

2014

BioTechnology

An Indian Journal

FULL PAPER

BTAIJ, 10(23), 2014 [14122-14127]

Glass insulator recognition based on HSL color space and SIFT matching

Yongjie Zhai¹, Yang Wu^{1*}, Haiyan Cheng¹, Zhenbing Zhao²¹School of Control and Computer Engineering, North China Electric Power University, Baoding, 071003, (CHINA)²School of Electrical and Electronic Engineering, North China Electric Power University, Baoding, 071003, (CHINA)

E-mail: wy1902827955055@163.com

ABSTRACT

This paper presents a method for recognizing glass insulators in aerial images from helicopter patrolling of power lines, in order to improve work efficiency, compared with manual inspection. This technique works by rough location and local recognition. In rough location, the hue and lightness components in HSL color space were extracted initially to segment with their relevance to glass characteristic, instead of traditional algorithm in RGB model. And insulators are roughly located by morphology, connected components analysis. Then, we select sub-modules from insulator samples, using hierarchical clustering based on SIFT matching rates and recognize insulators locally by matching method. Some experiments on aerial images indicate that our approach avoid requirements of mass high-quality samples and shows significantly improved performance on detection accuracy.

KEYWORDS

Insulator; HSL; SIFT; Hierarchical clustering.



INTRODUCTION

Automatic surveillance of electrical power infrastructure is turning into an important means of power line inspection in China, due to its efficiency, low-cost and applicability to various geographical areas. Using helicopter inspection as the main method and human inspection as the auxiliary is the development direction in line inspection of high pressure and super high pressure in China. At present, Chinese power grid corporations are attempting to monitoring electrical equipment. Thanks to the rapid development of image sensors and computer vision technologies, it is possible to apply the advanced image processing technique, such as target detection and recognition, to automatize the power transmission lines surveillance. Insulators play an important role^[1], supporting and fixing buses and charged conductors, and are aging even broken due to bad weather, so state monitoring of them is essential. Helicopter patrol inspection system has been applied to insulator monitoring^[2] and research reports about insulator detection are getting more concerned. Recognizing them from aerial images in natural light is challenging due to complex background, illumination, angle. As for glass insulators, color feature in HSL color space is the main issue to make segmentation of insulators^{[3][4]}. Lin used the statistical information and chain code to detecting the location^[5]. Some machine learning methods are used in this problem. In^[6], the authors used invariant features and cascade AdaBoost classifiers. The results depend on the quality and quantity of training samples greatly and the obtaining mass premium training samples is not easy. In this paper, we propose a method to avoid difficulty of obtaining mass samples, combining color features and SIFT features.

We divide recognition process into two parts, rough orientation and local recognition. Hue and lightness components in HSL color space were extracted initially to segment due to their relevance to glass characteristic and insulators are roughly located by morphology, connected regions analysis. Then, combination of SIFT features matching and hierarchical clustering are used recognized regionally.

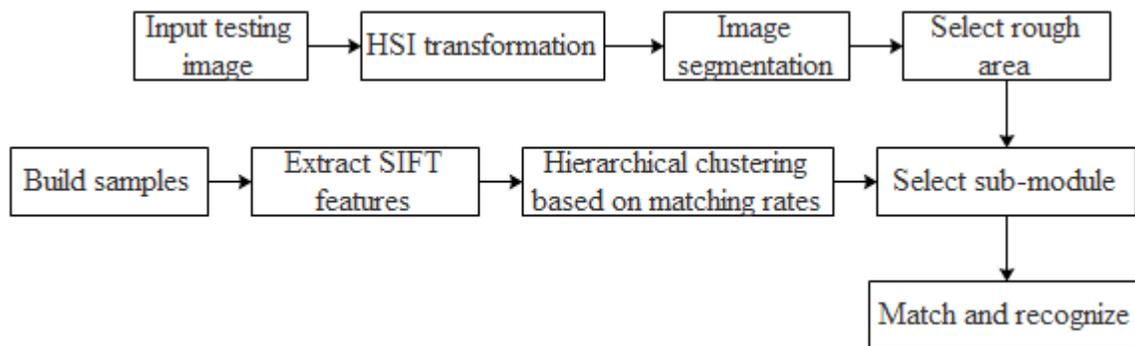


Figure 1 : Flowchart of recognizing glass insulators

ROUGH LOCATION

HSL color space

Glass insulators is different from complex background on color and glass characteristics apparently, so it is very vital to select some components, which can make full use of the difference above to segment. HSL color space can describe people's perception of color and is intuitive for people to observe colors. So, HSL model is ideal to segment and shown in Figure 2.

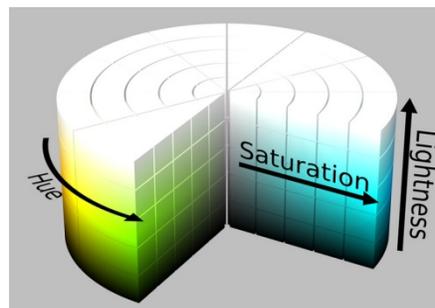


Figure 2 : HSL color space

HSL color space describes colors using hue, saturation and lightness. Hue is the basic property of pure color. Saturation reflect the color shades, depending on the content of white colored light. Lightness is the subjective descriptors

and is the key issue of describing color Lightness^[7]. The color of glass insulators is translucent and lightful, L components can be used to distinct objects and background. Unlike traditional methods, we extract H and L components of glass insulator images as the base of segmentation. The conversion from RGB to HSL space is shown in formula (1).

$$\begin{cases} H = \begin{cases} \theta, & B \leq G \\ 360 - \theta, & B > G \end{cases} \\ \theta = \arccos \left\{ \frac{\frac{1}{2}[(R-G) + (R-B)]}{[(R-G)^2 + (R-B)(G-B)]^{\frac{1}{2}}} \right\} \\ S = 1 - \frac{3}{(R+G+B)}[\min(R, G, B)] \\ I = \frac{1}{3}(R+G+B) \end{cases} \quad (1)$$

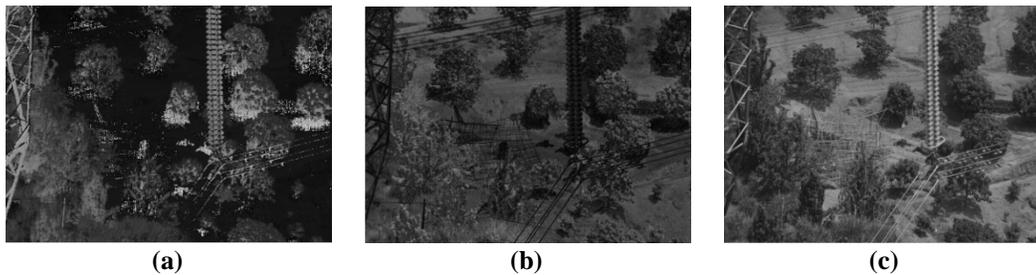


Figure 3 : Different components of the image in HSL color space. After transformation into HSL color space, (a) is the H components of the image and (b) is the S components of the image and (c) is the L components of the image

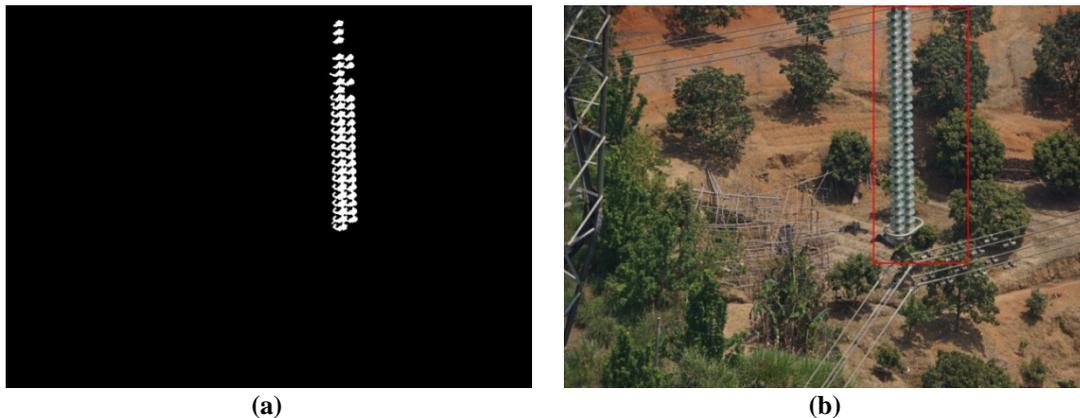


Figure 4 : Rough location results by segmentation in HSL color space. (a) is the binary image after segmentation and (b) is the rough location in original image and the rough area is marked

Segmentation and rough orientation

We convert testing images from RGB model to HSL model and Figure3(a), (b) and (c) are its HSL component images. Note that the region in which we are interested in has relatively high values of hue and lightness, indicating that colors are on the blue-magenta side of red and the glass insulators have strong light reflection. Firstly, we make binary processing generated by thresholding the lightness image with Otsu's method. Then, we make the product of the mask with hue image and make binary convention of the product with the threshold value by counting the histogram. With processing of morphology and connected regions, the insulators in the image are roughly located, shown in Figure 4(a) and the probable area in original testing image is marked, shown in Figure 4(b).

LOCAL RECOGNITION

Considering gaining the mass superior training samples for machine learning a hard stuff, a local recognition method based on rough location of glass insulators is proposed in this paper. We divide recognition process into two parts, rough location and local recognition. Hue and lightness components in HSL color space were extracted initially to segment with

their relevance to glass characteristic, instead of traditional algorithm in RGB model. And insulators are roughly located by morphology, connected components analysis. Then, we select sub-modules from insulator samples, using hierarchical clustering based on SIFT matching rates and recognize insulator locally by matching method.

SIFT generation process

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect and describe local features in images. The SIFT descriptor presented in paper^[8] provides a solution that characterizes an image region, invariant to image scale and rotation, so that it can be utilized for performing robust matching between different views of an object or scene. There are four main procedures of SIFT generation process and discussed below.

Scale-space extremum detection

The image is convolved with Gaussian filters at different scales, and then the difference of successive Gaussian-blurred images are taken. Keypoints are then taken as maxima of the Difference of Gaussians (DoG) that occur at multiple scales. To efficiently detect stable keypoint locations in scale space, Lowe^[9] has proposed the scale space defined as (2), the difference-of-Gaussian function convolves with the image.

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \end{aligned} \quad (2)$$

Keypoint localization

A detailed fit to the nearby data for accurate location, scale, and ratio of principal curvatures is performed. This information allows points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge point candidates.

Orientation assignment

Each keypoint is assigned one or more orientations based on local image gradient directions. This is the key step in achieving invariance to rotation as the keypoint descriptor can be represented relative to this orientation and therefore achieve invariance to image rotation. Each keypoint is assigned the dominant direction by using the gradient orientation histogram from the gradient orientations of sample points within a region.

Keypoint descriptor

The SIFT key-points are determined by finding the local maximums and minimums of the difference of Gaussians that occur at multiple scales. Each key-point is assigned one or more dominant orientations based on the directions of local image gradient which are calculated using the neighboring pixels around the key-point in the Gaussian-blurred image.

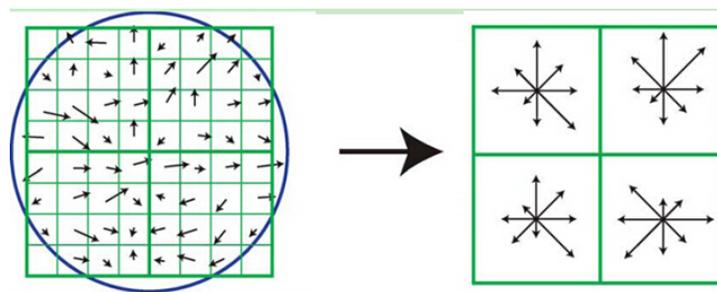


Figure 5 : Keypoint descriptors. (a) is the gradients and (b) is the keypoint descriptors

Hierarchical clustering based on matching rates

Clustering algorithm can divide a given data set into some clustering partitions and those clustering partitions are elements of clustering division for the given data set generated by the clustering algorithm. Usually, clustering divisions constructed by different clustering algorithm can be different. Even more, clustering division constructed by same algorithm with different initial parameters can be different. In data mining, hierarchical clustering is a method of cluster analysis which seeks to build hierarchy of clusters.

With the SIFT features above, hierarchical clustering^[10] will be used for selecting sub-modules to recognize insulators. Hierarchical clustering is a method of cluster analysis which seeks to build a hierarchy of clusters. Here, hierarchical clustering was used to cluster automatically and matching rates are designed as distance parameters in hierarchical clustering. The flowchart of the experiment is shown in Figure 6.

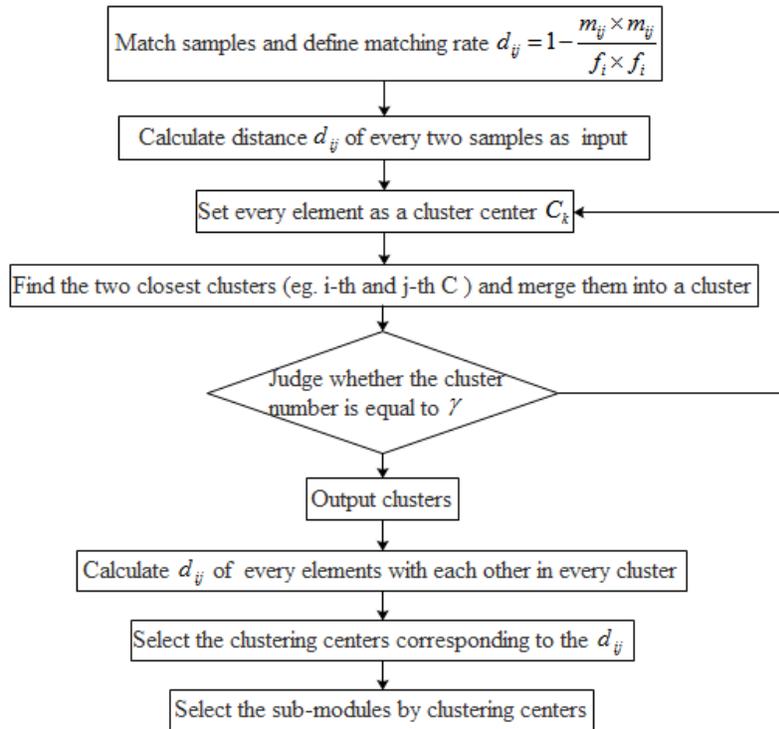


Figure 6 : Flowchart of the hierarchical clustering based on matching rates

1) In order to decide which clusters should be combined, matching ratio is defined in Eqn. (3).

$$d_{ij} = 1 - \frac{m_{ij} \times m_{ji}}{f_i \times f_j} \quad (3)$$

Where m_{ij} is the number of matching features of the i-th and the j-th sample. f_i is the number of features in sample i. Due to matching ratio independent from sample sequence, D is denoted in Eqn. (4).

$$D = \begin{bmatrix} 0 & d_{12} & d_{13} & \cdots & d_{1n} \\ d_{12} & 0 & d_{23} & \cdots & d_{2n} \\ d_{13} & d_{23} & 0 & \cdots & d_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{1n} & d_{2n} & d_{3n} & \cdots & 0 \end{bmatrix} \quad (4)$$

Make the metric D as the input of the hierarchical clustering elements. Determine the number of clusters and initial every elements as cluster centers $\{C_1, C_2, \dots, C_k\}, k = 1, 2, 3, \dots, N$. Find two closest elements as a cluster in Eqn. (5).

$$\|C_i(n) - C_j(n)\| = \min_{1 \leq i, j \leq k} \|C_i(n) - C_j(n)\|, i = 1, 2, \dots, k \quad (5)$$

3) We merge them further, taking the distance between the two clusters from the date we processed above and repeat this procedure until we get the γ clusters we need, assuming they are $\{C_1, C_2, \dots, C_\gamma\}$.

4) Matching rates of each elements with others in cluster C_i are computed and summed up and select them as sub-modules.

$$Center_i = \{C_p \mid \max \|\sum C_{pq}\|\}, i, p, q = 1, 2, \dots, \gamma \quad (6)$$

Testing images with sub-modules

After testing images are processed in rough location, SIFT features of rough area are calculated and matched with each sub-modules. Then, the recognition results with the best matching outcome is shown on screen. This part makes matching points present the position of the object edge and locate the glass insulators more precisely, shown in Figure 7.



Figure 7 : Recognition results

CONCLUSION

In order to test out method, we choose 20 images of glass insulators as our testing samples to cluster and get 6 sub-modules. Then, we randomly find ten aerial images to recognize glass insulators with our method. The recognition results are shown in TABLE 1. As can be seen from the table, the average recognition rate is 75% and because of the complex background, the recognition performance is not stable enough. But this method avoids false recognition absolutely and the problem of a large sum of training samples.

In this paper, a new insulator recognition method is put forward, which is based on the precise location of hierarchical clustering with SIFT matching. Before processing SIFT extraction, the image was segmented in HSL color space according to the H and L components characteristics of glass insulators. Due to the loss of pixels of insulators in removing disturbance of a complex background, this part is designed for rough location. Then, rough areas were extracted, SIFT features were matched with sub-modules, which were selected by hierarchical clustering based on matching rates before. Experimental results show that this method can avoid insufficient samples for the training process and also can recognize glass insulators from a complex background feasibly and effectively.

ACKNOWLEDGEMENT

This research is supported by the National Natural Science Foundation of China under Grant, No.61401154 and the Fundamental Research Funds for the Central Universities in China, No.2014MS140.

REFERENCES

- [1] N.Bashir, H.Ahmad; "Ageing of transmission line insulators, The past, Present and future, "Power and Energy Conference, (2008), PECon (2008), IEEE 2nd International, **30, 34**, 1-3 Dec, (2008).
- [2] Wei-Guo Tong, Bao-Shu Li, Yu-Long Pei; "Extraction and recognition of insulator based on aerial image, "Electric Information and Control Engineering (ICEICE), 2011 International Conference on, **4195, 4198**, 15-17 April, (2011).
- [3] Xinye Zhang, Jubai An, Fangming Chen; "A simple method of tempered glass insulator recognition from airborne image, "Optoelectronics and Image Processing (ICOIP), 2010 International Conference on, **127,130**, 11-12 Nov., (2010).
- [4] Bingfeng Li, Denglu Wu, Yang Cong, Yong Xia, Yandong Tang; "A method of insulator detection from video sequence, "Information Science and Engineering (ISISE), 2012 International Symposium on, **386, 389**, 14-16 Dec., (2012).
- [5] Jucai Lin, Jun Han, Fangming Chen; Fault diagnosis of glass insulator in color images, Power System Technology, **35(1)**, 127-133 (2011).
- [6] Si Yuan, He, Ling Wang, Yong Xia, Yan Dong Tang; Insulator recognition based on moments invariant features and cascade adaboost classifier, Applied Mechanics and Materials, 433-435, 362-367 (2013)
- [7] K.Yoshinari, K.Murahira, Y.Hoshi, A.Taguchi; "Color image enhancement in improved HSI color space, "Intelligent signal processing and communications systems (ISPACS), 2013 International Symposium on, **429, 434**, 12-15 Nov., (2013).
- [8] A threshold selection method from gray-level histograms, "Systems, Man and Cybernetics, IEEE Transactions on, **9(1)**, 62, 66, Jan., (1979).
- [9] D.Lowe; Distinctive image features from scale-invariant keypoints, International journal of computer vision, **60(2)**, 91-110 (2004).
- [10] Ma Fengying; "Optimal arithmetic for hierarchical cluster and pattern recognition applied in coal dust sensor, "Control Conference, 2008, CCC 2008, 27th Chinese, 582, 586, 16-18 July, (2008).