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Thermal Anomaly Detection in Unexploded Ordnance Environments

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Abstract— The main goal of this study is to enhance the method for applying thermal imaging techniques in non-technical terrain reconnaissance where combat operations are conducted and unexploded ordnance (UXO) remnants are present. The study involved conducting thermal image analysis obtained during aerial operations using standard methods within the DJI Thermal Tools environment in combination with elements of two-dimensional Gaussian distribution. This approach was then used to develop decision frameworks for UXO removal. The experiment used a conventional UAV MATRICE 300 RTK DJI rotorcraft equipped with an H20t DJI dual camera and was conducted at the Demining Center of the Republic of Serbia in Grocka.)

Keywords— demining, thermal mapping analysis, luminance, Gaussian distribution, modeling

I. INTRODUCTION

Recently, organizations and international bodies involved in demining are grappling with the effectiveness of land clearance efforts. General assessments and impact research often exaggerate the problem, labeling large areas as suspicious, complicating the task of distinguishing genuinely hazardous terrain from areas merely under suspicion. This complexity has led to a thorough review within the demining sector, highlighting an urgent need to reconsider perspectives, processes, and methodologies related to the clearance of Suspected Hazardous Areas (SHA). The reassessment is gaining importance due to impending deadlines associated with the Anti-Personnel Mine Ban Convention, prompting states and the demining community to embrace new land release concepts and establish comprehensive frameworks for their activities [1].

This research is a part of our effort to propose and validate an effective methodology for mapping minefields through terrain surveying using unmanned aerial vehicles (UAVs), equipped with advanced technologies, and developing methods for analyzing and processing the collected data [2-5]. For this study, a conventional UAV, the Matrice 300 RTK equipped with an H20t DJI dual camera, was provided. The research assumes that surface physical property data contain indicative information about the presence or absence of mines in the area. These data are obtained through precise recording sensors installed on the aerial platform. The decision on the presence or absence of UXO is made based on a comprehensive analysis of data from various sensors embedded in the platform, with results largely depending on recording conditions, camera characteristics, and calibration. For this purpose, in this paper, we presented a methodology concept based on a combination of practical data acquisition, image processing techniques, and ``tools`` like two-dimensional Gaussian distribution. This distribution is particularly effective for modeling the different quantities in a two-dimensional context. In this paper, we focus on the spatial luminance of a segment of an image [3-6]. This approach facilitates a more accurate and detailed analysis of luminance patterns within the image, enhancing the precision of subsequent image processing tasks. The subject of our study was RGB and thermal images of the terrain with suspected UXO present.

II. AN AERIAL SURVEY METHODOLOGY

Planning aerial surveys is carried out by existing instructional and methodological documents, carefully considering geographical details and equipment specifications. This process also considers specific operational requirements of the user, such as the maximum allowed time for task execution, the desired accuracy of the output product, and the required level of information protection [7].

When it comes to geographical details, key information about the territory, including precise coordinates of the area of interest, is meticulously gathered. Additionally, it

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encompasses a comprehensive understanding of the terrain configuration, including details such as soil type, vegetation cover, and the presence of any artificial objects. Furthermore, information about the expected categories of mines is taken into consideration in the planning process, distinguishing between anti-personnel and anti-tank mines.

By incorporating these factors, the planning of aerial surveys aims to align with the specific needs and preferences of the user, while ensuring a thorough and detailed assessment of a particular location. The task of planning aerial surveys involves establishing a route, calculating the UAV's flight altitude, and the frequency of image acquisition over the territory. The route is established based on the requirement for complete coverage of the entire minefield area and ensuring the desired cross-track overlap (typically 40-60%). The UAV's altitude is calculated based on the required number of pixels within an individual image of the mine segment - at least 50-70 pixels per mine object segment. The frequency of capturing images over the terrain within the frames should provide the necessary longitudinal overlap (typically 30-40%) of images generated by the embedded sensor [8, 9, 10].

The process of conducting aerial surveys involves a typical flight route of the unmanned aerial vehicle (UAV) during the imaging of a specific area (Fig.1). The key flight and control parameters during the survey process are programmable, allowing for precise adjustments according to requirements. Special attention is given to maintaining the pre-determined flight altitude and camera synchronization.

Fig. 1 Area of the terrain contaminated with UXO

During the aerial survey, the UAV follows a pre-defined route, and controlled parameters enable optimal coverage of the entire area of interest. This process is carefully planned to ensure complete documentation of the terrain, considering the specifics of each segment of the area.

Flight programmability allows adaptability to task requirements, and careful flight altitude and camera synchronization adjustment ensures high-quality imaging results. This programming capability enables flight optimization according to terrain specifics, ensuring the integrity and accuracy of the data collected during aerial surveys easy to comply with other image processing techniques [10, 11].

Each element of the surveyed area was simultaneously captured in two digital images: thermal and conventional in natural colors. The thermal image records thermal radiation intensity, quantified through surface temperature values in each pixel. The color image contains terrain information in a unified RGB (red, green, blue) display. Depending on the requirements and available technical capabilities, the full amount of data recorded using embedded sensors can either be stored on the aircraft's storage or transmitted to the ground station for reception and processing. Each of these images provides specific information about the surveyed area, enabling analysis from different aspects and spectral ranges. This combination of images provides comprehensive terrain data, and the option to retain or transmit data is tailored to the needs and technical capabilities of the project. However, data accuracy and projection remain debatable for several reasons [12].

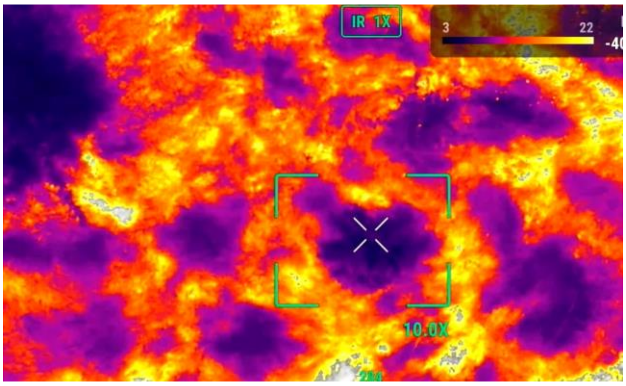

Fig. 2 Thermal view of the contaminated part of the terrain

In our case, Pix4D Mapper was used for terrain visualization. Typically, the services of most commercial aircraft include software packages for planning aerial photography missions, which often contain photogrammetric modules for compiling image mosaics. The application of PIX4D enables the creation of mosaic images in multiple spectral channels MM (consisting of L layers corresponding to the number of images in individual spectral channels), followed by the creation of mosaic thermal infrared images MT. This mosaic is single layered, a color mosaic with RGB images. It is essential to emphasize that all mosaic images have the same number of pixels (designated as K), and corresponding pixels of mosaic images have the same number.

The GSD (geometric spacing between pixels) size is projected to one pixel of any individual spectral band image. If the GSD size is around 1-3 cm, then it is much smaller than the actual diameter of the terrain segment [13].

Specific operations must be performed on the mosaic images to reduce the random variability of pixel signals. The sliding window method conducts These operations in a cycle [14]. This technique systematically moves a fixed-size window across the image and applies the desired operations to the pixels within the window at each position. By doing so, random noise and variability in the pixel signals are smoothed out, resulting in a more consistent and accurate representation of the image data.

III. Analysis

As previously highlighted, the application of the two-dimensional Gaussian distribution represents an efficient adaptive model for approximating the spatial luminance distribution in the image. The process of minimizing the mean square error contributes to achieving the optimal value of the Gaussian distribution. This result indicates a precise reflection of the key characteristics of spatial luminance distribution, which includes the identification of peaks, troughs, and the shape of the distribution. It is important to note that this process allows for precise image correction, resulting in the resulting Gaussian distribution faithfully reflecting the actual spatial luminance distribution. This precision is particularly significant in situations where the accuracy of reconstruction is essential, such as in medical diagnostics or satellite image processing.

The mean square error (MSE) metric serves as an evaluation indicator, measuring the average square error between the actual and modeled distributions. Minimizing MSE indicates successful adaptation of the model to the spatial luminance distribution, achieving a high degree of accuracy in image analysis. The Gaussian distribution can precisely identify peaks, troughs, and the shape of the luminance distribution. By comparing these characteristic points with actual distributions, we can assess how well the model reflects the key properties of the image.

In the context of thermal image processing, MSE can play a significant role in several aspects. Thermal cameras often have inherent characteristics and measurement errors, such as calibration inaccuracies, sensor inhomogeneities, or thermal effects.

Minimizing mean square error can be applied to adjust thermal images to correct these errors and improve measurement accuracy. During the detection and segmentation of objects in thermal images, minimizing mean square error can be used to adjust contour or region models of objects with actual thermal data. This can improve the accuracy of thermal shape detection and identification. In applications where thermal maps or temperature distributions need to be generated based on measurements, minimizing mean square error can help adjust models describing the thermal characteristics of the scene. This is especially important in thermographic inspections or medical thermal images. Applying mean square error minimization can contribute to image restoration when thermal images suffer from noise, blurring, or other artifacts. This approach can reduce noise's impact and improve thermal data quality. Minimizing mean square error can be used to calibrate thermal sensors. This process helps achieve a more precise relationship between thermal camera readings and the actual temperatures of objects.

When analyzing temperature profiles in a thermal image, applying MSE minimization can contribute to better adjustment of temperature variation models. By following the described approach, it is possible to transition from detecting point anomalies in thermal images to statistically detecting anomalies in the thermal mosaic corresponding to the size of explosive segments.

As previously mentioned, our analysis focused on RGB, and thermal images of terrain suspected to contain unexploded ordnance (UXO). These recordings were carried out under standard weather conditions, ensuring consistent data quality. The photos were captured at an altitude of 60 meters during the early morning hours. This timing was chosen to take advantage of stable atmospheric conditions and reduced thermal noise, enhancing the thermal images' clarity and accuracy. By integrating RGB and thermal imaging techniques, we aimed to create a comprehensive dataset allowing more effective identification and analysis of UXO within the surveyed area. After analyzing the images in the appropriate software environment, DJI Thermal Tool, points of interest were identified, which were the subject of further analysis. In the first step within MATLAB, based on the selected segment marked with point A containing UXO, the spatial luminance of the segment was calculated to precisely analyze the presence of UXO and its characteristics relative to the surroundings. In the next step, a two-dimensional Gaussian distribution was introduced.

By using a two-dimensional Gaussian distribution, we can identify key features of the image, including peaks, troughs, and the shape of the distribution. This is crucial in many applications, including shape recognition, image segmentation, and other areas of image analysis, which can be highly beneficial in our case. Adjusting the parameters of the two-dimensional Gaussian distribution allows for optimizing the model according to the specific characteristics of thermal anomalies of UXO and the environment. Sensitivity to changes in variance or other parameters enables adaptation to shift. Based on the Gaussian distribution model, it is possible to classify regions in the image according to the probability of mine presence. This classification can help prioritize areas that require additional attention or investigation.

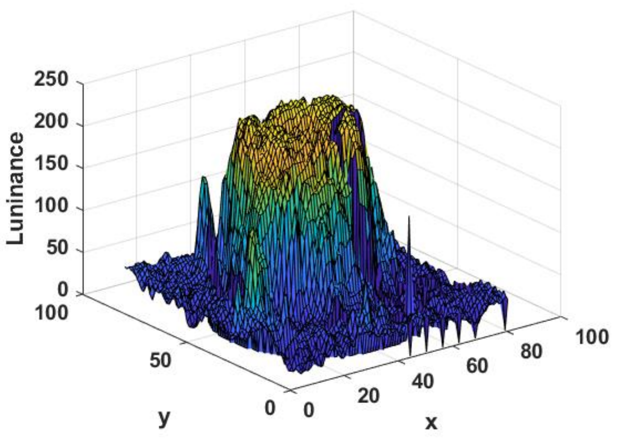

Fig.3 Spatial luminance distribution of the analyzed segment

Through the process of minimizing the mean square error (MSE) between the spatial luminance distribution of the image (as illustrated in Fig. 5) and the two-dimensional Gaussian distribution, we were able to derive the optimal Gaussian distribution parameters. This optimization process involved adjusting the Gaussian distribution to best fit the actual luminance data, thereby minimizing the MSE. The result of this process was the determination of an optimal Gaussian distribution with a specific variance, which was achieved when the MSE reached its minimum value. This minimal MSE indicates the point at which the Gaussian distribution most accurately represents the spatial luminance characteristics of the image, ensuring that the model aligns as closely as possible with the observed data. This optimization is critical for accurate image analysis, as it ensures that the model reflects the true luminance variations within the image.

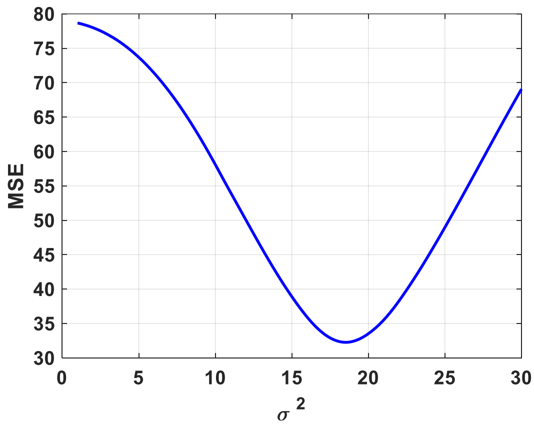

Fig. 4 Display of the minimum MSE

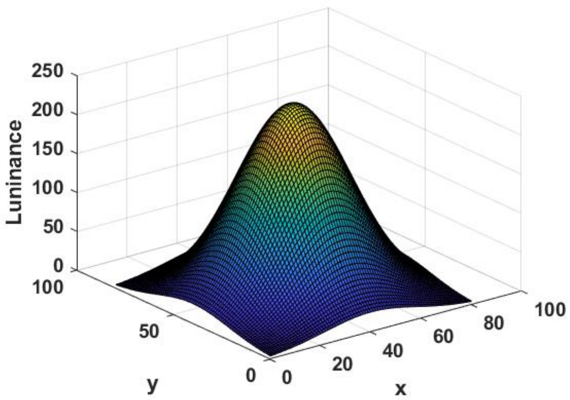

Fig. 5: Spatial luminance distribution of the analyzed segment with a determined optimal variance value

In further analysis, we conducted a detailed comparison between the actual luminance distribution of the image and the two-dimensional Gaussian distribution along both the x and y axes. This comparison aimed to evaluate the degree to which the Gaussian model accurately represents the true luminance characteristics of the image. By examining the fit of the Gaussian distribution to the actual data along these axes, we sought to identify any discrepancies and measure the model's effectiveness in capturing the light distribution within the image.

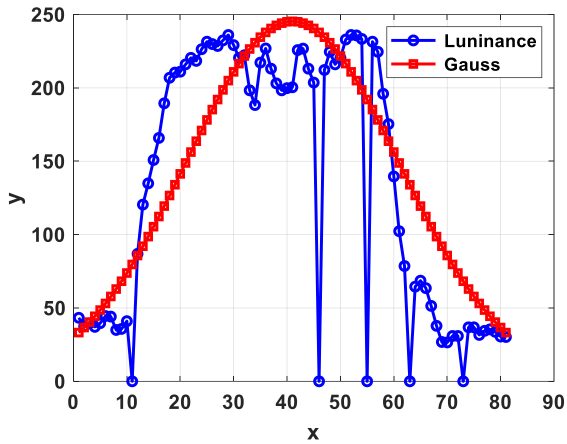

Fig. 7 Comparison of luminance distribution and two-dimensional Gaussian distribution along the x axis.

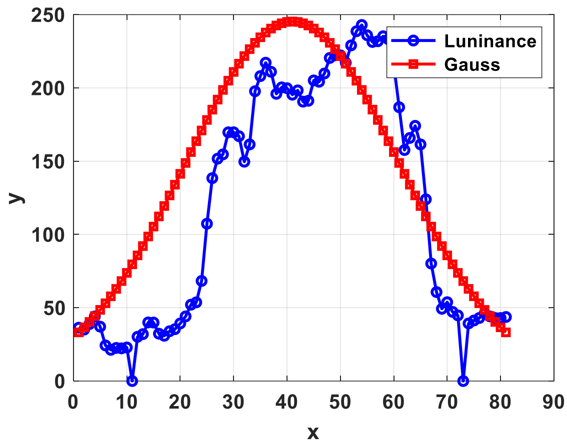

Fig. 6 Comparison of luminance distribution and two-dimensional Gaussian distribution along the y-axis.

By examining the mean square error (MSE) between the actual luminance distribution in the image and the modeled Gaussian distribution, we can effectively assess the accuracy of the model in representing the real data. The MSE serves as a quantitative measure of the discrepancy between the observed values and the values predicted by the model. A smaller MSE value signifies a closer fit between the model and the actual data, indicating higher accuracy. In our study, achieving a low MSE value demonstrates that the Gaussian distribution model accurately captures the spatial luminance characteristics of the image. This validation is crucial for ensuring that our model reliably represents the underlying luminance patterns, thereby enhancing the precision of further image processing and analysis tasks.

IV. CONCLUSIONS

Demining is becoming an increasingly significant challenge in contemporary society. The combination of available technologies that enable the collection of large amounts of information in real time, along with tools for their processing, provides a solid foundation for advancements in this field.

The application of two-dimensional Gaussian distribution in thermal image analysis has proven to be an extremely efficient and adaptable method for identifying key characteristics of spatial luminance distribution. Through the process of minimizing the mean square error, the optimal value of the Gaussian distribution was achieved, indicating a precise reflection of the actual light characteristics of the image. This method has proven to be useful in analyzing thermal anomalies, particularly in the detection and characterization of unexploded mines. The combination of visual conformity, mathematical measures, and parameter optimization has enabled the creation of a model that accurately describes the spatial luminance distribution in thermal images. Furthermore, by applying this method, it is possible to classify regions in the image according to the probability of mine presence, providing a practical tool for prioritizing areas that require additional attention or investigation. Such an approach has wide-ranging applications, from military operations to civilian sectors, and contributes to the advancement of technologies for detecting and analyzing thermal images in various applications.

V. References

[1] GICHD strategy 2023-2026 Available from https://www.gichd.org/fileadmin/uploads/gichd/Documents/Strategy_20232026_Full_V14_WEB_UPDATE_10.2023.pdf

[2] Blagojević, D., Milivojvic, Z., Glamoclija, B., Krstić, J., "Analiza termalnih Anomalija u okruženju neeksplodiranh sredstava," XXIV Međunaroni simpozijum IFOTEH Jahornina, Proceeding pp 213-217.

[3] Ball, M., "Landmine Detection with Drones," Unmanned Systems Technology [online], 2021, [viewed 2024-01-17]. Available from: https://www.unmannedsystems technology.com/2021/08/landmine-detection-with-drones/

[4] Ege, Y., A. Kakilli, O. Kiliç, H. Çalik, H. Çitak, S. Nazlibilek and O. Kalender, "Performance Analysis of Techniques Used for Determining Land Mines," International Journal of Geosciences, 2014, 5(10), pp. 1163-1189. DOI 10.4236/ijg.2014.510098.

[5] Maathuis, B.H.P., Remote Sensing Based Detection of Minefields. Geocortex International``, 2003, 18(1), pp. 51-60. DOI 10.1080/10106040308542263.

[6] Gaur, P., and T. Choudhary, "Aerial Landmine Detection. International Journal of Engineering & Technology," 2018, 7(3.34), pp. 710-713. DOI 10.14419/ijet. v7i3.34.19457.

[7] J. Zhihao, Weiche Chang, Yuan Li, Kezhong Wang, Dongjue Fan and Liang Zhao, "Microparameters Calibration for Discrete Element Method Based on Gaussian Processes Response Surface Methodology," Processes 2023, 11(10), 2944; https://doi.org/10.3390/pr11102944

[8] Fardoulis, J., X. Depreytere, P. Gallien, K. Djouhri, B. Abdourhmane and E. Sauvage, "Proof: How Small Drones Can Find Buried Landmines in the Desert Using Airborne IR Thermography," Journal of Conventional Weapons Destruction, 2020, 24(2), pp. 55-63. DOI 10.5281/zenodo.4409641.

[9] Raj, A., I. Rafiq, A.J. Gowda, and L.S. Krishna, "Landmines Detection Using UAV," International Research Journal of Engineering and Technology [online], 2019, 6(4), pp. 2716-2719

[10] Castiblanco, C., J. Rodriguez, I. Mondragon, C. Parra, and J. Colorado. "Air Drones for Explosive Landmines Detection," In: ARMADA, M., A. SANFELIU and M. FERRE, eds. ROBOT2013: First Iberian Robotics Conference. ("Deterministic phase resetting with predefined response time for CPG networks based on Matsuoka's oscillator") Advances in Intelligent Systems and Computing. Cham: Springer, 2014, pp. 107-114. ISBN 978-3-319-03652-6.

[11] Colomina, I. and P. Molina., "Unmanned Aerial Systems for Photogrammetry and Remote Sensing: A Review," ("Applications of unmanned aerial vehicle (UAV) surveys ... - ScienceDirect") ISPRS Journal of Photogrammetry and Remote Sensing, 2014, 92, pp. 79-97. DOI 10.1016/j.isprsjprs. 2014.02.013.

[12] Racek, F., T. Baláž T. and P. Melša, "Hyperspectral Data Conversion in the Case of Military Surveillance," Advances in Military Technology [online], 2015, 10(1), pp. 5-13, [viewed 2024-01-17]. Available from: https://aimt.cz/index.php/aimt/article/1054

[13] PIX4D support https://support.pix4d.com/hc/en-us/articles/202559809

[14] Droždž, M., Kryjak, T., "FPGA Implementation of multi-scale face detection using hog features and SVM classifier,", Image Processing & Communications, vol. 21, no. 3, pp.27-44 DOI: 10.1515/ipc-2016-0014.