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Методы удаления нежелательных объектов с изображений аэрофотосъемки с использованием итерационного подхода

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Удаление объектов с изображений относится как к задачам, позволяющим улучшить качество изображения, например, в области восстановления поврежденных фотографий, так и к задачам повышения безопасности при удалении людей или автомобилей при обработке изображений аэрофотосъемки. При этом методы удаления нежелательных объектов обычно включают в себя два этапа: выделение объектов для удаления и восстановление текстуры на участках изображения. Первый этап может выполняться вручную пользователями, если необходимо выделить конкретные объекты, либо автоматически путем обучения модели на различных классах объектов. Задача восстановления изображения в процессе исследований решалась различными методами, основной из которых включает использование значений соседних пикселов для отрисовки в удаленных областях. В последние годы хорошие результаты показывают методы с применением глубокого обучения на основе сверточных и генеративных нейронных сетей. Целью работы является разработка метода удаления объектов с изображений аэрофотосъемки с выделением объектов вручную и отрисовкой текстуры в обрабатываемой области. В работе выполнен обзор современных методов восстановления изображений, среди которых наиболее перспективным является использование сетей глубокого обучения, а также анализ текстуры в восстанавливаемой области. Предложенный алгоритм основан на итерационном подходе при анализе соседних областей и постепенном закрашивании восстанавливаемой области текстурой с соседних пикселов с учетом веса и контуров границ. В статье выполнена оценка эффективности предложенного метода с использованием базы видеопоследовательностей, полученных с квадрокоптеров и содержащих людей и природные объекты. При этом проводилась как экспертная оценка, которая показала хорошие визуальные результаты, так и сравнение качества работы алгоритма с известными подходами по метрике PSNR, которая показала лучшие результаты при наличии сложной текстуры в сцене.

Ключевые слова: Imageinpainting, *восстановление изображений, дистанционное зондирование земли, генеративные нейронные сети, текстурный анализ.*

Methods of removing unwanted objects from aerial photography images using iterative approach

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Removing objects from images refers both to the tasks of improving the quality of the image, for example, in the field of recovering damaged photographs, and the tasks of increasing safety when removing people or cars from aerial photography images with remote sensing of the earth. At the same time, methods for removing unwanted objects usually include two stages: selecting objects for removal and restoring texture in areas of the image. The first stage can be performed manually by users, if it is necessary to select specific objects, or automatically by training the model on different classes of objects. The problem of image restoration in the course of research was solved by various methods, the main one of which involves using of the values of neighboring pixels for rendering in distant areas. In recent years, methods using deep learning based on convolutional and generative neural networks have shown good results. The aim of the work is to develop a method for removing objects from aerial photography images with manually selecting objects and drawing textures in the processed area. The paper reviews modern methods of image restoration, among which the most promising are the use of deep learning networks, as well as texture analysis in the restored area. The proposed algorithm is based on an iterative approach when analyzing neighboring areas and gradually painting the restored area with a texture from neighboring pixels, taking into account the weight and contours of the boundaries. The article evaluates the effectiveness of the proposed method using the base of video sequences obtained from quadcopters and containing people and natural objects. At the same time, both an expert assessment was carried out, which showed good visual results, and a comparison of the quality of the algorithm with known approaches according to the PSNR metric, which showed the best results in the presence of a complex texture in the scene.

Keywords:Image inpainting, image restoration, earth remote sensing, generative neural networks, texture analysis.

Introduction

Earth remote sensing (ERS) and image processing of aerial photography from unmanned aerial vehicles is an indispensable tool for studying and monitoring the planet, helping to effectively manage its resources [1]. The use of remote sensing data makes it possible to ensure the safety and efficiency of the extraction of natural resources, to prevent emergencies and eliminate their consequences, as well as to help ensure environmental protection and control climate change.

The images obtained by aerial photography are used in many industries – agriculture, geological and hydrological research, forestry, environmental protection, territorial planning, educational, intelligence and military purposes. ERS systems allow getting the necessary data from large areas (including hard-to-reach and dangerous areas) in a short time. However, most often these images need to be preprocessed for a more accurate interpretation of the data. In particular, there is a need to remove unwanted objects from them, such as clouds.

This paper discusses the features of removing objects from images during aerial photography, which may be necessary for security tasks, improving the quality of data analysis and for artistic purposes. The paper proposes an algorithm based on the selection of objects and the use of an iterative approach to delete the selected object and restore image sections by painting over part of the areas with a weighted value from neighboring pixels.

Literature review

The task of removing objects from aerial photographs can be solved by several methods, including using neural networks. For example, the simplest segmentation method, the threshold value method, is often used to segment images consisting of bright objects on a dark background or vice versa. Thus, it is possible to detect, for example, clouds in the input image. In order for the image to be segmented correctly, an adaptive threshold should be selected, calculated separately for different areas of the image, then it will be possible to process images with a strong lighting gradient and uneven background due to poor lighting conditions. In addition, it should be taken into account that in the case of uneven illumination, the effectiveness of the method decreases and it is necessary to divide the image into subdomains, each with its own threshold value, in order to avoid reducing the effectiveness of the method [2].

Another approach uses modern convolutional neural network architectures. In December 2015, a new neural network architecture, *ResNet*, was introduced, which is easier to optimize and the classification accuracy of which is better due to the significant increase in depth; at the same time, it is easier to train it [3]. It contains fairly simple ideas: the output data of two successful convolutional layers is fed and the input data for the next layer is bypassed [4]. The architecture diagram is shown in Fig. 1.

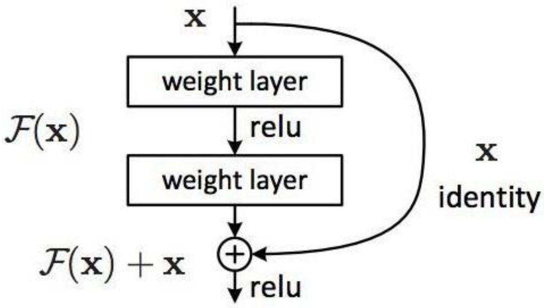

Fig. 1. *ResNet*architecture
Рис. 1. Архитектура*ResNet*

ResNets use shortest path connections: operations that skip some layers to transfer information to the lower parts of the network, which acts as a direct path for the information flow. In the initial case, the *ResNet* connection of the quick access performs an additive signal mapping, that is, the input state of the residual block is added to the output data of the bypassed layers.

Methods for detecting more complex objects in images can cover several different approaches, such as manually selecting the boundaries of an object, after which the algorithm refines the contours of the object automatically, or automatically selecting various types of objects using intelligent approaches, such as neural networks for area selection (*R-CNN*). For example, the authors of R. Girshick, J. Donahue, T. Darrell and Jitendra Malik describe an object detection system consisting of three modules. The first module generates offers of areas independent from categories. These offers define the set of possible detections available to the detector. The second module is a large convolutional neural network that extracts a fixed-length feature vector from each area. The third module is a set of linear *SVMs* of a certain class [6]. The selective search algorithm proposed by the authors J. Uijlings, K. van de Sande, T. Gevers and

A. Smeulders [7], works by generating image subsegments that can belong to the same object – based on color, texture, size and shape-and iteratively combining similar areas to form objects. This gives “object offers” of different scales. The *R-CNN* line does not depend on the area offer algorithm. The authors use a selective search algorithm to create 2,000 offers by categories of independent regions (usually indicated by rectangular areas or “bounding boxes”) for each individual image.

After deleting a certain object, an empty area remains in the image, which must be filled with information so that the image quality does not become worse. The task of image restoration (*Motion Inpainting*) is one of the most famous in the field of digital image processing. Initially, approaches related to content addition based on the values of neighboring pixels were used, for which bilinear and bicubic interpolation methods were used [8]. The most modern approaches include the use of convolutional and generative neural networks.

In 2017, the authors C. Burlin, Le Callonec and L. Duperier proposed an approach for recovering small images from *the CIFAR 10 dataset* based on the use of autoencoders and generative adaptive neural networks. They proposed a new *Flattened Row LSTM* model, which demonstrated high efficiency and stability, as well as compliance of the reconstructed images with the original data from the user's point of view [9].

V. Chandak, P. Saxena, M. Pattanaik and G. Kaushal used Wasserstein's generative adaptive neural network architecture to create their model. The Wasserstein distance, a measure of the distance between two probability distributions, was used as a loss function to train the generator. The proposed methodology can be divided into three stages. First, the data from the set is preprocessed*CelebA*, then a model based on generative adaptive Wasserstein neural networks fills in the missing pixels in the image. Noise is inevitable during generation, so the third stage is to pass the resulting image through the neural network for its further improvement. This approach makes it possible to increase the peak signal-to-noise ratio and the structural similarity index by 2.45 and 4 %, respectively, compared to the approaches used recently, however, in this methodology, training strongly depends on the data used for it [10].

In 2018 G. Liu, F. A. Reda, K. J. Shih, T. Wang, A. Tao и B. Catanzaro has developed a model that uses partial convolution operations with accumulation and step-by-step updating of the mask for the best rendering of the image. This model can work quite efficiently with holes of any shape, size, location or distance from the borders of the image. When the hole size increases, there is no critical deterioration in performance, which is also an advantage of the model [11].

In January 2020, authors Yi Jiang, Jiajie Xu, Baoqing Yang, Jing Xu and Junwu Zhu also used autoencoders and generative adaptive neural networks, adding a bandwidth connection to solve the gradient vanishing problem. Their proposed model consists of a generator and two discriminators. When testing on the datasets*CelebA* and *LWF* model demonstrated higher results in terms of PSNR and SSIM metrics in comparison with such models as *FMM*, *GLCIC* and *DIP* [12].

A key feature of image restoring methods based on deep training is the ability to recover missing data, which the algorithm obtains based on training on a number of examples, as a result of which the quality and realism of such approaches is much higher in comparison with classical methods.

Method of restoring aerial photography images

It is proposed to use a modified image restoring method, known as the *Telea* method, as well as the Navier-Stokes method. Consider the stages of operation of these algorithms in more detail.

The *Telea* method is based on the *Fast Marsh Method*. The in-painting of an area starts from its border and gradually goes inside, painting the pixel with a normalized weighted sum of all pixels in the neighborhood. The correct choice of weight is important: the greatest weight is given to pixels lying next to the point next to the border normal, and pixels lying on the border contours. As soon as a pixel is inpainted, it is moved to the next one by the fast transition method, which controls that the pixels next to the already inpainted ones are colored first.

Figure 2 shows a diagram of the *Telea* method. It is necessary to inpaint a point p located on the boundary of the $\partial\Omega$ area of coloring Ω. To do this, it is needed to take a small neighborhood of the point p, equal to the ε, the set of pixels of which is denoted as $B_\varepsilon(p)$. The in-painting of p should be determined by the values of the known neighbor points that belong to $B_\varepsilon(p)$.

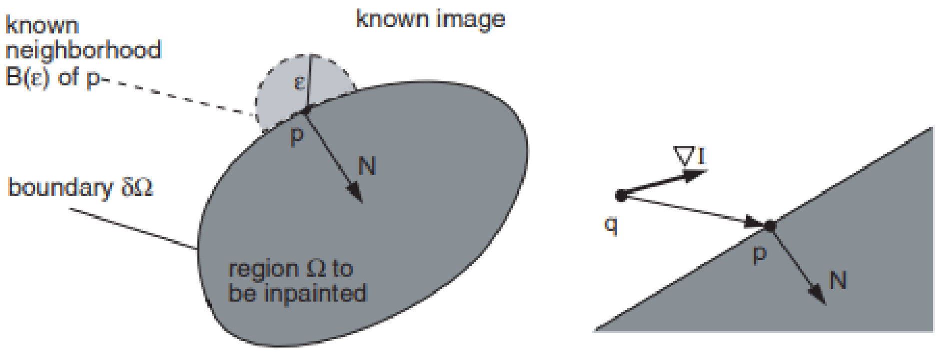

Fig. 2. Image inpainting principle
Рис. 2. Принцип зарисовки изображения

For relatively small values, ε the first order of approximation of the image $I_q(p)$ at point p is considered, taking into account the image $I(q)$ and the gradient of $\nabla I(q)$ values at point q:

$$I_q(p) = I(q) + \nabla I(q)(p - q). \tag{1}$$

Then the point p is defined as a function of all points q in the set $B_\varepsilon(p)$ summing up the estimates of all points q weighted by the normalization function $w(p, q)$:

$$I(p) = \frac{\sum_{q \in B_\varepsilon(p)} w(p,q)\big(I(q) + \nabla I(q)(p - q)\big)}{\sum_{q \in B_\varepsilon(p)} w(p,q)}. \tag{2}$$

Next, it is necessary to iteratively apply formula (2) to all discrete pixels $\partial\Omega$ as the distance from the initial position increases and advance the border inside the area Ω until it is completely inpainted [13].

The Navier-Stokes algorithm is based on hydrodynamics and uses partial differential equations. The basic principle is heuristic. First, the algorithm moves along the edges from known areas to unknown ones (therefore, the edges must be continuous). It continues isophotes (lines connecting points with the same intensity, just as contours connect points with the same height), while matching gradient vectors at the border of the drawing area. For this purpose, some methods from hydrodynamics are used. After they are received, they are filled with color in order to reduce the minimum dispersion in this area.

Let Ω be the area to be reconstructed from the surrounding data, and I_0 be the intensity of the image, presumably being a smooth function (possibly with large gradients), outside the area Ω. I_0 and ΔI_0 at the boundary of $\partial\Omega$ are known. Further, the Navier-Stokes method is adapted from the field of hydrodynamics for rendering images, comparisons are presented in table 1.

Table 1

Navier - Stokes method for in-painting images

Navier – Stokes method	Rendering images
Flow function Ψ	Image Intensity I
Fluid speed $v = \nabla^{\perp}\Psi$	The direction of the isophota $\nabla^{\perp} I$
Vorticity $w = \Delta\Psi$	Smoothness $w = \Delta I$
Liquid viscosity v	Anisotropic diffusion v

The vorticity transfer equation with respect to w is solved by the formula (3)

$$\frac{dw}{dt} + v \cdot \nabla w = v \nabla \cdot \left(g\left(|\nabla w| \right) \right) \nabla w, \quad (3)$$

where the function g takes into account the anisotropic diffusion of smoothness w. The intensity of the image I, which determines the speed field $v = \nabla^{\perp} I$ in formula (3), is recovered by simultaneous solution of the Poisson equation

$$\nabla i = w,\ I\,|_{\partial\Omega} = I_0. \quad (4)$$

The algorithm begins with calculating the vorticity w from the image I, using the data about the environment to determine the boundary vorticity. Then the shape of the vorticity flow (3) is developed using a simple Euler step, with centered differences in space for diffusion and the *minmod* method for the convection period.

After the first step (3), the intensity of the image I is calculated by solving the Poisson equation (4) using the Jacobi iterative method. For this updated value, w is recalculated and the algorithm repeats. Anisotropic diffusion on I is performed every few steps, which helps to determine the boundaries more precisely. A stable state is achieved after N iterations of this cycle, usually N = 300 [14].

Experimental studies

The efficiency of the image restoration algorithm was studied using the database obtained from unmanned aerial vehicles under various shooting conditions [15]. The database includes 12 video sequences with a duration of more than 3000 frames of various objects in Switzerland, obtained using the *DJI Mavic Pro* drone, and allows evaluating the quality of various algorithms for improving the quality of video sequences, motion tracking and object detection (Table 2).

Table 2

Description of the video sequence database

Name	Resolution	Number of frames	Screenshot	Characteristics
Berghouse Leopard.mp4	1280×720	1073		Complex camera movement, non-linear texture, presence of foreground objects
Bluemlisal Flyover.mp4	1280×720	957		Complex camera movement, simple texture, no moving objects
Creux du Van Flight.mp4	1280×720	1196		Complex camera movement, multi-dimensional scene, non-linear texture
DJI_0501.mov	3840×2160	232		Circular motion of the camera, presence of a static foreground object, variable lighting
DJI_0574.mov	3840×2160	928		Linear camera movement, nonlinear texture, presence of moving foreground objects, zooming
DJI_0596.mov	3840×2160	1015		Linear camera movement, simple texture, presence of moving foreground objects

The effectiveness of the image restoration algorithm was evaluated in comparison with known approaches based on texture methods and deep training in the task of removing objects from aerial images. Figure 3 shows the results of image restoration using various methods, as well as a comparison of quality by the *PSNR* metric (5), where the difference between the original image (Fig. 3, *a*) and the image from which the objects selected by the user were removed (Fig. 3, *b*) was estimated.

$$PSNR = 10\log_{10}\left(\frac{\max(I(i,j))^2}{MSE}\right). \tag{5}$$

The *MSE* value between the original and the restored image is calculated by the expression (6)

$$MSE = \frac{1}{m \times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\big(I(i,j) - I_w(i,j)\big)^2, \tag{6}$$

where m, n are the width and height of the image; I is the original frame; I_w is the restored frame.

Most of the known methods, when trying to remove a foreground object, generate noticeable artifacts in the corresponding area, especially if there is a complex texture. The quality assessment shows good results of the Amle method [16] under the condition of a simple texture in the restoration area. The best results in the presence of a complex texture are shown by the proposed method using generative neural networks (Fig. 3, *d*).

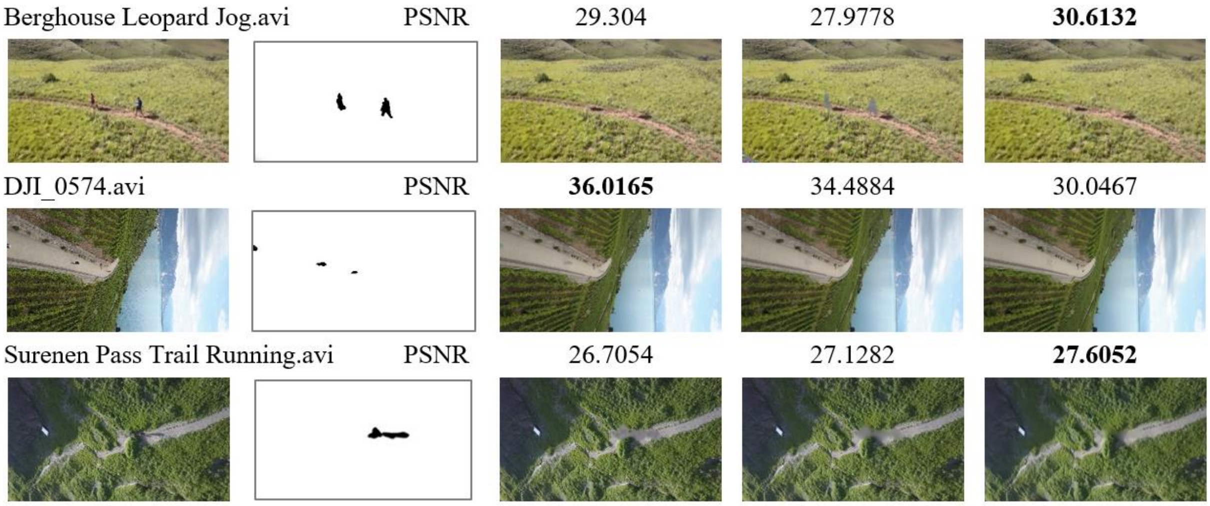

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Fig. 3. Examples of image restoration using various methods: *a* – original image; *b* – mask for selecting objects to delete; c – method of image restoration Absolute Minimizing Lipschitz Extension Inpainting [16]; *d* – Transport image restoring method [17]; *e* – proposed method

Рис. 3. Примеры восстановления изображений с применением различных методов: *а* – оригинальное изображение; *б* – маска выделения объектов для удаления; *в* – метод восстановления изображений AbsoluteMinimizingLipschitzExtensionInpainting [16]; *г* – метод восстановления изображений Transport [17]; *д* – предложенный метод восстановления изображений

The proposed method shows good visual results, while the quality strongly depends on the complexity of the textures and the number of connected pixels in the restored area.

Conclusion

The paper proposes a modified image restoration method using an iterative approach that allows removing unwanted masked objects, such as people, clouds or cars, from aerial photography images and obtaining visually high-quality results. The evaluation of the quality of the system based on the analysis of *PSNR* values and visual comparison of the quality of the results with the initial data was performed. The proposed method can reliably handle distortions of any shape, size, location or distance from the image boundaries. In addition, performance degrades slightly as the size of the missing areas increases.

The conducted experiments show that in order to further improve the quality of image restoration, it is necessary to take into account the texturing of the area and use training materials taking into account the content. In modern research, it is proposed to use convolutional generative neural networks to solve the problems of restoring damaged images in areas with complex texture. Thus, methods using neural networks demonstrate high efficiency in solving the problem of removing unwanted objects from images, in particular, people from remote sensing images. Recently introduced architecture of *ResNet* neural networks with residual training has a wide potential for use in this field.

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