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# "IDENTIFICATION OF JUMPER BOLT PROBLEMS IN TRANSMISSION LINE USING THERMAL IMAGES USING NEURAL NETWORK AND FUZZY C MEANS CLUSTERING TECHNIQUE"

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**Abstract:** A method for detecting power transmission line bolts and their defects based on positional relationship. Using thermal image and their temperature to identify the problem in jumper bolts on transmission line. Thus existing method we are using which fuzzy c means clustering. In the proposed system first we are taken image deonising of transmission line jumper bolts. Then with help of image deonising we take more image segmentation of thermal image of healthy and faulty jumper bolts. After the image segmentation of transmission line bolts we also can feature extraction. Then the prominent feature selection is used to improve power quality in hybrid distributed power generating systems. The fault classification of the distributed power generating system already tested and it is named as thermos vision which is used to measure an object temperature. The heat energy is converted into thermal image.

## INTRODUCTION

In recent years, more and more Unmanned Aerial Vehicles (UAVs) have been used domestically and internationally to replace manual inspection of transmission lines, effectively reducing labor costs and work hazards, and improving the efficiency and accuracy of inspection results. As a result ofthe high volume and low value density of aerial images obtained during inspections, relevant working personnel are faced with a significant data amount. This can lead to subjective experience and fatigue affecting their ability to maintain consistent judgment standards, resulting in more errors and potential safety hazards. However, massive datais not difficult for deep learning methods and can make the model more robust. Therefore, using appropriate deeplearning algorithms and computer technology to handle defects detect tasks of inspection can help overcome theshortcomings of manual drone inspection. Among the variouschallenges in transmission line defect detection, detectingdefective bolts has emerged as a crucial issue. The small scaleof the objects and the difficulty in distinguishing defects posesignificant challenges in this area. The goal of this task is to accurately detect the position of each bolt from the inspectionimage of the transmission line and classify it as a defective bolt. For a more intuitive display, Figure depicts the result of bolts detection, with green bounding boxes representing normal bolts and red ones indicating defective bolts.

## OBJECTIVE

In this demanding technological world the maintenance of reliable uninterrupted power supply is highly essential. In recent decade, several efforts are made to increase the quality of transmitted power using faulty diagnostic techniques in high voltage equipment.


  

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Most of these techniques aims at discovering the symptoms of faults and it ensures that the fault does not occur in the same location in the mere future. However, these techniques are affected by its own shortcoming that leads to high risk inspection and low reliability in monitoring, since the fault condition is not constant and keeps varying based on the environment. Thus, a novel fast and verdict approach to identify faults at an early stage to avoid serious faults which cause breakdown and supply interruption is required.

## EXISTING SYSTEM

The most common conventional procedure followed is regular ground line patrol carried out by the lines maintenance team. Performing special patrol and premonsoon inspection on towers to identify and symptoms of the cause producing the fault which include

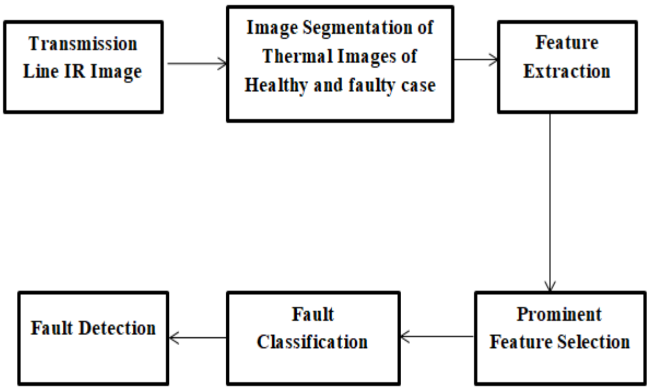
- Bolt nut loose in jumper joints and other fittings
- Crack or damages on tower legs
- Surface cramps developed over the insulators

The other techniques include unmanned aerial vehicle (UAV), Infrared Thermography etc.

## DISADVANTAGES

- Inspection of power lines by human visual observations are high cost, high risk, low efficiency, long-term operating and completely relies on human. As transmission lines involves large area the time required to identify and clear the faults becomes high.
- UAV inspection as a recent method greatly reduces the work intensity of inspectors and improves the efficiency of power lines inspection, but it also brings massive data and requires knowledgeable person to analyse and interpret faults.

## PROPOSED BLOCK DIAGRAM




First we take image deionising of transmission line jumper bolts. Then with help of image deionising we take more image segmentation of thermal image of healthy and faulty jumper bolts. After the image segmentation of transmission line bolts we also can feature extraction. Then the prominent feature selection is used to improve power quality in hybrid distributed power generating systems. The fault classification of thedistributed power generating system already tested and it is named as thermovision which is used to measure an object temperature. The heat energy is converted into thermal image.

## MULTIPLE MODEL DETECTION

| Methods | Normal bolts AP (%) | Pin losing AP (%) | Nut losing AP (%) | mAP (%) |
|---|---|---|---|---|
| Retina Net | 95.7 | 21.2 | 56.4 | 58.4 |
| Faster R-CNN | 89.0 | 60.9 | 33.7 | 61.2 |
| Cascade R-CNN | 89.9 | 77.9 | 27.3 | 65.0 |
| Sparse R-CNN | 87.1 | 54.2 | 60.6 | 67.3 |
| Ours | 90.7 | 65.3 | 47.4 | 67.8 |

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This table explain normal bolts, pin losing, nut losing are identified by various methods. Their accuracy are explained in percentage.

## FUZZY C-MEANS CLUSTERING

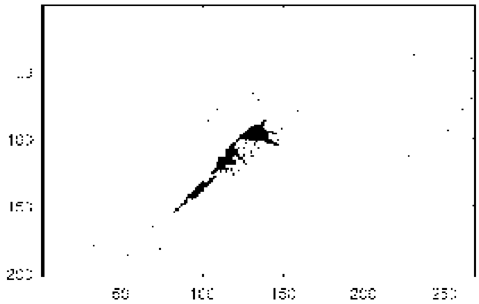
Fuzzy logic principles can be used to cluster multidimensional data, assigning each point a membership in each cluster center from 0 to 100 percent. This can be very powerful compared to traditional hard-threshold clustering where every point is assigned a crisp, exact label. This algorithm works by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center. Clearly, summation of membership of each data point should be equal to one.

## SCOPE OF THIS PROJECT

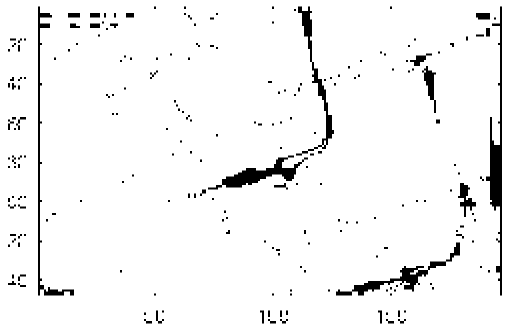
- Thermovision is a technique used to measure an object temperature.
- The proposed simplified inspection system ensures aerial thermal imaging under particular weather conditions and power line loading.
- The solution provides safe, high quality and cost-effective examination of the overhead power lines in the remote and flexible way.

## SIMULATION OUTPUT

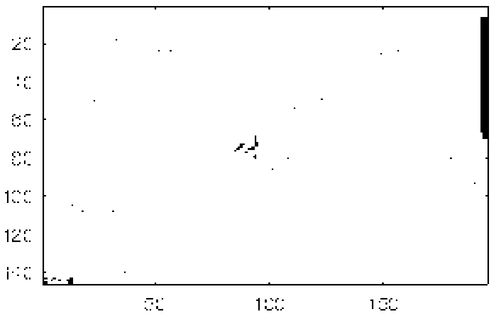
1. **Glow Portion segmented of high level failure**



2. **Glow portion segmented of medium level failure**



3. **Glow portion segmented of low-level failure**



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**Features and the values for three different forms of failures**

The Table which gives features and the values for three different forms of failure and their level with equivalent equation.

| Features | Normal Controls | Low level failure | Medium level failure | High level failure |
|---|---|---|---|---|
| Angular Sum (Fa)$\sum_{\theta_1{}^2 \leq tan^{-1}(\frac{v}{u}) \leq \theta_2{}^2} \lvert F(u,v) \rvert^2$ | 0.15 | 0.6 | 0.78 | 0.92 |
| Radial Sum (Fr) $\sum_{r_1{}^2 \leq u^2+v^2 \leq r_2{}^2} \lvert F(u,v) \rvert^2$ | 0.95 | 0.4 | 0.25 | 0.1 |
| Sum variance$\sum_{i=2}^{N}(i - f_{10})^2 I_{x+y}\ (i)$ | 0.9 | 0.6 | 0.4 | 0.25 |

- **The Fuzzy Classifier** correctly identified 22 instances (True Positives).
- It missed 3 instances that it should have identified (False Negatives).
- There were 21 instances where it wrongly identified as positive (False Positives).
- In 4 instances, it correctly identified as negative (True Negatives).
- The overall accuracy of the Fuzzy Classifier is 86%, indicating the proportion of correct predictions.
- The sensitivity of 88% signifies the classifier's effectiveness in correctly identifying positive instances.

- **The Neural Network** correctly identified 20 instances (True Positives).
- It missed 5 instances that it should have identified (False Negatives).
- There were 20 instances where it wrongly identified as positive (False Positives).
- In 5 instances, it correctly identified as negative (True Negatives).

## OUTCOME OF THIS PROJECT

classification and feature extraction can be used to identification to accuracy and sensitivity of jumper bolts faults in transmission lines.

| Method | TP | FN | FP | TN | % of Accuracy | % of Sensitivity |
|---|---|---|---|---|---|---|
| Fuzzy classifier | 22 | 03 | 21 | 04 | 86 | 88 |
| Neural Network | 20 | 05 | 20 | 05 | 82 | 80 |

## FUTURE SCOPE

1. Better segmentation concentrating on the bolt region instead of the whole image may be done to provide better results.
2. More work can be done on the extraction of better features.
3. Ensemble classifiers can be used for better classification results.

## CONCLUSION

In order to accurately detect transmission line bolts and their defects, this paper uses a joint board to construct a dataset of bolts and their defects, and further conducts the detection of normal bolts, pin losing and nut losing on the fixture. To address these problems of small bolt targets, low image resolution and lack of inference capability of the detection model. The overall accuracy of the Neural Network is 82%, indicating the proportion of correct predictions.

The sensitivity of 80% signifies the network's effectiveness in correctly identifying positive instances.
In summary, the Fuzzy Classifier demonstrates slightly higher accuracy (86%) and sensitivity (88%) compared to the Neural Network, which has an accuracy of 82% and sensitivity of 80%. These metrics provide insights into the performance of each classifier in terms of correctly identifying positive instances and overall accuracy.

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