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Effect of Block Size on Spark Detection in Power Transmission Lines using GLCM

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Abstract**—** In electrical power system the most unguarded element is the power transmission lines because of its physical dimensions. As a repercussion many fault detection algorithms have been proposed from last few years. Fault detection accuracy has been the matter of significant interest in distribution network. In this paper, a new method is proposed for detecting the faults in power lines from optical images based on Grey Level Co-occurrence Matrix (GLCM). GLCM extract the co-occurring intensity pattern with a specific displacement over a given image. The experimental results demonstrate its utility in detecting fault with the effect of block size for various features.

Keywords**—** Fault detection; Power transmission; GLCM.

I. INTRODUCTION

In both structure and operation the electrical power system is complex, therefore faults in any element of the system will affect its reliability, power quality. Some fault can be critical, which cause heavy economic loss. It's being essential faults on power transmission lines need to be detected as fast as possible, because they propagate energy to consumers and the functioning of transmission networks. Power transmission lines endure from many faults and can occur at any places and caused by different reasons. Protecting the transmission lines from faults two important processes has to be imposed: i) fault detection and ii) fault clearing.

The faults classifications can be found in diverse articles [1-2].They are categorized as: i) line-to-line (LL) fault due to short circuit between lines, ii) single line-to-ground (SLG)fault caused by a short circuit between one line and ground, and iii) double line-to-line(DLG) faults, when two lines come into contact with ground. As the type of fault is correctly identified possible action can be taken to solve the problem [3].

The two common ways used for inspection and maintenance of high voltage transmission lines are artificial inspection and helicopter inspection [5-6]. But artificial inspection occupies high labour strength, workers observe the lines from ground and it's difficult to accomplish accurate distance which led to blind zone inspection. Meanwhile, workers sometimes need to go far by areas for detecting faults which is full of challenge and danger for them. However, the helicopter inspection is costly and there is a risk of flight safety always. Through helicopter inspection fault in transmission line is detected by images which is of low precision, because of these limitations the helicopter inspection is not so popularize [4].

From last some years laser ranging and image processing are widely applied by researchers for different measuring works in America, England, Canada and China [7-12]. To enhance the automation level of inspection so that it become more safe and reliable a method is proposed based on image processing technology using GLCM. Images are most widespread and easy means of transmitting information. Images briefly convey information about positions, sizes and inter-relationships between objects [13].

In image retrieval system feature extraction is the base, mainly represented by visual features such as colour, shape and texture. Feature extraction is done by two ways: i) Feature extraction in spatial domain and ii) Feature extraction in transform domain [14]. In spatial domain feature extraction is done by statistical calculation on the image based on histograms. Most of the methods for spatial domain suffer from insufficient number of features and also sensitive to noise. For transform domain methods are generally used in image compression, as they give high energy compaction in transformed image. Many of the transform domain methods are that they do not capture edge information of an image efficiently [24-25].

Haralik first introduced the use of co-occurrence probabilities using GLCM for extracting various texture features [16-17]. In his research, he extracted the fourteen statistical features to depict the texture. By using a fusion of edge information in combination with GLCM statistical features, the ability of measurement in the system is improved [23].

GLCM simply defined as "A two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship" also called as Gray level co-occurrence Matrix [15, 18]. The Gray level co-occurrence matrix method is a way of extracting second order statistical texture features. The approach has been used in a number of applications [19-22].

In this paper an approach to the fault detection in power lines is presented from optical images based on Grey Level Co-occurrence Matrix (GLCM) by calculating the distinct texture information.

II. METHODOLOGY

In this section, fundamental knowledge about the methods applied in the study is introduced. Gray Level Co-occurrence

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Matrix is one of the most powerful methods for extracting texture information from an image. The GLCM is a matrix whose dimension depends on the number of gray levels (N) in the image. Which can be define as

$$P_r(i,j) = \{C(i,j) \mid (\delta,\theta)\} \quad (1)$$

$$C(i,j) = \frac{p_d(i,j)}{\sum_{i=1}^{G}\sum_{j=1}^{G} p_d(i,j)} \quad (2)$$

Where $C(i,j)$ is the co-occurrence probability between gray levels i and j . i and j = within the given image window, given a certain (δ, θ) Pair .G is the quantized number of gray levels.

A texture in an image is characterized by basic geometric features; in this work four features (contrast, correlation, energy, and homogeneity) are extracted to detect the faults in transmission lines with different block size. The following formulas are used to

$$contrast = \sum_{i,j} |i-j|^2 \; p(i,j)^2 \quad (3)$$

$$Correlation = \sum_{i,j} \frac{(i-\mu j)(j-\mu j)p(i,j)}{\sigma_i \sigma_j} \quad (4)$$

$$Energy = \sum_{i,j} p(i,j)^2 \quad (5)$$

$$Homogeneity = \frac{\sum_{i,j} p(i,j)}{1+|i-j|} \quad (6)$$

In this work the performance of the texture features are tested using thirty different images with different conditions as shown in Fig. 1 and 2 that acts as a test image for the experiment in our work.

Fig. 1. Input image taken for the proposed work without fault

An algorithm has been developed to identify the minute details that cannot be seen in the original input optical images from our naked eyes and also showing the effect of distinct block size to display differences in each image, so that the fault in any transmission lines can easily be detected.

Fig. 2. Input image taken for the proposed work with fault

(4)

Four different image features (Contrast, Correlation, Energy and Homogeneity) are extracted from the selected image for four colour channels, i.e., Blue, Red, Green and Gray. The Contrast, Correlation, Energy and Homogeneity were calculated by using (3), (4), (5) and (6). All four parameters are independent of image size and orientation.

The process for extracting texture features of images using GLCM is done as mention below:

1) Inputs of thirty images are considered.
2) All the images are resized.
3) Separate the R, G, B planes of image.
4) Compute four GLCM matrices.
5) For each GLCM matrix compute the statistical features (contrast, correlation, energy, homogeneity).
6) Compute the feature vector using the means and variances of all the parameters.
7) Final results are obtained.
8) Comparisons are done.

The original images have been resized so that every image is of 100 pixels x 100 pixels. All images are physically in .jpeg format with 256 different gray levels (0-255). All images is separated into 4 color components i.e., Red, Green, Gray and Blue, thus, generating 4 new images having red, green, gray and blue channels respectively. For each color component images are segmented into six distinct block sizes (2, 4, 8, 16, 32, and 64). To each block of Red component image, Gray Level Co-occurrence Matrix (GLCM) is applied and the image having red channel is finally reconstructed. The matrix of newly reconstructed image is multiplied with the matrix of input image so as to get an image in which the pixels having low contrast are highlighted. The four features

(Contrast, Correlation, Energy and Homogeneity) are obtained for Red component of image. The same process is done for Green, Gray and Blue components of image.

III. Result & Discussions

This experiment is done to evaluate four different features which are contrast, energy, homogeneity and correlation from the color components of input images for faulty and faultless conditions in power transmission lines with six different block sizes,. For the block size 2 results are not obtained, in the following graphs results are shown for block size 4, 8, 16, 32 and 64.

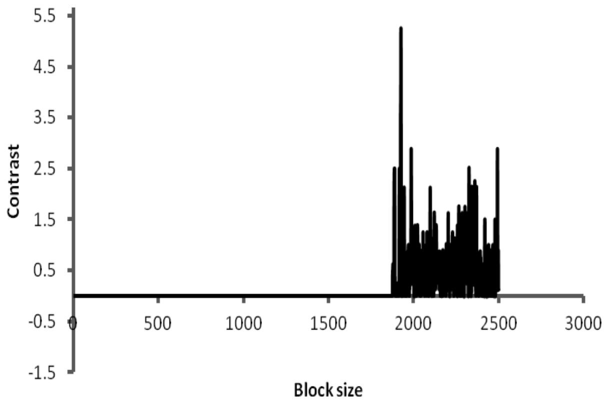

Fig. 3. Contrast for block size 4 in faultless condition

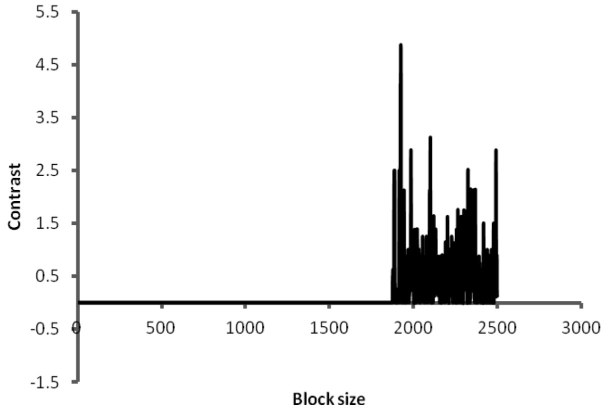

Fig. 4. Contrast for block size 4 in faulty condition

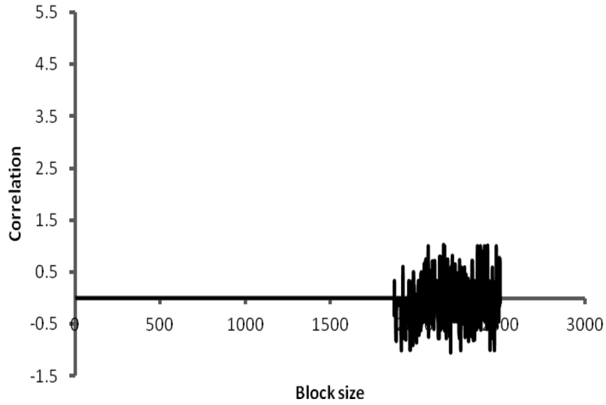

Fig. 5. correlation for block size 4 in faultless condition

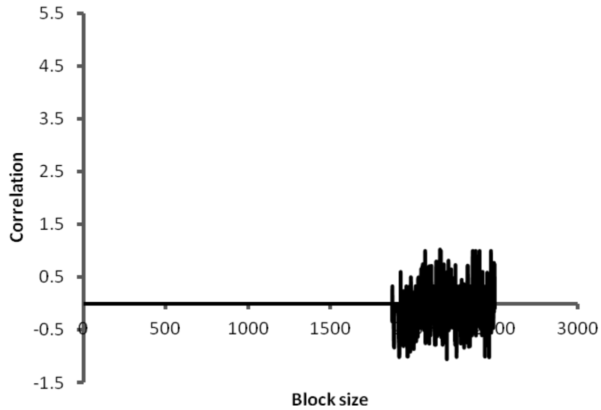

Fig. 6. Correlation for block size 4 in faulty condition

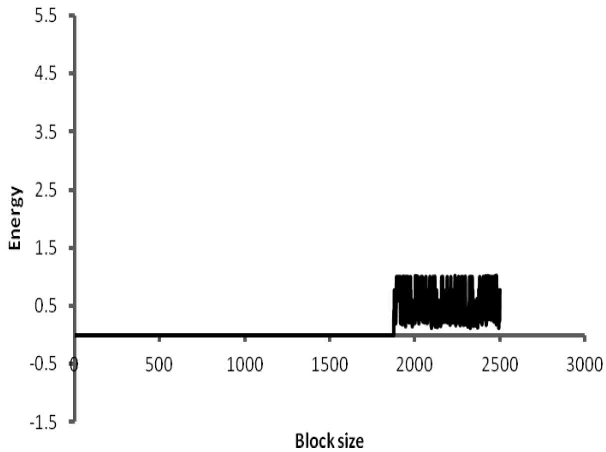

Fig. 7. Energy for block size 4 in faultless condition

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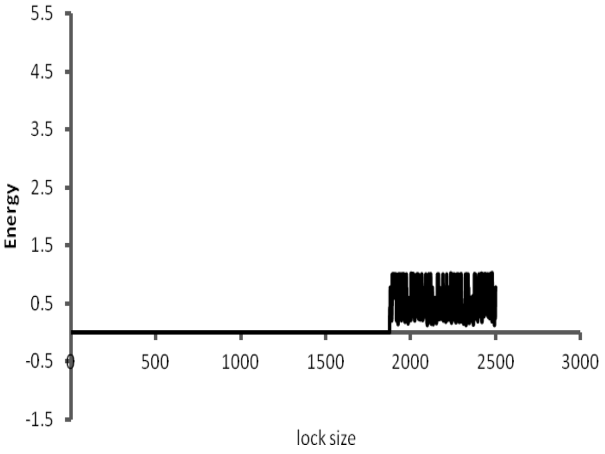

Fig. 8. Energy for block size 4 in faulty condition

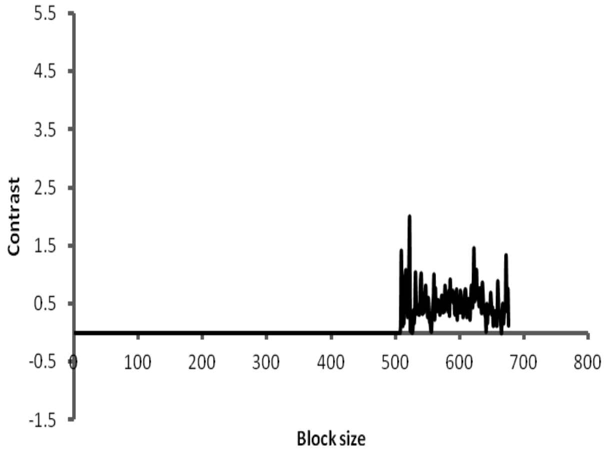

Fig. 11.Contrast for block size 8 in faultless condition

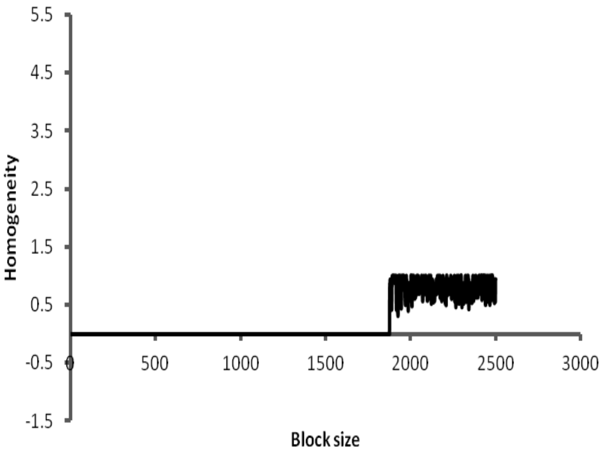

Fig. 9. Homogeneity for block size 4 in faultless condition

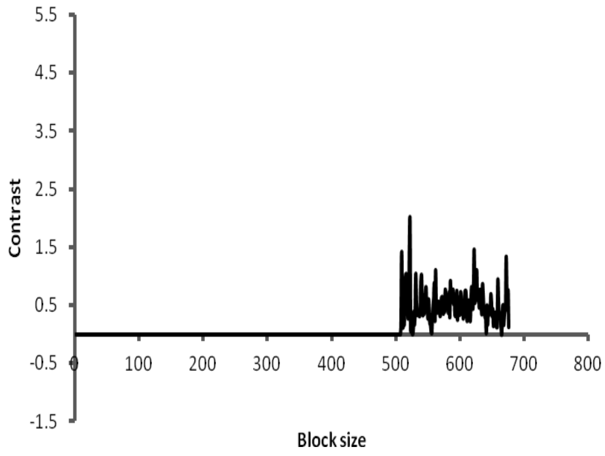

Fig. 11.Contrast for block size 8 in faulty condition

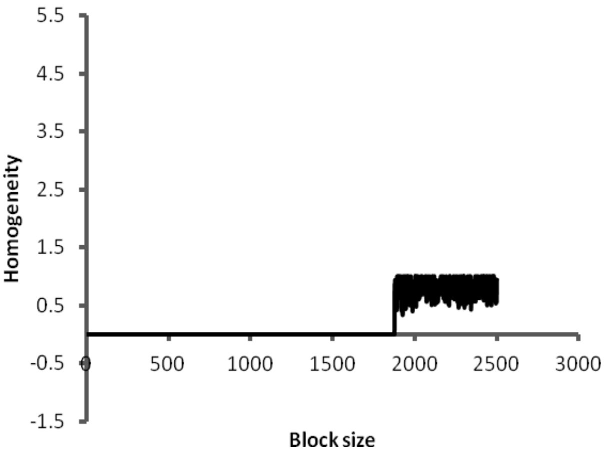

Fig. 10.Homogenetiy for block size 4 in faulty condition

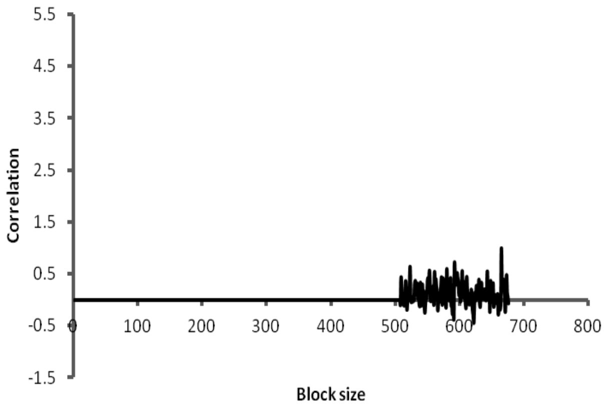

Fig. 12.Correlation for block size 8 in faultless condition

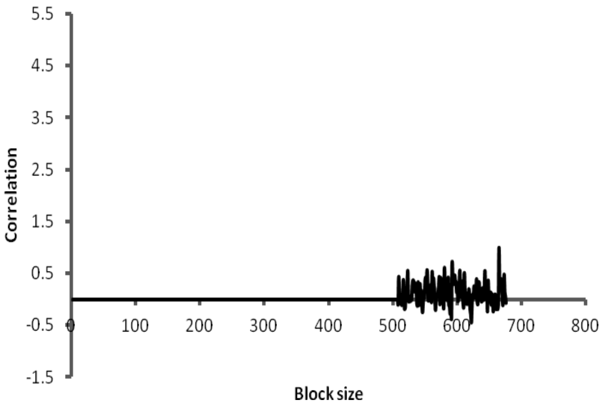

Fig. 13.Correlation for block size 8 in faulty condition

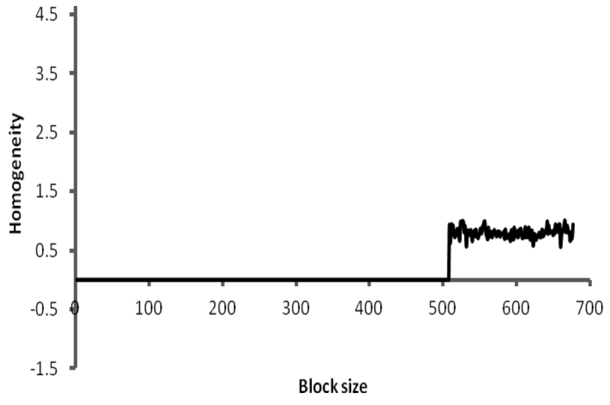

Fig. 16.Homogeneity for block size 8 in faultless condition

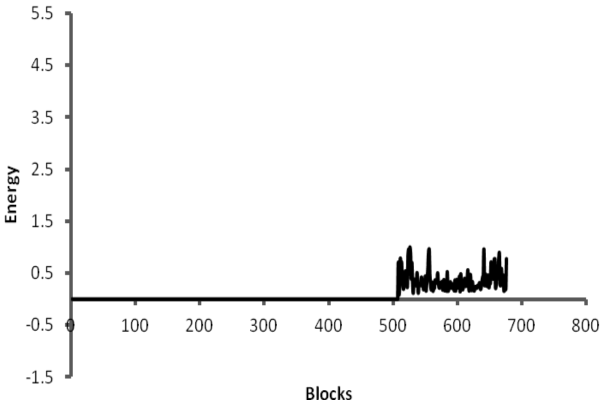

Fig. 14. Energy for block size 8 in faultless condition

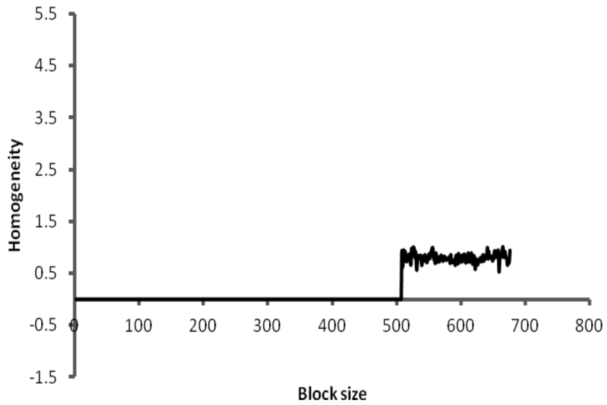

Fig. 17.Homogeneity for block size 8 in faulty condition

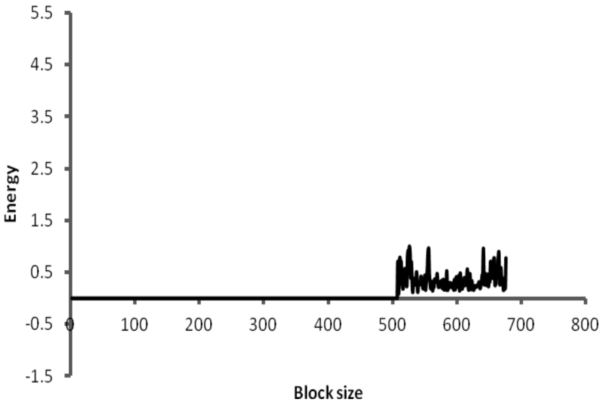

Fig. 15.Energy for block size 8 in faulty condition

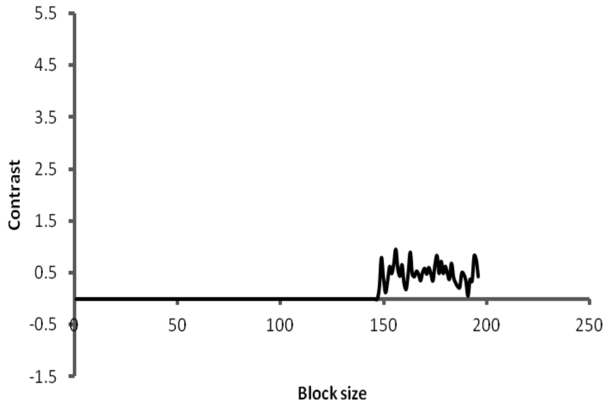

Fig. 18.Contrast for block size 16 in faultless condition

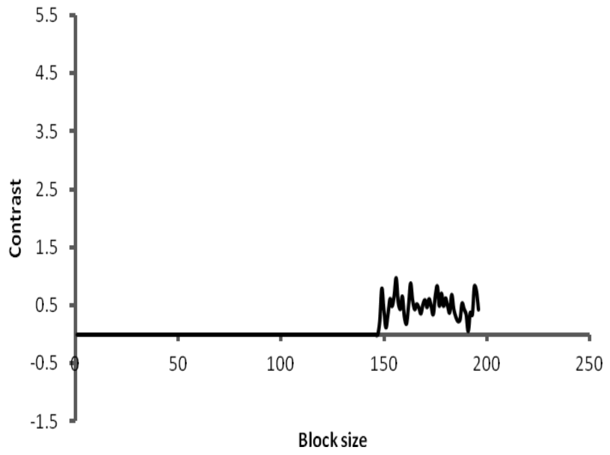

Fig. 20.Contrast for block size 16 in faulty condition

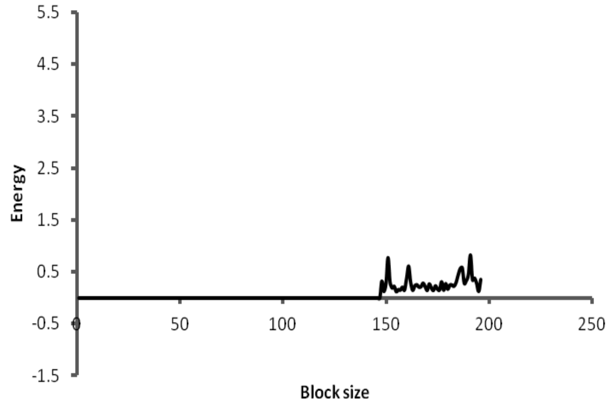

Fig. 23. Energy for block size 16 in faultless condition

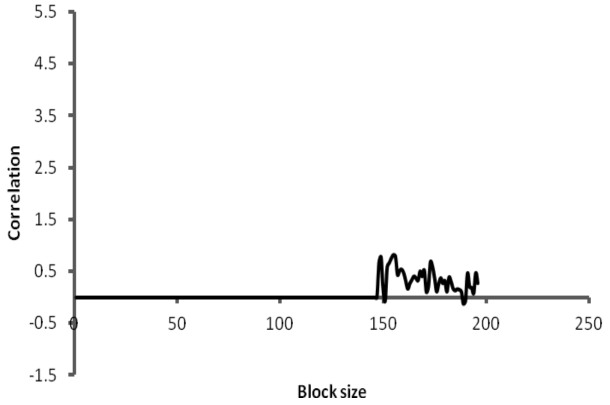

Fig. 21. Correlation for block size 16 in faultless condition

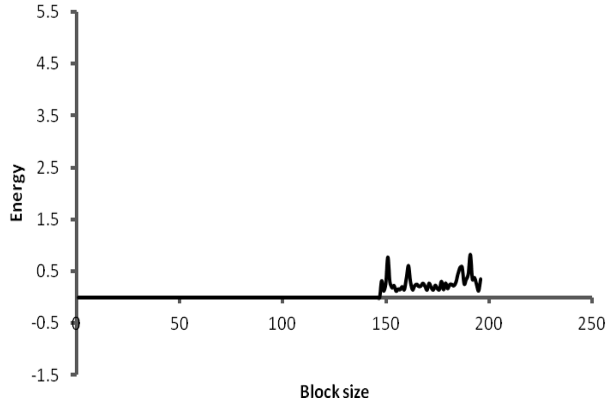

Fig. 24. Energy for block size in 16 in faulty condition

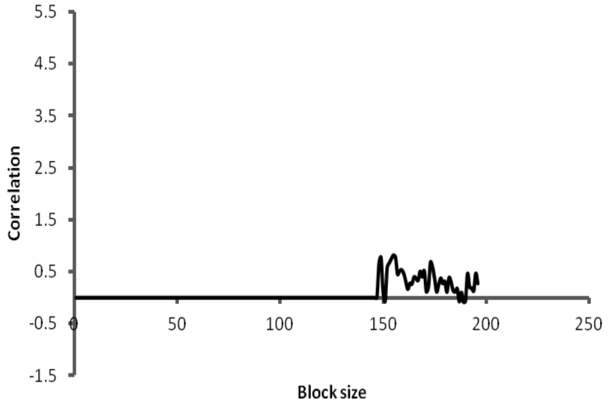

Fig. 22. Correlation for block size 16 in faulty condition

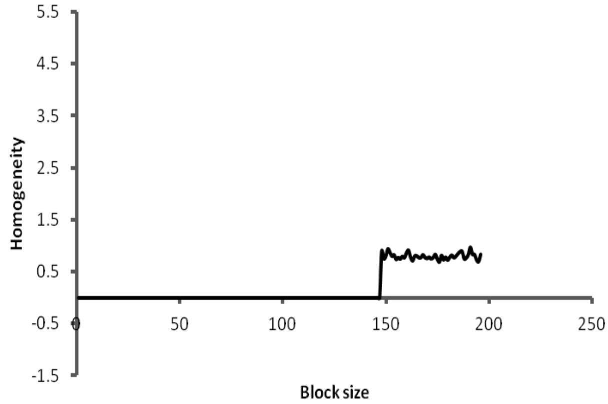

Fig. 25. Homogeneity for block size 16 in faultless condition

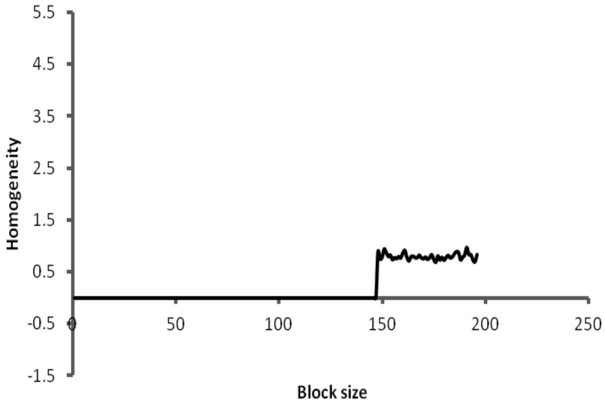

Fig. 26. Homogeneity for block size 16 in faulty condition

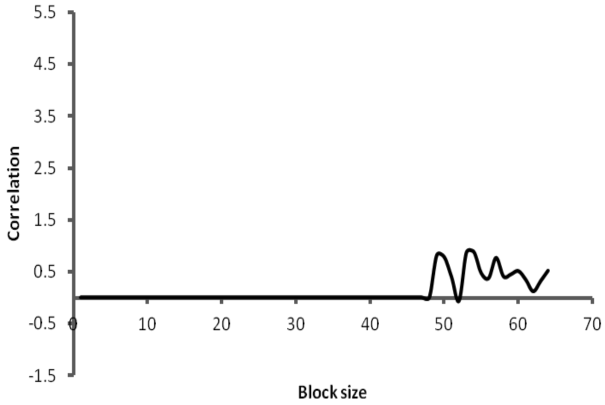

Fig. 29. Correlation for block size 32 in faultless condition

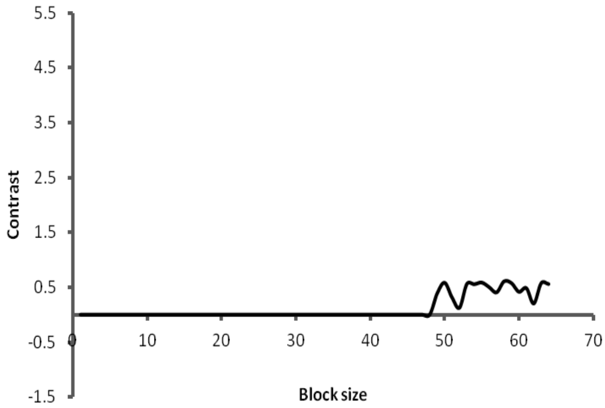

Fig. 27. Contrast for block size 32 in faultless condition

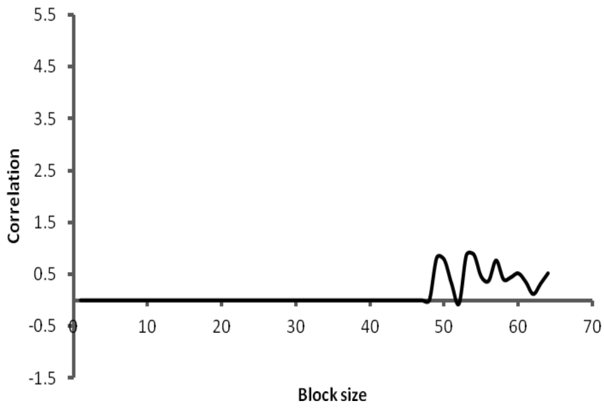

Fig. 31. Correlation for block size 32 in faulty condition

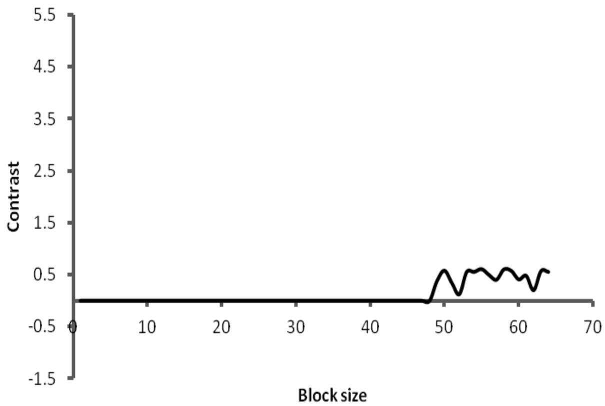

Fig. 28. Contrast for block size 32 in faulty condition

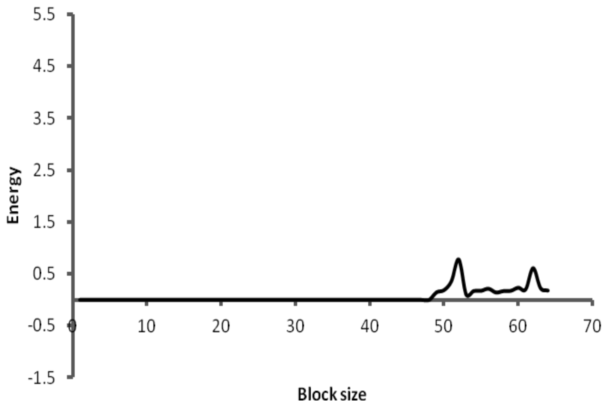

Fig. 32. Energy for block size 32 in faultless condition

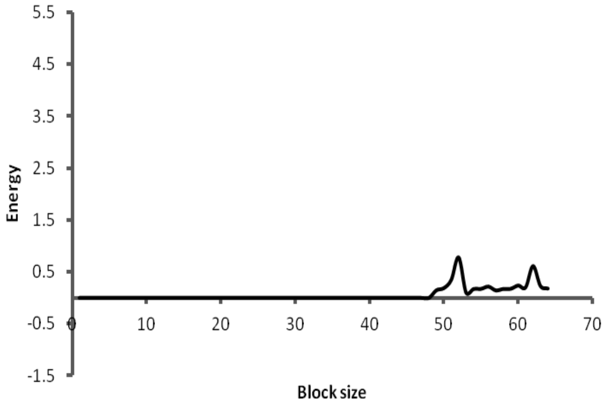

Fig. 33.Energy for block size 32 in faulty condition

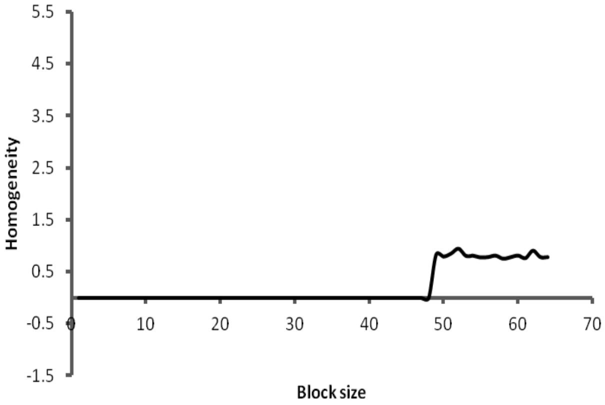

Fig. 34. Homogeneity block size 32 in faultless condition

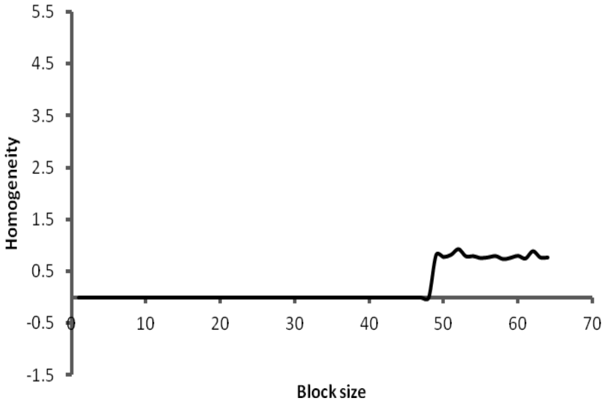

Fig. 35. Homogeneity block size 32 in faulty condition

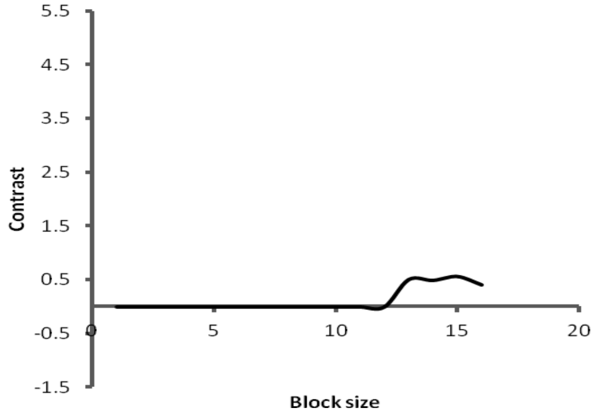

Fig. 36. Contrast for block size 64 in faultless condition

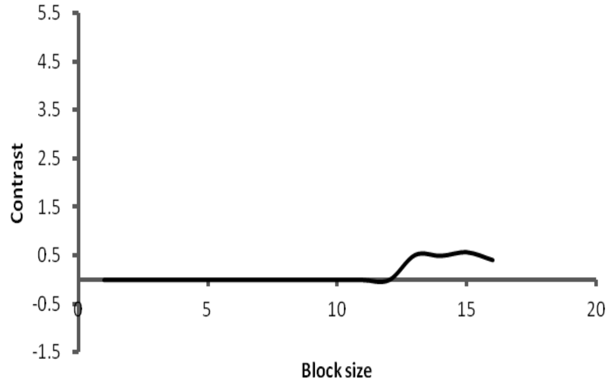

Fig. 37. Contrast for block size 64 in faulty condition

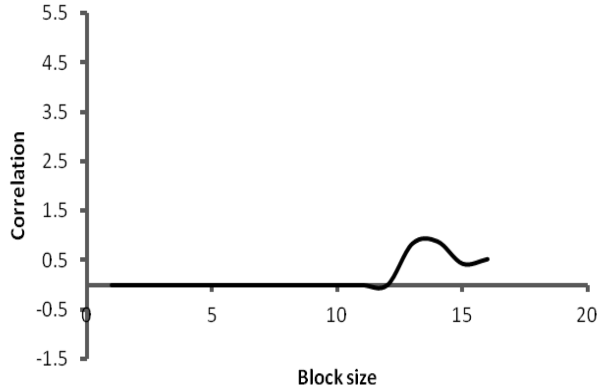

Fig. 38. Correlation for block size 64 in faultless condition

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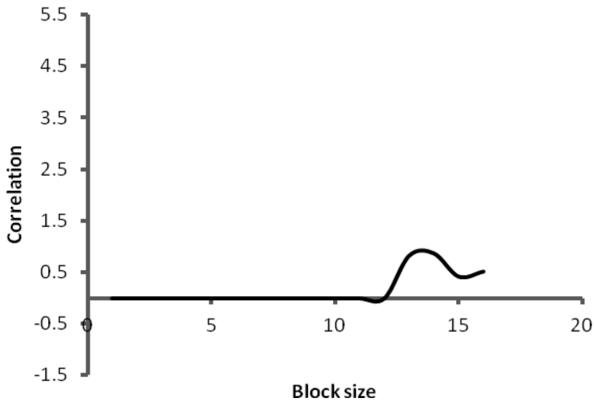

Fig. 39. Correlation for block size 64 in faulty condition

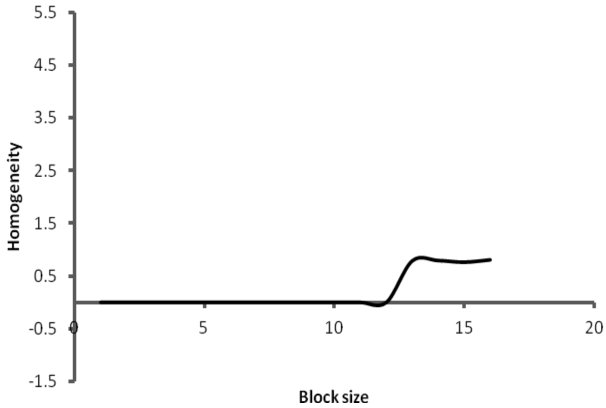

Fig. 42.Homogeneity for block size 64 in faulty condition

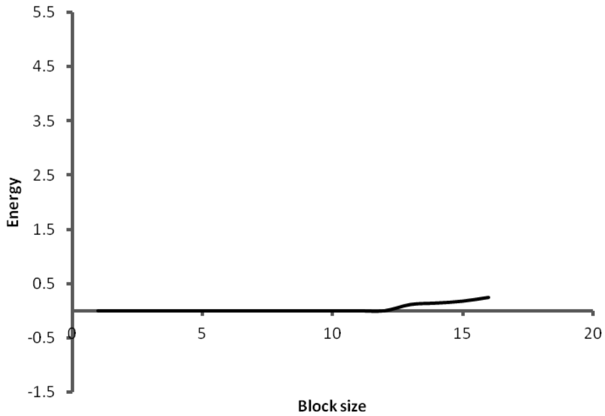

Fig. 40.Energy for block size 64 in faultless condition
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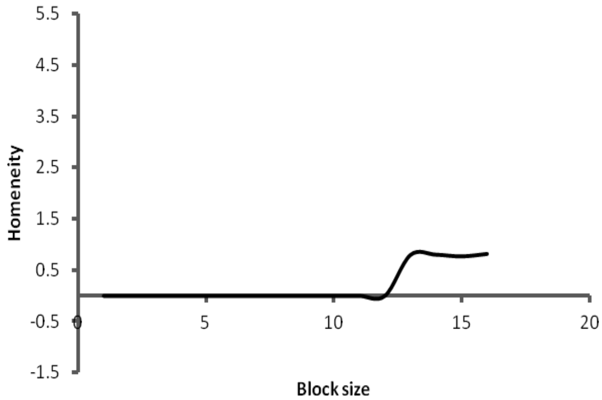

Fig. 43.Homogeneity for block size 64 in faulty condition

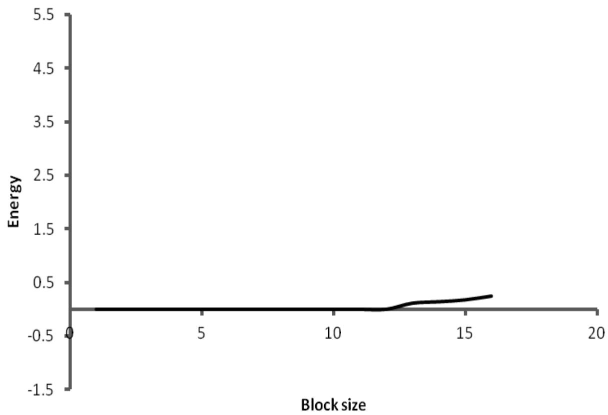

Fig. 41.Energy for block size 64 in faulty condition

The algorithm is implemented in MATLAB platform. Database of 30 images are used to check the performance of the algorithm developed. It is clear from the above results that block size has a great effect while detecting the faults. The mean and standard deviation (S.D) is obtained from the study of faultless and faulty image for different block sizes in gray color with all four features. In case of block size number 4, the mean is 0.0929 and standard deviation is 0.3984 for all the features in both faultless and faulty condition and maximum value changes from 6.1013 to 226. For the block size 8, the mean is 0.1313 and standard deviation 0.2932 as maximum value changes from 2.0637 to 55, showing the huge change in maximum value.

Meanwhile, for the block size 16, the mean is 0.1533 and standard deviation is 0.2697, in this block size maximum value changes from 1.4152 to 17 because of fault occurrence. In case of 32 block size number, the mean is 0.1259 and standard deviation is 0.169, but here for this block size small change in maximum value for faultless and faulty condition that is from 0.5618 to 3.For the last block size number 64 taken to compute the effect, shows little change in maximum value from 2.8798 to 3 and mean is calculated 1.5983 and standard deviation is 1.1317 for both faultless and faulty condition.

Overall, from all the above calculation it is cleared that for detecting the faults through this method, response is much better than the others, since it exactly examine the change in the image through all features.

IV. Conclusion

The paper presents a novel approach for detecting fault in power transmission lines. The proposed method extracts gray level co-occurrence matrix based features from 30 samples of different images. The proposed technique shows promising results for detecting the fault with block size effect. Colored images have been taken as input image and the enhancement of low contrast portions has been observed after processing of input images. Gray Level Co-occurrence Matrix (GLCM) based technique is applied and results are calculated after splitting of the colored images into their primary components. Parameters such as, contrast, energy, correlation and homogeneity are evaluated and these parameters are compared for both faultless images and faulty images. These features are useful in motion estimation of videos and in real time pattern recognition applications like Military & Medical Applications.

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