Choice of Spectral Range for Devices for Remote Sensing of Power Lines

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Abstract—This article describes the basic methodological aspects of designing multispectral optoelectronic devices for the remote inspection of overhead power lines. A method for selecting operating spectral areas for these devices was suggested on the basis of the proposed detection criteria. The proposed method considers physical phenomena that occur during the visual inspection and detection of objects. It allows the rational selection of operating areas of a multispectral device, including the number, width, and location of these areas in the optical spectrum. The author determines that effect of the spectral area width on object detection probability can be estimated by the correlation between spectral and integral contrasts.

The optimal operating areas for multispectral devices with direct image visualization are selected according to the developed method. The solution of the optimization problems suggests that the detection of the standard overhead power lines requires images to be formed in the following spectral areas: when power lines are located against the background of the green vegetation - 725…775 nm, 825…875 nm, 475…575 nm, 375…425 nm; and against a softwood forest - 625…675 nm, 375…425 nm, 875…925 nm. In addition, the study describes methods for estimating their efficiency and provided the simulation results of the operation process.

Keywords—multispectral device; power line; optimality criterion; detection; contrast; spectral area

I. INTRODUCTION

Backbone overhead power lines in Russia cover a total length of 150,000 km. The efficient operation of overhead power lines requires periodic diagnostics and precise localization of areas determined during fault diagnostics.

The preventive maintenance of overhead power lines is characterized by low responsiveness and low detection precision of emergency and pre-emergency conditions at energy sites. Flying vehicles equipped with multispectral optoelectronic devices for thermovision inspection can improve the efficiency of fault diagnostics and localization in power lines and other energy sites [1]. An effective solution for monitoring the condition of power lines is often complicated by the large length and inaccessibility for land vehicles of this type, especially taking into account the geographic specificity of Russia. Therefore, the only possibility of monitoring is to monitor such objects from the air using manned or unmanned aerial vehicles.

Regular inspection of power lines using large heavy manned aircraft may not be economically justified.

As an alternative, unmanned aerial vehicles carrying digital photo and / or video equipment can be used to solve this problem, which is a much more efficient solution from the economic point of view. In addition, modern achievements in such fields of science as computer vision and photogrammetry, as well as constant improvement of the onboard photo / video equipment, allow us to speak about the possibility of qualitative restoration of three-dimensional models of objects that require appropriate monitoring.

Currently, there is an acute problem of timely detection of transmission line defects with subsequent elimination in order to prevent an unplanned line trip. This work has both practical interest in terms of simplifying the operation of power transmission lines, as well as a great economic effect due to a reduction in the cost of replacing equipment, the cost of compensating for energy losses, as well as a reduction in the cost of wages for maintenance and repair personnel.

This would allow for the early detection of faults in hot lines thus minimizing the risk of premature failure [2].

II. METHOD

The selection of optimal operating areas for such devices is a crucial element in their design. The application of a particular optimality criterion could be an important element in the selection process. The classic theory of optimal operating area detection considers an area as optimal when type 1 and type 2 errors and the risk function are minimal. Within the context of this theory, the detection of optimal operating areas for multispectral optoelectronic devices involves determining the correlation between the errors or functions and wavelengths, and solving the optimization problem. The use of this method is complicated since comprehensive statistics of signal parameters are required to determine type 1 and type 2 errors and the risk function. This is practically impossible in the case of diffuse reflection of incoherent radiation from real landscapes. Hence, this study proposes the utilization of a criterion based on the utility theory for operating area selection [18-20].

According to the utility theory, each spectral area (wavelength) has a one-to-one correspondence with a number that characterizes the utility of the area (wavelength) for the
detection of certain objects. This number is taken as a utility indicator \( \Pi(\lambda) \). The spectral area \( \Delta \lambda \) is considered preferable for other areas \( \Delta \lambda \) if it meets the following condition [6]:

\[
\Pi(\Delta \lambda) = \max \{ \Pi(\Delta \lambda) \}; \quad i \in \{n\},
\]

where \( \Pi(\Delta \lambda) \) is the utility indicator of the \( i \) area and \( \{n\} \) is a countable set of spectral areas.

An operating spectral area is selected according to the maximal utility indicator. Evidently, a spectral area is considered useful if the probability of object detection during image interpretation is not zero. Given that the probability of object detection against a scenery depends on the brightness contrast between the object and the immediate background, it can be described with a dependence, specified by the following expression:

\[
P = 1 - \exp \left( \frac{a \times K^2 \times \delta^3 \times B^{0.5} \times t}{(2 \times \beta)} \right),
\]

where \( \delta \) is the provided angular size of an object, \( B \) is scenery brightness, \( K \) is the brightness contrast of an object against the background, \( 2\beta \) is the provided angular diameter of the field where an object is found, \( t \) is location time, and \( a \) is the proportionality factor characterizing the location capacity of an observer [12-16].

The brightness contrast is determined using the following formula:

\[
K_{\Delta \lambda} = \frac{B_{\Delta \lambda} - B_{\Delta \lambda}}{\max \{ B_{\Delta \lambda}, B_{\Delta \lambda} \}} = 1 - \min \left\{ \frac{B_{\Delta \lambda}}{B_{\Delta \lambda}}, \frac{B_{\Delta \lambda}}{B_{\Delta \lambda}} \right\},
\]

where \( B_{\Delta \lambda} \) is object image brightness, \( B_{\Delta \lambda} \) is background image brightness, and \( \Delta \lambda \) is the interval width of the wavelengths in the \( i \) spectral area, which depends on the brightness of objects, the scenery background, and the width and position of the area in the optical spectrum.

Thus, the probability values (\( P \)) are different for different wavelengths and different widths of the operating area \( \Delta \lambda \). This is also applicable for the utility of a spectral area.

The most useful area is the area with the maximal detection probability. According to the formula specified in equation (1), there is an obvious correlation between the detection probability and the object contrast with the scenery background. The detection probability increases with the increase in the contrast. Hence, the brightness contrast of an object against the scenery background could be taken as an indicator of spectral area utility.

However, contrast is a random value in the case of real objects and scenery backgrounds. This is because spectral brightness coefficients and luminance, which determine brightness values, depend on a number of random factors. Therefore, random implementations of contrast \( K_{\Delta \lambda} \) cannot be used as a utility indicator. With respect to the spectral area utility, the randomness of contrast requires its probabilistic characteristics such as mathematical expectation and dispersion to be taken into account. The use of such characteristics will lead to the understanding of average utility, i.e., the value that utility comes close to in probability. In this case, the average probability of the object detection and, consequently, the utility of the area increase with the increase in the mathematical expectation of contrast.

\[
\Pi(\Delta \lambda) = \max \{ \Pi(\Delta \lambda) \}; \quad i \in \{n\},
\]

Simultaneously, the utility of a spectral area will decrease with the increase in the average values of contrast deflection towards lesser values. This is because the growing probability of contrast \( K_{\Delta \lambda} \) outreaches the sensitivity of the human eye.

Therefore, the formula in equation (1) is proposed as an indicator of spectral area utility \( \Pi(\Delta \lambda) \) in the following equation:

\[
\Pi(\Delta \lambda) = m_i \left( k_{\Delta \lambda} \right) \left( 1 - m_i \left( \xi \times \Delta \lambda \right) \right),
\]

where \( m_i \left( k_{\Delta \lambda} \right) \) is the mathematical expectation indicating a brightness contrast in the \( i \) spectral area and \( m_i \left( \xi \times \Delta \lambda \right) \) is the mathematical expectation of brightness contrast deflection \( K_{\Delta \lambda} \) from the mathematical expectation towards lesser values.

The maximal utility indicator \( \Pi_{\text{max}}(\Delta \lambda) \) corresponds to the preferred spectral area (wavelength). The obtained utility indicator in equation (3) aids the determination of the wavelength required to create an image for improved conditions of object detection.

It is therefore proposed that the operating areas of the optoelectronic multispectral devices should be selected through the following steps:

1. Determining the minimal width of the spectral area based on the required range capability of the device.
2. Calculating the utility indicator (1) for various types of objects and backgrounds.
3. Determining areas corresponding to the maximums of the utility indicator.
4. The aforementioned problem of selecting an optimal number of channels by dynamic programming is solved.

III. RESULTS

The proposed method considers physical phenomena that occur during the visual inspection and detection of objects. It allows the rational selection of operating areas of a multispectral device, including the number, width, and location of these areas in the optical spectrum.

The optimal operating areas for multispectral devices with direct image visualization are selected according to the developed method. The proposed optimal width for an operating area is \( \Delta \lambda = 50 \text{ nm} \), given there are energy capabilities. The utility indicator for standard overhead power lines was calculated assuming that the standard overhead power lines are located against the vegetation. The results of the calculations are presented in an image that shows the changes in the relative value of the utility indicator (with regard to the value of the utility indicator for the visible area)
from wavelengths. The diagram shows that the utilities for different wavelengths are not similar and that there are several points of extrema.

The correlation matrices for the contrasts of overhead power lines against the background of green vegetation were also calculated. The following table shows the values of correlation coefficients.

| Wavelength | Utility Coefficient |
|------------|---------------------|
| 725…775 nm | 0.12 |
| 825…875 nm | 0.15 |
| 475…525 nm | 0.10 |
| 525…575 nm | 0.18 |
| 625…675 nm | 0.21 |
| 375…425 nm | 0.13 |

The calculation shows no significant correlation between areas corresponding to the maximal utility indicator. Thus, the number of operating spectral areas for multispectral devices with direct image visualization was selected according to equations (1) and (3).

The selection of the number of areas involved in solving a problem of integer programming determines the minimal time spent on object detection at the required level of probability. The required probability value was taken as 0.9, and the probability of a false alarm equalled zero. The total number of channels (spectral areas) was calculated by the condition of above-limit relative value of the one-level utility indicator and the lack of significant correlation between the areas.

The solution involved branch bound integer programming as each problem required the examination of 5,000 possible combinations.

IV. CONCLUSIONS

The solution of the optimization problems suggested that the detection of the standard overhead power lines requires images to be formed in the following spectral areas: when power lines are located against the background of the green vegetation - 725…775 nm, 825…875 nm, 475…525 nm, 375…425 nm; and against a softwood forest - 625…675 nm, 375…425 nm, 875…925 nm. Thus, the table detection of power lines required a multispectral device with direct image visualization to form an image in the following spectral areas: 375…425 nm, 475…525 nm, 525…575 nm, 625…675 nm, 725…775 nm, 825…875 nm, 875…925 nm.

Acknowledgment

This research was supported by the Russian Foundation for Basic Research, project No. 18-07-01117A.

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