Combined Fuzzy Local Binary Pattern and Wavelet Transform Features for Defect Detection of 11/33 kV Overhead Power Line Insulators

P. Surya Prasad , B. Prabhakara Rao

Abstract— The power line insulators are an important component of the power distribution system as consistent power delivery depends mainly on it. As the defected or damaged insulators on the electric poles leads to significant losses, there must be a regular monitoring system to check the insulator's condition. This requires taking pictures of the poles, sending them for processing, and applying pattern recognition for classifying the status of insulator into healthy or defective, and replacing the damaged insulator. The breakage condition of the insulators can be determined by the structures derived from the insulator images. The insulator images can be obtained from the pole image captured using a video camera. The structures of corresponding insulator images are extracted from using Fuzzy Local Binary Pattern (FLBP), a variant module of the Local Binary Pattern as well as the wavelet transform. The obtained features are forwarded to SVM (Support Vector Machines) classifier which determines the status circumstance of the insulator and the efficacy of the proposed experimental results are validated. The hybrid model proposed in this paper, by combining both the feature vectors has resulted in better performance compared to when individual feature vectors are used for analysis. The automatic status determination of powerline insulators would reduce the human efforts to a larger extent and so the proposed insulator health condition monitoring system can be considered as a reliable method for insulator defect detection and the necessary follow-up mechanism.

Index Terms— Feature extraction, classification, SVM, FLBP, Wavelet transform, pattern recognition.

I. INTRODUCTION

The overhead power line insulators used in electrical power distribution are generally made from porcelain material to isolate the same from line conductor and the allied supportive structure. The insulators are usually fixed in the exposed air and the gradual formation of impurity ultimately causes flashover on the insulator surface. The operation pertaining to the power line network is not consistent due to the reduced capability of the insulators and it leads to substantially high losses. The outdoor paddings are mainly the affected ones due to the changing atmosphere. So, continuous monitoring of the status of an insulator is essential in identifying a failure, followed by replacing them which will maintain uninterrupted source [1]. The definition of conditional monitoring (CM) is [2] to condition monitor the vigor of dissemination circuit online.

The traditional techniquesofinspecting transmission lines using pole climbing, aerial images are found to have disadvantages associated with them. Therefore, a surveillance set up has been employed with fixed video cameras on the posts as a viable alternative [7-9]. In this age, use of digital cameras offer better viability for capturing images. And a collection of a huge number of digital images is possible due to improved memory storage. With the increasing applications of smart grid, the automated conditional monitoring, image processing and machine learning is becoming more noticeable. Capturing of images is done by arranging video camera along with the Remote Terminal Units (RTU) over the pole, which can be remotely controlled.

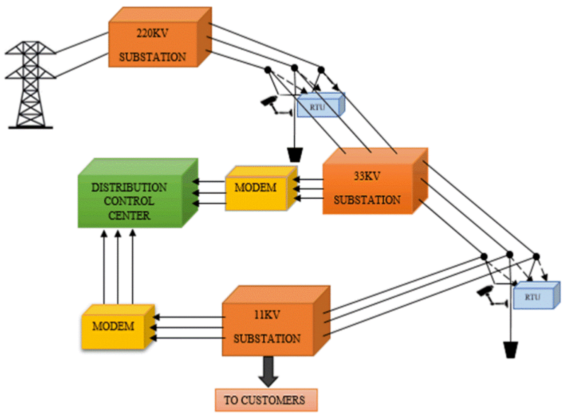

Fig. 1. Schematic diagram for insulator classification process

The pictures of insulators derived at prescribed time intervals using various image processing algorithms used in the literature are presented by numerous authors [10,11]. In this work, a method based on captured images of insulators to detect the state of the surface of insulators using image processing and machine learning is proposed. The block diagram [8]showing the insulator monitoring system implying image processing and machine algorithms is described in Fig. 1.

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P. Surya Prasad, MVGR College of Engineering, Department of ECE, Vizianagaram, Andhra Pradesh, India

B. Prabhakara Rao, JNT University, Kakinada, Department of ECE, Kakinada, Andhra Pradesh, India

In this work, two main parts are involved and they are i) a process of extracting features and ii) classification of insulator state. The fusion of Fuzzy Local Binary Pattern (FLBP) and Wavelet transform based features is used to train the Support Vector Machine (SVM) to organize the insulator images into one of the classes is done. The porcelain or ceramic insulators arranged on overhead power lines are very important equipment on the power distribution transmission line. There is a direct effect of the condition of insulator on the power network to be in safe condition. Therefore, it is so important to inspect the state of insulator's surface at regular intervals. The fuzzy rules of the FLBP are as follows. As per the rule1, if P_i is smaller than p_{center}, d_i is 0 and is greater. Rule2 says that if Pi is bigger p_{center} the certainty that d_i is 1, is greater. Based on the above, a 3×3 window of neighboring pixel values is converted into an FLBP set as {0, 0.1, 0.2, 0.3, . . . ,1}. The textures now can be represented by using the average membership values of FLBP neighboring pixels. As per the above rules, $m_0()$ and $m_1()$are obtained. The $m_0()$ defines the degree to which pi has a smaller grey value than p_{center}, and hence $m_1()$ is defined as the degree to which di is 0. The $m_0()$ is chosen to be a function as given below whose value decreases as shown in the Fig. 3.

Therefore, the defective state of an insulator and hence presence of any crack or break on the surface can be predicted. The imagestaken by using a digital camera on the RTU (Remote Terminal Unit) arranged on the pole, can be sent for analysis. The insulator's health statuscan be determined and necessary action can be taken, huge power loss can be prevented resulting in saving of national economy.

II. METHODOLOGY

The stepwise description for the proposed system is as depicted in the Fig. 2. The images acquired using the RTU converted to HSV color space, background color components are removed using color thresholding, and then insulator portions are segmented using k-means clustering. The procedure described in [8] is used to extract the cluster which includes the pole, cross-arm, and insulators. The cropped insulators from the selected boxes are resized to 128x128 pixels. The feature extraction means a set of features derived to effectually represent the image for the purpose of analyzing patterns and subsequent classification. The SVM is used to classify the insulator as an healthy order effective, based on the feature vector which includes the extracted features using different techniques.

III. FUZZY LOCAL BINARY PATTERN

The Localized Binary Pattern feature (LBP) descriptor is derived by applying a hard threshold on the neighboring pixels. This makes it easy to represent the textures less sensitive to the noise. The main difficulty with LBP is its failure in dealing with the natural image regions when variations of noise, contrast, brightness and capturing mechanism are present. In spite of different intensity values, the eye may still observe the two neighboring pixels to be same. The main advantage of the Fuzzy logic over the customary Boolean logic comes if the real images have to be texturally represented. The statements in fuzzy logic make it advantageous for the system to have understanding and reasoning like a human.

In the FLBP algorithm [12], the input variables are transformed into respective fuzzy variables, as per the set of fuzzy rules. The fuzzy rules are derived on a 3×3 LBP neighborhood which describes how the neighboring pixels (Pi) intensity values are related to the center pixel P0 in a more humanly perceivable fashion. Two fuzzy rules are formulated for this. They are used to define the relationship between intensity of the central pixel formed in 3×3 neighborhood p_center and the bordering pixels p_i. The 3x3 neighborhood denoted binary values, di, (0≤ i ≤7).

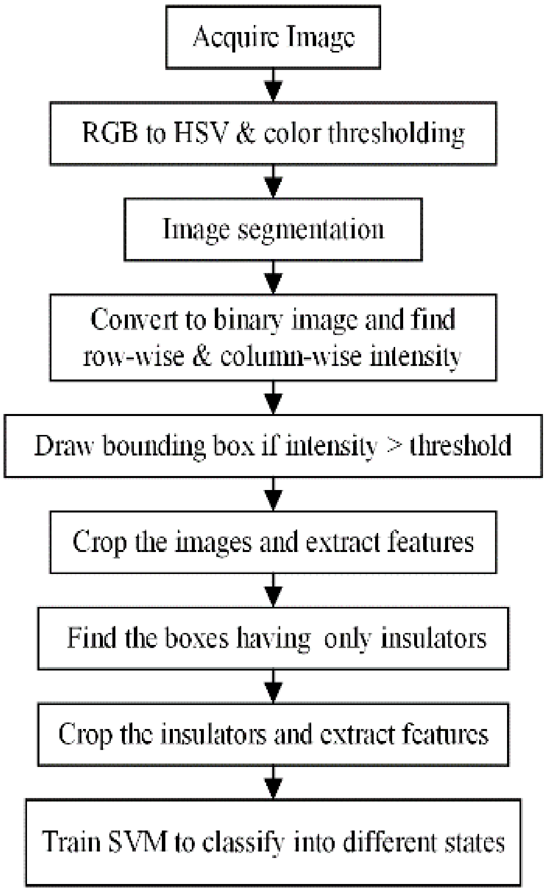

Fig. 2. Flowchart for insulator defect detection

$$m_0(i) = \begin{cases} 0 & if\, p_i \geq p_{center} + T \\ \frac{T - p_i + p_{center}}{2T} & if\, p_{center} - T < p_i < p_{center} + T \\ 1 & if\, p_i \leq p_{center} - T \end{cases} \quad (1)$$

The $m_1()$ is the degree to which the grey value of p_i is greater compared to p_{center}, and it is defined as the degree to which di is 1. Then$m_1()$ is chosen to be

$$m_1(i) = 1 - m_0(i) \quad (2)$$

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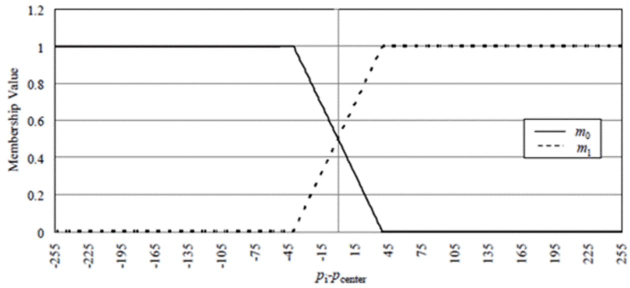

Fig. 3. The membership functions, $m_0(\,)$, $m_1(\,)$.

The extent of fuzziness of the membership functions is controlled by the parameter, T ∈[0,255].More than one LBP code can describe the neighborhood in the FLBP approach. The Fig. 4. shows an example in which a 3×3 neighborhood is characterized by two LBP codes. For any sub-image of size 3×3, each code of LBP contributes to the FLBP histogram using the relation:

$$C_{LBP} = \prod_{i=0}^{8} m_{d_i}(i) \qquad (3)$$

where d_i takes values either 0 or 1 and the corresponding LBP code is to be found. For each neighboring pixel, either 0 or 1is assigned to d_i corresponding to $m_0()$ or $m_1()$. This results in various LBP codes corresponding to different contributions as in eqation 5. Therefore, each 3×3 neighborhood, contributes to the FLBP histogram as:

$$\sum_{LBP=0}^{255} C_{LBP} = 1 \qquad (4)$$

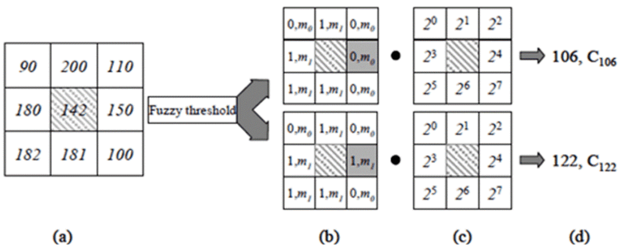

Fig. 4.Computation of FLBP on a 3×3 sample neighborhood with T=10 and (a) 3×3 neighborhood. (b) Fuzzy threshold and its membership parameters (c) Binomial load capacity. (d) LBP codes, and effectualities.

The Fig. 5. shows the sample images of insulators in good and defective condition and the Fig. 6. shows the corresponding FLBP histograms. From the LBP histogram bins, the information about the faulty and good insulator images can be differentiated. So, the histograms of the different set of images can be used for training another set can be used for testing purpose.

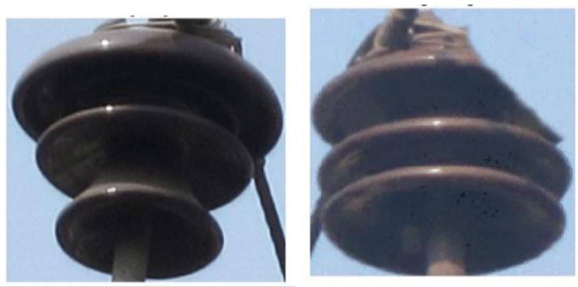

Fig. 5. Sample images (good and defective)

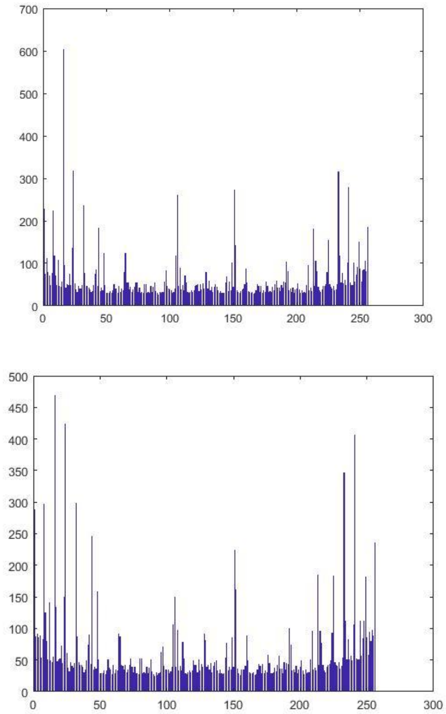

Fig. 6. FLBP histograms of good and risky insulators

IV. WAVELET-BASED FEATURES

As the insulator image to be analyzed has some breaks or discontinuities, their representation the insulator status can be done well by the features extracted from wavelet coefficients. The discrete wavelet transform (DWT) has several applications in the field of image processing as it allows the images to be analyzed at different scales. Being different from the Fourier transform, the DWT decomposes any given image into multi resolutions. The multiresolution analysis (MRA) actually implements the DWT of a signal as given by the following relation.

$$DWT(x,m,n) = \frac{1}{\sqrt{a_0^m}} \sum_l x(k)\psi\left(\frac{n-b_0^m}{a_0^m}\right) \qquad (5)$$

where l,m are integers and the constant coefficients a_0 and $b_0$are often chosen to be 2 and 1 respectively. The DWT is found by an image's passing through a set of low-pass and high-pass filters, which depends on the number of decomposition levels. The process of decomposing at several levels of decomposition is called sub-band coding.

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Several parameters can be extracted from each frequency band and a feature vector (FV) can be constructed to represent the given image.The wavelets were widely used in monitoring the insulator distribution system [8, 14].The two particular prime wavelets designated as bior2.2, and db4 were employed to extract the best wavelet characteristic parameters to represent the images and they are denoted by $\propto_{L1}, \propto_{L2}, \propto_{L3}$ and β.

TABLE 1
Classification Using SVM

Classification Using SVM			
Features used	**Accuracy**	**Sensitivity**	**Specificity**
FLBP	87.33	100	57.78
FLBP and Wavelet	90	100	66.67

First three features are obtained from the horizontal coefficients of first 3 decomposition levels. The value of β is obtained from these decomposition levels and subtracting the sum from the minimum horizontal coefficients which leads to the feature vector (FV) termed as extracted features.

$$\text{FV (wavelet)} = \{\beta, \propto_{L1}, \propto_{L2} \text{ and } \propto_{L3}\} \quad (6)$$

The feature vectors of all the images contained in the dataset of insulator images are to be found and use them for classification of given test images using SVM.

A. Fusion of features

The combined or hybrid approach has the advantages of both types of features extracted. Combining different sets of features for better object recognition [15] is reported by several authors. As the LBP or any of its variant can capture only the image's local structure they can represent only the basic variation in an image at the micro level, but they fail in representing macro level variations of an image. Also, in an image, the global dominant features can be represented by the Wavelet transform. As the FLBP has advantage over LBP, the FLBP features and Wavelet features are effectively fused to create a hybrid model to improve the performance of defect classification of insulator images. So, the spatial and spectral features obtained in the previous sections can be integrated as shown below to obtain a fused feature vector.

Wavelet_FLBP = {FV(wavelet), FV(FLBP)} (7)

V. RESULTS AND DISCUSSION

As there is no standard database available for 11 kV overhead power line insulators, the experiments are performed on a constructed dataset of 80 insulator images, having both healthy and defective states, captured with a digital camera. The camera is supposed to be arranged along with the RTU on an electric pole which can capture images with dissimilar orientations. The status can be categorized into good and defective states. The LBP and its several variants were primarily proposed to recognize and classify textures and were widely used for face recognition, texture classification, and object recognition and in this work, the FLBP, in combination with Wavelet transform based features are used to classify power distribution system insulators. The proposed work's effectiveness is validated by finding the percentage accuracy metric. The performance measures are given in Table 1. The classification accuracies obtained are 87.33 % with FLBP features and 90 % when FLBP features and wavelet features were concatenated and are proved to work for automatic defect detection of insulators. The obtained results specify the suitability of FLBP operator as well as its fusion with wavelet features for efficient automatic classification of distribution system insulators.

VI. CONCLUSIONS

In order to overcome the demerits of LBP, i.e. its sensitivity to noise and its tendency to characterize different structural patterns with the same binary code different variants of LBP were developed, among which FLBP is used in this work. In this work, automatic condition monitoring system for defect detection of overhead power line insulators is develped which is based on fuzzy local binary pattern and wavelet features and its performance is evaluated using SVM classifier and the metrics. Different atmospheric conditions prevailing at different geographic areas affects the health status of the outdoor insulators and hence needs a regular check-up and subsequent change of the change of the equipment.. Image processing and pattern recognition techniques have been successfully applied for condition monitoring analysis of overhead power line insulators.

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