Journal of Remote Sensing & GIS

Abdollahi, et al., J Remote Sensing & GIS 2016, 5:2
DOI: 10.4172/2469-4134.1000160

Research Article Open Access

Evaluation of the Full Lambda and SVM Methods Capability to Extract Roads from Digital Images

Abdollahi A[1*], Bakhtiari HRR[1] and Nejad PM[2]

[1]*Remote Sensing and Geographic Information Systems, Faculty of Geography, Kharazmi University of Tehran, Iran*

[2]*Dry and Desert Regions Management, Faculty of Natural Resources, Ferdowsi University of Mashhad, Iran*

[*]**Corresponding author:** Abdollahi A, Remote Sensing and Geographic Information Systems, Faculty of Geography, Kharazmi University of Tehran, Iran, Tel: +982188329220; E-mail: A_Abdollahi69@yahoo.com

Received date: Feb 17, 2016; **Accepted date:** Mar 03, 2016; **Published date:** Mar 09, 2016

Abstract

Automatic extraction of information on ground using photogrammetry and remote sensing requires the formulation of human data and image data, so that, it must include all the content of the image. Complex structure of the various objects in the image leads to the challenges for doing this. So, choose the type of digital data and a good way to extract the desired effect is important in mapping accuracy. This study has investigated the semi-automated method of extraction of various types, including straight, spiral, intersection, urban and non-urban roads from satellite and aerial images. Data used included UltraCam aerial image, Worldview satellite image of non-urban area with a resolution of 0.5 m, and Quick-Bird images of Tehran province with a resolution of 0.61 m. In the proposed method, upon performing image segmentation by using Full lambda method, image classification has been done using SVM algorithm, and morphological operations are used to improve the quality of discover ways and remove noise and cover gaps. For images in which Full lambda method has high accuracy in image segmentation, therefore, the accuracy of the image classification is increased and extraction of the road from it has been done better. The average overall accuracy of over 81 percent and the average accuracy Kappa coefficient more than 78 percent in the image classification into two classes of road and non-road indicates very good capability of the system introduced for semi-automatic extraction of different roads.

Keywords: Extract road; SVM; Full lambda; Digital images

Introduction

With the development of remote sensing technology, large volumes of spatial and spectral data are available. In order to take advantage of the potential of data collected by the satellite sensors, automatic extraction of complications is arisen as a serious need in remote sensing. Automatic extraction of information on ground using photogrammetry and remote sensing requires the formulation of human data and image data, so that, it must include all the content of the image. Of course, doing this is not so simple, because the effects in the image have a complex structure. The reason for the complexity is that, every image, may be a combination of different effects such as vegetation, geological and hydrological conditions and man-made features, such as buildings and roads that identification and extraction of these effects that are sometimes very similar and have overlapping, is very difficult using spectral characteristics. Also, problems that are created because of changing brightness of the scene like shadows, clouds, error of sensor, etc., increase the complexity. Therefore, in order to extract information, in addition to spectral data, digital data available, spatial data and connections between them should also be considered. In the meantime, human knowledge plays an important role in the correct identification and segregation of different effects. Automatic extraction of effects is a process in which by creating a clear description of effects and combining them with various techniques such as digital processing of images, pattern recognition, geometric modeling, and data processing, much of the processing and presentation models are created for better understanding [1]. Roads and buildings are examples of the important man-made effects. Extraction of the road is path possible manually, semi-automatically and automatically. Manual method has high accuracy, but in terms of time and cost is not cost-effective. The difference between automatic and semi-automatic method is related to the first step. In semi-automatic method, operator plays an important role at the first stage of extraction of the road, but in the automatic method, the stage is done automatically. The road has features which compared to the other man-made effects that help to extract it, including being long and continuous, having low curvature and parallel borders, difference between gray degree and the surrounding environment, constant gray degree and texture. At the same time, there are some limiting factors of automatic extraction of the road which can note to the type of the background coverage, or effects in the neighborhood of the road, complications such vehicles on roads, bridges, and of their shadows, tunnels and phenomena with the same gray levels on the image. Khwarizmi experts in extraction of the road, at first focused on the images with low spatial resolution, and because of the complexity of urban scenes, they focused on the rural roads [2]. They then used other sources, including contextual information such as texture, geometric and topological properties of the road. Much research has been done on the identification and extraction of the road from images, due to its widespread use in various fields. Das et al. [3] have proposed a method based on SVM (Support Vector Machine) to extract the roads. Using spectral contrast, there divided non-road areas and roads areas into two parts. Finally they concluded that, kappa coefficient and overall accuracy is 89% and 93% respectively. Sırmaçek and Ünsalan [4], have presented SVM method for the diagnosis of the road from images. They tried to identify roads by using color characteristics, and divided the image into two sections of road and non-road. Finally, the kappa coefficient and total accuracy was obtained 66.33% and 81.64%, respectively. Song and Civco [5], classified and extracted the road from the images using two methods of SVM method and GML, and based on pixel information of the image and concluded that, overall accuracy of SVM method is more than GML method, and it value is 99% and 96%, respectively. Zhang [6] has proposed an automatic method for extraction of road from images with high resolution based on fuzzy system and for separating the road from the car park. Wan [7] has proposed an extraction method of the road on the basis of processing of geometric characteristics, zoning based on fuzzy logic at the pixel level, the use of angular texture curves on multispectral with high resolution. Yong et al. [8] have developed a semi-automated method using an angular texture curve which uses features such as changing curve. Bonnefon [9] has done a complete process of updating linear effects by using a fully automated method and with quality evaluation. Zadeh [10] has been introduced a new segmentation method to extract road from the high-resolution images, that only a small number of pixels are needed as input of the model. Then, he has extracted the central axis using advanced morphological operators. Mokhtarzadeh [11] has used the optimal structure of neural networks and input data to extract the road from multispectral image of Ikonos satellite. Zhang and Couloigner [12] have evaluated the effect of the use of ATN in the separation of road from parking on the high-resolution satellite images. In the present study, in order to implement the proposed system of semi-automatic extraction of the road, first pre-processing operations, including contrast enhancement using histogram linear adjustment was made on the images. Then, Full Lambda method was used for image segmentation, as well as the SVM algorithm was used for image classification and extraction of the road. In the end, in order to remove noise and pixel unrelated to the class, and to increase the system's accuracy, morphological disruption and closing functions were used.

Materials and Methods

The data used

In this study, UltraCam aerial digital camera images of Shiraz region Figure 1 (a), World View images with spatial resolution of 0.5 m of Ahvaz, Figure 1 (b), as well as Quick-Bird image of Tehran province with a spatial resolution of 0.61 m, Figure 1 (c), were used.

UltraCam aerial digital camera produce multispectral images in the spectral ranges of blue, green, red and near infrared with the size of 2672 × 4008 pixels, and panchromatic image with the size of 7500 × 11500 pixels simultaneously. The physical size of the pixels is 9 microns in the panchromatic band, which leads to the high spatial resolution and according to altitude. For example, in the 330 and 1,400 m altitude, separation of the band, will be respectively 3 and 12.5 cm [13].

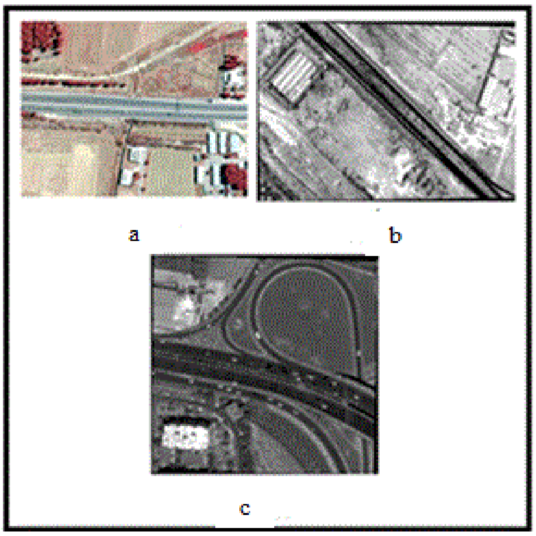

Figure 1: Images used (a) Ultracam image (b) World View image (c) Quick-Bird image.

The steps to implement the semi-automatic extraction system of road from the images

The stage of the discovery of the road extracts pixels belonging to the class of the road among complications in the image. For this purpose, the techniques supervised classification and morphological functions were used. In order to better understand the various stages of implementing the system of semi-automatic extraction of road from the images, flowchart of the system is presented in Figure 2.

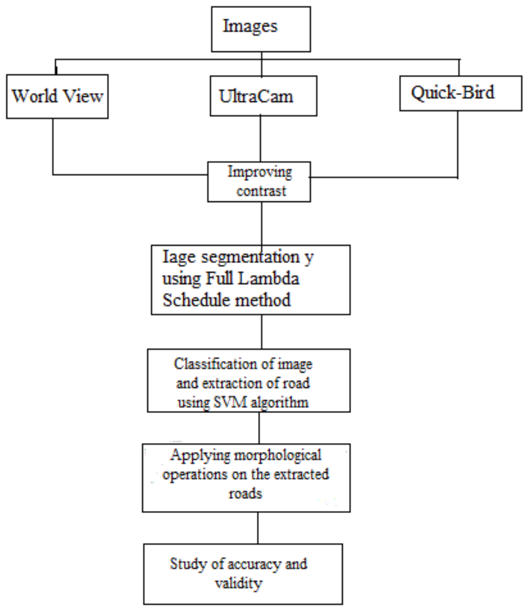

Figure 2: Flowchart of road extraction system.

Data: As previously mentioned, in this study, UltraCam aerial images, World View images with a spatial resolution of 0.5 m, and the QuickBird image with spatial resolution of 0.61 m were selected as input images of algorithm. In the images used in this study, the method of linear transformation histogram is used to perform preprocessing. In this method, gray degrees using a linear transfer function are converted of observations domain to fully dynamic range. This conversion makes more difference between levels of gray, and an increase in contrast. Of course, changing degrees of gray, which are created due to improved contrast of image, has an impact on clustering.

Segmentation algorithm full lambda schedule: This method integrates duplicate neighboring areas based on a combination of spectral and spatial information. This algorithm considers each possible value of λ_i the list λ to achieve the best segmentation. Full Lambda Algorithm considers all pairs of adjacent areas and in the end, chooses the best pair possible. Integration occurs when the algorithm finds a pair of adjacent areas i and j, so that the integration value $t_{i,j}$ is less than a threshold value of lambda (Equation 1):

$$t_{i,j} = \frac{\frac{|O_i| \cdot |O_j|}{|O_i| + |O_j|} \cdot \|u_i - u_j\|^2}{length\left(\partial\left(O_i, O_j\right)\right)}$$

Where, Oi is area i of the image, $|O_i|$ is an area of the region i, ui is average value in the area i, uj is average value in the area j, $\|u_i - u_j\|$ is Euclidean distance between the spectral value of the regions of i and j, length $\partial\left(O_i, O_j\right)$ is the length of common border between Oi and Oj.

Full Lambda algorithm in a simplified form is as follows:

It considers pixels of image as segmentation as Initial minor segmentation.

It finds the pair (O_j, O_i) which is the smallest $t_{i,j}$ in equation 1 among all pairs of adjacent areas.

Integration of O_i and O_j for formation $O_{i,j}$

Repeat the previous step to create just one area.

Support vector machine classification (SVM): Support vector machine is one of the supervised learning methods which are used for classification and regression. The method is one of the relatively new methods that in recent years show a good performance compared to older methods for classification of Perceptron neural networks [14]. It is based on linear classification of data. SVM uses a fan who called kernel trick, to convert the data, and then finds optimal border between possible outcomes based on this conversion. In other words, it does very complicated conversations, then determines how to separate the data based on outputs defined or labels. SVM Algorithm is one of pattern recognition algorithms. SVM algorithm can be used anywhere you need to pattern recognition and classification of objects in special classes. In a learning process, which consists of two classes, the purpose of SVM is to find the best function to classify, so that, to the members of two classes can be recognized in data collection. The criterion for best classification is determined as geometrical for the data collection which can be analyzed linearly. SVM is a relatively new learning method which is often used for binary classification. Suppose that, there are L observations, that every observation includes the pairs in which the input vector is a two-state vector (-1 or +1). The basic idea of SVM classification is multi-dimensional data mapping into a higher dimensional space, so that there is a B cloud page, which can be used for linear discriminant of original data. As a result, the border (margin) between different classes is maximized, and prevents interference between classes [15]. Based on the training data for classes which is difficult to separate them using a linear model, support vector machine separates both the classes optimally, which is done through repetition, data conversion and fitting a cloud page to separate these classes in n-dimensional space, which the Lagrange multipliers and core functions (e.g. polynomial) are used. Support vector machines is similar to artificial neural network method to do multi- pair and multi-class strategy in which an input layer and output layer is required.

Morphological operators: In the present study, morphological operations are used in order to post-processing and increase the accuracy of the obtained road class. The most important operators that were used in this research are opening and Erode operators. The morphology functions are based on the use of set theory in image processing, therefore, the morphology operators are fairly powerful methods for image processing problems. In general, operators lead to remove non-road noises and pixels, fill gaps in the roads and increase classification accuracy. The reason for use of morphological operators in binary images is to reduce the number of features. For this purpose, the opening operator is used in the binary images obtained in order to remove the roughness. The dimensions of the structural elements used in this section depend on the depth and roughness of the resulting image. As can be proven in the mathematical definition of opening operator, the image obtained of this operator is a subset of the original image, and this ensures not adding areas with non-1 value in binary image derived. Opening operator actions on the binary image causes the narrow connections of image have been removed and the softer image is obtained. Next, using erode morphology operator, which the size of its structural element to be determined empirically by the user to remove the smaller parts, optimal areas be extracted.

Accuracy assessment: In order to obtain the accuracy and verification of extracting the road, first 100 samples are extracted from the image, and then, half of these samples were used to classify and others samples were used to assess the accuracy and calculate the combined matrix and its parameters, including the overall accuracy, and kappa coefficient, of errors in classification [16]. These parameters provide classification accuracy in two phases. First stage is related to estimate accuracy and error after classification, and before applying post-processing operators, which its parameters are shown by OA, Kappa, C, O, which represent an overall accuracy, kappa coefficient, Commission error and Omission error. The second step is to estimate the accuracy and error after applying morphology operations on the image [17,18]. By comparing the corresponding values of these parameters before and after applying morphology operators, the role of these operators to improve its results can be understood.

Results and Discussion

As far as possible we try to use images that have different forms of roads to examine the advantages and limitations of the proposed system. In Figure 3 (a) to (c), semi-automatic extraction stages of the UltraCam aerial image is shown for a region of Shiraz. Figure 3 (a), is the original image of desired region. Figure 3 (b) is segmented image method by using Full lambda method. As seen in the figure, segmentation of effects is done with high precision and Full lambda method because of low diversity effects has high accuracy. Figure 3 (c) is the result of the supervised classification SVM on the image. In this method, first four categories (road, home, coverage and wastelands) are determined, and then, classification is applied by using SVM method on the image, the accuracy is very high in this image. Figure 3 (d) is the road extracted from the image before applying morphological operators, and Figure 3 (e), shows applying morphological operations on the road extracted. As can be seen, applying these operators leads to remove on-road pixels on the image, and fill gaps in the road, and increase the classification accuracy.

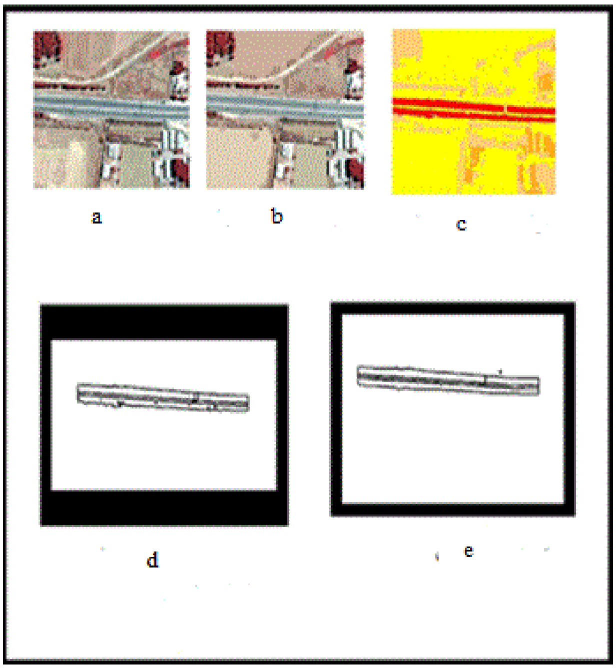

Figure 3: Semi-automatic extraction stages of road from UltraCam image.

Figure 4 (a) to (e), show the road extraction stages from the World View image of a non-urban area. Figure 4 (a), shows the original image of the desired region. Figure 4 (b), shows the segmented image by using Full Lambda. Figure 4 (c) shows the result of the supervised classification SVM on the image. Figure 4 (d) shows the extracted road before applying morphological operators. In this image, because the road has intersection, and there is a sub-road in there, a little of the proposed system accuracy is reduced, and as you can see, the extraction is more difficult in these places, and the proposed system is facing some problems. As a result, use of morphological operators has been able to solve this problem, and to increase the accuracy of the proposed system, which is shown in Figure 4 (e).

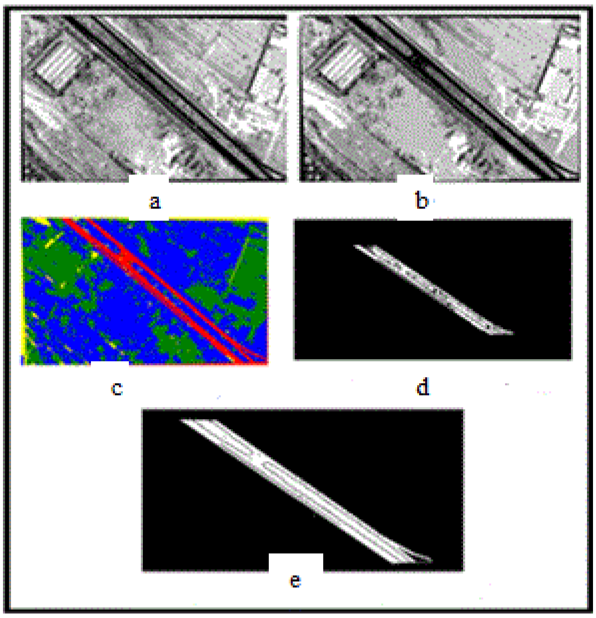

Figure 4: Semi-automatic extraction stages of road from World View image of a non-urban area.

Figure 5 (a) to (c), show extraction stages of road from a Quick-Bird image of an urban area. Figure 5 (a) shows the original image of the desired region. Figure 5 (b), shows segmented image by using Full Lambda method. Image has the urban texture, and the variety of ways ranging from the sub-main, main, intersection and so on. As a result, it will lead to create the challenges foe operation of the proposed system.

As shown in Figure 5 (c), image classification using SVM, particularly at corners and intersections has less accuracy, and road pixels are dedicated to the non-road pixels and vice versa. In Figure 5 (d), which shows the road extracted before applying morphological operators, the differences and the difficulties can be found, the road extraction in these regions is difficult. The use of morphological operators in Figure 5 (e), has reduced some of the differences and difficulties, and the system's accuracy has increased, but the proposed system does not have the accuracy to extract such ways.

Citation: Abdollahi A, Bakhtiari HRR, Nejad PM (2016) Evaluation of the Full Lambda and SVM Methods Capability to Extract Roads from Digital Images. J Remote Sensing & GIS 5: 160. doi:10.4172/2469-4134.1000160

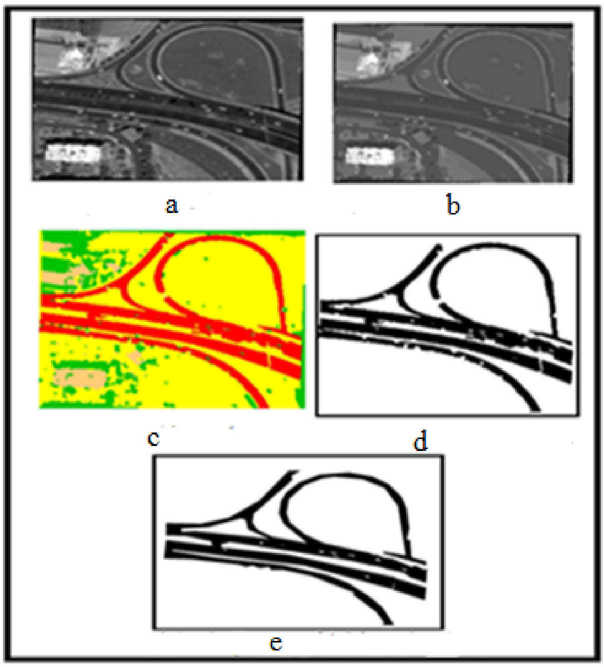

Figure 5: Semi-automatic extraction stages of road from Quick-Bird image of a non-area.

Assessment of the results of road extraction

In Table 1, the parameters of classification accuracy assessment before and after processing using the co-occurrence matrix for the image used in this study are presented. Evaluation results show that, in general, classification accuracy, after applying morphological operators, is increased, or in other words classification error (O, C) is decreased, and therefore, better class for road is derived. Kappa coefficient, also, that shows the worst classification accuracy than random classification, such as the overall accuracy after post-processing in the image is improved. The classification accuracy improvement on the kappa coefficient is more important than overall accuracy parameter.

As specified in Table 1, Figure 3, because of the lack of diversity on effects in the region, and apparent differences in gray degrees of road and the background, has more accurate compared with other images. Figure 4, due to more similarity between the pixels and the background, and also its intersection and sub-road has less accuracy than Figures 3 and 5 also, because of the urban complex texture and more similarities in road pixels and background pixels, and also, a variety of roads has less accuracy, and the proposed system faces difficulties in extracting it.

The results of classification before applying morphological operators (percent)			
World View image	**Quick-Bird image**	**Ultra Cam Image**	**Assessment Index**
80	73.27	85	Overall Accuracy
76.34	69.44	81.49	Kappa
1.43	3.57	1.21	Commission Error
0.9	2.1	0.7	Omission Error
Classification results after applying morphological operators (percent)			
82.14	75.1	88.2	Overall Accuracy
79.4	71.4	83.6	Kappa
0.76	3.2	1.1	Commission Error
0.71	1.8	0.6	Omission Error

Table 1: Evaluating the results of classification.

Conclusion

The present study has been carried out with the aim of introducing a system for semi-automatic extraction of road from UltraCam aerial images, World View satellite images for non-urban area, with a spatial resolution of 0.5 m, as well as Quick Bird image with spatial resolution of 0.61 mm, with using a combination of segmentation methods of Full Lambda, and supervised classification by using SVM algorithm, and the use of morphological operations. In a study that Das et al. [3] extracted the road from the images by using the SVM method, the average overall accuracy 93% and kappa coefficient 89 percent was obtained. Also, Sırmaçek and Ünsalan [4], by using the SVM method have extracted the road from the images and the overall accuracy and kappa coefficient for this method is achieved by 81.64% and 66.33%. However, in this study, the average overall accuracy and kappa coefficient obtained from the system is 81.8% and 78.13%, respectively. Full Lambda method in this study has high accuracy, and hence image segmentation and its classification are done better, and then the extraction of road is conducted with higher accuracy. The average overall accuracy (OA) more than 81%, and the mean kappa coefficient more than 78 percent in the image classification into two classes of non-road and road indicates the overall success of the proposed system for the semi-automated extraction of the road. Of course, the proposed system has limitations, which are discussed later. In the UltraCam aerial image, because there is much less variation in effects, and also the road pixels are determined, and there is a direct path, the proposed system is more accurate and has no limitations. But compared with Worldview Quick bird satellite images, which they have a variety of effects, as well as various forms of ways, including straight, spiral, intersection and so on, the proposed system has some limitations. Because the shape and thickness of the road are effective factors on semi-automatic extraction of the road with the use of the proposed system, and in general, whatever the road is more complex, the accuracy of the system is reduced, and therefore, there is need to perform additional operations for extraction of roads parts.

References

1. Sowmya A, Trinder J (2000) Modelling and representation issues in automated feature extraction from aerial and satellite images. Journal of Photogrammetry and Remote Sensing 55: 34-47.
2. Price K (1999) Road Grid Extraction and Verification. International Archives of Photogrammetry and Remote Sensing 32: 3-2.
3. Das S, Mirnalinee TT, Varghese K (2011) Use of salient features for the design of a multistage framework to extract roads from high-resolution multispectral satellite images. IEEE Transactions on Geoscience and Remote Sensing 49: 3906-3931.
4. Sırmaçek B, Ünsalan C (2011) Road detection from remotely sensed images using color features. Proceedings of International Conference on Recent Advances in Space Technologies, pp: 112-115.
5. Song MJ, Daniel C (2004) Road Extraction Using SVM and Image Segmentation. Photogrammetric Engineering & Remote Sensing 70: 1365–1371.
6. Zhang QP (2006) Benefit of the angular texture signature for the separation of parking lots and roads on high resolution multi-spectral imagery. Pattern Recognition Letters 27: 937-946.
7. Wan Y, Shen SH, Song Y, Liu SH (2007) A Road Extraction Approach Based on Fuzzy Logic for High-resolution Multispectral Data. IEEE Computer Society, Fourth International Conference on Fuzzy Systems and Knowledge Discovery.
8. Yong L, Jing S, Xiangguo L, Junfang B, Ying L (2008) Road tracking by Parallel Angular Texture Signature. IEEE International Workshop on Earth Observation and Remote Sensing Applications, China.
9. Bonnefon R, Dherete P, Desachy J (2002) Geographic information system updating using remote sensing images. Pattern Recognition Lett 23: 1073-1083.
10. Mohammadzadeh A, Tavakoli A, Valadanzoej M (2006) Road extraction based on fuzzy logic and mathematical morphology from pan-sharpened Ikonos images. Photogrammetric Record 21: 44-60.
11. Mokhtarzade M, Zoej MV (2007) Road detection from high-resolution satellite images using artificial neural networks. International Journal of Applied Earth Observation and Geoinformation 9: 32-34.
12. Zhang Q, Couloigner I (2006) Automated road network extraction from high Conference, Reno, Nevada. Resolution multi-spectral imagery.
13. Farzaneh A (2006) Digital aerial photographs (digital) of forest in the north of the country. Tabiat-e-sabz journal, the first year, pp: 15-17.
14. Vapnik VN (1995) The Nature of Statistical Learning Theory. Spring-Verlag, New York, p: 188.
15. Zhang R, Sun D, Yu Y, Goldberg MD (2012) Mapping Nighttime Flood from MODIS Observations Using Support Vector Machines. Photogrammetric Engineering & Remote Sensing 78: 1151-1161.
16. Richards JA, Xiuping J (2006) Remote sensing digital image analysis. (4th edn), Springer, Chapter 3, 9 & 11.
17. Rafael CG, Richard EW (2007) Digital image processing. Prentice-Hall, Inc, (3rd edn).
18. Salehi A, Muhammad A, Mokhtarzadeh M, Zoj MJW (2010) Automatic discovery of road network from large-scale satellite images using neural networks and angular texture information. Geomatics Conference 2010, National Cartographic Center, Tehran.