The technology of agricultural fields remote sensing image segmentation using morphological profiles

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Abstract. Automatic agricultural monitoring requires field borders to be known a priori. Although geoinformation systems contain vector field maps, the annual sowing pattern changes lead to noticeable field border changes. That is why remote sensing image segmentation is widely applied to achieve current field border estimation. However, agricultural remote sensing image segmentation becomes a very challenging task because of an oversegmentation. Oversegmentation consists in a multiple segments formation within one semantically homogenous region and usually arises from local brightness variations caused by relief irregularities, soil tillage variations and local differences in crop growth. The aim of our study was to develop a segmentation technology that would be able to reduce oversegmentation. The technology proposed in this paper includes three stages: feature extraction, segmentation and post-processing. We suggest using any multichannel image segmentation algorithm with two additional steps that might lead to oversegmentation decrease. The first step is feature extraction, which consists in morphological profiles of the normalized difference vegetation index (NDVI) calculation instead of applying simple brightness features. The second step is post-processing procedure, which controls the anthropogenic shape of parcels within the field. To evaluate the decrease in oversegmentation produced by our technology, we chose the basic segmentation algorithm and compared the quality of basic segmentation algorithm (using simple brightness features and without post-processing) with the results of the proposed technology (using morphological profiles and post-processing). The experimental results have shown that proposed technology provides more visually suitable segmentation and reduces the oversegmentation by 3% for morphological profiles with five components. The results of our investigation might be applied in different applications for automatic agricultural monitoring using remote sensing data.

1. Introduction
Field border estimation using remote sensing (RS) data and geoinformation systems (GIS) data plays an important role in automatic agricultural monitoring. The landuse structure noticeably changes annually so that an automatic border refinement mechanism is required as an initial step of automatic
agricultural monitoring. The agricultural field border refinement makes further sowing analysis more precise and robust because the image segments are used instead of individual pixels. GIS data usually serve as a preliminary source of field border information, whereas RS data reflect the current situation. Thus, the analysis of both RS and GIS data can be used to update the field map, which will be further applied in the other steps of agricultural monitoring.

Different image segmentation methods can be applied in agricultural border estimation using RS data [1-4]. The most widespread and yielding methods implement the so-called object-oriented approach [5,6]. This approach utilizes an a priori object border information that can be obtained from the user, another image or algorithm, or from the GIS vector map. A priory information acts as a constraint which helps segmentation to distinguish between the different types of objects in the scene. The other popular group is edge-based segmentation methods [7]. They apply edge detection to provide the segmentation. But these methods are much less useful in the agricultural RS image segmentation because of the brightness variations within a semantically homogenous parts of the field. In other words, these methods assume that there are no false edges inside the object, but actually these edges may arise from the relief height variations or uneven crop shoots. The other two groups of segmentation methods are per pixel segmentation and region-growth segmentation that are also inapplicable for the operational land use monitoring because they often result in oversegmented images with a lots of small segments. To overcome the disadvantages of particular segmentation methods the hybrid approaches have been proposed by several researchers [8-10].

However, it is still an open question for the RS data segmentation how the boundaries of the particular crops inside the field can be estimated. It is clear that the outside field borders change more slowly than the inside borders which separate the particular crop types. Therefore, the outside field borders are more distinguishable, whereas the inside field borders divide the field depending on differences in crop growth stages, relief properties and tillage. Traditional RS image segmentation methods rely on brightness and texture features to describe the homogeneity of the image segment. But the tillage, relief, and crop state variations increase the variation in brightness that may lead to oversegmentation. Thus, the additional a priori information should be applied to reduce the influence of these factors.

In our article, we propose a segmentation technology which utilizes existing GIS map borders as an initial boundary constraint and exploits such additional characteristics as inside border linearity and crop segment connectivity to decrease the degree of oversegmentation. We apply the grid-based region merging segmentation method proposed in [11] as a basic segmentation algorithm. To enhance the connectivity of the segmentation results, we propose to use a morphological profiles as an input features. We suggest to use the normalized vegetation index (NDVI) for the morphological profile feature extraction. To control the linearity of the defined internal segment borders we have developed the post-processing procedure based on least squares approximation for the set of internal border coordinates. If two segments are separated by the rough nonlinear border these segments are regarded as merging candidates on the final stage. The reason for checking linearity comes from the agricultural vehicle movement peculiarity. The machinery usually moves in a straightforward direction along the field. Therefore, the nonlinear borders detected in the field may arise only from brightness variations caused by relief structure or uneven crop state. As a result, the proposed segmentation technique consists of three steps such as morphological profiles feature extraction, basic segmentation algorithm and post-processing. The technology is intended to reduce the oversegmentation of the basic segmentation method.

The following part of our article is structured as follows. In Section 2 we describe our segmentation technology including feature extraction, the detailed description of the basic segmentation algorithm applied in experiments and the post-processing stage. In Section 3 we demonstrate the results of the oversegmentation reduction evaluation for the basic segmentation algorithm and for the proposed technology.
2. Proposed segmentation technology

The proposed segmentation technology aims to refine agricultural field vector map obtained from GIS using RS data. Therefore, the input data include the vector map with the agricultural field borders and the multichannel RS images of the middle (6-30 m) or high (1-5 m) spatial resolution. The input RS images have to be multichannel and contain red (R) and near-infrared (NIR) spectral bands.

According to object-oriented approach, we regard each of the fields in the input vector map separately and use their bounding box to extract the image of the region of interest (ROI). This helps us to localize an area of the most possible border changes around the field and to eliminate atmospheric effects that should be taken into account for the large territory RS images. Moreover, the localization allows reducing segmentation computational load and introducing additional constraints dealing with the size of the segmented object.

Without loss of generality, we will further assume that the input image contains only one field which borders correspond to the bounding box of this field. We regard the initial field boundaries as a binary image called border mask. The border mask has the same size and resolution as the input ROI image. It contains nonzero pixels only inside the original field borders. Both images can be obtained by means of standard image processing operations and GIS software, that is why the process of their forming is not described in this article in detail. The example of the ROI image data and the border mask is shown in Fig.1.

![Figure 1. The example of a) ROI image, b) border mask.](image)

The proposed technology produces a segmentation image in which each of the segments corresponds to a particular crop inside the field and has its own unique integer label. The outside borders of the field might be also corrected inside the ROI area.

The main steps of the proposed technology are feature extraction, basic multichannel image segmentation algorithm and post-processing. The further subsections describe these steps in detail.

2.1. Feature Extraction

At the first stage, we extract features from the ROI image. Extracted features should discriminate vegetation classes, preserve edge and connectivity properties of the segments. To satisfy these requirements, we select a normalized difference vegetation index (NDVI) [12] as the basic feature responsible for vegetation discrimination and morphological profiles [13] as the features responsible for textural information (segment edges and segment connectivity). The overall feature extraction process is described by the following stages:

1) compute per pixel NDVI using the following formula:

$$NDVI = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}},$$

where $\rho_{\text{NIR}}$ and $\rho_{\text{RED}}$ are reflectance values in NIR and R spectral channels accordingly.

2) calculate quantized NDVI value:
\[
\text{NDVI}_Q = \begin{cases} 
\left\lfloor \text{NDVI} \times 100 \right\rfloor, & \text{if NDVI > 0}, \\
0, & \text{if NDVI < 0}, 
\end{cases}
\]

(2)

where \(\lfloor \cdot \rfloor\) is a floor function. The quantization is used to apply the same segmentation algorithm settings that were used for 8 or 16 bit RS images, whereas the original NDVI values are in the range from -1 to 1. The NDVI values lower than zero correspond to non-vegetative types of objects and are not used in agricultural field segmentation.

3) build \(\text{NDVI}_Q\) morphological profiles. A morphological profile \(X\) of image \(I\) is a set of images derived from the input image \(I\) by means of grayscale morphological filters such as opening with reconstruction \(\gamma_R(I)\) and closing with reconstruction \(\varphi_R(I)\) [14]:

\[
X(I) = \left[ \varphi^n_R(I), \varphi^{n-1}_R(I), \ldots, \varphi^1_R(I), I, \gamma^n_R(I), \gamma^{n-1}_R(I), \ldots, \gamma^1_R(I) \right].
\]

(3)

Opening with reconstruction \(\gamma_R(I)\) is a geodetic reconstruction with dilatation followed by the morphological opening of an image \(I\) with the structural element \(SE\) of size \(i\). In a similar way, closing with reconstruction \(\varphi_R(I)\) is implemented as geodetic image reconstruction with erosion followed by the morphological closing of an image \(I\) with the SE of size \(i\). The structural element is defined as a binary image \(\Psi\) of the size \(i \times i\) pixels. If the pixel of the SE has the value 1, it means that this pixel belongs to the SE, otherwise it is ignored, i.e. the SE is regarded as a mask which describes the geometry of the pixel neighborhood. The opening with reconstruction and closing with reconstruction results in images with excluded domes and valleys which size is equal to or less than the size of the SE. Therefore, the bigger size of SE is used, the higher connectivity is obtained. Thus, the size of SE corresponds to the size of local peaks or minima that should be neglected. The details about morphological filters and other operations can be found in [15-17] and are omitted in this article due to the lack of space.

We suggest constructing morphological profiles for the quantized values of NDVI obtained on the second stage of our feature extraction procedure by means of Vicent’s algorithm [15]. This algorithm effectively produces morphological opening with reconstruction. Closing with reconstruction is implemented in dual form.

The morphological profile \(X\) is defined by parameter \(m\) that is the maximum size of the structural element used for its construction. Traditionally, the full morphological profile contains \(2m + 1\) features. In our study we offer to use a short morphological profile (SMP) that contains components computed with the odd-size structural elements and the smallest SE size is 3:

\[
X(I) = \left[ \varphi^n_R(I), \varphi^{n-2}_R(I), \ldots, \varphi^1_R(I), I, \gamma^n_R(I), \gamma^{n-2}_R(I), \ldots, \gamma^1_R(I) \right],
\]

(4)

where \(m\) is an odd number and \(m \geq 3\). The proposed representation for the morphological profile includes only \(m\) against \(2m + 1\) elements as it takes place in traditional representation. This results in faster segmentation and feature space dimension reduction.

To sum up, the extracted features are represented by the \(\text{NDVI}_Q\) short morphological profiles of size \(m\), where \(m\) is the maximum size of SE used for its construction.

2.2. Grid-based region merging segmentation algorithm

To accomplish the proposed technology, basic segmentation algorithm should be defined. This study was conducted for the grid-based region merging segmentation algorithm proposed in our previous work [10]. This algorithm provides multichannel image segmentation and it was successfully applied in agricultural image segmentation using simple brightness features. Here we provide a brief description of this algorithm and define its role in the proposed segmentation technology.
In the proposed technology the initial feature image \( X(n_1, n_2), 0 \leq n_1, n_2 \leq N - 1 \) is SMP with \( m \) components \( X_k(n_1, n_2), k = 1, \ldots, m \). Before the segmentation algorithm is applied, a variance of the features is normalized:

\[
f_k(n_1, n_2) = X_k(n_1, n_2) / \sigma_k, \quad k = 1, \ldots, m,
\]

where \( X_k(n_1, n_2) \) is the \( k \)-th component of feature vector at the position \( (n_1, n_2) \), \( \sigma_k \) is the variance of \( k \)-th feature before normalization. The normalized features \( f_k(n_1, n_2) \) have unit variances.

Grid-based region merging segmentation algorithm works with the normalized feature image as input and consists of two main stages: hypersegmentation and merging. On the first stage the excessive segmentation is produced and on the second stage the adjacent and similar segments are merged. The algorithm simultaneously analyses the feature image \( f(n_1, n_2) \) and the output segment image \( S(n_1, n_2) \) on both stages.

The hypersegmentation segmentation is produced iteratively for the different scales of the pixel position grid, which is defined as \( T_a = \{(n_1, n_2): n_1 \text{ mod } aW = 0, n_2 \text{ mod } aW = 0\} \) where \( A \text{ mod } B \) is a modulo of \( A \) by \( B \). For each of the grid elements, the neighborhood is defined. It includes the pixel positions distant from the current one by \( aW \). The current pixel of the segmented image \( S(n_1, n_2) \) is assigned to the next segment number if all of the neighbor pixels have zero segment index \( S(n_1 \pm aW, n_2 \pm aW) = 0 \). Otherwise, if there are some neighbors with only one nonzero segment index \( s \), the similarity between the current pixel feature vector and the neighbor feature vectors is examined:

\[
\rho(f(n_1, n_2), f(n_1 \pm aW, n_2 \pm aW)) < \epsilon, \quad (n_1, n_2) \in T_a,
\]

where \( \rho(z_1, z_2) = \left( \sum_{k=1}^{m} \frac{(z_{1k} - z_{2k})^2}{\sigma^2_k} \right)^{1/2} \), \( z_1, z_2 \in \mathbb{R}^m \) is a Euclid distance between two feature vectors. If the condition (6) is satisfied, the current pixel \( (n_1, n_2) \) is assigned the same segment index \( s \). If there are several nonzero segment indexes for the neighbor pixels \( (n_1 \pm aW, n_2 \pm aW) \), the similarity between current feature vector and average \( E(s) \) feature vector for each of the neighbor segments is tested:

\[
\rho(f(n_1, n_2), E(s)) < \epsilon, \quad (n_1, n_2) \in T_a, \quad s = \arg \min_{s \in \{S(n_1 \pm aW, n_2 \pm aW) \}} \rho(f(n_1, n_2), E(s)).
\]

The condition (7) defines the segment index \( s' \) assigned to the current pixel \( S(n_1, n_2) \) in this situation. As soon as all pixels in the grid \( T_a \) are operated, the scale of the grid decreases in two times \( a = a/2 \) and the described process is repeated. Hypersegmentation is carried out until \( aW \geq 1 \). As a result the image \( S(n_1, n_2), 0 \leq n_1, n_2 \leq N - 1 \) with tiny and highly homogenous in terms of distance \( \rho(\ldots) \) regions is achieved.

At the merging stage, the algorithm searches the pairs of adjacent segments \( s_1, s_2 \) and analyses average feature vectors of the segments by means of the following condition:

\[
\rho(E(s_1), E(s_2)) < \epsilon.
\]

If (8) is valid, the segments \( s_1, s_2 \) are merged. The algorithm ends with the final segment border pixels refinement using parabolic filter described in paper [11]. This filter is equivalent to the spatial weighting. The closest pixels have the smallest weights and the final segment number is selected as the number of segment belonging to the pixel with minimum weighted distance to the segment's average feature vector.
2.3. Post-processing

The proposed post-processing procedure controls the border shape for derived segments. The key assumption behind the proposed procedure is that human-made parcel within the one agricultural field have linear borders. It comes from the machinery exploitation rules in agriculture. If there are some natural sources of edges in the field, for example, the ditches, ravines and etc., their boundaries have significantly nonlinear form. This fact helps us to understand whether the resulting segments are the separate segments or not. On the post-processing stage we get the derived segmentation image \( S(n_1, n_2) \) and define the set of border pixels \( \{ (n_1, n_2) \mid (S(n_1, n_2) = s_1 \land \exists S(n_1 \pm 1, n_2 \pm 1) = s_2) \} \) for each pair of the adjacent segments \( s_1 \) and \( s_2 \). If this sequence of spatial coordinates is accurately approximated by linear function (the root mean square error of approximation is less than \( W \), where \( W \) is the basic segmentation algorithm parameter), the border between these segments is considered as valid. Otherwise, the average feature values of segments \( s_1 \) and \( s_2 \) are checked using Hotelling criterion for two sample sets [18]. Hotelling criterion defines the statistical significance of the difference between two sample sets in their average values. If the difference is not significant, the segments \( s_1 \) and \( s_2 \) are merged. Thus, the proposed post-processing procedure finds segment borders with nonlinear shape and merges the segments that are insignificantly different in average feature vector value.

3. Experimental evaluation

Our experimental research aimed to define the optimal length of morphological profiles used for feature extraction and to define the effects of the proposed feature extraction and post-processing procedures on the basic segmentation algorithm quality.

We conducted our experimental research using test dataset of 252 agricultural fields in Bogatovsky district, Samara region, Russia. To extract the ROI we used the agricultural field vector map from Agricultural Geoinformation System of Samara Region [19]. The average size of the segmented agricultural fields was 181 hectares and the smallest size was 50 hectares. RS images used in experiments were obtained by Landsat 8 [19] in September 2017 in near-infrared, red and green spectral channels (NIR-R-G). The reference segmentation was done manually.

In our experiments we compared three segmentation scenarios:
1) the proposed technology without post-processing stage,
2) the proposed technology with post-processing stage,
3) the basic segmentation algorithm with brightness of input RS image as input features.

For the proposed technology the morphological profiles of length \( m = 5, 7 \) and \( 9 \) were tested. As for the post-processing, the maximum segment boundary linear approximation error was equal to 3 pixels and the Hotelling criterion significance level was equal to 0.001. The basic segmentation algorithm parameters were \( W = 3 \) and \( \varepsilon = 0.4 \).

The segmentation quality was assessed using reference segmentation by means of the following measure:

\[
Q = 0.5 \left( \frac{1}{K_S} \sum_{i=1}^{K_S} \max_{\Omega \in \Omega_{S_k}} |\Omega \cap S_i| \right) + \frac{1}{K_\Omega} \sum_{i=1}^{K_\Omega} \max_{S \in \Omega_{S_k}} |S \cap \Omega_i|, \tag{9}
\]

where \( \Omega = \{ \Omega_i \}_i \) is ideal reference segmentation, \( S = \{ S_i \}_i \) is the segmentation derived by one the considered segmentation scenarios, \( |.| \) is the amount of pixels in particular pixel set. The quality measure \( Q \) takes values in the range between 0.5 and 1, where the higher value of \( Q \) correspond to the better segmentation.

Figure 2 demonstrates the experimental results for the first and third segmentation scenarios. It can be seen that the average segmentation quality \( Q \) is 0.88 for each of these scenarios. The increase in
average segmentation quality in comparison with the basic segmentation algorithm is 0.35% for the proposed technology with morphological profile of length \( m = 5 \) and without post-processing. The morphological profiles of length \( m = 7 \) and \( m = 9 \) result in 0.08% average segmentation quality increase. Nevertheless, the total number of fields segmented with the quality \( Q \) higher than 0.8 get up by 3% for the morphological profiles without post-processing. This fact proves that NDVI morphological profiles are more effective features in terms of agricultural fields segmentation than simple brightness features.

Moreover, morphological profiles provide more satisfactory segmentation in terms of visual assessment. Figures 3 and 4 illustrate this fact for the first and third scenarios. Higher visual quality of segmentation using morphological profiles is explained by their edge-preservation property. In addition to the high-quality edges, the morphological profiles produce less amount of additional segments, see Fig. 3.

The comparison of the first and second segmentation scenarios showed that post-processing might be eliminated in general case because few numbers of segmentation results were changed after post-processing. In our experiments post-processing remained the average segmentation quality on the same level. The correction after post-processing was made only for morphological profiles with \( m > 5 \). In other words, for the considered dataset the basic segmentation algorithm provides a significant partitioning in terms of Hotelling criterion.

**Figure 2.** The ratio of fields segmented with quality \( Q \) higher than threshold \( T_Q \) for the total number of fields (without post-processing).

**Figure 3.** a) morphological profile of length \( m = 5 \), b) reference segmentation, c) morphological profile segmentation \((Q=0.95)\), d) brightness in NIR-R-G spectral channels, e) NIR-R-G segmentation \((Q=0.92)\).
Figure 4. a) morphological profile of length $m=5$, b) reference segmentation, c) morphological profile segmentation ($Q=0.9$), d) brightness in NIR-R-G spectral channels, e) NIR-R-G segmentation ($Q=0.85$).

Post-processing was done for morphological profiles of length 7 and 9 and demonstrated the potential oversegmentation reduction in the case of irregular relief structure. The example of successful post-processing is shown in figure 5.

Figure 5. The example of successful post-processing: a) morphological profile with $m=9$, b) morphological profile segmentation without post-processing, c) morphological profile segmentation with post-processing, d) brightness in NIR-R-G spectral channels, e) NIR-R-G segmentation.

We expect that proposed post-processing will be beneficial for the oversegmentation reduction in large fields (more than 400 hectares) with the irregular relief structure and this is the topic of our future research.

4. Conclusion
An oversegmentation problem remains the main difficulty for an automatic agricultural monitoring based on remote sensing and geoinformation system data. The main reasons for oversegmentation are
brightness variations caused by different tillage and crop growth conditions. In this paper, we investigated two additional constraints which seem to be helpful in fighting with oversegmentation. These constraints are the linear shape of boundaries between different parts of the field and connectivity retention within each part of the field. We proposed the segmentation technology incorporating these two empirical constraints using least squares border approximation and morphological profiles feature extraction into the basic segmentation algorithm. We applied our grid-based region merging segmentation algorithm as the basic segmentation method to evaluate the quality of segmentation provided by the proposed technology. As for the proposed feature extraction, experimental research confirmed that morphological profiles lead to average segmentation quality increase and visual edge information enhancement in comparison with the basic segmentation algorithm with the simple brightness features. The optimal selection of the morphological profile length parameter was defined as 5, because the longer profiles the less average segmentation quality enhancement. The experimental results of post-processing were shown that for the regarded dataset composed from the fields with the average size of 181 hectares post-processing might be eliminated because few segmentation results were changed after post-processing. This fact is explained by the satisfactory properties of the basic segmentation algorithm in terms of linear segment boundary approximation and Hotelling criterion. However, testing dataset included few examples of large fields (over 400 hectares) and the fields with the relief irregularities. Therefore, the benefits of post-processing could be underestimated. Our further research will be devoted to the segmentation improvement in the case of large fields (with more than 400 hectares) and the fields with the irregular relief structure.

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Acknowledgements
This study was partially supported by the RFBR projects № 16-29-09494, 18-07-00748 and the Federal Agency for Scientific Organizations (Agreement № 007-GZ/43363/26).