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# LBP-HF Features and Machine Learning applied for Automated Monitoring of Insulators for Overhead Power Distribution Lines

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***Abstract*— With ever-increasing awareness on quality and reliable power distribution, the research in the area of automation of distribution system has great relevance from the practical point of view. Electric power utilities throughout the world are more and more adopting computer aided control, monitoring and management of electric power distribution system to offer improved services to the consumers of electricity. The purpose of on-line condition monitoring of cables or any electrical equipment is to predict possible failures before they actually occur. With phenomenal growth of distribution network even to remote areas, the traditional methods of inspecting the lines by foot-patrolling and pole-climbing to check them in close proximity do not seem to be viable. Since the damaged insulators of the distribution system affects the performance of distribution system significantly in terms of reduction in voltage, aerial patrolling has been adopted in developed countries for the purpose of insulator monitoring. The development of an efficient and alternative method for insulator condition monitoring uses image processing and machine learning techniques and is found to be a sustainable method. This work covers automatic defect detection and classification of insulator systems of electric power lines using vision-based techniques.**

***Index Terms*— Classification, feature extraction, LBP-HF, rotation invariance.**

## I. INTRODUCTION

Uninterrupted reliable operation of the modern power distribution system depends more on reliable and satisfactory performance of insulators operating under different conditions of environment [1]. If distribution equipment begins to weaken, it can be anticipated that an erratic incipient faults persist in the system probably from as little as several days to several months and so, it is very crucial to monitor distribution line, classify and discriminate the signatures of failure of the equipment before they actually breakdown or breakout [2]. Many items of overhead lines like insulators, conductors and fittings, can be continuously monitored online [3]–[9]. The on-line processing to monitor the health of equipment is commonly known as condition monitoring (CM) [10].

This work aims to analyze the condition of insulators on poles based on image processing and machine learning techniques. The traditional methods involved in condition monitoring of insulators arei) Pole Climbing and ii) Aerial Surveillance. Pole climbing means that one ascends a pole and can grip it with his hands. Mast climbing is related this activity in which one ascends on to an object similar to a pole, but it has a larger diameter which excludes gripping with the hands. An alternative detailed inspection approach to sending crew personally is that trained inspectors fly aboard helicopters, inspect the lines with binoculars, cameras and the data is recorded in a log book. This procedure is performed as the helicopter hovers over and around power lines and structures, but it creates an element of danger for the pilot and the inspector.

But, new difficulties arise in this case due to the fact that back ground always changes and it makes the clarity of the object of interest difficult to view. The difficulties involved in this method are 1) Changing background 2) Image blurring and 3) Sight control of camera [7]. Interestingly, video surveillance with fixed cameras has been applied for the case of pedestrian detection [11]. This method was found as a promising solution for surveillance of distribution system insulators. Hence this method can be extended to condition monitoring of insulators of overhead power distribution system. Design of the automation system can be done using the available technology in computer systems, control systems and metering systems and join the same into the existing power systems. The required tools such as computers, Remote Terminal Units (RTUs) etc., are all available. So, the images taken from the power distribution lines along with insulators at regular intervals of time, can be sent to the control room using remote terminal unit (RTU)s for further analysis [7].

For this work, the images containing the electric poles have been taken and the insulators are extracted using k-means clustering. The features for the extracted insulators are found using and LBP histogram Fourier (LBP-HF) features and then classification of the insulators is done using SVM.

## II. TYPES OF INSULATORS

The insulators used in transmission line are the devices which are used to contain, support or separate the electrical conductors which are laid on high voltage power distribution networks. The transmission insulators are available in various types and shapes, which includes individual or strings of disks, long rods or line posts. The insulators are made of glass, polymers and porcelain. Each model is made up with different tensile strengths, densities and different levels of performance in typical working conditions.

There are mainly three types of insulators used for the purpose of overhead insulator. They are i) Pin Insulator ii) Suspension Insulator and iii) Strain Insulator. There are two more types of electrical insulators which are available mainly for low voltage application and are called Stay Insulator and Shackle Insulator.

## III. PROBLEM DESCRIPTION

The flowchart for analyzing the insulator is as shown in the below Fig. 1. The acquired images at regular intervals of time are first converted to equivalent grey scale images. Edge detection is done using Sobel's operator and segmentation using K-means clustering to extract the insulators from the pole. Then feature extraction is done using LBP-HF features. The feature vector is to be processed using the Support Vector Machines (SVM) or any other machine-learning algorithm to classify the textural images. These classifiers are widely used for face recognition or texture analysis.

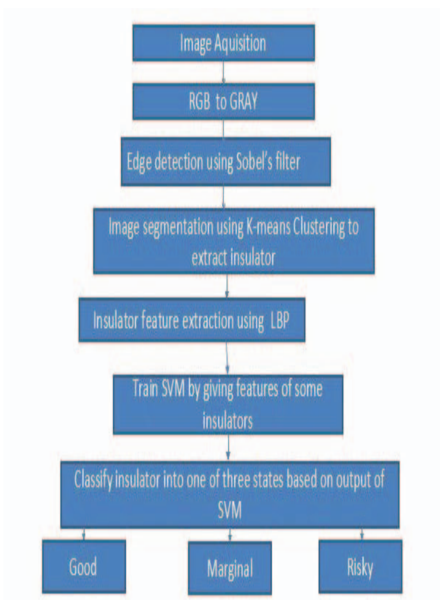


**Fig. 1**. Flowchart of the analysis process

## IV. LOCAL BINARY PATTEN DESCRIPTORS

The local binary pattern histogram Fourier (LBP-HF) is a novel rotation-invariant image descriptor which is computed from the discrete Fourier transforms of LBP histograms. The rotation invariant features are based on uniform local binary pattern (LBP) histograms. Despite being simple, the LBP is very descriptive and is widely in use for different tasks. The LBP histogram has been proved to be a promising solution for several applications like texture classification, face analysis, video background subtraction, and interest region description. LBP is a type of feature used for classification in computer vision and is widely being used in recent times by several researchers in diverse fields. LBP is the particular case of the Texture Spectrum model proposed in 1990 and was described first in 1994. It has been giving promising results and so is in wide use as a powerful feature to classify textures [12, 13]. The original version of the operator labels the image pixels by thresholding the 3x 3 neighborhood of each pixel with the center value and sum of the thresholded values weighted by powers of two results in a descriptor. The operator is also extended to use neighborhoods of different sizes [21] as shown in Fig 2. For each pixel in a cell, the pixel is compared with each of its 8 neighbors. In clockwise or counter-clockwise direction, the pixels are to follow along a circle. If the value of center pixel is greater than the neighbor's value, "1" is written, otherwise, "0" has to be written. The above procedure results in 8-digit binary number. Further extensions to the original operator are so called uniform patterns [12]. An LBP is called uniform if the binary pattern has at most two transitions, from 0 to 1 or 1 to 0 when the circular bit pattern is considered. This can be used to reduce the length of the feature vector and in implementing a simple rotation invariant descriptor. Uniform patterns are used to compute the LBP histogram, so that the histogram has a separate bin for every uniform pattern and a single bin is assigned with all non-uniform patterns. In the neighborhood of 8 sampling points, it results in 58 possible uniform patterns results [12]. Then the histogram has to be computed over the cell, of the frequency of each "number" occurring. The histogram has to be normalized optionally and the histograms of all cells are to be concatenated. This gives the feature vector for the window.

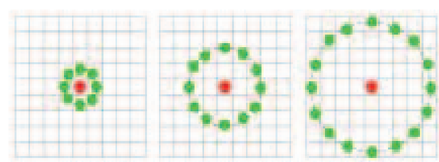

**Fig. 2** Three circular neighborhoods to calculate LBP

In computing Discrete Fourier Transform (DFT), the cyclic shift of the input vector results in a phase shift in DFT coefficients. Based on the property that rotations induce shift in the polar representation of the neighborhood, a class of features are proposed that are invariant to the rotation of the input image. Such features are computed along the input histogram rows, which are invariant to cyclic shifts. The LBP histogram Fourier (LBP-HF) is an innovative approach to extract rotation-invariant image feature which is computed by obtaining the discrete Fourier transforms of LBP histograms [14]. It is shown that the LBP-HF and its extensions outperform non invariant and earlier versions of the rotation-invariant LBP in the rotation-invariant texture classification [21].

## V. SUPPORT VECTOR MACHINES (SVM)

The Support vector machines (SVM) are a set of related supervised learning methods used for regression and classification. Vapnik and co-workers proposed the SVMs [15] as a very effective method for general purpose supervised pattern recognition. Classically, the SVM was designed to separate two classes and has been in wide use in separating the defects from good ones. If it is used for the purpose of health classification of insulators, this classifier separates a given set of labeled data with a hyper plane which is at a maximum distance from them. As most of the practical classification problems are non-linear at least in images; the SVMs uses the technique of kernels that realizes automatically a non-linear mapping to a feature space. The SVM has been extended also to solve multiclass separation problem mainly by using one-versus-all and one-versus-one techniques. The SVM is used for multiclass problem solution and this work has been reported in [17-19]. In applying the multiclass classification problems, it is required to train a few binary classifiers. The most commonly used approach is the one-versus-all strategy where a classifier is trained as a positive label for one class and a negative label for all other classes. The radial basis function (RBF) kernel non-linearly maps the samples into a higher dimensional space. The RBF kernel can handle the case if the relation between the class labels and attributes is nonlinear. It is to be noted that the linear kernel is a special case of RBF [16].

Support vector machines (SVM) and Adaptive neuro-fuzzy inference system (ANFIS) can be used [1] to estimate the condition of the insulator with the help of features extracted from Discrete Orthogonal S-Transform (DOST).

In the referred papers, SVM is used for two purposes [1]; Firstly, to locate the proper bounding boxes which contains the insulators amongst bounding boxes using the features like mean and standard deviation. These features are extracted from the cropped images by applying some segmentation technique. Secondly, the classification of the insulator according to its condition is done using the features acquired using DWT, DOST etc. So, the output of the first SVM gives bounding boxes having insulators and the second SVM discriminates about whether the insulator is healthy or broken.

## V. RESULTS

The insulators meant for classification are shown in Fig. 3. They are the samples corresponding to the healthy, marginal and risky types of insulators respectively.

**Fig. 3** Images of insulators for healthy, marginal and risky states

TABLE I. EXTRACTED FEATURES OF INSULATORS

| S. NO. | BR | BS | BT | BU | BV | BW | BX | BY | BZ | CA |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. | 82.14 | 5.00 | 0.77 | 3.68 | 34.01 | 29.29 | 165.66 | 103.17 | 2 | HEALTHY |
| 2. | 70.48 | 4.73 | 4.92 | 0.82 | 15.05 | 25.64 | 115.27 | 109.98 | 1 | MARGINAL |
| 3. | 86.29 | 1.81 | 1.64 | 1.22 | 1.76 | 54.86 | 119.55 | 154.26 | 2 | HEALTHY |
| 4. | 79.37 | 1.53 | 2.50 | 1.30 | 1.26 | 55.30 | 122.32 | 151.11 | 2 | HEALTHY |
| 5. | 81.00 | 2.74 | 8.02 | 3.49 | 24.06 | 30.61 | 153.19 | 113.44 | 2 | HEALTHY |
| 6. | 88.75 | 3.37 | 2.02 | 0.66 | 33.19 | 30.17 | 184.37 | 107.58 | 2 | HEALTHY |
| 7. | 80.18 | 1.80 | 2.90 | 3.10 | 1.70 | 55.74 | 114.58 | 142.10 | 1 | MARGINAL |
| 8. | 92.53 | 3.17 | 8.63 | 0.70 | 5.98 | 59.84 | 127.24 | 164.40 | 1 | MARGINAL |
| 9. | 90.89 | 2.96 | 1.59 | 1.64 | 3.97 | 57.63 | 128.18 | 156.53 | 2 | HEALTHY |
| 10. | 85.35 | 4.75 | 1.27 | 2.40 | 2.20 | 52.09 | 116.34 | 147.58 | 0 | RISKY |
| 11. | 86.92 | 1.04 | 7.81 | 1.17 | 10.58 | 55.81 | 112..69 | 154.70 | 2 | HEALTHY |
| 12. | 86.42 | 1.48 | 12.97 | 2.75 | 12.22 | 58.39 | 116.53 | 156.40 | 2 | HEALTHY |
| 13. | 77.92 | 3.09 | 3.45 | 2.30 | 39.12 | 18.83 | 167.99 | 85.54 | 2 | HEALTHY |
| 14. | 85.29 | 5.12 | 3.29 | 2.30 | 33.64 | 27.40 | 167.17 | 105.00 | 2 | HEALTHY |
| 15. | 82.14 | 5.00 | 0.77 | 3.68 | 34.01 | 29.29 | 165.66 | 103.17 | 2 | HEALTHY |
| 16. | 81.00 | 2.74 | 8.02 | 3.49 | 24.06 | 30.61 | 153.19 | 113.44 | 2 | HEALTHY |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 17. | 88.75 | 3.37 | 2.02 | 0.66 | 33.19 | 30.17 | 184.37 | 107.58 | 2 | HEALTHY |
| 18. | 83.59 | 2.43 | 1.74 | 1.63 | 24.38 | 32.19 | 169.31 | 110.99 | 2 | HEALTHY |
| 19. | 85.35 | 2.61 | 2.15 | 4.27 | 27.40 | 31.81 | 182.85 | 105.63 | 2 | HEALTHY |
| 20. | 82.83 | 1.94 | 2.73 | 1.35 | 28.41 | 28.72 | 201.81 | 96.62 | 2 | HEALTHY |
| 21. | 83.02 | 1.05 | 1.28 | 2.54 | 1.89 | 51.02 | 119.93 | 153.94 | 0 | RISKY |
| 22. | 81.32 | 0.57 | 3.06 | 0.35 | 31.05 | 26.58 | 180.84 | 99.52 | 2 | HEALTHY |
| 23. | 96.06 | 0.78 | 3.27 | 1.49 | 32.69 | 42.08 | 184.87 | 159.99 | 0 | RISKY |
| 24. | 82.83 | 1.94 | 2.73 | 1.35 | 28.41 | 28.72 | 201.81 | 96.62 | 2 | HEALTHY |
| 25. | 96.06 | 0.78 | 3.27 | 1.49 | 32.69 | 42.08 | 184.87 | 159.99 | 0 | RISKY |
| 26. | 68.78 | 4.33 | 8.25 | 2.78 | 15.75 | 16.82 | 168.30 | 59.21 | 2 | HEALTHY |
| 27. | 67.90 | 0.44 | 2.53 | 2.73 | 11.21 | 21.54 | 291.89 | 62.99 | 2 | HEALTHY |
| 28. | 55.05 | 2.04 | 3.81 | 1.57 | 22.05 | 4.98 | 105.06 | 36.34 | 0 | RISKY |
| 29. | 95.49 | 0.97 | 3.19 | 0.82 | 26.96 | 50.89 | 132.78 | 163.20 | 2 | HEALTHY |
| 30. | 78.92 | 1.94 | 1.67 | 2.77 | 12.03 | 34.64 | 102.48 | 123.39 | 1 | MARGINAL |

The LBP histogram Fourier (LBP-HF) features are found for the training set of insulator images and are given to the SVM for the classification purpose. 50 images of insulators after being extracted from the poles are considered for training the SVM and LBP is applied on this set of images for feature extraction. Now training of SVM is done using these feature set. Among them 25 images are healthy, 10 are marginal and 15 are bad. The features of these images are found. This feature set matrix is the training data set.

Then another 30 test images are considered for the purpose of classification. This set of images is given to the SVM for testing. Again the features of these images are found. This feature set matrix is called testing data set. Now SVM automatically classifies these images into different classes based on the previous trained data. Similar to those sample images shown in Fig. 3, 30 number of test images were considered for the purpose of testing. They belong to the categories corresponding to healthy, marginal and risky types of insulators respectively. Table I shows the feature set corresponding to the test images taken and the decision given by the SVM classifier. The SVM classifies these testing images into three classes, Class 2: healthy, Class 1: marginal and Class 0: risky.

From the Table 1, it can be concluded that SVM classified these testing images as: 21 are healthy, 4 are marginal and 5 are risky. The deviation occurred from the actual state of images through direct observation is 2 images. Hence, the efficiency is (30-2)/30*100 = 93.33 %.

## VI. Conclusion

Condition analysis of power distribution line insulators is very vital in improving the efficacy of overhead power distribution monitoring system (DSM) automation. In this paper, the insulators are being classified based on LBP-HF features extracted from the insulators. Three different states of insulators, Healthy, Marginal and Risky, are classified by calculating feature vectors from LBP. These feature vectors are considered as training data. The unknown features for a set of insulators are taken and the prediction has been obtained by using the SVM classifier. The classification of testing data is done by comparing with those that of the training data and by assigning the best matched class. From the results, it is concluded that health condition of insulators can be monitored easily by using the proposed method of classification.

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