Red Car Location Estimation of Satellite Image

Yixing Chen

***Abstract*—This paper focus on red car location estimation of satellite images. The satellite images in this project contain huge quantity of information. The image consists of RGB pixels. RGB value analysis is important to interpret information of the image. In this paper, a method Ratio Selection, which focus on the ratio of RED Pixels in a grid or square to sum of variance of pixels coordinates, is proposed to identify red car positions in the image. A training data image that contains 28 ground truth coordinates of red cars is used to train the model and a testing data image is utilized to test the model accuracy. The result shows the proposed method is able to provide precise estimation with small grid size.**

***Index Terms*—satellite image, RGB, RED Pixels, Ratio Selection**

I. Introduction

In computing systems, image processing is done by building up matrices and analysis of pixels[1]-[2]. The quality of images is able to be improved by having the square pixels as units of images. The main limit of the image quality is physical characteristics of sensors. An effective way is to raise the image resolution[3]. That means one image can contain more pixels with high resolution. More pixels are able to depict the objects in the image in a comprehensive way. The image collected by satellites contain huge amount of information. The images selected by satellites usually contain RGB value information[4]. Thus, RGB analysis is the initial but actually very important step of image processing.

In this paper, a novel method, the Ratio Prediction, is proposed and used to analyze RBG values of a satellite image to locate red cars. In Section II, the main principle and model of this method is introduced. In Section III, main steps and experimental results are presented. In Section IV, some conclusions and suggestions are proposed.

II. Implementation

The related work is based on the pixels' RGB values. Generally, red cars of the image have totally different RGB values compared with other stuff. Thus, RGB values should be analyzed before classifying red cars of the image. Since colors of trees, swimming pools and some blue-roof-buildings are green or blue, it is simple to filter these and they don't affect the classification of red cars. Thus, they are ignored for analyzing colors.

A. RGB Values Of Red Cars and building roofs

1) Red Cars

A typical red car in the image is shown in Fig. 1. We could find the R value dominates the RGB values of red car pixels. Mostly, the R values are greater than G values and B values. In fact, the difference between R values and G values are usually greater than 70, even 100. The difference between R values and B values are even greater. In Fig. 1, the RGB values of one typical pixel of all are 150, 55, 72, respectively.

Fig. 1. A red car pixels. The R value of this car varies from 70 to 180, but most R values of red pixels are 50 greater than G values or B values on average.

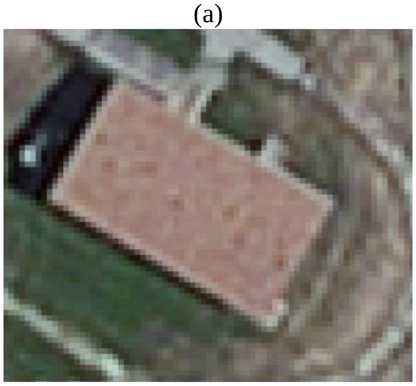
However, there are some dark red cars as well, which are close to black or brown cars in the image, and their RGB values are different from red cars. A dark red car is shown in Fig. 2. We can find the R values are still greater than G values and B values, but R values are around 30 greater than G values on average. In Fig. 2, the RGB values of one typical pixel of all are 99, 63, 80, respectively.

Fig. 2. A dark red car pixels. The R value of this car varies from 60 to 90, but most R values of red pixels are 30 greater than G values or B values on average.

2) Building Roofs and other noises

The satellite images of this project contain light red or pink roofs of buildings, which may affect the classification results. Actually, every roof color is different. Two roofs with different colors are selected in Fig. 3. In Fig. 3(a), the RGB values of one typical pixel of all are 98, 61, 69, respectively. In Fig. 3(b), the RGB values of one typical pixel of all are 159, 131, 124, respectively. The differences between R values and G values are around 30 on average.

(a)



(b)

Fig. 3. Two different color roofs with different RGB values.

With analysis above, we could find that RGB values of cars and roofs of buildings are complex. It may cost tedious computation to distinguish them. Traditional classifiers, such as K Nearest Neighbors classifiers, K Means classifiers, are not able to distinguish data sets with 100% accuracy. In addition, red cars need tedious computation to be located as well. Thus, a simplest method is used to save computation for cars' locations. *RED Pixels*, whose differences between R values and G values are greater than 35, are selected for cars' locations. Other pixels are directly ignored. After that, Ratio Selection is adopted. It could compensate for sketchy selection and classification of red pixels.

B. Ratio Selection

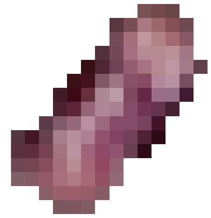
1) Red Cars

The Ratio Selection is a method considering the ratio of quantities of red car pixels and pixels coordinate variances.

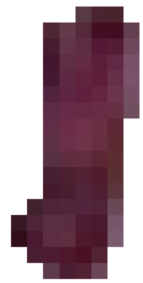
$$ratio = \frac{N}{\mathrm{var}_x + \mathrm{var}_y} \tag{1}$$

Where N is the number of *RED Pixels*, var_x and var_y are variances of *RED Pixels* x coordinates and y coordinates, respectively.

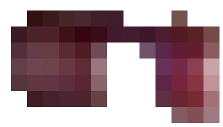
The ratio is calculated in grids. Grids are formed by dividing satellite images into continuous equal squares. The size of satellite images are 6250 pixels × 6250 pixels. A appropriate square width is 25 because it is divisible by 6250, and the satellite images are transferred into a matrix of 250 × 250.



(a)



(b)



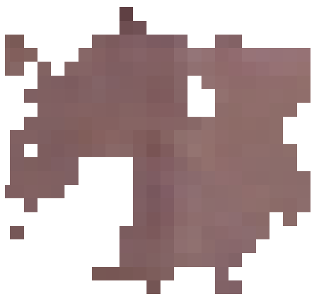
(c)

Fig. 4. Three grids of the satellite images after filtering non-RED Pixels

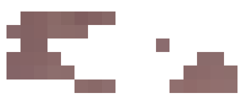
Three grids are shown in Fig. 4. In every grid, a complete red car is included. The number of *RED Pixels* is about 80 to 100. Other non-RED Pixels are set to white points. A red car consists of continuous *RED Pixels*. Some pixels are missing because they don't meet the requirements that differences between R values and G values should be greater than 35. Although some pixels are missing, we could image that mean x coordinates and y coordinates of *RED Pixels* are located near the center of the red car. Thus, the variance of x coordinates and y coordinates should be positively related to horizontal and vertical pixels numbers, respectively. Since a car has limited length and width, the variances of coordinates are limited as well in a range no matter which direction the car faces. Three red cars of Fig. 4 faces different directions, but the variances of x coordinates and y coordinates are in a range. Thus, the sum of two variances should also be in a range. The ratio in (1) should be in a range with limited *RED Pixels* and limited coordinates variances.

2) *Building Roofs and Other Noises*

Two building roofs after filtering non-*RED Pixels* are shown in Fig. 5. Apparently, building roofs also contain many *RED Pixels*, but the number of *RED Pixels* are far more than those of a red car in Fig. 5(a). The number of *RED Pixels* in Fig. 5(b) is close to a red car, but the pixels are widely distributed. Thus, its coordinate variances should be far greater than that of a red car. The ratio should be a lot smaller, thus Equation (1) could be used to classify roofs and red cars.



(a)



(b)

Fig. 5. Two building roofs after filtering non-RED Pixels.

III. Experiments

Experiments consists of three parts: Training, validation and testing

1) *Training Ground_truth Data Sets*

Data training is based on the classification model above. Training the model equals calculating the numbers, variances of x coordinates and y coordinates of RED Pixels. thus it is necessary to build up a 3 dimension matrix:

```
Set numbers of pixels a grid contain horizontally to gridnum=25
Set width of matrix to gridwidth=250
for i in range(satellite image horizontal size):
   for j in range(satellite image vertical size):
      if R values > G values+30
         find the corresponding square of each pixels by selecting the quotient of coordinates divided by 25
         number of pixels: network[i//25,j//25,0]+=1
         save coordinates of RED Pixels [i,j]
```

Means of x coordinates and y coordinates need to be calculated, then variances of them also need to be computed:

```
for i in range(250):
   for j in range(250):
      for k in range(numbers of all red coordinates):
         if red coordinate belongs to square [i,j]:
            calculate means and variances of all RED Pixels in each square
               network[i,j,1]= mean of x coordinates
               network[i,j,2]= mean of y coordinates
               network[i,j,3]= variance of x coordinates
               network[i,j,4]= variance of y coordinates
```

After numbers, means of x coordinates, y coordinates, variances of x coordinates and y coordinates of *RED Pixels* are calculated, ground truth data set is utilized to calculate ratio in (1):

```
for i in range(numbers of ground_truth)
   network[i,j,0]= numbers of RED Pixels coordinates
   network[i,j,1]= mean of x coordinates
   network[i,j,2]= mean of y coordinates
   network[i,j,3]= variance of x coordinates
   network[i,j,4]= variance of y coordinates
```

Thus, we have 28 set of numbers, means, and variances. We add variance of x coordinates and y coordinates and have sum variance. Then, Fig. 6 is a figure to describe the relationship between sum variance and numbers.

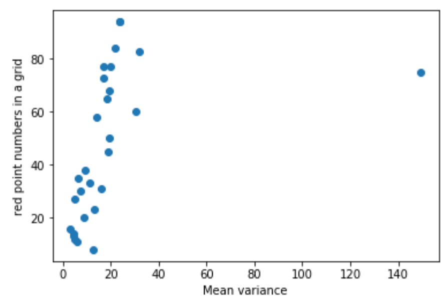


Fig. 6. The relationship between sum variance and numbers

It is simple to find that sum variance and numbers are positively related and the ratio in (1) is fluctuating with a rage. Polynomial curve fitting is used to find the ratio. One point is beyond the rage because the square of this point contains at least two cars, and the two cars are at edge of square, which cause the sum variance rising. Thus, this point is ignored for polynomial curve fitting. Linear Polynomial is adopted to describe the ratio. Fig. 7 is the fitting figure.

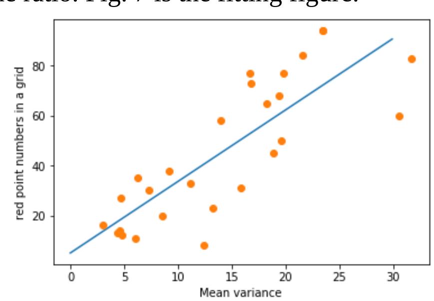


Fig. 7. Linear Polynomial curve to fit points

The rate of the blue line is 4.165. The average ratio of all points in Fig. 7 is 4.044 and the variance of ratio is 1.257. Then we can suppose that ratio of every square is subject to Gaussian Distribution with mathematical expectation 4.044 and variance 1.257. One trait of Gaussian Distribution is that 95% of data is within the range $|x - \mu| < 2\sigma$. Thus we can assume if the ratio of grid meets the requirements $|x - 4.044| < 2 \times \sqrt{1.257}$, this grid contains one red car. μ and σ are used as parameters to test data set.

2) Validation

Since the Ratio Selection uses mean of x coordinates and y coordinates as the location of red cars, the calculated coordinates may be different from ground_truth data coordinates for the same red car. Thus, cross validation is not utilized to validate the training parameter. The validation process is the same as testing data, but the validation aim is to find other red cars of the training data image.

3) Testing Data Set

We use the same steps shown in 1) to build up a similar matrix for RED Pixels of the test satellite image, then judge if the ratio of each square is within the range $|x - \mu| < 2\sigma$ with the parameter μ and σ. The square that meet the requirements contain red cars, and the location can be find:

```
Set test_result to empty
Set test_result_coordinate to empty
for i in range(250):
    for j in range(250):
        if (sum variance of square[i,j])!=0:
            ratio_cal=calculate the ratio in [1]
                if |ratio_cal − μ| < 2σ and RED Pixels<120
                    add [i,j] to test_result
                    add mean of x coordinate and y coordinate to
                    test_result_coordinate
                    make the location pixel of red car white to show
```

Part of the test result is shown in Fig. 8. Most red cars are successfully located, but some red cars are repeatedly reported because two white points appear on one car.

Fig.8. Part of the test result

The reason of repeated report is that one red car spans two grids as Fig. 9 shows and both grids report the location of the red car. This problem can be solved if gridnum is set to 50, which means the grid size is greater and decrease the probability of repeated reports.

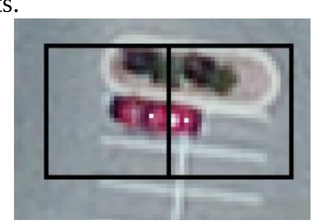


Fig.9. A red car spans two grids

Another problem is that this method is difficult to distinguish two cars in one grid as Fig. 10 shows. It considers two cars as one car. If these two cars are separated in the grid, the white point will locate on neither of them. It will deviate and the sum variance of RED Pixels will be a lot greater. This is why in Fig. 6 a point is far from other points. This problem can be solved if gridnum is set to 10, which means the grid size is smaller and decrease the probability of mixing two cars into one.

Fig.10. Two red car in one grid cause the error

IV. CONCLUSIONS

In conclusion, the Ratio Selection can easily report the location of red cars if a grid contains only one car. If one grid contains two cars, smaller grid size can avoid the problem, and the red location estimation can be more accurate but it cause repeated report and longer computing time. If one red car spans two grids, it can cause repeated reports, larger grid size can avoid the problem and it will need less time to compute, but it decreases estimation accuracy in general. Thus it is a tradeoff to choose an appropriate grid size. However, in the future, problems of repeated reports could be further researched, because selecting one pixel from two is not difficult to be implemented. In addition, theoretically, the method doesn't need many ground truth data points. Mean and variance of coordinates can be calculated with 2 ground truth points. The calculation can be more accurate with more points. However, the method is based on RGB values of images, so it is unlikely to test unseen test data.

REFERENCES

[1] A. S. Glassner, "Principles of digital image synthesis," Elsevier, vol. 1, 1995.

[2] Modular digital image generator, by J. K. Florence and J. K. Yan. (1986, Feb 11). Patent D 4,570,233.

[3] S. Sherin and A. P. James. "Irregular pixel imaging." In Advances in Computing, Communications and Informatics (ICACCI), New Delhi, India, Sep. 24-27, 2014.

[4] P. Genesan and V. Rajini. "Assessment of satellite image segmentation in RGB and HSV color space using image quality measures." International Conference on Advances in Electrical Engineering (ICAEE), Vellore, India, Jan. 9-11, 2014