A "MS Convolution-HC Texture" Filtering proposed Method to Spatially Enhance Supervised/ Unsupervised Land Cover Classification Analysis: Applied to ETM+ and SPOT data imagery.

Dr. Nermin A. Shoukry
Department of Geography, Faculty of Arts, Cairo University, Giza, Egypt
Email:nerminsh@hotmail.com

Abstract

Image Classification has formed an important part of the fields of remote sensing, image analysis, and pattern recognition. This paper is an attempt to introduce a new method of classification enhancement by merging both median spatial convolution filtering (MSCF) and grey level homogeneity co-occurrence texture filter (HCTF). The size of the neighborhood convolution mask or Kernel (n) is constrained to be 3×3 with nine coefficients (C_i). In this respect, two different spatially, spectrally, and temporally satellite data imagery are used. The American Landsat Enhanced Thematic Mapper Plus (ETM+) is used in comparison with the French SPOT data imagery. Two types of SPOT satellite images are used. The first is in the multispectral mode (Xs), which is SPOT-5 of High-Resolution Geometric (HRG) data. While the second is in the panchromatic (PAN) mode, which is SPOT-2 PAN. The proposed method involves applying the technique through examining both supervised and unsupervised classification by using the minimum distance classifier method and the ISODATA algorithm method, respectively. Furthermore, this study experiences the usage of the proposed method in different spatially resampled data imagery and ends with a post classification accuracy assessment that significantly offers satisfying overall accuracies and kappa coefficient results. Additionally, it reduces the error percentage up to approximately 7% difference when compared to the conventional method. Al-Madinah Al-Munawarah in Saudi Arabia was chosen as a case study area to conduct the analysis because of its diversity and variety in terms of land cover and land use classes.

(ISSN : 2536 - 9555)

أسلوب مقترح لترشيح "MS للإلتفاف المكاني-HC للنسيج المتجانس" مكانيا لتحسين تحليل تصنيفي الغطاء الأرضي الموجه و غير الموجه: بالتطبيق على بيانات الصور الفضائية +ETM و SPOT.

د. نرمين أحمد شكري

مدرس بقسم الجغرافيا – كلية الآداب – جامعة القاهرة

ملخص البحث:

إن تصنيف الصور الفضائية يشكل جزءًا مهمًا لا يتجزأ من مجالات منهج دراسة علم الاستشعار عن بعد وتحليلات الصور الفضائية وكذلك تحليلات التعرف على الأنماط. وتأتي هذه الورقة البحثية كمحاولة لإدخال أسلوبا جديدا لتحسين التصنيف في الصور الفضائية، وذلك من خلال دمج كل من مرشح الالتفاف المكاني المتوسط (MSCF) والمرشح النسيجي ذو البروز المشترك لمصفوفة التجانس على المستوى الرمادي (HCTF). حيث تم تحديد حجم قناع الالتفاف المجاور (n) Kernel ليكون بحجم3(× 3) مقيدا بتسعة معاملات(C_i) .وفي هذا الصدد تم استخدام صورتين فضائيتين مختلفتين في بياناتهما ودقتهما المكانية والطيفية والزمنية. واستخدمت الدراسة صور القمر الصناعى لاندسات الأمريكي المحسن الموضوعي (+ ETM) ومقارنته مع صور القمر الصناعى الفرنسىSPOT . وقد تم استخدام نوعين مختلفين من أنواع صور القمر الصناعيSPOT .وبحيث جاءت الصورة الأولى في الوضع متعدد الأطياف (Xs) ، وهي من القمر الصناعى SPOT-5 ذو البيانات الهندسية عالية الدقة (HRG) .بينما جاءت الصورة الثانية في الوضع البانكروماتيأحادي الطيف، وهوSPOT-2 PAN .وقد تضمن الأسلوب المقترح كيفية تطبيق التقنية من خلال مقارنة وفحص التصنيف االموجه وغير الموجه باستخدام خورزميات تصنيف المسافة الدنيا والأيزوداتا ISODATA على التوالي لكل من التصنيفين. علاوة على ذلك اختبرت هذه الدراسة استخدام الأسلوب المقترح في الصور الفضائية مختلفة البيانات بالنسبة لكل من قدرات التفريق المختلفة والمعاد تشكيلها مكانيًا ، وقد انتهت الدراسة بقياس تقييم دقة ما بعد التصنيف الذي قد قدم بشكل كبير دقة عامة مرضية ونتائج مرتفعة لمعامل كابا. بالإضافة إلى ذلك فإن الاسلوب المقترح قد قلل من نسبة الخطأ إلى ما يقرب من ٧٪ عند مقارنتها بالطريقة التقليدية. وقد تم اختيار المدينة المنورة في المملكة العربية السعودية كمنطقة دراسة حالة لتطبيق الأسلوب التحليلي المقترح بسبب تنوعها الجغرافى وتنوعها من حيث إختلاف فئات الغطاء الأرضي وفئات استخدامات الأراضي بها.

مجلة وادي النيل للدراسات والبحوث الإنسانية والاجتماعية والتربوية (مجلة علمية محكمة)

A "MS Convolution-HC Texture" Filtering proposed Method to Spatially Enhance Supervised/ Unsupervised Land Cover Classification Analysis: Applied to ETM+ and SPOT data imagery.

Dr. Nermin A. Shoukry

1. INTRODUCTION

Merging Median Spatial Convolution Filtering (MSCF) for both multispectral and grey level data, and the grey level Homogeneity Co-occurrence Texture Filter (HCTF) is produced as a new method of enhancing classification analysis. The spatial filtering approach is typically a "local" image enhancement algorithm that is usually applied to remotely sensed data to improve the appearance of an image for human visual analysis. All local operations are a pre-processing analysis that modifies the value of each pixel in the context of the brightness values surrounding it (Jensen, 2005). Because the local or what is called the neighboring spatial filtering deals with pixels over a given spatial region in the image, it is necessary for analysts to adopt the spatial statistics approach to extract the quantitative spatial information. The neighborhood ranking Median filter is one type of the spatial convolution filtering. It smoothes the applied image, while preserving edges larger than the kernel dimensions (ENVI: User's Guide Digital Manual, 2011). It has several advantages such as removing salt and pepper noise or speckle, not shifting boundaries, and preserving edges and corners. It was usually used by analysts separately as a one time use preprocessing operation, but not as a base to be incorporated into classification analysis.

1.1 Literature review

In this research, the literature review was directed towards three main study axes that discuss the developed method itself, the land cover classification analysis, and the filtering approaches.

(ISSN : 2536 - 9555)

In her doctoral dissertation, the researcher (2004) offered the first attempt to develop a preliminary method of merging both spatial convolution and co-occurrence textures filters and then combine it with classification to have highly accurate classified image to enhance both change detection analysis and for masking outputs as well. She applied her preliminary method to enhance the classification to detect, monitor, quantify, map, and project the settlement growth expansion in the eastern part of the Nile delta in Egypt as an integration of remote sensing (R.S) and geographical information science (GIS) technologies . The imagery data sets of both Landsat MSS and TM were used in her study. She experimented her developed method by using only the supervised classification analysis and was successfully reported an overall accuracy of 91%, 84%, and 93% for the years 1975, 1987, and 1998, respectively.

Many studies based on examining land cover classification as a whole. A number of research works have been carried out by using various methodologies and algorithms to derive land cover and change information from different sets of remotely sensed data. One of the first attempts to use SPOT images for land cover classification, was conducted by Philipson, et al., (1988). They used SPOT satellite data imagery to determine their capacity for monitoring Land cover changes. They used aerial photo and field verification to compute the accuracy to be approximately 95%. Hansen, et al., (2000), used an advanced very high resolution radiometer (AVHRR) with spatial resolution of 1 km images to conduct a global multispectral land cover supervised classification with their developed classification tree approach using time series from 1992 to 1993. In the year of 2007, Gamanya, et al., developed an automated satellite image land cover classification design using object-oriented algorithms. They tested the technique on Landsat and Aster images giving overall accuracies of 88%, and 84% respectively. To improve the classification accuracy, Lu & Weng (2007) made a survey of major advanced classification approaches and the techniques used for improving classification accuracy. They reported that non-parametric classifiers such as neural network, decision tree classifier, and knowledge-based classification have increasingly become important approaches for multisource data classification. In their paper, Rongqun & Daolin (2011) dealt with the limitation of visual interpretation of high-resolution remote sensing images and of automatic computer classification completely dependent on spectral data. They proposed a knowledge-rule method based on spectral features, texture features obtained from the grey level co-occurrence matrix, and shape features. They experimented their method by using QuickBird satellite data and they achieved a relatively high classification accuracy.

For the filtering approaches, many studies examined the use of different filters to incorporate into the classification analysis. Liu (2000) developed a simple spectral preserve fusion technique for improving spatial details of satellite images. Franklin, et al. (2001) analyzed forest structure and species composition with high spatial resolution multispectral images. Their study was conducted by using spatial co-occurrence texture analysis and maximum-likelihood classification. Their accuracy improved to reach up to 80% of overall accuracy. Clausi (2002) discussed the effect of grey level quantization on the ability of co-occurrence probability statistics to classify natural textures using synthetic aperture radar (SAR) images. He used correlation analysis to rationalize a preferred subset of statistics, and he performed only three co-occurrence texture measures such as contrast, correlation, and entropy disregarding other textural measures. Kiema (2002) used medium spatial resolution multispectral data imagery to examine the influence of multisensor data fusion on the automatic extraction of topographic objects. Various grey level co-occurrence based texture measures were experimented, as well as different kernel window size. He suggested the use of homogeneity texture measure. Puissant, et al. (2005) examined the utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery such as IKONOS, QuickBird, SPOT5. Results show that the optimal index improving the global

(ISSN : 2536 - 9555)

classification accuracy is the homogeneity measure, with a 7×7 window size.

1.2 Study area

The study area covers the Islamic holy city of Al-Madinah Al-Munawarah, which is considered as the urban capital city of Al-Madinah province in the Kingdom of Saudi Arabia (K.S.A) (Figure 1). It is located in the country's west side. Its geographic coordinate for longitudes is between 39º 36′ 00″ to 39º 42′ 36″ , and between 24º 21′ 00″ to 24º 36′ 00″ for latitudes. The province has an area of 151, 990 square kilometres, and population of 1,512,724 person in the year of 2008. It is administratively subdivided into seven governorates. Al-Madinah city has about 995,619 person as population size, which is formed about 66% of the population size of the entire province (CDSI, census 2008). It is situated in a depositional basin surrounded by lava plateaus and hills within the western part of Arabian Shield, within a maximum depth of 45 meters. The elevation of the lava plateau and the hills are in the range of 620 to 750 meters and of 900 to 1100 meters, respectively above the mean sea level (M.S.L). The sub-soil in the city consists of nine soil types. The rocks vary from weak limestone to massive gabbro. It has an arid climate with the maximum summer temperature, sometimes, reaching 48ºC and minimum winter temperature going down to 2ºC. The maximum average monthly rainfall (in winter) reaches up to 17mm (Matsah & Hossain, 1993).

Moreover, the study area is characterized by its multi-concentric irregular circular successive shape following mostly the multiple concentric city ring roads. The prophet's holy mosque at the city centre appears to have influenced the growth of the urban area outwards with two sets of roads: one set of radial roads and the other set of ring roads, leaving most areas of date palm gardens on the north, north-east, and south, south-east direction. In this research, the boundary area of the city have being subset to match the king khaled ring road or the third and last ring roads outwards to avoid the geology complexity of soil and rocks various types of

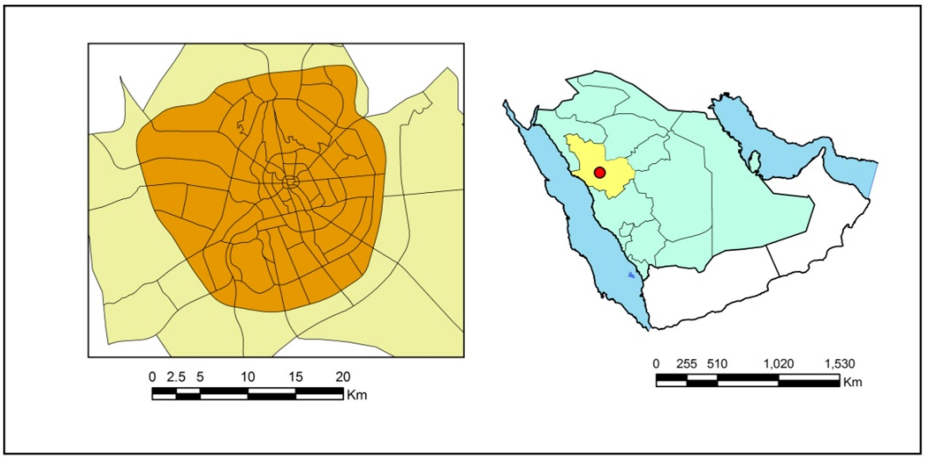

Figure 1. Location of study area (Al-Madinah Al-Munawarah City in K.S.A)

the surrounding lava plateau and hills, which may latter effect the classification analysis.

2. METHODOLOGY

The overall methodology of this research is outlined in the flowchart diagram depicted below (Figure 2).

2.1. Remotely Sensed Data Acquisition

This research utilized two types of satellite data. The first scene data is the Enhanced Thematic Mapper Plus (ETM+) of multispectral bands of Landsat-7 that contains 9 bands divided between both reflective and emitted spectral wavelengths, as follows: B1=Blue, B2=Green, B3=Red, B4= Near infrared (NIR), B5=Mid infrared-1 (MIR-1), B6-1=Thermal infrared-1 (TIR-1), B6-2=Thermal infrared-2 (TIR-2), B7=MIR-2, B8=Panchromatic band. The acquisition date is 30 January of the year 2005 with spatial resolution of 30×30 meters pixel size, and with path/row=170/043. It was originally obtained from USGS/EROS and publically acquired and downloaded from the Global Land Cover Facility (GLCF) in a GeoTIFF format (it is a Georeferenced

(ISSN : 2536 - 9555)

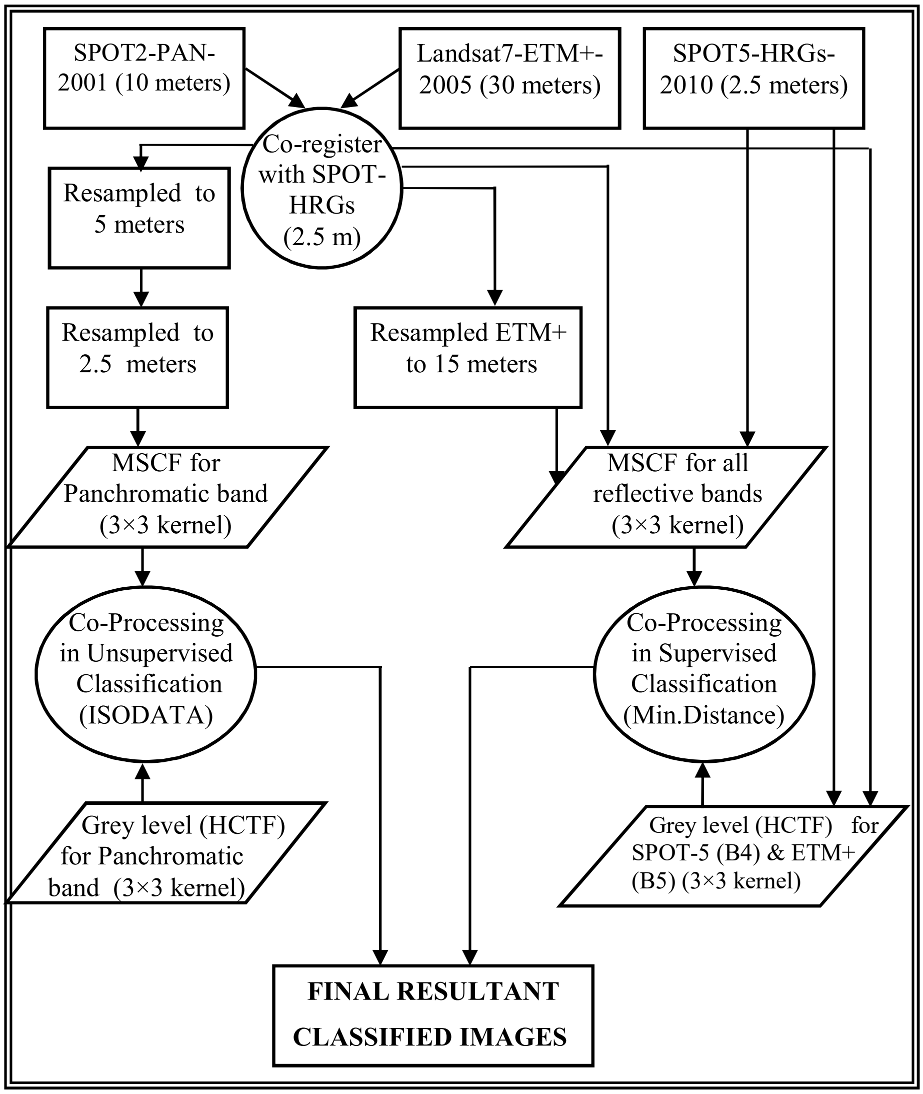

Figure 2. Flowchart of the overall technical research methodology.

version of the popular Tagged-Image File Format). It covers most of the administrative area of Al-Madinah province. Therefore, it was subseted to include roughly the urban administrative area of the capital city (Figure 3).

The second satellite data set is SPOT-*le Sytème pour L'observation de la terre* ("Earth Obesrvation System"). Two different SPOT images were used, SPOT-2 and SPOT-5. SPOT-2 data contains a single panchromatic band (PAN) in the visible spectrum, with path/row=132/301, and acquisition date of 19 February of the year 2001 with spatial resolution of 10×10 meters pixel size (Figure 4). SPOT-5 data of High Resolution Geometric (HRG) contains multispectral-four spectral bands as follows: B1=Green, B2=Red, B3=near infrared (NIR), B4=short wave infrared (SWIR). Its acquisition date is 12 September of 2010, and path/row=131/301 with spatial resolution of 2.5×2.5 meters pixel size (Figure 5). Both SPOT-2 and SPOT-5 data sets were obtained from "King Abdulaziz City for Science and Technology-space research Institute (KACST)".

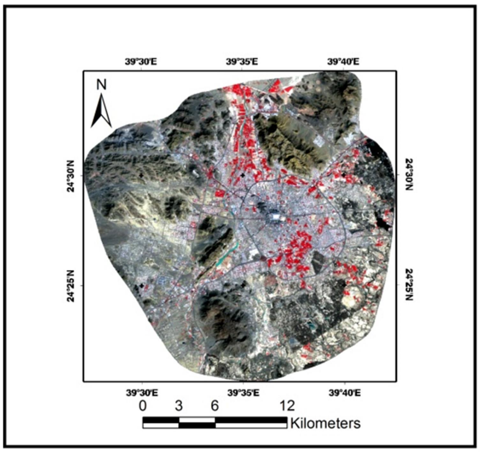

Figure 3. A false color composite (4,3,2) of a subset scene from a Landsat-7 (ETM+) image of the study area. Spatial resolution of 30 meters and acquisition date of 30 January of 2005.

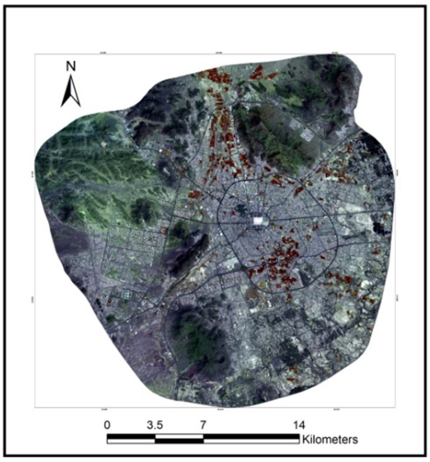

Figure 4. A false color composite (1,4,3) of a subset scene from a SPOT-5 (HRG) image of the study area. Spatial resolution of 2.5 meters and acquisition date of 12 September of 2010.

(ISSN : 2536 - 9555)

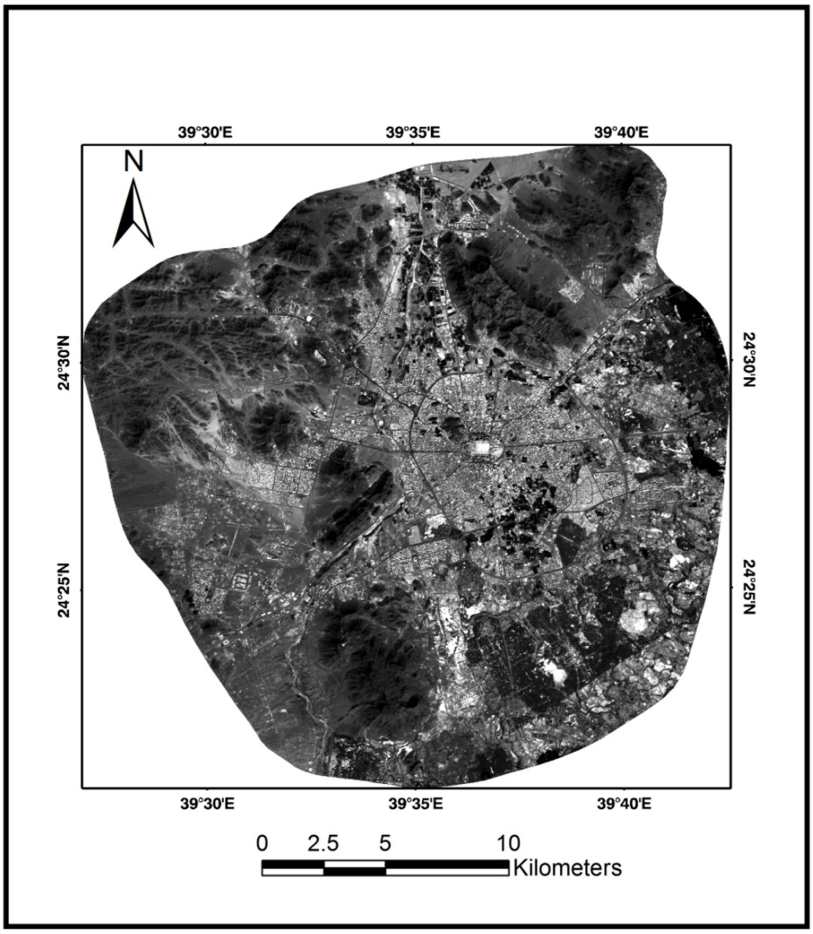

Figure 5. A Panchromatic subset scene from a SPOT-2 (PAN) image of the study area. Spatial resolution of 10 meters and acquisition date of 19 February of 2001.

2.2 Image Pre-processing

Radiometric and geometric errors are the most common types of errors encountered in remotely sensed imagery. In this study, all systematic satellite images errors were radiometrically and geometrically rectified by the commercial data provider, while the unsystematic geometric error remains in the images. The geometric errors of the landsat ETM+ and SPOT-PAN data were here corrected and co-registered with the SPOT-HRG data. The coregistration process is applied with an image-to-image registration process by using common ground control points (GCPs) to achieve a higher degree of spatial matching accuracy. It is also accomplished with a first order polynomial linear transformation and with a nearest neighbor resampling method to maintain the original data values without any averaging for the suitability of later use of both supervised and unsupervised classification. The resultant root mean square (RMS) error of the ETM+ and SPOT-PAN image were 0.289 and 0.256, respectively. All images were obtained the same projection and geiod (UTM projection-zone 37 North, with WGS "World Geodetic Survey" 1984 spheroid and datum). Moreover, the remotely sensed data used in this study were extracted as a subscene from the original dataset for each image. Several resampling processes were applied to both registered ETM+ and SPOT-PAN images while they were being subset. The SPOT-PAN with 10 meters spatial resolution was resampled to 5 meters and then to 2.5 meters pixel size. The ETM+ with 30 meters spatial resolution was resampled to 15 meters pixel size. Changing spatial resolutions of all co-registered images with SPOT-HRG were done for the purpose of comparison and for experimenting the analysis with different pixel size as well as different data set.

2.3 Remotely sensed data processing

Processing was conducted in three procedures. The first was generating median spatial convolution filtering (MSCF) for all reflective bands of each satellite image. The second was applying co-occurrence measures textural filtering that is based on brightness value spatial dependency grey level co-occurrence matrix (GLCM). The third and last procedure was the co-processing between the first two procedures and the classification analysis. In the context of the suggested method, all visible and infrared bands (except the thermal infrared) were included in the analysis. Remote sensing image processing was performed using the commercial remote sensing software ENVI® "the Environment for Visualizing Images".

(ISSN : 2536 - 9555)

2.4 Median spatial convolution filtering (MSCF)

A two-dimensional spatial convolution filter is the process of evaluating the weighted neighboring pixels values (Pratt, 1991). The neighborhood ranking median filter is useful for removing noise in an image, especially shot noise by which individual pixels are corrupted or missing (Jensen, 2005). Instead of computing the average (mean) of the nine pixels in a 3×3 convolution, the median filter ranks the pixels in the neighborhood from lowest to highest and selects the median value, which is then placed in the central value of the mask (Richards, 1986).

In this research, all reflective multispectral and panchromatic bands in the different imagery data set that were co-registered with the SPOT-HRG image were transformed into median spatial convolution filtering (MSCF) bands. The MSCF was used later as a base for a supervised and unsupervised classification in all reflective bands of the ETM+, SPOT-HRG and SPOT-PAN images. The reason for using this filtering process prior to the classification process is to smooth the images as well as preserve edges larger than the kernel dimensions as mentioned above. A 3×3 kernel size was applied to the process to produce the MSCF bands.

2.5 Grey level homogeneity co-occurrence texture filter (HCTF)

Texture is defined as the representation of the structure of a surface as distinct from color or form (Webster's dictionary, 2001). In remotely sensed analysis, it can be defined as the spatial variation in grey value, and is independent of color or luminance (Rongqun and Daolin, 2011). The co-occurrence texture is described mainly by histograms, the grey level co-occurrence matrix (GLCM), local statistics, and characteristics of the frequency spectrum. It describes the grey-level configuration of an image combined by different pixels. In general, it is possible to distinguish between the regular texture manifested by man-made objects from the irregular manner that natural objects exhibit texture. Hence, the texture characteristics can be used to discriminate between different objects (Kiema, 2002). This description of the grey-level configuration can show features of the texture well, and the spatial dependence of the grey level is emphasized. The GLCM filters include mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation. As shown in figure 6, different types of GLCM filters that applied on ETM+ image- as an example- were experimented. Because texture analysis makes use of single band, grey level homogeneity co-occurrence texture filter (HCTF) of both multispectral and panchromatic images was conducted. The reason for selecting this textural filtering is to be able to filter the image features either (uniform, homogenous, or smooth) or (coarse, heterogeneous, or rough). The panchromatic band of SPOT-PAN image was transformed to be an HCTF textural band mask. Meanwhile, band 4 (1.58-1.75 µm-SWIR band) was selected in the SPOT-HRG image. Conversely, band 5 (1.55-1.75 µm-MIR band), was selected in the ETM+ image. A 3×3 kernel size was applied to the process to produce the HCTF grey bands.

2.6 Land cover classification analysis

Image classification is one of the most commonly undertaken analyses of remotely sensed data. The main reason for undertaking an image classification is, in effect, to convert the image's information on the spectral response of the Earth's surface into a thematic map depicting classes of interest such as land cover (Foody, 2008). However, classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image processing and classification approaches, may affect the success of a classification (Lu and Weng, 2007). Moreover, the major steps of image classification may include determination of a suitable classification system, selection of training samples - also called regions of interest (ROI) or areas of

(ISSN : 2536 - 9555)

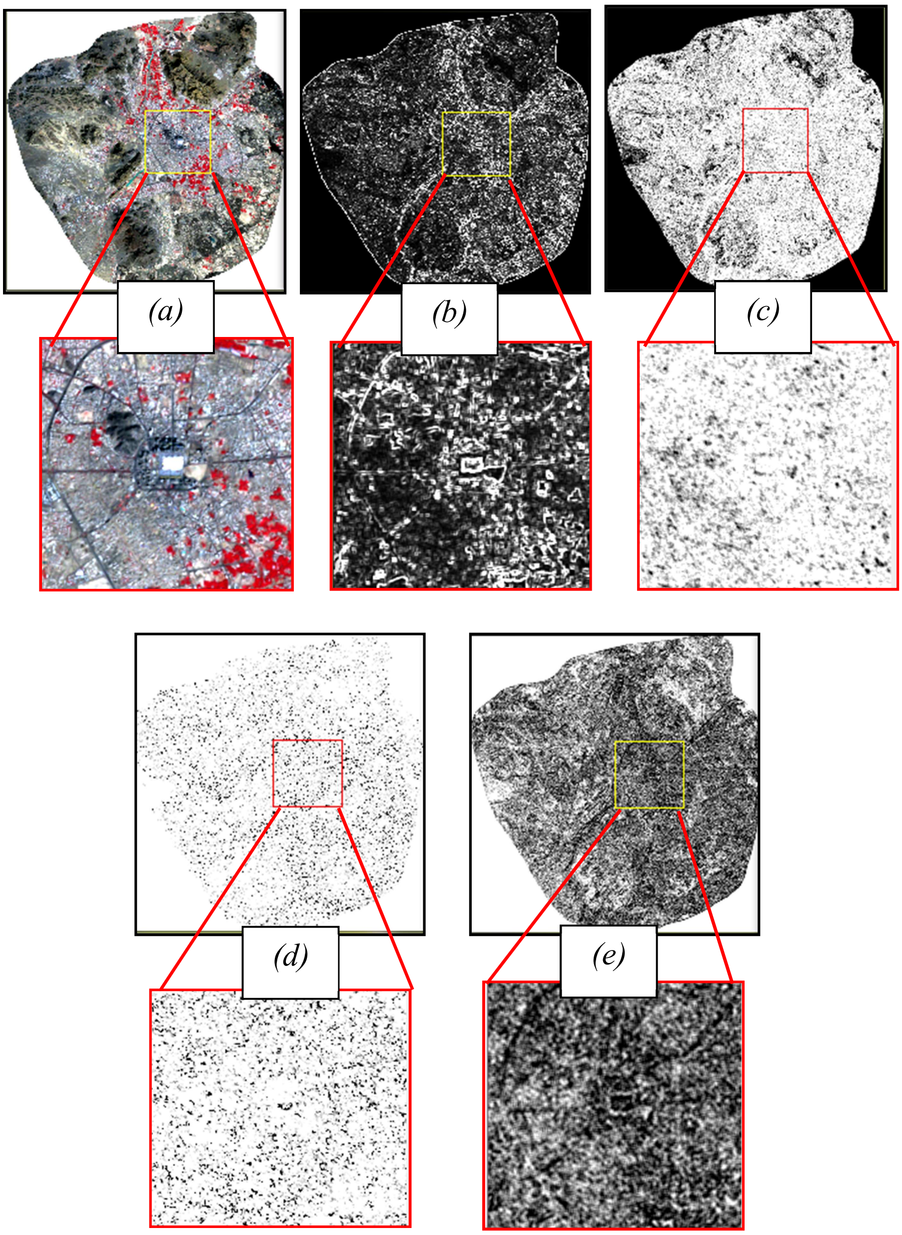

Figure 6. Examples of texture analysis with different co-occurrence -based texture measures: *(a)* Original ETM+ image, *(b)* Variance, *(c)* Entropy, *(d)* Correlation, *(e)* Homogeneity.

interest (AOI)-, image preprocessing, feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment. As for the classification system, the US Geological Survey's (USGS) land cover classification level was chosen and referred to for the classification system for this study. Typical data characteristics have different classification level as stated by USGS (Anderson, et al., 2001). The ETM+ data with 30 meters spatial resolution image ranked as classification level I, while the SPOT panchromatic (10 meters S.R.) and HRGs (2.5 meters S.R.) ranked as classification level II. Therefore, land cover classification classes was chosen and stabilized in all images. These classes are: Urban or Built-up land, Agricultural land, Barren land, and Mountain area. In this research, and due to the landscape diversity of the study area, the mountain area class was divided into two classes owing to the different rocks types. Two other classes were added. The first one is the remains of volcanic lava that exists in large extent in and outside the study area's boundary. The second added class is a red soil land area that is used for producing commercially red bricks.

Typically, classification analysis can be considered as principally a supervised and unsupervised classification. Supervised classification procedures require considerable interaction with the analyst, who must guide the classification by identifying areas on the image that are known to belong to each category. Conversely, unsupervised classification proceeds with only minimal interaction with the analyst, in search for natural groups of pixels present with the image. Thus, where spatial distribution information is not available, unsupervised classification is arguably the better strategy (Campbell, 1996; Franklin & Wulder, 2002). This research applied both supervised and unsupervised classification analysis to experiment the suggested classification enhancement method. The classification analyses were applied on a base of the previously produced MSCF images.

(ISSN : 2536 - 9555)

2.6.1 Algorithm selection for supervised classification

Training sites or regions of interest (ROI) selection was conducted before selecting the best algorithm for land cover classification for each image dataset. ROI refers to the informational classes that are the categories of interest to the users of the data. These classes form the information that we wish to derive from the data, and selected by the analyst based on the user knowledge of the study area. On the other hand, spectral classes are groups of pixels that are uniform with respect to the brightness in their several spectral channels. Thus, remote sensing classification proceeds by matching spectral categories to informational categories (Campbell, 1996). ROI were collected randomly from the false color composite images based on "Al-Madinah Al-Munawarah" topological map with scale 1:50,000 (General directorate of K.S.A military survey, 2001). The way used to collect ROI, was the "on-screen selection of polygonal training data" .

Various supervised classification algorithms may be used to assign an unknown pixel to one of a number of classes. The choice of a particular classifier or decision rule depends on the nature of the input data and the desired output (Jensen, 2005). Minimum distance classifier (also called MD spectral distance, MD algorithm, or MD decision rule) was selected to conduct the classification. It calculates the spectral distance between the measurement vector for the candidate pixel and the mean vector for each signature. Since the idea of this decision rule is to assign every pixel in the classification to a certain value, the pixels that are farthest from the means of their classes were thresholded out to control the classified classes spectrally. Therefore, every pixel was forced into a class except few unclassified pixels. In this study several trials were made to reach the best threshold value for each class in the image data sets. These thresholds (also called maximum distance error) enter the value in digital numbers (DNs), and those pixels that are located at a distance greater than the specified threshold, will not be classified in the process.

The median spatial convolution filtering (MSCF) multispectral SPOT 5 – HRG image of the year of 2010 with spatial resolution 2.5 meters was "supervised" classified. The grey level homogeneity co-occurrence texture filter (HCTF) of band 4 was merged as a mask band in the classification process. Minimum distance classifier were applied with multiple values of maximum distance error parameter to assign a DN value for each class. There were seven classes selected in the MSCF/HCTF Spot-HRG classification image (Figure 7). The classes are: Urban/Built-up area, Roads/Asphalt, Barren land/Cemeteries, Agricultural/Green area, Mountain area-1, Mountain area-2, Remains of volcanic lava, and Red soil land. Their maximum distance errors were selected as: 180, 100, 20, 110, 80, 30, 30, and 40, respectively, by visually inspecting every maximum distance error.

In the MSCF/HCTF ETM+ classification image with spatial resolution of 30 meters, same classes as the SPOT-HRG image was chosen in the same order (Figure 8). Their maximum distance errors were selected as: 180, 10, 10, 100, 50, 50, 50, and 50, respectively. The same classification process was applied and experimented to the previously resampled ETM+ image with spatial resolution of 15 meters (Figure 9). MD algorithm was used with assigning multiple values of the maximum distance error parameter. Figure 10 shows the resultant MSCF/HCTF ETM+ supervised classification image. In this image, Same classification classes as the two previously processed images, were obtained in the same order. Their maximum distance errors were selected as follows: 180, 15, 10, 50, 10, 30, 50, and 50, respectively. Noticeably, there were differences in the value of thresholds or the maximum distance error of each similar class between the three multispectral processed images.

Reasons behind these different values were monitored as follows: (1) each image was obtained in different date, (2) each image has different spatial resolution, (3) ROI was randomly selected and differentiated from one image to another, and (4) the landscape diversity and the environmental conditions of the study

(ISSN : 2536 - 9555)

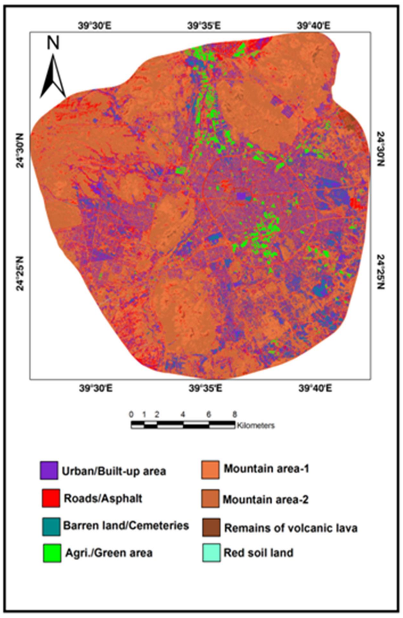

Figure 7. MSCF & HCTF Land cover supervised SPOT-5 (HRG) img.– 2.5 meters S.R.- of the study area.

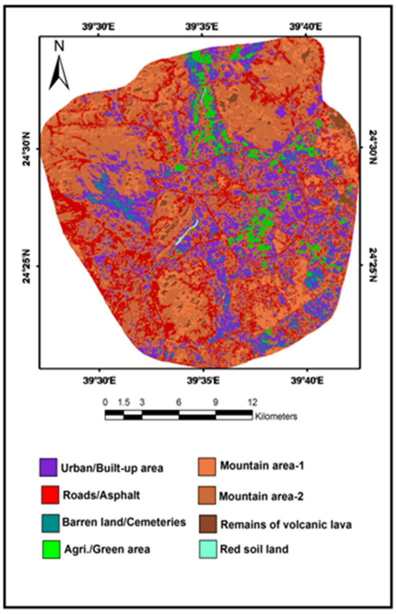

Figure 8. MSCF & HCTF Land cover supervised (ETM+) img. – 30 meters S.R.- of the study area.

area were significantly affected the ROI selection in each image.

2.6.2 Algorithm selection for unsupervised classification

Unsupervised classification usually refers to a classification in which the classes are not predetermined (Franklin & Wulder, 2002). It requires only a minimal amount of initial input from the analyst (Jensen, 2005). Thus, by using this type of classification analysis, the user allows the computer to select the classes based on clustering algorithms. The Iterative Self-Organizing Data Analysis Technique (ISODATA) as a widely used clustering algorithm was selected to conduct the unsupervised classification analysis. It calculates class means which are evenly distributed in the data space, then iteratively clusters the remaining pixels using minimum distance techniques (ENVI: User's Guide Digital Manual, 2011).

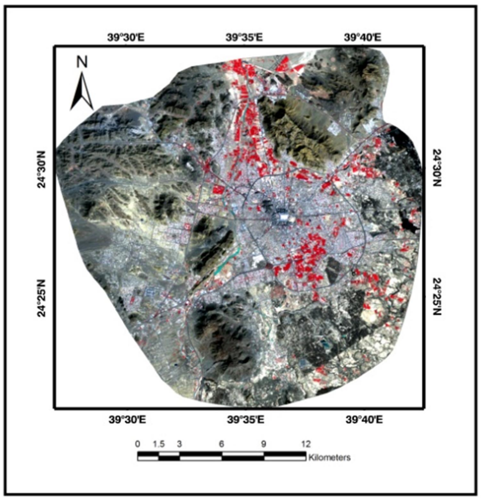

Figure 9. A false color composite (4,3,2) of a subset scene from the resampled Landsat-7 (ETM+) img.15m S.R.-of the study area.

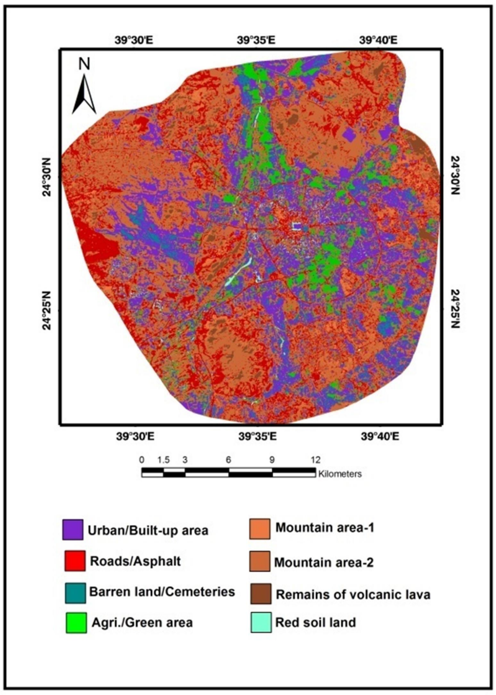

Figure 10. MSCF & HCTF Land cover supervised (ETM+) image, 15 meters S.R.- of the study area.

(ISSN : 2536 - 9555)

The usual ISODATA algorithm is self organizing because it requires relatively little human input, such as identifying the desired number of classes and then running the other default parameters or criteria in the computer. In this research, a sophisticated ISODATA algorithm was applied to perform the classification.

In addition to selecting the minimum and maximum number of classes to define, other parameters were specified. These parameters are as follows: (1) maximum number of iterations (the repetition of the computational procedures or the number of times that the ISODATA utility will recluster the data), (2) minimum number of pixels needed to form a class, (3) maximum number of merging class pairs, (4) maximum standard deviation – researches identified that the values between 4.5 and 7 are typical (Jensen, 2005) –, and (5) maximum distance error specified by one digital number stabilized for all classes (DNs). Each iteration recalculates means and reclassifies pixels with respect to the new means. Therefore, iterative class splitting, merging, and deleting was applied based on specifying and inputting the threshold parameters.

Three MSCF images were used to conduct the analysis. The first was the SPOT-2 (PAN) image with spatial resolution of 10 meters. The second was the resampled "SPOT-2 (PAN)" image to 5 meters S.R., and the third was the same panchromatic image, but resampled to 2.5 meters S.R. Prior to application, grey level masks was produced by transforming the panchromatic band in each image to an HCTF mask. All parameters' values for the three images were unified except for the maximum distance error parameter. As a result of experience gained through experimentation in this research, it was proved that there is a negative or inverse relationship between the spatial resolution of an image and the maximum distance error digital number specified in ISODATA application. Whenever one increases, the other decreases, and vise versa.

To conduct the analysis for the three panchromatic images, the grey level homogeneity co-occurrence texture filter (HCTF) of each panchromatic band was merged as a mask band in the classification process. The number of classes specified by the minimum of five and maximum of ten classes. The maximum iterations times was chosen as 25, and the minimum number of pixels defined in each class as 1000 pixels. The maximum number of merging class pairs was identified as four classes, and the maximum class standard deviation was chosen as the value of seven. The Maximum distance error differed from one image to the other because of the changing of the spatial resolution of the three images as stated before. For the SPOT-PAN of 10 meter S.R, it was found that the best maximum distance error to experiment was 100. As for the other two resampled images of 5 and 2.5 meters S.R, the maximum distance errors were specified as 70 and 40, respectively. Spectral classes were generated as a result of the classification. To match spectral classes to the informational classes, a comparison between the resultant ISODATA classification images to the color composite image of the multispectral SPOT-HRG image and the topographic map of the study area were applied. As a result of this comparison, an editing for classes' colors and names was performed to match the generated ISODATA classifier of the unsupervised classification to the MD classifier of the previously resultant supervised classification. Nearly similar classes were combined and merged together to form one instead of many of the same informational class. This process was repeated for the three unsupervised classified images. Classification results obtained from this analysis and a comparison between the different spatial resolution images are shown in figure 11.

2.7 Accuracy assessment

In order to examine the accuracy of the classification of the suggested method, same classification procedures were taken to produce identical supervised and unsupervised classified images. These identical images were generated without applying the developed analysis for the purpose of comparison. Both supervised and unsupervised procedures' parameters were chosen to be

(ISSN : 2536 - 9555)

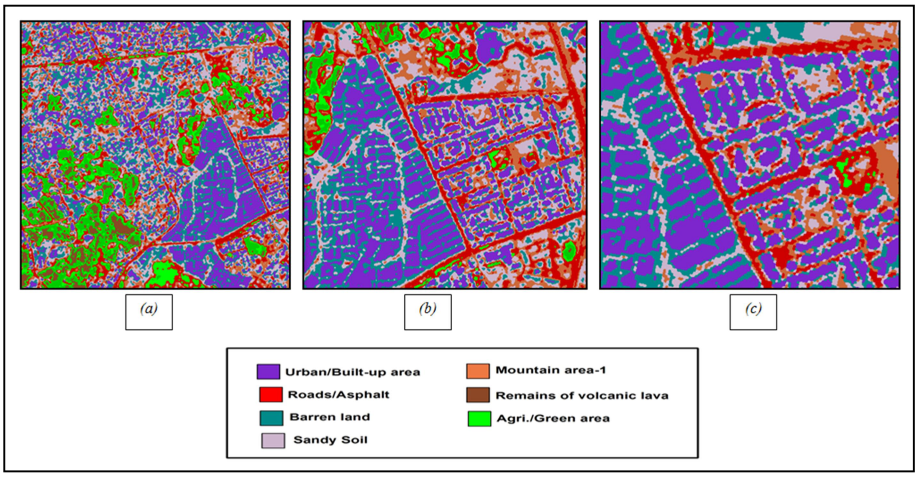

Figure 11. A comparison of one common part area of the three different spatial resolution ISODATA classification images. *(a)* 10 meters S.R., *(b)* 5 meters S.R., *(c)* 2.5 meters S.R.

identical with the previously generated analyzed classified images. Accuracy assessment was applied for both groups of classified images (with and without the developed analysis). The most widely used approach for image classification accuracy assessment is the error (also called confusion) matrix. The confusion matrix was produced in order to compare the classification result with ground truth information. It is constructed from testing sets drawn by simple random and stratified random sampling from the same classified images. The estimates of classification accuracy may differ substantially if the classes vary in abundance and spectral separability (Foody, 2008).

Additionally, the confusion matrix used to assess the general quality of the classification. It summarized by an overall accuracy (percentage of correctly classified pixels), and a Kappa coefficient calculated to express the proportion reduction error generated in the classification process, compared with the error of the random classification. Some researchers claimed that the Kappa statistic has been shown to be a statistically more sophisticated measure of classifier agreement (between resultant classification and ground truth information) and thus gives better interclass discrimination than overall accuracy (Ismail & Jusoff, 2008).

In the supervised classification accuracy assessment procedures, the ground truth information used in the post classification analysis was the ROIs associated with the classified images. Prior to confusion matrix process, a "generate random sample" subroutine from the ROIs in the remote sensing software was used to generate a random sampling of points. A stratified random sampling is selected in order to collect a proportionate representation of each category to produce a sample size directly related to that of classes' size. A minimum sample size of 10% from each stratum was chosen for each classified image individually to assure that every category would be sampled.

Concerning the unsupervised classification accuracy assessment procedures, the supervised classified SPOT-HRG image with spatial resolution of 2.5 meters was selected as a reference image for ground truth information. Applying the reference image in the process was done to compensate the lack of multispectral supervised ROIs. Generating random sample of minimum percentage of 10% followed by performing confusion matrix by using the specified ground truth image was applied for each panchromatic ISODATA classified image. An overall accuracy and a kappa coefficient statistics were calculated for each supervised and unsupervised classified image.

3. RESULTS OF PROPOSED METHOD

Results can be illustrated by comparing the proposed to the conventional classification approach.

3.1 Comparison of proposed to conventional approach

Conventional or traditional multispectral classification is typically the process of simplifying continuous spectral pattern into discreet groups of known identity (Hepner, 1990). This concept is also a subject of processing the monospectral (panchromatic) classification expect for the obstacle of having less visual

(ISSN : 2536 - 9555)

interpretation. Application of the conventional approach to land cover classification was substantiated in most academic books. No further procedure was taken except for unifying the classification parameters' values with the proposed method as stated in the methodology. This unification is done for the purpose of comparing the two methods with each other in order to evaluate the fundamental capabilities of merging MSCF and HCTF to enhance the supervised and unsupervised classification analyses.

3.1.1 Supervised classification results

The impact of merging the MSCF and the HCTF to conduct a supervised classification can be visually portrayed and can also be examined spatially. Figure 12 shows selected sample areas with 4x "zoomed in" displays. Some classes were displayed such as: green areas, some asphalt roads, sandy soil, barren land, and built-up areas. The conventional and proposed supervised classification approach were produced for ETM+ data imagery with spatial resolution of 30 meters, as well as the resampled image with spatial resolution of 15 meters. A comparison of Figure 12*a* to 12*b*, and of Figure 12*c* to 12*d* confirms the importance of incorporating the merging of MSCF and HCTF filtering measures in the classification analysis to smoothly distinguish land cover especially urban objects. It is proved to be the best measures to determine variability between land cover classes considering changing kernel size according to the original spatial resolution of the image. The less kernel size of 3×3 pixels with nine coefficients (C_i) was used in this application. It smoothing and maintaining fine edges, as well as removing noise and enhancing the classified classes. Moreover, it maintained thematic accuracy and spatial details. Therefore, the capability of producing fine, accurate, and naturally looking thematic maps increases when using this method.

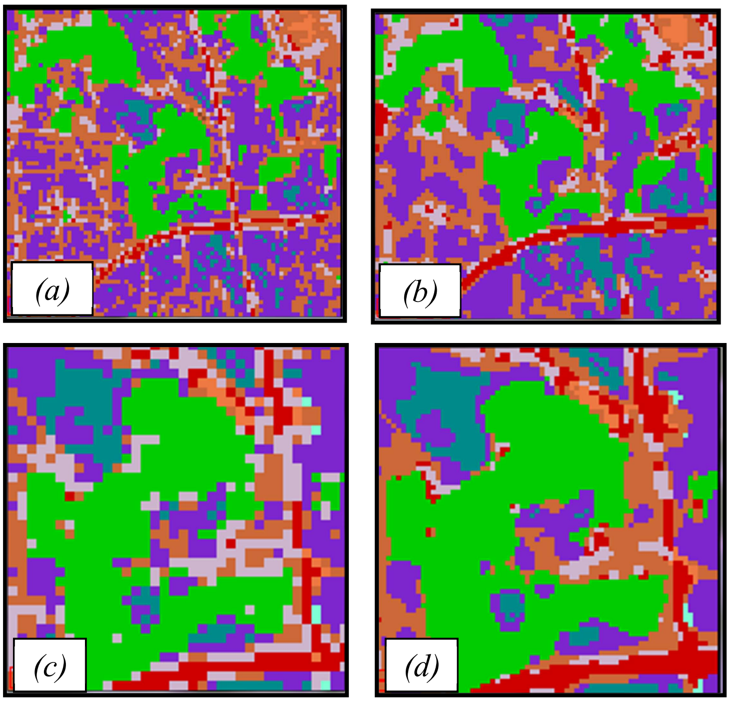

Figure 12. A comparison of one common "zoomed in" area of conventional versus proposed approach of multispectral supervised classification for the ETM+ imagery: *(a)* conventional with 30 meters S.R., *(b)* proposed with 30 meters S.R., *(c)* conventional with 15 meters S.R., *(d)* proposed with 15 meters S.R.

3.1.2 Unsupervised classification results

To produce highly accurate land cover classes, it is not a subject of applying a multispectral supervised classification only. The using of monospectral unsupervised classification is another facet to generate good land cover classification analysis. Although prior knowledge of the study area is not required, the use of the unsupervised classification may be unsatisfactory. The necessity to develop new methods to be merged with the classification is vigorously raised to enhance the analysis. Figure 13 illustrates the comparison between the two analyses (the conventional and the

(ISSN : 2536 - 9555)

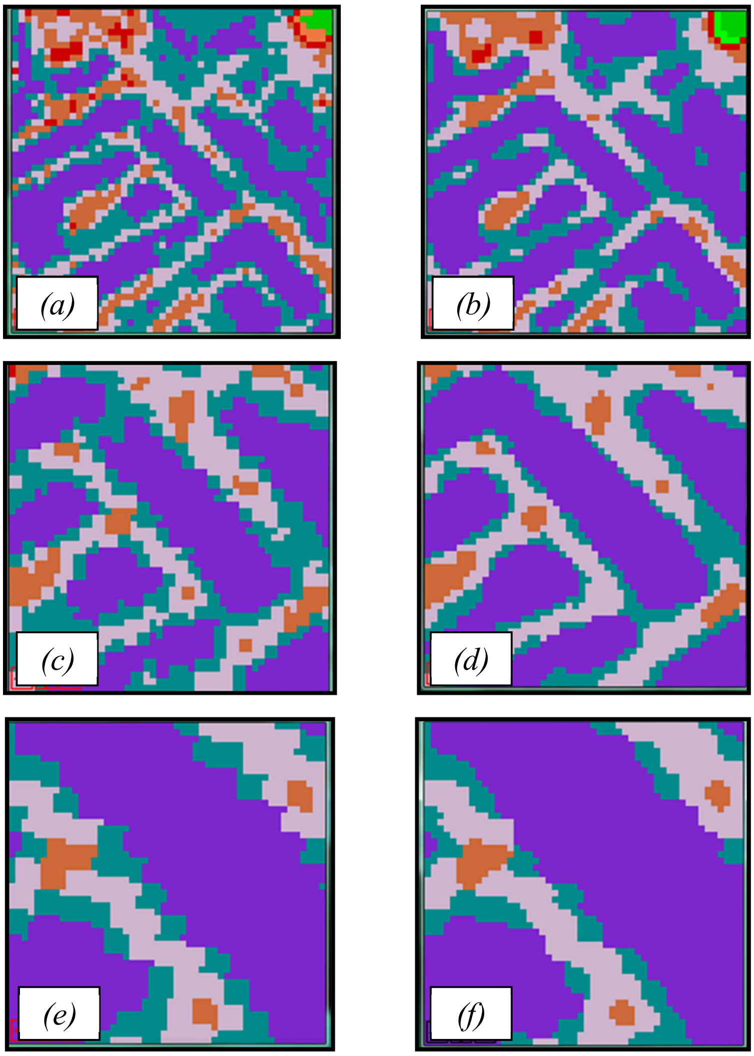

Figure 13. A comparison of one common "zoomed in" area of conventional versus proposed approach of monospectral usupervised classification for the SPOT-PAN imagery: *(a)* conventional with 10 meters S.R.,*(b)* proposed with 10 meters S.R.,*(c)* conventional with 5 meters S.R.,*(d)* proposed with 5 meters S.R.,*(e)* conventional with 2.5 meters S.R., *(f)* proposed with 2.5 meters S.R.

proposed panchromatic ISODATA analysis). A sample of 4x "zoomed in" common areas were displayed. A comparison of Figure 13*a* to 13*b*, was performed to compare the conventionally analysis of the unsupervised SPOT-PAN image data to the proposed method with same spatial resolution of 10 meters and same parameters' values. Figure 13*c* and 13*d* display the comparison process (conventional versus proposed) of the resampled ISODATA SPOT-PAN image with 5 meters spatial resolution for both images. Same comparison procedure was taken for the resampled ISODATA SPOT-PAN image with 2.5 meters spatial resolution that was performed in Figure 13*e* and 13*f*. The selected sample area is a newly built planned residential area that has no asphalt paved inner-roads in the time of the data acquisition. It is visually noticeable that the classification was efficiently smoothed and enhanced between the comparable images. Additionally, the effect of having a classification that integrate in one hand the accurate remotely sensed scientifically results, and the artistry results that matches a hand drawn classification with a real world similarity. Moreover, the proposed method removes all speckles and "salt and pepper" noises from the classified image as shown in Figure 14.

3.2 Classification accuracy assessment results

Normally, after classifying an image some quality measure is required in order to allow a statistically degree of confidence to be attached to the visual result. A key concern for any classification analysis evaluation is producing confusion matrix with computing an overall accuracy percentage and kappa coefficient measures.

A comparison of overall accuracy assessments and kappa coefficient measures were applied to both supervised and unsupervised analysis – the conventional versus the proposed method. Table 1. reported the accuracy assessment of the classification images derived from the different imagery data sets with different spatial resolutions. Both conventional and proposed approach were reported. By comparing the two methods, the

(ISSN : 2536 - 9555)

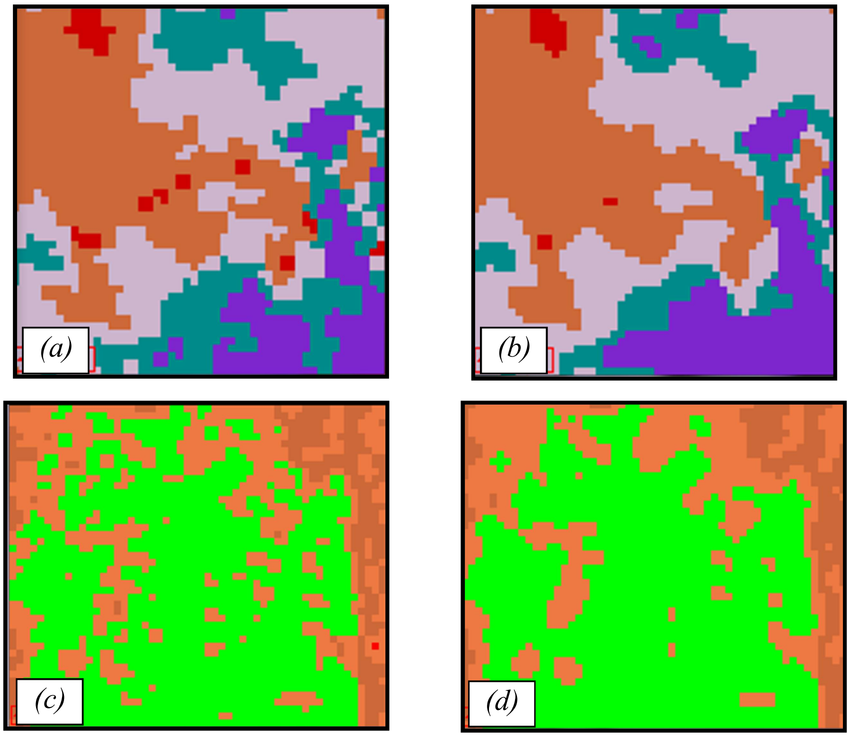

Figure 14. The effect of removing speckles and "salt and pepper" noises: *(a)* & *(c)* conventional method.*(b)* & *(d)* proposed method.

Table 1. Accuracy assessment of conventional Vs. proposed classification approach.

Imagery Data Sets	S.R	Conventional Method			Proposed Method		
		O.V	E %	K.C	O.V	E %	K.C
ETM +	30	84.77	15.23	0.82	91.88	8.12	0.89
ETM +	15	86.02	13.98	0.83	91.29	8.71	0.89
SPOT- HRG	2.5	90.38	9.62	0.88	93.20	6.80	0.91
SPOT- PAN	10	83.50	16.50	0.80	88.75	11.25	0.85
SPOT- PAN	5	84.33	15.67	0.82	89.10	10.90	0.86
SPOT- PAN	2.5	85.91	14.09	0.83	90.25	9.75	0.88

S.R = Spatial resolution (meters), O.A = Overall Accuracy %, K.C = Kappa Coefficient, E % = Error percentage.

obtained results confirm that a fairly good image classification was derived for each data set in the conventional classification. The lowest classification accuracy was reported in the SPOT-PAN classified image – 10 meters S.R – with a percentage of 83.50 and an error percentage of 16.5, and with a kappa coefficient of 0.80. The reason for the increasing error percentage for this specified image is that the barren land class was somewhat confused with many pixels and misclassified as roads. Moreover, many pixels that are related to the green areas were misclassified as remains of volcanic lava due to the reason of having nearly same grey brightness value of the two classes in the panchromatic image. Meanwhile, the highest classification accuracy was computed to the SPOT-HRG classified image – 2.5 meters S.R – with a percentage of 90.38 and a less error percentage of 9.69, and with a kappa coefficient of 0.88. The greatest degree of misclassification occurred between the barren land, some mountainous soils, and the roads classes.

As for the proposed method, it enhanced the classification accuracy as well as maintained thematic accuracy and spatial details of the final classification results. It decreases the error percentage to range from about 3% to about 7% difference from the conventional method, which is considered as a promising method to enhance the classification analysis. Clearly, the better image classification was resulted by having relatively homogeneous areas, smooth and sharp transition boundaries, and continuous connected features with no speckles and less noisy classification. Thus, the overall accuracies and kappa coefficient measures were computed to represent a satisfying and reasonably higher results with less error percentage compared to the conventional method.

4. CONCLUSIONS AND RECOMMENDATIONS

Image classification analysis has made great progress over the past decades in several issues and strategies. Internationally, most issues focus on development and usage of advanced

(ISSN : 2536 - 9555)

classification algorithms, incorporated of ancillary data (non-image information) into classification – such as census data or topographical data –, and generating advanced computer programming expert intelligent systems – such as Artificial Neural Networks (ANNs) – for more professional usage. This research focuses on the issue of enhancing classification analyses (both supervised and unsupervised). To reach this objective, a new method was developed based on some discrete information of textural analysis and its important role in discriminating topographic objects and determining textural variability between land cover classes in remotely sensed data imagery. Moreover, the knowledge of the necessity of removing classification noises in one hand and maintaining thematic accuracies and spatial details on the other hand, was the main motive to select the spatial convolution filtering. The fusion of all stated above knowledgeable discrete information and the preliminary experiments performed by the researcher, was the main corner stone of developing the proposed method.

Merging median spatial convolution (MSCF) with grey level homogeneity co-occurrence texture (HCTF) filtering and integrating them into classification analysis was examined and proved to have highly visual, textural, spatial, and statistical accuracy. The capability of removing spatial noises (salt and pepper noises or speckles) and having smoothly and sharp transition boundaries were provided by MSCF. Moreover, the capability of measuring and determining textural variability between land cover classes with the consideration of choosing the less kernel size of 3×3 pixels and the homogeneity filter that is proved to be the best co-occurrence based texture measure in the extraction of topographic objects were provided by HCTF. The capabilities of MSCF and HCTF were integrated with classification analysis and the corporate selected algorithms.

Both multispectral and monospectral (panchromatic) modes were experimented in addition to the supervised and unsupervised classification analyses. The minimum distance algorithm was experimented for the supervised classification. Similarly, maximum distance error threshold for each specified class was determined. Additionally, advanced ISODATA algorithm was conducted to the unsupervised classification analysis. In order to evaluate the accuracy of the classification results, an accuracy assessment based on error matrix for computing overall accuracies and kappa coefficient for the resultant classified images was employed. The evaluation was applied for both conventional and proposed approach. The demonstrated result confirms a significant increase in the overall accuracy and kappa coefficient in each classified image resulted from proposed approach when compared to the conventional one. Thus, it reduces the error percentage up to about 7% difference from the conventional method. Therefore, the proposed method provides remarkable and promising results for classification analysis.

For future researches, it is recommended to incorporate ancillary spatial data (such as maps of land use, transportation network, soils, and geology) into the land cover classification analysis to improve the resultant classified images' accuracies. It is also recommended to adopt and experiment different classification algorithms. Finally, the need to obtain high spatial resolution, spectral, and quality remotely sensed images combined with a good ancillary and multi-geographic data is a key success of having significant land cover or land use classification.

REFERENCES

1. Anderson, J., et al., 2001, A land use and land cover classification system for use with remote sensor data, USGS on line report http://landcover.usgs.gov/pdf/aderson.pdf.
2. Campbell, J.B., 1996, Introduction to remote sensing, 2nd ed., New York: The Guilford press.
3. CDSI (The central department of statistics and information), census 2008, Ministry of Economy and Planning, Detailed

(ISSN : 2536 - 9555)

results of population and housing census of Al-Madinah Al-Munawarah administrative area, Ryadh, K.S.A.

4. Clausi, D.A., 2002, An analysis of co-occurrence texture statistics as a function of grey level quantization, *Canadian Journal of Remote Sensing*, 28, 1, pp. 45-62.
5. Foody, G.M., Harshness in image classification accuracy assessment, *International Journal of Remote Sensing*, 29, 11, pp. 3137-3158.
6. Franklin, S.E., et al., 2001, Using spatial co-occurrence texture to increase forest structure and species composition classification accuracy, *Photogrammetric Engineering and Remote Sensing*, 67, 7, pp. 849-855.
7. Franklin, S.E. & Wulder, M.A., 2002, Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas, *Progress in Physical Geography*, 26, 2, pp. 173-205.
8. Gamanya, R., et al., 2007, *Expert Systems with Applications*, 32, pp. 616-624.
9. General Directorate of K.S.A Military Survey, 2001, Al-Madinah Al-Munawarah topological map, scale of 1:50000, Kingdom of Saudi Arabia.
10. Hansen, M.C., et al., 2000, Global land cover classification at 1 km spatial resolution using a classification tree approach, *International Journal of Remote Sensing*, 21, 6, pp. 1331-1364.
11. Hepner, G.F., 1999, Artificial neural network classification using minimal training set: comparison to conventional supervised classification, *Photogrammetric Engineering and Remote Sensing*, 56, 4, pp. 469-473.
12. Ismail, M.H. & Jusoff, K., 2008, Satellite data classification accuracy assessment based from reference dataset, *International Journal of Computer and Information Engineering*, 2, 6, pp. 386-392.

13. Jensen, J.R., 2005, Introductory digital image processing: A remote sensing perspective, 3rd ed., Englewood cliffs. NJ: Prentice Hall Inc.

14. Kiema, J.B.K., 2002, Texture analysis and data fusion in the extraction of topographic objects from satellite imagery, *International Journal of Remote Sensing*, 23, 4, pp. 767-776.

15. King Abdulaziz City for Science and Technology, Space research institute Saudi center for remote sensing (KACST).

16. Liu, J.G., 2000, Smoothing filter-based intensity modulation: a spectral preserve image fusion technique for improving spatial details, *International Journal of Remote Sensing*, 21, 18, pp. 3461-3472.

17. Lu, D. & Weng, Q., 2007, A survey of image classification methods and techniques for improving classification performance, *International Journal of Remote Sensing*, 28, 5, pp. 823-870.

18. Matsah, M.I. & Hossain, D., 1993, Ground conditions in Al-Madinah Al-Munawarah, Saudi Arabia, *JKAU: Earth science*, 6, pp. 47-77.

19. Philipson, W.R., et al., 1988, Land cover monitoring with SPOT for landfill investigations, *Photogrammetric Engineering and Remote Sensing*, 54, 2, pp. 223-228.

20. Pratt, W.K., 1991, Digital image processing, 2nd ed., New York: John Wiley and Sons, Inc.

21. Puissant, A., et al., 2005, The utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery, *International Journal of Remote Sensing*, 26, 4, pp. 733-745.

22. Richards, J.A., 1986, Remote sensing digital image analysis, New York: Spriger-verlag.

(ISSN : 2536 - 9555)

23. Rongqun, Z. & Daolin, Z., 2011, Expert systems with applications, 38, pp. 3647-3652.

24. Shoukry, N.A., 2004, Using Remote Sensing and Geographical Information Systems for Monitoring Settlement Growth Expansion in the Eastern Part of the Nile Delta Governorates in Egypt (1975-1998), Ph.D. Dissertation, Department of Geography, University of Utah: Salt Lake City, U.S.A.

25. Webster's II: New college dictionary, 2001, New York: Houghton Mifflin Company.