Water Area Extraction from RGB Aerophotograph Based on Chromatic and Textural Analysis

Meng Zhao Huazhe Shang Wenchao Huang Lizhi Zou Yongjun Zhang
School of Remote Sensing and Information Engineering,
Wuhan University
Wuhan, China
zmatwhu@yahoo.cn 754773310@qq.com 423036600@qq.com 867750650@qq.com yongjun_zhang@sina.com

***Abstract*—When triangulating RGB aerophotograph, if automatically and randomly selected matching pass points unfortunately locates into water areas, these points, limited by their inaccuracy, will decrease the precision of triangulation. Therefore, extraction of water area beforehand is conducive to eliminate water falling pass points and guarantee the quality of aerotriangulation. A new methodology to extract water area from RGB aerophotograph is put forth in this paper. Procedure initiates by segmenting the whole aerophotograph into homogenous and united segments. Subsequently, compute chromatic and textural features of every segment and compare each segment's features to sampled water segments' features. Finally extract those segments whose chromatic and textural features are similar to sampled segments' as water areas. This methodology has a relatively obvious merit in effectiveness and generality.**

Keywords—CIELAB; chromatic analysis; textual analysis; watershed segmentation; ISODATA

I. INTRODUCTION

Aerotriangulation is a key step in aerophotogrammetry. The basic goal of aerotriangulation is to compute all elements of exterior orientation and pass points of a region by block adjustment. The accuracy of matching points on aerophotograph directly relates to the precision of block adjustments and the final production of aerotriangulation. However, water areas, influenced by wind force and gravity, are usually in irregular motion. If automatically and randomly selected matching pass points (a few pass points selected beforehand to compute the exterior orientation elements) unfortunately falls into water areas, these points, limited by their inaccuracy, will decrease the precision of triangulation. Therefore, extraction of water areas beforehand is conducive to eliminate water falling pass points and guarantee the quality of aerotriangulation. In this paper, we concentrate on extracting water areas from RGB aerophotograph and mark them.

Multispectral aerophotograph and remote sensing image can synthesize information of different spectrums to extract water region. J. Deng operated different bands of SPOT-5 images to extract water area [1]. H. Xu modified MNDWI value to extract water area from multispectral remotely sensed data [2]. In contrast to multispectral data, RGB aerophotograph (every pixel of the image is consisted of red, green and blue values) has only three bands and little extra spectrum information. Consequently, until recently, no effective methodology has been proposed to extract water area from RGB aerophotograph. In order to supply such a gap, we put forth a methodology in this paper to extract water area from RGB aerophotograph.

With the enhancement of image resolution, aerophotographs contain more abundant space information as well as geometric and textual features, which create a favorable condition for extracting objects via chromatic and textual analysis. W. Ma and B. S. Manjunath had used textural analysis to create a texture thesaurus for browsing large aerophotographs and achieved relatively good retrieval effect [3]. Other trials include W. Niblack's querying image using color, texture and shape [4]. All these researches manifest a fact that chromatic and textural analyses are effective in extracting and retrieving objects.

Enlightened by chromatic and textural analysis, we propose a new series of procedures to extract water areas from RGB aerophotographs. Procedure initiates by segmenting the whole aerophotograph into homogenous and united regions. Subsequently, compute chromatic and textural features of every region and then compare each region's feature to sampled water regions' features. Finally extract those segments whose chromatic and textural features are similar to sampled segments' as water areas. This methodology has a relatively obvious merit in effectiveness and generality.

Water areas on aerophotographs are usually homogenous and united; therefore water regions after segmentation always are homogenous and united. We have no need to care about the accuracy in segmentation of other objects because they contribute little to water extraction. We choose watershed segmentation algorithm (Section Ⅲ) because it can help attain satisfactory segmentation result. The homogenous and united characteristic of water region also provides pleasing condition to conduct chromatic analysis (Section Ⅱ) and textural analysis (Section Ⅳ). Chromatic and textural features of every region will be added to its own feature vector (Section Ⅴ). Water appears differently on photographs. In order to automatically recognize water areas, we need to sample water regions of all appearances beforehand and classify them. ISODATA algorithm (Section Ⅴ) is employed to classify those samples into several categories. If the distance is within a threshold between a certain region's feature vector and any one of those

 ISBN: 978-1-61208-118-2

categories', then this segment will be identified and extracted as water area.

RGB aerophotograph consists of three channels (Red, Green, and Blue) and they are closely pertinent to each other. We need to integrate them into one channel in order to conduct image segmentation and textural analysis. In this paper, we utilize CIELAB color space to integrate those three channels, which decreases their pertinence as well as provides prerequisites for image segmentation and textural analysis later on.

Any color is unable to be both green and red or both blue and yellow. This principle prompts the CIELAB color space. CIELAB color space inherits the XYZ standard color system. CIELAB indicates distinctions between light and dark, red and green, and blue and yellow by using three axes: L*, a*, b*. The central vertical axis represents lightness (L*) whose value ranges from 0 (black) to 100 (white). On each axis the value runs from positive to negative. On a-a' axis, positive values indicate amounts of red while negative indicate amounts of green. On the b-b' axis, yellow is positive and blue is negative. For both axes, zero is neutral [5].

"Texture" refers to the arrangement or characteristic of the constituent elements of anything. A texture feature is a value, computed from the image of a region, which quantifies gray-level variation within the region. According to Kenneth [6], a texture feature value is irrelevant to region's position, orientation, size, shape and brightness (average gray level). Therefore, the shape and size of segmented area do not interfere with the result of chromatic and textural analysis.

According to Julesz [7] and his deduction, human texture discrimination is based on the second order statistic of image intensities, which gave rise to the emergence of a popular textural descriptor: co-occurrence matrix. A co-occurrence matrix counts the exact times of different grey level pairs of pixels, separated by a certain distance (one pixel, two pixels, etc.). The (i, j) element of the co-occurrence matrix P for a certain region is the number of times, divided by M, that gray levels i and j occur in two pixels separated by that distance and lying along that direction in the region, where M is the number of pixel pairs contributing to P. The P matrix is N by N, where the gray scale has N shades of gray [6].

Watershed segmentation is an approach based on the concept of morphological watersheds. In such a "topographic" interpretation, every pixel's gray level denotes its "height". For a particular regional minimum, the set of points at which a drop of water, if placed at the location of any of those points, would fall with certainty to a single minimum is called the catchment basin. And the points at which a water drop would be equally likely to fall to more than one such minimum constitute crest lines on the topographic surface and termed watershed lines. Assume that a hole is punched in each regional minimum and that the entire topography is flooded from below by letting water rise through the holes at a same rate. When the rising water from different catchment basins is about to merge, a dam is built to prevent the merging. The flooding will finally reach a stage when only the tops of the dams are visible above the water lines. These dam boundaries correspond to the divide lines of the watersheds. Therefore, they are boundaries extracted by a water shed segmentation algorithm [7].

II. CIELAB Color Space and Chromatic Analysis

There are two steps to transform RGB color space to CIELAB color space [5]. The first step is to apply the following matrix to convert RGB color space to CIEXYZ color space.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

Subsequently, (X^*, Y^*, Z^*) need to be calculated.

When $X / X_n, Y / Y_n, Z / Z_n > 0.008856$,

$$X = \sqrt[3]{X / X_n} \tag{2}$$

$$Y = \sqrt[3]{Y / Y_n} \tag{3}$$

$$Z = \sqrt[3]{Z / Z_n} \tag{4}$$

When $X / X_n, Y / Y_n, Z / Z_n \leq 0.008856$,

$$X^* = 7.787 \cdot (X / X_n) + 0.138 \tag{5}$$

$$Y^* = 7.787 \cdot (Y / Y_n) + 0.138 \tag{6}$$

$$Z^* = 7.787 \cdot (Z / Z_n) + 0.138 \tag{7}$$

(X_n, Y_n, Z_n) = (0.312779, 0.329184, 0.358037) represents the white reference point, which indicates a completely matte white body.

Then L*, a*, b* can be calculated through following equations:

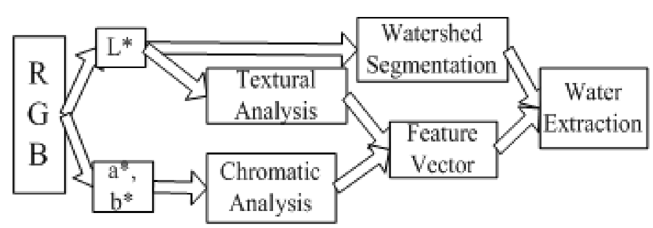
$$L = 116 \cdot Y^* - 16 \tag{8}$$

$$a^* = 500 \cdot (X^* - Y^*) \tag{9}$$

$$b^* = 200 \cdot (Y^* - Z^*) \tag{10}$$

The application of CIELAB color space in this paper can be briefly illustrated using diagram Ⅰ.

Diagram Ⅰ Application of Cielab Color Space

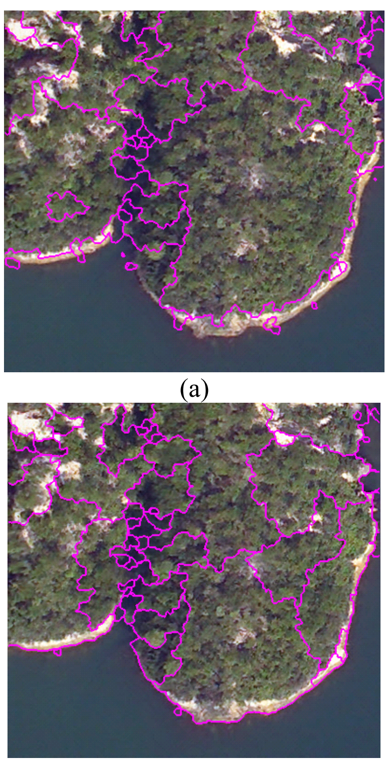


The L* component of CIELAB color space can be used in watershed segmentation (Section Ⅲ). L* component can also be used in textual analysis (Section Ⅳ). We use equations mentioned above to convert every pixel on an aerophotograph from RGB color space to CIELAB color space. Then form a gray image by using the L* component of every pixel's CIELAB color space. Although the gray photograph is no longer quantified 256 gray levels, L* component brings unexpected results in chromatic analysis and textural analysis later on.

Segmented areas usually have similar color space and we can use the average a*, b* of all pixels in a region to represent its chromatic feature. Experiments have demonstrated that chromatic feature between non-water areas and water areas is obvious, which means a*, b* can be employed to chromatically describe a region. We utilize a* and b* as parameters to describe a segmented region chromatically in feature vector (Section Ⅴ). If regions have similar chromatic feature with sampled water areas, they are possibly water areas we want to extract.

III. IMAGE SEGMENTATION

In our methodology, we replace the 256 gray level with L* component of CIELAB color space. Using this replacement, we could form a gray picture by synthesizing three channels of RGB aerophotographs. Compared to simply using average gray level of three channels to form a gray photograph, the usage of L* component can decrease fragments after segmentation and attain a relatively clear and accurate edge.



(a)

(b)

Figure 1. Comparison of Segmentation: (a) is attained by using the average gray level of RGB to form a gray picture. (b) is attained by using L* component of CIELAB color space to form a gray picture

In Fig. 1, (b) shows a correct and clear boundary between water area and non-water area, while result (a) displays an inaccurate boundary. This manifests effectiveness and correctness of the L* component in segmenting RGB aerophotographs.

IV. TEXTURAL ANALYSIS

In our methodology, we replace traditional 256 scale gray with the L* component of CIELAB color space. We attain two advantages by this substitute. First of all, the RGB components of aerophotograph has been integrated into one L* component, which ranges from 0 to 100; in addition, the dimension of co-occurrence has been decreased from 256*256 to 101*101. Traditionally, we reduce quantization level of the input data (e.g., from 8-bit data with values from 0-255 to 5-bit data with values from 0 to 31) when creating co-occurrence matrices so that the matrices will not become too large. But this method usually causes texture information loss, especially detailed information. Taking advantage of the L* component of CIELAB color space, the co-occurrence matrices will decrease its dimension with relatively little textural information loss.

Haralick proposed 14 features based on co-occurrence matrices [8]. The angular second-moment feature (ASM) is a measure of homogeneity of the image.

$$\mathrm{ASM} = \sum_i \sum_j p(i,\ j)^2 \tag{11}$$

p(i, j) is the joint probability of gray pair (i, j) in co-occurrence P.

Texture is an innate property of virtually all surfaces [8]. Although water seems homogenous and with little obvious texture, texture feature can still be utilized to discriminate water area from other non-water area because water area has a bigger homogeneity than other objects.

In a homogeneous image, there are very few dominant gray-tone transitions. Hence the P matrix will have some entries of large magnitude and the ASM feature will be relatively bigger. In contrast, an image with irregular textures will have a large number of small entries and hence the ASM feature will be smaller [8]. Because water areas are usually homogeneous and united, so the ASM feature for water areas is relatively bigger than other objects. So we employ ASM as a textural descriptor.

In order to avoid texture rotating, we compute the average value of ASM in four directions (0°, 45° ,90° and 135°) to texturally describe a region. ASM is added to the feature vector (Section Ⅴ).

V. CLASSIFICATION AND WATER EXTRACTION

A. Feature Vector

A vector is a quantity that has magnitude and direction and that is commonly represented by a directed line segment whose length represents the magnitude and whose orientation in space represents the direction. Feature vector in this paper denotes that the quantity consists of a region's feature values. We define feature vector as following:

$$\mathbf{FV} = \left(\mathrm{ASM},\ a^*,\ b^*\right) \tag{12}$$

Different regions have different chromatic and textural features; therefore every segmented region possesses its exclusive **FV**, which represents its uniqueness among other regions. However, slight difference in **FV** exists among regions with similar textural and chromatic features, which means we could use classification algorithm to categorize regions with similar feature vectors. Every region's **FV** has to be computed for later extraction.

B. *Sampling and Unsupervised Classification Using ISODATA Classification*

Practical experience tells us that variances, such as contamination, fluctuation, ship transportation, etc, render water display different color and texture feature on RGB aerophotographs. Therefore, the segmented image has more than one kind of water. From the segmented image we need to sample a certain number of water regions via our practical experience. Such experience can simply tell water regions apart from other regions like forest and residence, however, it is less reliable when applied to discriminate differences within waters. To settle down this problem, we propose to use ISODATA algorithm to automatically classify sampled water regions into several categories.

The ISODATA algorithm [9], abbreviated for Iterative Self-Organizing Data Analysis Technique, is a modification of the k-means clustering algorithm. ISODATA is self-organizing because it requires relatively little human input. Therefore it is a good choice to substitute human perception to classify waters.

ISODATA algorithm begins by setting a certain amount of cluster centers for all the samples. Then classify all samples by shortest distance algorithm. Modify the centers of every cluster. If two clusters' separation distance in feature space is below a user-specified threshold, then the two cluster centers should be merged into one and reclassify all the samples. If the current iterative time is odd or the amount of clusters is half fewer than expected, then split the cluster that has the maximum subparameter of standard deviation vector and reclassify all samples. If the current iterative time is even or the amount of clusters is twice bigger than expected, then merge two clusters whose separation distance is the closest and reclassify all samples. When the iterative time has reached maximum time, then the whole algorithm stops. We have conducted quite a number of experiments and find that the result of classification is satisfactory if only the maximum standard deviation and minimum distance between cluster means are properly set (details, [9]). In our methodology, every segment's **FV** is the sample in ISODATA algorithm.

C. *Water Extraction*

Each sampled water region has its unique **FV**. As discussed above, similar water regions have slight difference in **FV**; therefore, ISODATA algorithm will automatically classify regions with analogous **FV** into one same class. After the completion of ISODATA algorithm, each class has a cluster center vector (**CCV**) and a standard deviation vector (**SDV**). Both have the same dimensions as **FV**. The j^{th} class's $\mathbf{CCV}_j$ and $\mathbf{SDV}_j$ can be computed out using following equations.

$$\mathbf{CCV}_j = \sum_{i=0}^{W} \frac{\mathbf{FV}_j}{W} \tag{13}$$

$$\mathbf{SDV}_j = \sum_{i=0}^{W} \sqrt{\frac{(\mathbf{FV}_j - \mathbf{CCV}_j)^2}{W^2}} \tag{14}$$

(Where W is the number of regions in j^{th} class and **FV** denotes the i^{th} region's **FV**.)

According to statistical principles, when the amount of samples in each class has reached a certain level, the distribution of segments' vectors in every class is subject to Gauss distribution. Nearly all members of the class fall within $\mathbf{CCV}_j \pm 3\cdot\mathbf{SDV}_j$. Ideally, we can sample numerous regions within a class and work out its **CCV** and **SDV**. Then compare remaining regions' feature vectors to the class center. If a region's feature vector falls within $\mathbf{CCV}\pm 3\cdot\mathbf{SDV}$, we identify it belonging to the class.

Unfortunately it is impossible to sample enough water regions to form Gauss distribution within a class, but we can still eliminate those non-water regions by checking whether their **FV**s locate within a threshold of a certain class's **CCV**. We define a parameter "ratio" to mark the dynamic range of each **CCV**, that is to say regions with **CCV** falling into $\mathbf{CCV}\pm\mathrm{ratio}\cdot\mathbf{SDV}$ will be extracted as water area.

VI. TRIALS AND RESULTS

In order to test the feasibility of our methodology, we conduct following five trials. We define three indexes to evaluate the result of extraction. First index is "w-w", which means pixels extracted as water using methodology in this paper and perceived as water by human eyes. Second index is "w-n", which means pixels extracted as water using methodology in this paper but perceived as non-water by human eyes. Third index is "n-w", which means pixels extracted as non-water using methodology in this paper but perceived as water area by human eyes.

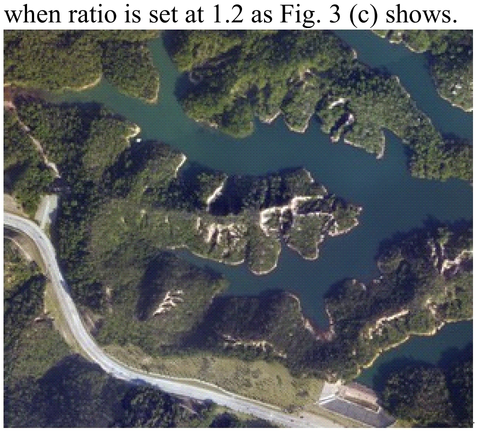
Trial 1: The following Fig. 2 is the water extraction effect of Fig. 1 (b). We have 9 samples of water segments. ISODATA algorithm classifies those 9 samples into 3 different types. The final extraction is attained when ratio is set at 1.1.

Figure 2. Extraction Result of Trial 1 by setting the ratio at 1.1

TABLE I. EVALUATION OF TRIAL 1

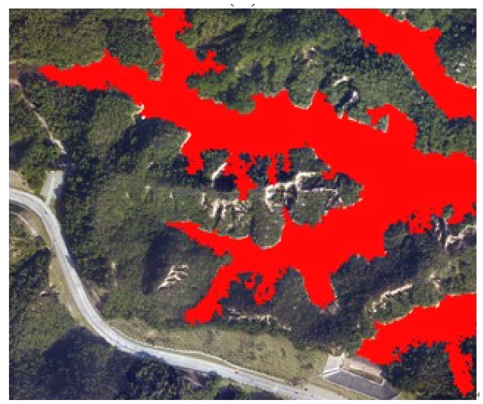
Fig. 2	w-w	w-n	n-w	Total Pixels
Pixels	260018	2108	18	262144
Percentage	99.2%	0.79%	0.01%	100.0%

Trial 2: The following Fig. 3 (a) is taken of somewhere in Shenzhen, China. We notice that the segmentation of water area is homogenous and united in Fig. 3 (b). We have 8 samples of water segments. ISODATA algorithm classifies those 8 samples into 2 different types. The final extraction is attained when ratio is set at 1.2 as Fig. 3 (c) shows.



(a)

(b)



(c)

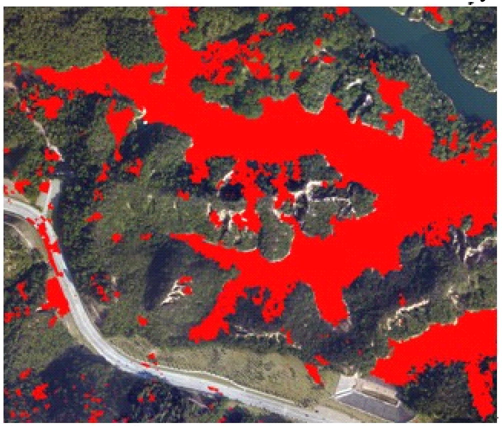
Figure 3. Extraction Result of Trial 2: (a) is the original aerophotograph of Shenzhen, China. (b) is the result of watershed segmentation. (c) is the final extraction of water by setting the ratio at 1.2

TABLE II. EVALUATION OF TRIAL 2

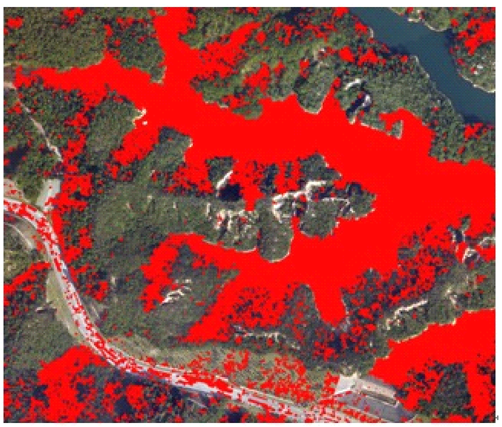
Fig. 3 (c)	w-w	w-n	n-w	Total Pixels
Pixels	3941135	70597	43726	4055458
Percentage	97.2%	1.7%	1.1%	100.0%

Trial 3: To test the effectiveness in the combination of chromatic and textural analysis, we conduct another extraction using the aerophotograph in Trial 1. When conducting chromatic analysis only, the feature vector will be shortened to have only a* and b* parameters. When conducting textural analysis, the feature vector will be shortened to have only ASM parameter. We also selected 8 same water areas as samples in trial 1. In chromatic extraction only, ISODATA classifies those 8 samples into 3 classes and the extraction result is Fig. 4 (a). In textural extraction, ISODATA classifies those 8 samples into 4 classes and the extraction result is Fig. 4 (b). For both trials, the ratio is set 1.2 as the ratio set in trial 1. From the result we can see that the chromatic extraction or textural extraction individually can not attain an effect as good as the combination of them. The percentage of w-n and n-w is

a nightmare for correctively extract water areas compared to the combination of both chromatic and textural analysis.



(a)



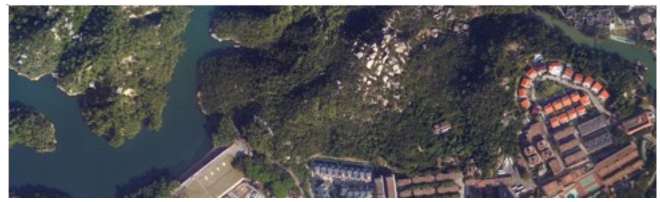
(b)

Figure 4. Extraction Result of Trial 3: (a) is attained using ony chromatic analysis when ratio is set 1.2. (b) is attained using only textural analysis when ratio is set 1.2

TABLE III. EVALUATION OF TRIAL 3

Fig. 4 (a)	w-w	w-n	n-w	Total Pixels
Pixels	2601923	391245	425432	3418600
Percentage	76.1%	11.4%	12.5%	100%
Fig. 4 (b)	w-w	w-n	n-w	Total Pixels
Pixels	2615619	398715	743726	3758060
Percentage	69.6%	10.6%	19.8%	100.0%

Trial 4: In order to test the generality of this methodology, we use the **CCV** generated in trial 1 to extract water area from another aerophotograph (Fig. 5 (a)) taken of the same area. Because they are the same region, therefore their chromatic and textural features are similar. The following result (Fig. 5 (b)) is attained when ratio is set 1.2.



(a)

(b)

Figure 5. Extraction Result of Trial 4:(a) is the orginal RGB aerophotograph. (b) is attained using the **CCV** generated in trial 1 when ratio is set 1.2.

TABLE IV. EVALUATION OF TRIAL 4

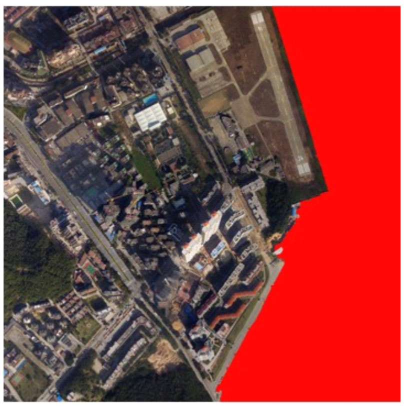
Fig. 5 (b)	w-w	w-n	n-w	Total Pixels
Pixels	1437772	26133	10216	1474121
Percentage	97.5%	1.8%	0.7%	100.0%

Trial 5: In order to further test the generality of this methodology, we apply it to extract water areas from aerophotograph with many fluctuations. Following aerophotograph (Fig. 6 (a)) is taken of somewhere in Qingdao. The biggest characteristic of this aerophotograph is its rippled surface. As a result of this irregular fluctuation, the segmentation result (Fig. 6 (b)) is not very satisfactory. There are many fragments in water area, but we can manually merge those fragments into united one in order to improve the result of segmentation. We choose 12 water samples from Fig. 6 (b). ISODATA algorithm automatically classifies those samples into 4 categories. When ratio is set 1.5, we can attain a pleasing result (Fig. 6 (c)).

(a)

 ISBN: 978-1-61208-118-2

(b)



(c)

Figure 6. Extraction Result of Trial 5: (a) is the orginal RGB aerophotograph. (b) is the result of segmentation. (c) is the final result of extraction.

TABLE V. EVALUATION OF TRIAL 5

Fig. 6 (c)	w-w	w-n	n-w	Total Pixels
Pixels	316823	10192	716	327731
Percentage	96.7%	3.1%	0.2%	100.0%

VII. CONCLUSION

It is innovative to combine watershed segmentation, CIELAB color space and chromatic and textural analysis as well as ISODATA classification together to extract water from RGB aerophotograph. Through numerous experimental comparisons, we discover that ratio set between 1.1 and 1.8 is optimal for water extraction. However, it is undeniable that ripples or ship transportation will cause a few fragments after segmentation, which put sand in the wheel of chromatic analysis and textural analysis because feature values of those fragments are not accurate and not representative. Although merging those fragments into united and homogenous areas is a good solution to this problem, it demands much more time and manual involvements. This is what we could do to improve the result of water extraction later on.

ACKNOWLEDGMENT

Special thanks to Professor Yongjun Zhang's guide in this research and the cooperation of our team members.

REFERENCES

[1] J. Deng, "An Effective Way for Automatically Extracting Water Body Information from SPOT-5 Images", Journal of Shanghai Jiaotong University (Agricultural Science), vol. 23, no. 2, pp. 198-201, 2005, June.

[2] H. Xu, "A Study on Information Extraction of Water Body with the Modified Normalized Difference Water Index(MNDWI)", Journal of Remote Sensing, vol. 9, no. 5, pp. 589-595, 2005, September.

[3] W. Ma and B. S. Manjunath, "A Texture Thesaurus for Browsing Large Aerial Photographs", Journal of the American Society for Information Science, CA, vol. 49, no. 7, pp. 633-648, 1999.

[4] Niblack W, Barber R et al., "The QBIC project: Querying images by content using color, texture and shape", Proc of SPIE: Storage and Retrieval for Image and Video Database, San Jose, CA, pp. 58-70, 1994.

[5] A. R. Robertson, "Historical development of CIE recommended color difference equations", Color Research and Application, 15(3), pp. 458-461, 1990.

[6] K. R. Castleman, Digital Image Processing, New Jersey: Prentice Hall, Inc., a Simon&Schuster Company, pp. 499, 1996.

[7] B. Julesz, "Experiments in the visual perception of texture", Scientific Americian, vol. 232, pp. 34-43, 1992, May.

[8] R. M. Haralick and K. S. Dinstein, "Textural Features for Image Classification", IEEE Transactions on Systems Man and Cybernetics, pp. 610-621, 1973, November.

[9] J. R. Jensen, Introductory Digital Image Processing-A Remote Sensing Perspective, 3rd ed., New Jersey: Prentice Hall, pp. 383-389, 1995.