Automatic Road Network Extraction Based on Spectral Angler Mapper

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Abstract—Sinai peninsula is considered an important region for Egypt at both the national and strategic levels. Roads network is necessary for urban planning. Also base maps forms a base for determination of the soil suitability for reclamation, urban development and selection of the suitable type of development and investment that could be made in the area.

An accurate and up-to-date road network database is essential for GIS (Geographic Information System) based applications such as urban and rural planning, transportation management, vehicle navigation, emergency response, etc.

Since Sinai have rough terrain (hilly and mountainous areas), when producing base maps (orthoimages) the topography should be taken into consideration. DTM and DSM will be produced from the stereo satellite images of SPOT4 so we will get a representation of height.

The production of DSM and DTM have been performed on the digital photogrammetric workstation (Leica Photogrammetric Suite) LPS. The digital photogrammetric procedures include collection of GCPs,tie point measurements, aerial triangulation,block adjustment,manual DTM creation for the bare land, automatic DSM creation andDEM editing. The quality of the generated DTM has been validated. After that orthorectification of stereo satellite images has been performed on the digital photogrammetric workstation LPS. Orthorectification of mono multispectral images that is available for the study area has been implemented on the Erdas imagine. This has been followed by assessment of the quality of orthorectification using check points after that a mosaic of images has been made which has been used as base map. The results of producing the orthoimage from digital photogrammetric workstation and from image processing software have been evaluated.

Spectral Angler Mapper and maximum likelihood classification algorithms have been comparedfor classifying fused SPOT4 mosaic and SPOT5 imagewith and without incorporation of DSM as an additional channel. It was found that Spectral Angler Mapper was considerably more accurate thanmaximum likelihood classification.

After producing base maps roads have been extracted from manual digitizing of orthoimages and from automatic classification usingSAM taking into consideration DSM that have been produced from SPOT 4 stereo satellite images as a channel with the satellite image.

In comparing between high and medium spatial resolutions for the classification using SAM algorithm, it was found that even if SPOT4 has a medium spatial resolution and that sub-pixel contamination from different land cover is evident while selecting endmembers, it has given good results. On the other hand, SPOT5, which has a fine spatial resolution there are no sub-pixel contamination, gave lower accuracy results.

The majority of roads can be detected even without a DSM, though there are a relatively high number of false positives, mostly urban area. Both the completeness and the correctness values have notably improved compared to the results without the DSM.

Using a DSM improves both the completeness and the correctness of the results, primarily because urban can now be clearly separated from roads. The correctness is improved because urban are not extracted as false positives.

Keywords— road network extraction –digital photogrammetric workstation- stereo satellite images- DEM-Image fusion-Quality assessment – SPOT5-Spectral Angler Mapper.

INTRODUCTION

Roads are probably the most important topographic object class.Various existing and emerging applications require in particular up-to-date, accurate and sufficiently attributed road databases, including car navigation, tourism, traffic and fleet management and monitoring, intelligent transportation systems, internet-based map services, location-based services urban and rural planning, , etc (Zhang,2004). Often, road database is generated through field surveys with the help of GPS (Global Positioning System) enabled instruments. This approach of road extraction, however, is time consuming and labor intensive. With increase in availability of satellite imagery both in high and low resolutions, automatic road network extraction from satellite imagery has received considerable attention and has been studied extensively since 1970s. Since road region appear as linear segment in low resolution images, earlier research on road extraction focused on extracting road center-line from low resolution images. (Pandit,2009)

In low- and medium-resolution images, the road extraction was often considered as a linear feature extraction method, and roads as continuous and smooth lines.

For extraction of roads there are three approaches manual approach by overlaying road layer of map data on the orthoimage mosaic and inspecting the result visually in order to detect differences between the two data, semi automatic and automatic approach.

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Many approaches for road extraction have been developed. However, only few approaches work in urban or suburban areas due to the highly complex structure found in urban scenes which complicates the task of automatic road extraction. In some researches, the road network is expected to be a more or less regular grad but this constraint is not suitable for many urban areas. Another approach can use a very sophisticated road and context model and is based on grouping small extracted entities to lanes, carriageways and road networks (Naouai et al. , 2010)

The extraction of roads from digital images has drawn considerable attention in the last few decades, and is still one of the current challenges in digital photogrammetry and computer vision. Various existing and emerging applications require in particular up-to-date, accurate and sufficiently attributed road databases

One extraction approach cannot serve to deal with all kinds of images. For example, the appearance of roads strongly depends upon the given resolution and is therefore sensor-dependent. While roads appear as narrow lines, composed of only a few pixels in width in low-resolution images (ground pixel size > 2 m), they appear as elongated regions in images bearing higher resolution.

Furthermore, it is evident that the road appearance itself varies in different areas. Therefore, context information has been introduced in most road models, offering, similar general appearance of roads within the same context region. Once the distinction between low and high resolution as well as different contextual appearance has been made, a closer look at different road models can be taken (Hoheisel,2003).

The existing approaches cover a wide variety of strategies, using different resolution aerial or satellite images.

Semi-automatic schemes require human interaction to provide interactively some information to control the extraction. Roads are then extracted by profile matching, cooperative algorithms, and dynamic programming or LSB-Snakes. Automatic methods usually extract reliable hypotheses for road segments through edge and line detection and then establish connections between road segments to form road networks. Contextual information is taken into account to guide the extraction of roads. Roads can be detected in multi resolution images. The existing approaches show individually that the use of road models and varying strategies for different types of scenes are promising.

However, all the methods are based on relatively simplistic road models, and most of them make only insufficient use of a priori information, thus they are very sensitive to disturbances like cars, shadows or occlusions, and do not always provide good quality results. Furthermore, most approaches work in single 2D images, thus neglecting valuable information inherent in 3D processing.

The general methodology of automatic road extraction consists of the following steps:

Acquisition of images and pre-processing;

- Acquisition of the ground Control Points (GCPs) with image coordinates and map coordinates;
- Computation of the unknown parameters of the mathematical functions used for the geometric correction model;
- Image orthorectification using an appropriate DEM;
- Determination of classification system
- Preparation of ground truth data based on the predetermined classification system
- Classification by satellite data
- Correction and modification
- Validation using ground truth data (Tateishi, 2002)

Developments in digital photogrammetry have provided the availability to generate Digital elevation models (DEMs) from stereo satellite images. The achieved accuracy of DEMs based on space images is mainly depending upon the image resolution, the height-to-base-relation and the image contrast.(Jacobsen,2003) The manual measurement of DEMs is too time consuming, so most of the data acquisition has to be made by automatic image matching. This includes the disadvantage of a not selected point location. Instead of a DTM, a Digital Elevation model (DEM) or (DSM) will be generated. DTM could be produced manually.

The inputs for the orthoimage production are the interior orientation (CCD look angles), the six parameters of the exterior orientation for each image line (interpolated from the measured sampling points) and the DSM.

One approach for reducing spectral confusion between some land cover types would be to incorporate a third dimension into the analysis(Herold and Roberts,2010)

One of the objectives in this study was to assess the contribution of incorporating elevation data in image classification to improve the spectral information accuracy.

In this research, Spectral Angler Mapper and maximum likelihood classification algorithms were compared for automatic classification after thatSpectral angle mapper classifier has been used for automatic road extraction. A major difference between the spectral angle classifier and standardclassifiers (ISODATA, minimum distance, maximum likelihood, decision trees, neural nets, etc.) is that the spectral angle classifier rests on the spectral shape pattern, i.e., the "identity" of the spectral pattern, while conventional classifiers rest on the statistical distribution pattern. Even though it is true for all the classifiers, especially when the spectral angle classifiers are used, the analyst's ability to relate field information to spectral characteristics and spectral shape patterns of different land-cover land-use types is an important factor for acquiring accurate and adequate mapping results (Sohn and Rebello,2002)

The Spectral Angle Mapper (SAM) is a physically-based spectral classification that uses an n-dimensional angle to match pixels to reference spectra. The algorithm determines the spectral similarity between two spectra by calculating the angle between the spectra, treating them as vectors in a space with dimensionality equal to the number of bands(ENVI User's Guide,2005).

II. Study Area and Data Set

North Sainai Governorate has been selected as study area. It covers a total area of 27574 km^2.

The following data Sources were available

- A 1:50 000 topographic maps.
- Spot 4 resolution 20m Multispectral and panchromatic 10m Dated 2011.
- Stereo images Spot 4 Dated 2007,2008,2009
- Spot 5 imageDated 2011.
- DGPS Ground control points and check points obtained with 10 cm accuracy in X,Y,Z.

III. Methodology

1-Importing images
2-Collection of GCPs
3-Image orientation and aerial triangulation
For the orientation of SPOT 4 images rigorous sensor model for pushbroom linear array sensors has been used.
4-Creation of DEM&DSM
5-Assessment of DEM quality using check points (vertical accuracy)
6-Orthorectification of stereo images using digital photogrammetric workstation& use of DSM for orthorectification of mono images using image processing software
7- Assessment of the orthorectification quality (horizontal accuracy)
8-Mosaicking of orthorectified images and use it as a base map.
9-Fusion of pan mosaic with multispectral mosaicusing high pass Filter fusion.
10- Automatic classification offused SPOT4 mosaic and SPOT5 imageusing Spectral Angler Mapper and maximum likelihood classification with and without incorporating DSM.
11-Assessment of classification accuracy.
12- Road extraction using two techniques (manual &automatic classification using maximum likelihood classification and SAM)

A. Digital photogrammetric workstation environment

LPS consists a core part and several add-on modules. The major functions of the core include project setup, sensor modeling, control point measurement, automatic tie point collection, triangulation, automatic terrain model extraction, orthorectification and mosaicking as shown in Figure 1.

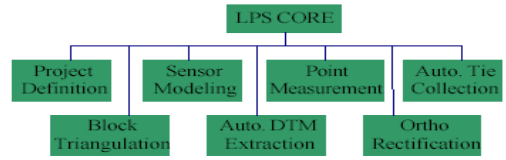

Fig1. Modules of digital photogrammetric workstation LPS.

A.1. Photogrammetric project creation.

A project was created to include SPOT4 images, the datum were chosen WGS84 and the projection UTM ZONE 36. Leica Photogrammetric Suite (LPS) Module of Erdas Imagine 9.2 software was utilized. Figure 2 illustrates project creation.

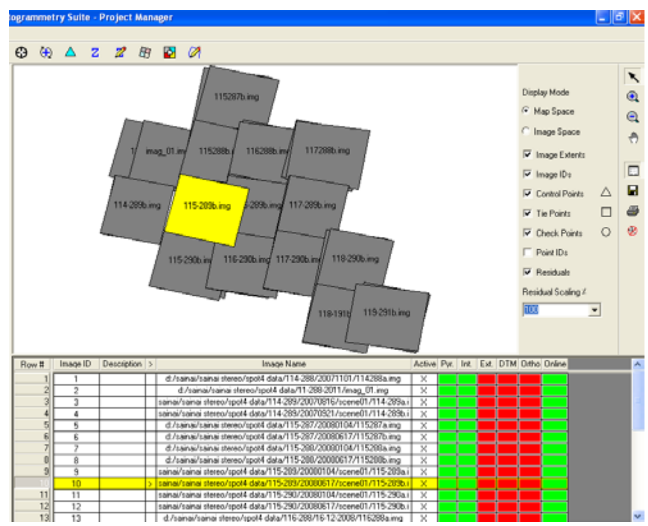

Fig 2.Project creation.

A.2. Importing images

Importing images is the most sophisticated data conversion process because it usually involves a file with a relatively large size .The technique to be used to import data depends on the type of the sensor that is associated with the imagery.

A. 3. Interior orientation

Interior orientation is not required with SPOT images. The software read it from the header file.

A. 4. Automatic point measurement (APM)

Automatic Point Measurement (APM) includes automatic assistance of ground control point measurement, automatic tie point collection over entire block or sub-block and automatic tie point transfer from one image or sub-block to another. The APM procedure of LPS includes block connection to set up the relationship between images, feature extraction and matching, and robust gross error checking and least square correlation (Wang et al.,2007).Figure 3shows image matching.

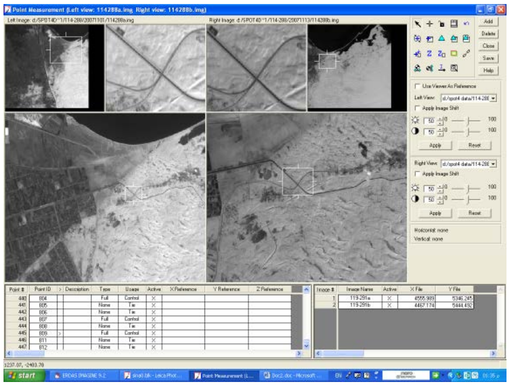

Fig 3.Image matching.

A. 5. Ground control points and check points collection

Through field trip the following data have been collected:
-DGPS Ground control points
-Check points ,
The term ground control refers to a set of fixed points on the ground for which precise horizontal and vertical coordinates can be determined. These coordinates enable the photogrammetrist to position and correlate map features from satellite stereopair accurately and to tie the mapping to an established horizontal and vertical coordinate system, or datum. Surveyors can select appropriate image identifiable points on the ground. Figure 4 shows distribution of differential GPS stations on Spectrum survey program. Figure 5.shows the distribution of differential GPS over the orthomosaic of SPOT4. Figure 6 illustrates localization of GCPs using& image matching.

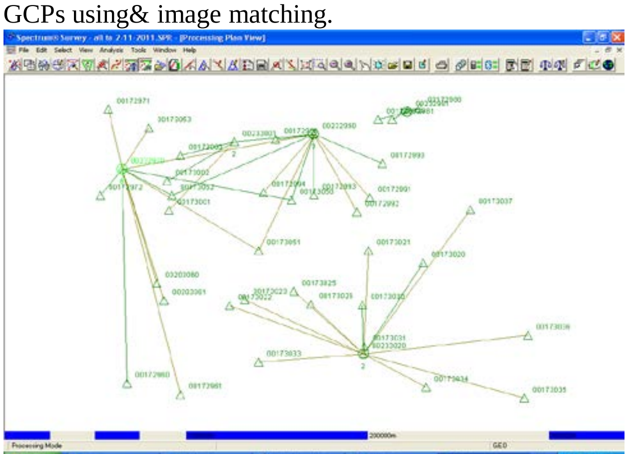

Fig 4.Distribution of differential GPS stations on Spectrum survey program.

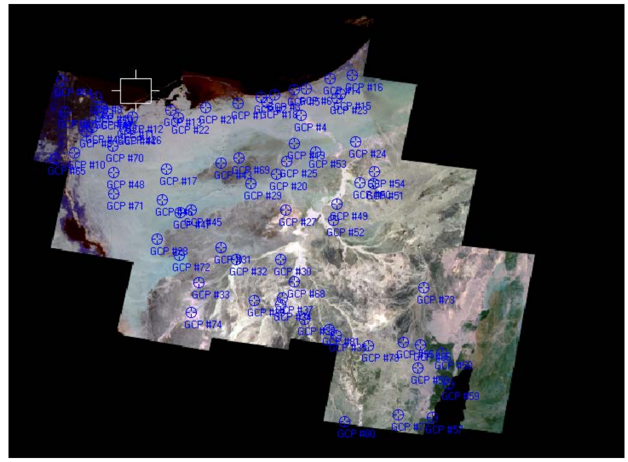

Fig 5.Distribution of differential GPS over the orthomosaic of SPOT4.

A. 6.Block Adjustment

In order to improve accuracy, multiple overlapping images are block adjusted together. Block adjustment of multiple overlapping images uses least-squares estimation process to estimate the sensor model parameters for each image. The images are tied together by tie points whose image coordinates are measured on multiple images.

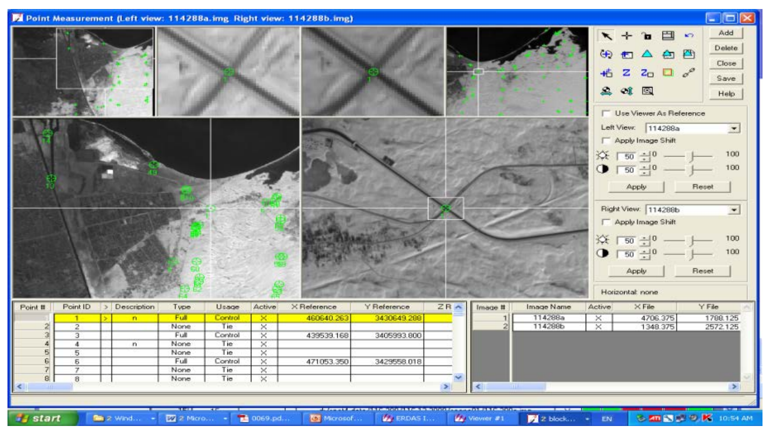

Fig 6.Localization of GCPs using& image matching.

4. 7.DEM generation

DEM data can be obtained from stereo images in photogrammetry methods. The manual measurement of DEMs using photogrammetric instruments and digital systems is time consuming. Therefore, the automation of DEM from aerial photographs/ stereo satellite images is preferred. Automation of the photogrammetric working process is one of the major subjects for image correlation (Karabork et al.,2008). Figure 7 shows flowchart of DEM and orthoimage generation from digital photogrammetric workstation.

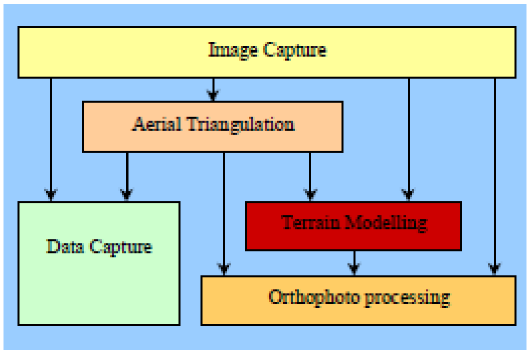

Fig 7.Flowchart of DEM and orthoimage generation from digital photogrammetric workstation.

A. 8.Automatic DSM generation

Tools for automated photogrammetric DEM generation are now available. These tools employ image-matching techniques, or autocorrelation, to automate the measurement of DEM points. They generally produce surface models posted on a regular grid that incorporate vegetation and buildings within the model. Mostly, a technique is used, named area based matching, based on pattern, target and search window, when points are identified if they have similar grey values (Ruzgien ,2007). DEMs that have been produced through autocorrelation are subject to random errors and must be examined and edited while superimposed on the imagery. The correlation software can produce erroneous results in areas of relatively uniform tone and texture and in areas of vegetation (U.S. Army Corps of Engineers,2004). Figure 8 indicates an example of automatically generated DSM using digital photogrammetric workstation.

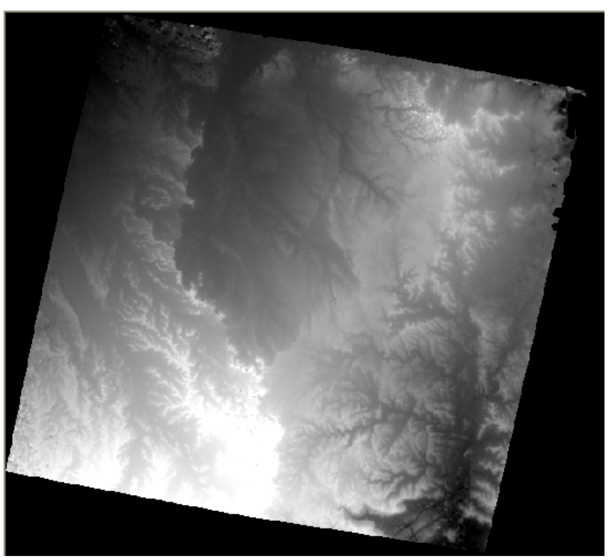

Fig8. Example of automatically generated DSM using digital photogrammetric workstation.

A. 9.Accuracy assessment

Inaccurate DEMs may introduce errors in image classification. Because DEM accuracy is critical for topographic effect correction(Fahsi et al.,2000)

DEM quality validation has been performed using DGPS check points that observed in different topography. Figure 9 shows the ellipsoidal heights of check points. The accuracy of the generated DEM was found 12 m.

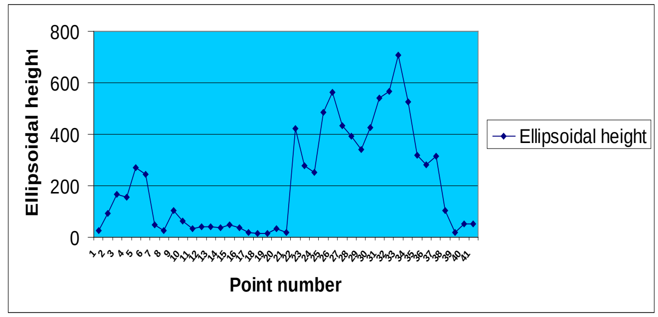

Fig 9.Ellipsoidal heights of check points.

A. 10.Manual DTM measurement SPOT height measurement

In all 15 stereomodels elevations were measured manually.

B. Manual road extraction from orthoimage

B.1.Orthorectification of SPOT 4 images using stereo SPOT DEM

Orthorectification is the process of geometrically adjusting a perspective image to an orthogonal image by transforming coordinates from the image space to the ground space and removing tilt and relief displacement (Liu et al.,2007)

For areas with high terrain relief a differential registration procedure is necessary to ensure that the images are in perfect registration.

SPOT4 images were orthorectified using control points and a digital elevation model obtained from stereo pairs of SPOT level 1A, differential rectification of SPOT, which includes elevation data was used in performing a polynomial geometric correction and the images were resampled using nearest nighbour method to 10 m for pan and 20 m for multispectral images to match the SPOTpan and SPOT multispectral resolutions. The image was corrected to WGS84 datum and the Universal Transverse Mercator (UTM) map projection zone 36 and. The X and Y root mean square error was less than 5 m and 10 m respectively (0.5 pixels) for all images, guaranteeing a precise geometric match among them. After geometric correction the pan images were mosaicked and also the multispectral images were also mosaicked after that the multispectral image were resampled to 10 m resolution and finally two mosaics were fused using high pass Filter fusion method this mosaic will be used for image classification.

Figure 10 illustrates an example of generated orthoimage from digital photogrammtric workstation. Figure 11 shows mosaic of panchromatic images. Figure 12 shows mosaic of multispectral images. Figure 13 shows coregisteration between mosaic of panchromatic images and mosaic of multispectral images. Figure 14 shows fused mosaic. Figure 15.indicatesManual extracted roads from SPOT 4 mosaic.

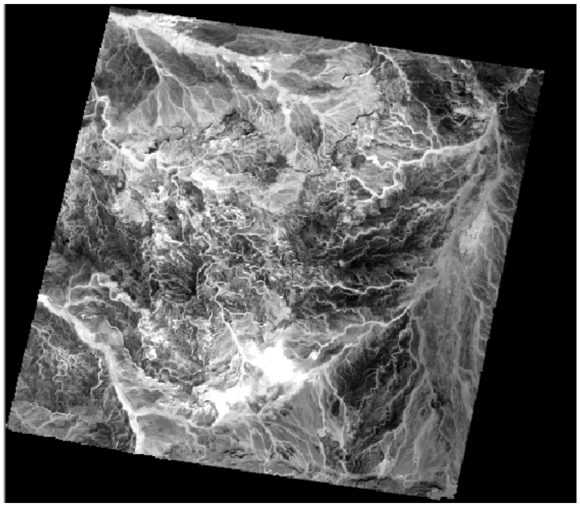

Fig10. Example of generated orthoimage from digital photogrammtric workstation.

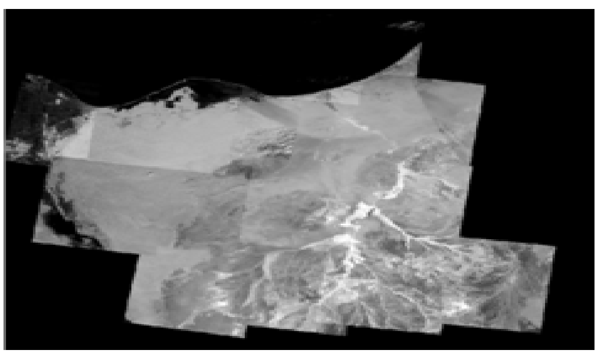

Fig 11. Mosaic of panchromatic images.

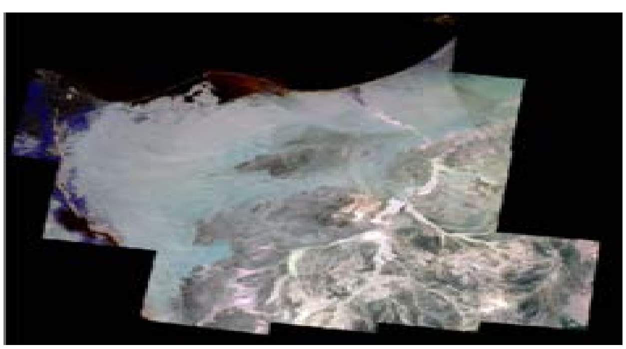

Fig 12.Mosaic of multispectral images.

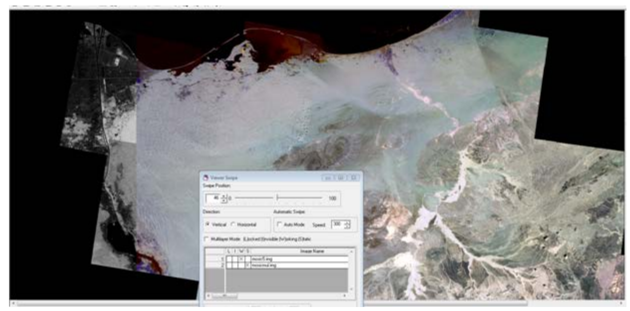

Fig 13.Coregisteration between mosaic of panchromatic images and mosaic of multispectral images.

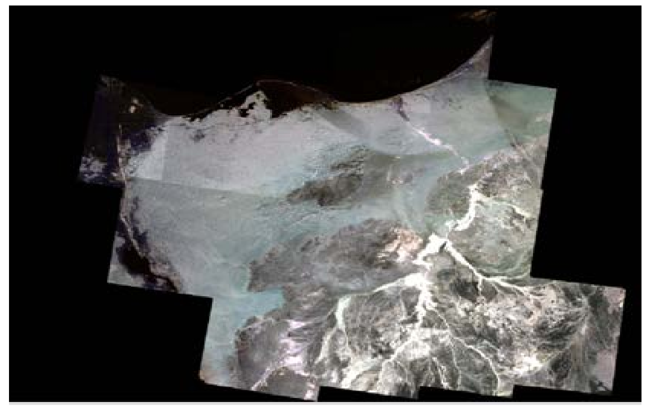

Fig 14.Fused mosaic.

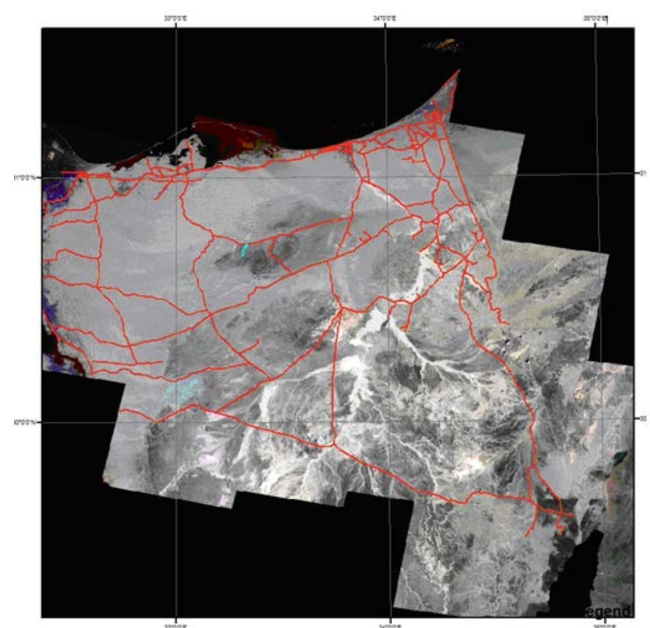

Fig 15. Manual extracted roads from SPOT 4 mosaic.

B.2.Orthorectification of SPOT 5 images using stereo SPOT4 DEM

SPOT5 image was radiometrically and geometrically corrected and orthorectified using control points observed using DGPS and a digital elevation model obtained from stereo pairs of SPOT level 1A, to WGS84 datum and the universal transverse Mercator (UTM) coordinate system zone 36 and resampled to 2.5 m to match the fused SPOT5 resolution. The image was orthorectified following the method of differential rectification of SPOT5, which includes elevation data in performing a polynomial geometric correction. The X and Y root mean square error was 1.2 m.
Figure 16.indicates Manual extracted roads from SPOT 5 image using on screen digitizing of orthoimage.

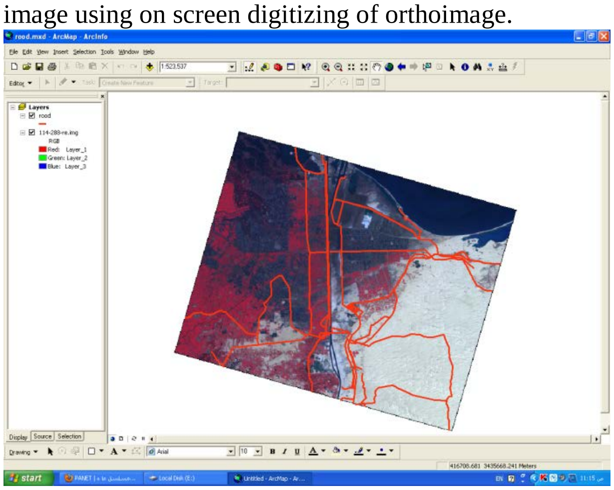

Fig 16. Manual extracted roads from SPOT 5 image.

C. Automatic road extraction from orthoimage

C.1. Maximum Likelihood
The maximum-likelihood classifier is a parametric classifier that relies on the second order statistics of a Gaussian probability density function model for each class. The class probability density functions usually are assumed to be normal, then the discriminant function becomes

$$g^{i} = p(X \mid w_i)\, p(w_i)$$

$$= p_i (2\pi)^{-n/2} |\Sigma_i|^{-1/2} \bullet \exp\left\{-\frac{1}{2}(X-M_i)' \Sigma_i^{-1}(X-M_i)\right\}$$

where$n$ is the number of bands, X is the data vector, $M_i$is the mean vector of class i, and $\Sigma_i$is the covariance matrix of class i,

$$X = \begin{bmatrix} x_i \\ x_i \\ x_i \\ \vdots \\ x_i \end{bmatrix} \qquad M_i = \begin{bmatrix} \mu_{i1} \\ \mu_{i2} \\ \mu_{i3} \\ \vdots \\ \mu_{in} \end{bmatrix} \qquad \Sigma_i = \begin{bmatrix} \sigma_{i11} & \sigma_{i12} & \sigma_{i13} & \cdots & \sigma_{i1n} \\ \sigma_{i21} & \sigma_{i22} & \sigma_{i23} & \cdots & \sigma_{i2n} \\ \sigma_{i31} & \sigma_{i32} & \sigma_{i33} & \cdots & \sigma_{i3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{in1} & \sigma_{in2} & \sigma_{in3} & \cdots & \sigma_{inn} \end{bmatrix}$$

In the maximum-likelihood classification, pixels are allocated to their most likely class of membership. Given equal *a priori* probabilities, this can be achieved by allocating each case to the class with the highest probability density function, or equivalently, by allocating each pixel to the class with which it has the highest *aposteriori* probability of membership. For equal *a priori* probabilities, the *a posteriori* probabilities are assessed as the probability density of a case relative to the sum of the densities (Han et.al. , 2005).

Two approaches were used .The first approach utilizes the spectral properties and the second approach utilizes the spectral properties and the elevation generated from the stereo panchromatic bands.

C.2. SAM classification

The classification methods for feature spectra are based on a comparison of the spectral image with a reference spectrum (endmembers or spectral libraries).

SAM is a non-probability-based algorithm that separates image spectra according to a cumulative angular coefficient that is derived from each spectral data point. Fundamentally, there is an inverse relationship between the number of bands and the probability of a key band being removed that was associated with a subtle spectral feature needed to differentiate one or more classes. If only two bands were used, each spectrum would be reduced to a single, decision-space vector, and all subtle features would be lost (Becker et al.,2007).

The spectral angle classifiers classify the image pixels based on the minimum "angular distance" rule. SAM performs supervised classification using provided training data (signatures).

C.2. 1.Spectral angle and spectral distance

In two-dimensional feature space defined by bands x and y, two spectral signatures that represent two different surface objects can be represented as vectors v1, and v2, (Figure 18). Then the spectral distance (Euclidean distance) is the length of the line segment d connecting the end points of the two vectors v1 and v2. The spectral angle ϴ is the angle between the two vectors v1, and v2 : i.e.,

$$\theta_{\mathbf{v}_1,\mathbf{v}_2} = \cos^{-1} \frac{\mathbf{v}_1^{\mathrm{T}} \mathbf{v}_2}{\|\mathbf{v}_1\| \|\mathbf{v}_2\|}$$

Figure 17 shows spectral angle and spectral distance.

If we linearly scale the length of vectors v1, and v2, by distance r, the spectral distance will be scaled by r. On the other hand the cosine of the angle ϴ between the two vectors vl and v2, remains the same. Because of this invariant nature of the cosine of the angle ϴ to the linearly scaled variations, it becomes sensitive to the shape of the spectral patterns.
When a spectral angle classifier based on "angular distances" is used, image pixels that have similar shape patterns will be

classified together into the same cluster or information class (Sohn and Rebello,2002).

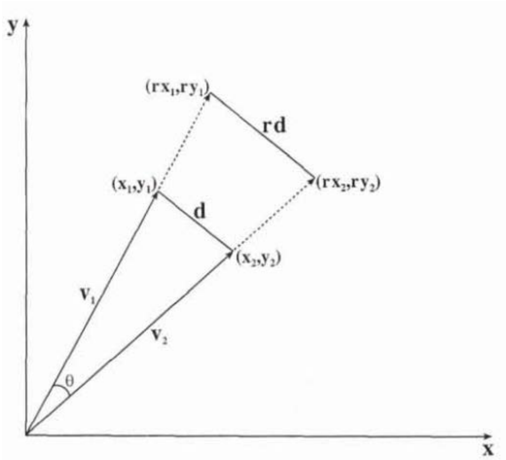

Fig17. Spectral angle and spectral distance.

C.2. 2.supervised Spectral Angle Classifier

One of the most applied strategies for material mapping is the use of similaritymeasures. This study makes use of a deterministic similarity measure to compare an unknown pixel spectrum with a library of reference spectra.

Step 1: Find the spectral angle Θi,

image and every reference class r:

$$\theta_{i,r} = \cos^{-1}\left[\frac{\sum_{k=1}^{m} x_{i,k}\,\mu_{r,k}}{\sqrt{\sum_{k=1}^{m} x_{i,k}^{2}\sum_{k=1}^{m}\mu_{r,k}^{2}}}\right]$$

Where Θ

referencespectrum r, m is the number of bands, xi,k is the pixel value in band k, and μr,k is the mean pixel value of reference class r in band k.

Step 2: Assign each pixel to the reference class r that has the smallest spectral angular distance between pixel i and reference class r. For each pixel i = 1 to n, find the reference class r such that Θ

Rebello,2002).

Maximum-likelihood andSAM classification were performed for both fused SPOT4 mosaic and SPOT5 satellite image classified into six spectral classes using ENVI4.8 software.

After determining the number and type of classes to be studied, training samples (ROI) have been collected in each class about thirty signatures in each of the six classes “road - urban-agriculture-water- desert and wetland”. The training data for two separate classes should not overlap. Spectral plot was checked before classification. Figure 18 shows ROI collection on SPOT5. Figure 19 shows endmember collection. Figure 20 Statistics results.

Figure 21indicates example of classified image of fused SPOT 4 mosaic using SAM.

Figure 22 indicates example of classified image of SPOT 5 image using SAM.

When the six image endmembers were processed via the SAM algorithm, excellent discrimination between the different endmembers was found.

Two approaches were used.The first approach utilizes the spectral properties and the second approach utilizes the spectral properties and the elevation generated from the stereo panchromatic bands.

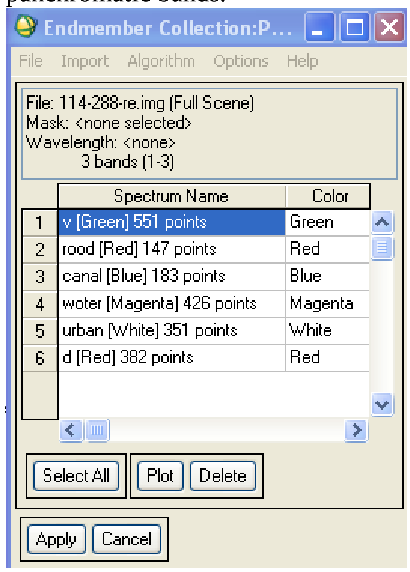

Fig19.Endmember collection.

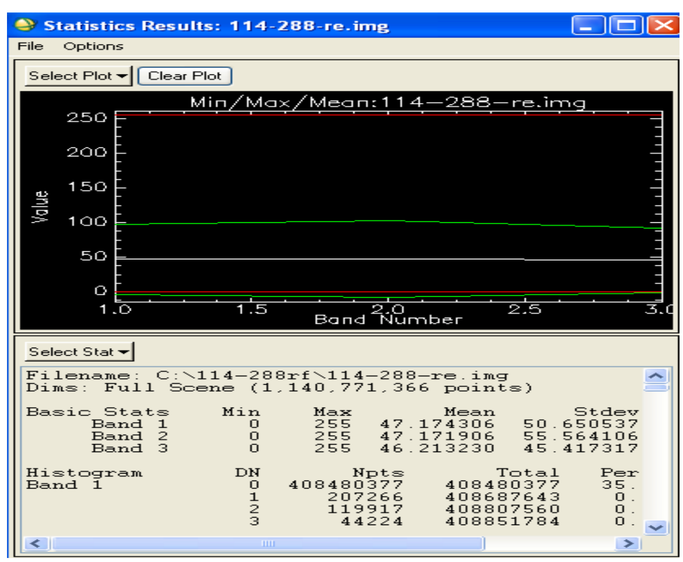

Fig 20.Statistics results.

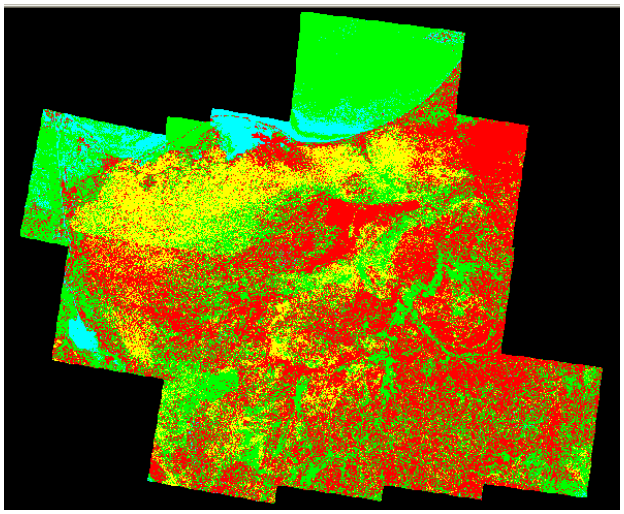

Fig 21. Example of classified image of SPOT 4 mosaic using SAM .

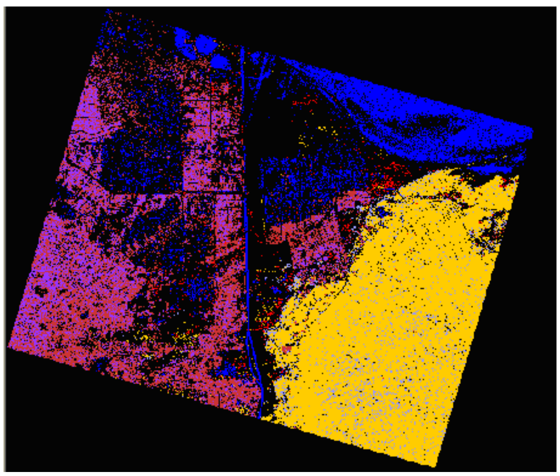

Figure 22.Example of classified image of SPOT 5 image using SAM.

Thematic accuracy check points have been collected from the field and used for classification accuracy assessment.
The overall accuracy and a KAPPA analysis were used to perform classification accuracy assessment based on error matrix analysis.
Using the simple descriptive statistics technique, overall accuracy is computed by dividing the total correct by the total number of pixels in the error matrix. KAPPA analysis is a discrete multivariate technique used in accuracy assessments
The comparison of classification accuracies of fused SPOT4 mosaic is carried out between the first approach and the second approach for both classifiers.For Maximum-likelihood classifier, it is found that the second approach has the overall accuracy of 88.12% and the Kappa coefficient of 0.79. The first approach has the overall accuracy of 86.23% and the Kappa coefficient of 0.72. It clearly indicates that the second approach has a better accuracy than the first approach.For SAM classifier, it is found that the second approach has the overall accuracy of 94.17% and the Kappa coefficient of 0.91. The first approach has the overall accuracy of 91.63% and the Kappa coefficient of 0.84. It clearly indicates that the second approach has a better accuracy than the first approach. Figure 23 illustrates overall accuracy and Kappa coefficient of fused SPOT4 mosaic using Maximum-likelihood and SAM classifier.
The comparison of classification accuracies of SPOT5 is carried out between the first approach and the second approach.For Maximum-likelihood classifier, it is found that the second approach has the overall accuracy of 87.33% and the Kappa coefficient of 0.79. The first approach has the overall accuracy of 84.16% and the Kappa coefficient of 0.65. It clearly indicates that the second approach has a better accuracy than the first approach.
For SAM classifier,it is found that the second approach has the overall accuracy of 93.02% and the Kappa coefficient of 0.93. The first approach has the overall accuracy of 90.25% and the Kappa coefficient of 0.81. It clearly indicates that the second approach has a better accuracy than the first approach. Figure 24 illustrates overall accuracy and Kappa coefficient of SPOT5 image using Maximum-likelihood and SAM classifier. The results show that SAM classifier was considerably more accurate than Maximum-likelihood classifier.

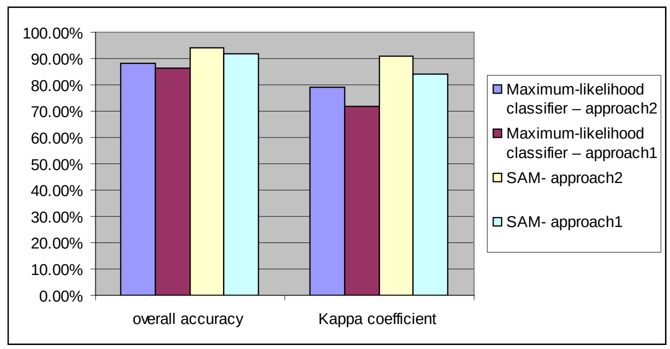

Fig 23. Classification accuracies of fused SPOT4 mosaic using Maximum-likelihood and SAM classifier.

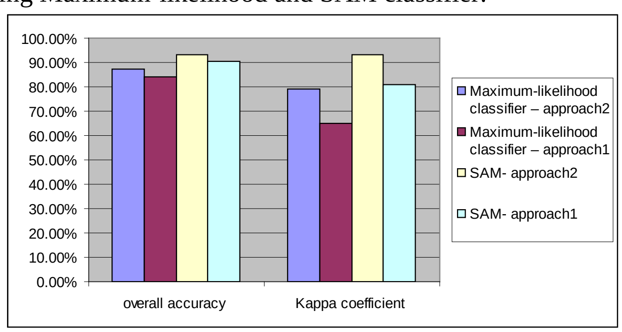

Fig24. Classification accuracies of SPOT5 image using Maximum-likelihood and SAM classifier.

Figure 25.indicates automatically extracted roads from SAM classification of SPOT4 mosaic with DSM.

Fig 25. Automatically extracted roads from SAM classification of (SPOT4 mosaic with DSM).

Figure 26 indicates overlay of automatically extracted roads from SAM classification of (SPOT5 image with DSM) over the orthoimage .

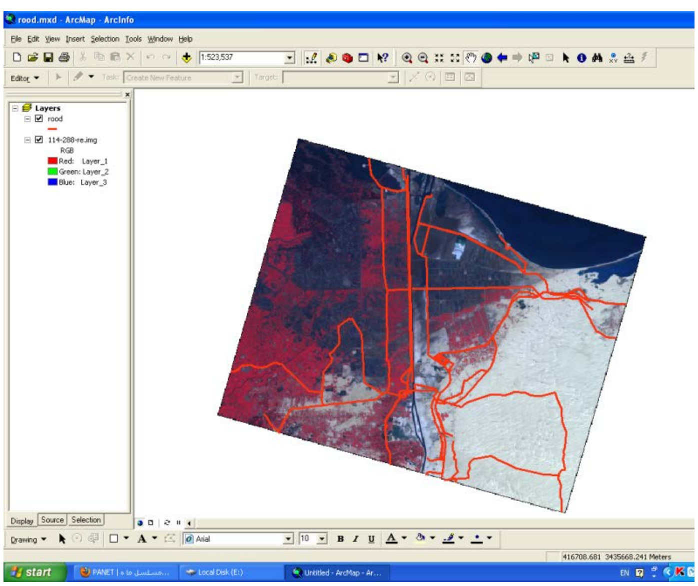

Fig 27.Overlay of automatically extracted roads from SAM classification of (SPOT5 image with DSM) over the orthoimage.

Morphological opening with kernel size of 3×3 followed by morphological closing with kernel size of 3×3 have been applied to each of the resulted roads masks using ENVI 4.8 software.

IV.EVALUATION OF THE ROAD EXTRACTION RESULTS

Completeness is defined as the percentage of reference data that is covered by the extracted data. The coinciding amount of reference data and extracted data is the measure of completeness:

Completeness = Length of matched reference/ Length of reference

Practically, a buffer of a certain extension is created around the extracted vectors. The choice for the buffer width generally depends on the geometric uncertainty. For all investigated imagery in this work, however, the buffer width was set to 7.5 meters. This enables a direct comparison of the imagery's reliability and its usefulness for road extraction. Consequently, this immediately affects the quality measures, as any reference data not situated within the extraction's buffer results in a loss of completeness. Therefore, inaccuracies are expressed directly by this quality measure.

Correctness is defined as the percentage of extracted data that lies within a buffer around the reference data. The correctness therefore represents the percentage of correctly extracted road data:

Correctness = Length of matched extraction/ Length of extraction

Quality is defined as a combination of the measures completeness and correctness, representing an overall single measure for the final result:

Quality Completeness .Correctness/ Completeness - Completeness Correctness Correctness (Hoheisel,2003)

Table 1.indicates Correctness and completeness indexes of the four approaches of SAM.

Table 1.Correctness and completeness indexes of the four approaches of SAM.

Method	**Completeness**	**Correctness**
Fused SPOT 4 mosaic without DSM	89 %	62 %
Fused SPOT 4 mosaic with DSM	94 %	66%
SPOT 5 image without DSM	86 %	59 %
SPOT 5 image with DSM	87 %	60 %

V. CONCLUSIONS

SPOT 4 and SPOT 5 satellite images have been orthorectified based on DSM generated from stereo SPOT images using automatic image matching and DGPS control points. Digital photogrammetric workstation (Leica photogrammetric suite) LPS was utilized for this purpose.

DEM quality validation has been performed using DGPS check points that observed in different topography .The accuracy of the generated DEM was found 12 m.The X and Y root mean square error was less than 5 m and 10 m respectively (0.5 pixels) for all images, guaranteeing a precise geometric match among them. After geometric correction the pan images were mosaicked and also the multispectral images were also mosaicked after that the multispectral image were resampled to 10 m resolution and finally two mosaics were fused using high pass filter fusion method. This mosaic has been used for image classification.

In this study, Spectral angle mapper and maximum likelihood classification algorithms were compared with and without incorporation of DSM as an additional channel.

After determining the number and type of classes to be studied, training samples (ROI) have been collected in each class about thirty signatures in each of the six classes “road -urban-agriculture-water- desert and wetland”. The training data for two separate classes should not overlap. Spectral plot was checked before classification.

Quantitative accuracy assessments of the classification results were performed using a confusion matrix computed using ground truth testing data that was distinct from the training data that used to perform the classification

For Maximum-likelihood classifier the comparison of classification accuracies of fused SPOT4 mosaic is carried out between the first approach and the second approach, it is found that the second approach has the overall accuracy of 88.12% and the Kappa coefficient of 0.79 whilethe first approach has the overall accuracy of 86.23% and the Kappa coefficient of 0.72. It clearly indicates that the second approach has a better accuracy than the first approach. For SAM classifier, it is found that the second approach has the overall accuracy of 94.17% and the Kappa coefficient of 0.91whereasthe first approach has the overall accuracy of 91.63% and the Kappa coefficient of 0.84. It clearly indicates that the second approach has a better accuracy than the first approach

The comparison of classification accuracies of SPOT5 is carried out between the first approach and the second approach.For Maximum-likelihood classifier, it is found that the second approach has the overall accuracy of 87.33% and the Kappa coefficient of 0.79 whilethe first approach has the overall accuracy of 84.16% and the Kappa coefficient of 0.65. It clearly indicates that the second approach has a better accuracy than the first approach.

For SAM classifier, it is found that the second approach has the overall accuracy of 93.02% and the Kappa coefficient of 0.93 whereasthe first approach has the overall accuracy of 90.25% and the Kappa coefficient of 0.81. It clearly indicates that the second approach has a better accuracy than the first approach.

It was found that Spectral Angler Mapper was considerably more accurate than maximum likelihood classification.When the six image endmembers were processed via the SAM algorithm, excellent discrimination between the different endmembers was found.

After that Spectral angle mapper classification has been used for road detection from fused SPOT 4 and SPOT 5 image with and without incorporation of DSM as an additional channel approach.The classification maps generated with SAM show that this method could effectively be used for automatic road extraction.

In comparing between high and medium spatial resolutions for the classification using SAM algorithm, it was found that even if SPOT4 has a medium spatial resolution and that sub-pixel contamination from different land cover is evident while selecting endmembers, it has given good results. On the other hand, SPOT5, which has a fine spatial resolution there are no sub-pixel contamination, gave lower accuracy results.

The majority of roads can be detected even without a DSM, though there are a relatively high number of false positives, mostly urban area.

Using a DSM improves both the completeness and the correctness of the results, primarily because urban can now be clearly separated from roads. The correctness is improved because urban are not extracted as false positives.

It is recommended to investigate other soft classifiers for road extraction and to make transportation network connecting the roads between urban areas that have large population densities.

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