A methodology for processing of thermographic images for diagnostics of electrical equipment

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***Abstract* - The paper presents a methodology for processing thermographic images for improving accuracy and reducing the duration of the electrical equipment diagnostics process by using thermovision.**

Keywords - thermography, diagnostic of electrical equipment, diagnostic criteria, statistical features of images.

I. INTRODUCTION

Thermographic imaging is increasingly used in the field of diagnostics and monitoring of the technical condition of electrical equipment. This field covers a huge number of different applications, many of which are related to the industrial sector, but also includes many applications in the field of electricity generation, conversion, transmission, and distribution.

The changes in the operating temperature are one of the most common indicators for the technical state of electrical equipment and its components. Thermal imaging is an effective, non-destructive testing technique used to locate faults in complex technological, electrical, and mechanical systems. It offers many advantages such as low response time, wide temperature range, two-dimensional data acquisition, high spatial resolution and more. Sudden failures often occur in electrical and mechanical systems. However, the failure of the equipment is often preceded by a considerable period of work with the increased temperature of the various components of the system. In case of timely detection of the temperature rise, it is possible to take measures to improve the technical condition of the systems and to prevent possible sudden failures [1].

Despite the enormous potential of thermography, there is still a great deal of uncertainty in the assessment of the condition of machines and devices due to the lack of clear criteria for assessing the status based on the results of thermographic tests. This requires that the processing and analysis of received thermographic images and the classification of detected defects by priority level be performed manually by highly qualified personnel. This process is time-consuming, requires a lot of human effort, and may have errors in image interpretation. Therefore, the latest trends in the development of thermal imaging diagnostics are directed specifically at the field of automatic processing and interpretation of the images obtained. The development of such systems involves the selection of appropriate features of images to be used by modern machine learning systems [2].

The application of thermography for automatic diagnosis of electrical equipment with the help of artificial intelligence systems is still in the early stages of its development. This is due to the complex analysis and various factors that need to be considered in developing such system.

Surveys on how individual statistical features are affected by different types of failures in electrical equipment and the selection of a suitable model for the machine learning system can allow the classification of failures based on thermographic images.

II. CRITERIA AND METHODS FOR ASSESSING THE TECHNICAL CONDITION OF THE OBJECTS

The assessment of the technical condition is based on both the maximum temperature obtained from the image and the distribution of the thermal field within the elements of the object.

Depending on the procedure and timing of the acquisition of thermographic images, the methods for assessing the technical condition are classified into the following two groups:

- Methods based on absolute values of temperature;
- Comparative methods.

These methods are examined in existing standards and guidelines related to thermal imaging of electrical and mechanical systems.

The main and most widely used criterion for assessing the technical condition of the equipment is the so-called ΔT criterion. Based on this criterion, two comparative methods have been developed for the evaluation of the technical condition - quantitative comparative thermography and qualitative comparative thermography [3].

Quantitative comparative thermography is based on a comparison of the temperature of the test object with a reference value obtained from regulatory documents (Fig. 1), where ΔT_1 and ΔT_2 are the temperature rises in the moments t_1 and t_2. The other way to determine the reference value is based on operating similar facilities under similar operating conditions, the so-called baseline measurement (Fig. 2). A specific set of benchmarks should be developed on a case-by-case basis, since similar components in different installations may have different operating conditions [4].

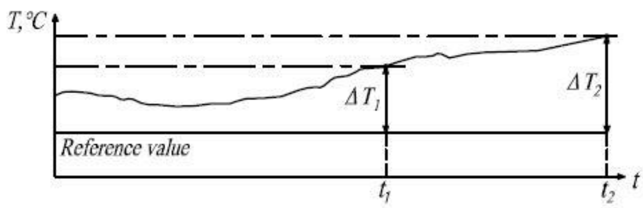

Fig. 1. ΔT criteria based on reference temperature determined by regulations

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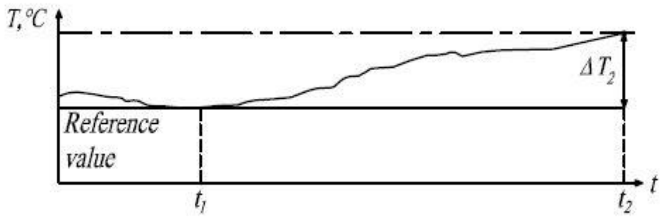

Fig. 2. ΔT criteria based on baseline measurement

The results and assessments obtained on the basis of quantitative comparative thermography are highly dependent on the conditions under which the study is conducted. On the other hand, using this method makes it possible to estimate the severity of the damage.

Quality comparative thermography is based on a comparison of the characteristics of the thermal field distribution in two or more objects with the same structural features. The thermographic images of the objects can be taken simultaneously (in a general image) or in separate images and moments of time. The main advantage of this method is that it is not necessary to know the exact values of the measurement parameters. Therefore it is slightly dependent on the camera settings and the conditions under which the survey is conducted.

In the assessment of the condition of the elements of the electrical equipment, through qualitative comparative thermography, a visual analysis of the forms, dimensions, pseudo-color representation of the thermal field, forms of temperature profiles, etc. can be used. To overcome the limitations of manual visual analysis, automated image analysis systems can be used to detect temperature anomalies in electrical equipment quickly and accurately [5].

Automated image analysis systems require a considerable amount of computing resources, as thermographic images contain a very large amount of information - 76800 variables at a resolution of 320x240. It follows that a significant reduction in the number of input parameters is required to facilitate the processing of the image and reduce its duration [6]. For this purpose, the image processing is divided into two main tasks (pre-processing and obtaining statistics), which are discussed in more detail.

III. PRE-PROCESSING

In pre-processing several basic operations are performed with the aim of converting the input data into a convenient format for further processing and reducing the volume of data by excluding unsuitable information - segmentation.

A. *Conversion of input data*

Most often, the input data is obtained in the form of thermographic images with different pseudo-color representations of the thermal field. In this case, the input data is converted to a gray scale image. This step is necessary because the color coordinates used in the pseudo-color representation do not represent a direct relationship between the intensity and the temperature in a given pixel. There are many dependencies in the literature for the transition from color coordinates to gray scale intensities, but the generalized equation used for this purpose is:

$$g(x,y) = 0.3R + 0.59G + 0.11B \ , \qquad (1)$$

where R, G and B are the color coordinates of pixel x, y.

Another way of presenting the input data is through a matrix of temperature or signal values. In this case, the data is first normalized to the maximum value of the temperature or signal, and then the data is converted into an image. This procedure is done by using the following equation:

$$g(x,y) = L_{\max} \frac{(T(x,y) - T_{\min})}{(T_{\max} - T_{\min})} \ , \qquad (2)$$

where: *T(x,y)* is the temperature of pixel *(x,y)*;

L_{max} - maximum value of gray scale intensity;

T_{min}, T_{max} are the minimum and maximum temperatures.

B. *Segmentation*

The main purpose of segmentation is to identify the image areas in which the relevant information is located. The segmentation process can be done semi-automatically or automatically.

− Semi-automatic segmentation

In semi-automatic segmentation, the operator needs to select a region from the image in which the element of interest is located

$$r = f(j,k) \ , \qquad (3)$$

where: $f(j,k)$ is the selected region of the image.

After which a search for regions with similar geometric characteristics is conducted. This search is realized by calculating the normalized mutual correlation (NCC), i.e. determining the degree of similarity or difference between two areas of the image. The correlation coefficient between the selected region and any other image region can be determined by using the dependency:

$$\lambda(u,v) = \frac{\sum_{y=1}^{k}\sum_{x=1}^{j}[r(x,y)-\bar{r}][t(x+u,y+v)-\bar{t}]}{\sqrt{\sum_{y=1}^{k}\sum_{x=1}^{j}[r(x,y)-\bar{r}]^2 \sum_{y=1}^{k}\sum_{x=1}^{j}[t(x+u,y+v)-\bar{t}]^2}} \ , \qquad (4)$$

where: $\bar{r}$ is mathematical expectation in the selected region;

$t(x+u, y+v)$ - region for which the degree of similarity is determined

$\bar{t}$ - mathematical expectation in the region for which the degree of similarity is determined

u,v - offset of the compared region in the corresponding coordinate.

Even if there are no elements with similar geometric characteristics in the image, there will always be some peak in the correlation coefficient. This requires the use of a correlation coefficient threshold to confirm the similarity of the regions.

− Automatic segmentation

Automatic segmentation methods are based on determining the threshold, according to which the processed image is converted into a binary image. Most often, threshold values are obtained on the basis of image histograms or by the Otsu method. In some cases, other types of segmentation algorithms may be needed, such as K-means clustering, but they are of limited use due to the increased complexity and execution time [7].

Let the pixels in the image be represented by the set g consisting of L on a number of gray scale levels $\{0, 1, \dots, L-1\}$. The number of pixels in the *i-th* level is h_i, and the total number of pixels is *N*. In this case, the histogram presents the discrete probability density p_i

$$p_i = \frac{h_i}{N} . \tag{5}$$

The separation of the image according to the threshold value k leads to the formation of two pixel-sets (pixel classes) - C_0 with values of the intensity *{0,1,… k-1}* and C_1 with intensities within the limits *{k,k+1,…, L-1}*. When using the Otsu method, the threshold value k is chosen so that the variance σ_B^2 between the two pixel-classes is maximal. The variance between the two classes of pixels is determined by the dependence:

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 , \tag{6}$$

where: μ_T is the mathematical expectation of intensity for the whole image;

ω_0 and ω_1 are the probabilities for occurrence of the corresponding pixel class - $\omega_0 = \sum_0^{k-1} p_i$ and $\omega_1 = \sum_k^{L-1} p_i$;

μ_0 and μ_1 - the mathematical expectation of intensity for the two classes of pixels - $\mu_0 = \sum_0^{k-1} \frac{g_i p_i}{\omega_0}$ и $\mu_1 = \sum_k^{L-1} \frac{g_i p_i}{\omega_1}$.

The results of applying the Otsu method are unsatisfactory when the intensities of the object and the background are highly variable. Another disadvantage of the Otsu method is that the image is being split into two classes, even if the split does not make real sense. These disadvantages are largely due to the fact that in the above method, only the intensity information of each pixel is taken into account, without taking into account the information from the surrounding pixels. To avoid these drawbacks, an improvement is made to the method, which uses a two-dimensional histogram to take into account the information from surrounding pixels.

IV. STATISTICAL FEATURES OF IMAGES

After the segmentation is performed, the information contained in the image is extracted. For this purpose, statistical features (statistical indicators) are calculated. These features can be divided into three groups: histogram-based features, features of the gray scale co-occurrence matrix (GLCM), and component-based features of intensity.

A. Histogram-based statistical features

The features in this group are used to describe the distribution of intensity (temperature) values throughout the image. These features include mean value μ, variance σ^2, standard deviation σ, skewness, kurtosis, maximal intensity and entropy *H*. The following dependencies are used to determine histogram-based statistical features:

$$\mu = \frac{1}{xy} \sum_{i=0}^{L-1} g_i h_i \; ; \tag{7}$$

$$\sigma^2 = \frac{1}{xy} \sum_{i=0}^{L-1} (g_i - \mu)^2 h_i \; ; \tag{8}$$

$$\sigma = \sqrt{\frac{1}{xy} \sum_{i=0}^{L-1} (g_i - \mu)^2 h_i} \; ; \tag{9}$$

$$Skewness = \frac{1}{xy\sigma^3} \sum_{i=0}^{L-1} (g_i - \mu)^3 h_i - 3 \; ; \tag{10}$$

$$Kurtosis = \frac{1}{xy\sigma^4} \sum_{i=0}^{L-1} (g_i - \mu)^4 h_i \; ; \tag{11}$$

$$H = -\sum_{i=0}^{L-1} p_i \log(p_i) \; ; \tag{12}$$

B. Features of the gray scale co-occurrence matrix

The co-occurrence matrix of gray scale levels (intensities) $m \times n$ is a square matrix with dimensions equal to the number of gray scale intensity levels. The individual elements of the matrix represent the values of the probability of occurrence of pixels with definite levels of intensity that are distant at a certain distance in a given direction.

The two-dimensional statistical indicators that can be determined on the basis of the gray scale level co-occurrence matrix are a total of 14. Some of them relate to specific structural features of the image, such as homogeneity and contrast, that reflect the presence of an organized structure within the image. Others illustrate the complexity and nature of intensity transitions. Although all of these indicators contain information about the structural features of the image, it is difficult to identify which particular structural feature is represented by each of these features [8].

Different combinations of indicators are used in different fields of science depending on their specifics. The following indicators are being used in the processing of thermographic images for needs of the diagnosis the technical condition of electrical equipment: homogeneity, energy, entropy, contrast and correlation coefficient. The following dependencies are used to determine the values of these indicators for the region of interest obtained after segmentation:

$$Homogeneity = \sum_{m=0}^{L-1} \sum_{n=0}^{L-1} \frac{p(m,n)}{1 + |m-n|} \; ; \tag{13}$$

$$Energy = \sum_{m=0}^{L-1} \sum_{n=0}^{L-1} p^2(m,n) \; ; \tag{14}$$

$$Entropy = -\sum_{m=0}^{L-1} \sum_{n=0}^{L-1} p(m,n) \log_2[p(m,n)] \; ; \tag{15}$$

$$Contrast = \sum_{q=0}^{L-1} q^2 \sum_{m=0}^{L-1} \sum_{n=0}^{L-1} p(m,n), q = |m-n| \; ; \tag{16}$$

$$Correlation = \frac{\sum_{m=0}^{L-1}\sum_{n=0}^{L-1} p(m,n) - \mu_x \mu_y}{\sigma_x \sigma_y}, \quad (17)$$

where: $p(m,n)$ is the probability of occurrence of pixels with intensities m and n at a given distance from each other;

μ_x and μ_y are the mathematical expectations of the values of the gray scale level co-occurrence matrix in the horizontal and vertical directions;

σ_x and σ_y - standard deviations of the values of the gray scale level co-occurrence matrix in the horizontal and vertical directions.

C. Component-based features of intensity

Component-based intensity features are similar to histogram-based features but are only determined for the region of the image obtained after the segmentation process. The most commonly used component-based indicators are minimum and maximum intensity, average intensity, variance, and standard deviation. The formulas used to determine these indicators are:

$$g_{\max} = \max g_i ; \quad (18)$$

$$g_{\min} = \min g_i ; \quad (19)$$

$$\mu_g = \frac{1}{ab}\sum_{i=0}^{L-1} g_i h_i ; \quad (20)$$

$$\sigma^2 = \frac{1}{ab}\sum_{i=0}^{L-1} (g_i - \mu_g)^2 h_i ; \quad (21)$$

$$\sigma = \sqrt{\frac{1}{ab}\sum_{i=0}^{L-1} (g_i - \mu_g)^2 h_i}, \quad (22)$$

where a and b are the dimensions of the region obtained from the segmentation for which the features are calculated.

Using these indicators as input parameters in modern machine learning-based systems would greatly reduce their complexity and time for image analysis and technical state estimation.

V. CONCLUSION

The methodology considered includes all the necessary steps for extracting information from thermographic images.

The resulting statistics can be used as diagnostic parameters for quality comparative thermography.

The use of image statistical features in thermal imaging results in a decrease in the dependence of the results of the conditions under which the measurement was performed.

The use of image statistics significantly facilitates the development of automated image analysis systems and the resources they require.

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