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DEVELOPMENT OF A DYNAMIC PARTITIONING MODEL AND A SOFTWARE SYSTEM FOR IMAGE SEGMENTATION IN THE IMPLEMENTATION OF COMPUTER VISION FOR ROBOTIC SYSTEMS

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The article presents an approach to image segmentation using modern mathematical and software tools. In particular, it applies the apparatus of the theory of optimal set partitioning in dynamic formulations, as well as modern languages, technologies, and software development tools for implementing image segmentation algorithms and methods. The work emphasizes the use of the obtained results in training robotic systems, which can be employed for mitigating the consequences of man-made disasters.

The methods and algorithms of the theory of optimal set partitioning are used to formalize the problem, identify key factors and segmentation objects, and specify the components of the objective functional. The software implementation of the methods and algorithms is carried out using modern programming languages, technologies, databases, and database management systems.

The article provides a sufficient number of computer experiment results, which clearly demonstrate the adequacy of the applied models, methods, and their algorithmic implementations. The scientific research outcomes have been tested on real land-based unmanned devices. The article outlines both the identified advantages and shortcomings.

The main results of the study include the application of the proposed models for image segmentation aimed at isolating individual objects in photos and videos. The paper systematizes and classifies approaches to image segmentation. A comparative analysis of classical and AI-based methods is performed, based on experimental applications to images simulating emergency conditions.

The study substantiates the appropriateness of using U-Net in cases where annotated data are available, and Watershed for resource-constrained devices without the need for training. The results enable flexible selection of tools tailored to the specific nature of the task.

The aim of the research is to develop a mathematical model and methods for implementing graphical image segmentation, as well as a software system for executing the mentioned algorithms and obtaining segmented images.

The research was conducted on a personal computer with the following configuration: Intel Core i7-12700K, 8 cores, 3.6 GHz; RAM: 32 GB, DDR4 3200 MHz; HDD: 2 TB.

The obtained results demonstrate the high accuracy of the proposed mathematical model and the correct implementation of the algorithms, as confirmed by the graphical output. The root mean square relative error did not exceed 6%.

The model is not only theoretically grounded but also practically suitable for integration into digital monitoring and control systems for autonomous robotic platforms. The mathematical model and software application have been practically tested and have shown high efficiency and accuracy.

Keywords: mathematical model, robotic systems, image segmentation, optimal set partitioning theory, clustering, classification.

Formulation of the problem. In today's world, robotics plays a key role in addressing tasks related to safety, automation, and rapid response in emergency situations. Robots are used for exploring hazardous areas, detecting victims, manipulating objects in inaccessible conditions, and monitoring the environment during man-made or natural disasters. In such scenarios, computer vision is a critical component — it enables systems to autonomously analyze their surroundings, make decisions, and perform actions with high precision.

One of the most important tasks of computer vision is image segmentation – the process of identifying and isolating objects or regions in an image that belong to the same class. For robotic systems operating under challenging conditions (poor lighting, noise, unpredictable environments), high accuracy and adaptability of segmentation algorithms are essential. In this context, the study and comparison of both classical approaches (such as Watershed and GrabCut) and modern AI-based methods (such as U-Net and DeepLab) remain highly relevant.

Analysis of recent research and publications. Image segmentation is a key task in computer vision, particularly in the context of robotics and emergency response. A wide range of segmentation methods exists, which can be broadly categorized into classical (traditional) methods and modern deep learning-based approaches [5; 6].

Classical algorithms, such as *Watershed* and *GrabCut*, are widely used due to their simplicity and effectiveness in environments with limited computational resources [4; 3].

– Watershed is based on morphological analysis of an image, treating it as a topographic surface. This method is effective for separating images with well-defined boundaries, but it is sensitive to noise and may result in over-segmentation [4].

– GrabCut uses energy minimization and Gaussian Mixture Models (GMM) to separate the foreground from the background. It requires minimal user interaction for initialization, which makes it convenient for interactive applications [3].

These methods do not require large amounts of training data, which makes them suitable for use in resource-constrained environments or where labeled datasets are unavailable [5].

Modern segmentation approaches heavily utilize deep convolutional neural networks (CNNs), which demonstrate high accuracy and strong generalization capabilities [1; 2].

– U-Net, proposed by Ronneberger et al. in 2015, combines encoding and decoding paths with skip connections, allowing precise localization of objects in the image even with a limited amount of training data. U-Net is widely used in medical image segmentation and shows high performance in tasks requiring pixel-level accuracy [1].

– DeepLab, developed by Chen et al. in 2016, incorporates atrous convolutions and atrous spatial pyramid pooling (ASPP) to capture multi-scale contextual information. Additionally, integration with Conditional Random Fields (CRFs) helps refine object boundary localization. DeepLab has shown high segmentation accuracy on datasets such as PASCAL VOC and Cityscapes [2].

A comparison of classical and modern segmentation methods reveals that the choice of approach depends on the specific requirements of the task. Classical methods like Watershed and GrabCut are less computationally intensive and do not require training [3; 4], making them appropriate for use in environments with limited computing power or lacking labeled data. In contrast, deep learning-based methods such as U-Net and DeepLab offer higher accuracy and generalization capabilities but require large datasets and powerful computational resources [1; 2].

In the context of emergency scenarios — such as search and rescue missions, firefighting, or humanitarian demining — accurate image segmentation is critically important for object identification and real-time decision-making [6; 7; 8]. For instance, U-Net and DeepLab can be used for automatic detection of victims or hazardous objects in images captured by drones or robotic systems, significantly increasing the efficiency of rescue operations.

Formulating the purposes of the article. In today's conditions, the challenge of effectively deploying robotic systems in emergency situations has become increasingly urgent. Robots are actively used for territory exploration after shelling, humanitarian demining, debris removal, victim search, inspection of damaged buildings, basements, confined spaces, as well as for monitoring zones hazardous to human presence [6; 7].

The performance quality of such systems largely depends on the ability of computer vision to accurately segment objects in images — for instance, identifying people, debris, mines, traversable zones, and explosive objects. This task is particularly difficult in real-world environments characterized by poor lighting, smoke, dust, noise, dynamic scenes, and unpredictable factors.

Moreover, the computational and energy resources of these systems are often limited, and connectivity with cloud services may be unavailable. Under such constraints, it is critically important to select an appropriate segmentation method. Traditional algorithms (e.g., GrabCut, Watershed) do not require training and consume fewer resources [3; 4], whereas neural network–based methods (U-Net, DeepLab) offer higher accuracy and better generalization capabilities [1; 2].

Main part.

Mathematical Problem Statement

It is required to find a partition $\varpi = \{\Omega_1, ..., \Omega_N\} \in \Sigma_\Omega^N$ of the set $\Omega \subset E_n$ and a vector function $c(x, \tau, t) = (c_1(x, \tau_1, t), ..., \; c_N(x, \tau_N, t))$, defined a.e. for $x \in \Omega$ for a given fixed set of centers $\tau = \{\tau_1, ..., \tau_N\} \subset \Omega^N$ and all $t \in [0, \; T]$, which ensure

$$\inf_{\varpi \in \Sigma_\Omega^N;\; c(\cdot,\cdot,\cdot) \in L_2^N(\Omega \times \Omega \times [0,T])} F(\varpi, \; c(\cdot,\cdot,\cdot)), \tag{1}$$

where

$$F(\varpi, \; c(\cdot,\cdot,\cdot)) = \int_0^T \sum_{i=1}^N \int_{\Omega_i} (c_i(x, \tau_i, t) \cdot m(x, \tau_i) + a_i) \rho(x) dx dt, \tag{2}$$

subject to the conditions

$$\begin{gathered} \frac{\partial c_i(x, \tau_i, t)}{\partial t} = \sum_{j=1}^N A_{ij} \cdot f_j(c_j(x, \tau_j, t)), \quad 0 \le t \le T; \\ c_i(x, \tau_i, t_0) = c_{0i}(x, \tau_i), \;\; i = 1, ..., N, \end{gathered} \tag{3}$$

a.e. for $x \in \Omega$, with fixed $\tau_i = (\tau_i^{(1)}, ..., \tau_i^{(n)}) \in \Omega_i$, $i = 1, ..., N$, and the closure conditions of the system

$$\sum_{i=1}^N A_{ij} = 1, \quad j = 1, ..., N \;. \tag{4}$$

Here $c_i(x, \tau_i, t), \; i = 1, ..., N$, are the desired real-valued functions defined on $\Omega \times \Omega \times [0, T]$, which for any fixed $\tau_i = (\tau_i^{(1)}, ..., \tau_i^{(n)}) \in \Omega_i$ are continuously differentiable with respect to the argument t on the interval $[0, T]$ a.e. for $x = (x^{(1)}, ..., x^{(n)}) \in \Omega$, are bounded and measurable with respect to the argument x on Ω for all $t \in [0, \; T]$. $m(x, \tau_i)$, $c_{0i}(x, \tau_i)$ are given real-valued functions defined on $\Omega \times \Omega$, bounded and measurable with respect to the argument $x \in \Omega$ for any fixed $\tau_i \in \Omega_i$ for all $i = 1, ..., N$ (in particular, $m(x, \tau_i)$ may play the role of a metric on $\Omega \times \Omega$). $f_i(c_i(x, \tau_i, t)), \; i = 1, ..., N$, are given real-valued Lipschitz functions on their domain; $\rho(x)$ is a given non-negative function, bounded and measurable on Ω. $a_i, \; i = 1, ..., N$, are given, usually non-negative numbers; $0 \le A_{ij} \le 1$, $i, j = 1, 2, ..., N$, are given numerical parameters; $T > 0$ and $t_0 \in [0, \; T]$ are given.

Here and henceforth, the integrals are understood in the Lebesgue sense. We will assume that the measure of the set of boundary points of the subsets $\Omega_1, ..., \Omega_N$ is equal to zero.

A pair $(\varpi^*, \; c^*(x, \tau, t))$, that delivers the minimal value of functional (2) on the set $\Sigma_\Omega^N \times L_2^N(\Omega \times \Omega \times [0, T])$ subject to constraints (3), (4), we shall consider as an optimal solution to problem (1)–(4). In this case, the partition $\varpi^* = \{\Omega_1^*, ..., \Omega_N^*\} \in \Sigma_\Omega^N$ we shall consider as an optimal partition of the set $\Omega \subset E_n$ into N subsets, and the vector function $c^*(x,\tau,t) = (c_1^*(x,\tau_1,t), ..., c_N^*(x,\tau_N,t)) \in L_2^N(\Omega \times \Omega \times [0,T])$ – as an optimal phase trajectory of the dynamical system in problem (1)–(4).

From a subject-matter point of view, the independent variable $t \in [0, T]$ in the given mathematical formulation of the dynamic optimal partitioning problem can play the role of the time variable, and $T > 0$ and $t_0 \in [0, T]$ are the given final and initial moments of time in the studied dynamic process, respectively. Thus, the functions $f_i(c_i(x,\tau_i,t))$, $i = 1,2,\dots,N$, in the differential relations (3), which reflect the dynamics of transportation prices, may have forms the inflation/deflation model reflects the tendency of prices to constant (exponential) growth/decline (5).

$$f_i(c_i(x,\tau_i,t)) = d_i \cdot c_i(x,\tau_i,t),$$
$$x \in \Omega, \tau_i = (\tau_i^{(1)}, ..., \tau_i^{(n)}) \in \Omega_i, i = \overline{1,N}, 0 \le t \le T \quad (5)$$

Theoretical Foundations Underpinning the Study

Image segmentation is the process of dividing a digital image into homogeneous regions corresponding to different objects or parts of a scene. The primary goal of segmentation is to simplify or transform the image representation to facilitate its analysis, classification, or interpretation [1; 5].
Segmentation methods are conventionally divided into:

- Classical (traditional) approaches — based on thresholding, edge detection, clustering, and morphological transformations. This group includes algorithms such as *Watershed* [4] and *GrabCut* [3].
- Deep learning–based methods — utilizing convolutional neural networks (CNNs), such as *U-Net* [1] and *DeepLab* [2].

The former are less resource-intensive, operate quickly, and do not require training, but often fall short in terms of accuracy and generalization. The latter offer high accuracy and adaptability to complex input data, but require large volumes of annotated data and powerful computational resources.

Segmentation is a key stage in the architecture of computer vision systems. It enables:

- Identification of objects of interest (people, equipment, hazardous items);
- Reduction of the volume of input data for further processing;
- Localization of identified objects;
- Generation of depth maps, traversable paths, or hazard zones for autonomous navigation.

In pattern recognition tasks, segmentation often precedes classification: regions of interest are first extracted and then assigned to a specific class.

For robotics — particularly in unstable or poorly structured environments — segmentation significantly improves the reliability of autonomous decisions

[6]. For example, in scenarios requiring not just detection of a person but precise delineation of their contour for subsequent manipulation, high-quality pixel-level segmentation is critical.

In the field of emergency response and defense, segmentation is used in:

– Search and rescue robotics — to detect people or bodies under rubble;

– Drones — for territory monitoring and automatic recognition of vehicles, smoke, fire, or footprints;

– Demining operations — to detect mines, cluster munitions, and shells using video from drones or ground-based platforms [7; 8];

– Firefighting — for automatic identification of fire or smoke sources.

U-Net and *DeepLab* are used for recognizing people, injuries, mines, and structural damage — even in cases of partial occlusion [1; 2]. Classical methods (*Watershed*, *GrabCut*) are employed in embedded systems with limited hardware — such as portable demining robots operating without internet access [3–5].

Selection of the Segmentation Method

This work considers four image segmentation methods, namely:

– Watershed — a classical morphological algorithm simulating terrain flooding [4]. It requires no training, runs quickly on a CPU, but is sensitive to noise.

– GrabCut — a graph-based approach using energy minimization that combines segmentation and pixel classification via Gaussian Mixture Models (GMM) [3].

– U-Net — a convolutional neural network with an encoder-decoder architecture featuring skip connections [1]. Suitable for medical images, rescue scenarios, and demining.

– DeepLabv3+ — a modern deep model utilizing dilated convolutions and the Atrous Spatial Pyramid Pooling (ASPP) module, enhancing object localization [2].

These methods were selected to represent two types of approaches: classical (Watershed, GrabCut) and deep learning–based (U-Net, DeepLab).

Segmentation Algorithm Descriptions

Watershed:

1. Apply Gaussian filter for smoothing.
2. Transform the image into a gradient map.
3. Define markers to initiate flooding.
4. Perform segmentation based on the watershed algorithm [4].

GrabCut:

1. Initialize with a rectangular region of interest (ROI).
2. Construct a graph of pixels and nodes.
3. Estimate foreground/background probabilities using GMM.
4. Perform minimum cut to separate regions [3].

U-Net:

1. Input image passes through multiple convolutional layers (encoder).

2. Decoder reconstructs resolution by combining features from corresponding encoder layers via skip connections.
3. Output is a segmentation mask of the same size as the input image [1].

DeepLabv3+:

1. Input image is processed through a backbone network (e.g., ResNet, Xception).
2. Multi-scale context is formed in the ASPP module.
3. The result is refined by a decoder module and merged with low-level features [2].

Description of the Software Environment

The segmentation algorithms were implemented using Python 3.10 with the following main libraries:

– OpenCV — for implementing classical methods Watershed and GrabCut.

– NumPy — for array and image processing.

– Matplotlib — for visualization of segmentation results.

– PyTorch — for neural network operations, implementation, and inference of U-Net and DeepLabv3+ models.

– Google Colab — as an execution environment supporting GPUs to accelerate deep learning.

All implementations are provided as reusable Jupyter Notebook/Colab files.

Program Results.

The mathematical model proposed in this work, along with the corresponding algorithm and software implementation, was applied to 12 test images of varying content and composition (Figs. 1–5).

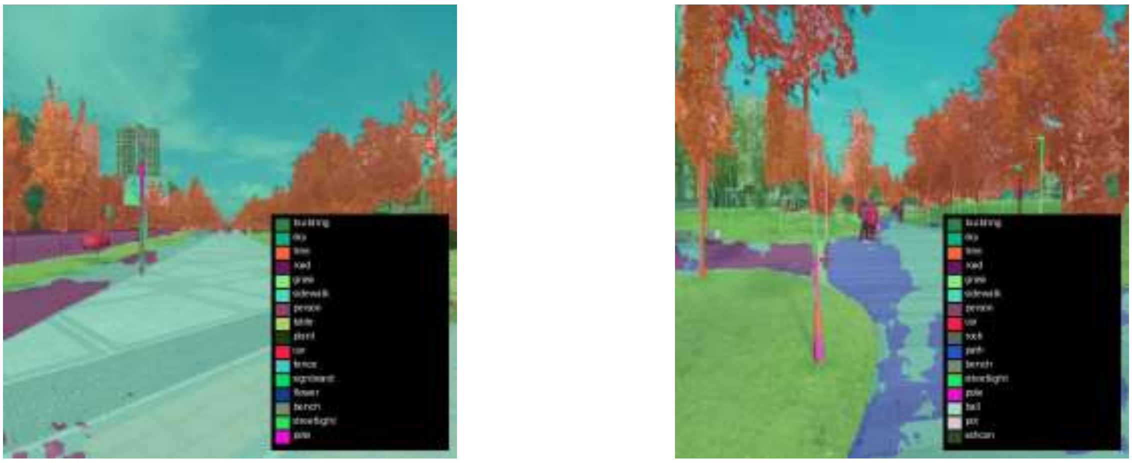
a) b)

Figure 1. Results of the Image Segmentation Software Application:
a) Architectural Landscape and b) Natural Landscape

As shown in Figure 1, the results of applying the developed software application to images of a) an architectural landscape and b) a natural landscape are presented. The program demonstrates sufficiently accurate identification of buildings, sky, trees, roads, grass, soil, architectural elements, flowers, fences, lighting fixtures, and poles.

The segmentation visualization is performed using a dynamic color palette, which adapts independently of the number of identified object classes to enable clear visual differentiation.

A comparison was made between the program's results and the averaged outputs of three AI applications: ChatGPT, Midjourney, and Runway. For the example shown in Figure 1a, the relative error was 2.1%, while for the case in Figure 1b, it was 2.7%, respectively.



a) b)

Figure 2. Results of the Image Segmentation Software Application for Mixed Content Images

Figure 2 presents the segmentation results obtained using the mathematical model and proposed algorithm for images of an urban park landscape. These images contain a large variety of object types and numerous individual objects. As observed, the program successfully identified buildings, sky, trees, roads, grass, people, plants, cars, and many other elements.

A comparison between the program's results and the averaged outputs from three AI tools — ChatGPT, Midjourney, and Runway — demonstrates a high degree of consistency among these approaches. Specifically, the relative error for the example shown in Figure 2a is 3.1%, and for Figure 2b, it is 4.2%. Considering the complexity and rich detail of the images, the accuracy of the algorithm's application in this case can be regarded as satisfactory.

Figure 3 presents the segmentation results obtained using the mathematical model and proposed algorithm for images of a typical urban landscape. The images include more than ten types of objects, each of which was successfully identified. Using the mathematical model and the proposed algorithm, buildings, sky, vegetation, people, roads, vehicles, and other elements of a typical urban scene were accurately recognized.

a) b)

Figure 3. Results of the Image Segmentation Software Application for Mixed Urban Content Images

A comparative analysis of the program’s results with the averaged outputs from the three previously mentioned AI tools confirmed a high degree of model adequacy. The relative error was 2.8% for the case shown in Figure 3a, and 3.6% for Figure 3b. Considering the complexity of the typical urban landscape images, the accuracy of the algorithm’s application is deemed acceptable.

a) b) c)

Figure 4. Results of the Image Segmentation Software Application for Images Containing Wheeled and Aerial Vehicles

Figure 4 presents segmentation results obtained using the mathematical model and proposed algorithm for images containing isolated vehicles. This example is simpler compared to the one shown in Figure 5, which features images with a large number of vehicles. The purpose of this comparison is to understand the difference in segmentation accuracy between images with isolated objects and those with numerous typical objects.

Specifically, the relative error for the cases shown in Figures 4a, 4b, and 4c are 2.3%, 2.8%, and 3.1%, respectively. In comparison, segmentation of images with a large number of vehicles shows nearly double the error. For example, the relative errors for Figures 5a, 5b, and 5c are 4.6%, 5.1%, and 5.1%, respectively.

This demonstrates that the complexity and density of objects in the image significantly affect segmentation accuracy, although the results remain within sufficiently acceptable limits.

a) b) c)

Figure 5. Results of the Image Segmentation Software Application for Images Containing a Large Number of Wheeled Vehicles

Conclusions. This work proposes a mathematical model of dynamic segmentation, an algorithm, and its implementation encompassing both classical mathematical and modern AI-based segmentation methods. All methods were implemented using Python and open-source libraries.

Existing and developed neural networks demonstrate superior accuracy but require significant computational resources for conducting numerical experiments. In simpler scenarios, the proposed toolkit can deliver results acceptable for practical applications.

The results confirm the appropriateness of combining different approaches depending on the application context.

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РОЗРОБКА ДИНАМІЧНОЇ МОДЕЛІ РОЗБИТТЯ ТА ПРОГРАМНОГО КОМПЛЕКСУ ДЛЯ СЕГМЕНТАЦІЇ ЗОБРАЖЕННЯ ПРИ РЕАЛІЗАЦІЇ КОМП'ЮТЕРНОГО ЗОРУ РОБОТОТЕХНІЧНИХ СИСТЕМ

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У статті розглянуто підхід сегментації зображень з використанням сучасних математичних та програмних засобів. Зокрема, використаний апарат теорії оптимального розбиття множин для задач в динамічних постановках та сучасні мови, технології і засоби створення програмного забезпечення для реалізації алгоритмів та методів графічної сегментації. В роботі зроблено акцент на використанні отриманих результатів для навчання робототехнічних систем, що можуть бути використані для ліквідації наслідків техногенних катастроф. Методи та алгоритми теорії оптимального розбиття множин використовуються для формалізації задачі, визначення ключових факторів та об'єктів сегментації, а також для конкретизації складових цільового функціоналу. Програмна реалізації методів та алгоритмі, здійснена з використання сучасних мов та технологій програмування, баз даних та систем управління ними. В роботі наведено достатню кількість результатів

комп'ютерного експерименту, що дозволяють наочно впевнитись в адекватності застосованих моделей та методів, алгоритмів їх реалізації.

Результати наукового дослідження використані та апробовані на реальних сухопутних безпілотних пристроях, винайдені недоліки та переваги, які в тому числі окреслені в статті. Основними результатами роботи є застосування запропонованих моделей для сегментації зображень, з метою виокремлення на фото та відео окремих об'єктів.

У роботі систематизовано та класифіковано підходи до сегментації зображень. Проведено порівняльний аналіз класичних і AI-методів на основі експериментального застосування до зображень, що моделюють умови надзвичайних ситуацій. Обґрунтовано доцільність застосування U-Net у випадках з доступом до розмічених даних, та Watershed – для ресурсно обмежених пристроїв без потреби навчання. Результати дозволяють гнучко обирати інструменти під специфіку задачі.

Метою дослідження є розробка математичної моделі та методів для реалізації графічної сегментації зображень, а також програмного комплексу для реалізації згаданих алгоритмів та отримання сегментованого зображення.

Дослідження проводилося на персональному компютері Intel Core i7-12700K, 8 ядер, 3.6 GHz, RAM: 32 ГБ, DDR4 3200 MHz, HDD: 2 ТБ

Отримані в роботі результати свідчать про високу точність запропонованої математичної моделі, та коректну реалізації алгоритмів, що підтверджено отриманими графічними результатами. Середньоквадратична відносна похибка не перевищувала 4.12%.

Модель є не лише теоретично обґрунтованою, а й практично придатною до впровадження у цифрові системи моніторингу та керування робототехнічними самохідними установками. Математична модель та програмний додаток апробований на практиці, показав високу ефективність та точність.

Ключові слова: математична модель, робототехнічні системи, сегментація зображень, теорія оптимального розбиття множин, кластеризація, класифікація.

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