Towards an Automatic Road Lane Marks Extraction Based on Isodata Segmentation and Shadow Detection from Large-Scale Aerial Images

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Key words: road marking extraction, ISODATA segmentation, shadow detection, aerial image

SUMMARY

Extraction of road features from satellite or aerial images has been a long-term topic of research. The majority of the early work only focused on linear feature extraction approaches, with restrictive assumptions on image resolution and road appearance. With the widely available of high resolution digital aerial images, the detection of sub-road features becomes possible. In this paper, we will focus on the automatic extraction of road lane markings, which are required by various applications, e.g. autonomous vehicle navigation, and lane departure warning. The unsupervised ISODATA segmentation algorithm is utilized to classify the road surface from other ground features in the image, whereas the result of segmentation is greatly affected by shadows on the road surface casted by vehicles and above trees. Therefore, a shadow detection method based on YC_rC_b color space is employed to detect and compensate the shadowed regions. Finally, the road lane markings are extracted on the generated road surface by co-occurrence contrast enhancement and histogram segmentation. The proposed method was tested on the aerial imagery dataset of Gympie, Queensland, and the results demonstrate the efficiency of our approach.

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Abstract:

The automatic extraction of road features from remote sensed images has been a topic of great interest within the photogrammetric and remote sensing communities for over 3 decades. Although various techniques have been reported in the literature, it is still challenging to efficiently extract the road details with the increasing of image resolution as well as the requirement for accurate and up-to-date road data. In this paper, we will focus on the automatic detection of road lane markings, which are crucial for many applications, including lane level navigation and lane departure warning. The approach consists of four steps: i) data preprocessing, ii) image segmentation and road surface detection, iii) road lane marking extraction based on the generated road surface, and iv) testing and system evaluation. The proposed approach utilized the unsupervised ISODATA image segmentation algorithm, which segments the image into vegetation regions, and road surface based only on the C_b component of YC_bC_r color space. A shadow detection method based on YC_bC_r color space is also employed to detect and recover the shadows from the road surface casted by the vehicles and trees. Finally, the lane marking features are detected from the road surface using the histogram clustering. The experiments of applying the proposed method to the aerial imagery dataset of Gympie, Queensland demonstrate the efficiency of the approach.

1. INTRODUCTION

Accurate and detailed road model is required by many applications, such as city planning, traffic monitoring, virtual tourism, and advanced driver assistance system (i.e. autonomous vehicle navigation, lateral control, collision prevention, and lane departure warning). These road features can be acquired either by ground based surveying or remote sensed images. Although the ground surveying can obtain highly accurate and detailed road information, it is tedious, time-consuming, and costly. Therefore, great efforts have been focused on the automatic extraction of road details from aerial or satellite images to simplify the data acquisition procedure.

The majority of the early work focuses on linear feature extraction approaches, with restrictive assumptions on image resolution and road appearance. Research continues at a number of institutions on various approaches to the problem, including multi-scale approaches (Baumgartner et al., 1999), knowledge-based extraction (Trinder and Wang, 1998) and context cues (Hinz and Baumgartner, 2000). Only a few approaches involve the detection of lane marking in the processing of road extraction. For example, Steger et al. (1997) extract the collinear road markings as bright objects in large scale photographs when the roadsides exhibit no visible edges. However, the extracted pavement marking segments are manually selected and connected with optimal paths through the graph. Hinz and Baumgartner (2003)

utilized road mark features, detected as thin bright lines with symmetric contrast, as the evidence for the presence of a road. Besides, an automatic vehicle detection module is also employed to eliminate the gap of lane segments caused by cars. Another approach of road extraction with pavement markings detection is presented in (Zhang, 2004), where the road marks and zebra crossing are segmented based on coloristic and geometric characteristics. The detected road marks and zebra crossing are then used as clues for the local direction and width of the road. The similar work can also been found in (Rushone and Airault, 1997), where the road mark portions are extracted primarily based on radiometry variation to provide topology and geometry support. On the whole, road pavement marks are only regarded as a clue to reconstruct the road network, and thus not being focused. Therefore, the quality requirements (Tournaire and Paparoditis, 2009), such as robustness, quality, completeness, are far below the lane level applications.
Although many different methods have been proposed, they are limited to the detection of road centrelines and their corresponding edges. There is no efficient method with which to detect the number of lanes and their locations due to a critical reason: the limited resolution of remote sensing image makes it difficult or even impossible to extraction the sub-road details. With the widely application of highly accurate aerial digital camera systems, i.e. Microsoft UltracamX system and Leica ADS40, the high resolution digital aerial images are easily available, which will promote the development of sub-road surface features detection from remotely sensed images.
In this paper, we will focus on the automatic detection of road lane markings. The reminder of this paper is organized as follows. In section 2, the data preprocessing techniques used to geo-rectify and enhance the raw aerial image are described. In section 3, the geometrically rectified image is segmented using the ISODATA algorithm, and the road surface is further extracted. To eliminate the affection from shadow regions, an efficient shadow detection and compensation approach is employed as well. In section 4, road lane marking extraction on the generated road surface is then described. In section 5, quantitative testing and the system evaluation is given. Finally, conclusion remarks are presented in Section 6.

2. IMAGE PREPROCESSING

The preprocessing is designed to geometrically correct the raw aerial image and improve its quality. Raw digital images usually contain significant geometric distortions introduced by factors such as variations of the sensor platform, relief displacement, and nonlinearities in the sweep of a sensor's IFOV, which makes it impossible for these images to be used directly as a map base without subsequent processing. Therefore, the geometric correction is employed to compensate for the distortions. The traditional photogrammetric triangulation process can be applied to the sequence of aerial digital images to generate ortho images under a predefined spatial coordinate system, which can be easily accomplished with the standard commercial digital photogrammetric software, i.e. ERDAR Leica Photogrammetry Suite (LPS). After the image ortho-rectification step, the distances between matched road lane markings can be accurately measured, and therefore the geometric specification of the lane marks can be utilized in the processing of road marking extraction.

3. ROAD SURFACE DETECTION

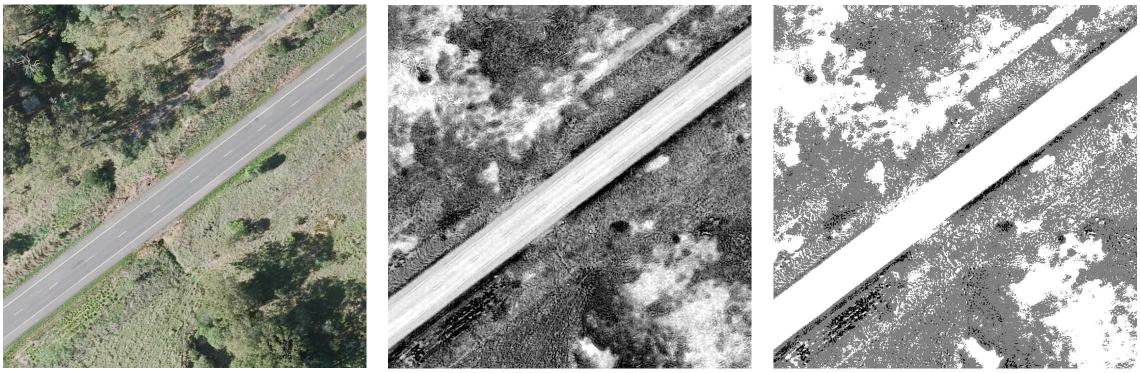
In order to efficiently detect the road surface, the road characteristics on the aerial images must be inspected. The road surface, which is made of asphalt, appears to be continuous, narrow belt-like areas, and have a smooth texture in the aerial images. In rural and suburban areas of Australia, road pavement materials (i.e. concrete or asphalt) show quite different characteristics from the grasslands or bushes growing along both sides of roads.

The first step of image analysis is image segmentation, the success of which is critical for the successfully detection of road centrelines. As the vegetation areas, including trees and grass lands, have relatively low value of blue component in RGB, the C_b component in YC_rC_b color space is a good measurement to distinguish the road surface from these vegetation lands. YC_rC_b is independent of the primaries and commonly used by video and image compression schemes such as MPEG and JPEG. The YC_rC_b color spade is defined as:

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix}$$

where Y is the brightness, C_r is the red-difference $(R-Y)$, and C_b is the blue-difference $(B-Y)$.The 2% linear contrast stretching algorithm is further utilized to enhance the image contrast, since the C_b component image has a relatively short gray scope.

After the data preparation, the approaches of image segmentation can be used to classify road surface from other ground objects. An unsupervised clustering method is usually superior to a supervised clustering approach as no training set is required. Therefore, the unsupervised Iterative Self-Organizing Data Analysis Techniques Algorithm (ISODATA) is used here to segment the aerial image.



a b c

Figure 1. Image unsupervised segmentation, (a) original aerial image, (b) enhanced the C_b component image, and (c) image segmentation result

Two classes, which correspond to road regions, vegetations areas are determined. The image segmentation is as shown in Figure 1, the original aerial image Figure 1(a) has a resolution of 0.1 meter and the size of 1024× 1024. The C_b component of Figure 1(a) is enhanced using 2% contrast starching method as illustrated in Figure 1(b). The ISODATA clustering method is then applied on the C_b image, and the result is given in Figure 1(c). We can find that the road surface has been perfectly segmented as white object in the image. Segments are selected as road features if the following two criteria are satisfied: (i) the mean width of the segment is within a certain range, (ii) the length to width ratio is larger than a preset threshold. Besides, the area filter method is utilized to remove small noises that are misclassified into road class.

The road sides should have homogeneous local orientation distributions. However, the generated road edges are actually zigzag thanks to the disturbances from shadows or color variation of road surface. The least squares line approximation is an appropriate method to fit a linear relation between the extracted road edge points. Suppose the data points are $(x_1, y_1), (x_2, y_2) \cdots (x_n, y_n)$, in order to approximating them to a line $y = a + bx$, the unknown coefficients *a* and *b* must yield zero first derivatives: $\frac{\partial E}{\partial a} = 0$, and $\frac{\partial E}{\partial b} = 0$. The coefficients *a* and *b* can therefore be given by:

$$a = \left(\sum_{i=1}^{n} y_i - \left(\sum_{i=1}^{n} x_i\right) b\right) / n$$

$$b = \left(n \sum_{i=1}^{n} x_i y_i - \left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)\right) \Big/ \left(n \sum_{i=1}^{n} x_i{}^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right)$$

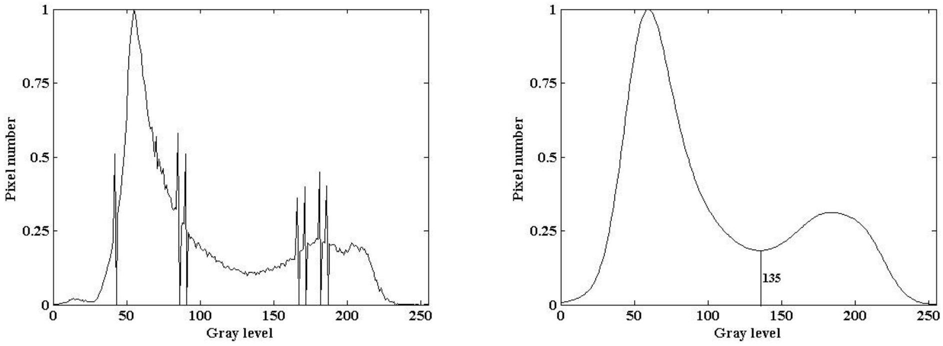
In order to minimize errors when the slope of the fitted line is too large or small, we used a linear fit $x = a + by$ instead if the calculated coefficient $b < -1$ or $b > 1$. Individual points with large residuals lie far from the line that describes the overall pattern, would reduce the overall accuracy of the line and therefore should be removed from the line approximation processing. Here, points with residual $\mathrm{abs}(y_i - a - bx_i) > 3\sigma$ would be abandoned, where σ is the standard deviation of the y value of data points. The above procedure is repeated until the final fitted line is obtained. An example of the least squares line approximation is shown in Figure 2(b), as we can see that the line represents the road sides very well.

a **b** **c**

Figure 2. Road surface extraction, (a) segmented road surface, (b) road side smoothed by the least square line approximation, and (c) is the final extracted road surface

The detection of road surface is greatly affected by shadows casted by trees above the road surface or vehicles on the road. Cast shadows may cause loss of feature information, false color tone, shape distortion of objects (Tsai, 2006), which makes the classification of road surface even more difficult. Therefore, to detect the road surface accurately, the shadows within the image must be detected and compensated so as to restore the lost feature information. Here, we presented an efficient shadow detection and compensation algorithm to eliminate the affection from shadows.

Tsai (2006) found that the spectral ratioing technique can be utilized to effectively enhance the increased hue property of shadows with low luminance, i.e., pixels in shadowed regions will have higher values of $(H_e + 1)/(I_e + 1)$ ratio than those in non-shadowed regions. H_e and I_e are refer to hue-equivalent and intensity-equivalent components respectively. Here we utilized $(C_r + 1)/(Y + 1)$ to obtain the ratio image, which is scaled to have pixels' value in $[0,255]$. An example is given as in Figure 4, the original aerial image is as shown in Figure 4(a). Figure 4 (b) is the $(C_r + 1)/(Y + 1)$ ratio image, it can be easily found that the shadowed regions in Figure 4 (a) have relatively larger digital numbers (DN), which can be further extracted using image segmentation methods.



a **b**

Figure 3. Homogram, (a) the original homogram of the ratio image, (b) Gaussian smoothed homogram using Lin's method

After we obtained the ratio image, the clustering approach can be further utilized to detect the shadow regions. Histogram thresholding is a simple and widely used technique for monochrome image segmentation, but it is based on only gray level and does not take into account the spatial information of pixels with respect to each other. Therefore, we utilized a homogram image segmentation approach (Cheng et al., 2002) instead, which take into account not only the color information but also the spatial relation among pixels to explore the features of an image, which means that both the local and global information are employed. Homogram thresholding approaches tend to be more effective in finding homogeneous regions than histogram thresholding approaches. The homogram of ratio image Figure 5(b) is given in Figure 3(a), as we can see that it is difficult to find the threshold from the homogram thanks to its complexity.

a b c

Figure 4. Shadow detection, (a) the original aerial image (512× 512 pixels), (b) $(C_r + 1)/(Y + 1)$ ratio image of (a), and (c) extracted shadow regions

Thus, instead of using a complex peak-finding algorithm as in (Cheng and Sun, 2000) to identity the valleys between any adjacent significant peaks as the boundaries for the segmentation in homogeneity domain, we employ an automatic Gaussian smoothing algorithm (Lin et al., 1996) to smooth the homogram so that the valleys can be easily and effectively determined. The smoothed homogram is given in Figure 3(b), the threshold value "135" can be determined by compare the adjacent pixel numbers in the smoothed homogram. Then the ratio image can be segmented into shadow region and non-shadow region using the obtained threshold, and the result is as shown in Figure 4(c). The shadow regions in the image are effectively detected, and the detected region areas can be further utilized to recover the amount of incident illumination of the shadowed regions to the value when not obstructed by cultural features.

a b c

Figure 5. Shadow compensation, (a) contrast stretched C_b component image, (b) shadow recovered C_b component image, and (c) detected road surface from the shadow compensated C_b image

As can be seen from Figure 1(b), both the road surface and the shadow regions have relatively higher DN within C_b component image, which makes it difficult to extract the road surface when it is adjacent or overlapped with shadow areas. Therefore, an efficient shadow compensation method is proposed here to separate the road surface from shadow region. As we can see, the DN is greatly enhanced in areas when the shadow regions are superimposed with the road surface (See Figure 5(a)), which means subtracting the DN of shadow will not affect the road surface but will remove the affection from shadows. After the extraction of shadow regions, an automatic de-shadowing processing can be carried out as follows:

$$I' = m_c + \frac{I - m_s}{\sigma_s}\sigma_c$$

where I is the DN before shadow compensation, I' is the de-shadowed DN, m_s and σ_s are the mean and standard deviation of the shadow region, m_c and σ_c are the mean and standard deviation of the non-shadow areas, respectively.

a b c

Figure 6. Road surface extraction, (a) classified road surface, (b) road surface smoothed with least square approximation, and (c) final extracted road surface

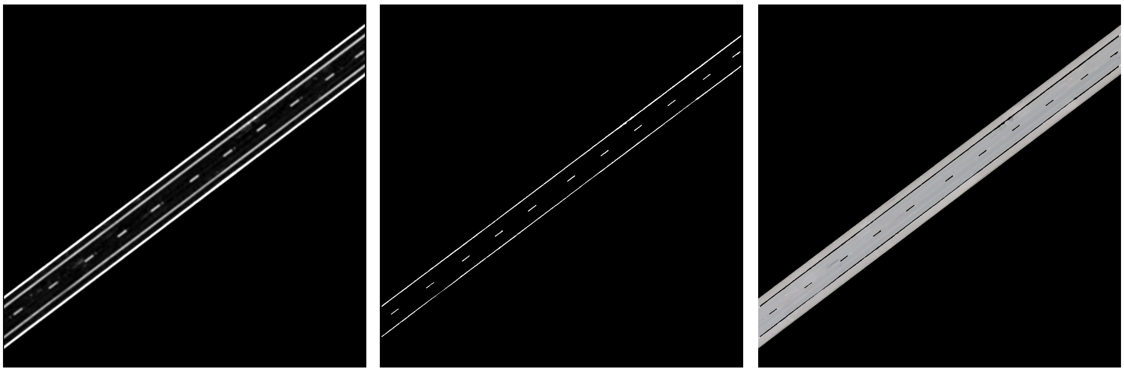
An example of the proposed image de-shadowing approach is given in Figure 5, the shadow compensated result is shown in Figure 5(b). The shadow affection has been predominately eliminated, and the road surface appears brighter than its surrounding features (See Figure 5(b)), which greatly improves the image segmentation and road surface detection (Figure 5(c)). Then the road surface is classified and its two sides are smoothed by least square line approximation method, the final result of road surface extraction is as shown in Figure 6(d).

4. ROAD LANE MARKING EXTRACTION

Up to now, we have already obtained the road surface, and the road lane marking can be further extracted within the generated road surface. Road lane markings have the following characteristics: (i) their shapes and sizes are constricted by strict specifications; and (ii) they constitute high contrasted objects. The color of lane marking is generally white, which has distinct contrast with its background - road surface made of asphalt. Therefore, in order to extract road lane marks from the road surface, the co-occurrence contrast measurement is employed to enhance the lane marking lines, based on the strong contrast between the lane marking and road surface. According to Haralick et al. (1973), the co-occurrence contrast can be given by:

$$f = \sum_{n=0}^{N} n^2 \left\{ \sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j) \right\}$$

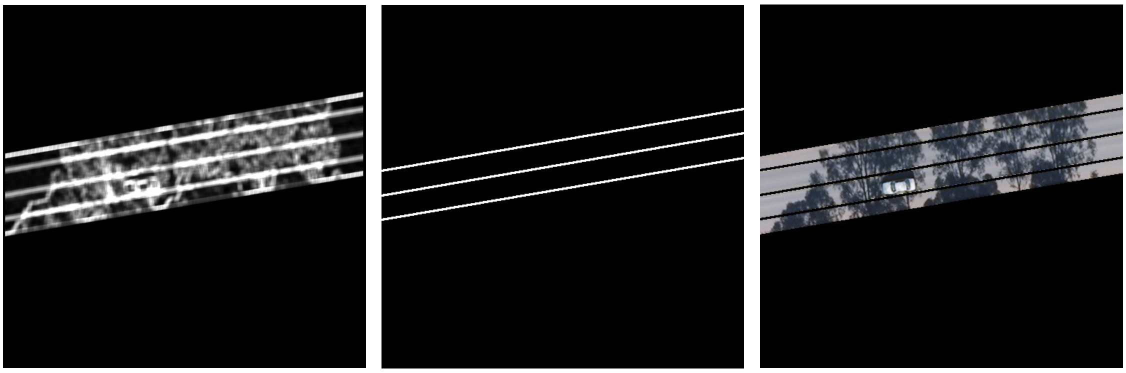
where $p(i,j)$ is ith entry in a normalized gray-tone spatial-dependence matrix, N is the number of distinct gray levels in the quantized image, and $|i-j| = n$.



a b c

Figure 7. Road marking extraction, (a) co-occurrence contrast image, (b) extracted road lane markings, and (c) generated road lane marks superimposed on the original road surface

As the contrast measurement only works on the gray image, the original RGB road surface is first transformed using the Principal Component Analysis (PCA) approach. Then only the 1st component is selected, since it accounts for over 90% of the total information in the original image. After that, the co-occurrence contrast measurement is used on the generated gray image to calculate texture values, which is as shown in Figure 7(a). The road lane marking is enhanced greatly through the employment of contrast measure, while the outer two white lines are the edges of the road surface, which can be easily removed by using morphological operations and images intersecting operation. The filtered image is further binarized to obtain the final lane markings, as shown in Figure 7(b). The generated road markings superimposed on the original road surface image is given in Figure 7(c), we can see that the extracted road lane marking fit the original image very well.



a b c

Figure 8. Road marking extraction in shadowed region, (a) co-occurrence contrast image, (b) generated road markings smoothed with least square approximation, and (c) extracted road marks overlapped on the original road surface

It is more difficult to detect the lane markings in the shadowed road surface, as the illumination condition is changed largely within the shadow region. Cast shadows would cause loss of feature information, false color tone, and shape distortion of objects, thus the lane marking extraction method used previously is required to be improved for this complex condition. After the generation and binarization of the co-occurrence contrast image, morphological opening and closing operations are further utilized to remove the enhanced edges of shadow regions. Then the generated lane features are thinned using a modified Wang-Zhang algorithm (Wang and Zhang, 1989), and the lane marking skeletons are further fitted by least square linear regression, the smoothed lane features are as given in Figure 8(b). Figure 8(c) shows the generated road lane marking superimposed on the original road surface.

5. RESULTS AND DISCUSSION

A set of high-resolution aerial panchromatic images taken on 28 November 2008 using the UltraCam-D digital camera was used as the data set. The image scale is 1:11081, and pixel size is 9μm (about 10 cm ground spatial resolution). The test sites were parts of the Bruce highway, located in Gympie, Queensland. The testing road is a single carriageway with 2 lanes in the majority of road segments. The width of traffic lane is 3.5 m on average.
In order to evaluate the results, we compare the obtained road lane feature to a manually digitized reference road dataset. The quantitative evaluation was conducted in terms of completeness, correctness and quality index, according to Wiedemann et al. (1998). The completeness is defined as the percentage of the correctly extracted data over the reference data and the correctness represents the ratio of correctly extracted road data. The quality is a more general measure of the final result combining the completeness and correctness.
We selected 6 testing areas from the dataset, which covers an area of approximate 2 km^2. The average completeness is about 83.7%, correctness 91.5%, and quality 76.6%. The success of lane feature detection in shadow scene depends largely on the least square linear regression, thus it only works when the lane marking within the image is approximately linear. Therefore, the processing image has to be restricted within a limited area, and large image can be first divided into smaller blocks before the further extraction processing.

6. CONLSUDING REMARKS

A novel road surface and lane marking detection approach for high accurate digital road map generation from large scale remote sensed images is proposed in this paper. The experimental results from 10 cm Ground Sampled Distance (GSD) photogrammetric digital aerial images have demonstrated that the proposed method achieved considerable success, especially in shadowed region thanks to the shadow detection and compensation algorithm. Further improvement may be achieved by using knowledge based image analysis, and directional image filters, such as Gaussian filter.

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BIOGRAPHICAL NOTES

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