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Research Paper

# Semi automatic road extraction from digital images

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Road extraction from digital images is of fundamental importance in the context of automatic mapping, effective urban planning and updating GIS databases. Very high spatial resolution (VHR) imagery acquired by airborne and space borne sensors is the main source for accurate road extraction. Manual techniques are fading away as they are time consuming and costly. Hence, road extraction method that is significantly more automated has become a research hotspot in remote sensing information processing. This paper proposes a semi-automatic approach to extract different road types from high-resolution remote sensing images. The approach is based on edge detection and SVM and mathematical morphology method. First the outline of the road is detected based on Canny operator. Then, Full Lambda Schedule merging method combines adjacent segments. Then the entire image was classified using Support Vector Machine (SVM) and various spatial, spectral, and texture attributes to form a road image. Finally, the quality of detected roads is improved using morphological operators. The algorithm was systematically evaluated on a variety of satellite images from Worldview, QuickBird and UltraCam airborne Images. The results of the accuracy evaluation demonstrate that the proposed road extraction approach can provide high accuracy for extraction of different road types.



## 1. Introduction

Road extraction from aerial and satellite images is of great importance for urban and transportation planning, urban disaster management and automotive navigation (Mena, 2003).

With the development of high resolution optical satellite imagery, large volumes of spatial and spectral data are available. In order to take advantage of these data accurate and efficient information extraction methods are crucial in remote sensing (Salehi et al., 2010). Manually extracting roads from digital imagery, although has high accuracy, but in terms of time and cost is not cost-effective especially when the scenes are very complex. Therefore, it is urgent to develop a semi-automatic/automatic road extraction method. In the literature, an automatic method implies a fully automatic process. An automatic road extraction method based on different Morphological direction filtering and road intersections is presented by Ahmed and Rahman (2011). An automatic road detection approach in urban region based on preprocessing to reduce the unwanted objects and extraction of road segments using texture progressive analysis and normalized cut method is proposed by Senthilnath et al. (2009). Pankaj et al. proposed a road network segmentation technique using adaptive global thresholding along with morphological operations (Singh and Garg, 2013). Road regions are segmented using average intensity values, and morphological operators are used for further processing. They gave experimental result for an image and evaluated their work by measuring quality parameters. Theoretically, a fully automatic approach requires no human intervention, but this is not practical (Subash, 2011). There are some limiting factors of automatic extraction of roads such as background coverage, features in the neighborhood of the road, complications such vehicles on roads, bridges, and their shadows. Moreover, problems that are created by shadows, clouds, error of sensor, etc., increase the complexity. In semi-automatic method, operator plays an important role at the first stage of extraction of the road. Therefore, human knowledge plays an important role in the correct identification and segregation of different objects. A semi automatic road network extraction method based on neural-dynamic tracking framework is presented in Wang et al. (2015) and Chaudhuri et al. (2012)

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proposed a semi-automatic method for urban road extraction based on customized directional morphological filter and a set of post-processing steps, including hole-filling, pruning, and segment linking (Huang et al., 2014; Sghaier and Lepage, 2016) applied multi kernel SVM for multi-index learning, to separate the road class from other classes a set of indices such as morphological shadow index, morphological building index and variation indices based on the wavelet transform were employed. Miao et al. (2015) presented a semi-automatic object-based method. The proposed method consisted of five main steps. First, satellite images were segmented to generate objects. Then, object-based Frangi's filter (OFF) and object-based shape filter (OSF) were applied to compute object features to select road candidates. After that, the road class is extracted using the support vector machine (SVM) based on the extracted feature set. Finally, tensor voting (TV), active contour, and the geometrical information are integrated to eliminate road gaps and improve road smoothness. In a recent study (Khesali et al., 2016) a semi Automatic Road Extraction based on two fusion methods, including neural network and knowledge-based fusion are proposed. The first method consists of two stages: separate road detection using each dataset and fusion of the results obtained using a neural network. The second method is a knowledge-based fusion using thresholds of narrow roads and vegetation gray levels. 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.

The main purpose of this paper is to present a semi automatic method that combines the edge detection and SVM techniques to extract different type of roads. As an application, the proposed method is used to extract roads from high-resolution remote sensing images such as worldview, QuickBird and UltraCam images.

## 2. Materials and methods

### 2.1. Data

In this study, UltraCam aerial digital camera images of Shiraz region Fig. 1(a), WorldView images of Ahvaz, Fig. 1(b), as well as QuickBird image of Tehran, Fig. 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 $2672 \times 4008$ pixels, and panchromatic image with the size of $7500 \times 11{,}500$ pixels simultaneously. The physical size of the pixels is 9 $\mu$ 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 panchromatic and multispectral bands will be 3 and 12.5 cm respectively (Leberl and Gruber, 2005).

### 2.2. Methodology

In this paper, a semi automatic method is presented to detect the roads in high-resolution satellite images i.e. WorldView and QuickBird and UltraCam aerial images. The proposed method is based on four main steps. Firstly, canny edge detector is employed to segment roads from the images. Secondly, Full Lambda Schedule merging method applied to combine adjacent segments. The third, Support Vector Machine (SVM) was used to classify entire image.

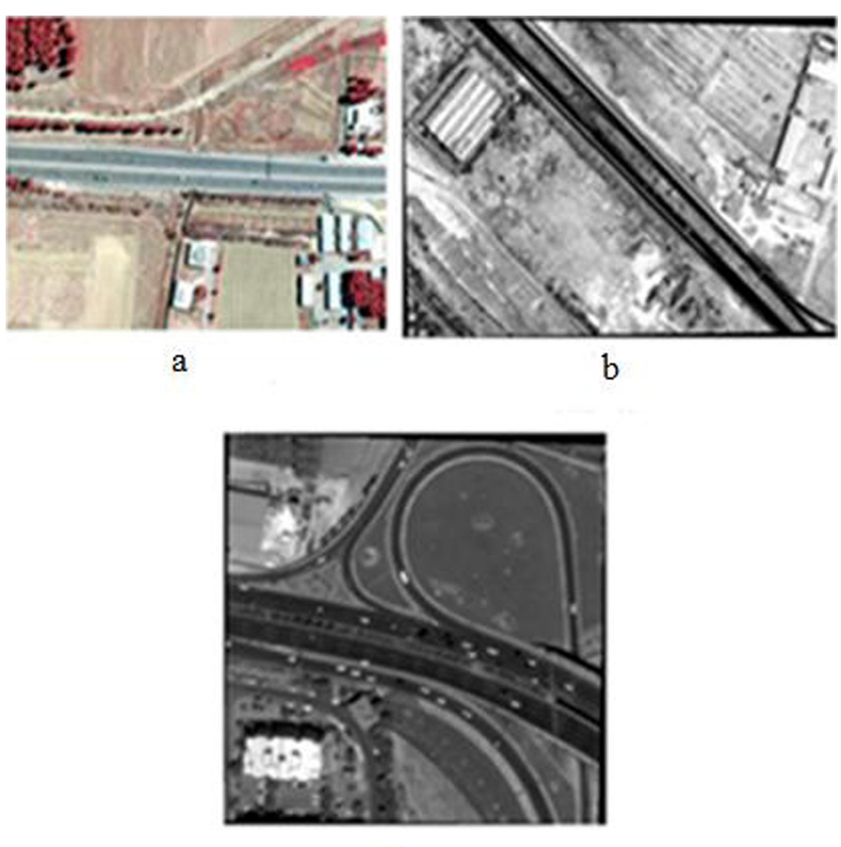


**Fig. 1.** Images used (a) Ultracam image (b) World View image (c) Quick-Bird image.

Finally, the morphological operation procedure such as dilation, erosion, opening, and closing techniques are performed to remove the undesired objects. 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 Fig. 2.

*2.2.1. Image segmentation*

The main aim of image segmentation is dividing an image into regions having similar properties, such as gray level, color, texture, brightness, contrast, etc. The concept of image segmentation is based on discontinuity or similarity of gray levels. In an image, the boundary between an object and background or border between overlapping objects, can be defined as edges. If it assumed that the intensity of each object is continues and in compare with the intensity of adjacent objects is different, any significant changes in the intensity can be defined as edge. There are many ways to perform edge detection. However, the most may be grouped into three categories, gradient (Approximations of the first derivative), Laplacian (Zero crossing detectors) and Image approximation algorithms. The Canny edge detector computes the squared gradient magnitude. Local maxima of the gradient magnitude that are high are identified as edges. After an image is segmented, its adjacent regions can be merged to form a less fragmented segmentation based on their similarity. The full lambda schedule algorithm (FLSA) was developed as a fast and efficient merge Algorithm.

The full lambda schedule algorithm of Redding et al. (1999) for image segmentation maintains a list of merge costs (as measured by the Mumford-Shah functional) for all relevant pairs of neighboring regions and at each step selects the best pair to merge from the list. This is done by using a Mumford-Shah energy functional and sophisticated data structures. Such function also provide a measure of the "goodness" of a segmentation by trading off the total model fitting error across all regions against the total model complexity of the boundary. According to this view point, a good segmentation not only allows the image model to be fitted with small total error but also has a simple boundary. Thus the aim is to find the segmentation which minimizes the functional. In the Mumford-Shah energy functional, the trade-off of model fitting error against boundary complexity is controlled by a regularization parameter which is denoted by $\lambda$. The parameter $\lambda$ is applied as a weighting to the boundary complexity term. Thus, if $\lambda$ is increased, the penalty on boundary complexity is increased and coarser segmentations result. Conversely, if $\lambda$ is decreased, the penalty on boundary complexity is reduced and finer segmentations result.

*2.2.2. Support vector machine classification (SVM)*

Support vector machine is one of the supervised learning methods which are used for classification and regression. The basic idea of SVM classification is multi-dimensional data mapping into a higher dimensional space, so that there is a cloud page, which can be used for linear discrimination of original data. SVM uses kernel trick technique, to convert the data, and then finds optimal border between possible outcomes based on this conversion. In other words, it does very complicated conversions and then determines how to separate the data based on defined outputs or labels. Four different SVMs kernels can be applied to classify images.

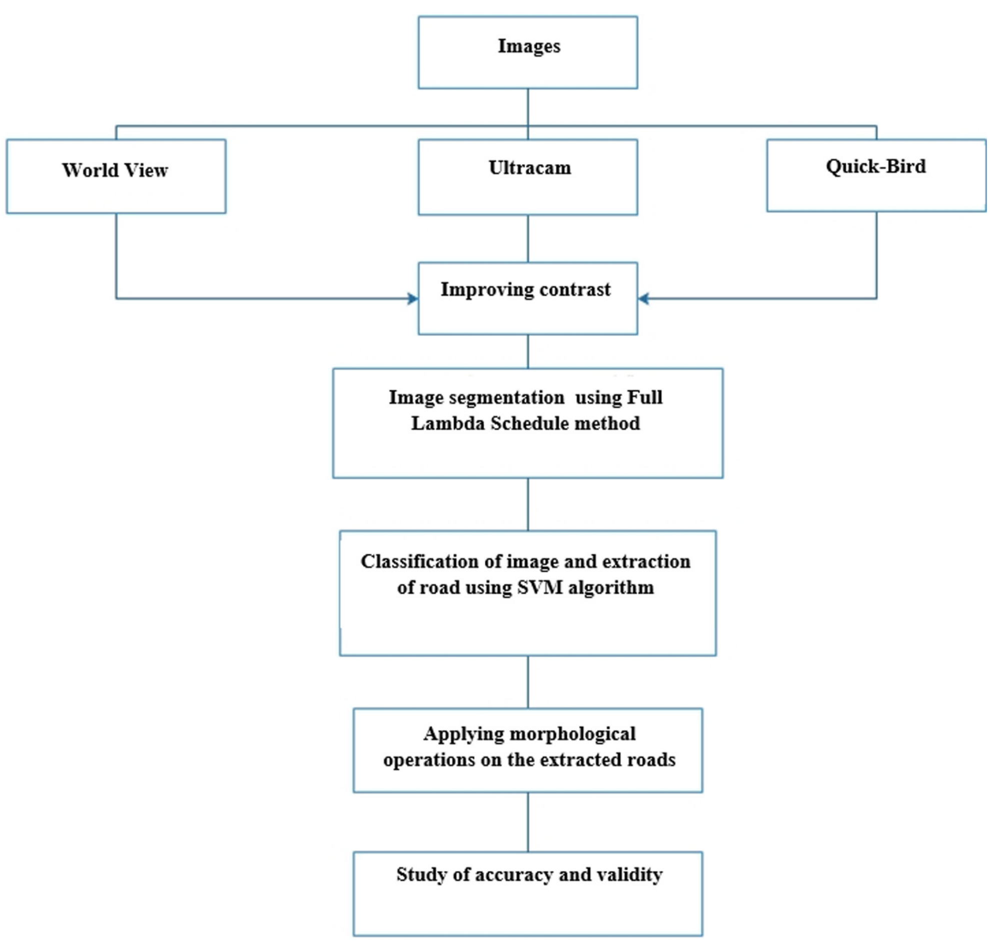


**Fig. 2.** Flowchart of road extraction system.

These kernels include: linear, polynomial, radial basis function (RBF), and sigmoid which radial basis function was used in this study. Parameters of gamma, penalty and texture kernel size were considered 0.03, 100 and 3 respectively. Also threshold value is considered 5 percent, which means segments that have less than 5 percent confidence in each class are set to unclassified. The criterion for best classification is determined as geometrical for the data collection which can be analyzed linearly. 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). As a result, the border (margin) between different classes is maximized, and prevents interference between classes (Zhang et al., 2012). 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. By their nature SVMs are intrinsically binary classifiers (Melgani and Bruzzone, 2004) however there exist strategies by which they can be adapted to multiclass tasks associated with remote sensing studies. Two of the common approaches are the One-Against-One (1A1) and One Against-All (1AA) techniques. As mentioned before, SVM classification is essentially a binary (two-class) classification technique, which has to be modified to handle the multiclass tasks in real world situations e.g. derivation of land cover information from satellite images. Two of the common methods to enable this adaptation include the 1A1 and 1AA techniques. The 1AA approach represents the earliest and most common SVM multiclass approach (Melgani and Bruzzone, 2004) and involves the division of an N class dataset into N two-class cases. The 1A1 approach on the other hand involves constructing a machine for each pair of classes resulting in N(N − 1)/2 machines. When applied to a test point, each classification gives one vote to the winning class and the point is labeled with the class having most votes. This approach can be further modified to give weighting to the voting process. In this experiment, a 1A1 technique was used to extend the binary SVM classifier to a multi-class task.

**Table 1**
Evaluating the results of classification.

| World View image | Quick-Bird image | Ultra Cam Image | Assessment Index |
|---|---|---|---|
| The results of classification before applying morphological operators (percent) | | | |
| 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 |

### 2.2.3. Morphological operators

In the present study, morphological operators 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. The morphology functions are based on the application of set theory in image processing. In general, operators

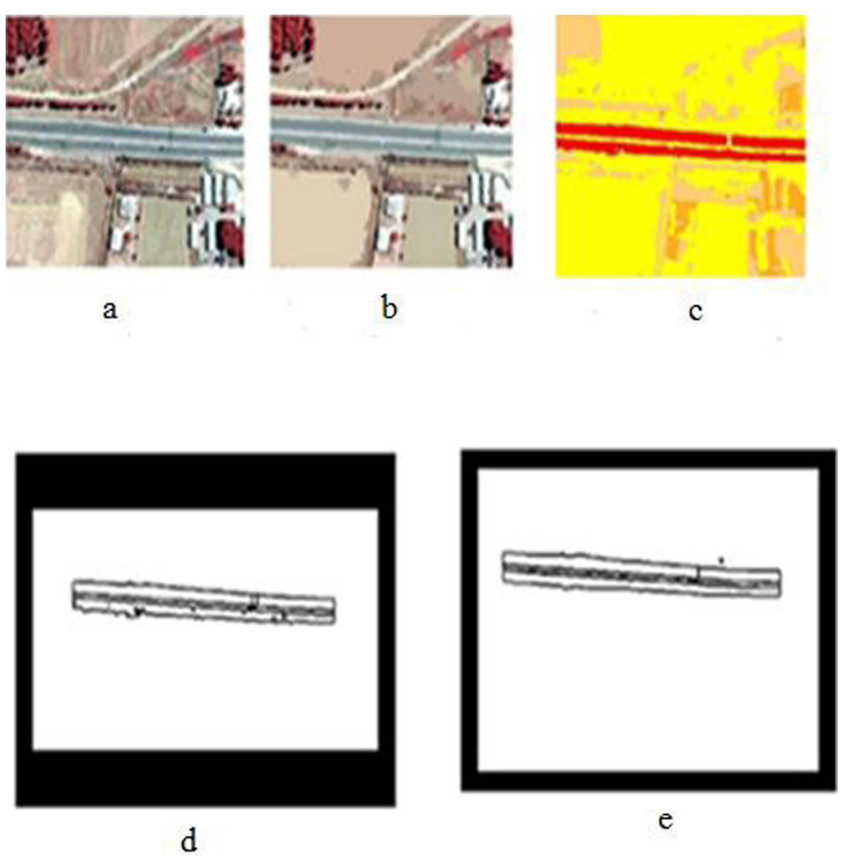


**Fig. 3.** Semi-automatic extraction stage of road from UltraCam image.

lead to remove non-road noises and pixels, fill gaps in the roads and increase classification accuracy. For this purpose, the opening operator is used in the binary images obtained 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 acts on the binary image causes the narrow connections of image have been removed and the smooth image is obtained. Next, using erode morphology operator to remove the smaller parts, optimal areas be extracted (Gonzalez et al., 2007).

*2.2.4. Accuracy assessment*

In order to evaluate the accuracy of the extracted roads, first 100 samples are selected from the image, and then, half of these samples were used as training areas for classification and other samples were used for accuracy assessment and calculate the confusion matrix and its parameters, including the overall accuracy, and kappa coefficient, of errors in classification. The accuracy assessment was performed in two phases. First stage was 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 morphological operators. By comparing the corresponding values of these parameters before and after applying morphological operators, the role of these operators to improve its results can be understood.

*2.2.5. Assessment of the results of road extraction*

The performance of proposed method is compared with ground truth which is manually extracted from images. The results obtained before and after applying morphological operators are compared with this reference, and this comparison is given in Table 1. The accuracy measures such as overall accuracy and Kappa coefficient are evaluated for proposed method on various satellite and airborne images.

Evaluation results show that, in general, extraction accuracy, after applying morphological operators, is increased, or in other words classification error (O, C) is decreased, and therefore, better results for road extraction is derived. Kappa coefficient, also, that shows the worst classification accuracy than random classification, such as the overall accuracy after post-processing of the images is improved. The classification accuracy improvement on the kappa coefficient is more important than overall accuracy parameter.

As specified in Table 1, UltraCam aerial image, because of the lack of diversity on features in the region, and apparent differences in gray degrees of road and the background, has more accurate

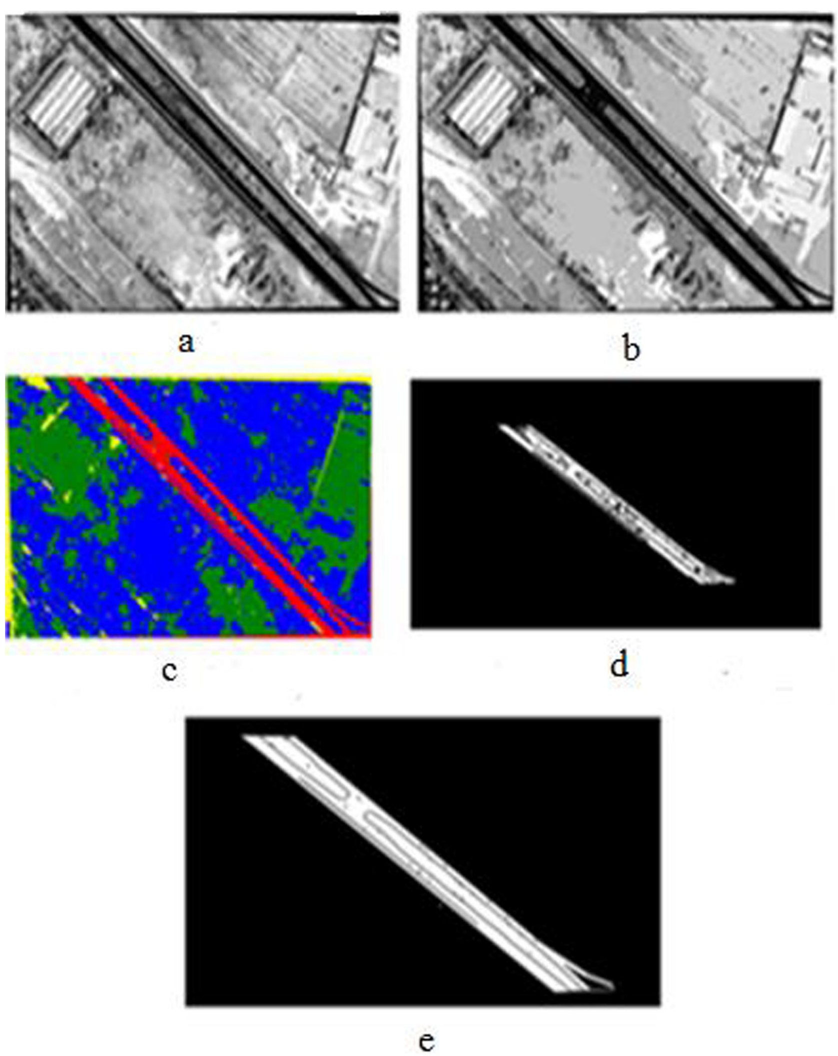


**Fig. 4.** Semi-automatic extraction stages of road from World View image of a non-urban area.

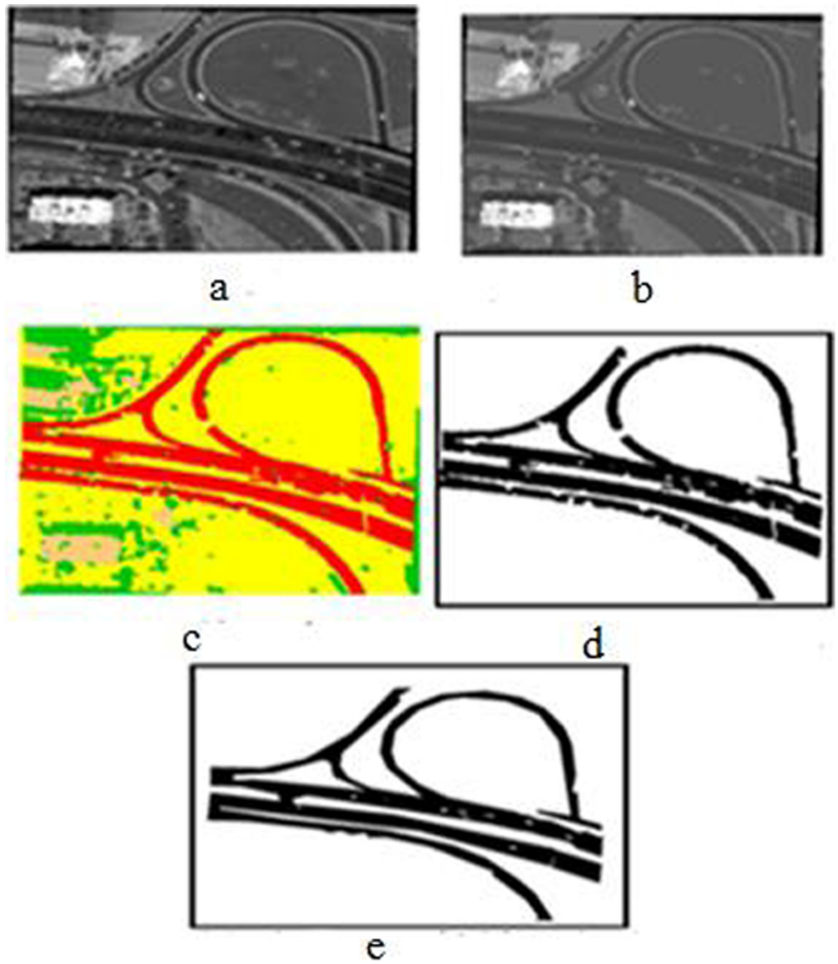


**Fig. 5.** Semi-automatic extraction stage of road from Quick-Bird image of a non area.

results compared with other images. In World View image, due to more similarity between the pixels and the background, and also its intersection and sub-road has less accuracy than UltraCam aerial image. QuickBird image also, because of the urban complex texture and more similarities in road pixels and background pixels, and diverse road shapes has less accurate results, and the proposed method faces difficulties in Successful road extraction.

## 3. Experimental results and discussion

As far as possible we tried to use images that have different forms of roads to examine the advantages and limitations of the proposed method. The results of different steps of the proposed method for UltraCam aerial image are given in Fig. 3(a)–(e). The segmented result using adaptive canny edge detector is given in Fig. 4(b). In Fig. 3(a), is the original image of desired region. The segmented result using adaptive canny edge detector is given in Fig. 3(b). The resultant road region segmented image consists of some unwanted regions. Fig. 3(c) is the result of the supervised SVM classification. Fig. 3(d) is the extracted road from the image before applying morphological operators, and Fig. 3(e), shows the results after applying morphological operators. As can be seen, applying these operators leads to remove non-road noises and pixels on the image, and fill gaps in the road, and increased the extraction precision.

Fig. 4(a)–(e), illustrate the road extraction stages for the World View image of a non-urban area. Fig. 4(a), shows the original image of the desired area. Fig. 4(b), shows the segmented image by using canny operator. Fig. 4(c) shows the result of the supervised classification SVM on the image. The resultant image has holes due to objects on roads or trees along the road which is shown in green circled area Fig. 4(d) shows the extracted road before applying morphological operators. The resultant image is further filtered using morphological opening operation to remove unwanted portions. As a result, use of morphological operators increased the precision of extracted road, which is shown in Fig. 4(e).

The proposed method is implemented on interchange road. Fig. 5(a)–(e), show road extraction stages from a QuickBird imagery of an urban area. Fig. 5(a) shows the original image of the desired region. Fig. 5(b) shows segmented image by using canny edge detector. In this image, because the road has intersection and there is a bridge and road underpass, the proposed approach is facing some difficulties. As shown in Fig. 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 Fig. 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 Fig. 5(e), has removed some of unwanted areas.

## 4. Conclusion

The present study has been carried out with the aim of introducing a method for semi-automatic extraction of roads 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 and Full Lambda, supervised classification by using SVM algorithm, and the use of morphological operations. In this study, the radial basis function method and the one-against-one (1A1) technique have been used and the average overall accuracy and kappa coefficient obtained from the method is 81.8% and 78.13% respectively which compared to other methods have shown the better results. 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 method for the semi-automated extraction of the roads. Of course, the proposed method has limitations, which are discussed later. In the UltraCam aerial image, because there is much less variation in objects and there is a direct path, the proposed method is more accurate and has no limitations. But compared with Worldview and QuickBird satellite images, which they have a variety of objects, as well as various forms of roads, including straight, spiral and 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 method, and in general, whatever the road is more complex, the accuracy of the method is reduced, and therefore, there is a need to improve the method to be able to extract complex roads more accurately.

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