AUTOMATIC EXTRACTION OF SUB-BOUNDARIES WITHIN AGRICULTURAL FIELDS FROM REMOTE SENSING IMAGES

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ABSTRACT
An integrated system was developed for the automatic extraction of sub-boundaries within agricultural fields from remote sensing images. The permanent field boundaries are known and stored in a database. The detection of within-field sub-boundaries is carried out on field-by-field basis. The image is filtered using the Canny edge detection filter. The detected edges are then vectorized to generate the straight line segments. To reduce the number of line segments, a line simplification algorithm is carried out. Next, the line segments are associated with the existing field boundaries through perceptual grouping and the within-field sub-polygons are generated based on an iterative decision mechanism. To implement the approach, a software was developed using ANSI C++. The approach was tested in a selected study area of the Karacabey plain in Turkey. The main crops grown in the region include tomato, corn, pepper, wheat, rice, onion, watermelon, cauliflower, pea, and sugar beet. The data used include SPOT4 and SPOT5 HRV images, and the existing field boundaries. For both images, the first component of the Principle Component Analysis (PCA), and the intensity image of the first three bands were analyzed. For the SPOT4 images, the undersegmented fields were found to be slightly more than the SPOT5 images. Of the four segmentation results, the SPOT5–PCA image provided the highest accuracy of 83.8%. However, the accuracy of the SPOT5–Intensity image (82.6%) was not significantly different than the SPOT5–PCA image. On the other hand, the accuracies of the SPOT4–PCA and SPOT4-Intensity images were computed to be 78.8% and 76.2%, respectively.

INTRODUCTION
Per-pixel classification techniques often yield results with limited reliability. The reliability of image classification can be improved by including apriori knowledge about the contextual relationships of the pixels in the classification process. Agricultural field boundaries integrated with remotely sensed data divide the image into homogeneous units of pixels. For each field, the geometry of the boundaries defines the spatial relations between the pixels contained within and enables those pixels to be processed in coherence. Final decision on class assignment of the pixels contained within each field is made based on their coherent processing. This is unlike per-pixel classification where the decision for each pixel is reached independently. Therefore, the conventional per-pixel image classification can be replaced by a classification which operates on field-by-field basis.

In agricultural areas, the permanent boundaries are defined by the roads, trees, canals, ditches etc. and are expected not to change frequently. Therefore, the permanent field boundaries can be used as apriori information to perform image classification in field specific manner. One major problem associated with the field-based classification techniques is that the within field multiple crops. If a field contains multiple crops, the entire field can be classified incorrectly. As the number of fields, which contain multiple crops, increase in a study area the accuracy that can be achieved through field-based classification may decrease. In order to avoid the problems caused by the misclassifications, it becomes therefore, necessary to delineate the within field sub-boundaries.
In this study, we present an integrated system, which was developed to perform within field segmentation for extracting the sub-boundaries within the permanent agricultural fields from remote sensing images. The segmentation procedure is carried out using an edge based methodology within the permanent boundaries of the existing fields, which are available and stored in a database. The sub-fields that enclose the homogeneous cover types are detected using the perceptual grouping rules. First, the within field edges are detected using the Canny edge detection filter. Then, the detected edges are vectorized to generate the straight line segments. Next, the line segments are reduced by means of applying a line simplification algorithm. Finally, the line segments are associated with the permanent field boundaries using a rule based perceptual grouping procedure.

METHODOLOGY

The main steps of the proposed sub-field extraction method include (i) within field edge detection, (ii) vectorization and line simplification, and (iii) perceptual grouping of the line segments.

Edge Detection

The agricultural fields to be analyzed are selected one by one through a database query. For each field, the coordinates of the vertices are stored as a formatted text file. The vector field boundaries and the raster image are integrated by geometric registration. Therefore, for each field, the raster image falling within the field being considered can be selected and processed individually. The small and thin fields, in which no sub-fields are expected, are excluded from further processing. Simply, if the shape factor and the area of a field fall below the predefined thresholds then, the field is not included in the segmentation process. Figure 1 illustrates the image patches of two fields to be further processed for detecting the within field sub-boundaries.

Next, the edges are detected using the Canny edge detector, which provides a connected single line of pixels. The Canny operator requires three parameters; (i) the width of the Gaussian mask, (ii) the upper threshold, and (iii) the lower threshold. In the present case, the lower threshold is selected to be very low and the upper threshold is selected to be rather high because if a narrower threshold range is chosen, the smooth transitions between different crop types may not be detected. On the other hand, it is more logical to remove the noise caused by the over segmentation. Therefore, we recommend that the image used should be over-segmented. In the present case, the threshold values are adaptively determined based on the field sizes.

After conducting the edge detection procedure, a binary image is obtained, in which the white pixels represent the edges and the black pixels represent the others. For each field, the processing operations are carried out using the corresponding image patch only. Therefore, the edge pixels that correspond to the perimeter of the field are masked out and excluded from
further processing because these pixels are also detected as the edge pixels. For field #2140, the image patch, the edge image, and the edge image after the boundary masking procedure applied are illustrated in figures 2a, b, and c, respectively.

![Image](https://via.placeholder.com/150)

**Figure 2**: For field #2140, (a) the image patch, (b) the edge image, (c) the boundary masked edge image, and (d) the vectorized and simplified data.

**Vectorization and Line Simplification**

There are several known methods and algorithms to perform a vectorization process (i). In the present case, the vectorization of the edge image was carried out using the Suzuki algorithm (ii). First, the thinning of the binary edge image is carried out. Then, a chain graph is constructed using the connected eight edge pixels. All the possible lines that may exist within the edge image are extracted by constructing the graphs. Finally, the detected edges are converted into the line segments using the vectorization process and, for each line segment, the coordinates of the end points are determined. After detecting the line segments, a line simplification procedure is carried out. To do that the well known Douglas–Peucker algorithm (iii) is used. Once the line simplification procedure is completed, the remaining lines to be further processed are grouped according to the connectivity and intersection relations between each other. For field #2140, the vectorized and simplified data is illustrated in figure 2d.

**Perceptual Grouping of the Line Segments**

The vectorized and simplified line segments still do not represent the closed regions. Therefore, the unconnected line segments are further processed to detect the within field sub-boundaries. In order to do that the vertices of the line segments are associated with the existing field boundaries and with the other line segments using a rule-based perceptual grouping procedure, which is specifically designed for this study. The procedure consists mainly of two steps that are (i) removing the noisy line segments and (ii) modifying the vertices of the remaining line segments. The logic of the perceptual grouping is illustrated in figure 3 using a sample field, which contains the line segments to be detected for generating within field sub-polygons. The main input set to be processed consists of the contour lines. A contour line contains a group of connected line segments. The input main set (MS) for the sample field given in figure 3 is expressed as;

\[ MS = \{ \text{Contour-A, Contour-B, Contour-C, Contour-D, Contour-E, Contour-F, Contour-G} \} \]

For example: Contour-E = ([E1-E2], [E3-E4]), Contour-A is the existing field boundary.
Figure 3. A sample field that contains the detected line segments to be processed.

The line segment pairs within a contour set and between the contour sets are analyzed and the end points of the line segments are modified (extended and shortened) in order to remove the noisy lines and to construct within field sub-polygons. In addition, the distance, slope, and the intersection between the line segments are also checked. Some of the parameters used to perform the analyses between the line segment pairs are given in figure 4.

Figure 4: Some of the analysis parameters used to construct within field sub-polygons.

The analysis parameters are used through a sequential rule-based process. The rules are summarized as follows:

Rule 1: In each contour set, remove the overlapping and the intersecting line segments.
Rule 2: In the main set, remove those line segments that are close to each other.
Rule 3: Extend the line segment so that it intersects with the existing field boundary.
Rule 4: Extend the line segments to see if they intersect with each other.
Rule 5: Remove those line segments that are not extended and shorter than the threshold.
Rule 6: Shift the vertices so that they intersect with the closest line segment
Rule 7: Remove the dangling line segments.
Rule 8: Remove the overlapping line segments and resolve deviations

For the other rules, the detailed definitions and the algorithmic expressions can be found in (iv). In figure 5, the sequence of the perceptual grouping rules as applied to field #5210 is illustrated.
Constructing the Sub-Polygons

For each line segment, after detecting the coordinates of the vertices and finding the connectivity relations between the line segments, the connected line segments are grouped together such that each group defines a disjoint sub-polygon. This is carried out through a chain tree of the line segments, which is constructed using the connectivity relations of the segments and finding the cyclic paths from a point back to itself in the tree. A cyclic path from a point to itself represents a closed polygon. In the tree structure, each node is a vertex of a line segment and this node has child nodes, which can be directly reached from that vertex. For each vertex, finding all the possible cyclic paths means that constructing all the possible polygons contained by the vertex.

After constructing the sub-polygons, it is likely that a number of polygons will have a small size, which is caused by the noisy lines generated through edge detection. Therefore, the small polygons falling below the predefined threshold are merged with the adjacent larger polygons. This is because it is unlikely that the small polygons represent distinct segments of crop types. The merging process is the last step of the proposed segmentation approach and the final output is obtained after this step. In figure 6, the merging of the small fields to the adjacent larger fields is illustrated for fields #2290 and #4402.

<table>
<thead>
<tr>
<th>Image Patch</th>
<th>Segmented image</th>
<th>Final output</th>
</tr>
</thead>
<tbody>
<tr>
<td>2290</td>
<td><img src="image1" alt="Segmented image 2290" /></td>
<td><img src="image2" alt="Final output 2290" /></td>
</tr>
<tr>
<td>4402</td>
<td><img src="image3" alt="Segmented image 4402" /></td>
<td><img src="image4" alt="Final output 4402" /></td>
</tr>
</tbody>
</table>

Figure 6: The merging of the small fields to the adjacent larger fields for fields #2290 and #4402.
THE IMPLEMENTATION

Software

To implement the proposed field-based segmentation and sub-polygon extraction procedure, Field-Based Image Segmentation Software (FBISS) was developed using Visual C++ 6.0 and Open Computer Vision (OpenCV, Version 4 Beta) Library. The software includes a number of analysis functions, which provide the capability of performing the whole segmentation process. The following operations can be performed using the developed software: Open/Save/Save As/Print Images (several formats), Zoom In/Out, Fit to Window, Full Screen Display, Load Vector File (Formatted Text File), Determine Application and Segmentation Parameters, Perform Segmentation, Display the Results and Intermediate Outputs, Compare Between Truth Segments and Results, Generate Reports of Results (Formatted Text File), and Merge Segments or Fields.

Study Area and Data

The selected agricultural area is located in the Karacabey plain in northwest of Turkey. The area measures 4600×7200 m and contains 514 fields of various sizes. The area is level plain and largely fertile agricultural with a number of crops under cultivation and several pasture fields for feeding the animals. The crops grown in the region include tomato, corn, pepper, wheat, rice, onion, watermelon, cauliflower, pea, and sugar beet. In the region, a land consolidation project was conducted between 1988 and 1992. Therefore, majority of the fields are rectangular shaped, which affects the field-based segmentation procedures. However, despite the land consolidation project conducted in the region a significant number of small sized fields also exist in the area.

The remote sensing data used include the 20m-resolution SPOT4 XS image and the 10m-resolution SPOT5 XS image. The existing vector field boundaries were also available. The sub-boundaries within those fields planted with multiple crops were delineated manually by on screen digitization for a previous study conducted in the department (v). Therefore, this updated field boundary data set was used as the reference to assess the accuracy of the proposed field-based segmentation procedure. Before starting the segmentation procedure, the small and thin fields were excluded from further processing. We found that of the total 514 fields, 222 were small and/or thin and therefore they were not included in the further processing procedures.

To perform the segmentation procedure, the four spectral bands (Green/Red/NIR/SWIR) of the SPOT4 and SPOT5 images were combined using two different methods and, for both image data sets, two separate single band images were generated. These are; (1) the 1st Component of the Principle Component Analysis bands, (SPOT4-PCA and SPOT5-PCA), and (2) the intensity image - (Green+Red+NIR)/3, (SPOT4-I and SPOT5-I)

Accuracy Assessment

The accuracy assessment was performed by overlaying the field geometries obtained through the segmentation process (the result segments) with the geometries of the manually digitized field geometries (the truth segments). The match between the two objects $M_{ij}$ can be expressed as a geometrical mean of the two conditional probabilities of $M_i$ and $M_j$ (vi).

\[ M_{ij} = \sqrt{(M_i \cdot M_j)} \]
\[ M_i = \frac{\text{Area}(i \cap j)}{\text{Area}(i)} \]
\[ M_j = \frac{\text{Area}(i \cap j)}{\text{Area}(j)} \]

$M_{ij}$ gets a value between 0 and 1. The value of 0 means that there is no matching between the two data sets at all, while the value of 1 indicates a complete matching. For each perma-
nent field, a mean percentage (MP) was calculated by selecting the overlapping pairs between the manually extracted sub-fields (truth segments) and the result segments. Therefore, for each permanent field, the mean of the computed MP values was accepted as the assessed overall accuracy, which was named as Verification Parameter1 – (VP1).

Several other parameters were also considered for assessing the results of the segmentation. First, a success criterion was determined by defining a threshold value of 75% for the matching percentage (vi). Those truth segments with a matching percentage higher than the threshold with the result segments were accepted to be successfully detected. The outputs for the other truth segments were considered to be unsuccessful. Another verification parameter used was the ratio of the successfully detected truth segments to all truth segments. This was named as Verification Parameter2 - (VP2).

In addition, the matching percentage averages were calculated for the successfully detected segments (VP3) and for the unsuccessfully detected segments (VP4). Finally, a quantitative analysis was performed between the result segments and the truth segments by means of measuring the over- and under-segmentations.

Results & Discussion

The proposed sub-field detection procedure was carried out using each of the four single band images. For a part of the study area, the result (output) segments and the SPOT4-PCA band with the segments superimposed are illustrated in figures 7a and b, respectively.

![Figure 7. For a part of the study area, (a) the result segments and (b) the SPOT4-PCA image with the result segments superimposed.](image)

The quantitative results are summarized in table 1, which contains the number of over-segmented (OS), under-segmented (US), and equally segmented (ES) fields for the processed 292 fields. For the equally segmented fields, the geometric errors (GE) are also provided in Table 1. The results indicate that neither a significant under-segmentation nor a significant over-segmentation is seen in the outputs. In the segmentation of the SPOT4 images, the under-segmented fields were found to be slightly more than those obtained for the segmentation of the SPOT5 images.

<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>OS</th>
<th>ES</th>
<th>GE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPOT5-PCA</td>
<td>52</td>
<td>60</td>
<td>180</td>
<td>3.5</td>
</tr>
<tr>
<td>SPOT5-Intensity</td>
<td>62</td>
<td>53</td>
<td>177</td>
<td>2.8</td>
</tr>
<tr>
<td>SPOT4-PCA</td>
<td>81</td>
<td>46</td>
<td>165</td>
<td>2.6</td>
</tr>
<tr>
<td>SPOT4-Intensity</td>
<td>95</td>
<td>43</td>
<td>154</td>
<td>2.0</td>
</tr>
</tbody>
</table>
The results of the analyses, which were carried out based on geometrical relations between the detected and the truth segments, are given in table 2, where the overall accuracy (VP1 =83.8 %) is the highest for the SPOT5-PCA image. The values for VP2, which is another accuracy measure, seem to be lower than the overall accuracies. However this parameter must be considered together with VP3 and VP4. The matching percentage averages for the successfully detected truth segments (VP3) are generally very high. This means that the successfully segmented fields have the geometric accuracy of about 95%. Also the unsuccessfully segmented fields have the geometric accuracy of about 50% (VP4), which means that these fields are not completely unsuccessful.

Table 2. The results based on geometrical analyses between the result and the truth segments.

<table>
<thead>
<tr>
<th></th>
<th>VP1 (%)</th>
<th>VP2 (%)</th>
<th>VP3 (%)</th>
<th>VP4 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPOT5-PCA</td>
<td>83.8</td>
<td>70.6</td>
<td>94.6</td>
<td>54.8</td>
</tr>
<tr>
<td>SPOT5-Intensity</td>
<td>82.6</td>
<td>67.5</td>
<td>94.6</td>
<td>54.1</td>
</tr>
<tr>
<td>SPOT4-PCA</td>
<td>78.8</td>
<td>61.5</td>
<td>94.2</td>
<td>52.1</td>
</tr>
<tr>
<td>SPOT4-Intensity</td>
<td>76.2</td>
<td>57.6</td>
<td>93.9</td>
<td>49.3</td>
</tr>
</tbody>
</table>

As can be seen, better performance was achieved for the segmentation of the SPOT 5 images although they have higher spatial resolution than the SPOT 4 images. When the performance of the intensity and the PCA images were compared, it was found that the PCA images provided slightly better results than the intensity images. It appears that the PCA images contain higher contrast and sharper transitions between the crop fields. Therefore, these might be the reasons for achieving better results from the PCA images.

CONCLUSIONS

The performance of the proposed field-based segmentation technique strongly depends on the performance of the edge detection. Better results can be obtained if the edge detector successfully detects the edges. On the other hand, unsatisfactory results can be obtained if the output of the edge detector contains a large amount of noisy edges or does not contain the proper edges, which might form the missing boundaries.

For both the SPOT4 and SPOT 5 images, the accuracy was computed to be 80% ± 5%. The over-segmentation was largely caused by the erroneously detected edges and also the modifications (Rule 4) applied on them. On the other hand, the under-segmentation was largely caused by the missing lines that are difficult to be detected by the Canny edge detector, the erroneously deleted line segments through perceptual grouping, and the erroneously merged sub-fields. In addition, the transformation of the multi-spectral satellite images into a single band image might have also caused the loss of information.

The accuracy of the proposed field-based segmentation technique can be improved. An edge detection technique to be applied on multi-band images can be developed. In addition, the rules of the perceptual grouping can be improved. The authors believe that the proposed field-based segmentation is a starting point for the development of a high performance field-based image analysis operation that includes both the segmentation and the classification procedures.

REFERENCES


