Generalizing the Simple Linear Iterative Clustering (SLIC) superpixels

Jakub Nowosad[1]
Institute of Geoecology and Geoinformation, Adam Mickiewicz University, Poznan, Poland
`https://nowosad.github.io/`
nowosad.jakub@gmail.com

Tomasz F. Stepinski
Space Informatics Lab, Department of Geography and GIS, University of Cincinnati, Cincinnati, OH, USA
stepintz@uc.edu

Abstract

Superpixels are a promising group of techniques allowing for generalization of spatial information. Among this group, the Simple Linear Iterative Clustering (SLIC) superpixels algorithm proved to be first-rate, both in terms of the quality of the output and the performance. SLIC, however, is limited to detecting homogeneous areas and uses the Euclidean distance only. Here, we propose an extension of SLIC allowing to use any specified distance measure for single or multi-layered spatial raster data. To present our idea, we use the extension to create an over-segmentation of areas with similar proportions of different land cover categories in Ohio. Given a proper distance measure, the proposed extension can also be used for other scenarios, including creating regions of similar temporal patterns or similarly ranked areas. Depending on the use case, the resulting superpixels could be either the result of the analysis or the input for further classification or clustering.

1 Introduction

Generalization of spatial information is one of the pillars of GIScience. It is especially vital for spatial raster data, for which considering single cells' values without its spatial context often are not enough to understand underlying objects or processes. For remote sensing data, generalization is often associated with (geographic) object-based image analysis (OBIA) [2], with the main goal to partition space to identify homogeneous objects.

OBIA applies many generalization techniques, including the multiresolution segmentation (MRS) that uses cells as the underlying representation [8]. Recently, an approach of superpixel become considered as a promising alternative [6]. Its main idea is to create groupings of cells with similar values, which result in an over-segmentation [15, 1]. Each superpixel represents a desired level of homogeneity while at the same time maintains boundaries and structures [12]. Superpixels also carry more information than each cell alone, and thus they can speed up the subsequent processing efforts [15, 1].

A large number of methods for creating superpixels were developed in the last decades [17], mostly for image processing. They are based on different ideas, from graph-based to

---

[1] Corresponding author

cluster-based. Among them, Simple Linear Iterative Clustering (SLIC) [1] proved to be not only one of the best performing for image processing [1, 17], but also for remote sensing data analysis [6]. It has also been implemented in a number of GIS software, including GRASS GIS [10], SAGA-GIS [5], and Google Earth Engine [9].

Simple Linear Iterative Clustering (SLIC) [1] is a spatially constrained version of the k-means algorithm. Instead of searching for similar values in the whole area, it starts with regularly located centers, and each center has only a limited search window. The distance between the center value and each applicable cell is an intermixing of spatial distance with the values' distance. The original formulation of SLIC [1] focussed on creating superpixels based on images, including converting the sRGB input images into the CIELAB space. In it, each cell in the image was described by five values divided into two groups - a pixel color in the CIELAB space ([lab]) and a pixel location ([xy]). Comparing a given pixel with the cluster centroid requires, however, calculating distances for these two parts independently before joining them together into one distance value.

The SLIC algorithm can also be used for different color spaces, for any number of color dimensions, but also for different variables than colors. In principle, it enables creation of superpixels based on less and more than three variables. However both color (spectral) and spatial distances are based on the Euclidean distance. Using the Euclidean distance to calculate color distances is adequate in many cases, however, it limits the possible usability of the SLIC algorithm for spatial raster data.

Here, we present an extension of SLIC, allowing it to work with any number of layers and various distance measures between values. In this extension, the distance between values can be replaced with any applicable dissimilarity measure [4]. To demonstrate the aftermentioned idea, we apply the extended SLIC algorithm on multi-layered raster data representing proportions of land cover categories.

2 Simple Linear Iterative Clustering (SLIC) Superpixels

SLIC starts with regularly located cluster centers spaced by the interval of S. Next, each cell is assigned to the nearest cluster center, and the distance D is calculated between the cluster centers and cells in the $2S \times 2S$ region.

$$D = \sqrt{\left(\frac{d_c}{m}\right)^2 + \left(\frac{d_s}{S}\right)^2}$$

where d_c is the color (spectral) distance, m is the compactness parameter, d_s is the spatial (Euclidean) distance, and S is the interval between the initial cluster centers.

The color (spectral) distance is calculated between values $I(x_i, y_i, s_p)$ and $I(x_j, y_j, s_p)$ for a spectral band s_p in the set of spectral bands B:

$$d_c = \sqrt{\sum_{p \in B} (I(x_i, y_i, s_p) - I(x_j, y_j, s_p))^2}$$

The spatial (Euclidean) distance between cells represents spatial proximity:

$$d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$$

The color distance controls the homogeneity of superpixels, while the spatial distance is related to spatial contiguity.

Superpixels are created by assigning each cell to the cluster center with the smallest distance. Afterward, new cluster centers (centroids) are updated for the new superpixels, and their color values are the average of all the cells belonging to the given superpixel. The SLIC algorithm works iteratively, repeating the above process until it reaches the expected number of iterations. Experiments of [1] showed that between 4 and 10 iterations suffices in the case of RGB images. The last, optional, step enforces the 4-connectivity of the cell belonging to the same superpixels by reassigning disjoint cells.

SLIC has two main parameters - S and m. The first one controls the size of each superpixel, which is directly related to the number of output superpixels. The m parameter, compactness, controls the influence of the spectral distance on the results. Its large values result in more regularly shaped superpixels, while lower values create more spatially adapted, irregularly shaped, superpixels. In other words, the m parameter oversees the balance between the color and spatial distance.

3 Extending SLIC

We propose an extension of SLIC that allows using any distance measure to calculate the color distance. In this extension d_c can be replaced with any distance/dissimilarity measure [4]. For example, raster time-series could be compared with dynamic time warping, while distances between sets of categorical variables could be calculated using Jenson-Shannon distance [11]:

$$d_c = H(\frac{A+B}{2}) - \frac{1}{2}[H(A) + H(B)]$$

where A and B are normalized sets of values characterizing the compared cells, and $H(A)$ and $H(B)$ indicates values of Shannon's entropy [16] for these sets:

$$H(A) = -\sum_{p \in A} A_p log_2 A_p$$

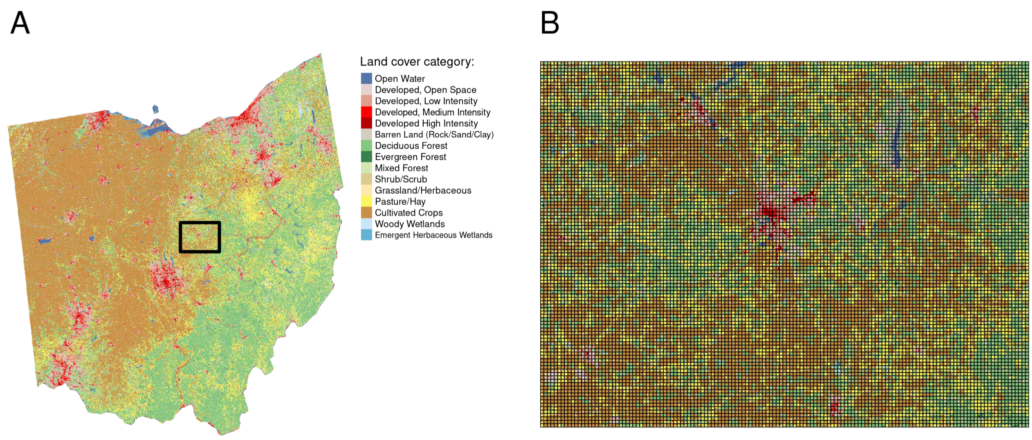
A_p is the pth value of the first of the compared cell.

We implemented the above idea in the R programming language [14] as an open source package **supercells**. The package installation instructions and documentation can be found at https://github.com/Nowosad/supercells. Currently, the package accepts any number of variables (raster layers) and Euclidean, Manhattan, Jensen-Shannon, and dynamic time wrapping distances.

4 Example

The capability of extended SLIC is described below using an example of delineating areas with similar land cover patterns. Importantly, we are not looking for areas with homogeneous land cover, but rather with a similar proportion of different land cover categories. This example focuses on the area of Ohio and uses the NCLD 2016 land cover data [7] (Figure 1:A). The NLCD 2016 for this area has 173,322,810 cells with a spatial resolution of 30 by 30 meters and is represented by 15 categories. Code and data to recreate this example are available at https://github.com/Nowosad/giscience-2021-examples.

Figure 1 (A) A land cover classification of Ohio with a rectangle indicating the area around Mount Vernon, Ohio, (B) A 10 by 10 cells grid overlayed on top of the land cover classification for the area around Mount Vernon, Ohio



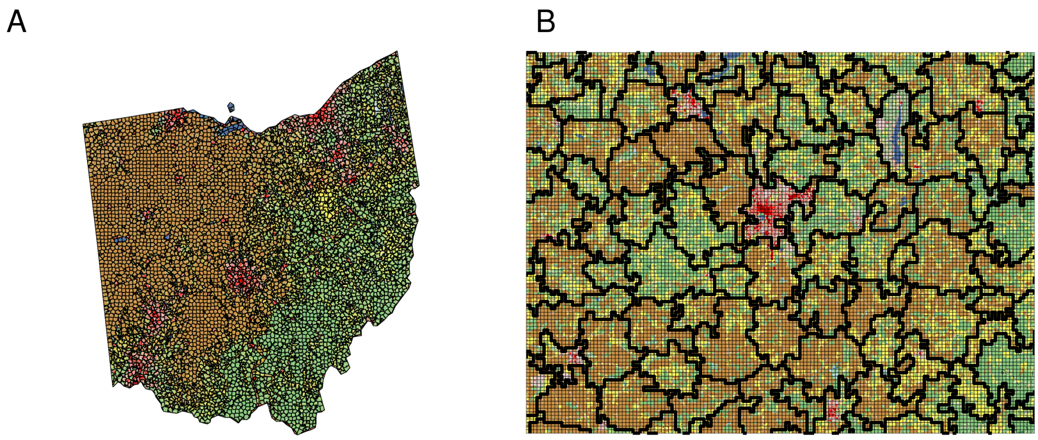
The basic SLIC algorithm should not be used on categorical rasters, as it calculates Euclidean distance between values. Therefore, it would treat Open Water (11) to be more similar to Developed areas (21, 22, 23, 24) than to Woody Wetlands (90). SLIC also aims at finding homogeneous areas (e.g., areas with similar colors) only, while it is not well suited for analysis of areas with consistent heterogeneity (e.g., areas with similar proportions of different land covers).

Our SLIC extension can be applied in the cases mentioned above, given appropriate preprocessing. First, instead of using values of cells directly, the whole area of Ohio is divided into a regular grid, where each grid cell contains a mix of different land cover categories. To keep this mix able to encapsulate meaningful local spatial patterns [3], we decided on its size of 10 by 10 cells (Figure 1:B). Each 10 by 10 cells' area contains a mixture of land covers that can be described by 15 values related to land cover categories. Therefore, we can transform this data from a one-layer raster data of 30 by 30 meters to 15-layers raster data with a resolution of 300 by 300 meters. We also normalized all of the values of the layers to sum to one, as it enables us to calculate a large number of existing distance or dissimilarity measures between pairs of cells [11, 4].

Normalized 15-layer raster data with the resolution of 300 by 300 meters was used as an input to our extended SLIC algorithm, with the Jenson-Shannon distance [11] as the dissimilarity measure. For this example, we set S to 13 and the compactness parameter (m) to 0.3. Figure 2:A shows an output of the extended SLIC algorithm.

The result is 741 superpixels that, depending on the location, encapsulated homogeneous or heterogeneous areas (Figure 2:B). Importantly, all superpixels are internally consistent – we calculated the intra-cluster dissimilarity of each superpixel, δ, based on the average dissimilarity between all cells within its scope [13]. The resulting δ values were normally distributed with the average value of 0.26 and standard deviation of 0.12. Note, that by decreasing the input S value we could lower the average value of δ, while reducing the m value would decrease its variation.

Figure 2 (A) Superpixels created based on the proportions of land cover categories superimposed on the land cover classification of Ohio. (B) Superpixels overlayed on top of the land cover classification for the area around Mount Vernon, Ohio. Land cover legend is available in Figure 1



5 Conclusions

We propose an extension of the Simple Linear Iterative Clustering (SLIC) algorithm that allows the use of any specified distance measure for single or multi-layered spatial raster data. This extension, given a proper distance measure, opens many new research possibilities. The example above shows how it could be used to delineate areas with a similar proportion of different land cover categories based on the Jensen-Shannon distance. However, other distance measures can also be used, such as dynamic time warping (DTW) to create superpixels of homogeneous temporal patterns or earth mover distance (EMD) to delineate similarly ranked areas. The resulting superpixels maintain the average values of their inner cells, and thus, depending on the application, they may also be used in further merging or clustering. This also allows to perform Object-based Image Analysis (OBIA) by classification of the obtained superpixels. On the other hand, even if clustering or classification is not applied, superpixels still offer benefits of dimensionality reduction/data compression. Related R software, supercells, is available at https://github.com/Nowosad/supercells.

References

1 R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and Sabine Süsstrunk. SLIC Superpixels Compared to State-of-the-Art Superpixel Methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(11):2274–2282, November 2012. `doi:10/f39g5f`.

2 T. Blaschke. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(1):2–16, January 2010. `doi:10/d4ksqf`.

3 Barry Boots. Developing local measures of spatial association for categorical data. *Journal of Geographical Systems*, 5(2):139–160, August 2003. `doi:10/fjm8dk`.

4 Sung-Hyuk Cha. Comprehensive Survey on Distance/Similarity Measures between Probability Density Functions. *International Journal of Mathematical Models and Methods in Applied Sciences*, 1(4):300–307, 2007.

5 O. Conrad, B. Bechtel, M. Bock, H. Dietrich, E. Fischer, L. Gerlitz, J. Wehberg, V. Wichmann, and J. Böhner. System for Automated Geoscientific Analyses (SAGA) v. 2.1.4. *Geoscientific Model Development*, 8(7):1991–2007, July 2015. `doi:10/f7m4tt`.

6 Ovidiu Csillik. Fast Segmentation and Classification of Very High Resolution Remote Sensing Data Using SLIC Superpixels. *Remote Sensing*, 9(3):243, March 2017. doi:10/f92zgd.

7 J Dewitz. National land cover database (NLCD) 2016 products. *US Geological Survey data release, https://doi. org/10.5066/P96HHBIE*, 2019.

8 T. Esch, M. Thiel, M. Bock, A. Roth, and S. Dech. Improvement of Image Segmentation Accuracy Based on Multiscale Optimization Procedure. *IEEE Geoscience and Remote Sensing Letters*, 5(3):463–467, July 2008. doi:10/c3jxnf.

9 Noel Gorelick, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 2017. doi:10/gddm6z.

10 GRASS Development Team. *Geographic Resources Analysis Support System (GRASS GIS) Software, Version 7.2.* Open Source Geospatial Foundation, 2017.

11 Jianhua Lin. Divergence Measures Based on the Shannon Entropy. *IEEE Transactions on Information Theory*, 37(1):145–151, 1991. doi:10/djxkkh.

12 Peer Neubert and Peter Protzel Chemnitz. Superpixel benchmark and comparison. 2012.

13 Jakub Nowosad. Pattern-based identification and mapping of landscape types using multi-thematic data. page 17, 2021.

14 R Core Team. *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria, 2021.

15 Ren and Malik. Learning a classification model for segmentation. In *Proceedings Ninth IEEE International Conference on Computer Vision*, pages 10–17 vol.1, Nice, France, 2003. IEEE. doi:10/c6s237.

16 C E Shannon. A Mathematical Theory of Communication. *The Bell System Technical Journal*, 27:55, 1948.

17 David Stutz, Alexander Hermans, and Bastian Leibe. Superpixels: An Evaluation of the State-of-the-Art. *Computer Vision and Image Understanding*, 166:1–27, January 2018. arXiv:1612.01601, doi:10/gcvnsc.