Electrical Inspection Oriented Thermal Image Quality Assessment

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Abstract. This paper presents an approach to access the quality of thermal images that are specially used in electrical inspection. In this application, no reference images are given for quality assessment. Therefore, we first analyze the characteristics for these thermal images. Then, four quantitative measurements, which are one-dimensional (1D) entropy, two-dimensional (2D) entropy, centrality, and No-Reference Structural Sharpness (NRSS), are investigated to measure the information content, the centrality for objects of interest, and the sharpness of images. Moreover, in order to provide a more intuitive measure for human operators, we assign each image with a discrete rate based on these quantitative measurements via the k-nearest neighbor (KNN) method. The proposed approach has been validated in a dataset composed of 2,336 images. Experiments show that our quality assessment results are consistent with subjective assessment.

1. Introduction

Thermal imaging systems are able to capture the surface temperature without contact, so that they are widely used in electric power industry for equipment inspection. However, the quality of captured thermal images highly depends on operating conditions, such as background radiation, the range of operation of thermal imaging sensors [1][2], and so on. Poor images may bring much more challenges for succeeding automatic analysis including equipment detection and fault diagnosis. It is therefore important to assess the quality of thermal images before conducting analysis, but also helpful to improve thermal imaging for human operators.

Image quality assessment (IQA) is a problem that has been studied for decades. Most existing works focus on visible light images [3][4], in which various quantitative measurements have been developed for objective assessment. For instance, the mean squared error (MSE), the peak signal-to-noise ratio (PSNR), as well as some models based on human vision system (HVS) and structural similarity image measurement (SSIM) were proposed to measure the quality of images when reference images are given. In practical applications, reference images are unavailable. Therefore, no-reference IQA approaches [5] have also been developed to evaluate the degree of noise, blur, or block effects. In contrast to the studies on visible light images, the quality assessment for inferred and thermal images are relatively few. Although different modal images should share something in common, inferred and thermal images present different characteristics due to their distinct optical and electrical performance. Therefore, Xu et al. [6] and Yue et al. [7] proposed a couple of quantitative measurements specific to inferred images, for instance, pesudo SNR, histogram based image information capacity, and energy ...
spectrum entropy. Agaian et al. [1] and Amon and Lock [8] designed measurements, such as cross entropy brightness-darkness and brightness-darkness intensity, for thermal images. This paper aims to assess the quality of thermal images which are used in electrical equipment inspection, and no reference images are available. In contrast to the related works mentioned above, the thermal images that we evaluate have the following characteristics:

1. In electric power industry, thermal images are commonly displayed with iron palette in order for human to visually interpret them better. Typical examples are shown in Figure 1. Therefore, the images that we evaluate are the iron colored thermal images.

2. Although thermal cameras can capture the temperature distribution of imaging environments in a great range, the contrast of displayed thermal images highly depend on the range of temperature of interest that are set by human operators.

3. Electric equipment is often of higher temperature than environment. Therefore, different from thermal images studied in [1], the images in electric power industry are of high contrast between object and background if appropriate temperature range is set.

4. In order to perform equipment inspection, it is expected to have equipment of interest located at the center of thermal images.

By considering the above phenomena and existing image quality measures, we investigate four quantitative measurements, which are, respectively, one-dimensional (1D) entropy, two-dimensional (2D) entropy, centrality, and No-Reference Structural Sharpness (NRSS) [9]. Moreover, instead of integrating them together to get a final continuous value, we take these measurements as features and classify each image into one of five rating category. Each category is associated with a score following the rating scheme used in mean opinion score (MOS) [10]. The discrete rating score is more helpful for guiding human operators to capture better images. Our approach is validated in a dataset composed of 2,336 images. Experiments show that our quality assessment results are consistent with subjective assessment.

Figure 1. Thermal images with iron palette. From (a) to (e), the image quality degenerates.

2. Proposed approach

Given a thermal image, we assess its quality by considering the amount of information it contains, whether the object is located at the image center, and how clear the image is. With respect to these considerations, four measurements are investigated, which are 1D entropy, 2D entropy, centrality, and NRSS. In this section, we first explain these measurements, and then introduce the way of using them to rate each image.

2.1 Quantitative measurements

2.1.1. 1D Entropy. Entropy is a measure of information content. 1D entropy is to measure the information content based on the histogram of pixels’ color. Given a thermal images with iron palette, the 1D entropy is computed by

$$H_{1D} = - \sum_{i=1}^{B} p_i \log(p_i)$$  \hspace{1cm} (1)

Here, $p_i$ represents the probability for a pixel whose color falls into the $i$-th bin, and $B$ is the total number of bins. It is reasonable to expect a small 1D entropy for an image with high quality.
2.1.2. 2D Entropy. The above 1D entropy measures the information content of pixels while simply ignoring spatial information. In order to take spatial information into account, 2D entropy is also adopted. Let \( i \) be a pixel's intensity value and \( j \) be the mean intensity value of the pixel's neighbors. Then, 2D entropy is computed by

\[
H_{2D} = -\sum_{i=0}^{255} \sum_{j=0}^{255} p_{ij} \log p_{ij}
\]  

(2)

Here, \( p_{ij} \) is the probability of the spatial pattern in which the center pixel is \( i \) intensity value and its neighbors are of \( j \) intensity value in average. \( p_{ij} \) is estimated from a 2D histogram. Analogously, a high quality image should have a small 2D entropy.

2.1.3. Centrality. The centrality is to measure the degree that objects of interest occupy an image’s central part. In our case, the central part refers to the half size region located at the center of the image. Considering that electric equipment has higher temperature than background, we binarize the image with certain thresholds to get foreground and background regions. The percentage that the foreground region occupies within the central region is taken as the centrality. It is

\[
C = \frac{N_{F}}{N_{T}}
\]

(3)

in which \( N_{F} \) is the number of foreground pixels with the central region, \( N_{T} \) is the total number of foreground pixels.

2.1.4 NRSS. The no-reference structural sharpness (NRSS) [9] is proposed by Xie et al. to measure the quality of visible light images. It is adopted in this work to evaluate the sharpness of thermal images as well. We briefly introduce it here for the purpose of self-containedness.

Given a thermal image \( I \), the first step is to smooth it using a Gaussian filter to get a reference image \( I_r \). Then, by dividing both images into \( M \) blocks, NRSS is computed by

\[
NRSS = 1 - \frac{1}{M} \sum_{i=1}^{M} SSIM (x_i, y_i)
\]

(4)

Here, \( SSIM \) is the structural similarity [3] defined as

\[
SSIM(x, y) = \frac{2\mu_x \mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \cdot \frac{2\sigma_{xy} + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \cdot \frac{\sigma_x + \sigma_y + C_3}{\sigma_x + \sigma_y + C_3}
\]

(5)

in which \( x \) and \( y \) are blocks in \( I \) and \( I_r \), \( \mu_x \) and \( \mu_y \) are the mean intensity values of \( x \) and \( y \), and \( \sigma_x^2 \) and \( \sigma_y^2 \) are the corresponding standard deviations. \( C_1, C_2, \) and \( C_3 \) are three constants empirically set.

2.2 Discrete rating

One way of assessing image quality is to integrate different quantitative measurements by multiplying or summing up them together. Instead of taking this way, we prefer to assign each image with a discrete rate based on the above measurements. The rating scheme follows the one used in mean opinion score (MOS) [10], which is listed in Table 1. In contrast to continuous scores, the 5-level rating score is not only more intuitive for human operators, but also appropriate for succeeding automatic analysis.

| Table 1. The discrete rating scores |
|-----------------------------------|
| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Bad | Poor | Fair | Good | Excellent |
We treat the discrete rating task as a classification problem. The four quantitative measurements are taken as features associated with each image. Therefore, rating an image is essentially classifying it into one of the five categories. A training set composed of 1,400 images are given, in which each image is manually labeled as one of the 5-level score. The centroids of each category is computed. When a test image is given, the nearest neighbor approach is used to determine its rating score.

3. Experiments

3.1 Datasets
In order to validate our approach, we first construct a dataset that consists of 2,336 images in total. Most of the images are taken for the purpose of inspecting current transformer, lightning protector, and other electric equipment. High quality images are often with an equipment located at the center and with high contrast. While poor images may be blurred, with no obvious equipment, or with low contrast. Besides Figure 1, more typical examples are presented in Figure 2.

![Figure 2. Typical thermal images for electric inspection.](image)

In the dataset, each image is manually labeled with a 5-level score for training and evaluation purpose. Among all the images, 60% images are randomly selected as training samples and the remaining is for testing. Table 2 presents the number of images for each rating level. Each image is colored with iron palette.

|       | 1  | 2  | 3  | 4  | 5  |
|-------|----|----|----|----|----|
| 517   | 359| 419| 369| 672|

3.2 Experiments
We first investigate the four quantitative measurements. Table 3 lists the results for the images in Figure 1, in which low entropy values and high centrality and NRSS values indicate high quality. From which we can observe that these measurements can access the corresponding considerations well. They are also discriminative and consistent with subjective assessments.

|       | Fig1.a | Fig1.b | Fig1.c | Fig1.d | Fig1.e |
|-------|--------|--------|--------|--------|--------|
| 1D Entropy    | 2.657  | 4.261  | 5.305  | 6.528  | 6.566  |
| 2D Entropy    | 2.446  | 3.813  | 4.315  | 5.022  | 4.771  |
| Centrality    | 0.543  | 0.830  | 0.690  | 0.476  | 0.219  |
| NRSS         | 0.678  | 0.717  | 0.620  | 0.749  | 0.432  |
Figure 3 plots the distributions of the four measurements for all images in the training set. From which we observe that 1D and 2D entropy can separate Bad and Poor images from the others well, centrality alone mostly separates Fair and Excellent images from the others, and NRSS alone can separate Bad images from the others. When integrating the four measurements together, better performance should be expected.

![Graphs of 1D entropy, 2D entropy, centrality, and NRSS](image.png)

(a) 1D entropy  
(b) 2D entropy  
(c) Centrality NRSS

**Figure 3.** The distributions of four measurements for training images.

For rating test images, we first compute the centroids of each rating category. Each image is then assigned the rating score with the one have the nearest centroid. The accuracy of each rating score images are presented in Table 4. It implies that our approach is highly consistent with subjective assessment.

| Score | No. of images | Accuracy  |
|-------|---------------|-----------|
| 1     | 207           | 96.6%     |
| 2     | 144           | 97.2%     |
| 3     | 168           | 95.2%     |
| 4     | 148           | 95.9%     |
| 5     | 269           | 96.3%     |

**Table 4.** The number of test samples for each score

4. Conclusion

In this paper, we have presented an approach to discretely rating thermal images for better imaging and inspecting electric equipment. Four quantitative measurements are investigated with respect to the considerations of information content, location of object of interest, as well as the sharpness of images. Then, the discrete rating task is transformed into a classification problem based on the four measurements and the nearest neighbour method is applied. Experiments have validated the effectiveness of our approach.

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