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ВЫДЕЛЕНИЕ ОБЪЕКТОВ ИЗОБРАЖЕНИЙ ДЛЯ АВТОНОМНОЙ ЛОКАЛИЗАЦИИ БЕСПИЛОТНЫХ ЛЕТАТЕЛЬНЫХ АППАРАТОВ И ПОСТРОЕНИЯ КАРТЫ ОКРУЖАЮЩЕГО ПРОСТРАНСТВА

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Аннотация. Рассмотрена задача автономной локализации беспилотного летательного аппарата и построения карты его окружения. Показана низкая устойчивость детекторов ключевых точек к изменению погодных и временных условий формирования изображений окружающего пространства по сравнению с устойчивостью детекторов линий. Для повышения устойчивости локализации беспилотных летательных аппаратов в качестве ключевых объектов идентификации предложено использовать однородные по яркости области изображений (сегменты). Разработан алгоритм сегментации по локальным минимумам градиента яркости полутоновых изображений, получаемых из исходных цветных изображений окружающего пространства беспилотного летательного аппарата. Для выравнивания скоростей роста областей локальных минимумов предложен алгоритм волновой сегментации с автоматическим остановом, основанный на определении новых начальных и дополнительных точек роста областей с помощью монотонно изменяющегося порога, а также на учете скорости изменения градиента яркости вдоль траектории роста области в критерии останова. Показано, что предложенные алгоритмы обеспечивают более устойчивую локализацию областей при изменении погодных и временных условий формирования изображений по сравнению с известными алгоритмами выделения линий и ключевых точек.

Ключевые слова: одновременная локализация и картографирование; волновая сегментация изображений; выращивание областей; идентификация объектов изображений; детекторы точек; детекторы линий.

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DETECTION OF IMAGE OBJECTS FOR AUTONOMOUS LOCALISATION OF UNMANNED AERIAL VEHICLES AND MAP FORMATION OF THE SURROUNDING SPACE

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Abstract. The problem of autonomous localisation of an unmanned aerial vehicle and construction of a map of its environment is considered. The low stability of keypoint detectors to changing weather and time conditions of image formation in the surrounding space is demonstrated compared to the stability of line detectors. To improve the stability of unmanned aerial vehicles localisation it is proposed to use image regions (segments) with uniform brightness as key identification objects. An algorithm for segmentation based on local minima of the brightness gradient of halftone images obtained from the original colour images of the unmanned aerial vehicle's surrounding space has been developed. To equalise the growth rates of local minima a wave segmentation algorithm with automatic stopping is proposed. This algorithm is based on identifying new initial and additional growth points of regions using a monotonically varying threshold and taking into account the rate of change of the brightness gradient along the region growth trajectory in the stopping criterion. It is shown that the proposed algorithms provide more stable localisation of areas, when changing weather and time conditions for image formation in comparison with known algorithms for extracting lines and key points.

Keywords: simultaneous localisation and mapping; SLAM; wave segmentation of images; region growing; image object identification; point detectors; line detectors.

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Introduction

Simultaneous localisation and mapping (SLAM) technology is widely used in autonomous mobile robot systems, allowing for the construction of a map of the environment and spatial orientation [1–6]. This technology is based on the comparison of images generated at different points in time during the mobile robot's movement, the binding of objects identified in the images to a digital map of the area, and the identification of objects in the images and the map. A pressing challenge is to ensure the operation of such systems in open space conditions with significant changes in weather and time conditions for image recording.

The aim of the work is to increase the stability of localisation of key objects under changing weather and time conditions for image formation.

Statement of the problem

Basic SLAM methods utilise low-level geometric objects – points extracted by analysing the brightness gradient of images – for identification [1–6]. Newer SLAM methods [7–9] typically utilise semantic objects, whose intrinsic identification parameters are less dependent on weather and time conditions during image formation. However, detecting semantic objects requires significant computational effort. Therefore, relatively simple detectors that extract less complex, high-level geometric objects – lines and segments – are of interest. These objects exhibit reduced localisation stability in response to changing weather and time conditions, while the computational complexity of detection is reduced compared to semantic segmentation.

Segmentation by local minima of the brightness gradient of grayscale images

To identify areas of uniform brightness that are resilient to changes in weather and time conditions during image formation we propose a segmentation algorithm based on local minima of the brightness gradient, MinLGS (minimum local gradient segmentation). This algorithm is based on growing neighbourhoods of local minima of the brightness gradients of grayscale images obtained from the original colour images of the unmanned aerial vehicles (UAV) surroundings using standard colour transformations. This algorithm differs from known segmentation algorithms by taking into account the maximum brightness difference in the neighbourhood of a 3 × 3 pixel as the gradient value for thresholding the smoothest image areas; by identifying not only point-based but also the most stable area-based local minima as the starting point for segmentation; by ensuring consistency in the growth rates of the local gradient minima regions. The algorithm consists of the following steps:

1) converting a colour image $I_{\text{RGB}} = \left\| i_{\text{RGB}}(y, x) \right\|_{\left(y = \overline{0, Y-1},\, x = \overline{0, X-1}\right)}$ of $Y \times X$ pixels into a grayscale image $I_{\text{HT}} = \left\| i_{\text{HT}}(y, x) \right\|_{\left(y = \overline{0, Y-1},\, x = \overline{0, X-1}\right)}$;

2) formation of a gradient image $I_{\text{G}} = \left\| i_{\text{G}}(y, x) \right\|_{\left(y = \overline{0, Y-1},\, x = \overline{0, X-1}\right)}$, whose pixel values $i_{\text{G}}(y, x)$ are calculated using the expression $i_{\text{G}}(y, x) = \max\left(\left| i_{\text{HT}}(y+m, x+n) - i_{\text{HT}}(y, x) \right|\right)$, $m = \overline{-1, 1}$, $n = \overline{-1, 1}$;

3) cycle through brightness levels $q = \overline{0, 255}$. This step includes search for local minima of gradients in the gradient image I_{G} at level q using the algorithm proposed in work [10], which identifies not only point but also stable area local minima, and coordinated growth of regions of local gradient minima by joining existing regions of pixels, whose brightness gradient value corresponds to the q level;

4) merging adjacent segments with close brightness gradient boundary values. The merged segment inherits the smallest number among the merged segments;

5) reassigning numbers to segments to ensure continuity and reduce the maximum number row value.

Gradient-wave segmentation of halftone images

In order to improve the accuracy of division into regions of halftone images, containing objects on a uniform background, and to simplify the processing by eliminating the stage of preliminary determination of the initial growth points a Gradient-Wave Region Growing (GWRG) algorithm is proposed. This algorithm is based on wave growing of regions of local maxima with their selection in the order of decreasing values according to a monotonically changing threshold and analysis of the intensity gradient in the direction of region growth. The algorithm differs from known segmentation algorithms in the following way:

1) defining as initial growth points of regions single or groups of adjacent pixels, whose intensities coincide with the value of a threshold that monotonically changes from the maximum value to the minimum and determines the iteration of processing new pixels selected for joining to existing regions or forming new regions;

2) matching the growth rates of regions (joining new pixels to regions) by taking into account the values of the first derivative with respect to intensity;

3) cessation of region growth upon a decrease relative to the threshold of the local value of the second derivative with respect to intensity, calculated along the growth chain of the region connecting adjacent pixels, namely the base pixel located inside the region, the boundary pixel of the region joined to it at the previous iteration and the candidate pixel processed at the current iteration for joining to the boundary pixel of the region.

The algorithm is built on a cycle through brightness levels q ($q = \overline{2^B - 1, 0}$) in which the following is performed:

1) determination of significant elements in a matrix of $M_P = \left\| m_P(y, x) \right\|_{\left(y = \overline{0, Y-1},\, x = \overline{0, X-1}\right)}$ pixels ($m_P(y, x) \in \left[0, 2^B - 1\right]$, where B is the pixel bit depth) with the size of the $Y \times X$ relative to the threshold q (function F_{MP});

2) growing regions (function F_{RG}) is the formation of a segmentation matrix $M_S = \left\| m_S(y, x) \right\|_{\left(y = \overline{0, Y-1},\, x = \overline{0, X-1}\right)}$, the values of whose elements indicate the numbers of segments n_S to which they belong ($n_S \in \left[1, N_S\right]$, where N_S is the number of segments);

3) selection of growth grains of regions – single-pixel and multi-pixel (areal) local maxima (function F_{SP}) – pixels that were not connected to any region at the threshold value q;

4) initial growth of the region (function F_{PRG}).

The function F_{MP} is defined by the expression

$$q \le m_P(y, x) < q - \Delta q \Rightarrow m_S(y, x) \leftarrow 1,\ y = \overline{0, Y-1},\ x = \overline{0, X-1}.$$

The function F_{RG} is defined by the expressions

$$y \leftarrow y_C\left(n_S, p_C(n_S)\right),\ x \leftarrow x_C\left(n_S, p_C(n_S)\right),\ p_C(n_S) \leftarrow p_C(n_S) - 1$$

$$\forall j,i,k,l\big(m_S(y+j,x+i)=1\big)\wedge\big(m_2(k,l,y,x,j,i)>g\big)\Rightarrow$$
$$\Rightarrow\big\{m_S(y+j,x+i)\leftarrow m_S(y,x),\, y_C\big(n_S,p_C(n_S)\big)\leftarrow y+j,\, x_C\big(n_S,p_C(n_S)\big)\leftarrow x+i,$$
$$m_D(y+j,x+i)\leftarrow m_1(y,x,j,i),\, p_C(n_S)\leftarrow p_C(n_S)+1,$$
$$j\in\{-1,0,1\},\, i\in\{-1,0,1\},\, |j|+|i|\neq 0\big\},\, n_S=\overline{2,N_S},$$

where y_C and x_C are coordinates of adjacent pixels in matrix M_P from the stack sets $\Big\{Y_C(n_S)=$ $=\big\|y_C\big(n_S,p_C(n_S)\big)\big\|_{\left(p_C(n_S)=\overline{0,P_C(n_S)-1}\right)}\Big\}_{\left(n_S=\overline{0,N_S}\right)}$ and $\Big\{X_C(n_S)=\big\|x_C\big(n_S,p_C(n_S)\big)\big\|_{\left(p_C(n_S)=\overline{0,P_C(n_S)-1}\right)}\Big\}_{\left(n_S=\overline{0,N_S}\right)}$; $m_2(k,l,y,x,j,i)=m_1(k,l,j,i)-m_1(y,x,j,i)$ is the second derivative with respect to intensity calculated on the basis of the first derivatives with respect to intensity for pixels $m_P(y+j,x+i)$, $m_P(y,x)$ and the base pixel $m_P(k,l)$; $m_1(y,x,j,i)=m_P(y,x)-m_P(y+j,x+i)$ is the first derivative with respect to intensity for the boundary pixel $m_P(y,x)$ and the candidate pixel $m_P(y+j,x+i)$; $m_1(k,l,y,x)$ is the first derivative with respect to intensity for the base pixel $m_P(k,l)$ and the boundary pixel $m_P(y,x)$. For all boundary $m_P(y,x)$ and attached $m_P(y+j,x+i)$ pixels $m_1(y,x,j,i)\geq\Delta q$ is performed.

The function F_{SP} is defined by the expression

$$m_S(y,x)=1\Rightarrow\{N_S\leftarrow N_S+1,\, m_S(y,x)\leftarrow N_S,\, y_S(0)\leftarrow y,\, x_S(0)\leftarrow x,\, p_S\leftarrow 1,$$
$$y_C(N_S,0)\leftarrow y,\, x_C(N_S,0)\leftarrow x,\, p_C(N_S)\leftarrow 1,\, F_{\mathrm{PRG}}\},\, y=\overline{0,Y-1},\, x=\overline{0,X-1},$$

where $y_S(0)$ and $x_S(0)$ are coordinates of the initial point of growth of the local maximum from the stacks of coordinates $Y_S=\|y_S(p_S)\|_{\left(p_S=\overline{0,P_S-1}\right)}$ and $X_S=\|x_S(p_S)\|_{\left(p_S=\overline{0,P_S-1}\right)}$; p_S is the pointer to stacks Y_S and X_S.

The function F_{PRG} is executed, while $p_S>0$ and is defined by the expressions

$$p_S\leftarrow p_S-1,\, y\leftarrow y_S(p_S),\, x\leftarrow x_S(p_S)\,\forall j,i\big(m_1(y,x,j,i)=0\big)\wedge\big(m_P(y,x)=q\big)\Rightarrow$$
$$\Rightarrow\big\{m_S(y+j,x+i)\leftarrow N_S,\, y_S(p_S)\leftarrow y+j,\, x_S(p_S)\leftarrow x+i,\, p_S\leftarrow p_S+1,$$
$$y_C\big(N_S,p_C(N_S)\big)\leftarrow y+j,\, x_C\big(N_S,p_C(N_S)\big)\leftarrow x+i,$$
$$p_C(N_S)\leftarrow p_C(N_S)+1,\, j\in\{-1,0,1\},\, i\in\{-1,0,1\},\, |j|+|i|\neq 0\big\}.$$

In contrast to the conventional Region Growing (RG) algorithm [11], which uses sequential segment processing, the proposed algorithm expands the boundaries of all regions in a wave-like manner by adding unprocessed adjacent significant pixels, whose brightness satisfies a threshold that is lowered after all significant pixels have been processed. In contrast to the conventional wave Seed Region Growing (SRG) algorithm and its modifications [12–14], which determine all growth points during initialisation, the proposed algorithm selects the initial growth points during the segmentation process and is associated with a threshold value that is gradually reduced from maximum to minimum.

The GWRG algorithm provides incomplete image segmentation into N_S non-overlapping regions, corresponding to objects and the background. The number of regions is unknown in advance and is refined during the segmentation process by gradually lowering the brightness threshold q ($q=\overline{2^B-1,\,0}$) with each cycle and detecting new local maxima, which can be single-pixel or multi-pixel (areal). New local maxima and subsequent pixels added to existing regions are detected by comparing with the threshold q. Wave-like growth of regions and weighted separation of regions with smooth boundaries are ensured by monitoring the values of the first and second derivatives of intensity.

The GWRG algorithm can be effectively used as part of the MinLGS algorithm for segmentation based on local minima of the brightness gradient to identify homogeneous regions with high localisation stability under changing weather and time conditions. In this case the initial pixel matrix M_P for the GWRG algorithm should be an inverse gradient image $m_P(y,x)=255-i_{\mathrm{G}}(y,x)$, calculating the pixel values of the matrix M_P using the expression $m_P(y,x)=255-i_{\mathrm{G}}(y,x)$ for $y=\overline{0,Y-1}$, $x=\overline{0,X-1}$.

Evaluation of the stability of geometric objects to changes in weather and time conditions for image formation

The examples of test halftone images I_1 and I_2 generated from the same angle but at different times are showed in fig. 1. The images differ in brightness, contrast, shadow distribution and the positions of dynamic objects. Differences in image generation conditions lead to changes in the number and positions of key objects identified by the detectors. As a result, many objects in one image are missing at corresponding coordinates in the other image. As an example, fig. 2 shows the lines identified in images I_1 and I_2 by the Sobel detector [11] and the developed MinLGS algorithm (based on GWRG).

a *b*

Fig. 1. Test halftone images I_1 and I_2

a *b*

Fig. 2. Lines highlighted in images I_1 and I_2 by the Sobel detector

To assess the stability of geometric objects to changes in weather and time conditions for image formation dependencies were obtained for the values of the weighted number $\hat{N}_{\mathrm{E}}$ of non-conforming objects calculated by reducing the number $N_{\mathrm{E}} = N_{\mathrm{E}}(1, 2) + N_{\mathrm{E}}(2, 1)$ of non-conforming objects in one $N_{\mathrm{E}}(1, 2)$ and another $N_{\mathrm{E}}(2, 1)$ images to the total number $N_{\mathrm{O}} = N_{\mathrm{O}}(1) + N_{\mathrm{O}}(2)$ of objects in one $N_{\mathrm{O}}(1)$ and another $N_{\mathrm{O}}(2)$ images using the expression $\hat{N}_{\mathrm{E}} = \dfrac{N_{\mathrm{E}}}{N_{\mathrm{O}}}$.

The weighted characteristics of the detection results are presented in table 1. The table shows that segments extracted by the MinLGS algorithm (based on GWRG) are significantly more resistant to changes in weather and time conditions of image formation compared to points.

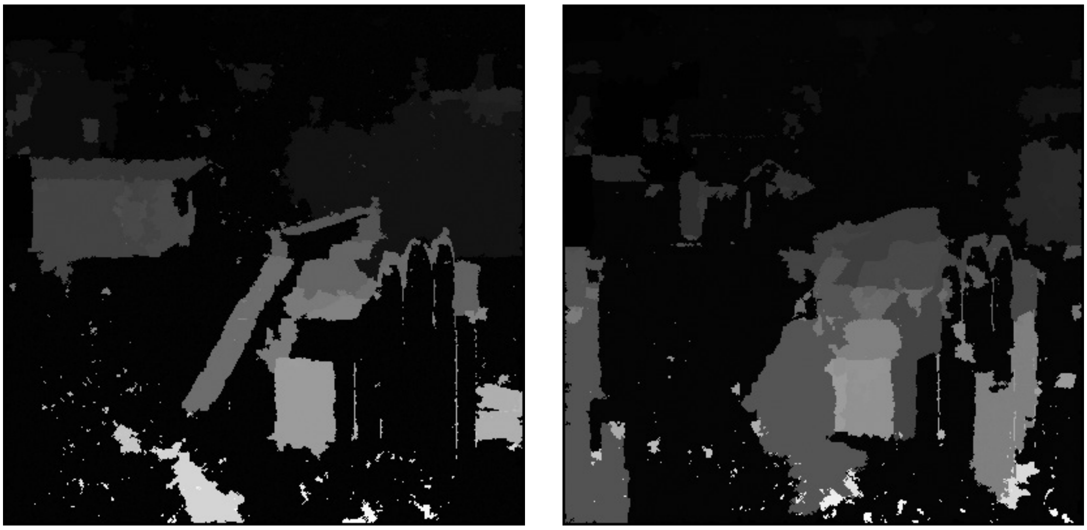

Fig. 3. Segments extracted from images I_1 and I_2 using the MinLGS algorithm (based on GWRG)

Weighted characteristics of the results of detection of points and lines of images I_1 and I_2

Detectors	N_O	$\hat{N}_E$	Source
SIFT	1861	0.960	[15]
SURF	626	0.965	[16]
Sobel	1251	0.951	[11]
Canny	1005	0.961	
MinLGS (based on GWRG)	849	0.124	This work

Conclusions

Algorithms for segmenting grayscale images based on local brightness gradient minima and gradient-wave region growing of local maxima have been developed. It has been established that the developed segmentation algorithms provide more stable region localisation under changing weather and time conditions for image formation, compared to existing line and keypoint extraction algorithms, albeit with higher computational complexity.

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