Insulator Infrared Image Denoising Method Based on Wavelet Generic Gaussian Distribution and MAP Estimation

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Abstract—The infrared techniques on failure detection in power grid have attracted widely attention in recent years. Since the infrared image of the insulator string has high noise and low contrast, it will affect the judgment accuracy of the zero value insulators. This paper proposes a method based on wavelet generic Gaussian and maximum posterior probability estimation for the noise removing of insulator infrared images. Due to the sharp peak and long tails features of the wavelet coefficients of the infrared images, generalized Gaussian distribution (GGD) is used as the probability distribution function. Maximum posterior probability estimation is used to obtain denoised signal from the posterior probability distribution function. Because the resolution of the maximum posterior probability estimation based on GGD cannot be achieved directly, Newton–Raphson law is used to obtain the resolution of the real signal wavelet coefficients. Compared by signal noise ratio and mean square error, the results indicate that the proposed method can effectively remove the infrared image noise and the performance is much better than the wavelet soft threshold method and wavelet hard threshold method.

Index Terms—Generalized Gaussian distribution (GGD), Infrared image of zero-value insulator, maximum posterior probability estimation, Newton-Raphson method, Wavelet denoising.

I. INTRODUCTION

Due to its noncontact, secure, and real-time characteristics, the infrared image diagnostic technology has been widely used in operating status and fault monitoring of equipment in power systems [1]–[4]. A zero value insulator in an insulator string on a power supply line will reduce the insulation creepage distance, easily lead to flashover accident, and seriously threaten the safe operation of the grid [5]–[7]. A FLIR S65 thermal infrared imager was used to take the thermal images of the insulators in this paper. According to the Stephen–Boltzmann law that the radiation energy of objects is proportional to the fourth power of the absolute temperature and the emissivity coefficient [8]. As to the material of porcelain, the emissivity coefficients rang is 0.90–0.94, when the emissivity coefficient is set, the temperature of the objects can be obtained.

FLIR S65 is an uncooled infrared focal plane arrays (IRFPA) detector which has been widely used. Due to the source noise of the IRFPA detector itself [9] and the influence of the noise of the background, the infrared image has high-noise and low-contrast characters, especially in the situation that the insulators’ temperature is close to the background. The quality of the infrared image affects the accurate judgment of the zero-value insulator in the string. The denoising performance is critical for the accuracy of the subsequent judgment. Therefore, a highly effective denoising algorithm is necessary to improve zero-value insulator detection when using infrared imaging.

Many denoising algorithms have been proposed in the literatures [10]–[12]. Due to its excellent time–frequency characteristics, wavelet denoising has been widely used in image filtering [13]–[15]. To reduce the computational burden, most wavelet denoising methods usually deal with the wavelet coefficients by truncation or shrink processing, such as the soft threshold and the hard threshold method. These methods may result in loss of details and fuzzy the edge of the image. Therefore, the key point of improving the denoising performance is how to estimate the real signal from the noised wavelet coefficients. The commonly used wavelet algorithms use the Gaussian distribution model [16], [17] as the probability distribution model of the wavelet coefficients; but, in fact, the probability distribution of the wavelet coefficients of the infrared image has a sharp peak and long tails [18]. Therefore, generalized Gaussian distribution (GGD) is more suitable for the wavelet coefficients probability statistics [19], [20]. For the low-frequency section of the wavelet coefficients represent image contour and the high-frequency sections are the noise and some image details. Denoising processing mainly aims at the high-frequency wavelet coefficients.

In this paper, a new method based on GGD and MAP (maximum posterior probability) [21]–[23] estimation is proposed for noise removing of the zero-value insulator images. GGD model is used as probability distribution function of the high-frequency wavelet coefficients of the real signal. Because of some parameters of the GGD are unknown, a moment estimation method is proposed to obtain these parameters. Then, MAP estimation is used to get the real-signal wavelet coefficients from the Generalized Gaussian distribution. Since the solution of the maximum...
posterior probability estimation based on GGD is unable to obtain directly, Newton–Raphson law [24] is used to obtain the solution of the real signal wavelet coefficients. The experiment results indicates that the proposed method performs better on the phenomenon of edge missing, blurred image, and details loss over the traditionally algorithms. It suppressed the noise, restored the signal very well, and greatly improved the quality of the image.

II. GGD MODEL OF HIGH-FREQUENCY WAVELET COEFFICIENTS OF ZERO-VALUE INSULATOR IMAGE

A. GGD Model

GGD is also known as generalized Laplace distribution, its probability density function is

\[ p(x; \mu, \alpha, \beta) = C \cdot \exp \left( - \left| \frac{x - \mu}{\beta} \right|^\alpha \right) \]

where

\[ \beta = \sigma \sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}} \]

\[ C = \frac{\alpha}{2\beta \Gamma(1/\alpha)} \]

\[ \Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt. \]

For the generalized Gaussian distribution, \( \mu \) is the mean, \( \alpha \) is the shape parameter, \( \beta \) is the scale factor, \( \sigma \) is the variance, \( C \) is normalizing factor, and \( \Gamma(\bullet) \) is gamma function. In a particular case, the GGD is a symmetric distribution of standard Gaussian form with 0 mean when \( \mu \) is equal to 0, \( \alpha \) is equal to 2, and \( \beta \) is equal to \( \sqrt{2} \sigma \). Since the GGD probability density function is determined by the parameters \( \mu, \alpha, \beta, \) and \( C \), these parameters must to be estimated.

B. GGD Parameters Acquirement Based on Moment Estimation

The insulators image was decomposed into four sub-bands by wavelet transform: LL, LH, HL, and HH. Among them, LL is the low-frequency section; LH, HL, and HH are high-frequency sections at horizontal, vertical, and diagonal directions, respectively. In fact, the wavelet coefficients of the image are the superposition of the real-signal wavelet coefficients and the noise in each subband, i.e.,

\[ y = x + n \]

where \( y \) is the noised signal wavelet coefficients, \( x \) is the real-signal wavelet coefficients, and \( n \) is the noise wavelet coefficients. The essence of denoising is to restore the real signal from the contaminated signal by suppressing the noise at a large extent. The noise of the infrared image is caused by electronic devices of the camera and it follows the Gaussian distribution with 0 mean in the statistical property. As the noise mainly concentrates in the high-frequency part, the whole restoration process focuses on retaining the low-frequency section, and using GGD as probability density function at each decomposed direction of high-frequency section of each subband. Since the high-frequency wavelet coefficients and the noise are superimposed together, how to estimate the real signal probability density function from the noised signal is the key of getting the real signal. It is reasonable to assume that the high-frequency wavelet coefficients obeys the zero-mean generalized Gaussian distribution, which means \( \mu \) is equal to 0, and \( C \) is the function of \( \alpha \) and \( \beta \). Therefore, the main tasks of the parameters estimation of the GGD is to estimate parameters \( \alpha \) and \( \beta \). Second order moment estimation and fourth moment estimation [25] are used to estimate the parameters \( \alpha \) and \( \beta \) in this paper. The signal contaminated by Gaussian white noise can be expressed with the following equations:

\[ \sigma^2 = \sigma_n^2 + \frac{\beta^2 \Gamma \left( \frac{2}{\alpha} \right)}{\Gamma \left( \frac{4}{\alpha} \right)} \]

\[ m_4 = 3\sigma_n^4 + \frac{6\sigma_n^2 \beta^2 \Gamma \left( \frac{4}{\alpha} \right)}{\Gamma \left( \frac{6}{\alpha} \right)} + \frac{\beta^4 \Gamma \left( \frac{6}{\alpha} \right)}{\Gamma \left( \frac{8}{\alpha} \right)} \]

where \( \sigma^2 \) is the second order moment, namely the variance of the wavelet coefficients of the noised signal. \( m_4 \) is the fourth moment of the noised wavelet coefficients. \( \sigma_n^2 \) is the wavelet coefficients variance of the noise. \( \alpha, \beta \) are parameters of the GGD of the wavelet coefficients of the real signal. For the discrete random variables, as long as the front \( k_{th} \) moments of population \( y \) exist, the sample moment can be taken as the estimation of the population moment [26]. Therefore, the second order moment and the fourth moment of the samples are

\[ m_2 = \sigma^2 = \frac{1}{N} \sum_{i=1}^{N} y_i^2 \]

\[ m_4 = \frac{1}{N} \sum_{i=1}^{N} y_i^4 \]

where \( y_i \) is the noised signal wavelet coefficient of each subband and \( N \) is the length of the wavelet coefficients. Noise variance of each subband is estimated by Donoho’s absolute deviation of the median [27]

\[ \sigma_n^2 = \frac{\text{median} |y_i|}{0.6745} \]

By solving (6) and (7), the following equation can be obtained:

\[ \frac{(\sigma^2 - \sigma_n^2)^2}{m_4 + 33\sigma_n^2 - 6\sigma_n^2\sigma_n^2} = \frac{\Gamma^2 \left( \frac{4}{\alpha} \right)}{\Gamma \left( \frac{6}{\alpha} \right) \Gamma \left( \frac{8}{\alpha} \right)} \]

Substitute (8)–(10) into the left of (11), the value of the parameter \( \alpha \) can be obtained by searching in a gamma function lookup table. \( \beta \) can be obtained by plugging \( \alpha \) into (6). Then, the probability density function of wavelet coefficients of the real signal can be obtained by parameter \( \alpha \) and \( \beta \), and \( C \) is the determined by \( \alpha \) and \( \beta \) [as in (3)], thus, GGD probability density function of the wavelet coefficients of the real signal can be obtained. GGD fitting of the wavelet coefficients of the real signal is shown in Fig. 1. In this paper, the infrared image of the zero-value insulator is decomposed on two scales. On
where \( p_x(x) \) and \( p_n(n) \) are the marginal probability density functions.

As (14) is the convolution about the marginal probability density \( p_x(x) \) and \( p_n(n) \), it is integration about \( x \), its result is only an expression of \( y \), and it is irrelevant to \( x \), namely the denominator of the posteriori probability distribution \( p_{x|y}(x|y) \) [as in (13)] is irrelevant to \( x \) and only the molecular of (13) is related to \( x \). Therefore, the estimation value of the signal \( x \) is equivalent to the value of \( x \) when \( p_{y|x}(y|x)p_x(x) \) get the maximum value, namely

\[
\hat{x}(y) = \arg\max_x p_{y|x}(y|x)p_x(x)
\]

\[
= \arg\max_x p_n(y - x)p_x(x)
\]

\[
= \arg\max_x p_n(y - x)p_x(x)
\]

where \( p_{y|x}(y|x) \) is a likelihood function, \( p_n(y - x) \) is the probability density function of the noise, \( p_x(x) \) is the prior probability density function of the signal \( x \). Equation (15) indicates that Bayesian posterior probability formula is actually a method which uses the priori probability to describe the posterior probability and the likelihood function is a function which is used to express the similarity between the priori probability density function and the posteriori probability density function. In this paper, the noise probability density function \( p_n(n) \) is a known Gaussian distribution function with mean 0, variance \( \sigma_n^2 \). \( \sigma_n^2 \) was estimated by Donoho’s median absolute deviation.

The solution of (15) cannot be attained directly, in this paper, Newton–Raphson method is presented to solve (15), that is

\[
\hat{x}(y) = \arg\max_x p_n(y - x)p_x(x)
\]

\[
= \arg\max_x e^{-\frac{(y - x)^2}{2\sigma_n^2}} \cdot C \cdot e^{\frac{-y^2}{2\sigma_n^2}}
\]

\[
= \arg\max_x e^{-\frac{(y - x)^2}{2\sigma_n^2}} \cdot C \cdot e^{\frac{-y^2}{2\sigma_n^2}}
\]

where \( p_n(n) = p_n(y - x) = e^{-\frac{(y - x)^2}{2\sigma_n^2}} \), for \( y = x + n \), \( p_x(x) = C \cdot e^{\frac{-y^2}{2\sigma_n^2}} \) is the probability distribution density function of \( x \) obtained by GGD estimation and moment estimation.

Let

\[
L(x) = e^{-\frac{(y - x)^2}{2\sigma_n^2}} \cdot C \cdot e^{\frac{-y^2}{2\sigma_n^2}}.
\]

As \( L(x) \) and \( \ln L(x) \) obtain the maximum value at the same \( x \), so, let

\[
\frac{d\ln L(x)}{dx} = 0.
\]

The solution of (18) is the solution of (16). Substituting the expression of \( L(x) \) into (18), we obtain

\[
\alpha |x|^{\alpha - 1} + \frac{x}{\sigma_n^2} - \frac{y}{\sigma_n^2} = 0.
\]
Because the solution of the above equation is unable to obtain directly, an iterative method using Newton–Raphson law is used in this paper to get the resolution. Let

$$f(x) = \frac{\alpha |x|^\alpha - 1}{|\beta|} + \frac{x}{\sigma_n^2} - \frac{y}{\sigma_n^2}$$

(20)

where $y$ in (19) and (20) corresponds to the noised wavelet coefficients. Substitute every $y$ of the noised wavelet coefficients array into (20) to get $f(x)$ for each $y$. Initialize $x$ and substitute $f(x)$ into (21), carrying on the iteration by using (21) until the error satisfies requirement, or meets the upper limit of the iterative times, then, getting the real-signal wavelet coefficients array. Implementing the wavelet inverse transformation on the real-signal wavelet coefficients at each decomposition direction and each decomposition subband, then get the denoised image

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}.$$  

(21)

IV. RESULTS OF THE EXPERIMENTS

FLIR S65 Infrared imager was used to take images of the insulators. The size of the experimental insulator infrared image is 480$\times$640. A good quality of the image provides good foundation for the insulator strings segmentation from the background and the subsequent identification of the zero-insulators. Fig. 2 is an incomplete segmented insulator image resulting from heavy noise. It can be concluded from the vision of Fig. 2 that some details of the insulators have been lost (especially of the fourth piece insulator); therefore, the images without denoising processing will result in the incorrect subsequent identification of the zero-insulators.

At different Gaussian white noise level ($\sigma = 0.06, \sigma = 0.04, \sigma = 0.02$), using the proposed method which based on wavelet (GGD) and MAP estimation to remove the noise of the image. The orthogonal wavelet Coiflets 2 is used as experiment wavelet. The wavelet decomposition levels are three. For comparison purpose, the experiments also present the denoising effects of an adaptive wavelet soft threshold method [28] and wavelet hard threshold method which proposed by D. L. Donoho. Figs. 3–6 are the noised image and denoised insulator images by using wavelet hard threshold method, the adaptive wavelet soft threshold method and the proposed method at Gaussian white noise level $\sigma = 0.06$, respectively.

Fig. 2. Incomplete segmented image.

Fig. 3. Noised image ($\sigma = 0.06$).

Fig. 4. Denoised image using wavelet hard threshold method.

Fig. 5. Denoised image using adaptive wavelet soft threshold method.

Fig. 6. Denoised image using the proposed method based on GGD and MAP estimation.

It shows from the visual comparison of Figs. 3–6, that the wavelet hard threshold method can reduce the noise to a certain degree, but the denoising effect is not very good and it causes edge fuzzy of the insulator. The denoising effect of the adaptive wavelet soft threshold method is better than the wavelet hard threshold method, but the noise suppression effect is still not satisfactory enough. The method presented in this paper has achieved a good noise filtering effects, the profile of the insulator is complete, the edge is clear, and the visual effect is good, it
provides a good foundation for subsequent identification of the fault insulator.

In this paper, the minimum mean-square error (MSE) and signal-to-noise ratio (SNR) are used to estimate the denoising performance

\[
MSE = \frac{1}{l \times m} \sum_{i=1}^{l} \sum_{j=1}^{m} (\hat{f}(i, j) - f(i, j))^2
\]  

where \( l = 480, m = 640, \hat{f}(i, j) \) is pixel gray value of the denoised image, \( f(i, j) \) is the pixel gray value of the original noised image.

\[
SNR = 10 \times \log \left( \frac{\sigma^2_{f(i,j)}}{MSE} \right)
\]  

where \( \sigma^2_{f(i,j)} \) is the variance of the pixels’ gray value of the denoised image. Table I shows the MSE and SNR of the denoised insulator images after processed by wavelet hard threshold method, adaptive wavelet soft threshold method and adaptive soft threshold method at Gauss noise level \( \sigma = 0.06, \sigma = 0.04, \sigma = 0.02 \).

It can be seen from Table I that the MSE and SNR of the image have significantly improved compared to the original noised image by using the proposed method. Compared with wavelet adaptive soft threshold method and the wavelet hard threshold method, the proposed method has higher SNR and smaller MSE at the same noise level. It indicates that the denoising performance of the proposed method is better than the adaptive wavelet soft threshold method and the wavelet hard threshold method.

### V. CONCLUSION

In this paper, an image denoising algorithm based on GGD and MAP estimation is proposed for zero insulator infrared image denoising. According to the high peak and long tails shape characteristics of the high frequency wavelet coefficient distribution of the zero insulator infrared images, GGD distribution is used as the highfrequency wavelet coefficient distribution at horizontal, vertical, and diagonal directions. Moment estimation was carried out to obtain the parameters of the generalized Gaussian distribution. MAP estimation combined with Newton–Raphson method were implemented to obtain the real wavelet coefficients from the noised wavelet coefficients. Results from the experiments show that the proposed method is more efficient on noise filtering. The details of the image are clear and the profile of the insulator is complete. It is better than the wavelet adaptive soft threshold method and wavelet hard threshold method by the comparison of MSE and SNR. The signal to noise ratio has greatly improved and the MSE has largely dropped by using the proposed method. This method is highly effective in insulator infrared image denoising. It improves the image quality and provides a good foundation for the detection of the zero value insulators. This method also serves as a useful reference on infrared image processing of other power equipment status and fault recognition.

### REFERENCES


### TABLE I

MSE and SNR of Original Images and Denoised Images by Different Methods

<table>
<thead>
<tr>
<th>Noise intensity</th>
<th>Noised signal</th>
<th>Wavelet hard threshold method</th>
<th>Adaptive soft threshold method</th>
<th>The proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNR(dB)</td>
<td>MSE</td>
<td>SNR(dB)</td>
<td>MSE</td>
<td>SNR(dB)</td>
</tr>
<tr>
<td>( \sigma = 0.06 )</td>
<td></td>
<td></td>
<td>14.59 68.83</td>
<td>18.57 43.28</td>
</tr>
<tr>
<td>( \sigma = 0.04 )</td>
<td></td>
<td></td>
<td>17.38 55.39</td>
<td>21.94 35.46</td>
</tr>
<tr>
<td>( \sigma = 0.02 )</td>
<td></td>
<td></td>
<td>20.17 28.06</td>
<td>23.64 24.87</td>
</tr>
</tbody>
</table>


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