Automatic Sown Field Detection Using Machine Vision and Contour Analysis

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Abstract. The paper proposes a prototype of an algorithm based on the use of machine vision methods, which allows automatic identification and selection of fields sown with agricultural crops on images. The algorithm works with satellite images and consists of two stages. At the first stage, the image undergoes initial processing, after which edge detection and contour finding algorithms are applied to it. At the second stage, the obtained image areas enclosed within the contours are represented as a set of numerical and logical parameters which are used for filtering and classification of the areas.

Keywords: Image processing · Machine vision · Contour analysis

1 Introduction

The need to analyze and control the state of arable land in the north-west of the Caspian Sea has existed for several decades, since the degradation of lands suitable for use as pastures is observed due to the retreat of the sea [1,5]. One of the tasks is to track the use and condition of the fields sown with agricultural crops, instantaneously and in dynamics. Currently, the processing of data from satellite images at facilities in this region is carried out in manual mode. In this paper, we propose an algorithm that allows to automatically detect the areas corresponding to the sown fields on satellite images, as well as to determine their properties for the purpose of further processing, monitoring (e.g. sowing date detection [12] or yield analysis [9]) and assessing their condition.

2 Region Boundaries Locating

2.1 Preprocessing

The image preprocessing consists of the following steps:

1. Bilateral filtering [15] is applied to reduce the amount of noise while preserving the boundaries of objects.
2. The image is converted from the RGB color space to grayscale.

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Bilateral filtering is performed before converting the image to grayscale, since the areas of interest may differ significantly from the neighboring ones in color while being quite similar in brightness. This processing allows more efficient use of edge detection algorithms based on gradient values.

2.2 Contour Detection

For the contour detection, the image undergoes the following transformations:

1. Canny edge detection algorithm is applied [3].
2. The resulting image goes through the erode and dilate stages with a rectangular kernel.
3. Artificial edges are added along the boundaries of the image.
4. The Suzuki contour detection algorithm [14] is applied.

Erode and dilate stages are necessary to close small gaps in contours that may have emerged at the first stage due to insufficient difference in brightness and color between, for example, a sown field and a neighboring natural meadow. The rectangular core of erode and dilate is used because the sown fields that we are looking for in the image have pronounced corners that can be lost when using, for example, an elliptical core.

The edge that runs along the boundaries of the image is necessary in order to create closed contours for fields that have been separated in the middle by the image border, since we only consider the field as a closed region. Figure 1 shows the result of the described process.

3 Region Filtering

The resulting set of contours contains both the sown fields and unseeded fields, along with various natural objects, parts of urban infrastructure and various noise. To distinguish the sown fields from other elements of the set, we need to determine a vector of parameters for each contour, so we can make a decision on the object classification depending on its values.

3.1 Region Properties Selection

We select the following properties of the contour to compose the vector of its parameters:

Closedness. A contour is considered to be closed if its area exceeds its perimeter. The presence of an artificial edge at the borders of the image allows us to close all the fields near it. Any other contour that touches the border of the image in two places (but does not coincide with it) will also be closed.

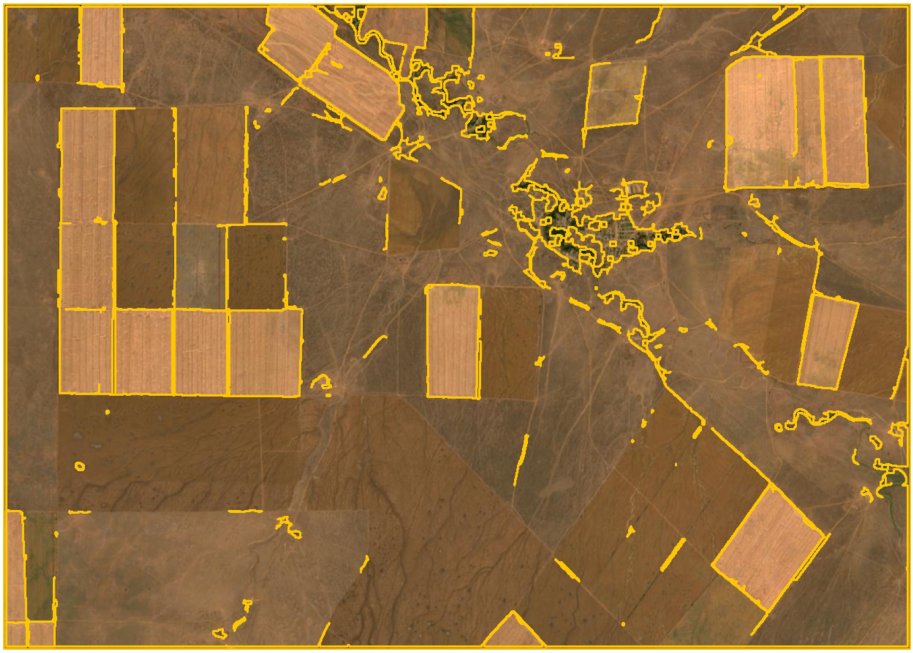

Fig. 1. The obtained raster edges drawn on the original image. (Color figure online)

Area. The area of the region within a contour is an important parameter, since the required fields are industrial and take up a fairly large space. Knowing the scale of the image and having an expert estimate of the minimum size of the industrial field, we can cut off areas that are too small. In addition, due to the presence of edges at the borders of the image, we can get very large closed regions, which area will be comparable to the area of the entire image. They are also easily identified using this parameter.

Parent Region (if exists). If one region is entirely inside another, the larger region is considered the parent of the smaller region.

Minkowski-Bouligand Dimension. We estimate the Minkowski-Bouligand dimension of a region through counting the boxes of different sizes that completely cover the area. The sizes of the boxes are chosen as 2^k for all k from 2 to $p-1$, where $p = \lfloor \log_2 m \rfloor$ and m is the size in pixels of the smaller side of the bounding rectangle of the region.

Median Brightness. We use the median brightness and not the average, since in some cases crops on the field can be partially collected or the field can be partially eroded, which affects the accuracy of the results.

Standard Deviation of Brightness Distribution. Since we locate the boundaries after bilateral filtering, a significant spread in brightness may indicate the presence of a color gradient within the area.

Number of Corners of the Approximating Polygon. We use the Ramer-Douglas-Peucker algorithm [6,11] to approximate the region with a polygon. In addition to counting the number of corners in it, this approximation also allows an efficient storage of the detected regions.

3.2 Initial Filtering

We use the following rules to mark some regions as ineligible for being considered a sown field:

- The region is open.
- The area of the region does not exceed a predetermined minimum threshold.
- The area of the region exceeds a predetermined maximum threshold.
- Minkowski-Bouligand of the region dimension exceeds the specified threshold.

The result of applying these basic filters is shown in Fig. 2.



Fig. 2. Regions left in the set after applying the initial filters. (Color figure online)

3.3 Region Clustering

Applying the Clustering Algorithm. The remaining regions undergo the clustering procedure. Since we do not know the number of clusters, and their sizes can vary greatly, we use the DBSCAN [7,13] algorithm to determine them. Of the remaining three parameters, not used in the previous steps, we use the median value and standard deviation of the area brightness to build the clusters. The clustering result is shown in Fig. 3.

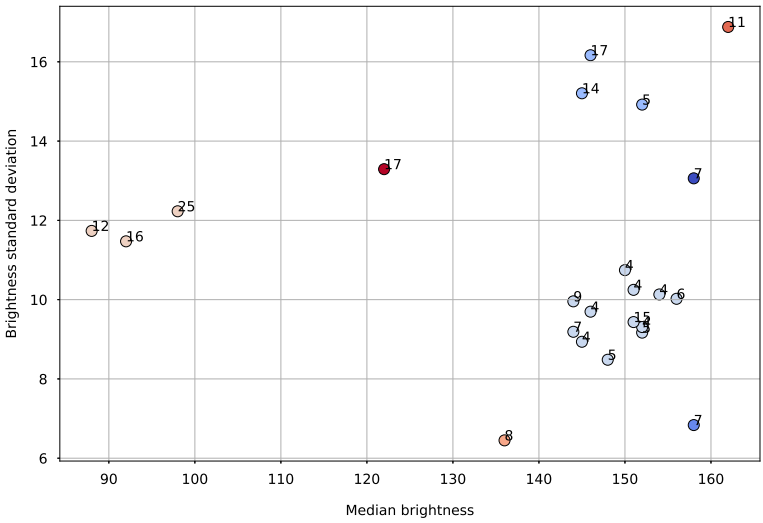

Fig. 3. The result of clustering the regions by the median value and standard deviation of brightness. Areas belonging to the same cluster are highlighted with the same color. Each point is annotated with a number of corners of the Ramer-Douglas-Peucker approximating polygon. (Color figure online)

Clustering Results Processing. For each of the resulting clusters, we calculate the average value of the standard deviation of brightness and the median number of corners of the approximating polygon. Among all the clusters, those for which the value of the median number of corners does not exceed 6 are selected (the fields tend to have a rectangular shape, but this is not always the case), and the cluster with the maximum number of elements in it is selected and marked as the "main cluster". This cluster is considered to contain the desired elements - the areas corresponding to the seeded fields. Among all the remaining areas, ones that meet the following conditions are selected:

- The median brightness of the region differs from the median brightness of the main cluster by no more than two standard deviations.
- The number of corners of the approximating polygon does not exceed 8.
- The parent area, if it exists, does not belong to the main cluster.

These areas are also marked as sown fields. For example, partially harvested or eroded fields fall into this category. The result can be seen in Fig. 4.



Fig. 4. Regions marked as "sown fields" after going through all the steps of the algorithm. Regions that belong to the main cluster are drawn in green. Regions that were subsequently selected are drawn in yellow. Ramer-Douglas-Peucker polygons are drawn in blue. (Color figure online)

4 Limitations and Disadvantages of the Method

4.1 Large Number of Parameters

The main disadvantage of the method is the large number of parameters, the values of which must be somehow determined before using it. According to the stages of processing the original image, they can be distributed as follows:

Preprocessing

- Image scale.
- Color and space restrictions of bilateral filtering.

Region Boundaries Locating

- Parameters of the Canny algorithm (in particular, upper and lower bounds for the hysteresis procedure).
- Number of iterations and kernel size for erode and dilate stages.

Region Filtering

- Minimum area size.
- Maximum area size.
- Maximum Minkowski-Bouligand dimension.

Region Clustering

- Parameters of the DBSCAN clustering algorithm (in particular, the maximum distance between points).

Clustering Results Processing

- Accuracy of polygon approximation by the Ramer-Douglas-Peucker algorithm.
- Maximum allowed median number of corners of an approximating polygons in the main cluster.
- Maximum number of corners of the approximating polygon for the appended regions.

While for some of these parameters (for example, the image scale, the minimum and maximum allowed sizes of the regions, the maximum allowed Minkowski-Bouligand dimension, the accuracy of the polygon approximation using the Ramer-Douglas-Peucker algorithm) sufficiently adequate values can be obtained using an expert judgment, or based on limitations of the initial data (for example, available image scales), for other parameters it is much more convenient to search for them by training the algorithm on a sample of known and pre-labeled data. We do not currently have such a sample.

4.2 Region Distorting

Image filtering allows to get rid of noise, but in the case of a fuzzy border, it can become more blurry even when using filtering algorithms that preserve borders. The erode and dilate stages allow to close open contours, but at the same time distort the boundaries. Both approaches represent a trade-off between false-negative and false-positive results, and the choice of their parameters greatly affects the quality of the algorithm.

In some cases roads are taken as a part of the region, both outside and inside of the actual boundaries.

4.3 Overlapping Regions

As can be seen from the central part of the Fig. 4, sometimes drawn regions are overlapping. In this case, the reason is that the region from the main cluster is inside of one of the appended regions. At the moment, we are not sure how to deal with such areas (leave one of them, leave both, calculate the difference between areas, or add a new heuristic to dynamically determine this behavior) and are awaiting for an expert opinion of the agricultural workers. A similar problem is observed in the case of one of the appended areas being the parent of another (in Fig. 4 this case can be seen in the lower-right corner).

5 Conclusion

The proposed algorithm has shown its fundamental applicability to the available source data. With its help, fields sown with agricultural crops can be automatically located and highlighted on satellite images with sufficient accuracy, and their boundaries are preserved. Its application to a single image makes it possible to estimate the use of arable lands and their parameters, while, by using the algorithm on the same region over the several years period, it is possible to monitor the state of the same agricultural land, and also estimate the number of fields subject to erosion.

Its disadvantages include a significant number of parameters, as well as some distortion of areas. One of the ways to reduce their impact on the quality of the algorithm is training and validation of the method on a training set.

6 Further Work

6.1 Obtaining a Training Set

The presence of a training set will allow finding the optimal parameters of the algorithm, objectively validating the quality of its work, and applying more complex algorithms for filtering the region set based on decision trees, clustering or classifying the objects by metrics which are now used in the rules based on the maximum and minimum thresholds.

6.2 Extended Expert Assessment

Additional involvement of experts in the field of agriculture can help with the selection of new metrics, improvement of existing ones, as well as with the selection or construction of a training set.

Acknowledgements. The proposed algorithm is implemented in Python using the OpenCV [2] image processing library and the Scikit-learn [10] machine learning library. The Matplotlib [8] library was used for graph visualization. We use Copernicus Open Access Hub [4] for satellite images.

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