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APPLICATION OF THE COMBINED METHOD OF RASTER IMAGE RECOGNITION IN THE COMPUTER VISION SYSTEM OF UNMANNED VEHICLES IN THE MINING INDUSTRY

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Abstract. The mining industry is rapidly moving towards the practical implementation of the achievements of the fourth industrial revolution, Mining 4.0, based on the automation of underground mining processes. And smart mines, as a trend of the near future, are already taking shape with the development of technologies for the next stage of mining development - Mining 5.0. The use of autonomous intelligent robots and cobots, self-driving equipment and vehicles in a single production and information space of a smart mine will improve the safety of production processes and mine personnel. The challenging environment of a mine puts specific demands on the development and operation of autonomous robots and monitoring systems in the underground space. Therefore, the problem of eliminating errors in the identification of any stationary and moving objects in the mine requires the development of effective methods for recognising the received images in computer vision systems. Computer vision, as one of the areas of artificial intelligence, allows you to extract useful information from digital images, videos or visual data. The aim of this paper is to study the methods of image processing and analysis and to develop a combined method for recognising dark objects on a light background. The article deals with the problem of integrating innovative technologies into the system of remote monitoring of the technological environment in a mine with the use of robotic means, in particular, unmanned aerial vehicles. The method is based on image processing, then the concept of image enhancement based on appropriate algorithms is considered. Experiments on the recognition and counting of coal particles (ITES Vranov, s.r.o., Slovakia), which are dark objects on a light background, showed the effectiveness of the combined method in changing observation conditions (image size, illumination, object size), adaptability to the use of various technical means of image registration, and flexibility in setting detection parameters. For an image with a size of 600 pixels, which is sufficient to ensure correct measurements, the maximum processing time was 7.3 ms. The size of the error increases with the size of the image, which indicates an increased variability of time when processing large images. The largest share of the processing time is taken up by component filtering (this stage also includes marking the original image), which retains a consistently high percentage of time as the image size increases. The Hough transform and Yen's binarization also have a significant part. Other stages, such as resizing, blurring, masking, have a less significant contribution.

Keywords: mine, security, computer vision, image processing.

1. Introduction

Modern technological advances and global trends in the mining industry form the basis for improving the safety of underground operations [1, 2, 3]. However, statistics of accidents in underground mining [4, 5, 6, 7] show that the mining industry remains one of the most dangerous in the industry.

In addition to mining equipment, the main factors that lead to accidents and incidents in a mine include the mistakes or inattention of mining personnel [8, 9, 10].

The introduction of Industry 4.0 - the fourth industrial revolution - into mining has reduced the level of underground mining hazards by significantly automating the production process and providing real-time information about its parameters. Industry 4.0, known in the mining industry as Mining 4.0, has made it possible to obtain, process and analyze data faster and more efficiently, while ensuring trouble-free production. The radical transformation of underground mining operations has changed the entire technological paradigm of mining [11, 12, 13, 14].

And the emergence of new technologies is already outlining the trend of transition from Mining 4.0 technologies to artificial intelligence, the Internet of Things, metadata, autonomous intelligent robots, and the use of collaborative robots (Mining 5.0) [15, 16, 17]. Cobots will be the next generation of industrial robots (au-

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tonomous and independent of humans) with increased sensitivity to human activity and readiness to interact with people [18]. In conditions where real-time analysis of the external environment is required to solve the tasks of controlling robotic machines, computer vision systems are one of the main means of controlling the movement of the machine. And even the presence of modern computer vision systems in autonomous mining machines does not yet allow us to avoid restrictions on their use in the underground space. This is due to the influence of a wide range of risk factors in mine operations: a limited confined space with significant relief differences; gas and dust pollution, high temperature and humidity in the mine atmosphere; insufficient or no lighting; technical problems with the organization of communication channels and the transfer of large amounts of data.

And at the same time, in these conditions of the mining environment, a wide range of various sensors and devices based on them, which are capable of identifying obstacles and moving objects, including people, are available for use on mobile platforms.

Computer vision (Computer Vision, CV) is the basis of practically implemented systems for navigation, obstacle recognition, mapping [19]; monitoring of moving objects [20]; search and rescue missions [21], and others (fig. 1).

a) b) c)

(a) – mapping of underground mines [19]; (b) – pedestrian identification [20];
(c) – rescue of the injured [21]

Figure 1 – Implementation of computer vision for practical use in a mine environment

Unmanned aerial vehicles (UAVs) or drones can be considered to be quite efficient, maneuverable, technologically advanced and the most promising robotic device for use in mine workings (fig. 2).

Figure 2 – UAV in a mine [22]

The drone's functionality allows for maneuverable unmanned flights, controlling the drone using an intuitive interface.

UAVs can move autonomously in an uncontrolled environment and follow a predefined route in a controlled space, or be controlled remotely by an operator.

In the specific conditions of a mine, UAVs provide a real-time way to calculate distances to surrounding objects and create a map of the surrounding space, obtain visual information about the working environment, perform inspection flights to monitor the condition of mine workings and analysis the composition of the mine atmosphere, search for personnel in emergency situations, etc.

Thus, the use of this class of unmanned vehicles for surveying confined spaces and hazardous areas underground can not only reduce the risk to personnel, but also improve the level of safety of mining operations in general.

Computer vision systems play a key role in improving the efficiency and accuracy of unmanned vehicles, especially in difficult underground conditions. Therefore, research, development of new and optimization of existing approaches to building computer vision systems is an urgent scientific and technical task.

The aim of this paper is to study the methods of image processing and analysis and to develop a combined method for recognizing dark objects on a light background.

2. Methods

Identification and measurement of rock fragments that can be formed as a result of technological mining or blasting operations, as well as due to emergencies in the mine is an actual task for optimal control of the production process and remote monitoring of the technological environment in the mine, including rescue operations.

A computer vision method based on a series of segmentation, filtering and morphological operations is proposed, specially designed to determine the size of rock fragments from digital images obtained by an unmanned research vehicle.

To process the experimental data, a combined method of image processing and analysis is proposed. The task of the developed method is to count coal particles (ITES Vranov, s.r.o., Slovakia), which are dark objects on a light background.

3. Theoretical and experimental part

The input data is an image of a coal sample in a round vessel. The image is color, the dimension is arbitrary, the dimensions of the object under study are arbitrary. The output is a number indicating the quantity of detected objects and an image with labelling of all detected objects. The method should be resistant to changes in observation conditions (image size, illumination, object size), adaptive to the use of various technical means of image registration, flexible in setting detection parameters. The proposed method consists of 9 stages as shown in the block diagram (fig. 3):

- resize the image;
- converting to a greyscale representation;
- Gaussian filtering;
- identification of the region of interest (ROI);

- applying image masking;
- binarization;
- analysis of related components;
- component filtering;
- marking the area of interest and detected objects.

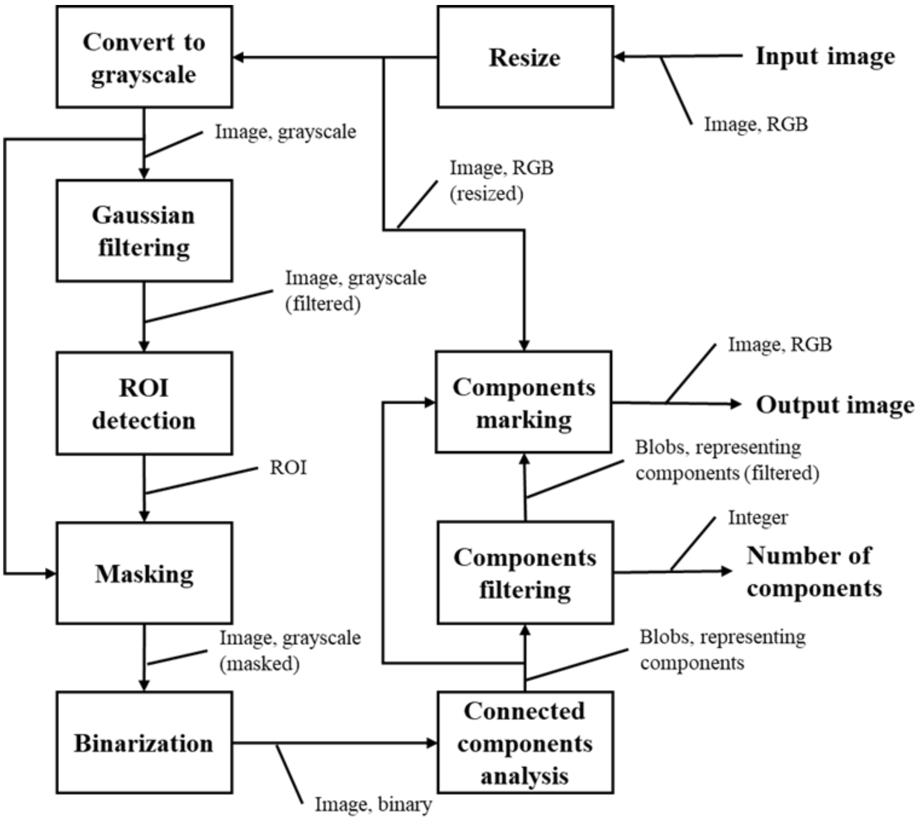


Figure 3 – A combined method of image processing and analysis

The first stage of processing the input image is to resize it to the maximum value set. It is expected that the input image will have a higher dimensionality, and at this stage the image will be reduced. This stage will allow unifying the dimensions of the input images, which should lead to improved consistency and stability of the detection algorithm. In addition, the reduction of data dimensionality leads to improved method performance and the prevention of unnecessary computational losses.

To perform the following processing steps, the image is converted from the RGB color space to grayscale. The intensity level for a pixel is formed by averaging the color components of the input image.

The next step is to identify the region of interest. In accordance with the shape of the object of study, which contains the sample under investigation, the region of interest will be a circle with a radius slightly smaller than the radius of the object image. This is necessary to ensure that the edge of the object is not covered by the region of interest. Therefore, the algorithm for determining the region of interest will include detecting a circle in the image, determining the coordinates of its center and radius, and reducing the last by a certain empirically determined value.

To detect circle-shaped contours, the Hough Transform (HT) method was applied [23]. The Hough Transform is used to detect circles in images by transforming the coordinates of contour points into a parametric space. If a circle is defined by the equation:

$$(x-a)^2+(y-b)^2=r^2,$$

where (a, b) are the coordinates of the center of the circle, and r is its radius, then each point of the contour (x_i, y_i) in the image corresponds to the surface of a cone in the space of parameter values (a, b, r). The intersection of these cones indicates the parameters of the desired circle.

The result of circle detection using the Hough transform method is shown in Fig. 4.

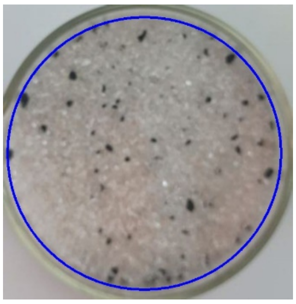


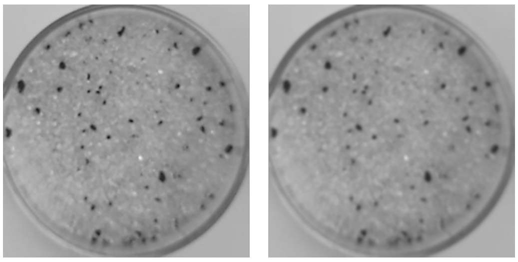
Figure 4 – Circle detection using the Hough transform method

The original HT algorithm for circles involves storing votes in three-dimensional space (a, b, r), which requires significant computing resources and memory. To optimize the process, the direction of the gradient at each contour point is used to reduce the number of required votes and increase accuracy. A modification of the Hough 2-1 (21HT) transformation method is used to reduce computational costs and save memory. During the search for the center of the circle, a set of votes is built for each point in two-dimensional space (a, b), assuming that the center of the circle should lie on the normal to each contour point. The votes are accumulated in a two-dimensional matrix, and the peak values determine the possible centers of the circles. For each center found, the distances to the points of the contour are calculated, which allow constructing a histogram of radii, the maximum of which is considered to be the radius of the circle.

This modification of the Hough transform was used because of a significant reduction in the amount of memory required, since instead of a full-fledged three-dimensional accumulator, a two-dimensional accumulator for the center and a one-dimensional histogram for the radius are used. The method also reduces computational costs, since the second stage is performed only for the found candidates for the centers.

To improve the stability of the algorithm for detecting the region of interest, the image is processed using a Gaussian filter [24]. Smoothing the image with Gaussian

Blur helps to emphasize the general contours of objects, reduce noise and make the image more uniform (Fig. 5).



a) b)

Figure 5 – Images before (a) and after (b) application of the Gaussian filter

By using a Gaussian function as a basis, the algorithm provides a natural distribution of weights, which reduces sharp transitions between neigh bouring pixels. The size of the convolution kernel and the standard deviation value determine the degree of blurring: the larger they are, the more image details are smoothed out. The coefficients for constructing the convolution kernel are calculate dusting the normal (Gaussian) distribute on formula:

$$G(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}},$$

where σ – standard deviation of the normal distribution, which determines the degree of blurring, x and y – horizontal and vertical offset from the center of the kernel.

Once a circular region of interest is found, the image is cropped and converted to grayscale according to the square circumscribed around the found circle. This allows to reduce the image dimension to the dimension of the region of interest in order to save computing resources and memory space. To remove uninformative data, which are objects outside the detected circle that are part of the square area of interest, the image is masked. The mask is a square matrix whose dimension corresponds to the dimension of the region of interest. The matrix elements belonging to the detected circle are marked with one, all other elements are marked with zero. After applying the masking procedure, uninformative pixels will be filled with zero values (Fig. 6).

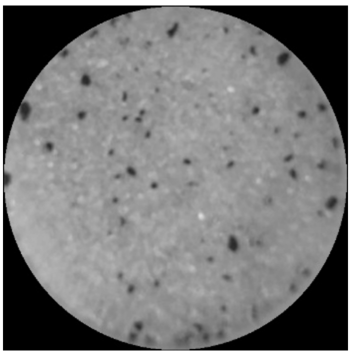


Fig.6 – Image after applying the masking operation

The next step in image processing is binarization. The binary form allows you to significantly reduce the amount of data to be stored and processed. Threshold binarization is one of the simplest image processing algorithms when all pixels of an image whose attribute exceeds a predetermined threshold value are encoded with bit 1 (white), and the rest are encoded with bit 0 (black) [25].

Thus, the threshold binarization method requires setting an intensity threshold value that divides pixels into two classes. The choice of this value can be complicated by a number of factors:

- non-stationary and correlated noise, which can lead to false segmentation;
- scene lighting, which can change the brightness of objects and background, low contrast between the object and the background, which makes it difficult to separate them.

In the context of the task, the most effective (among the listed methods) was the Yen binarization method [26]. This method is one of the entropy threshold binarization methods based on the concept of entropy correlation.

Entropic correlation to be maximized to find the optimal threshold:

$$TC(T) = C_b(T) + C_f(T),$$

where $C_b(T)$ – entropy measure for the background (background), $C_f(T)$ – entropy measure for an object (foreground).

$$C_b(T) = -\log\left\{\sum_{g=0}^{T}\left[\frac{p(g)}{P(T)}\right]^2\right\};$$

$$C_f(T) = -\log\left\{\sum_{g=T+1}^{G}\left[\frac{p(g)}{1-P(T)}\right]^2\right\},$$

where $p(g)$ – the probability of meeting the grey level g, $P(T)$– cumulative probability up to the threshold T.

This method was chosen because of its resistance to lighting changes and operation in uneven scene lighting conditions, high efficiency for binarizing low-contrast images, and the ability to work automatically without the need for manual parameter adjustment. An image of the sample under study at the binarization stage is shown in Fig. 7.

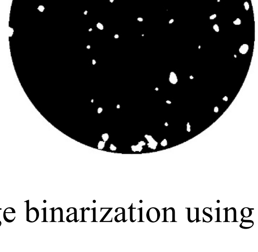


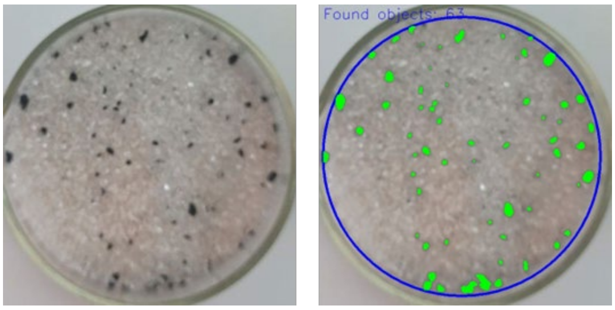
Figure 7 – Image binarization using the Yen method

After obtaining a binary representation of the area of interest, it is possible to detect and count the required objects. To do this, the input binary image is converted into a symbolic image, where all pixels belonging to the same connected region receive a unique label.

To mark the connected components, the method [27] is used, which is a combination of a block approach, state prediction, and code compression to improve the performance of the algorithm.

The next step is to filter the linked components by area by setting boundary limits for the objects to be taken into account in the calculation. The resulting objects can be of various sizes, including those that are too small (noise) or too large (merged background areas). Filtering by area allows you to remove irrelevant objects from further analysis, leaving only those that meet the a priori criteria. This helps to reduce the number of false detections and increase the accuracy of the count. The obtained value of the number of detected objects is the result of the developed method of analyzing experimental images and will be used for segmentation, filtering and morphological operations when determining the size of rock fragments from digital images.

Additionally, in order to visualize the results of image processing and analysis, the detected area of interest (using a blue circle) and the found objects are marked (objects that meet the filtering criterion are marked in green, those that do not are marked in red). An inscription indicating the number of components found is also included. An example of a marking image is shown in Fig. 8.



a) b)

Figure 8 – The result of the experimental image analysis: input (a) and labelled image (b)

The proposed method was implemented in software written in Python. The software libraries used were freely available: Open CV - for all types of image processing and analysis, Scikit-Image for the implementation of the Yen binarization method.

To evaluate the performance of the software implementation of the developed method, a series of experiments were performed using images of different sizes, and time intervals were measured during each processing stage. The experimental study was carried out on a personal computer with an AMD Ryzen 5 3500 CPU. The obtained values were averaged, the impact of each processing stage on the total execution time was analyzed, and the results were visualized. A graph of the dependence of the average execution time on the size of the image with the standard deviation was constructed (Fig. 9) and a histogram of the distribution of the share of each processing stage depending on the image size (Fig. 10). These results allow us to better understand the "bottlenecks" in the algorithm and can be used to further optimize it.

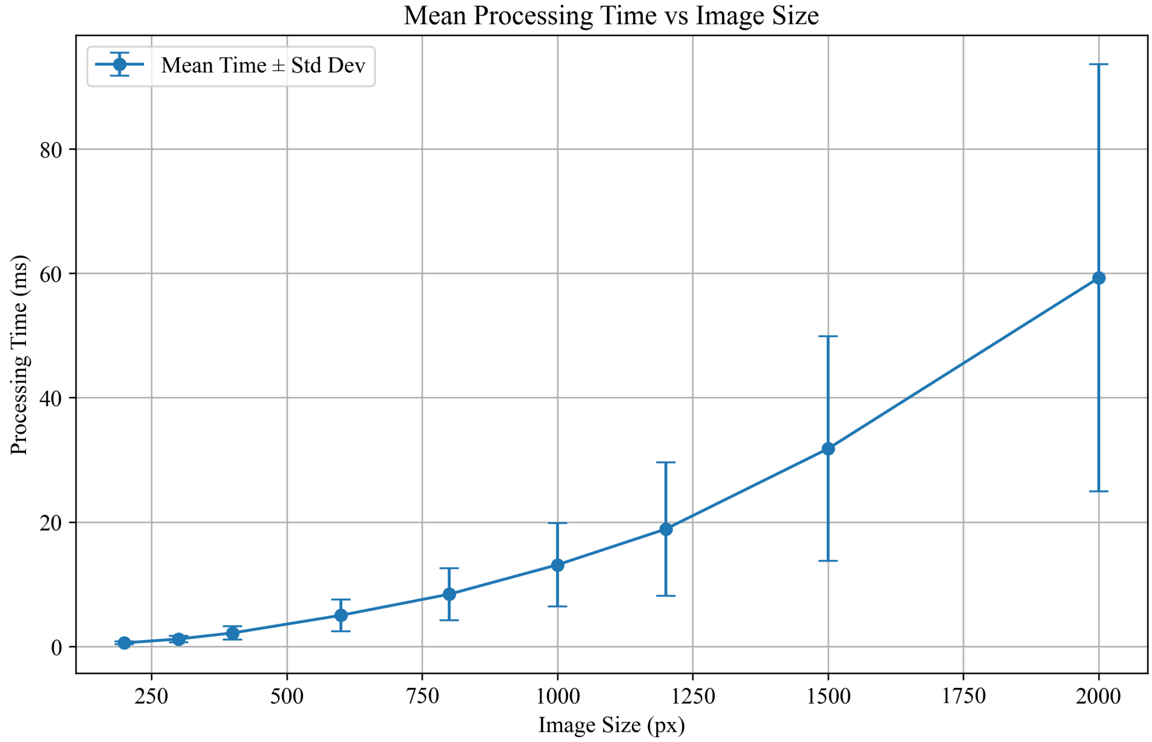


Figure 9 – Dependence of processing time on image size

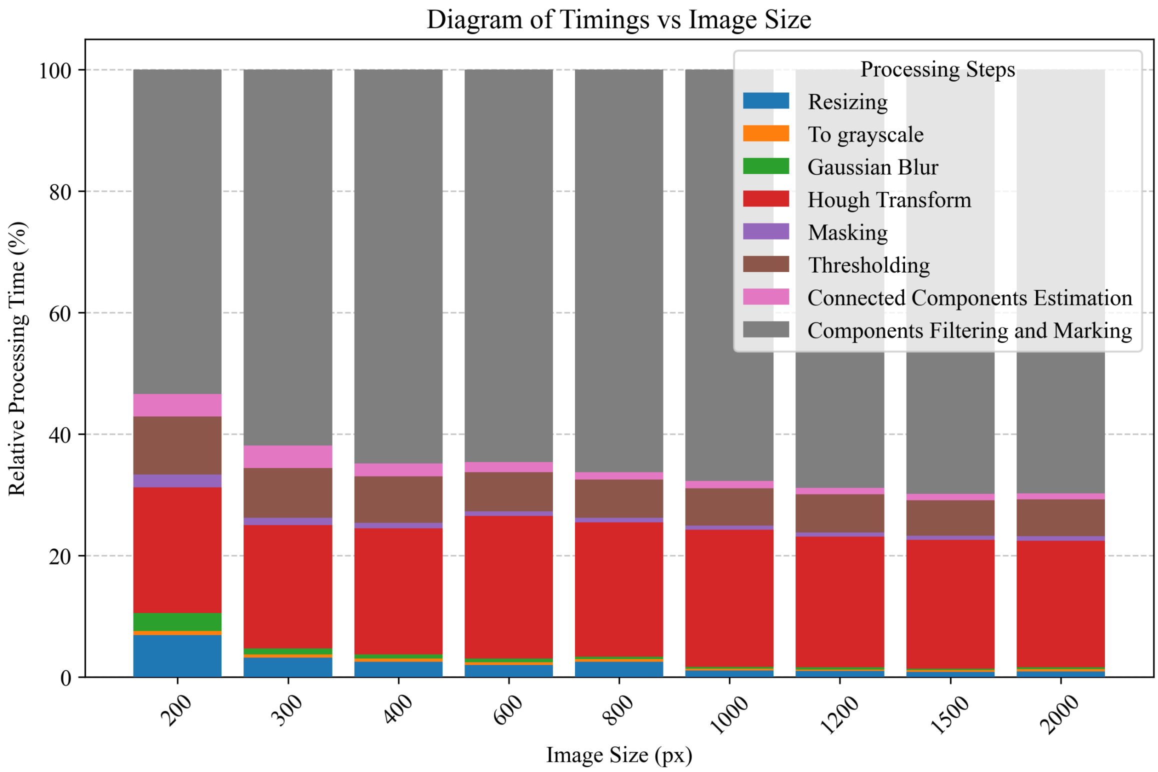


Figure 10 – Histogram of processing time distribution by each stage

It is important to mention that there is a clear increasing dependence: as the image size increases, the total processing time increases exponentially. The size of the error increases with the size of the image, which indicates an increased variability of time when processing large images. The largest share of the processing time is taken up by component filtering and marking the original image, which retains a consistently high percentage of time as the image size increases. The Hough transform and Yen's binarization also have a significant part. Other stages, such as resizing, blurring, masking, have a less significant contribution.

Thus, the developed method shows good performance results: for an image with a size of 600 pixels, which is sufficient to ensure correct measurements, the maximum processing time was 7.3 ms. Therefore, this method can be used in the embedded software of a microprocessor system, in particular, located on board UAV.

In the future, the proposed combined method can be adapted for use in computer vision systems of mobile platforms to recognize and monitor moving objects, including mine personnel.

Processing of information from thermal imaging cameras and distance sensors will allow to implement a collision avoidance system in the unmanned vehicle. To detect people who are at a dangerous distance from the device, it is possible to segment the ROI based on temperature features from the camera images and identify them as a background object or a person using a classifier [28, 29]. The distance sensor will provide information about a person's location in a three-dimensional coordinate system.

4.Conclusions

The global mining industry is already in a transition period from the era of Industry 4.0 to the shape of Industry 5.0. The use of robotic tools in the technological process and monitoring of the mine space contributes to the organization of smart production, which improves the safety of mining personnel.

Navigation, obstacle detection, and mapping systems for autonomous unmanned vehicles are based on computer vision technology. Computer vision is based on algorithms for recognizing and processing digital images obtained from various types of sensors and devices of such a vehicle.

The study demonstrates the effectiveness of the developed combined method for recognizing dark objects on a light background, the key features of which are automatic detection of the region of interest, adaptive image binarization, detection and analysis of connected components. The developed method is proposed as one of the components of computer vision algorithms for unmanned aerial vehicles.

The proposed method was implemented in software. To evaluate the performance of the method, experiments were conducted using images of different sizes. For an image of 600 pixels, the maximum processing time was only 7.3 ms. The method proved to be suitable for use in the embedded software of microprocessor-based systems, in particular on board UAVs.

To test the method, experiments were conducted on the recognition and detection of coal particles (ITES Vranov, s.r.o., Slovakia), which are dark objects on a light background. The results showed the effectiveness of the combined method when changing the observation conditions (image size, illumination, object size), adaptability to the use of various technical means of image registration, flexibility in setting the detection parameters.

These results are important in the context of Industry 4.0 as an innovative system for the digital transformation of the mining industry. This approach is in line with the mining industry's drive to improve the safety of production processes and mine personnel.

For future research, we aim to improve and adapt the combined method to recognize and monitor moving objects in a complex mine environment, including people.

Conflict of interest

Author states no conflict of interest.

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ЗАСТОСУВАННЯ КОМБІНОВАНОГО МЕТОДУ РОЗПІЗНАВАННЯ РАСТРОВИХ ЗОБРАЖЕНЬ В СИСТЕМІ КОМП'ЮТЕРНОГО ЗОРУ БЕЗПІЛОТНИХ АПАРАТІВ В ГІРНИЧОДОБУВНІЙ ПРОМИСЛОВОСТІ

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Анотація. Гірничодобувна промисловість швидко просувається у напрямку практичної реалізації досягнень четвертої промислової революціїї Mining 4.0 на основі автоматизації виробничих процесів підземного видобутку. І вже розумні шахти, як тренд недалекого майбутнього, набувають чітких обрисів з розробкою технологій наступного етапу розвитку гірничої галузі - Mining 5.0. Використання автономних інтелектуальних роботів та коботів, самокерованого обладнання та транспортних засобів в єдиному виробничо-інформаційному просторі розумної шахти дозволить покращити безпеку виробничих процесів та персоналу шахти. Складні умови середовища шахти пред'являють специфічні умови до розробки та експлуатації автономних роботів та систем моніторінгу у підземному просторі. Тому проблема виключення помилок ідентифікації будь-яких стаціонарних та рухомих об'єктів в шахті потребує розробки ефективних методів розпізнавання отриманих зображень в системах комп'ютерного зору. Комп'ютерний зір як одна з областей штучного інтелекту, дає змогу отримувати корисну інформацію з цифрових зображень, відео або візуальних даних. Метою даної роботи є дослідження способів обробки та аналізу зображень і розробка комбінованованого методу розпізновання темних об'єктів на світлому фоні. У статті розглядається проблема інтеграції інноваційних технологій в систему дистанційного моніторингу стану технологічного середовища в шахті при застосуванні роботизованих засобів, зокрема безпілотних літальних апаратів. Метод базується на обробці зображень, потім розглядається концепція покращення зображення на основі відповідних алгоритмів. Експерименти з розпізнавання та підрахунку частинок вугілля (ITES Vranov, s.r.o., Slovakia), що являють собою темні об'єкти на світлому фоні, показали ефективність застосування комбінованого методу при зміні умов спостереження (розмірів зображення, освітленості, розмірів об'єкту), адаптивність до використання різних технічних засобів реєстрації зображення, гнучкість у налаштуванні параметрів виявлення. Для зображення розміром 600 пікселів максимальний час обробки склав лише 7.3 мс. Показана чітка зростаюча залежність: зі збільшенням розміру зображення експоненціально зростає загальний час обробки. Розмір похибки збільшується з розміром зображення, що свідчить про підвищену варіативність часу при обробці великих зображень. Найбільшу частку у часі обробки займає фільтрація компонентів (у даний етап також входить маркування вихідного зображення), яка зберігає стабільно високий відсоток часу при збільшенні розміру зображення. Значну частку займають також перетворення Хафа та бінаризація Йена. Інші етапи, як зміна розміру, розмиття, маскування, мають менш виражений внесок.

Ключові слова: шахта, безпека, комп'ютерний зір, обробка зображень.