Electric Equipment Image Recognition Based on Sparse Representation for the Safety of Power Distribution

Ni Changsong¹, Lin Xuesong², Liu Guicai¹, Liu Shijun³

¹ Distribution Operation Inspection Room, State Grid Dalian Power Supply Company, Dalian 116032 China
² Transportation Inspection Department, State Grid Dalian Power Supply Company, Dalian, 116001 China
³ Dalian E-link Information Technology Co., Ltd., Dalian 116085 China

Abstract. Electric equipment image analysis has important meanings to power line inspection and repairment. This paper proposes an electric equipment image recognition method based on sparse representation. Considering the image collection is inevitably influenced by the light condition and noise corruption, this paper uses Bayesian compressive sensing algorithm to solve the sparse representation problem. The algorithm has good robustness to noises and interferences, which is suitable to handle the conditions in electrical equipment images. In the experiments, three electrical equipments, i.e., insulators, power transformers, and breakers, are classified and the accuracy reaches 93.56%. In addition, the robustness of the proposed method under noise corruption is also superior. All the results validate the effectiveness of the proposed method.

1. Introduction

With the increase of electric equipments, the traditional ways of overhaul can hardly meet the demands. Under this situation, the computer-aid methods were applied. Electric equipment image recognition could help find the possible faults in an electric equipment thus providing warnings. In the previous works, some electric equipment image recognition algorithms were proposed [1-5], which generally comprised of two modules, i.e., features and classifiers. Some used geometrical features to describe the electric equipments such as region moments and contour descriptors. Others may used projection features extracted by principal component analysis (PCA). During the classification stage, these features are classified by the specifically selected or designed classifiers to obtain the object label of some unknown images. The usually used classifiers in this field include nearest neighbour (NN), support vector machines (SVM), etc.

With the development of pattern recognition and signal processing techniques, many advanced classifiers are available for electric equipment image recognition, among which sparse representation-based classification (SRC) is a typical representative [6-8]. Originated from compressive sensing theory [6], SRC has been successfully applied to face recognition [7], radar target recognition [8], etc. In this study, SRC is applied to electric equipment image recognition. First, PCA is used to reduce the original electric equipment images thus obtaining low-dimensional feature vectors. Then, the feature vector from the test sample is classified based on the global dictionary formulated by all the training samples using SRC. Finally, the reconstruction errors of different training classes as for representing the test sample can be calculated, which are used to determine the object label of the test sample.
Specifically, the orthogonal matching pursuit (OMP) algorithm is used to solve the sparse representation problem, which has good precision and efficiency. To properly test the proposed method, images of three typical electrical equipments, i.e., insulators, power transformers, and breakers, are classified in the experiments. The results show the high effectiveness of the proposed method.

2. Method Description

2.1. SRC

According to the compressive sensing theory, the sparse representation technique was widely used in the data analysis and pattern recognition. SRC is a typical application of sparse representation, which was validated to has good classification performance. For the test sample \( y \) to be classified, it is first linearly represented as follow:

\[
\hat{x} = \arg \min_{x} \|x\|_0 \quad \text{s.t.} \quad y = Ax
\]  

In equation (1), \( A = [A^1, A^2, \ldots, A^M] \in \mathbb{R}^{d \times N} \) denotes the global dictionary comprising of \( M \) training classes; \( x \) represents the coefficient vector, which has a high sparsity level. As the core of SRC, the sparse coefficient vector should be solved with high precision thus the reconstruction errors of different training classes can be calculated and compared.

In the previous works, several ways to solve the optimization task in equation (1) were proposed such as basis pursuit (BP), orthogonal matching pursuit (OMP) [8], and \( l_1 \) norm approximation [7], etc. As validated, OMP has higher precision and efficiency, which is much more suitable to be used in a classification task.

Based on the solved sparse coefficient vector \( \hat{x} \), the reconstruction errors of different classes can be obtained to determine the object label of the test sample \( y \) as follows:

\[
r(i) = \|y - A\hat{x}(i)\|_2 \quad (i = 1, 2, \ldots, M) \\
\text{identity}(y) = \arg \min_{i} (r(i))
\]  

2.2. Recognition Procedure

Fig. 1 shows the basic procedure of recognizing an unknown electric equipment image using the proposed method. In detail, the whole process can be explained as following steps.

Step 1: Extract the features of all the training samples by PCA to formulate the global dictionary;
Step 2: Extract the feature vector of the test sample;
Step 3: Represent the feature vector of the test sample over the global dictionary;
Step 4: Solve the sparse coefficient vector using OMP;
Step 5: Calculate the reconstruction errors of different training classes to determine the object label of the test sample.

![Fig. 1 Basic procedure of the proposed electric equipment image recognition method.](image-url)
3. Experiments

3.1. Images of Three Electric Equipments
In the experiments, images of three typical electric equipments, i.e., insulators, power transformers, and breakers, are used. For each equipment, it has 2000 images collected from real-world scenarios with the sizes of 400 pixels × 400 pixels. We randomly select 1400 images from each of the three equipments as the training samples while the remaining ones are classified. For comparison, some reference methods are used for comparison including Method 1 from [1], Method 2 from [2], and Method 3 from [3].

3.2. Results and Analysis
Based on experimental setup in the former subsection, the recognition results of the proposed method on the three electric equipments are displayed as Table 1. As shown, each of the three objects can be classified with a recognition rate over 91% and the average recognition rate reaches 93.56%. Table 2 compares the average recognition rates of different methods. The proposed method achieves the highest one, which validates its high effectiveness.

In addition, it is normal that the measured images in the real-world conditions may be corrupted by high level of noises. Therefore, we further test the proposed method under noise corruption as shown in Fig. 2. In comparison with those reference methods, the proposed method could obtain the highest recognition rates at each signal-to-noise ratio (SNR). So, the results could validate the superior robustness of the proposed method to possible noise corruption.

Table 1. Recognition results of the proposed method on three electric equipments.

| Test samples      | Classification result | Recognition rate (%) |
|-------------------|-----------------------|----------------------|
| Insulator         | 546 24 30             | 91.00                |
| Power transformer | 11 576 13             | 96.00                |
| Breaker           | 13 15 562             | 93.67                |
| Average recognition rate (%) | | 93.56 |

Table 2. Average recognition rates of different methods on three electric equipments.

| Method | Proposed | Method 1 | Method 2 | Method 3 |
|--------|----------|----------|----------|----------|
| Average recognition rate (%) | 93.56 | 91.17 | 91.86 | 92.24 |

Fig. 2 Performance of different methods under noise corruption.
4. Conclusion
In order to improve the recognition performance of electric equipment images, this paper applied SRC to the classification tasks. PCA is first used to notably reduce the dimensionality and SRC is performed in the classification stage. Owing to the merits of OMP, the sparse coefficient vectors could be solved with high precision and efficiency. Therefore, the whole recognition performance could be significantly enhanced, which is also validated by the experimental results on three typical electrical equipments. Also, the proposed method could work more robust than the compared methods under different levels of noise corruption.

Acknowledgment: This work was supported by Technology Funding Project of State Grid Corporation of China (Grant No. 2018YF-38).

References
[1] Wang J, Shao J 2017 Image recognition of icing thickness on power transmission lines based on a least squares Hough transform Energies vol 10 no 4 pp 415-430.
[2] Tian Y, Yu 2009 L An Image Recognition Method of the Electric Equipment Operation States Proc. Asia-pacific Power & Energy Engineering Conference pp 1-4.
[3] Lu J, et al. 2011 An image recognition algorithm based on thickness of ice cover of transmission line Proc. International Conference on Image Analysis & Signal Processing pp 37-41.
[4] Yan S, et al. 2014 Power line image segmentation and extra matter recognition based on improved Otsu algorithm Proc. International Conference on Electric Power Equipment-switching Technology pp 1-4.
[5] Jin L, et al. 2014 Temperature rising recognition of IR image of electrical equipment based on seeded region growing Proc. International Conference on Electric Power Equipment-switching Technology pp 23-27.
[6] Candés E J, Wakin M B 2008 An introduction to compressive sampling IEEE Signal Processing Magazines vol 25 no 2 pp 21-30.
[7] Wright J, Yang A, Ganesh A, et al. 2009 Robust face recognition via sparse representation,” IEEE Transactions on Pattern Analysis and Machine Intelligence vol 31 no 2 pp 210–227.
[8] Thiagaraianm J J, Ramamurthy K N, Knee P, et al. 2010 Sparse representations for automatic target classification in SAR images Proc. of 4th Int. Symp. Commun. Control Signal Process pp 1-4.