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Research paper

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The use of artificial intelligence methods for analyzing images obtained through low-altitude photogrammetry technology to calculate the volume of mass in open-pit mines

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Summary

Measurements using drones have enabled significant changes in the inventorying and monitoring of mining areas. Drone-based measurements can be faster and more accurate [Mazurek 2018]. Aerial photographs taken with drones allow the surveying department in mines to accurately represent the photographed terrain and make precise measurements, which can be used, among other things, to calculate the volume of mass. The aim of the article is to present the results of research on the automated process of acquiring and processing photogrammetric data for the purpose of calculating mass volumes. As part of the research, an algorithm based on classical methods and deep learning was developed.

In collaboration with the Silesian University of Technology and 3D Format company from Gliwice, the AGH University of Krakow has developed a system for automated volumetric measurements based on low-altitude photogrammetry using non-metric photos and artificial intelligence (AI) algorithms to provide cyclical volume measurement services on the Polish market. The idea of the system is to acquire data automatically, then provide the data in the cloud, maximize measurement automation, and provide results in near real-time. The entire process is to be conducted using software available through the website.

The project was divided into several stages. This particular publication focuses on the automation of the measurement of surveying points.

Keywords

photogrammetry • UAV • artificial intelligence • open pits mines

1. Introduction

The surveying services in open-pit mining are responsible for providing frequent and rapid information about the geometry of the workings and mining dumps, which is necessary to ensure the safety of machinery operation. Measurements are taken at monthly intervals and include measuring the volume of excavated rock masses [Kulczycki et al. 2004]. Just a few years ago, this task was carried out using classical methods, i.e., geodetic measurements applying GPS receivers. Since the emergence of UAV (Unmanned Aerial Vehicle) technology, low-altitude photogrammetry has been used for these tasks [Kosieliński 2023].

The idea of the system is to acquire data automatically, then provide the data in the cloud, maximize measurement automation, and provide results in near real-time. The entire process is to be conducted using software available through a website.

The project was divided into several stages. This publication focuses on the automation of the measurement of surveying points.

1.1. Artificial Intelligence (AI) Method

Artificial Intelligence (AI) is a rapidly developing field of computer science that utilizes the latest advancements in computer technology. The rapid development of electronics and computer science contributes to the growth of this field. AI is used in various areas of life, including medicine, economics, and mining [Różanowski 2007]. AI and its associated algorithms can be applied in various areas of mining [Młynarczyk et al. 2014], including decision-making regarding reducing the impact of mines on the natural environment and automating machinery operations, adapting them to work in specific environments such as open-pit mines [Rzeźnik 2023].

Attempts to automate the measurement of feature points (fiducial markers) have been the subject of the author's research since the beginning of his research work [Gryboś and Mikrut 2007]. Following the application of classical methods, there was an attempt to use artificial intelligence for image correlation. Authors of the publication [Mikrut et al. 2010] also studied the use of neural networks in photogrammetry.

1.2. UAV Method

Development of technology has generated growing interest in small Unmanned Aerial Vehicles (UAV) for civilian purposes [Szóstak et al. 2022]. UAVs are equipped with measurement devices and supported by computer software for processing the acquired data in mines [Bojarczuk et al. 2019]. Low-altitude photogrammetry based on drones significantly changes the way mining areas are inventoried and monitored [Juszczyk et al. 2021]. Photos of workings and dumps taken with unmanned drones equipped with high-resolution cameras and measurements of photopoints enable the creation of a skeletal model with texture fitted into the geodetic system, thus facilitating the development of a digital model of the real terrain. While maintaining geodetic accuracy, drones make it possible to create an accurate terrain model, accommodating irregular shapes. Drones enable volume calculations with an error margin of up to 0.5%, and that level of accuracy brings many benefits to the decision-making process [Dron 2023].

Volume measurement using this method affords shorter measurement time, aerial photographic documentation, high measurement accuracy, delivery of accurate measurement reports, enabling the creation of precise and reliable studies, and non-invasiveness [Kosieliński 2018]. The image obtained from the drone is precise and provides a wealth of data for research [Kossowski 2022].

2. Materials and methods

2.1. Research area and data collection

The research was conducted on aerial imagery data obtained from UAV flights (by different drones). Various algorithms were tested during the research, with a particular focus on machine learning methods. The study involved testing algorithms considering different flight altitudes, various types of reference markers, and several objects such as open-pit mines.

The research area encompassed four mining sites, and images were acquired from three drones at five different altitudes. This provided several thousand markers for analysis.

A neural network was trained twice to locate Ground Control Points (GCPs). The trained data was saved in *.XML files, with variations depending on the markers.

2.2. Research object and methodology

The aim of the research was to automate the procedure of acquiring and processing photogrammetric data for calculating mass volumes. First task (described in this paper) was to automate the process of identifying GCPs in an isolated environment. Two algorithms were developed as part of the research. **Algorithm 1** was based on classical methods, while **Algorithm 2** used deep learning techniques.

2.3. Research assumptions

As part of the work, algorithms were implemented both for individual objects and collectively for all objects, in order to increase the training and testing database for the trained networks.

For markers to be considered correctly detected, those identified by the Intersection over the Union algorithm (or Jaccard index), which is a useful tool for assessing model effectiveness and optimizing object detection processes, were utilized. The IoU algorithm [Mazur-Milecka 2021] measures the percentage of mutual coverage between predicted bounding boxes and actual bounding boxes, yielding a value greater than 0 (the average coverage of correctly detected markers was usually above 85%).

Table 1. Experimental results dependent on flight altitude

High [m]	Positive	Negative	Manual markers	Correct markers	Incorrect markers	Accuracy [%]	Precision [%]
50	149	10	408	301	2	73.77	99.34
60	100	17	363	316	42	87.05	88.27
70	134	7	630	370	51	58.73	87.89
80	105	1	617	81	86	13.13	48.50
90	99	0	675	0	764	0.00	0.00

The formula for Intersection over Union is:

$$\mathrm{IoU} = \frac{\text{area of intersection of two rectangular areas}}{\text{area of sum of two rectangular areas}}$$

The application of the IoU algorithm allowed for the exclusion of such results from the pool of correctly detected markers and classified them as incorrectly detected. Markers considered incorrectly detected are those that did not intersect in the slightest with manually marked markers.

Other networks were selected for testing, particularly for images taken at heights of 50m to 70m above the ground level, and in most cases, they performed very well. However, problems with training the networks began to arise at the height of 80m. At that point, the accuracy and precision of the model dramatically deteriorated. Problems with properly training the network also arose, including frequent underfitting and overfitting. In such cases, it was practically impossible to configure the network appropriately.

The algorithms were implemented into the system using a library written in C++ and through the containerization of algorithms. After running the algorithms, their correctness was verified during a measurement session conducted in a selected research area where 10 GCPs were placed. The average positioning error for the detected GCPs was 1.5 cm.

The data makes it possible to determine the center of the GCP. The visualization of automatic marker detection is presented below (Fig. 1). Results are presented in Table 1.

Number of GCPs

The minimum number of GCPs in the surveyed area should be 7 to ensure that the error in calculated volumes does not exceed 3%. To reduce the error in calculated volumes to 1%, it is recommended to stabilize a minimum of 10 GCPs in areas exceeding 20 hectares. Areas between 5 hectares and 20 hectares maintain good height accuracy with 10 GCPs. For small areas of 1 hectare, it is a sufficient number GCPs, according to recommendations regarding their distribution.

Distribution of GCPs

It is recommended to place GCP in the corners of the area, along its outer edges, and at least one point in the center of the area. It is also recommended to place GCP at different height elevations, with the minimum difference in elevation between the lowest and the highest point being equal to at least the height of the highest surveyed object. If possible, GCP should be placed in the immediate vicinity of the surveyed object.

Control Points

It is recommended to establish additional points in the field that are unambiguously identifiable in photographs for quality control purposes. Control points should be placed in locations furthest from the GCPs. Depending on the size of the measurement area, the number of control points should range from 3 for areas up to 3 hectares to 10 for areas exceeding 20 hectares. It is also suggested that control points be located at different elevations to detect any height-related errors increasing with the terrain's elevation

The above recommendations are confirmed by field experiments carried out by 3DFormat Company in collaboration with the AGH University in a joint testing effort.

3. Analysis of the data

3.1. Method 1 – Classical approach based on histogram comparison

Histogram comparison involves the following steps:

- Selection of the image for analysis: grayscale or color,
- Coarsening the image, i.e., converting it to a binary form [0, 1] or 256 bits,
- Histogram comparison (counting the number of matching bits),
- Selection of a measure for comparison – four measures were tested in the study [Nattinga 2019],
- Defining the range of images (limited by a search window) [Mikrut et al. 2010],
- Correlation – determining the position of the point where the best measure is found.

3.2. Method 2 – Deep Learning – MLP Neural Network

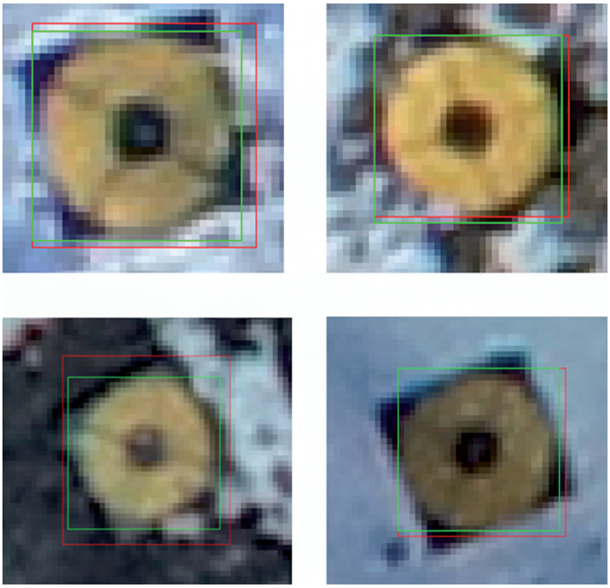
For the research purposes, an MLP (multilayer perceptron) network from the OpenCV library was applied, implemented in the C++ language. Before detecting markers, it is necessary to specify whether the created image should be degraded to grayscale or color (the 'grey' parameter). These settings should be entered before running the algorithm. Algorithm Steps:

- Divide the image into two sets: A – positive and B – negative.

  A – select images that contain the desired elements.

  B – images that do not contain the desired elements but are under similar lighting conditions - i.e., false positives.

- Then, annotations were made on the positive images, i.e., those containing the elements we are looking for. Subsequently, the required parameters were set.



Source: Author's own study

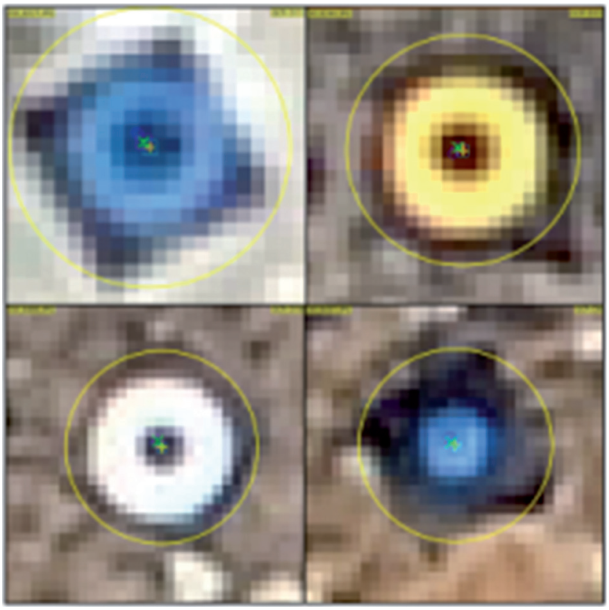
Fig. 1. Example of detection of a ground control point (GCP) using the MLP method: the red marker indicated by the user, and the green marker detected by the network

Initial parameters:

- Determine the height and width of the desired object (marker),
- Specify the minHitRate parameter,
- Number of levels in the network: from 5 to 7,
- Minimum number of neighbors: mindneighbors (during the conducted research, we assumed between 5-10, which allowed the creation of a separate classifier / *.xml file for different heights),
- ScaleFactor – e.g., the closer to 1, the slower the network operates albeit more accurately.

The study was conducted using images acquired from various heights. The algorithm's operation involves loading the appropriate cascade directory. Having done that, the number of neighbors was adopted, ranging from 2 to 16. The algorithm detects the survey marker and provides the number of markers actually detected in the image (Fig. 1). The first average value represents the percentage of recognized survey markers in the image area. This information also includes incorrect marker indications, and their number is presented in a table format (Table 1). The second average value expresses the percentage of absolute detection, i.e., the target value of the conducted tests. An identification level of survey points above 62% and flawless detection of over 63% was achieved for each of the 10-image set.

Different height levels in open-pit mines can exceed 100m. To obtain an accurate image of error distribution, survey points are established at each level. A greater number of points make it possible to determine internal camera orientation parameters.



Source: Author's own study

Fig. 2. Measurement of GCP's on images from Phantom 4 Pro

Both methods operate automatically, but Method 2 is much faster (a few seconds for Method 2 compared to several minutes for Method 1) on a computer with average specifications such as a Core i7 processor, Quadro M2000 graphics card, and 16GB RAM.

For training the neural networks, internal Picture software was used, which utilizes the OpenCV library (Fig. 2). Training was conducted three times on different resolutions of images – 60, 70, and 80 meters drone flight altitude. As an outcome, three models were produced, which were used to test the neural network on a sample of 100 images for each resolution (Table 2).

Table 3 shows the calculated accuracy of each model. In this calculation method, accuracy indicates the percentage of markers in the image recognized by the model. Incorrect recognition was treated as a lack of recognition of a non-existent marker, resulting in a decrease in accuracy.

Table 2. The training and model search parameters after training

	High 60 [m]	High 70 [m]	High 80 [m]
Neighbours	8	8	8
Scale	1.01	1.01	1.01
Width [px]	16	16	16
Height [px]	16	16	16
Num_Pos	94	200	163
Num_Neg	45	108	108
Stages	6	6	5
MinHit	0.999	0.999	0.999

Table 3. The calculated accuracy of each model

	Average accuracy	Overall accuracy	Accuracy without considering cases of incorrect marker	Overall accuracy without considering cases of incorrect marker
60 [m]	66.06%	68.92%	70.67%	75.97%
70 [m]	79.94%	81.77%	84.09%	85.68%
80 [m]	69.97%	73.56%	73.90%	78.65%

The tables describe four cases: average accuracy, which is calculated based on separate accuracies for each image, overall accuracy, which indicates how comprehensively the model recognized the markers (the ratio of all recognized markers to all markers in the images). Additionally, the accuracy was calculated without considering cases of incorrect marker recognition for both aforementioned values.

4. Conclusions

The model trained on images taken from a height of 70 m yielded the best results. In the case where we ignore instances of incorrect marker recognition, the model recognized almost 86% of the markers. In the worst-case scenario (average accuracy), the model had an accuracy of 80%.

Below, there are examples of objects that were often incorrectly recognized (Fig. 3), thus resulting in underestimated accuracy parameters for the model. Objects that the model recognized included, for example, circular concrete shapes or texts on heavy-duty trucks. One of the proposed solutions is to set a maximum size that the model can recognize (markers should have similar resolution in images taken from the same height).

Source: Author's own study

Fig. 3. Examples of objects that were often incorrectly recognized

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