Review of Edge-based Image Segmentation on Electrical Tree Classification in Cross-linked Polyethylene (XLPE) Insulation

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Abstract. Electrical trees are the degradation events most linked with partial discharge (PD) activity in cross-linked polyethylene (XLPE) insulation of high voltage (HV) cables. To investigate tree structures and forms, study of electrical tree structures for morphological analysis often carried out using optical microscopy. However, since the noise induced by the occlusion and illumination, as well as by non-uniform intensity either from optical device’s setting or the non-standard readout procedure, causes the deterioration of the original microscopy images, resulting in critically loses of information pertaining the tree structures making it difficult to obtained accurate measurement. Image segmentation is one of the potential solutions as it is well-suited for extracting information or certain features from microscopy images. This paper provides review of several segmentation techniques applied on the classification of electrical tree image acquired through lab environment. The works can be separated into three stages. The first step includes the preparation of samples and collection of treeing images by means of real-time microscopy observations. The captured data would then be pre-processed to achieve image binarization. In the next step, image segmentation process is conducted using existing edge-based segmentation methods including Prewitt, Roberts, Canny and Kirsch’s templates. Later, comparative analysis will be performed using IQA (image quality assessment) metrics of accuracy, sensitivity, specificity, false-positive-rate and the Matthews Correlation Coefficient (MCC) as the final step. Performance-wise indicates that Kirsch’s template able to segment most of the treeing pixels with accuracy of 97.63%, 63% sensitivity, 98.18% specificity and 0.46 MCC while showing low pixels misclassification. This result provides better justification for the integration of the edge-based technique in developing image segmentation algorithm well-matched for the electrical tree analysis in the future.

1. Introduction

Based of magnificent electrical properties, lightweight structure, simple to twist and high transmission limit, Cross-linked polyethylene (XLPE) has been widely used and gaining performance advantages over other type of medium to high-voltage (HV) cables [1]–[3]. Although XLPE cable has high thermal stability that can withstand high temperatures, it can undergo partial discharge (PD) that initiated
breakdown and power failure [4],[5]. PD is usually caused by the manufacturing process or in power cables accessories such as joints or terminations [6],[7]. Electrical tree initiation is the most associated deformation classified as internal discharge in cable insulation.

Impurities and protrusions, particularly metal ones, were most lethal among the factors that affect the electrical treeing and insulation failure of XLPE cables [8]. In order to simulate the local field distortion and electrical tree damage caused by impurities and protrusions, the implementation of needle-plane geometries in laboratory environment were used [9],[10], where high fields can be attained at very low voltages, and tree growth in transparent XLPE materials can be easily observed. The direct optical observations of transparent polymers under HV stress have become standard practice to gain insight of electrical tree growth particularly in XLPE insulation material [11]–[13]. These microscopy image can be further examined through image processing techniques such as segmentation to accurately measure the tree growth. However, subjects of illumination variation is still a tough challenge to consider when examining features in an optical image [14],[15]. Occlusion and shadows are two main categories of appearance variation due to illumination causing degradation of the captured image [16],[17].

For this very cause, extensive research in image segmentation has contributed to the development of various segmentation algorithms for many applications across different fields. Following the trends, this paper presents the performance assessment of multiple segmentation algorithms on the segmentation of the electric tree image.

2. Background
The occurrences of electrical tree is a well-known mechanism of PD that leads to the breakdown of polymer insulation in a high-voltage stress environment. Electrical trees are hollow, bifurcated tubules that emerge like botanical trees growing slowly over a long period of time until the breakdown occurs.

2.1 Electrical tree growth
Electrical trees generally are categorized as one of three distinct kinds, based upon their obvious resemblance to botanical trees: a branch, bush or a bush-branch [18],[19]. Treeing growth model has been developed over the years as 3-stage phenomenon: Stage 1: Inception, Stage 2: Propagation and Stage 3: Runaway and breakdown. The initiation of electrical tree is the event where electric trees first emerges from locations in which impurities, voids or metallic protrusions creating an electric field strength greater than the breakdown strength of dielectric material of the insulation forming PD. Next, the electrical tree begins to spread in the shape of a branch, bush or bush branch structure towards the opposite electrode. This growth is caused by discharges in the hollow branches of a gas-filled electric tree, expanding the branches of the tree even more. The final stage of electrical tree growth is when the area at its branch’s tip would rise as the tree propagates. The growth speed would speed up the tree channel until the polymer is much more weakened, in the end triggering the irreversible breakdown in insulation material.

2.2 Image segmentation
Segmentation refers to the process of separating individual elements of image into sets of groups so that all elements in such group have a similar attributes [20],[21]. In an image containing only one subject, the subject (foreground) is distinguished from its background. Segmentation mainly used to extract region of interest (ROI) containing critical information which can describe the morphological feature of the subject largely employed on microscopy images. Segmentation can be categorized into several methods as illustrated in Figure 1. Edge-based method typically associated with microscopy images since the region of ROI comprise of potential edges and boundary information which provides information on tree features that reside in an image. Edge-based segmentation transforms images into edge images by modifying the gray value of images. This can either be achieved by using edge-operators or through soft-computing approaches.
Figure 1. Methods of image segmentation [22]

In the year 2019, Yue Yang et al have proposed method for measuring the displacement of the dam surface based on double vision sensors with the combination of Roberts edge filter that provided smoother edge marker in the image [23]. M. Syahrir et al meanwhile have come out with image segmentation and edge detection algorithm based on Prewitt operator to enhance Magnetic resonance imaging (MRI) images for mammogram disease. They proved that the technique combine with high-pass filter in the post-processing have yield better segmentation result compared to previous study [21]. In 2016, Venmathi et al also carried out a study to use edge detection method for detecting micro calcification clusters in mammograms images. They employed the use of Kirsch’s template which achieves the good tradeoff between keeping edge details and suppressing the noise component in mammograms images [24]. Their algorithm was proved superior to Canny edge filter [25] in terms of noise, over-detected points and closed boundaries.

Therefore, it is the best course of action to adopt some of these techniques in segmenting electrical tree features from microscopy images to test their performance and accuracy with the process. Since imaging study on electrical tree analysis is quite scarce, this research aims to provide further insights into particular matters.

2.3. IQA measurement approach
An objective approach to assess the visual quality of an image is through Image Quality Assessment (IQA) which plays a key role in many image processing techniques. Image quality assessment may be defined as the evaluation or measurement of the image quality in reference to the original image based on computational algorithms referred as IQA metrics.

In the subject of treeing segmentation process, the outcome is a pixel-based classification result. Any pixel is classified either as tree structure (foreground) or surrounding cable insulation (background). Consequently, the true positive (TP) and true negative (TN) when a pixel is correctly segmented as a treeing region or non-treeing region respectively while a false negative (FN) appears when a pixel which belong to a tree is segmented as background, and a false positive (FP) when a background pixel is segmented as a treeing pixel. Over the years, wide range of objective image quality measurement metrics has been introduced pertaining to pixel-based classification result such as accuracy, sensitivity, specificity, false-positive rate, MCC and so on.
2.3.1. Accuracy

Accuracy, Acc is one of the most commonly used measures for the classification performance. Acc measures identification of the proportion of true prediction denoted as:

\[
Acc = \frac{TP + TN}{TP + TN + FP + FN}
\]

where P (TP+FP) and N (TN+FN) indicate the number of positive and negative pixels, respectively. Acc result are prone to imbalanced results as they can produce misleading returns [26]. Therefore, additional metrics often used together with the metrics to compensate the error.

2.3.2. Sensitivity

Sensitivity can also be refer as true positive rate (TPR), or recall, of a classifier represents the positive correctly classified pixels to the total number of positive pixels, and it is estimated as:

\[
TPR = \frac{TP}{TP + FN} = \frac{TP}{P}
\]

2.3.3. Specificity

The specificity of a test also known as true negative rate (TNR), or inverse recall is stated as the ratio of the correctly classified negative pixels to the overall number of negative pixels is given as:

\[
TNR = \frac{TN}{FP + TN} = \frac{TN}{N}
\]

It specifies the proportion of negative labelled instances that are predicted as unwanted background pixels.

2.3.4. False-positive rate (FPR)

This metric is the inverse instances of sensitivity or TPR. It is an outcome of algorithm incorrectly predicts the positive sample or the probability of false-alarm. It is given as:

\[
FPR = \frac{FP}{FP + TN} = \frac{FP}{N}
\]

2.3.5. The Matthew’s Correlation Coefficient (MCC)

MCC provides more precise and descriptive results. The value between −1 and +1 is returned by MCC. A coefficient of +1 represents a perfect classification, 0 is the predicted value for random inference, and −1 implies a complete misclassification. MCC is given by the

\[
MCC = \frac{TP \times TN \times FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}
\]

MCC is considered to produce more informative and authentic result since the metric is unaffected by imbalance dataset [26].
3. Methodology

The procedure of electrical tree imaging and analysis comprises of several stages: XLPE sample preparation and image acquisition, pre-processing, image segmentation, tree classification and analysis as depicted in Figure 2.

![Figure 2. Electrical tree imaging and analysis flow diagram](image)

In earlier stage, XLPE samples were created in the shape of rectangular sample with dimension 15 mm x 25 mm x 2 mm. Samples were prepared using Haake internal mixer at a temperature range of 115 °C which later pre-heated at 160 °C for 6 min and heat for 3 min under a pressure of 1,000 psi by hot press before being cooled down. Tungsten needle was inserted slowly into the sample after pre-heating procedure to form a needle-plane geometry with the gap between needle tip and plane electrode measured at 2 mm. Complete HV experiment setup is as shown in Figure 3. Details of sample preparation and image acquisition setup were explained in [27] and [28].

![Figure 3. Electrical tree image acquisition experimental setup](image)

The aim of pre-processing is to enhance the original image for better segmentation later. Initially, brightness and contrast correction were performed using open-source image editing software GIMP 2.10 to attain standard level of intensity of the image. Finally, enhance image will be reduced in size for faster processing in the latter stage. The third stage involve segmentation of the pre-processed input image using several edge-based techniques as formerly discussed in Section 2. Several edge-operators such as Prewitt, Roberts, Canny and Kirsch’s template were put into test for performance evaluation.
In the final stage, output of image segmentation of each techniques will be evaluated using several IQA metrics to provide quantitative analysis for performance evaluation based on reference image obtained through hand-drawn technique. This reference image is the most accurate representation of the tree that will be used for comparison with the output of image segmentation. Example of original image and reference image is as depicted in Figure 4. As for image segmentation result, light-coloured pixels (foreground) represent the desired tree region along with the needle tip while dark-coloured pixels (background) belong to the XLPE insulation. Outcome of each metrics will be compared and analysed to determine the well-suited technique apt for image segmentation of electrical tree.

Figure 4. (a) Original image of the tree propagation in pure XLPE sample obtained from optical microscopy through laboratory HV experimental condition; (b) Reference image

4. Experimental result and discussion

The entire process of electrical tree segmentation has been implemented on Microsoft Windows 7, Intel® Core™ i5, CPU 2.5 GHz with 8 GB RAM, under MATLAB R2017a environment. Original image of electrical tree image acquired through experiment and the reference image (ground truth) generated through pre-processing stage have a dimension of 1920x1080 pixels. The reference image is employed to evaluate the performance of all segmentation techniques using IQA metrics of accuracy (Acc), sensitivity (TPR), specificity(TNR), false-positive rate (FPR) and MCC.

Figure 5 concise of the image segmentation output based on all the techniques employed. It can be observed that, out of all techniques, Canny provide the worst performance based on image segmentation result suggested that the technique mistakenly classified portion of the background pixels as foreground pixels much more than any other edge-operators. This elevation in false-alarm classification is probably due to the Canny’s algorithm which designed to detect wide ranges of edges that is also susceptible to noise such as the non-uniform illumination of the original treeing image. Prewitt, Roberts and Kirsch’s filter provide a better segmentation in term of false-alarm detection where it can be observed that just a small fragment of background was misclassified as foreground in each image segmentation output.
Based on the accuracy and specificity performance in Figure 6, it can be summarized that all techniques performed exceptionally well particularly in detection of the background pixels with relatively high specificity, where Robert operator proved to have the most accurate background classification with highest rate of 99.58% specificity. In contrast to that, performance of segmentation the foreground pixels has not been very good for Canny, Roberts and Prewitt operator based on their low sensitivity rate averaging at 21.35%. This low sensitivity rate signifies that those three edge-operators failed to identify almost 80% of foreground pixels resides in the image. Uneven lighting and contrast of the original treeing image again proved to be quite a challenge for segmentation task. Kirsch’s template on the other hand, managed to detect most of the foreground pixels compared to others with fair rate of 63% sensitivity showing robustness under the presence of the same noise.

Figure 5. Output of treeing image segmentation (cropped due to large image dimension): (a) Prewitt; (b) Roberts; (c) Canny; (d) Kirsch’s template
Based on overall performance, it can be summarized that in segmenting the desired tree region apart from its insulation background, Kirsch’s template performance is much more preferable compared to other edge-based technique under review. Even though, Roberts and Prewitt attained a slightly better rate of accuracy and specificity than Kirsch’s template, their low sensitivity rate which signifies their inability in segmenting the foreground (tree region) pixels making them incompatible for this particular segmentation task. Furthermore, based on the highest MCC rating of 0.46 over any other technique in Figure 7 further justifies the Kirsch’s template suitability with image segmentation of electrical tree and ability to perform under non-uniform illumination image condition. Table 1 summarized the IQA result of all the techniques based on selected metrics.
Table 1. Performance comparison of electrical tree segmentation via IQA metrics

| Segmentation Technique | IQA metrics |  |
|------------------------|-------------|---|
|                        | Accuracy (Acc) | Sensitivity (TPR) | Specificity (TNR) | False-positive rate (FPR) | MCC |
| Prewitt [29]           | 98.30%       | 22.31%             | 99.51%             | 0.49%               | 0.30 |
| Roberts [23]           | 98.36%       | 21.71%             | 99.58%             | 0.42%               | 0.31 |
| Canny [25]             | 91.14%       | 20.05%             | 92.27%             | 7.73%               | 0.06 |
| Kirsch’s templates [30]| 97.63%       | 63.00%             | 98.18%             | 1.82%               | 0.46 |

5. Conclusion and future directions

This paper presented performance evaluation of segmentation techniques based on edge-based method including Prewitt, Roberts, Canny and Kirsch’s template. The aim of this evaluation is to identify compatible techniques that can be adapted into microscopy image segmentation of electrical tree structures scientifically known to initiate PD inside XLPE insulation. Based on the performance comparison using several IQA metrics, Kirsch’s template managed to outperform the other classic edge operator based on highest MCC value, high accuracy and specificity while having relatively low misclassification during segmentation with electrical tree microscopy image. In the future works, more image data sets of electrical tree will be acquired to further test the robustness of segmentation techniques under different image degradation in order to attain well-tuned algorithm of treeing image segmentation in addition of employing different variation of segmentation methods.
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