International Science Group

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INTERNATIONAL SCIENTIFIC AND PRACTICAL CONFERENCE "SCIENCE FOUNDATIONS OF MODERN SCIENCE AND PRACTICE"

Athens, Greece
November 23-26, 2021

ISBN 978-1-68564-519-9

DOI 10.46299/ISG.2021.II.X

SCIENCE FOUNDATIONS OF MODERN SCIENCE AND PRACTICE

Abstracts of X International Scientific and Practical Conference

Athens, Greece
November 23 – 26, 2021

Library of Congress Cataloging-in-Publication Data

UDC 01.1
The X International Science Conference «Science foundations of modern science and practice», November 23 – 26, 2021, Athens, Greece. 674 p.

ISBN - 978-1-68564-519-9
DOI - 10.46299/ISG.2021.II.X

RESEARCH OF SUPERPIXEL IMAGE SEGMENTATION METHOD

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Superpixel processing has always been a popular method of incorporating spatial a priori points into a wide range of computer vision tasks [1-4]. It is used both to influence the resulting statistical models and for computational purposes. For example, superpixel techniques have been widely used for graphical inference based on graph sections to reduce computational costs.

The method of superpixel processing has somewhat lost its popularity due to the fairly rapid popularization of deep neural networks for classification, segmentation, and many other image processing tasks [5-7]. However, the statistical and computational advantages of the superpixel method can be very successfully applied in the context of deep networks. The main reason for this is that deep neural networks designed for computer vision tasks have become deeper and more complex in recent years. Although this improves the accuracy of many tasks, it is also associated with increased computational costs [8, 9].

Therefore, our main goal is to increase the accuracy of networks by simplifying the segmentation process, rather than building more complex models. We suggest doing this by combining superpixels. This level has two main advantages: grouping information and introducing a priori information into segmented output.

This approach facilitates segmentation that preserves the boundaries that superpixels provide us. The application of the segmentation algorithm aims to quickly form a superpixel representation of the image, in which the brightness information would be stored with high accuracy [10-14].

However, there is no guarantee that each superpixel corresponds to the interpreted area (object) of the image, because, most likely, these objects will be divided into a number of segments. Moreover, individual small areas will be created for pixels that are significantly different from neighboring ones, when, for example, the image is distorted by pulsed noise. To improve the correspondence of superpixels to objects, the procedure of enlarging (merging) areas is applied.

An image represented by superpixels is traditionally described by an undirected planar adjacency graph, in which nodes correspond to areas of superpixels (contain their attribute description), and edges indicate adjacent areas. Within the framework of our approach, there is no need to specially create such a data structure, since the adjacency graph is specified indirectly, through multiple features F_3 – lists of neighbors for superpixels, see formula:

$$F_3 = \{L^{(k)}\}_{k=0}^{K_D-1}, \tag{1}$$

where $L^{(k)}$ – conditional indices (labels) of areas adjacent with area D uniquely specified for the processed image;

K_D – the length of this list.

Let the image be divided into M regions of superpixels as a result of primary segmentation, indexed with the same number of unique (not repeating) marks. And let the description of the area D_M include multiple features (1) with labels indicating K_{Dm} adjacent areas ($0 \leq m \leq M-1$). Then the simplest procedure for enlarging superpixels is that all superpixels are considered sequentially and for each of them all neighbors are checked for the possibility of their joining to the current superpixel. The union of the current region D_M with the adjacent region D_n will be carried out if the given homogeneity predicate for the enlarged region is true:

$$Q(Dm \cup D_n) = TRUE. \tag{2}$$

Note that the maximum number of these checks is equal to twice the number of edges in the adjacency graph (each edge corresponds to two “opposite” links in the F_3 features of adjacent superpixels):

$$\sum_{m=0}^{M-1} K_{Dm} = 2R\ , \tag{3}$$

where R – the number of edges in the graph.

In practice, there can be fewer checks if you dynamically adjust (shorten) the lists of links as the regions are attached. Note also that by Euler’s formula for planar graphs

$$R \leq 3M - 6. \tag{4}$$

It follows from (3), (4) that the amount of computations when combining regions will depend no faster than linearly on the number of superpixels of the primary segmented image. Given that this number is relatively small, it can be expected that the merging procedure will not be computationally difficult.

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