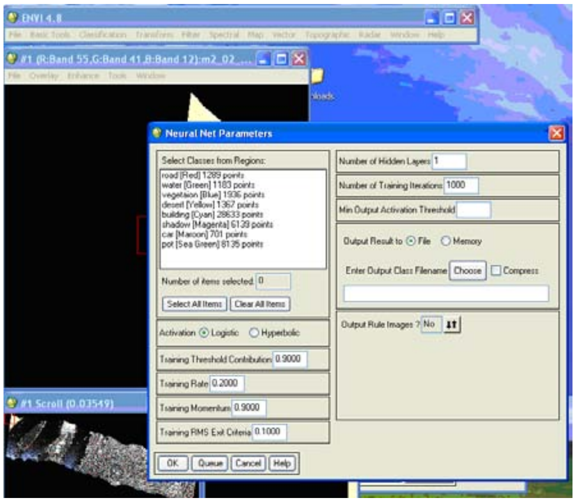

Fig 10 .Parameter of neural network.

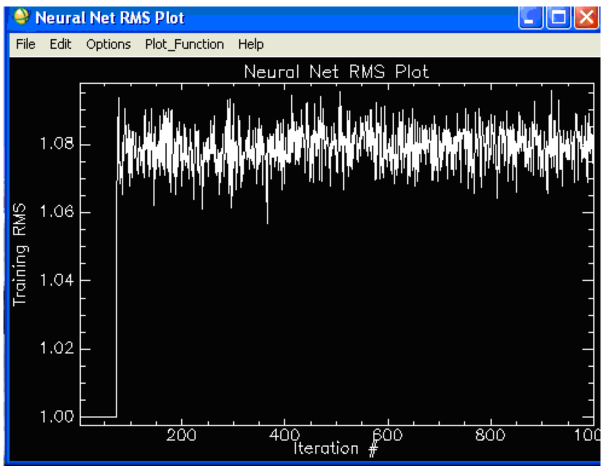

Fig11. Neural network RMS plot.

Fig12. shows maximization on a part of classified image using neural network.

Fig12. Maximization on a part of classified image using neural network.

Fig13. illustrates maximization on a part from vector that produced from classification to vector method of neural network results.

Fig13. Maximization on a part from vector that produced from classification to vector method of neural network results.

H.2. 1.2. Support vector machines (SVM)

Support vector machines (SVM) have grown speed up and shown a great potential as subpixel classifiers for remotely sensed data in recent years. (Yuhendra et al,2010). SVM is basically a binary classifier, which finds the maximal margin (hyperplane) between two classes. SVM can classify nonlinearly separable data sets by plotting the data into a high-dimensional feature space using kernels. In comparison to other data mining techniques such as ANNs, it is easier to use, and only a few parameters need to be adjusted by the users. (Naguib et al., 2009)

The selection of the SVM kernel classifier is regarded as the most important task in the implementation and the performance of the SVM classifier (Yuhendra et al,2010).

As a supervised classification method, the SVMs need a training procedure to construct the classifier from examples before applying to those unseen instances.

The same signatures that were used for training the neural network classifier have been used for training SVM classifier.

The SVM parameters are determined by gridding search model. In our experiment, radial basis function is adopted. Penalty parameter(C) is 150 and Gamma in kernel function (γ) is 0.17. The classification process was implemented in ENVI5 software.

Sieving and clumping techniques were conducted after supervised classifications. The function of sieving is to remove the isolated classified pixels in classification images using blob grouping.
The sieve classes method look at the neighboring 4 or 8 pixels to determine whether that pixel is grouped with pixels of the same class. When pixels were removed from a class using sieving, black pixels, which are unclassified, were left. Classified images usually faced some problems such as the lack of spatial coherency like speckle or holes in the classified

areas. Low pass filtering was later used to smooth these images, but the class information was contaminated by adjacent class codes. After that morphological operations were performed in order to remove noise.

The selected classes were clumped together by first performing a dilate operation and then an erode operation on the classified image.
Classification has been converted to vector form using ENVI software. It was found the vector needs some editing.

Fig14. illustrates maximization on a part from vector that produced from classification to vector method of SVM results.

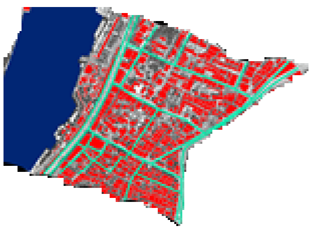

Fig14. Maximization on a part from vector that produced from classification to vector method of SVM results.

H.2. 2.Evaluation of the classification accuracy

Accuracy assessment is an important step to ensure the quality of the classification accuracy. Quantitative accuracy assessments of the classification results were performed using a confusion matrix. Finally, the overall accuracy and the Kappa coefficient are estimated. Fig15. shows the overall accuracy and Kappa coefficient of the two approaches.

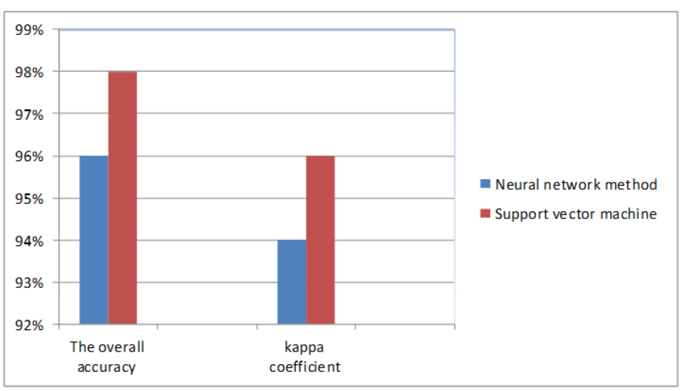

Fig15. The overall accuracy and Kappa coefficient of the two approaches.

III. Results and Discussion

The objective of this study was to investigate the large scale mapping from airborne hyperspectral data (VNIR image) in urban areas.
Geometric correction and atmospheric corrections have been performed. After that band selection has been implemented by eliminating the noisy and redundant bands whilst preserving the useful bands.

Quality of rectification has been assessed using twenty five well distributed DGPS check points. A program has been developed using paython language for assessment of geopositioning accuracy and used for assessment of the result of direct georefrencing. From table 2, one can notice that the horizontal accuracy of rectified images is 0.4 m, which is consistent with the standard horizontal accuracy of 1:1000 map scale. Also the information content of the VNIR image is consistent with the map scale of 1:1000 so, the scale of map that can be produced from the generated VNIR rectified image is 1:1000.

The rectified images were analysed and all the features present in the specifications of the various mapping scales has been attempted to interpret and capture. The features distinguished in this study included roads, urban, vegetation,water,desert, shadows, cars and boats. Many of the feature types those are required for 1:1000 scale mapping could be satisfactorily identified and captured in VNIR image. Figure 16 shows workflow of assessment of cartographic potential of airborne hyperspectral data.

It should be emphasized, however, that special attention must be paid to the accuracy of the mapping products generated by direct orientation of airborne hyperspectral system. The requirements of position and attitude accuracy are application dependent, defined primarily by the scale of the resulting maps.

Manual Planimetric map production has been performed using on screen digitizing of the data by utilizing ArcGIS10. In this research also automatic map production has been conducted. Firstly the performance of support vector machines (SVM) and artificial neural networks (ANNs) has been evaluated and compared for automatic classification of hyperspectral data. The subpixel classifications were implemented on ENVI5.

By comparing the overall accuracy and kappa index of the ANN classifier and SVM classifier, based on Figure 15, it is clear that the overall accuracy of the neural network method was 96%, and kappa coefficient was 0.94 and the overall accuracy of the Support vector machine method was 98%, and kappa coefficient was 0.96. It was observed that the Support vector machine classification is better than the neural network classification. The classification step was followed by morphological operations in order to remove noise then classification to vector conversion.

From visual examination of Figure 12, it is seen that, the road island has been classified correctly.

The analysis of results of class discrimination of both SVM and ANN has been shown that SVM yielded high quality thematic maps in urban areas.

It was found that the manual map production method is faster than the automatic methods and automatic methods needs manual editing compared to the resulted vector map from on screen digitizing.

V. Conclusions and Recommendations

In this research, the cartographic potential of airborne hyperspectral data was evaluated; Geometric correction using direct georefrencing and atmospheric have been performed.

After that optimal bands that are located at wavelengths that are known to be useful for discriminating urban have been selected.

Quality of rectification has been assessed using well distributed DGPS check points. A program has been developed using paython language for assessment of geopositioning accuracy of airborne hyperspectral data. Twenty five check points collected using DGPS were used for assessment of direct georefrencing of VNIR image. Accuracies better than a pixel can be achieved from rectification of VNIR using direct georefrencing(GPS/IMU).

Planimetric vector map has been produced using on screen digitizing of the data.

This research examined the potential of sub-pixel classification for automatic map production. In this study, the SVM and neural network classification algorithms were compared for automatic map production. Implementation of both the ANN and SAM was done using the same set of training and validation points.

The overall accuracy of the neural network method was 96%, and kappa coefficient was 0.94 and the overall accuracy of the Support vector machine method was 98%, and kappa coefficient was 0.96. After that morphological operations were performed in order to remove noise. It was found that the Support vector machine classification gives better results than the neural network classification.

It was found that the manual map production method is faster than the automatic methods and automatic techniques needs manual editing compared to the resulted vector map from on screen digitizing.

The map produced from SVM is better than the map produced from neural network.

The planimetric accuracy of airborne hyperspectral data depends on flying height and field of view (FOV).

The overall results showed that the planimetric accuracy and information content of VNIR image meet the requirements for map scale 1000. In conclusion, VNIR image is able to produce and update map of scale 1:1000. The relief displacement of building should be corrected using digital building height. It is recommended to use digital building height for orthorectification of urban area such as that resulted from LIDAR data to improve the accuracy of the results. Our future work will be investigating orthorectification of airborne hyperspectral data for hilly terrain by utilizing a DEM. Also it is recommended to use spectral library or field measurements using spectroradiometer.

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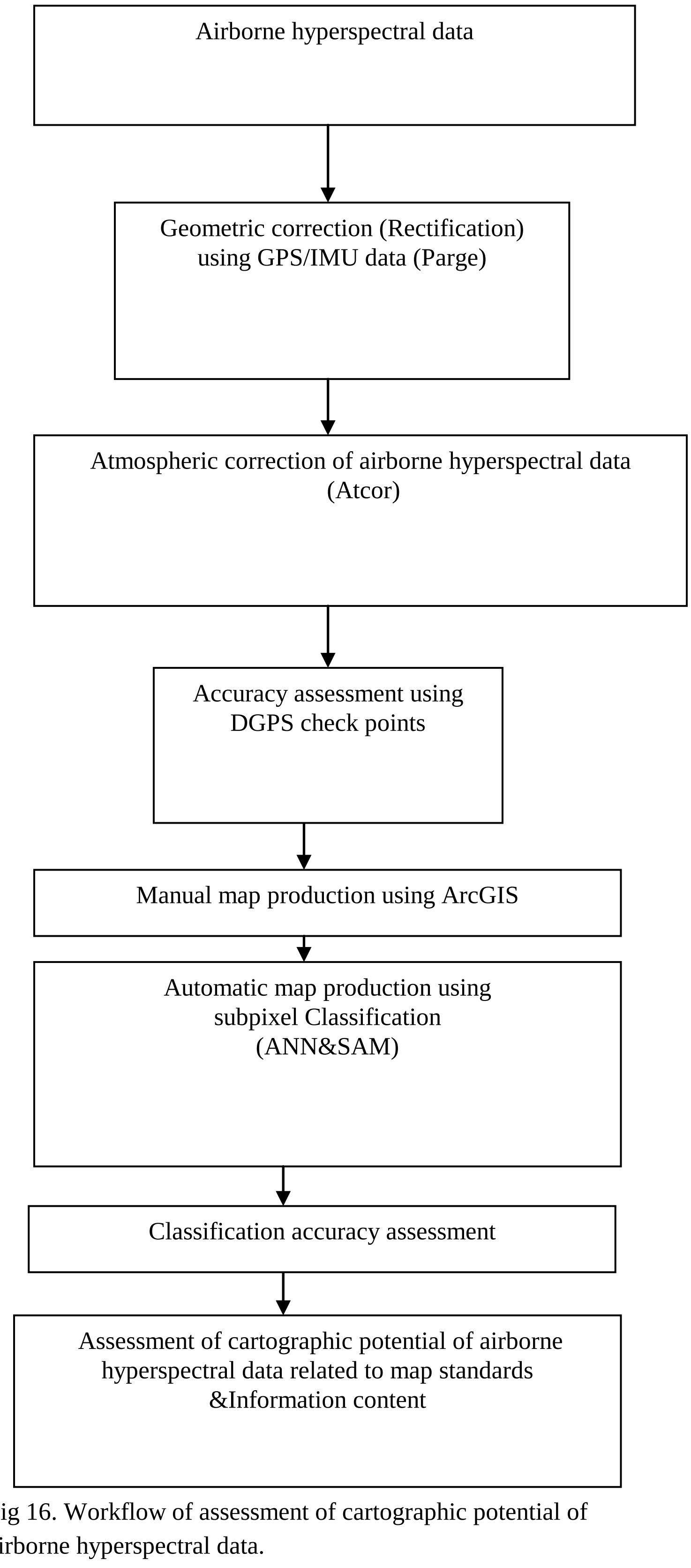

Fig 16. Workflow of assessment of cartographic potential of airborne hyperspectral data.