Agricultural Field Border Line Retrieval Using Optical and SAR Imagery

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Abstract. This work introduces a workflow to retrieve agricultural field border lines from remote sensing images in a fully automatic manner. The methodology builds upon the joint usage of optical and SAR images and is composed of three main processing blocks: (1) Pre-processing of image data including a geometric adjustment of the optical images w.r.t. the highly accurate SAR data, (2) Field border line extraction based on a novel definition of stable features and a custom-tailored segmentation algorithm. (3) A feature-based matching principle that aligns the field border lines to a reference GIS dataset. The proposed framework is evaluated on TerraSAR-X (SAR) and optical RapidEye imagery, yielding sufficiently accurate agricultural field border lines.

Keywords. Field border lines, multi-modal matching, RapidEye, TerraSAR-X.

1. Introduction

Agricultural parameter retrieval is an important task in GMES. One pre-requisite is the extraction of field border lines from remote sensing data so that change detection, surveillance, or crop monitoring of the individual agricultural fields become possible. In addition, such extracted border lines should be automatically registered to existing GIS data to allow efficient updating.

The presented methodology for field border line retrieval builds upon the joint usage of optical and SAR images. The core concept of this joint usage is to fuse the highly precise 2D geolocation accuracy of SAR images [1], [2] with the spectral information of optical images. Therefore, a three step approach is introduced and the corresponding workflow is sketched in Figure 1:

- SAR images are geocoded and stored as geo-referenced image stacks. Optical images are geo-coded as well, except in cases where they are already delivered as geo-coded products. Then, they are additionally co-registered to remove residual geolocation inaccuracies and they are adjusted radiometrically. These optical stacks are then registered to the SAR stacks by employing a multi-modal matching principle described in [3]. Therefore, the 2D geolocation accuracy of the optical images is adjusted to the SAR images.
- Second, the geometrically refined optical data stack is used to extract stable features, i.e. edge information that is stable over multi-temporal image acquisitions. These stable features are then used to iteratively extract the field border lines.
- Third, a feature-based matching principle is employed to align the extracted field border lines with GIS-based border lines, i.e. vector data, utilizing the coherent point drift method [4].

For validation, satellite data from TerraSAR-X (SAR) and RapidEye (optical) were acquired for two test sites. Results show that image matching between SAR and optical images is possible with the so-called mutual-information cost function known from probability theory, introduced in the field of computer vision by [5]. Field border line extraction based on stable features is feasible and
the matching to available GIS border lines is possible with high accuracy. The idea of using multi-temporal optical data is stimulated by the fact, that field borders are changing within the seasons due to phonological effects and that neighbouring fields could have very similar properties only when observing the scene at one point in time. Therefore, employing multi-temporal data increases the overall accuracy.

Figure 1: Our proposed workflow showing the three main processing steps: (1) Pre-processing, (2) field border line extraction and (3) registration of the border lines to reference GIS data.

2. Methodology

Three main steps (cf. Figure 1) are proposed to efficiently extract field border lines from multi-temporal optical and radar images. First, the images are pre-processed to achieve geometrically coherent and accurate data. This step also involves a relative radiometric adjustment. Second, field border lines are extracted by means of an edge based image segmentation algorithm. Third, the field border lines, i.e. vector information, are co-registered towards an existing GIS vector layer.

2.1. Data pre-processing

2.1.1. Co-registration of multi-temporal optical imagery

The geometry of ortho-rectified optical satellite data is frequently not satisfying, as errors of several (tens of) pixels may be observed for instance in very high-resolution optical data [3]. To co-register multi-temporal images of the same optical sensor, a rather simple approach can be used since the spectral properties are very similar at least in some regions in the images (spectral properties are of course varying due to the phenology of vegetation). The proposed algorithm is based on matching automatically extracted interest points using normalized cross-correlation as the cost function. Backmatching is performed to detect incorrect matches. Then the parameters for a linear transformation are estimated using robust statistics.

2.1.2. Radiometric adjustment of multi-temporal optical imagery

Optical images are normally radiometrically calibrated. However, due to atmospheric properties and due to different illumination of the sun during the seasons, the individual spectral bands show diverse brightness over multi-temporal acquisitions. Therefore, a radiometric adjustment w.r.t. a reference scene is applied by a linear regression of the pixel values of manually defined regions. Those regions are selected over radiometrically stable areas, such as forests. An alternative would be to employ algorithms that automatically detect such stable regions using a correlation measure.
However, this is not in the focus of this specific work. After the adjustment, all images share the same brightness properties and are therefore suitable for further processing.

2.1.3. SAR pre-processing

The SAR images are ortho-rectified using the highly precise sensor models and the SRTM digital surface model to define the height of the terrain. The geo-coding procedure is a direct method and does not need any additional information (like GCPs) since the SAR sensor model is very precise [1], [2].

2.1.4. Co-registration of optical to SAR imagery

The aim of this co-registration is to increase the absolute 2D geolocation accuracy of the optical image stack by relating the stack to SAR images. This calibration method is described in our previous work [3] and builds upon the highly accurate SAR sensor model. The main steps involve a custom-tailored pre-processing method based on bilateral filtering, to reduce noise and to eliminate small details from the optical images that are not available in the SAR images, a histogram compression method and a multi-modal point matching using an area mutual-information similarity measure. Due to accuracy deficiencies of the SRTM, DSM where especially buildings and vegetation structure are absent, objects above the surface are displaced in SAR range direction. To compensate this effect, SAR images acquired from ascending and descending orbit, where such displacements occur in a similar but opposite disposition, are fused, so that this effect could be averaged out. A more detailed algorithmic description and an evaluation of results can be found in [3].

2.2. Field borderline extraction

Before applying the field borderline extraction algorithm the optical images are smoothed using the bilateral edge-preserving smoothing filter. This filter preserves the field border lines, while simultaneously removing small artifacts (cf. [3]). To ensure that such algorithm can deal with multi-temporal images, all bands of all images are stacked together. E.g. seven RapidEye images with five bands each form one stack with 35 bands. To extract the field border lines, a stability image is derived from this smoothed stack of images, highlighting pixels of large and relatively constant edge magnitude. The main concept is to derive edges in the different image bands using the Canny edge detection algorithm [6]. Each pixel belonging to an edge is set to the edge strength. Next, for all bands the mean edge strength and standard deviation are extracted. Stable features S for the image I are then gathered by clipping 1% of the highest values of the mean and standard deviation images and converting them to the domain [0,1]:

$$S(I) = \frac{\mu(I)}{(1 - \sigma(I)) + 1}$$  \hspace{1cm} (1)

In addition, the stability image S is converted into a binary mask by taking the 12.5% of strongest edges (both thresholds were set manually to our best knowledge based on several variations). To remove small edges a region labelling approach is applied [7]. Regions with a size smaller than 15 pixels are discarded. A visual example is given in Figure 2 showing a subset with 1000x1000 pixels.
Starting from the binary stability image the regions of agricultural fields should be extracted. The developed algorithm is given below in Algorithm 1 and is based on an iterative procedure.

<table>
<thead>
<tr>
<th>Algorithm:</th>
<th>Field border extraction and image segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input:</td>
<td>Edge image</td>
</tr>
<tr>
<td></td>
<td>Edge magnitude image</td>
</tr>
<tr>
<td>Output:</td>
<td>Image segmentation</td>
</tr>
<tr>
<td></td>
<td>Boundaries for each object</td>
</tr>
<tr>
<td>1:</td>
<td>For a given number of iterations</td>
</tr>
<tr>
<td>2:</td>
<td>Take edge image and calculate the distance image</td>
</tr>
<tr>
<td>3:</td>
<td>For all pixels with distance equals one</td>
</tr>
<tr>
<td>4:</td>
<td>Construct a new edge if edge magnitude larger than a threshold</td>
</tr>
<tr>
<td>5:</td>
<td>Label the inverted edge image</td>
</tr>
<tr>
<td>6:</td>
<td>For all regions</td>
</tr>
<tr>
<td>7:</td>
<td>If area of region is larger than a threshold</td>
</tr>
<tr>
<td>8:</td>
<td>Extract the region</td>
</tr>
<tr>
<td>9:</td>
<td>Enlarge the region by one pixel using dilation</td>
</tr>
<tr>
<td>10:</td>
<td>Fill the region</td>
</tr>
<tr>
<td>11:</td>
<td>Extract region boundary pixels</td>
</tr>
</tbody>
</table>

Algorithm 1: Field border extraction and image segmentation.

For each iteration, new suitable edge pixels are added. After convergence or after a given number of iterations, the resulting binary image is segmented.

In the first step, the stability edge image (cf. Figure 2 (d)) is taken and a distance transform is calculated. For the proposed method the ‘chessboard’ distance works best, since horizontal, vertical and diagonal neighbours should be treated equally (when using the Euclidian distance a diagonal step would have the distance of \( \sqrt{2} \) while horizontal and vertical would have 1). Then, all pixels with a distance of 1 are scanned and set to new edges if the underlying edge magnitude is above a threshold, where \( 1/8 \) is used (this parameter was set empirically).

In the second step, the edge image is segmented into regions. For doing so, a region labelling is applied on the inverted edge image. For each of the regions larger than 100 pixels the corresponding binary region is gathered. Then this region is enlarged by one pixel using morphology, a dilation with a diamond shaped structuring element to be precise. The region must be enlarged as the boundary shrinks in the inversion process. Next, holes in the region are filled and the boundary of this new object is extracted.
The result consists of image segmentation and of individual object boundaries illustrated in Figure 3.

![Figure 3: Examples of intermediate results of the proposed segmentation algorithm.](image)

### 2.3. Co-registration to GIS

The field border lines extracted from optical data stacks are available as binary images at a given ground sampling distance (GSD) and in a certain map projection. Therefore, the first task in the GIS update procedure is the conversion of the GIS vector data into a binary image of same map projection and GSD via rasterizing the boundary of those vectors. As a result two images are available holding the GIS contours and the extracted contours. The alignment procedure itself takes those 2D points or edge chains and performs a feature based matching. Simple algorithms like the iterative closest point algorithm (ICP) [8] yield unsatisfying results (e.g. it often does not converge or it approaches into a local minima, an incorrect solution). Therefore, a more complex algorithm should be employed, namely the coherent point drift (CPD) method [4]. The outcome of such feature based matching is a transformation which maps the input field borders (the one extracted from the optical data stack) to the reference GIS vectors. In our experiments a linear transformation, such the affine transformation, was sufficient for warping one vector layer onto the other.

### 3. Test sites and data

Two test sites were chosen in Graz, Austria and in Brandenburg, Germany. For both areas multi-temporal RapidEye images with 5 bands each were acquired together with multi-temporal TerraSAR-X Stripmap imagery in 2009. The optical images were delivered as ortho-rectified products with 5 meters GSD, whereas the TerraSAR-X imagery was delivered in raw format and was ortho-rectified to 5 meters GSD by the authors using the SRTM DSM. The reference GIS field border lines were manually measured from high resolution ortho-photos with 1 meter GSD.
(about 1900 polygons for Graz and 1100 for Brandenburg). Overall, the dataset consists of 33 images with approximately 33 GB of information.

4. Results

The presented topic involves many intermediate steps. Therefore, the results of the pre-processing methodologies are only given on an exemplary level and the analysis is focused on the field border line extraction method and on the GIS registration.

4.1. Data pre-processing

4.1.1. Co-registration of multi-temporal optical imagery

Quantitative results of the co-registration process for optical imagery are given in Table 1. The two underlying images are shown in Figure 4. The RMS values are reduced from 5 meters to less than 1.5 meters, which corresponds to one third of a pixel.

<table>
<thead>
<tr>
<th></th>
<th>Mean (before)</th>
<th>RMS (before)</th>
<th>RMS (after)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>East</td>
<td>North</td>
<td>East</td>
</tr>
<tr>
<td>RapidEye</td>
<td>2.9</td>
<td>-4.3</td>
<td>3.2</td>
</tr>
</tbody>
</table>

Table 1. 2D geo-location displacements and RMS values between two RapidEye images of the test site Graz given in meters.

4.1.2. Radiometric adjustment of multi-temporal optical imagery

The results of the radiometric adjustment are visualized in Figure 4. The corresponding “correction” parameters are given in Table 2 for every RapidEye band.

<table>
<thead>
<tr>
<th>Band</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offset</td>
<td>988.6</td>
<td>592.4</td>
<td>245.3</td>
<td>892.7</td>
<td>2012.3</td>
</tr>
<tr>
<td>Scale</td>
<td>1.042</td>
<td>1.168</td>
<td>1.131</td>
<td>1.049</td>
<td>1.290</td>
</tr>
</tbody>
</table>

Table 2. Parameters of the relative radiometric adjustment between two RapidEye images shown in Figure 4.

Reference scene, 05-10-2009
Input scene before adjustment, 08-08-2009
Input scene after adjustment

Figure 4: Radiometric adjustment for test site Graz.
4.1.3. **SAR pre-processing**

The TerraSAR-X images were ortho-rectified to 5 meters GSD employing the SRTM DSM and then smoothed with the bilateral filtering adapted for a multiplicative noise model [3].

4.1.4. **Co-registration of optical to SAR imagery**

Table 3 shows the mean 2D displacements, RMS before and after co-registration using a translation only. For the exemplary RapidEye image, the initial displacement of about 20 meters drops down to about 3 meters, i.e. well in the subpixel range of the underlying ortho-image and almost corresponding to the reference TerraSAR-X Stripmap data accuracy [1], [2].

<table>
<thead>
<tr>
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<th>Mean (before)</th>
<th>RMS (before)</th>
<th>RMS (after)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>East</td>
<td>North</td>
<td>East</td>
</tr>
<tr>
<td>RapidEye</td>
<td>20.2</td>
<td>16.3</td>
<td>20.5</td>
</tr>
</tbody>
</table>

4.2. **Field borderline extraction**

Figure 5 illustrates our field segmentation results, which are the input scene, the pure segmentation, the segmentation superimposed on the input image, and the GIS reference field border lines superimposed on our segmentation. Visually, the segmentation fits the image very well. Figure 6 gives the convergence properties of our algorithm. It can be seen, that it converges after 10 to 15 iterations.

![Figure 5: Visualisation of the segmentation results for a subset of test site Brandenburg.](image)

![Figure 6: Plots showing the fast convergence of the segmentation algorithm. Shown are the number of grown, i.e. new, edge pixels per iteration and the number of extracted regions.](image)
4.3. Co-registration to GIS

The co-registration of field border lines to the reference GIS layer starts with a binary field border line definition as shown in Figure 7. In Figure 8 the correspondence of those data sets is shown before and after applying the feature based registration procedure.

Figure 7: An exemplary RapidEye image patch of the test site Brandenburg is visualised (left) together with the extracted field border lines (middle). The reference GIS field border lines are show as well (right).

Figure 8: Visualisation of the initial situation showing an additional artificial rotation of the input data set (left) and the results of registration (right). The extracted border lines are shown in green and the reference GIS border lines in red. On bottom one band of the RapidEye image is shown before and after registration with superimposed GIS data for test site Brandenburg.
For speedup it would be beneficial to take only very \( n \)-th point and match those reduced point sets (taking every \( n \)-th point is denoted as using a step size of \( n \)). Figure 9 visualises the percentage of correctly matched points with respect to the step size and also gives the remaining mean residual errors for all datasets. It can be seen, that the speedup comes with a loss of accuracy, as a lower percentage of points are matched with increasing step size. Also, the residual error increases with the step size. One reason for this behaviour stems from the sampling procedure which is independent for search und reference point sets. Therefore, the chance that a corresponding point from one set does not exist in the other set increases with the step size.

![Figure 9: Evaluation of the matching results. Percentage of correctly matched points (left) and remaining residual errors of all matches and of inliers only with respect to the step size (right).](image)

It should be noted that the real accuracy of the proposed matching algorithm is of higher quality than the numbers given in Figure 9 (right), for three reasons:

- Input data for matching is discretized to integer coordinates, therefore introducing an initial location error of ±0.5 pixels
- The proposed usage of a step size for speedup increases the residual error as in worst case points are sampled alternating and therefore introducing a bias of the half step size
- The shown residuals result from calculating the smallest distance of points between both datasets. Whereas, on a field border line there are an infinite number of points between two discrete boundary points, so that the real residual could be much smaller
- The matching procedure aligns two point sets. Thus, if different points on ground are detected, the matching can only align those points. A classic example would be a road separating two fields. In the GIS set, two fields are delineated with one sharp line, while the proposed field border line extraction may find two field outlines left and right of the road (cf. Figure 7, lower right part of the shown border lines).

Overall, with a step size of eight or lower, about 95% of the points are matched correctly (cf. Figure 9) while the remaining points do not have a corresponding partner in the other image. The mean residual error with 1.9 pixels for a step size of two is very accurate, since the initial uncertainty is 0.5 pixels independently for both images (from discretization process) and up to 1.0 pixel bias could originate from the step size.
5. Conclusions and outlook

A workflow was presented which is able to extract field border lines from remote sensing images and relate those border lines to reference GIS data. One key issue was the use of SAR data to enhance the 2D geolocation accuracy of optical images. The other novelty was a field border segmentation algorithm that incorporated multi-temporal optical imagery to form stable features. Those features were then used to extract the field border lines and to segment the fields. It was also shown that such vector information can be registered to GIS data by means of feature based matching.

Overall, it was shown that field border lines could be extracted from pure feature based information. Nevertheless, some issues remain that limit a commercial exploration of the proposed method due to resulting inaccuracies:

- Pure feature based methods have problems to distinguish regions of agricultural fields from other regions, e.g. from lakes
- Very small fields, like in the test site Graz, are sometimes not retrieved especially in the case when the contrast is low to the adjacent regions
- Adjacent fields holding the same plants and therefore represented with very similar pixel values cannot be separated

In conclusion, such retrieved field border lines cannot be used to automatically update GIS data reliably. However, the presented method can assist the GIS update in a semi-automatic workflow. In this case, the user would get the retrieval results superimposed on an image and can easily refine those results. Such manual “error correction” is a lot more efficient than performing the whole measurements by hand.

References