Detection of power line insulators on digital images with the use of laser spots

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Abstract: The massive growth of technologies used to register and process digital images allow for their application in evaluating the technical condition of power lines. However, it is not possible without a set of dedicated methods for obtaining diagnostic information based on registered video data. The method described here details the detection of power line insulators in digital images featuring diversified backgrounds using laser spots. The algorithm of detecting an insulator in analysed images is based on testing the digital signal of pixel intensity profiles read between subsequent pairs of laser points in the image. The method is comprised of the following stages: import the image with laser spots, detection of spots on the image, and pattern classification of each image profile that is calculated for each found laser spots pair. The evaluated profiles depicting an insulator were characterised by regular patterns that reflect the target structure. To classify profiles as either insulator containing or non-containing, several steps should be followed: averaging the signal, removing the linear trend, finding and alternating the minima and maxima. The performance of the proposed method was verified using an open-access dataset, comprised of various scenes featuring high-voltage power line insulators.

1 Introduction

The evaluation of power line condition is a process that directly decreases the number of failures in electric power distribution systems. When it comes to the safety of the energy system, high-voltage and highest-voltage power lines play a vital role. The collection of diagnostic data on power lines can be divided into:

- operations carried out from the ground by teams of people, on foot or with the use of terrain vehicles,
- operations carried out from the air, with the use of aircraft or unmanned aerial vehicles (UAV) [1–4],
- operations carried out by devices which are fixed directly to – or within a very short distance from – the components of a power line, i.e. various types of CCTV systems and diagnostic robots [5–7].

Researchers are actively working towards applying different types of equipment for registering digital images in visible light, ultraviolet, and infrared (e.g. [6, 8, 9]), as well as on new diagnostic methods based on computer vision solutions (e.g. [10–12]). In the case of diagnostic operations conducted by teams of people, the evaluation of damage to power line components is done during an inspection. This approach to documentation has its advantages and disadvantage. The primary drawback is the excessive time required to complete. The advantage is that the collected material – commonly photographs – is used mainly for documentation purposes of damaged power line components. The remaining diagnostic methods, such as those calling for aircraft use, focus solely on collecting data using sensors, and the detection and analysis of damage is carried out at the stage of data. This approach requires a large amount of data to be processed, obtained from various types of sensors, which in turn requires considerable computational power.

The components of power lines most prone to damage are [13]: conductors, connectors, clamps, support structure elements (poles) and, especially, insulators. It is estimated that upwards of 50% of the overhead power line maintenance costs pertain to insulators (replacement, repair, and technical diagnostics). Insulator failures due to mechanical and electric forces account for ∼70% of power line downtime [14]. As detailed in [15], a failure is a situation where one of the two basic functions of an insulator (electrical insulation or carrying mechanical load) is not fulfilled.

Insulators used in overhead power lines are made either of porcelain, glass, or polymer composite materials. Regardless of the material used in its production, the shape of the insulator was designed to maximise the leakage path along its surface from one end to the other. To achieve this, the insulator's surface is a series of corrugations or downward facing cups. Due to the varied nature of failures occurring in different types of insulators, the task of developing a universal tool for the localisation and diagnosis of damage to different insulators is highly complex.

The main goal of video-based power line insulators diagnosis is the reduction of failure risk by:

- controlling the construction of the power line (detection of assembling errors, verification of insulator selection),
- localisation of damaged insulators, verification of the degradation stage.

The issue presented in this article concerns the localisation of insulators in digital images, which is a key stage of insulator damage detection. Insulators are poorly visible from the ground due to their position on the upper parts of the supporting structure. Obtaining high-quality images, which can be used in further analysis, requires images to be taken near overhead power lines and components. The proposed solution is employing recording systems mounted on aircraft (both manned and unmanned).

2 Study of the detection of electrical insulators in digital images

Several research centres are in the process of conducting insulators detection studies using digital images. The method developed in [16], based on speeded up robust features (SURF) and intuitionistic fuzzy set (IFS) algorithms, allows insulator detection in aerial images without using a pattern or segmentation. The first stage consists of searching for key features with the SURF algorithm, and the obtained points are then divided into a specific number of classes using the IFS algorithm based on the correlation coefficient.
If the correlation between the obtained sets is higher than the set point, then both classes can be treated as sets from the same class. The insulator is identified based on the characteristic value of a shape coefficient, such as the slenderness ratio and duty ratio.

In [17], the authors used scale-invariant feature transform (SIFT) algorithm to localise insulators. The localisation was done with a pattern obtained from an image in the infrared band. The localisation of an insulator is done by analysing points of a given colour that represent temperature. One example is research published in [18].

Although the methods based on SIFT and SURF algorithms are capable of detecting and localising an object with precision, there are limitations to their application. Depending on the complexity of the background, the images generate substantial numbers of local features, which translates into an increase in computational costs. In the case of aerial pictures, insulators often appear on highly diversified backgrounds. Most of the time, the object's detection requires a pre-made pattern.

Another approach for detecting and localising an insulator, which uses template matching, is presented in [19]. The author segmented images into defined classes with the use of the statistical region merging method; the image was then converted to greyscale, and the resulting histogram analysed. At this stage, the histogram represents single objects in the image. The insulator was identified based on template matching with the use of the correlation method. This method, however, does not work when the insulator's structure is irregular, and it is sensitive to image distortion.

A large number of studies have analysed insulator texture to localise the feature using methods such as: Markov random field, Gabor filters, or grey-level co-occurrence matrix (GLCM) [12, 20]. In [21], the author used the principal component analysis and texture descriptor active contour method; allowing insulators to be localised in low-contrast images. The authors tested the algorithm on 100 insulator containing images, taken from a helicopter. To work correctly the method required identifying a series of parameters selected by the authors empirically, which could reduce the method's efficacy if the input samples are highly diversified. Another disadvantage of methods based on GLCM is high computational complexity.

Additional attempts included training an support vector machine (SVM) classifier on the basis of various feature vectors [22]. In [23], an SVM algorithm was used to locate insulators utilising features obtained from a Gabor filter (Gabor features). These approaches require a high number of samples in the process of teaching an SVM classifier.

Another potential method that could improve the detection process to deal with damages localisation is graph-based anomaly detection. This technique is used to detect abnormal substructures contained in the data. The anomalies are defined as unusual events, which means that abnormal events are infrequent patterns. The main difficulty of the graph-based anomaly detection method is the size of the search space [24].

It has been stated that insulators share a recurring component in their structure regardless of their type, which is why a number of approaches apply a defined, cyclic pattern in the localisation process. In [25], the authors obtained a set of features describing an insulator with the use of the discrete orthogonal S-transform method. The collected set of features was then passed through a classification algorithm as a template. However, the approach proposed by the authors has proven to be ineffective for locations with high background diversity.

An interesting approach is the use of deep learning techniques in the identification of power line components, including insulators. Deep convolutional neural networks, such as YOLO [26], R-FCN [27], SSD [28] in conjunction with networks used for classification, like VGG-Net [29, 30], Inception-V4 [31], show promising results. ‘Connected drone project 2016–2018’ deserves special attention; implemented by eSmart SYSTEMS, the project aims at automating power line diagnosis with the use of methods employed in deep learning. Methods such as convolutional neural networks use an approach that does not require the operator to adjust search parameters after the training stage, which is a highly desirable feature. As noted in [11], this approach has several key disadvantages, which currently hinder it from being applied on a wider scale.

One drawback is the lack of data, which could be used to train appropriate classes to networks. The data should describe the object in the various angles and scales and could be generated using augmentation methods. The other option for small training sets is the usage of CNN architectures which are scale and rotation invariant [32, 33]. Another problem arises from the complexity of the power line itself. In the network's learning process, each object class is required to have the same number of training samples. Insulators may be divided into several classes of a lower level; the type of insulators along a line may not be homogeneous. This leads to a situation where a network learns by using the number of samples equal to the rarest component. Other issues identified by the authors are problems with the detection of small and covered elements and with the filtration of power line components on a diversified background. Finally, the last inconvenience is a lack of comparative samples in the form of datasets for particular components, which would allow the method to come into effect.

3 Instrumentation

The developed method of insulator detection is based on using a dedicated system consisting of: a Canon EOS 5D Mark II camera, a powerful laser with 532 nm wavelength, and a dedicated unit (to control both devices). The system is designed to locate electrical insulators in an image with a diversified background and with changing lighting conditions. As pointed out in the literature review, the methods which are currently in development do not achieve this task due to the computational cost incurred while locating the insulator.

The present method was developed using a laser that generates a grid of spots (luminous patterns) with a defined electromagnetic wavelength. The laser is located on the camera's horizontal optical axis to ensure even coverage of the scene by luminous spots. The system is equipped with a self-made control device that regulates the laser's operating time and allows image sequencing. This approach enables us to obtain two frames of one scene, where one frame includes luminous patterns, and the other does not, ensuring that during further analysis of the insulator's surface the final frame does not contain luminous patterns, which could hinder its analysis by introducing additional data to the images in the form of non-existent luminous spots. The driver allows operators to regulate the time of the laser's operation and to release the camera's shutter at a specific moment, which enables us to obtain test series within a particular time frame.

The presented method has been verified assessing a dataset (Appendix) [31] consisting of four testing scenes featuring an insulator on a background (e.g. farmland, forest, and grass), which is most commonly registered during UAV inspections. The background was purposefully selected so that the scene contained the maximum number of green and near-green elements. This approach assessed the effectiveness of detecting laser spots with a wavelength of 532 nm in near-natural conditions.

The insulator was positioned in an outdoor scene, to assess the effect of sunlight on the method, with the use of a stand that enabled a change of position in relation to the observation point. A series of measurements were carried out for each scene, comprised of pictures taken cyclically with and without a laser grid in a specific time interval. The insulator was analysed in two most common positions – horizontal and vertical line with variable outdoor illuminance between 632 and 45,479 lx. The test yielded 1233 pictures with laser spots and 1166 pictures without laser spots. The scene was prepared in a way that allowed for the maximum of four laser spots to be visible on the insulator. As a result of changing atmospheric conditions, the recorded shot contained one of the four variations of the numbers of visible laser spots captured on the insulator (0, 2, 3, 4). To assess the effectiveness of the presented method, the pictures were also manually classified and labelled to specific variations.

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4 Method of detecting power line insulators in digital images with the application of laser spots

The process of detecting an insulator in the analysed digital images is based on verifying pixel intensity profiles read between subsequent different pairs of points contained in the image. Examples of profiles classified as part of the verification step of the described method are presented in Fig. 1.

To accurately evaluate the effectiveness of this process, it is essential to select an appropriate initial and final point of the profile. Verifying a large number of pairs is time consuming; the complexity of the computational process for an image consisting of n points is O(n²), and the number of all pairs of points that could be generated is precisely Cₙ = n(n - 1)/2. Verifying all profiles for all combinations of points in an image would be highly ineffective; for a picture with the resolution of 1920 × 1080, the number of points/pixels in that picture is over 2 × 10⁶ (2,073,600), which yields almost 2.15 × 10¹² pairs of points or profiles for a single photograph analysis. It is worth noting the SIFT algorithm (with the following parameters: octave layers = 3, contrast threshold = 0.04, edge threshold = 10, sigma = 1.6) for one picture from the dataset provides 62,686 local points, most of which are not on the insulator.

To avoid comparing a high number of pairs, it was decided to apply laser markers emitted onto the object at the moment of shooting. The laser light is emitted with the use of a suitable lens for dispersing to light, forming a grid of spots. Electrical insulators are usually placed on supporting structures with no other objects in the vicinity, allowing for most of the emitted laser light to disperse and the resulting laser spots fall only onto objects that are located in the closest proximity of the camera: insulators, supporting structures, power lines, and so on.

The next stage of the analysis was searching for laser spots in recorded picture f'(x, y) and checking pixel value profiles between the pairs of detected markers only. Once laser spots in the analysed image were detected correctly, all possible profiles between them were determined and tested using a developed algorithm, resulting in a decision on whether the characteristics of an analysed profile matched an insulator pattern or if the result did not yield enough data to generate this decision. If the profile verification revealed the presence of an insulator in a picture, the coordinates of the appropriate segment were displayed. Fig. 2 presents the subsequent stages of the proposed insulator detection method. The algorithm for the proposed method of detecting power line insulators in digital images with the application of laser spots is presented as Algorithm 1 (see Fig. 3). Individual operations are explained further in the paper.

The next sections provide a detailed description of the two main stages of detecting long rod insulators (i.e. detecting laser spots in a digital image and classifying intensity profiles between the detected laser spots). The study was carried out with the set of mentioned earlier images taken with diverse backgrounds in changing lighting conditions. The main objective of this study was to verify the developed method by analysing the average error of detecting laser spots and testing its precision, recall, and accuracy for verifying intensity profiles.

5 Detection of laser spots in a digital image

To accurately detect an insulator it is necessary to load image f('_RGB(x, y)′) registered with the use of a camera supported by a laser beam emitting device. We decided to use lasers operating in a 532 nm band, whose light is registered most clearly in the green spectrum of the camera's imaging sensor as it was important later in the analysis.

Laser markers were detected in the image with the use of the L'a*b' colour space, which proved to be useful in completing this task, as a colour space records information about each pixel separately, coding its lightness level and colour components (e.g. green to magenta, yellow to blue). This is why after loading picture f('_RGB(x, y)′), it is converted into image f'_Lab(x, y)′ with the use of CIE Standard Illuminant D₆₅ for translating specific values of pixels.
Before carrying out further computations, it was vital to pre-set two variables, which were used later to break loops. These variables were blob counter \( n_B \) and threshold value \( \mu \). For the present operation, the variables were set to \( n_B = 0 \) and \( \mu = 0 \) respectively.

The threshold update \( \mu = \mu + \delta \) occurred in the first attempt with this procedure, as applying the initial state would not yield any results anyway.

The image \( f_{LAB}(x, y) \) was segmented, and its binary equivalent \( f_{BW}(x, y) \) was determined with the use of image channel \( a' \) entirely, as it excluded only the green laser markers.

Based on the initial analysis, observations established that the use of channel \( a' \) enabled efficient distinction of the registered laser spots with appropriately adjusted threshold \( \mu \), which is substantially different for individual analysed images. Fig. 4 shows histograms of channel \( a' \) for two images taken in identical lighting conditions, without changing the position of the object and the camera. The lower panel (Fig. 4b) refers to an image with laser spots, and the upper panel (Fig. 4a) refers to an image without spots. Histograms for the whole spectrum of channel \( a' \) are presented on the left-hand side.

The far left region of the histograms is presented on the right-hand side (labelled as: left tail) to provide a clear view of the part of the histogram where the information that maps green laser spots was recorded.

To determine the correct level of dilation, simulations of blob detection were performed with different dilation levels. The results of the dilation simulations ranged from 0 to 9 pixels and compared in Fig. 6. It was observed that for higher dilation values, the average number of errors in marker detection decreased, which is why this parameter was set to \( \alpha = 7 \) in further analysis.

For the provided parameters used in the method, the level of erroneously detected laser spots was verified to assess the accuracy of the method. Additionally, to confirm the method’s resistance to the change in the character of the registered images, the findings of the analysis were recorded with reference to individual scenes (the results are presented in Table 1).

High accuracy of laser spot detection was observed in each of the analysed scenes. At a dilation of 7 pixels, which was assumed for the whole set of images processed, 98.78% of markers were detected on average. The lowest efficiency obtained for scene \( E_{trees_v} \) (91.76%) was a result of an increased distance between the source of laser spots and the observed object.
were tested using an evaluation algorithm (presented further in the study), and generated characteristics of the analysed profile corresponding to insulator: $d_1 = 1$, or without an insulator: $d_1 = 0$ was found.

The presented algorithm enabled tested pixel profile verification for indicated regions of an insulator-containing image. Due to the specific structure of insulators, which are mostly comprised of multiple identical elements, the profile cropped from a fragmented image of an insulator should be characterised by a regular pattern that reflects its structure. The following profile analysis aimed to verify whether the tested pixel profiles contained these regular and structured pixels, enabling unambiguous separation of images which do and do not contain insulators. At the same time, if possible, it should be done with the smallest possible number of computational operations, employing the simplest possible methods.

For the purposes of insulator detection in digital images, an algorithm [Algorithm 2 (see Fig. 7)] was developed for classifying the profiles obtained from the application of laser spots.

For the classification to be performed, it was vital to read pixel profile $P_{RGB}(z)$ from the image. A positive ($d = 1$) or negative ($d = 0$) decision was made following the test. A positive decision concerns profiles containing a set of values of pixel intensity characteristic of an insulator along the whole length. A negative classification was formed for profiles not containing an insulator, and those which contain an insulator only in their fragment.

After initial tests of the method and numerous profile revisions, it was observed that these profiles – more specifically their beginning and end – were highly distorted by the recorded light from laser markers. The characteristics of these markers were distinguished by very high-profile values, which on the one hand allow swift marker detection but can be problematic in cases requiring further profile analysis. This is why the first two methodology operations were aimed at removing the effect of these markers on the analysed profile. The beginning and end of a profile were determined to be places the laser marker is most visible. Thus, the cropping of these fragments from their beginning and end to obtain a profile, $P_{RGB}(z)$, equal to 95% of the length of the input profile.

To avoid distortions, which may be caused by randomly registered laser reflections on the remaining parts of the analysed profile, the green channel of the profile is omitted in further analysis, as the light the laser emits is green. Averaged profile $P_{RGB}(z) = (P_{R}(z) + P_{B}(z))/2$, consisting of only red and blue channels is forwarded for further analysis.

A profile standardisation is required to conduct the final analysis. Firstly, images of insulators were registered in various lighting conditions and with different camera positions, which can yield different values, depending on lighting intensity. Secondly, profiles are read from a 2D image along straight lines, which do not have to be parallel to the axis of the insulator itself. This may result in a decreasing or increasing profile characteristic. Both these phenomena were levelled out by standardising the profile by determining a profile trend through linear regression $R_{\Delta z}(t) = \rho_1 + \beta_{\Delta z} + \epsilon$ and subtracting it from the profile, which gives: $P_{\Delta z}(z) = P_{RGB}(z) - R_{\Delta z}(t)$.

Further analysis of the intensity profile is achieved by profile smoothing. This next stage of normalisation aimed to reduce excess fluctuations of the verified values. It also allowed us to avoid shifted minima and maxima of the profile and facilitated insulator template recognition. The values of the colour profile were processed using a moving average as determined by

**Table 1** Accuracy of detecting markers in individual scenes

| Scene name | Number of spots | Number of beams emitted | Accuracy, % |
|------------|----------------|-------------------------|-------------|
| A_corn_h   | 613            | 613                     | 100.00      |
| B_corn_v   | 739            | 780                     | 94.74       |
| C_trees_h  | 815            | 816                     | 99.88       |
| D_grass_v  | 452            | 452                     | 100.00      |
| E_trees_v  | 245            | 267                     | 91.76       |
| F_grass_h  | 293            | 293                     | 100.00      |
| G_grass_v  | 254            | 254                     | 100.00      |
| H_grass_v  | 846            | 856                     | 98.83       |
| all images | 4278           | 4331                    | 98.78       |

specific to the applied dilatation

For subsequent segments the use of coordinates for individual blobs and the pairs of coordinates were allocated as presented in the following equation:

$$B_k(x_i, y_i) : S_{i, n_i} = \left\{B_1(x_i, y_i), B_2(x_i, y_i), \ldots, B_{n_i}(x_i, y_i)\right\}$$

Next, for each segment $S_i$ (with the use of two pairs of coordinates for its component points) colour intensity profile $I_{RGB}(z)$ was calculated from image $f_{RGB}(x, y)$.

The resulting profiles $P_{RGB}(z)$ were tested using an evaluation algorithm (presented further in the study), and generated characteristics of the analysed profile corresponding to insulator: $d_1 = 1$, or without an insulator: $d_1 = 0$ was found.

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Input: \( P_{RGB}^i(z) \)
Output: \( d \)

01: \( \text{set } d = 0 \)
02: \( \text{set } P_{RGB}^j(z) \) middle 95% of \( P_{RGB}^i(z) \)
03: \( \text{compute } P_{\delta}^j(z) \) by averaging red and blue channels of \( P_{\delta}^i(z) = (P^i_B(z) + P^i_R(z))/2 \)
04: \( \text{compute } \) standardized \( P_{\delta}^k(z) \) removing the linear trend \( P_{\delta}^k(z) = P_{\delta}^i(z) - R_{\delta}(t) \)
05: \( \text{set } P_{\delta}^k(z) \) by applying the moving average with the step \( \alpha_4 \) to \( P_{\delta}^k(z) \)
06: \( \text{search for minima } m^-_i \) and maxima \( m^+_j \) in \( P_{\delta}^k(z) \) with minimum peak prominence \( \alpha_5 \)
07: \( \text{if all } m^-_i < 0 \wedge \text{ all } m^+_j > 0 \wedge \text{ number of } m^-_i > \alpha_6 \wedge \text{ number of } m^+_j > \alpha_6 \) then
08: \( \text{if the set of sign (sort (join } (m^-_i \wedge m^+_j)) \text{ order by } z) \)
do alternate then
09: \( \text{compute } \Delta m^-_i, \Delta m^+_j, \mu_{\Delta m^-_i}, \mu_{\Delta m^+_j} \)
10: \( \text{if } \left| 1 - \mu_{\Delta m^-_i}/\mu_{\Delta m^+_j} \right| < \alpha_7 \) then
11: \( \text{compute } C_v(\Delta m^-_i), C_v(\Delta m^+_j) \)
12: \( \text{if } C_v(\Delta m^-_i) < \alpha_8 \wedge C_v(\Delta m^+_j) < \alpha_8 \) then
13: \( \text{set } d = 1 \)
14: \( \text{end} \)
15: \( \text{end} \)
16: \( \text{end} \)
17: \( \text{end} \)
18: \( \text{return } d \)

**Fig. 7 Algorithm 2: classification of intensity profiles**

**Table 2** Values of prediction quality measures for insulator detection depending on changes in the prominence parameter of the analysed profiles \( \alpha \).

| Performance | Accuracy | Recall | Precision |
|------------|----------|--------|-----------|
| \( \alpha_1 = 0.10 \) | 0.9611 | 0.9332 | 0.9864 |
| \( \alpha_1 = 0.15 \) | 0.9674 | 0.952 | 0.9806 |
| \( \alpha_1 = 0.20 \) | 0.9816 | 0.9811 | 0.9911 |
| \( \alpha_1 = 0.25 \) | 0.9887 | 0.9949 | 0.9922 |
| \( \alpha_1 = 0.30 \) | 0.9991 | 0.9983 | 0.9979 |
| \( \alpha_1 = 0.35 \) | 0.9887 | 0.9983 | 0.9979 |
| \( \alpha_1 = 0.40 \) | 0.9991 | 0.9983 | 0.9979 |
| \( \alpha_1 = 0.60 \) | 0.9916 | 0.9931 | 0.9988 |
| \( \alpha_1 = 0.80 \) | 0.915 | 0.8295 | 0.9959 |

**Fig. 8** Profile after standardisation and application of moving average \( \alpha = 3 \) with initial minima, maxima and distances between them

Relation to the values of the minima and maxima of the whole intensity profile

\[
\alpha \cdot \left( \max(P_{\delta}(z)) - \min(P_{\delta}(z)) \right)
\]  

Table 2 contains an analysis of the effect a change of prominence parameter had on the obtained accuracy and precision of the results in order to designate value \( \alpha_5 \) for further analysis.

Based on the conducted observations, it was noted that the highest values of prediction quality measures were obtained for \( \alpha_5 \in (0.2; 0.5) \). As predicted, the values of the observed measures increased with increasing parameter \( \alpha_5 \) and after exceeding \( \alpha_5 = 0.3 \) a significant decrease in accuracy and recall measures was observed. In further deliberations, \( \alpha_5 = 0.3 \) was taken, for a high level of observed accuracy (98.91%) and recall (99.83%) measures.

To decide whether the analysed profile was obtained from an image depicting an insulator, several conditions need to be verified. The designated minima of standardised profile \( P_{\delta}(z) \) needed to be negative \( m^-_i < 0 \) and the maxima needed to be positive \( m^+_j > 0 \). The size of minima and maxima sets, determined with parameter \( \alpha_6 \), also needed confirmation (4). The application of easy to verify conditions allowed swift algorithm termination if the profile did not contain a suitable number of minima and maxima for further testing. The presented study assumed \( \alpha_6 = 3 \)

\[
\text{count}(m^-_i) \geq \alpha_6 \wedge \text{count}(m^+_j) \geq \alpha_6
\]

Next, it was verified whether minima \( m^-_i \) and maxima \( m^+_j \) sorted according to variable \( z \) were alternating (denoted in Fig. 8 with broken arrow symbols).

Following a positive classification of the preceding dependencies, the distances between subsequent minima \( \Delta m^-_i = m^-_i - m^-_{i-1} \) and between maxima \( \Delta m^+_j = m^+_j - m^+_{j-1} \) were calculated and their average values were determined by

\[
\mu_{\Delta m^-_i} = \sum_{i=1}^n (\Delta m^-_i) \cdot n^{-1}
\]

\[
\mu_{\Delta m^+_j} = \sum_{j=1}^n (\Delta m^+_j) \cdot n^{-1}
\]

Next, it was verified that the average distances between minima and maxima are similar, the following dependency needs to be met:

\[
\mu_{\Delta m^-_i} = \mu_{\Delta m^+_j}
\]
Parameter $\alpha_i$ denotes the tolerance when comparing both average values of the distance between minima and between maxima. The presented study assumed a parameter value of $\alpha_i = 0.05$, meant that there was great similarity between both verified variables. For comparison, the effectiveness of the method was determined for $\alpha_i = 0.15$; but increasing the value of this parameter resulted in a decrease in accuracy and precision (results are shown in Table 3).

The final condition required by the method was the comparison of two coefficients of variance calculated separately for the minima and maxima of the profile according to the following dependency:

$$C_V(\Delta m^i) = \frac{\mu_{\Delta m^i}}{\sigma_{\Delta m^i}}$$

$$C_V(\Delta m^j) = \frac{\mu_{\Delta m^j}}{\sigma_{\Delta m^j}}$$

The values of distance deviations between minima $\sigma_{\Delta m^i}$ and maxima $\sigma_{\Delta m^j}$ were calculated, respectively, using the following equations:

$$\sigma_{\Delta m^i} = \left(\sum_{i=1}^{n} (m_i - \mu_{\Delta m^i})/(n-1)\right)^{0.5}$$

$$\sigma_{\Delta m^j} = \left(\sum_{i=1}^{n} (m_j - \mu_{\Delta m^j})/(n-1)\right)^{0.5}$$

In order for the condition (12) to be met, the tested minima and maxima were required to be characterised by small relative variance, which is why both of the determined variance coefficients were smaller than $\alpha_i$:

$$C_V(\Delta m^i) < \alpha_i \land C_V(\Delta m^j) < \alpha_i$$

Parameter $\alpha_i = 0.2$ was assumed in the course of this study, which allowed us to properly identify the verified profiles of insulators.

If all the mentioned conditions were met, the tested profile was deemed to be derived from an insulator. Otherwise, failure to meet one of the conditions, even in the first instance, broke the procedure and resulted in a negative outcome. Further calculations were no longer required, shortening the process of classifying subsequent profiles.

Table 4 details the final results of intensity profile classifications and insulator detection, for the values of method parameters set in the course of the study. The calculations were performed with the use of the following parameters: step parameter for profile smoothing $\alpha_i = 3$, minimum peak prominence for minima and maxima searching $\alpha_j = 0.3$, required minimal number of minima $m^i$ and maxima $m^j$ set to $\alpha_k = 3$, maximum permissible difference between $\mu_{\Delta m^i}$ and $\mu_{\Delta m^j}$ set to $\alpha_7 = 0.05$, and maximum permissible coefficient of variance for found distances between minima $\Delta m^i$ and maxima $\Delta m^j$ set to $\alpha_8 = 0.2$. For 20,118 verified profiles, the right decision was made in 94.26% of the cases (true positive = 17%, true negative = 77.26%), with 98.79% precision and 75.44% sensitivity for the classification method. The final result of the method was successful insulator detection, and an efficacy of 98.91% was achieved for the analysed scenes in this dataset.

The additional experiment was conducted to compare the performance of the proposed method with current methods. This was done using the previously mentioned convolutional neural networks (Section 2 of the paper): YOLO [26] (Yolo 3.0 version), Faster R-CNN [34] and SSD [28] (the implementation of SSD with Inception was used). The required training was conducted using the dataset composed of the images with and without power line insulators, with additional image augmentation (using scale and rotation operations to extend training set). The resulting performance comparison (Table 5) was calculated on the test set comprised of 250 images (augmented and containing laser spots). The high accuracy and precision of the method was due to the use of laser spots – the main advantage of the tested CNN methods. To improve performance, much larger image sets should be provided.

### Table 3: Values of prediction quality measures for insulator detection depending on changes in the parameter for admissible tolerance for the comparison of average distances between minima and between maxima of analysed profiles $\alpha_i$.

| Performance | $\alpha_i = 0.05$, % | $\alpha_i = 0.15$, % |
|-------------|----------------------|----------------------|
| accuracy    | 98.9                 | 97.5                 |
| recall      | 99.8                 | 99.8                 |
| precision   | 98.0                 | 95.3                 |

### Table 4: Results of classification and values of prediction quality measures for the final insulator detection for 2389 processed images of insulators and 20,118 classified profiles containing insulator templates.

| Parameter                  | Classification of intensity profiles, % | Insulator detection, % |
|----------------------------|----------------------------------------|------------------------|
| Result comparison          |                                        |                        |
| TN                         | 77.26                                  | 50.15                  |
| FN                         | 5.53                                   | 0.08                   |
| FP                         | 0.21                                   | 1.00                   |
| TP                         | 17.00                                  | 48.77                  |
| Prediction quality measures|                                        |                        |
| accuracy                   | 94.26                                  | 98.91                  |
| recall                     | 75.44                                  | 99.83                  |
| precision                  | 98.79                                  | 97.98                  |

### Table 5: Performance comparison of the proposed method and CNN implemented insulator localisation.

| Method           | Accuracy, % | Recall, % | Precision, % |
|------------------|-------------|-----------|--------------|
| proposed method  | 96.101      | 96.317    | 98.982       |
| Yolo_V3          | 86.667      | 89.412    | 89.412       |
| SSD              | 89.629      | 92.941    | 90.804       |
| faster R-CNN     | 94.074      | 98.823    | 92.308       |

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Appendix

9.1 Supplementary data

Dataset associated with this article can be found in the online version at: http://cv.po.opole.pl/dataset1.